Cognition in embodied and situated nervous systems.
Lecture 1: Foundations

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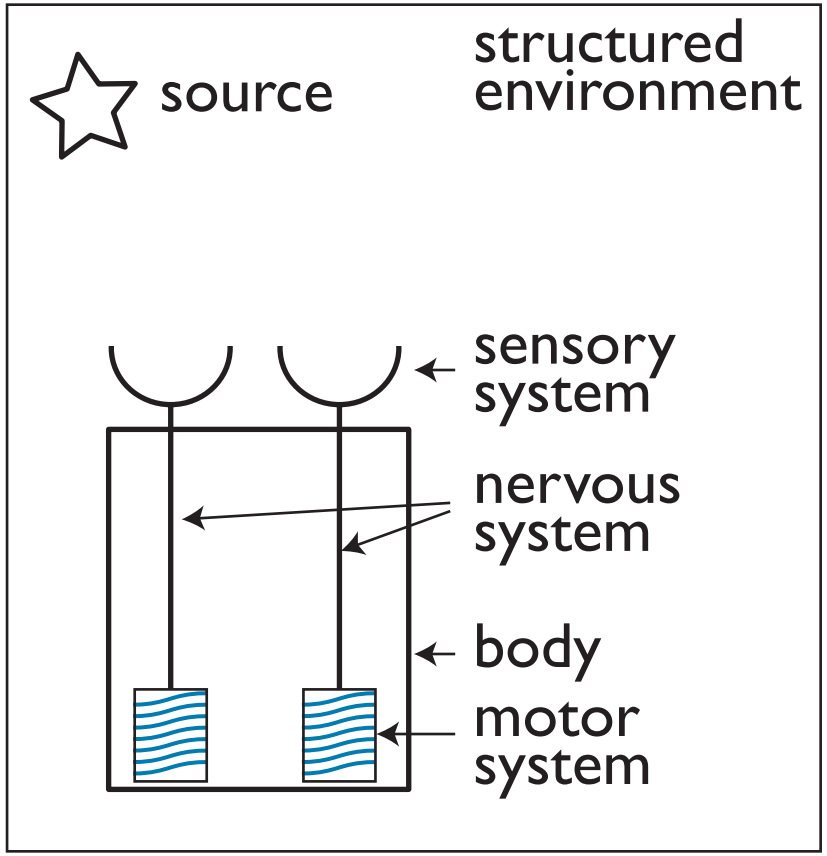
- Lecture 1 Foundations
  - Braitenberg vehicles
  - neural dynamics
  - dynamic field theory (DFT)
  - back to Braitenberg
- Lecture 2 Toward higher cognition
  - embodied cognition
  - multi-dimensional fields for association/transformation
  - sequences
  - architectures
  - higher cognition

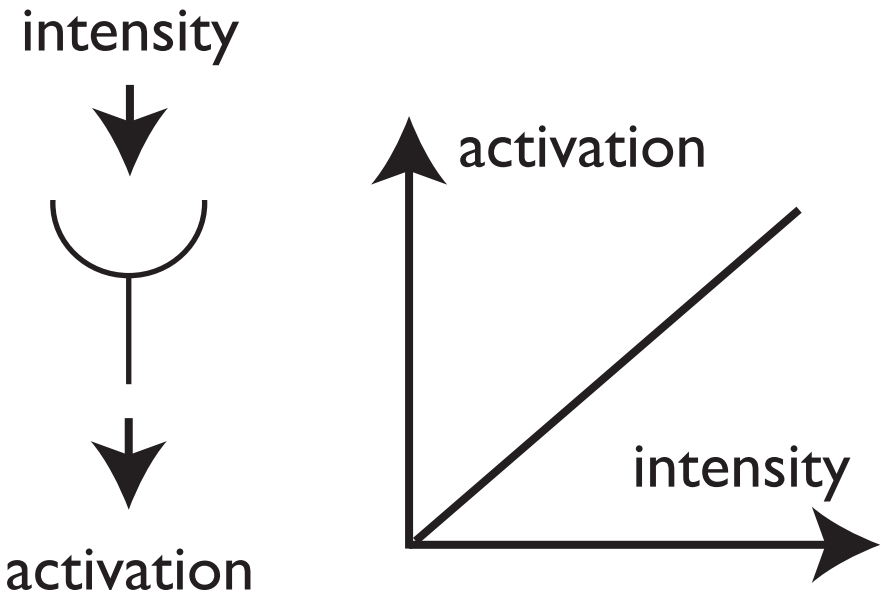
Braitenberg vehicles

- =embodied nervous systems with:
  - effectors
  - sensors
  - a nervous system
  - a body
- + situated in a structured environment
- = emergent function



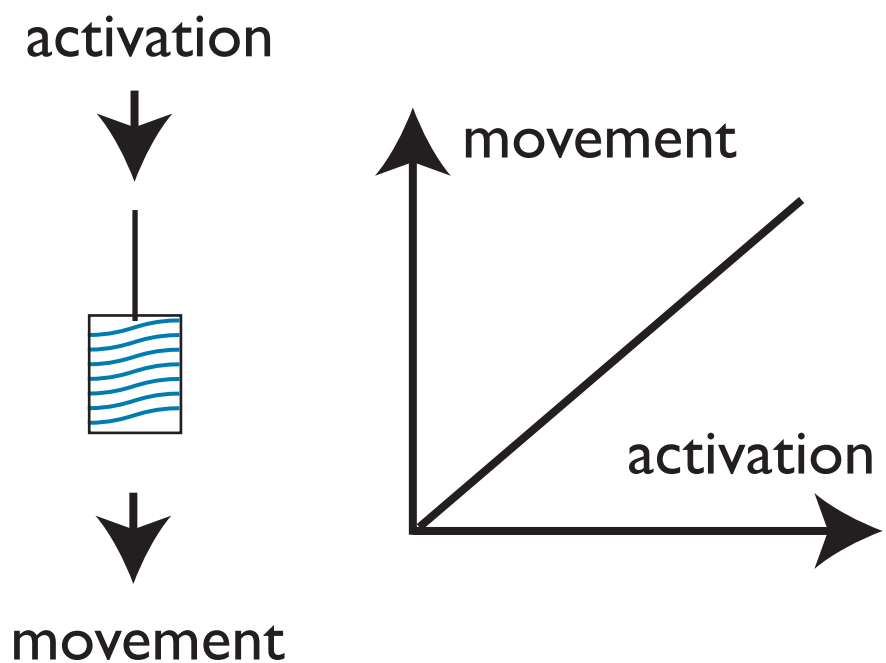
Sensors

- are characterized by a sensor characteristic= relationship between the physical quantity (e.g. sound, luminance, chemical concentration, mechanical pressure....) and an inner state variable: "activation"



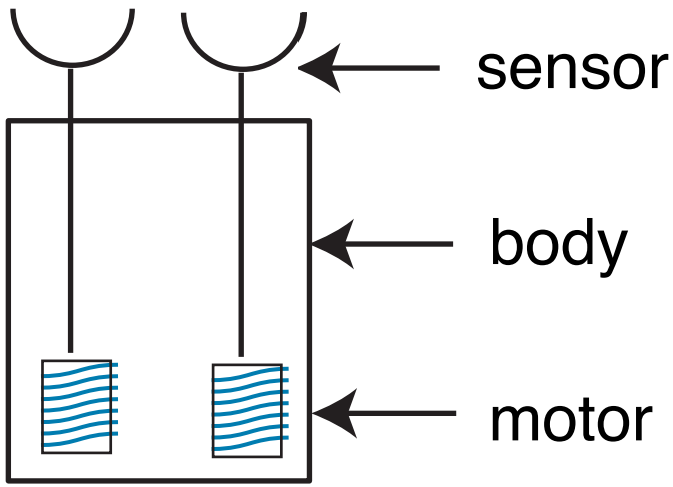
Effectors

- are defined by a motor characteristic = a functional relationship between an inner activation state and a physical effect generated in the world (e.g., turning rate (rotations per minute rmp), force level, stiffness, …)



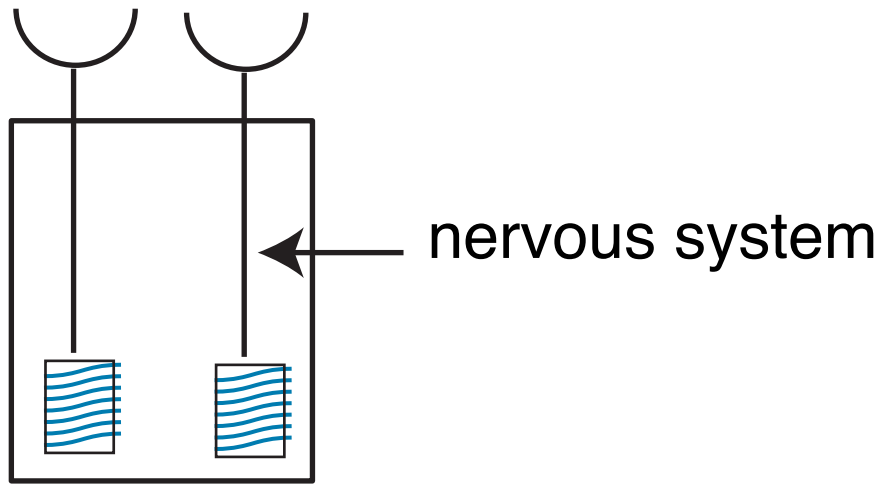
Body

- mechanically links the sensors to effectors



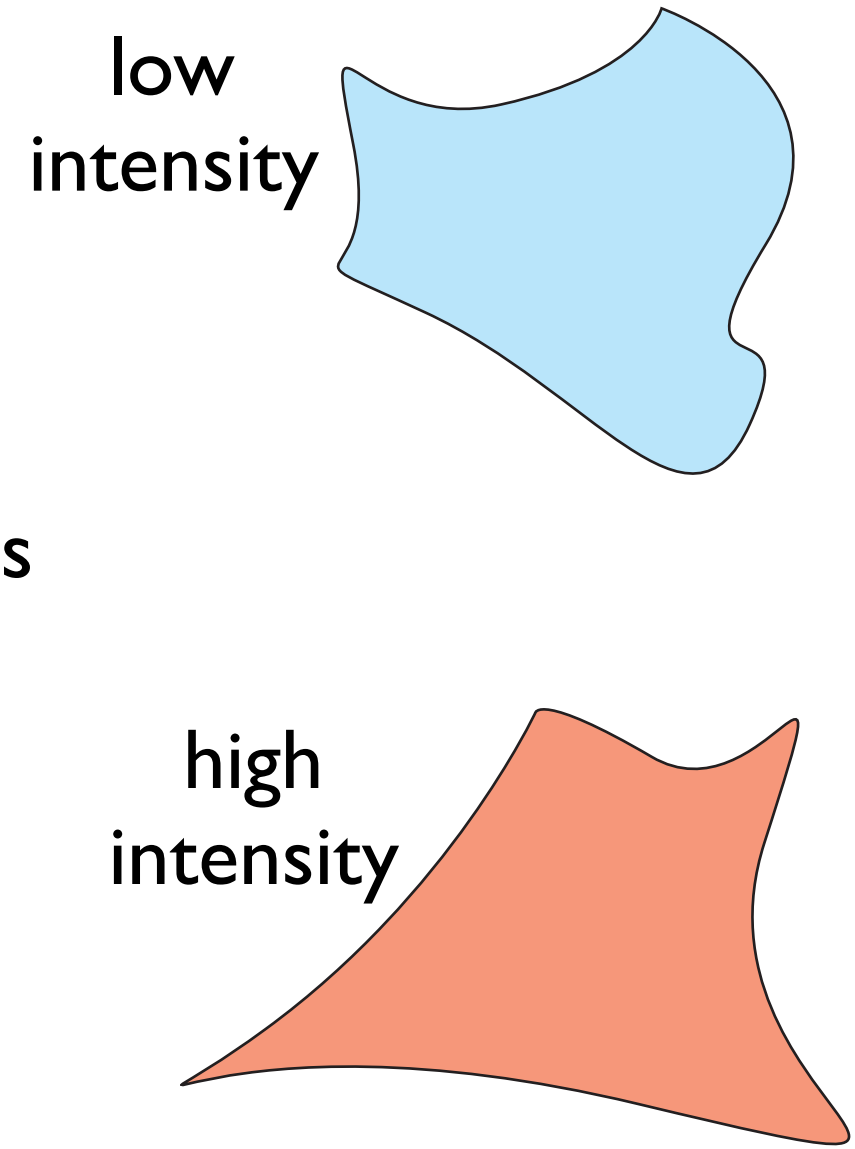
Nervous system

- links sensors to effectors through the inner activation state

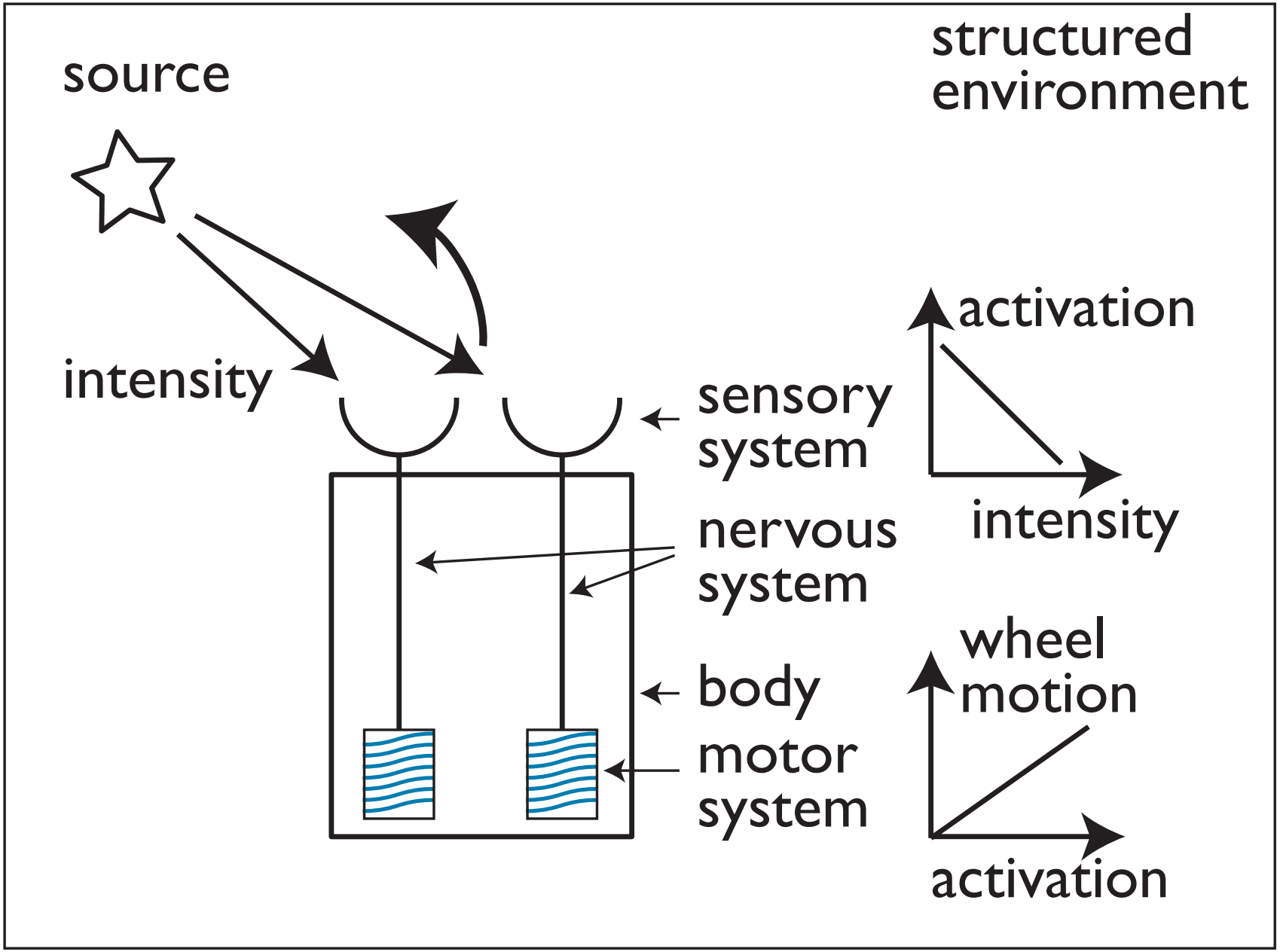


Environment

- is structured at a relevant scale in terms of the physical variables to which organism is sensitive

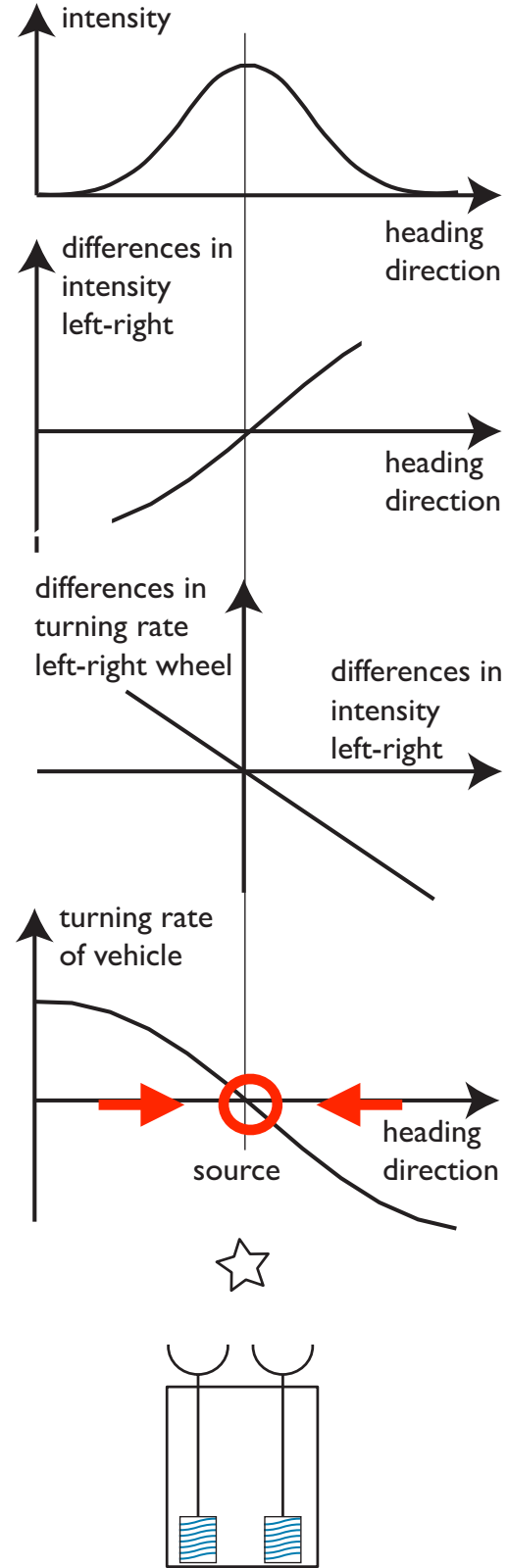


Emergent behavior: taxis



Behavior emerges as the solution of a dynamical system

- feedforward nervous system
- + closed loop through environment
- => (behavioral) dynamics



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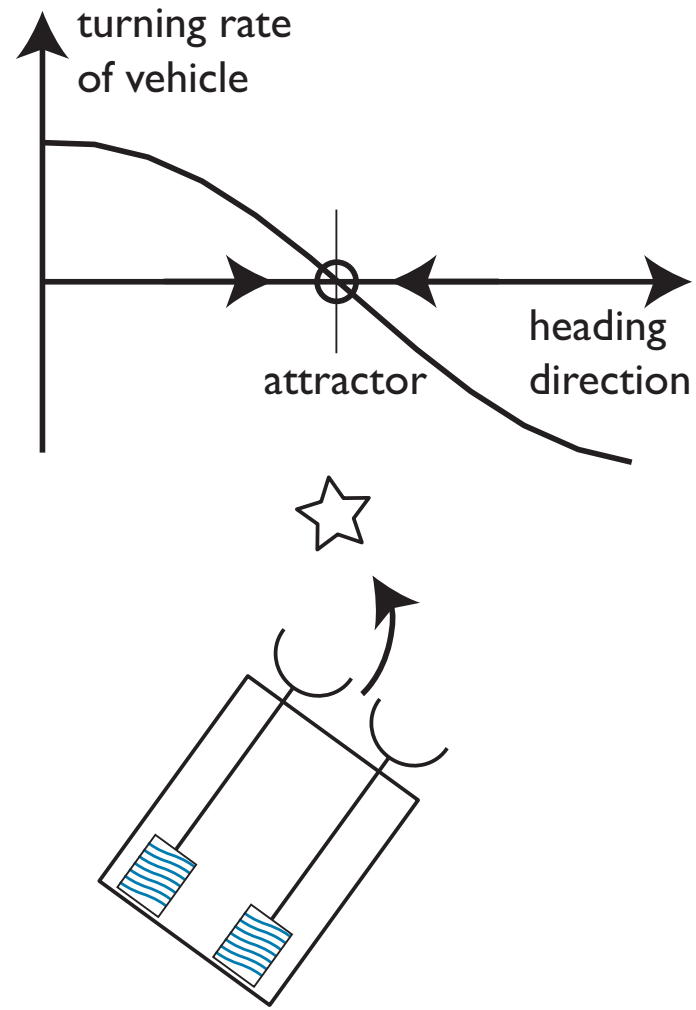
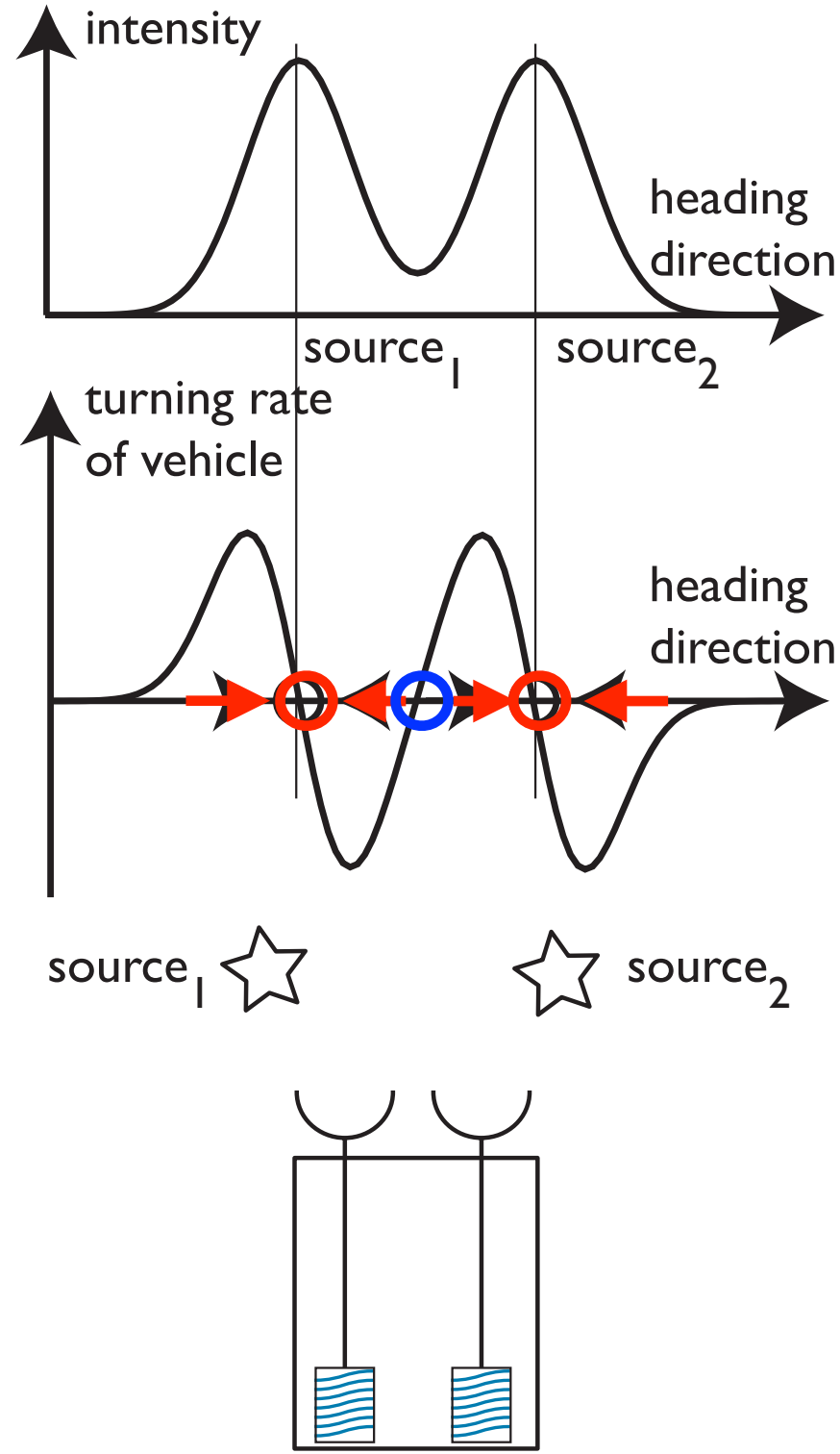
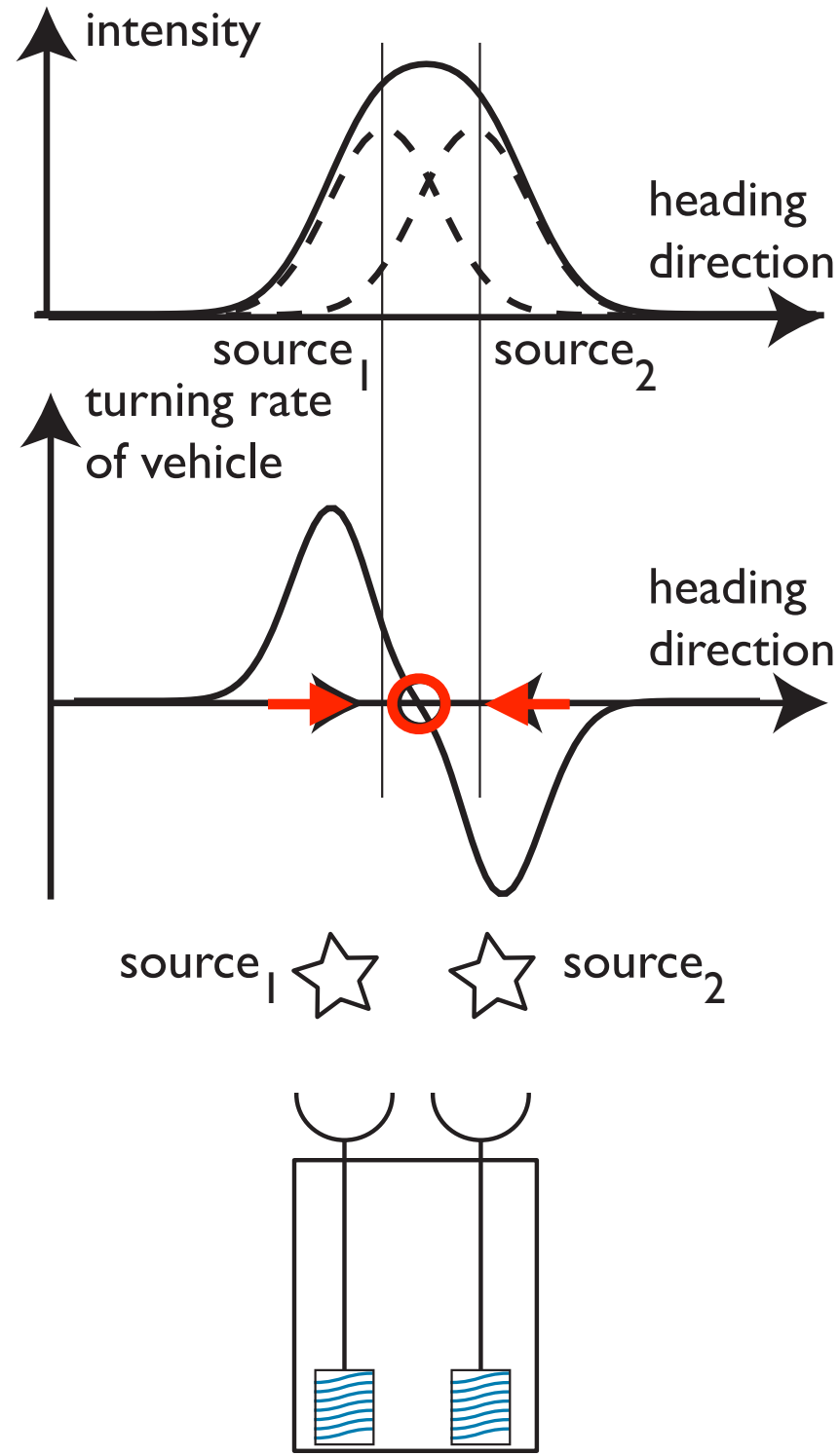


Complex environment => complex dynamics

- bistable dynamics for bimodal intensity distribution
- => nonlinear dynamics makes selection decision



- transition to monostable for mono-modal distribution
- => instabilities lead to qualitative change of behavior



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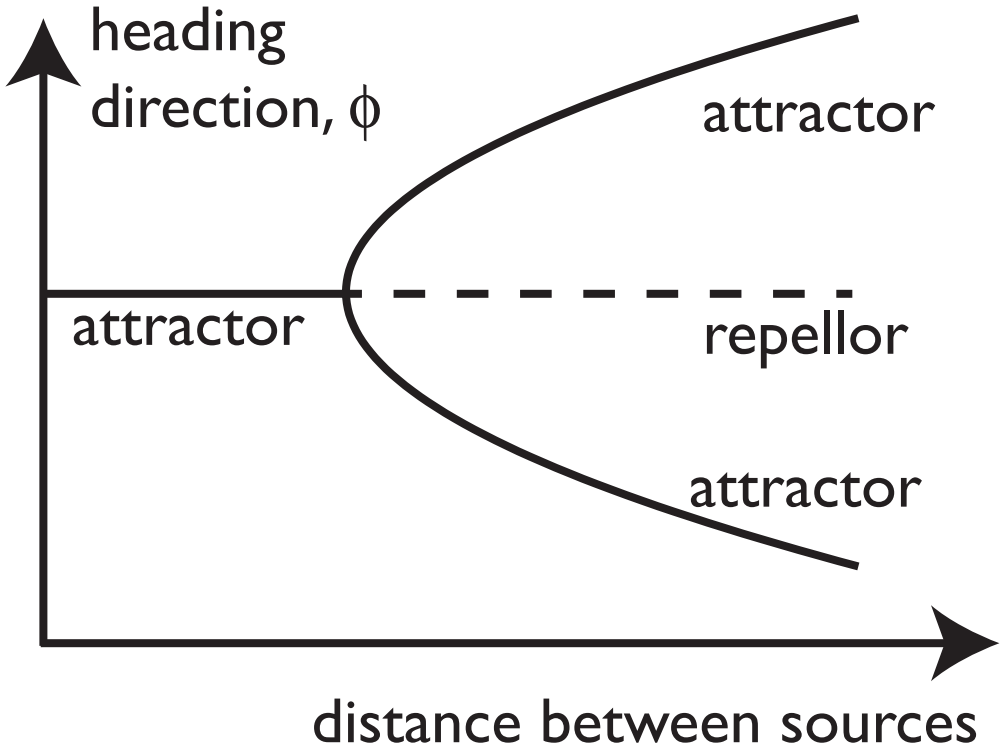
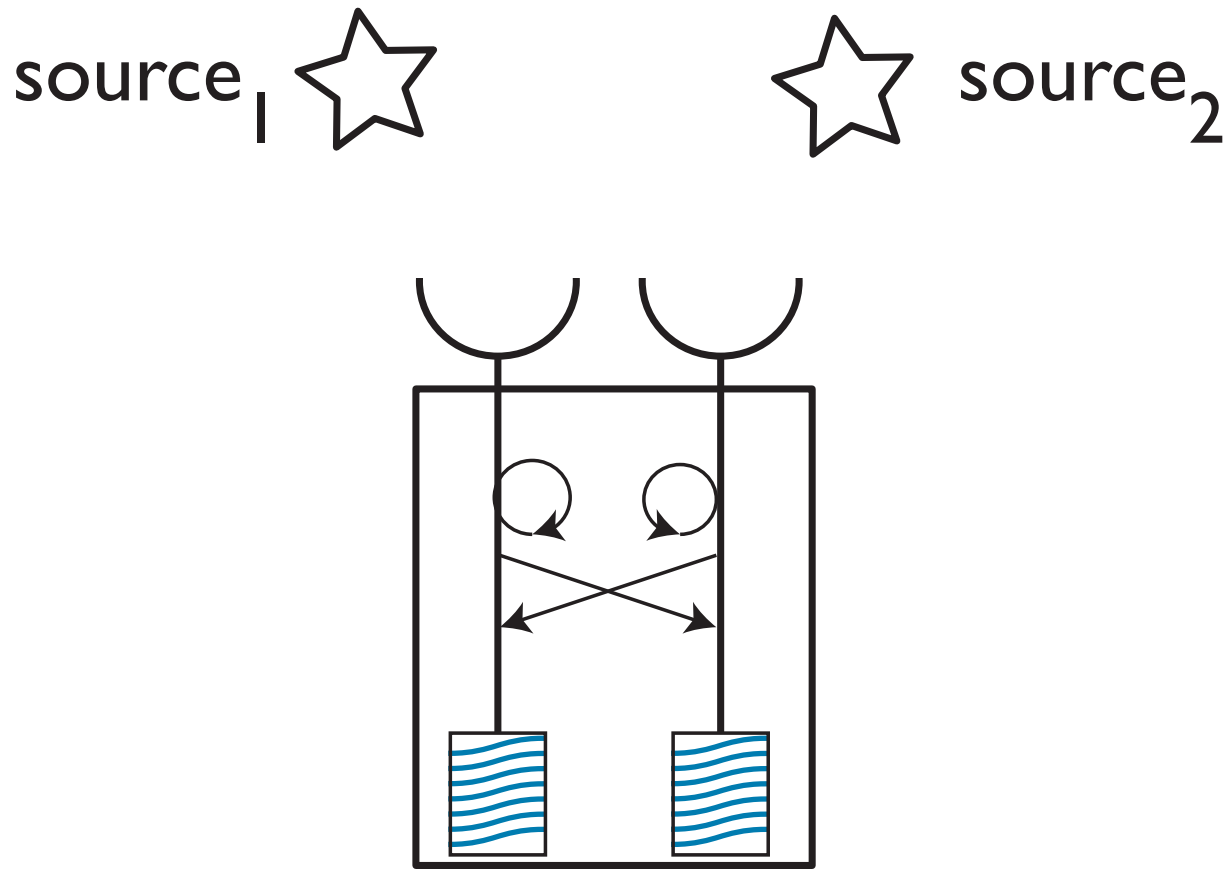
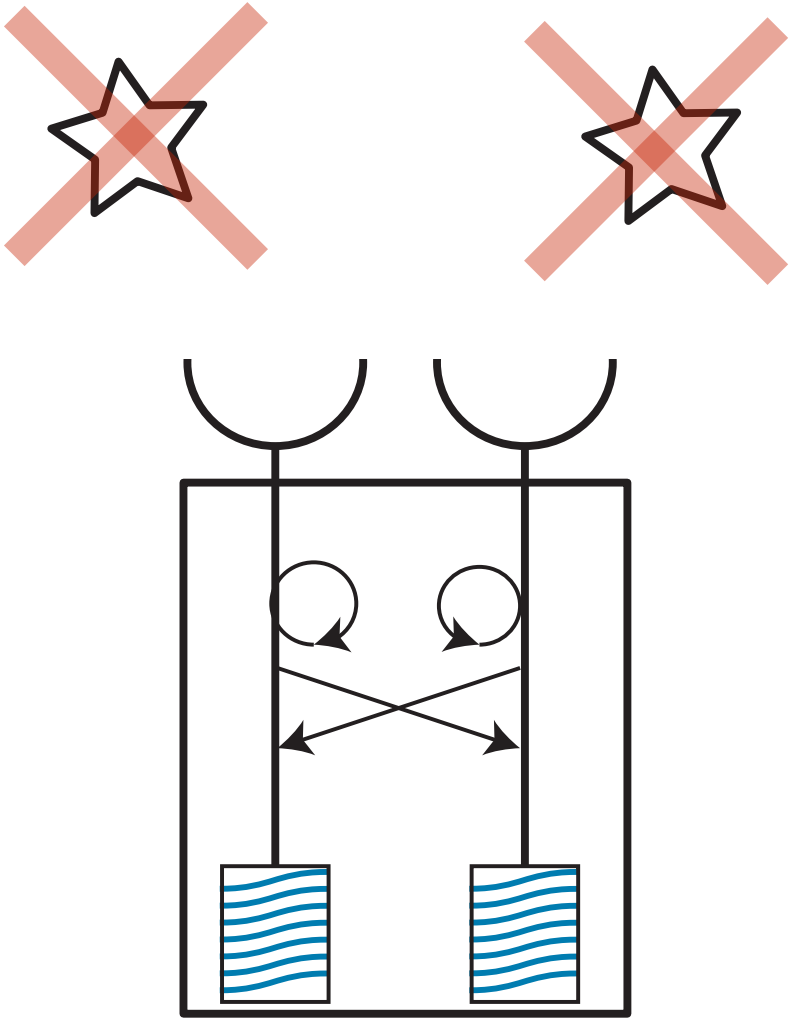


Beyond sensory-motor cognition…

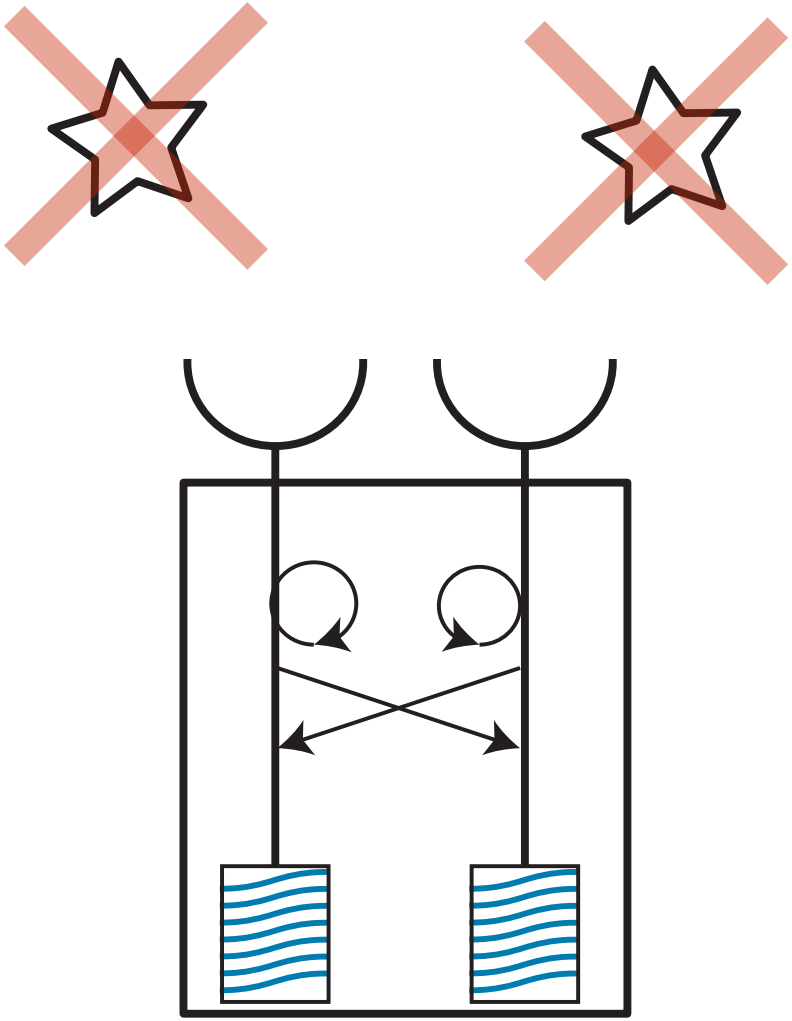


Beyond sensory-motor cognition…



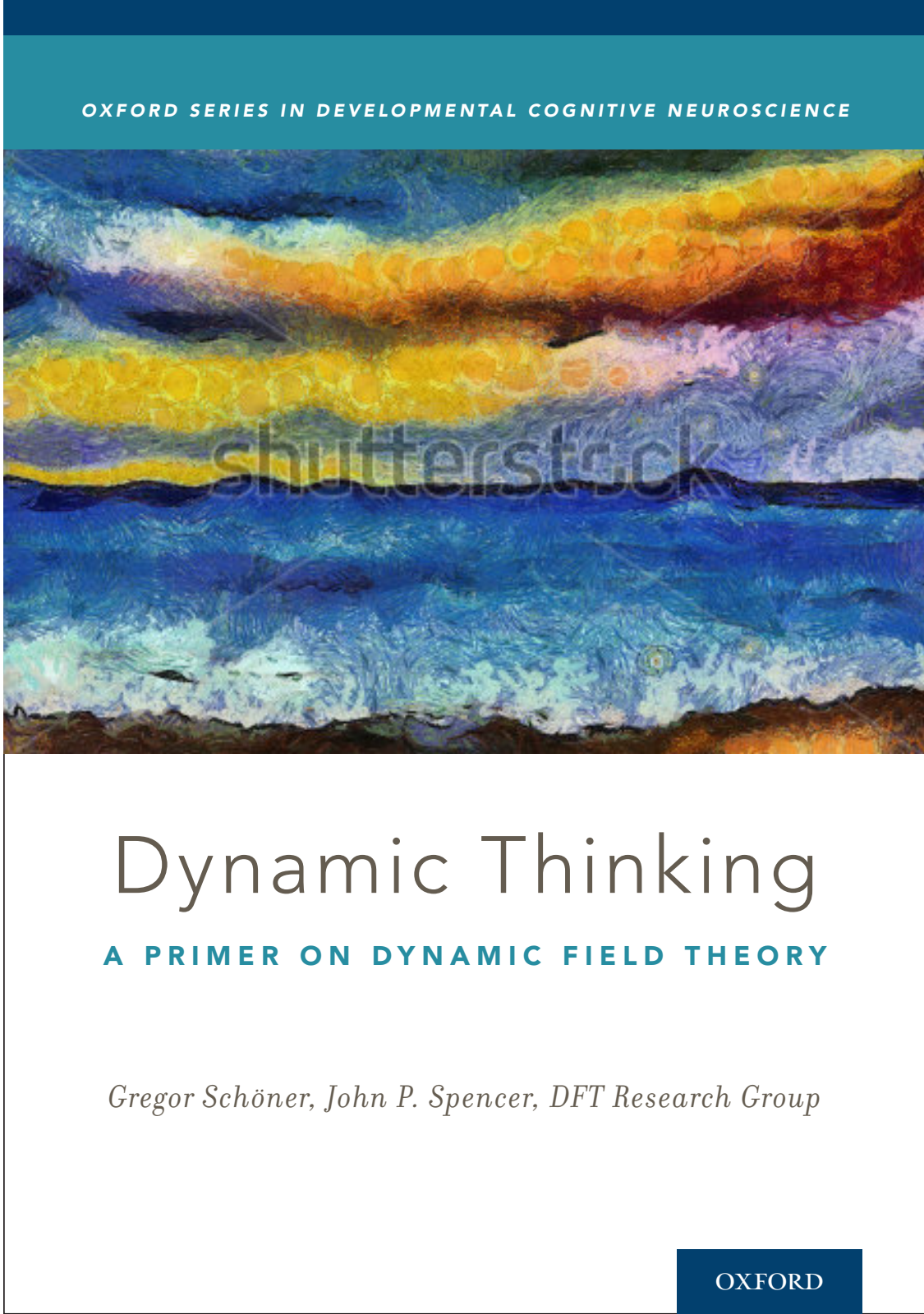
Beyond sensory-motor cognition…

- if sensory information about source not always available on the sensory surface
- => working memory
- need "inner state" that is independent of body or sensors:
- => activation



Advertisement

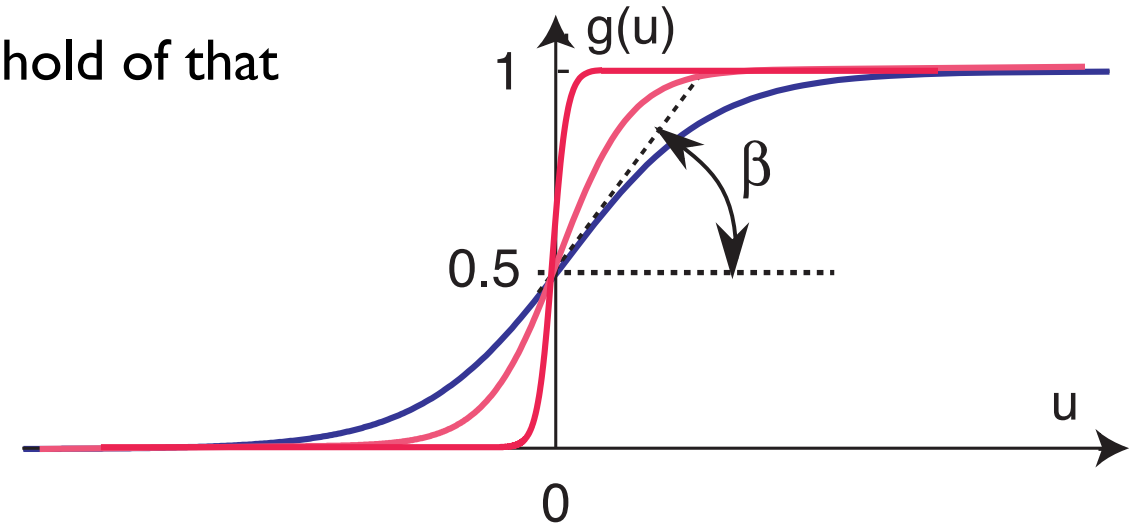
- argument is expanded in: Schöner, G., Spencer, J. and the DFT research group: Dynamic Thinking: A Primer on Dynamic Field Theory. Oxford University Press, 2015



Neural dynamics

Activation

- activation as a state variable, that abstracts from biophysical details
  - low levels of activation: not transmitted to other systems (e.g., to motor systems)
  - high levels of activation: transmitted to other systems
  - as described by sigmoidal threshold function
  - zero activation defined as threshold of that function

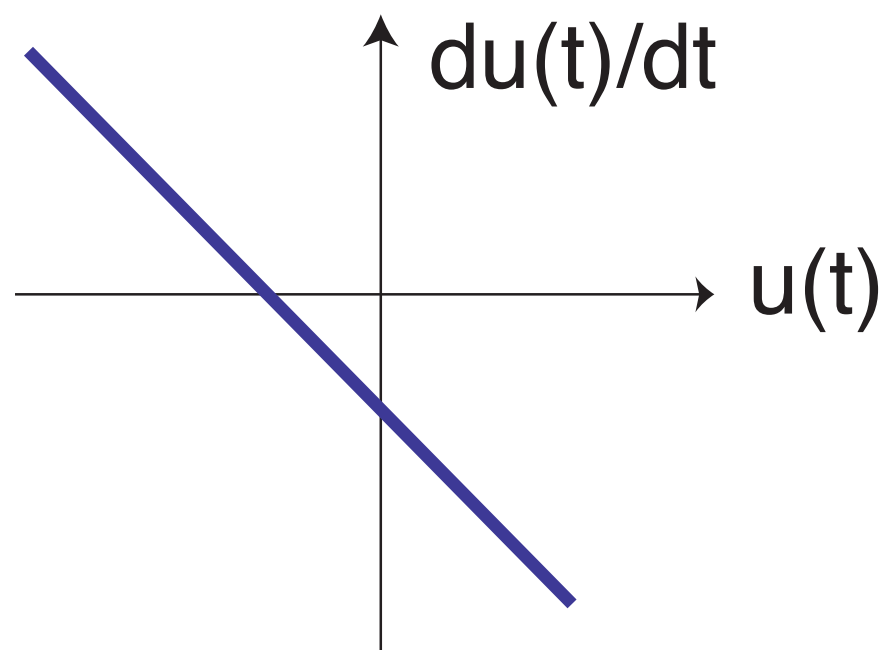


Activation dynamics

- activation varies continuously in time…
- activation variables u(t) as time continuous functions...

$$\tau \dot{u}(t) = f(u)$$

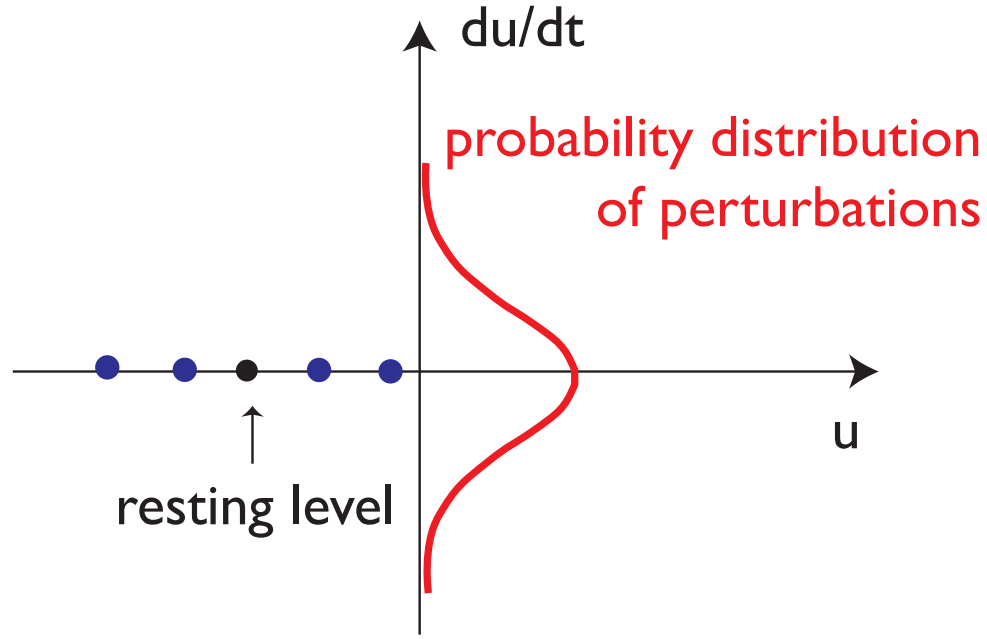
- what function f?

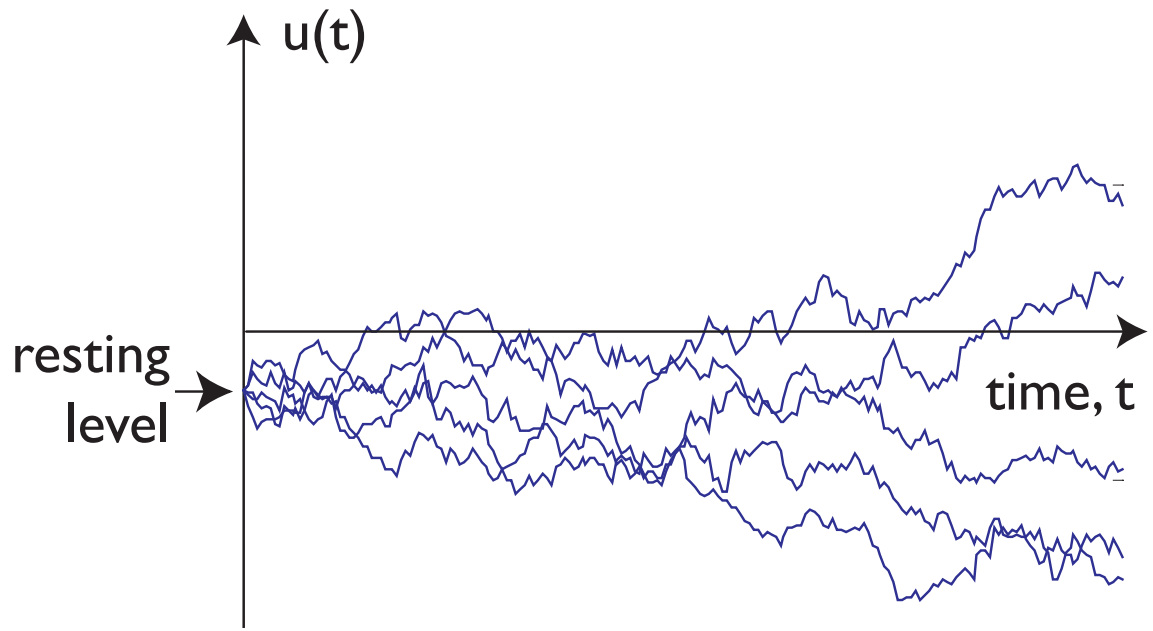


Activation dynamics

- start with f=0

$$\tau \dot{u} = \xi_t$$

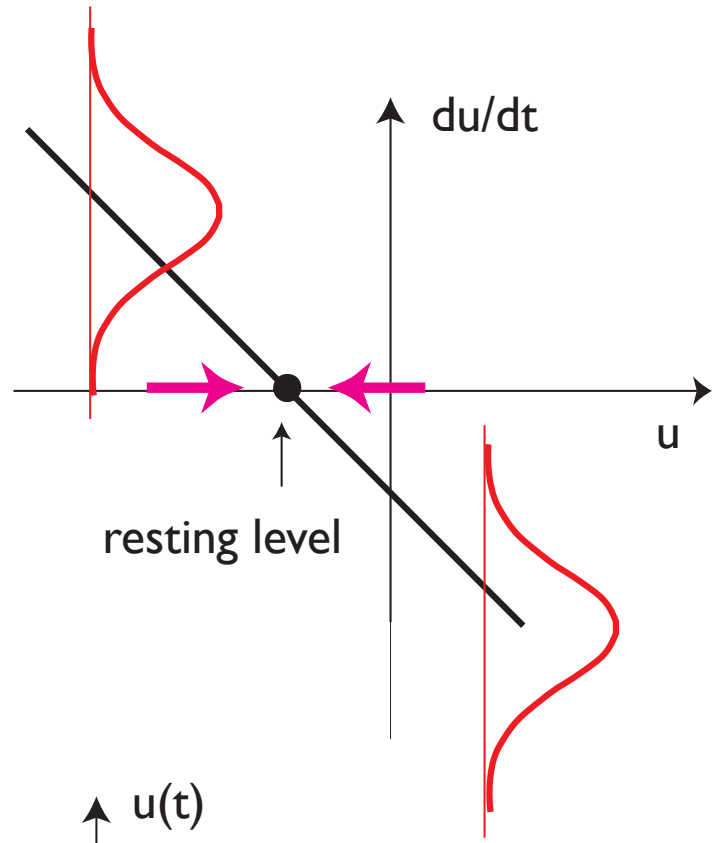


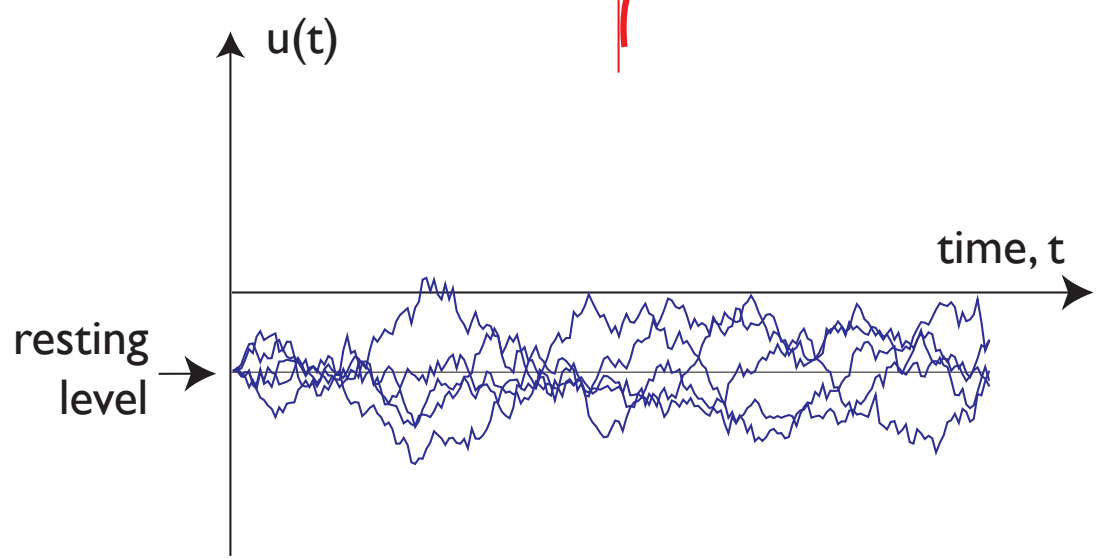


Activation dynamics

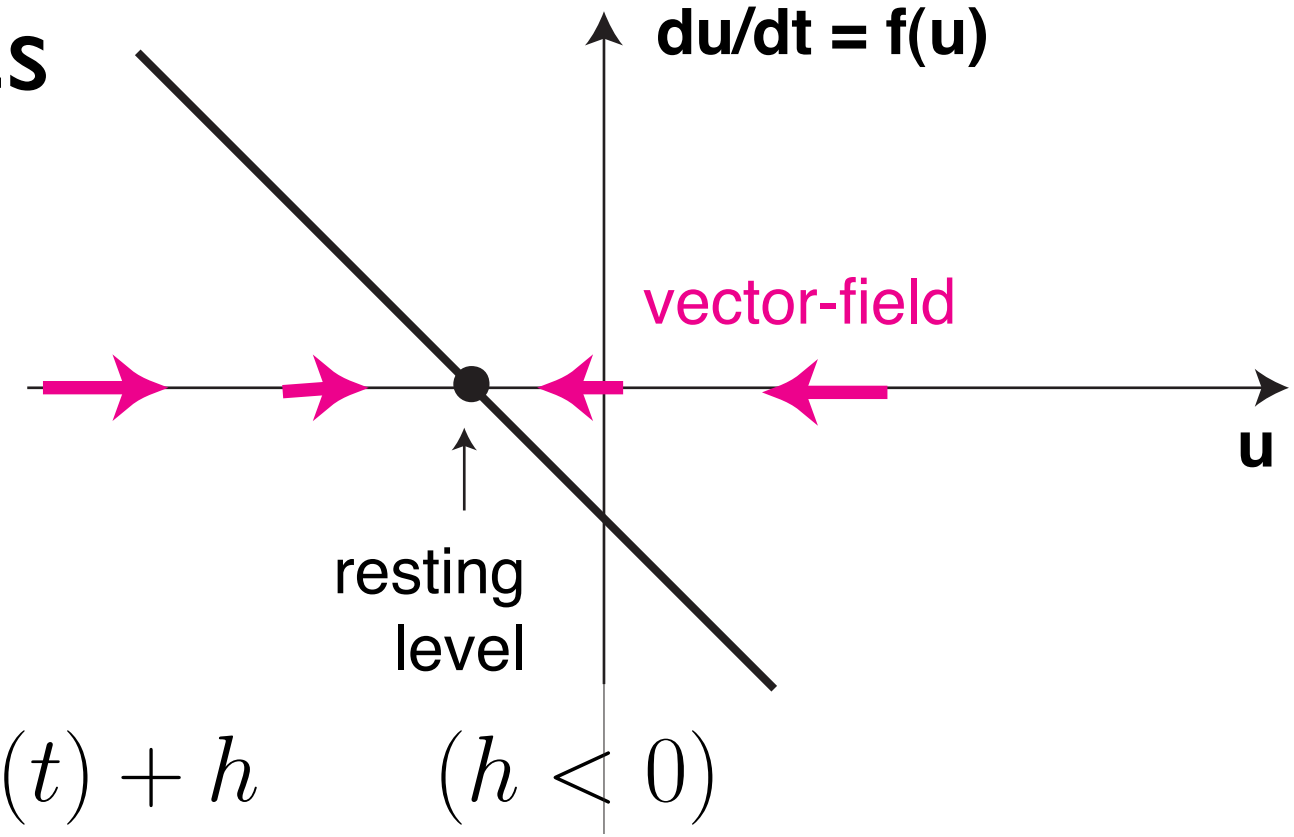
- need stabilization

$$\tau \dot{u} = -u + h + \xi_t.$$





Neural dynamics

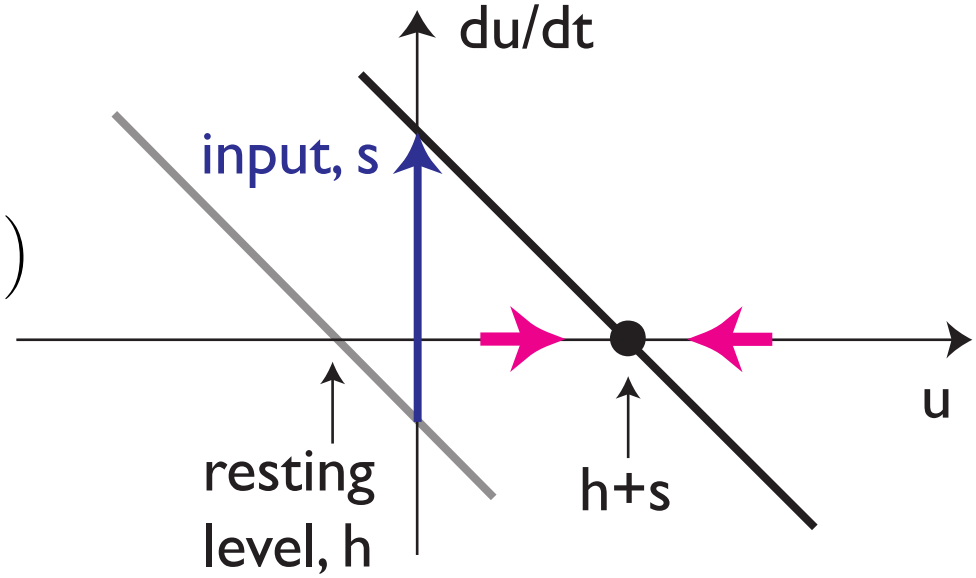


$$\frac{du(t)}{dt} = \dot{u}(t) = -u(t) + h \qquad (h < 0)$$

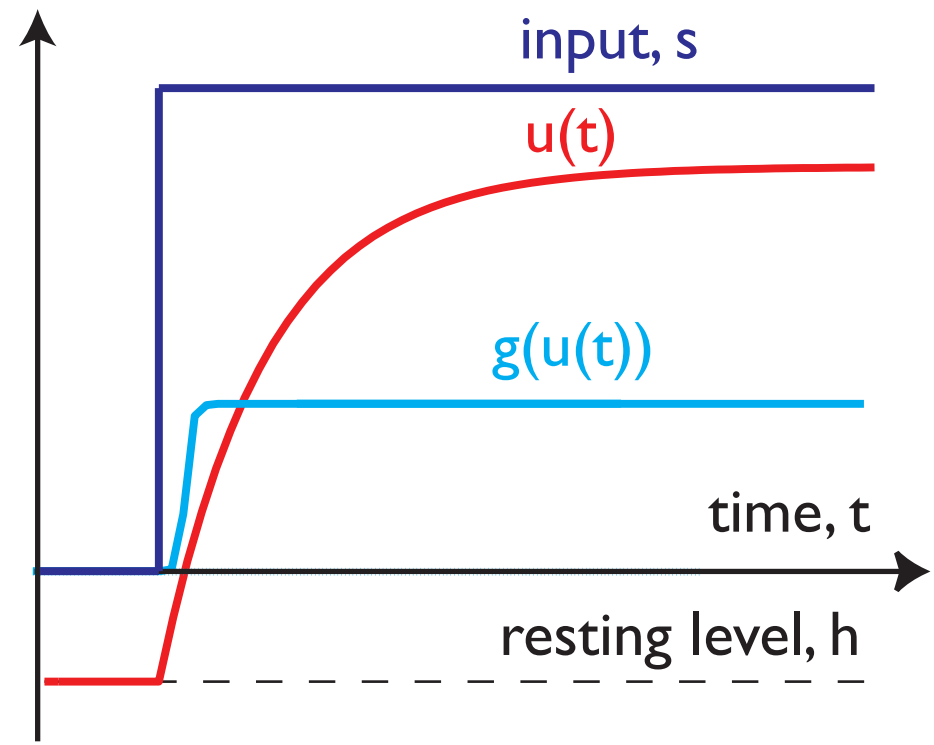
- stationary state=fixed point= constant solution
- stable fixed point: nearby solutions converge to the fixed point=attractor

Neuronal dynamics

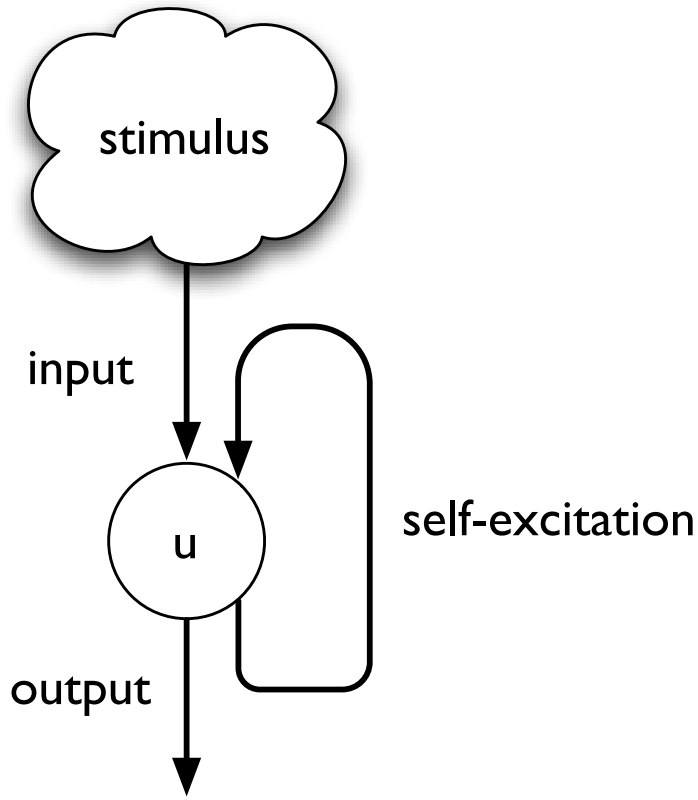
$$\tau \dot{u}(t) = -u(t) + h + \text{ inputs(t)}$$

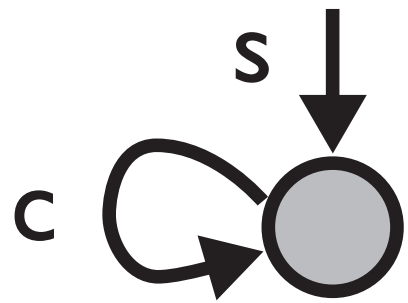


- inputs=contributions to the rate of change
  - positive: excitatory
  - negative: inhibitory
- => shift the attractor
- => activation tracks shift based on stability



Neuronal dynamics with self-excitation





$$\tau \dot{u}(t) = -u(t) + h + S(t) + c\sigma(u(t))$$

Neuronal dynamics with self-excitation

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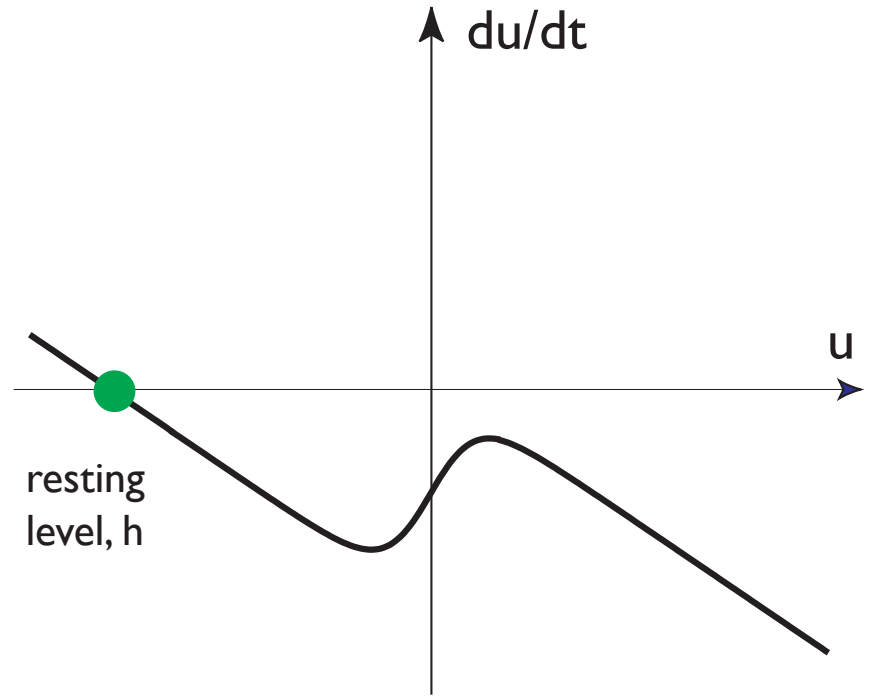
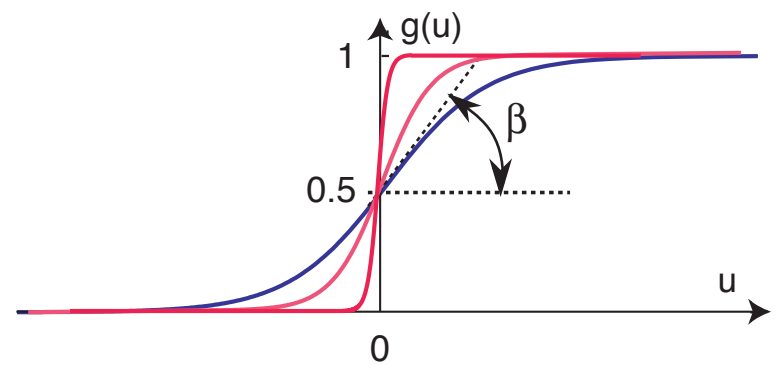
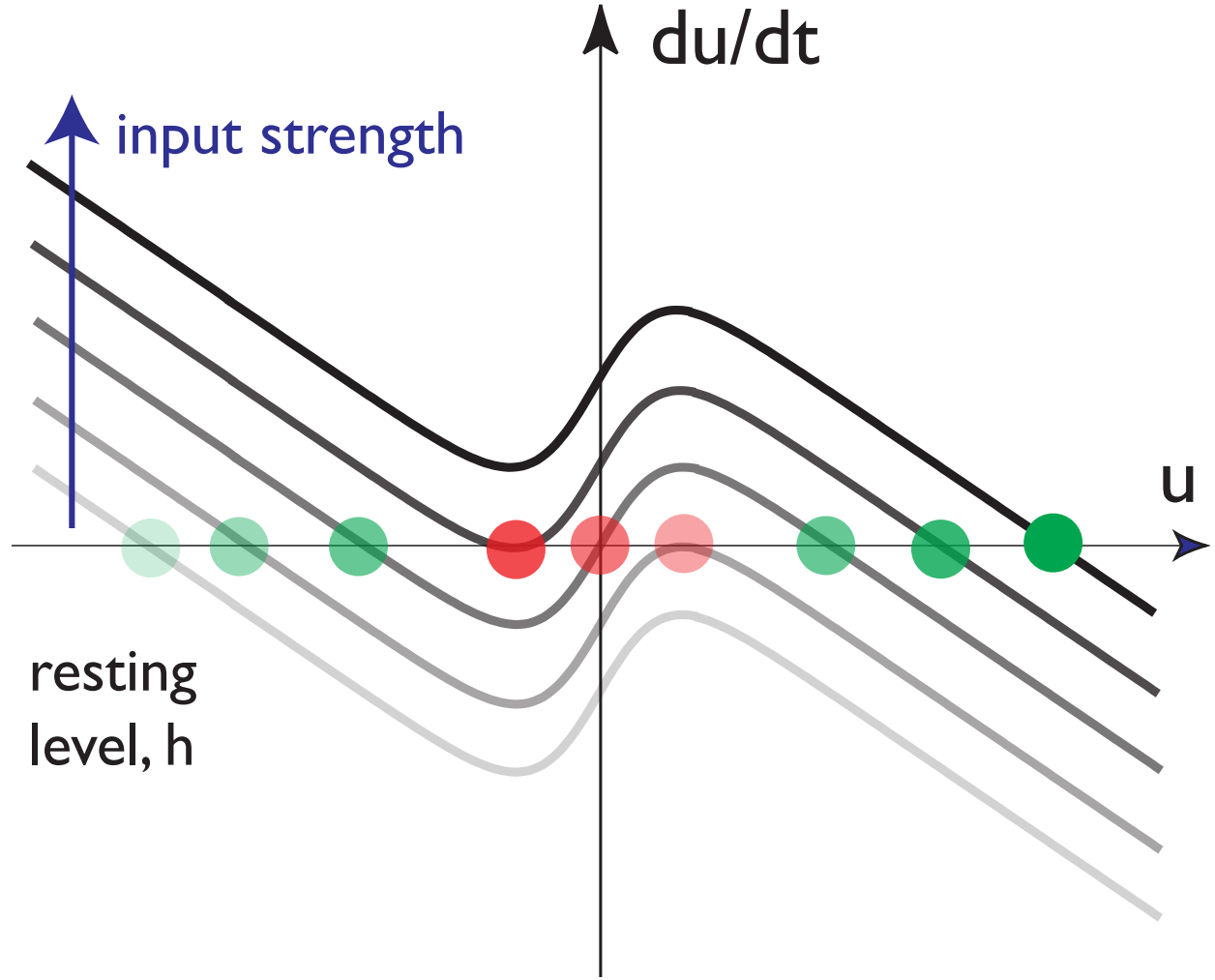


- => nonlinear dynamics!

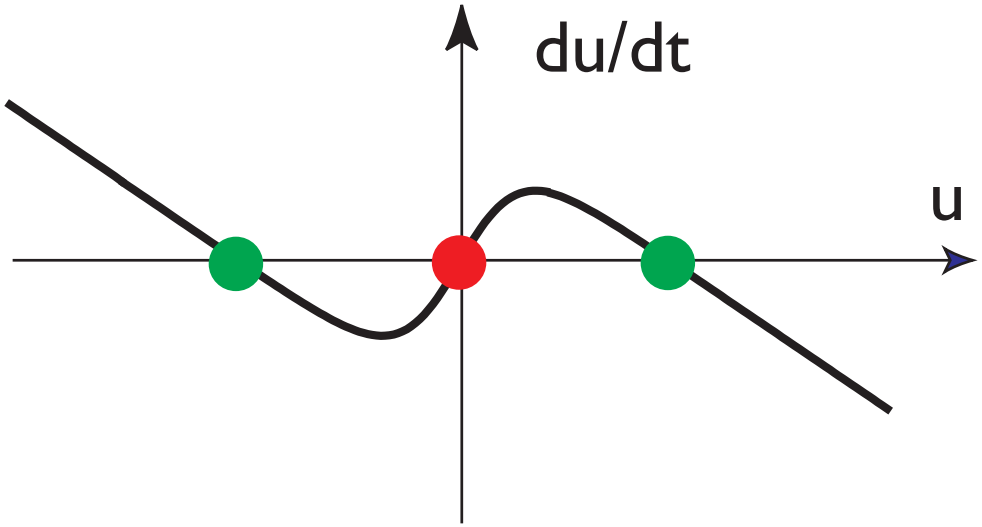


Neuronal dynamics with self-excitation

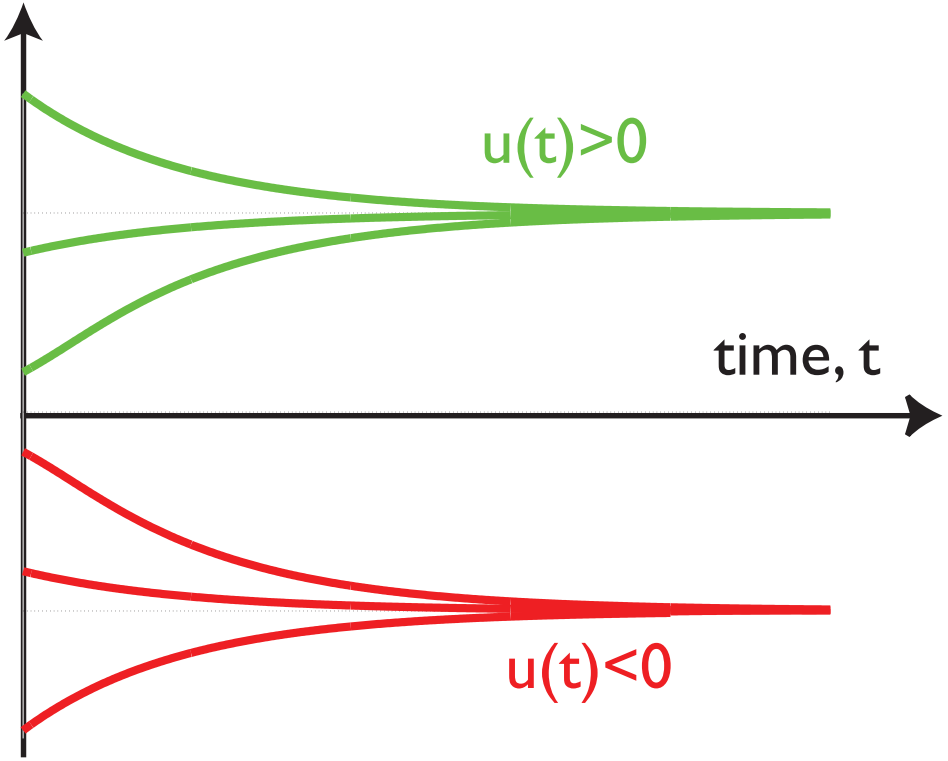


$$\tau \dot{u}(t) = -u(t) + h + S(t) + c\sigma(u(t))$$

Neuronal dynamics with self-excitation

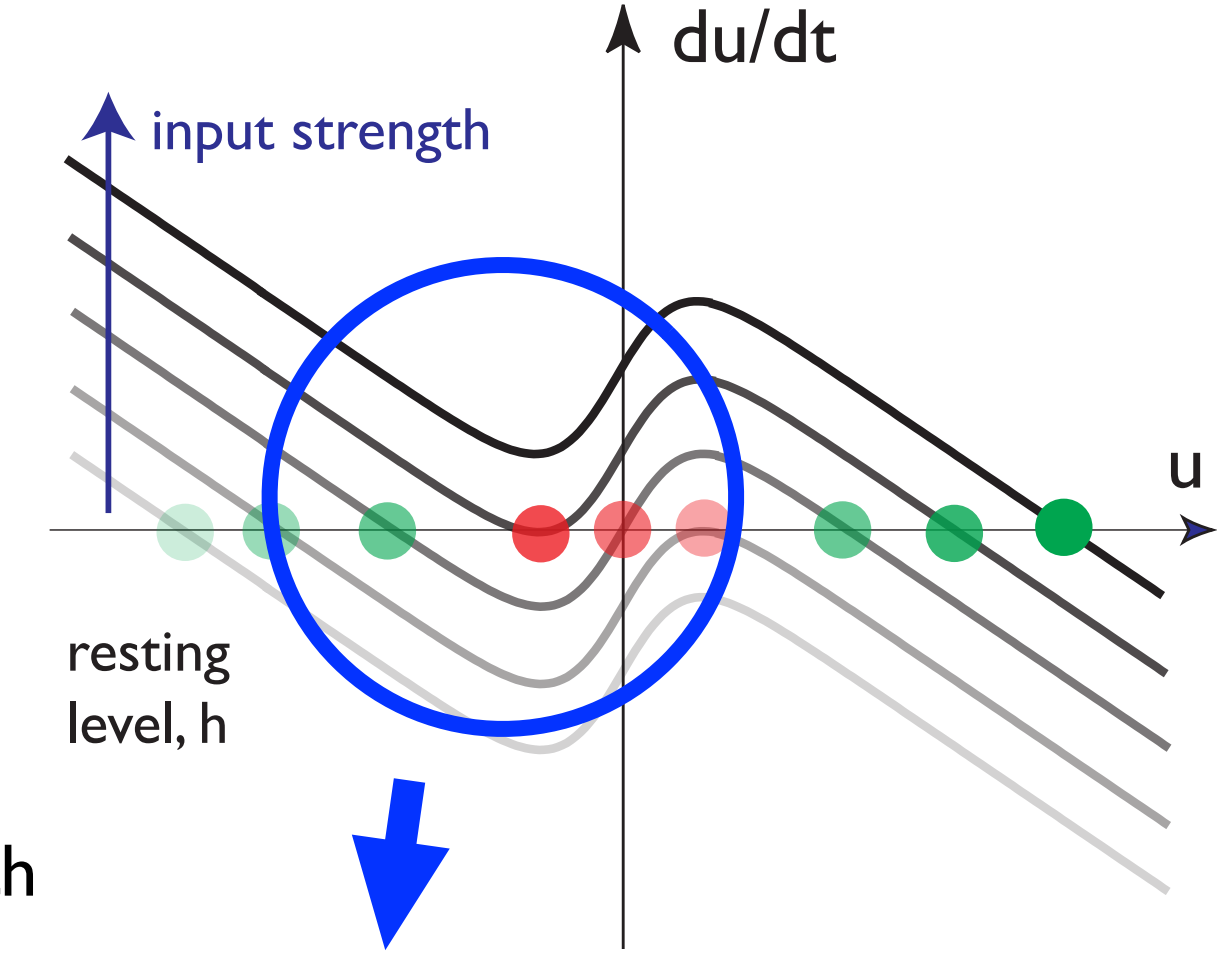


- at intermediate stimulus strength: bistable
- "on" vs "off" state

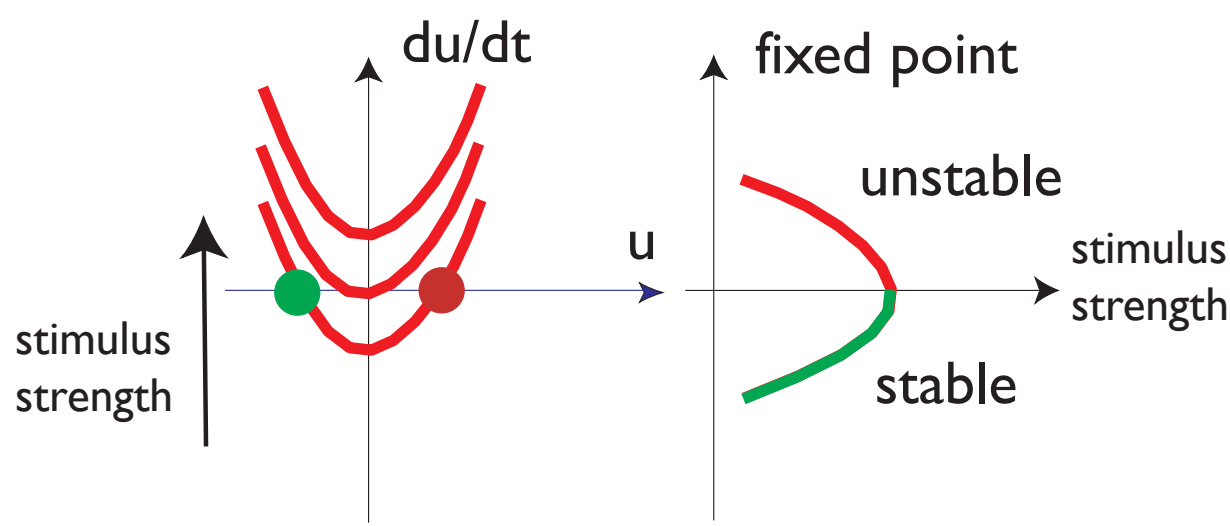


$$\tau \dot{u}(t) = -u(t) + h + S(t) + c\sigma(u(t))$$

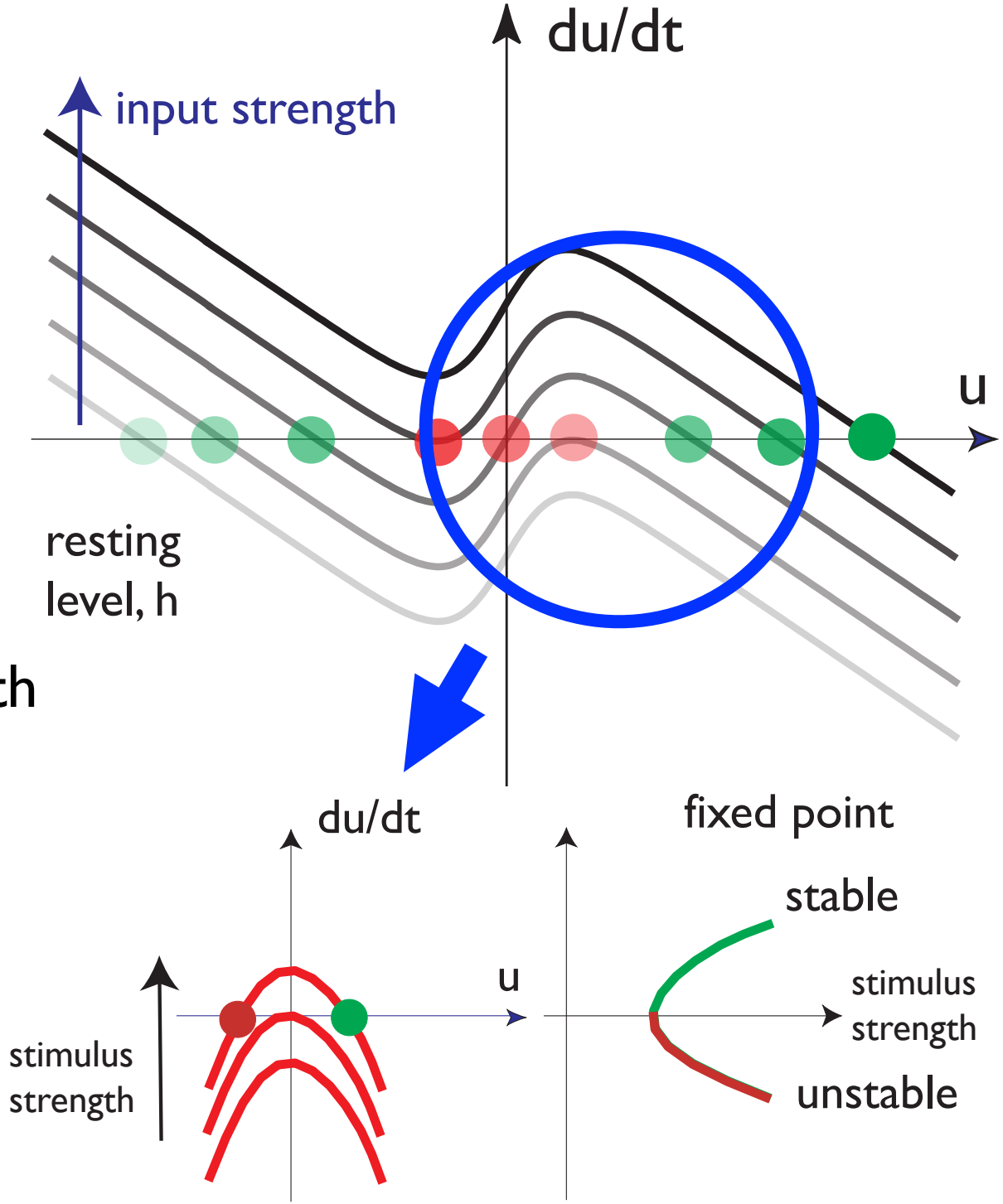
Neuronal dynamics with self-excitation



- increasing input strength
  => detection instability

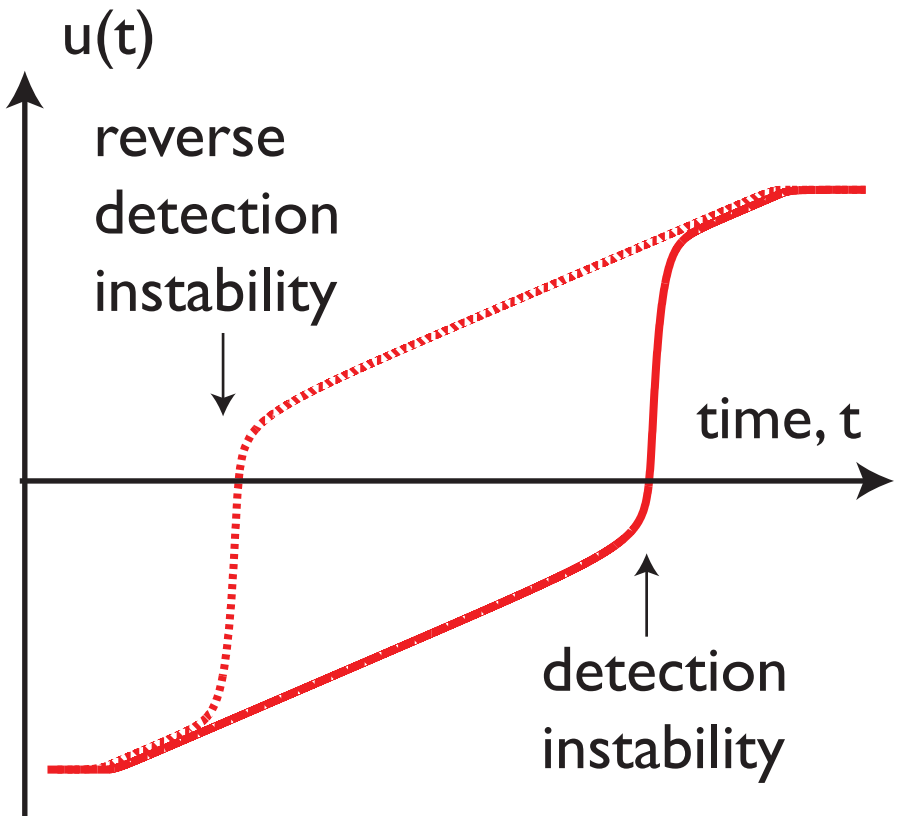


Neuronal dynamics with self-excitation



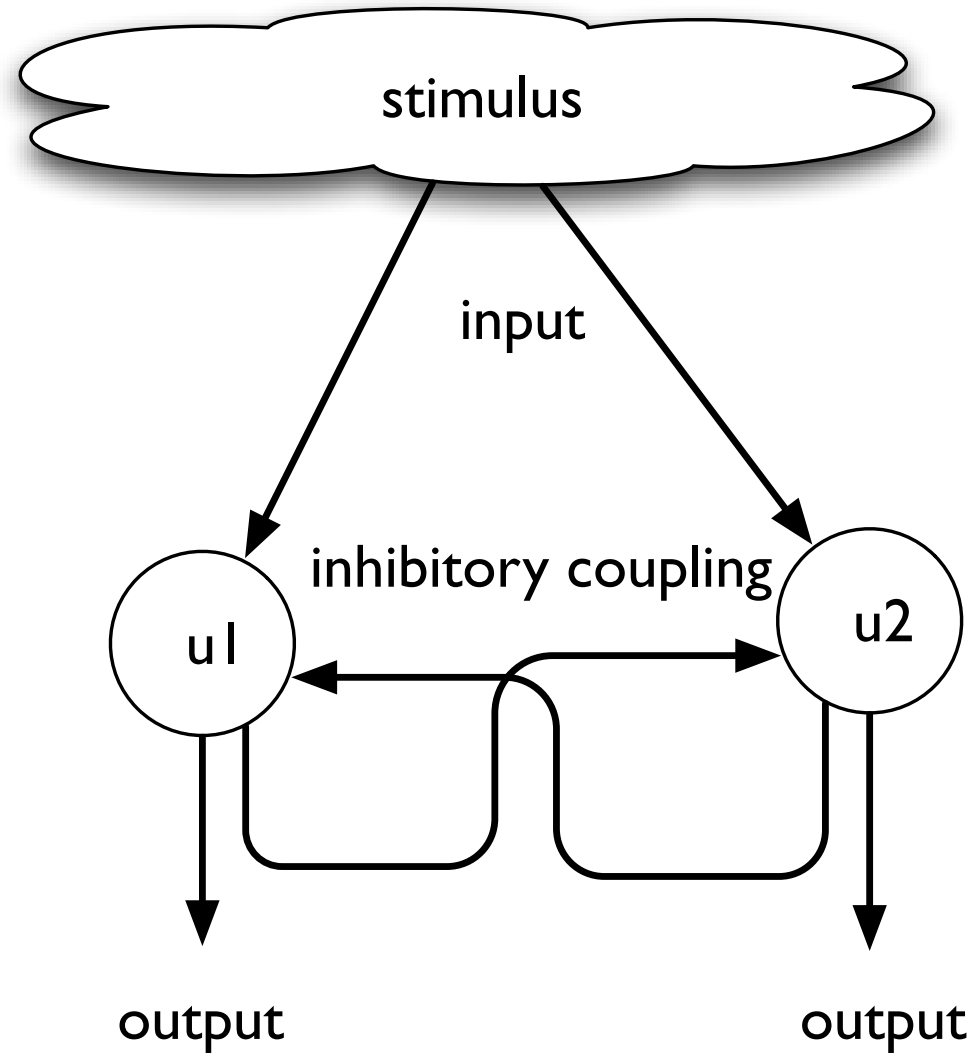
- decreasing input strength => reverse detection instability

Neuronal dynamics with self-excitation



- the detection and the reverse detection instability create discrete events out of input that changes continuously in time

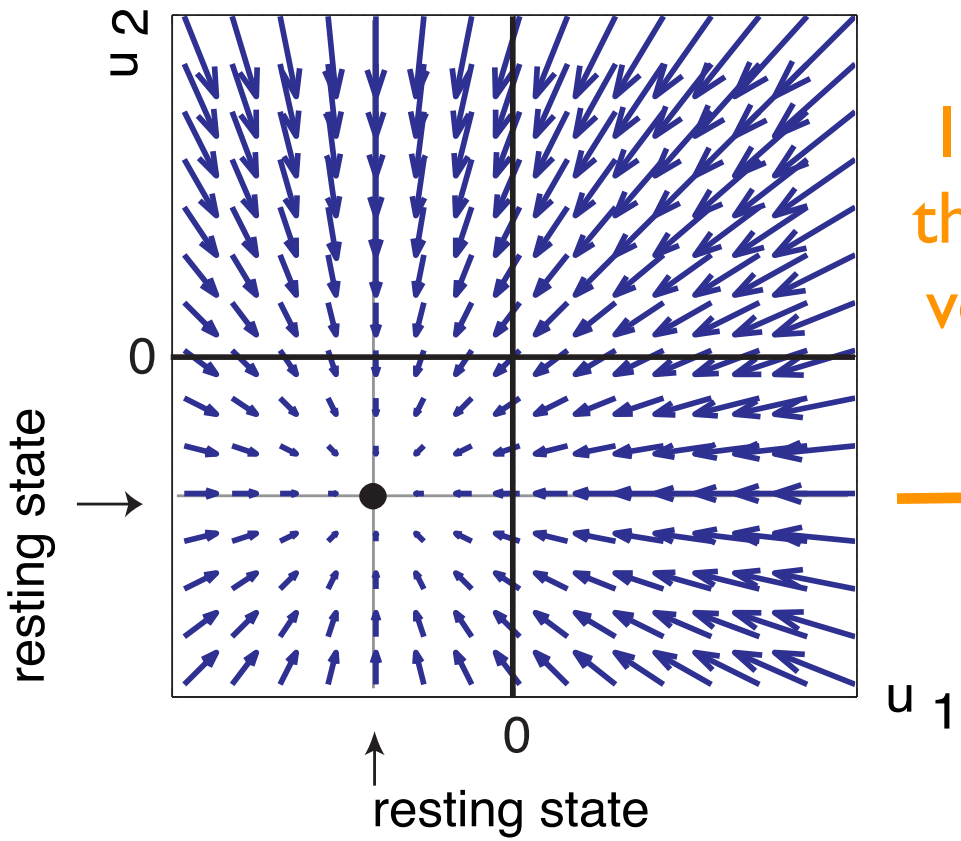
Neuronal dynamics with competition



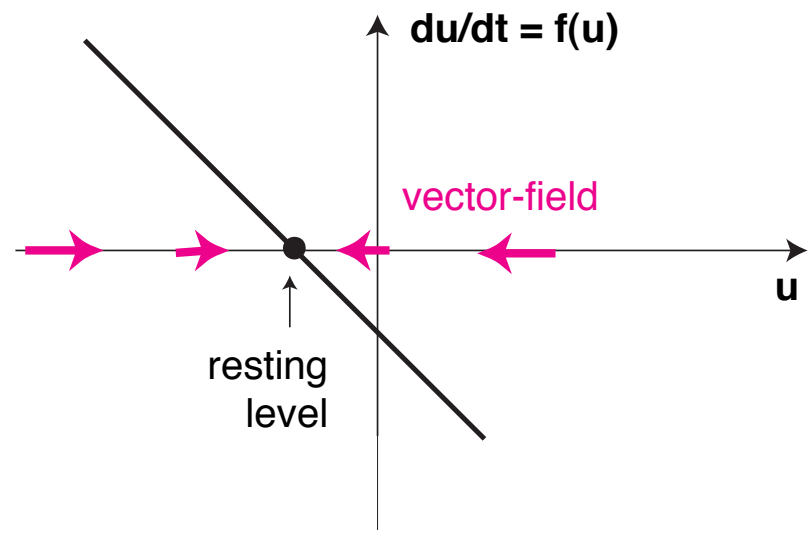
$$\tau \dot{u}_1(t) = -u_1(t) + h - \sigma(u_2(t)) + S_1$$
$$\tau \dot{u}_2(t) = -u_2(t) + h - \sigma(u_1(t)) + S_2$$

Neuronal dynamics with competition

vector-field in the absence of input

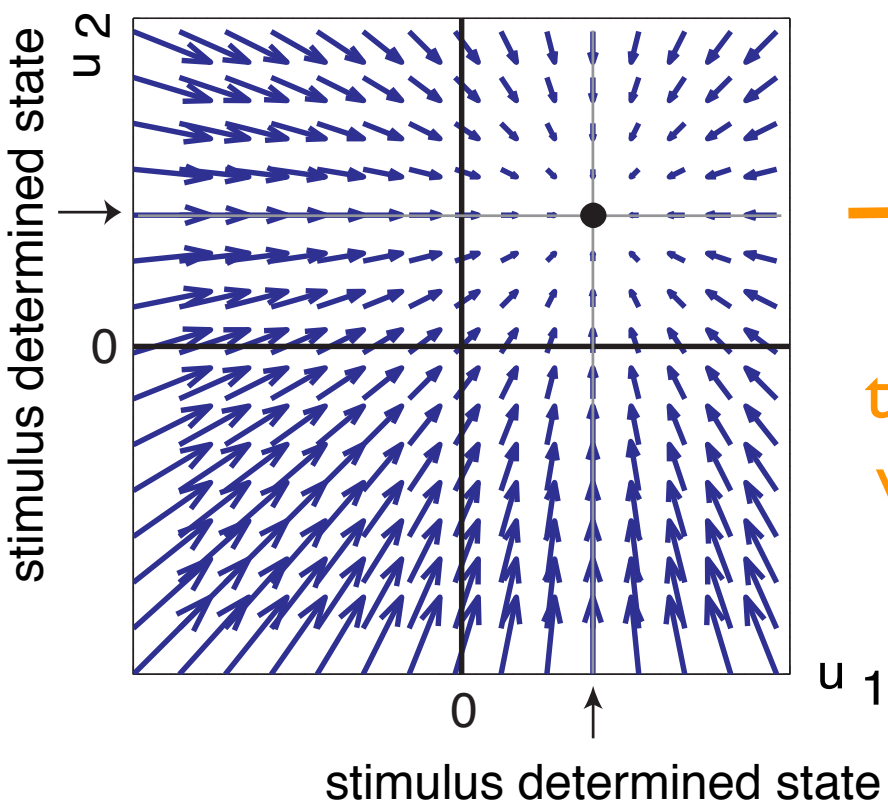


1D cut through vector-field

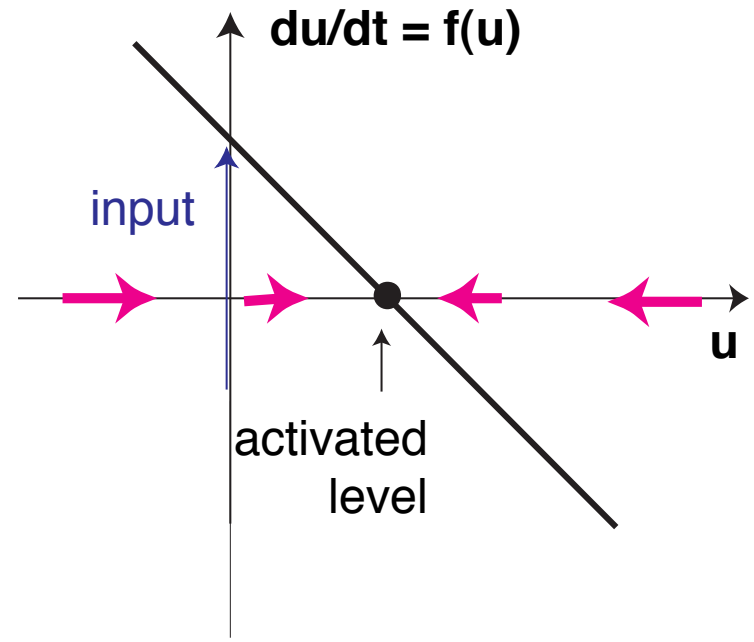


Neuronal dynamics with competition

vector-field (without interaction) when both neurons receive input

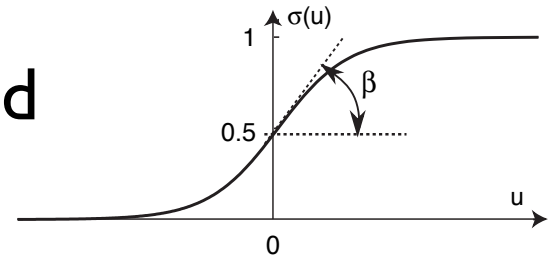


1D cut through vector-field

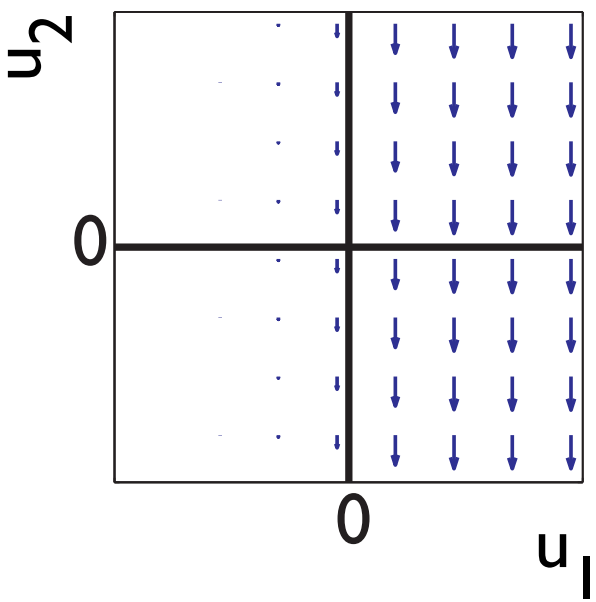


Neuronal dynamics with competition

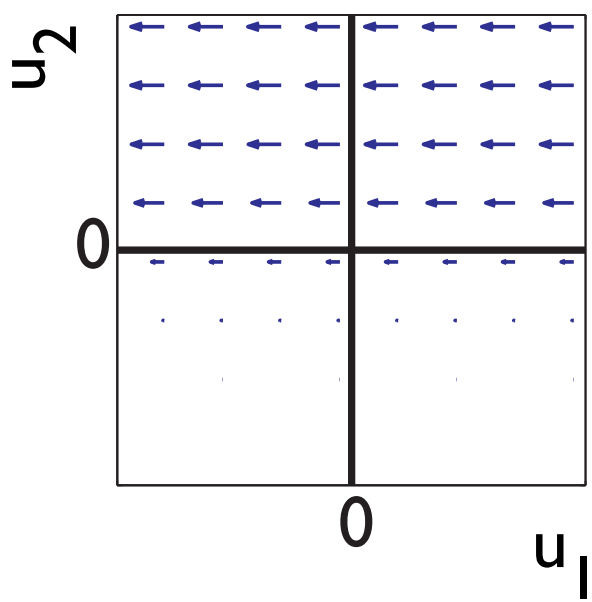
- vector-field of mutual inhibition: only activated neurons participate in interaction



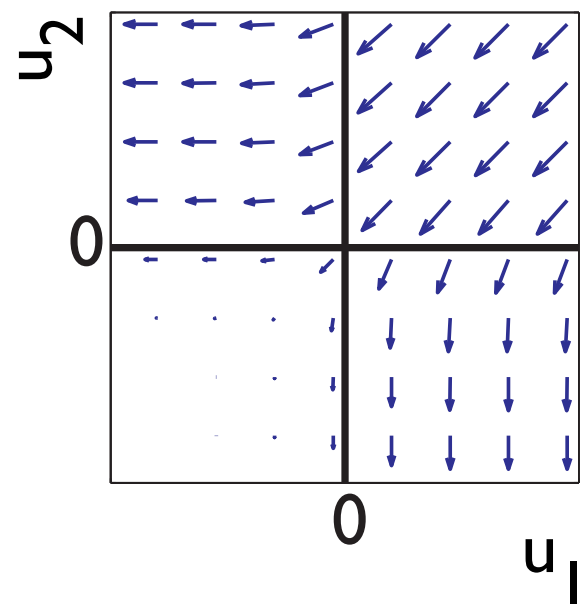
site 1 inhibits site 2



site 2 inhibits site 1

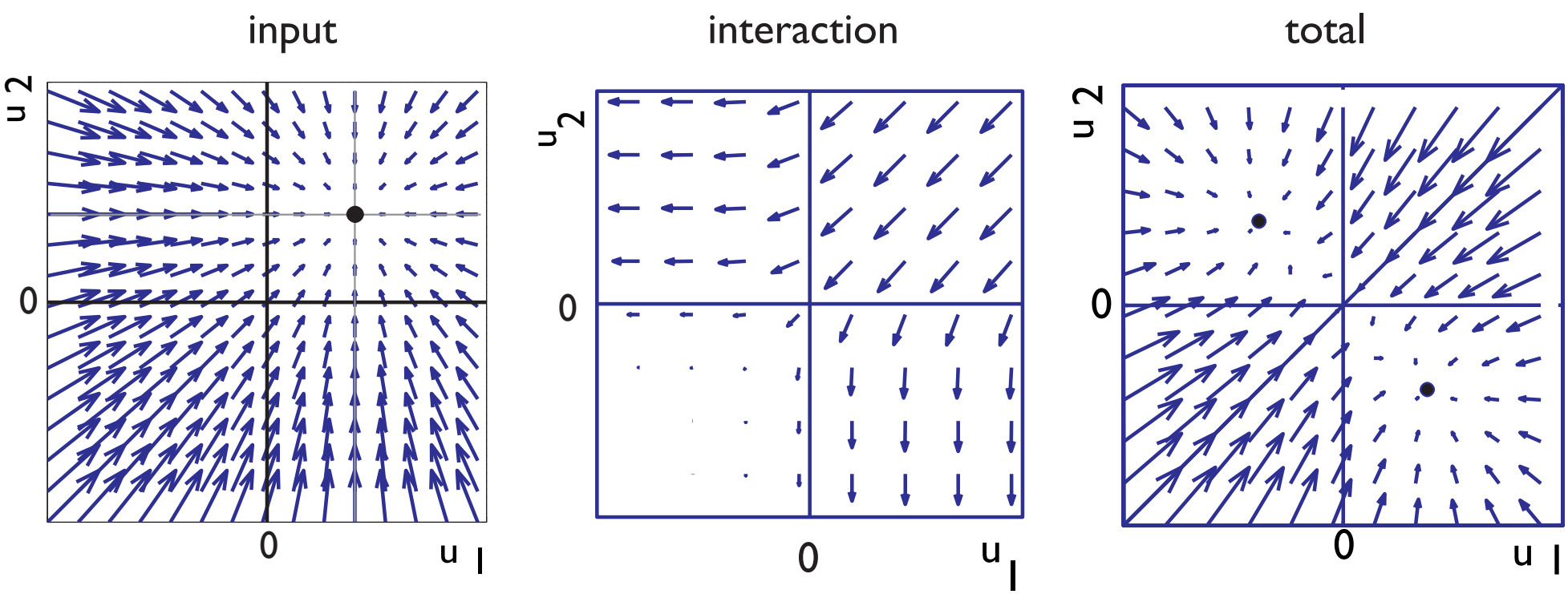


interaction combined



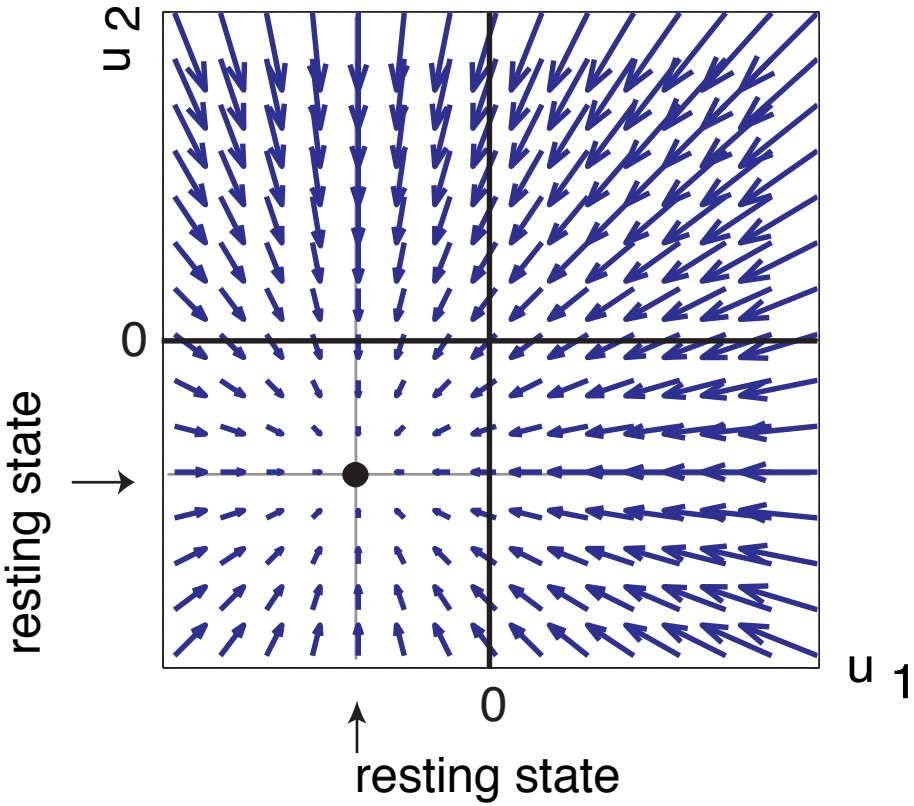
Neuronal dynamics with competition

vector-field with strong mutual inhibition: bistable

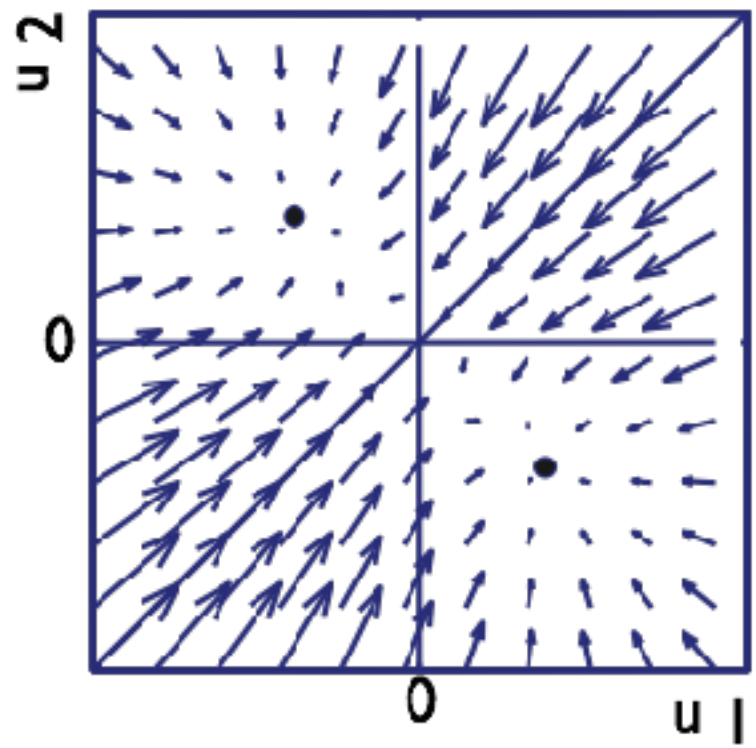


Neuronal dynamics with competition

before input is presented



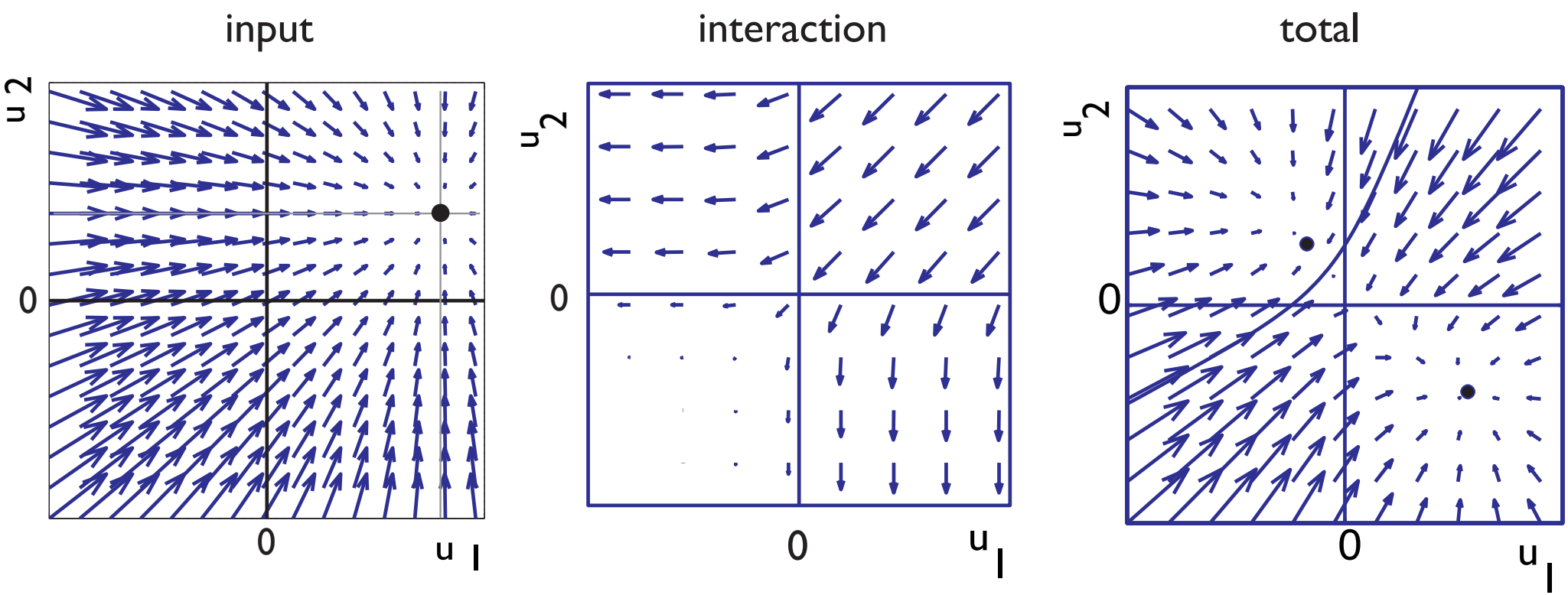
after input is presented



Neuronal dynamics with competition

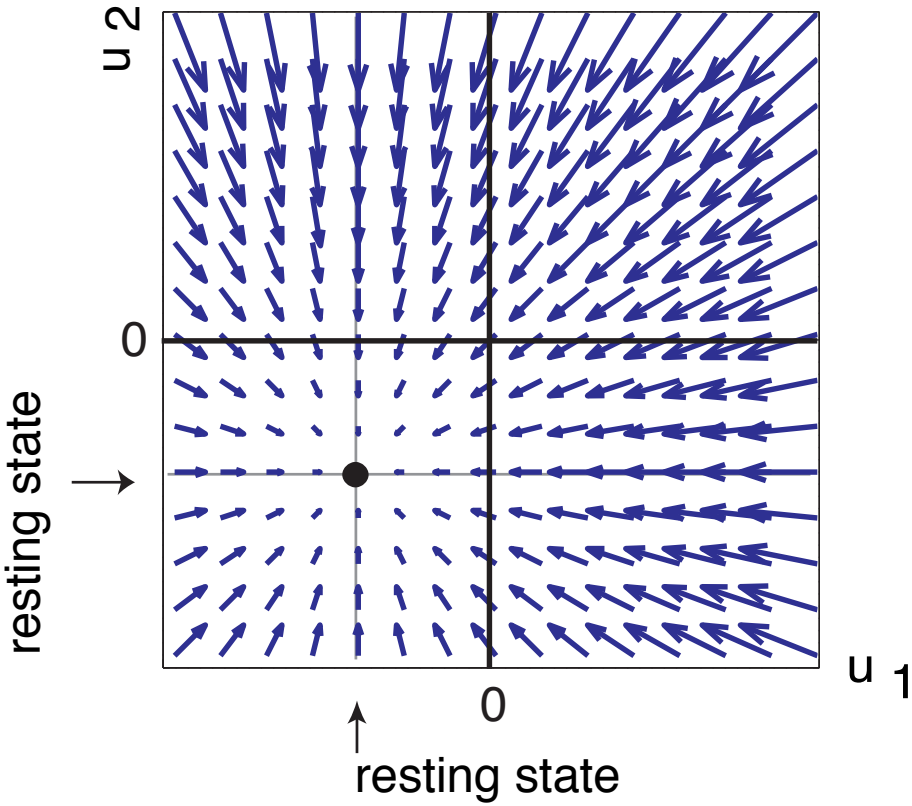
=>biased competition

stronger input to site 1:
attractor with activated u_1 stronger,
attractor with activated u_2 weaker, may become unstable

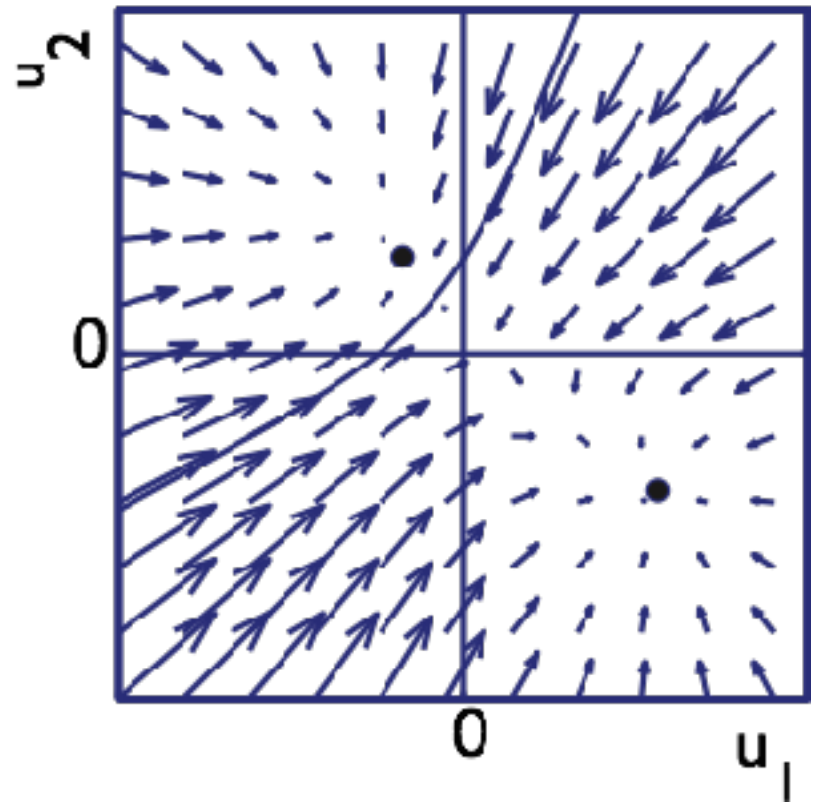


Neuronal dynamics with competition =>biased competition

before input is presented



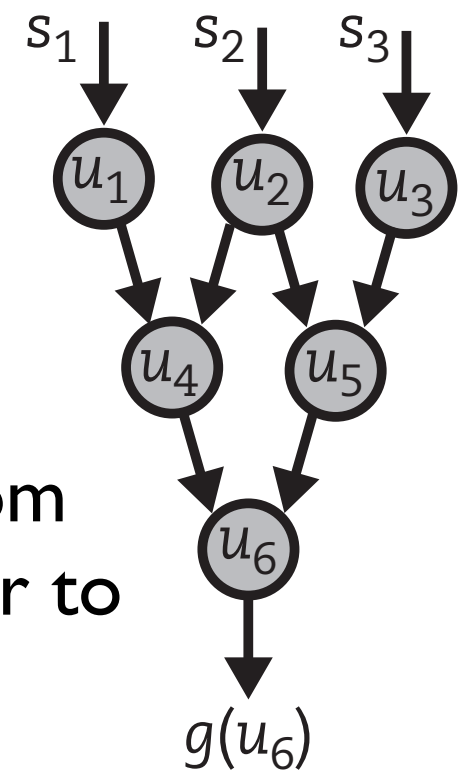
after input is presented



Dynamic Field Theory (DFT)

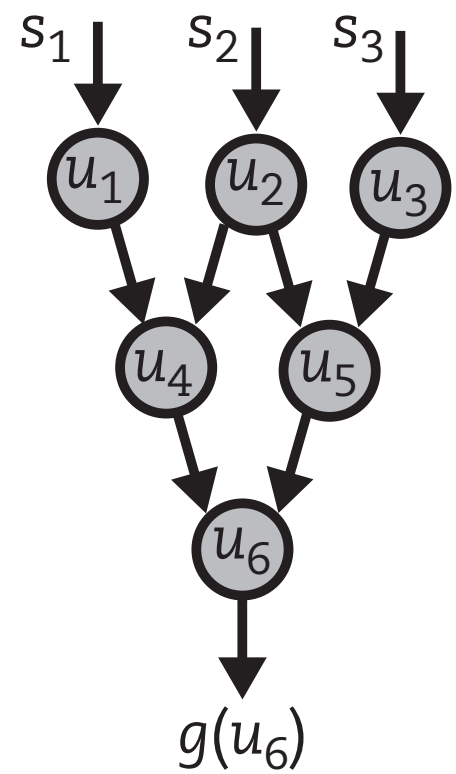
Dynamic Field Theory (DFT)

- where do "inputs" come from…?
  - from sensory systems
  - from other neurons
- => activation variables gain their meaning from the connections from the sensory surfaces or to the motor surfaces

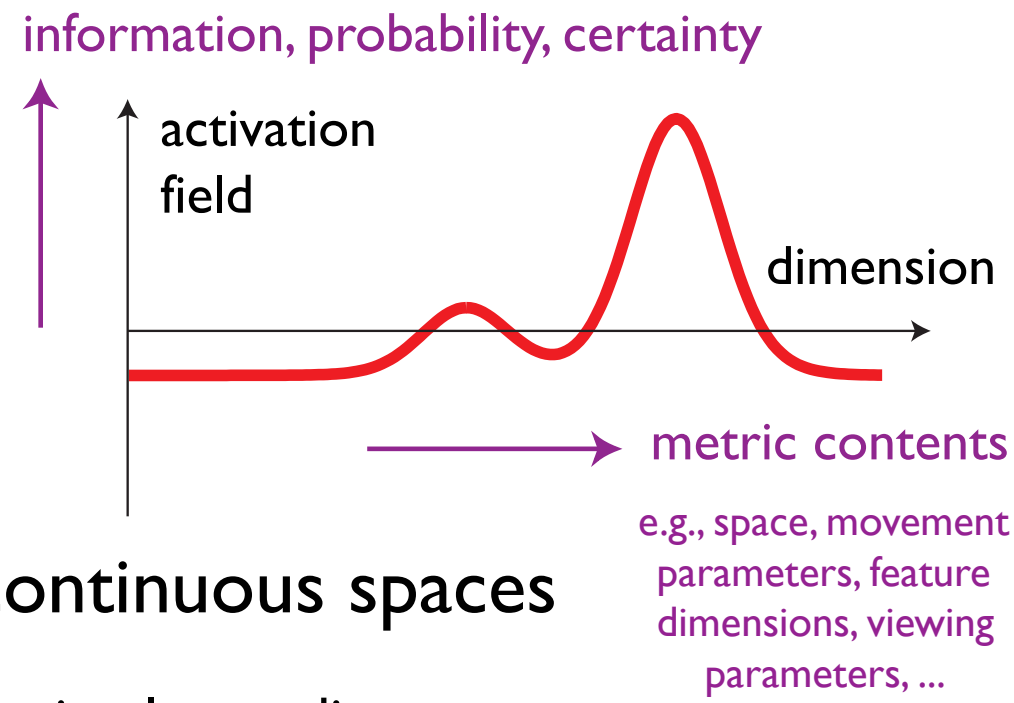


Dynamic Field Theory (DFT)

- there is no behavioral evidence for discrete sampling…
- => abstract from discrete sampling…

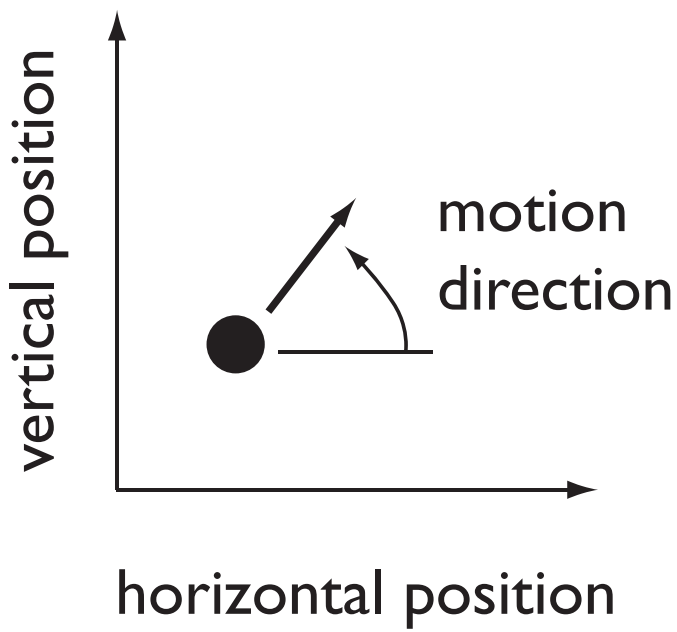


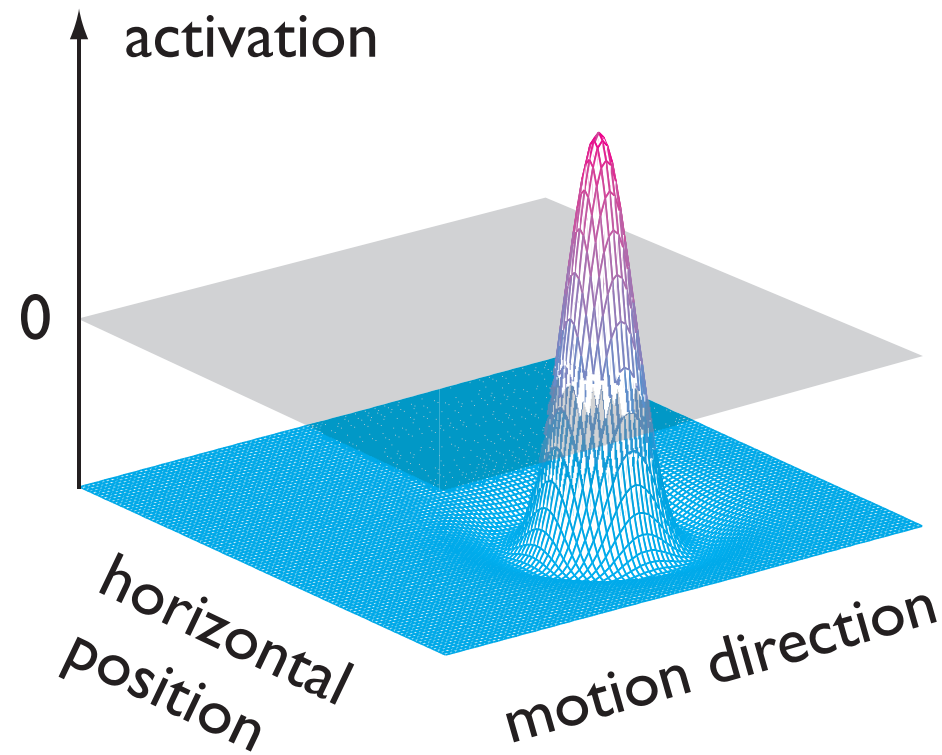
DFT



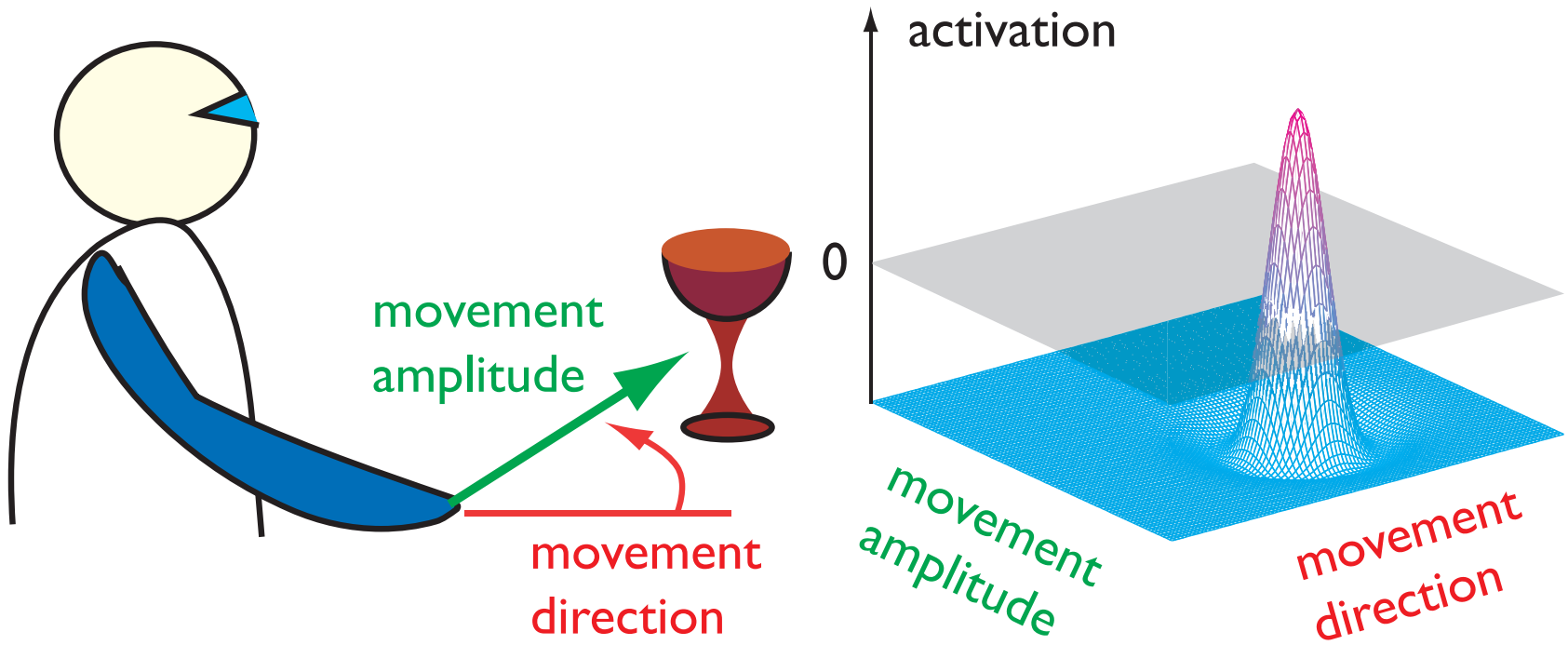
- define activation fields over continuous spaces
  - homologous to sensory surfaces, e.g., visual or auditory space (retinal, allocentric, ...)
  - homologous to motor surfaces, e.g., saccadic end-points or direction of movement of the end-effector in outer space
  - feature spaces, e.g., localized visual orientations, color, impedance, ...
  - abstract spaces, e.g., ordinal space, along which serial order is represented

Example motion perception: space of possible percepts

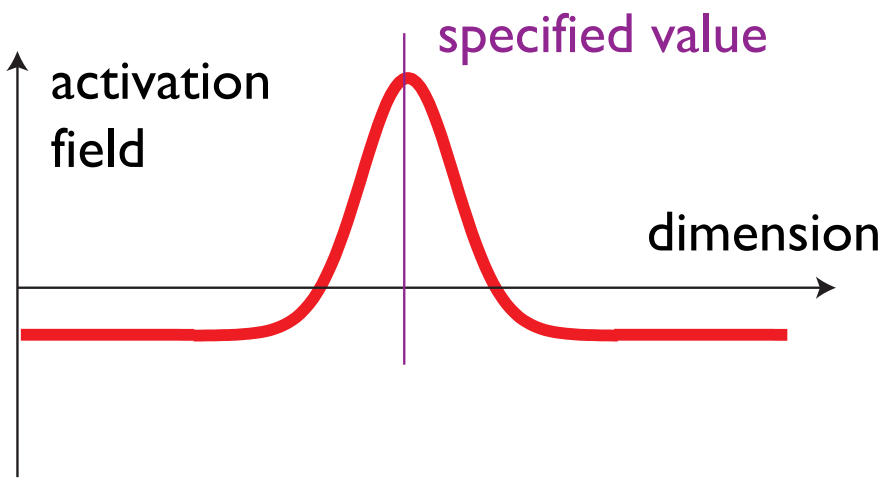


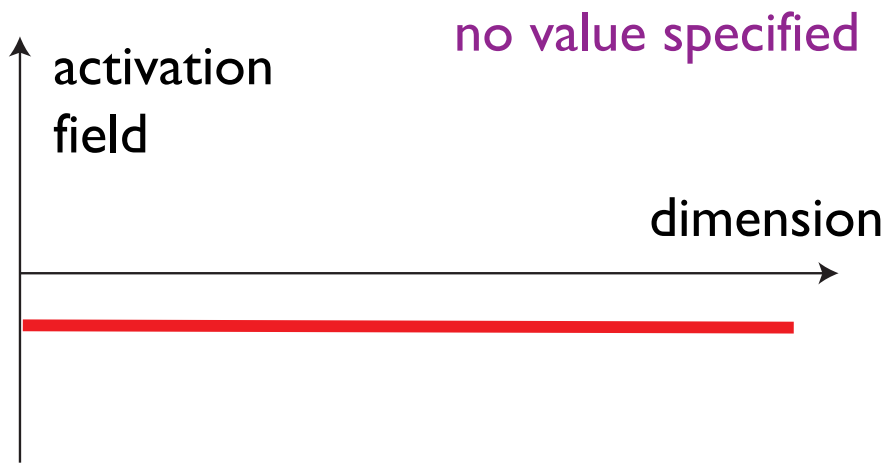


Example: movement planning: space of possible actions



Activation fields

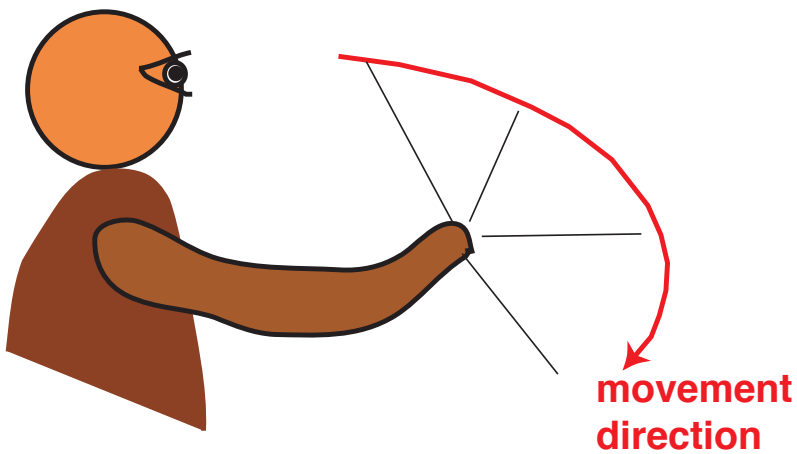


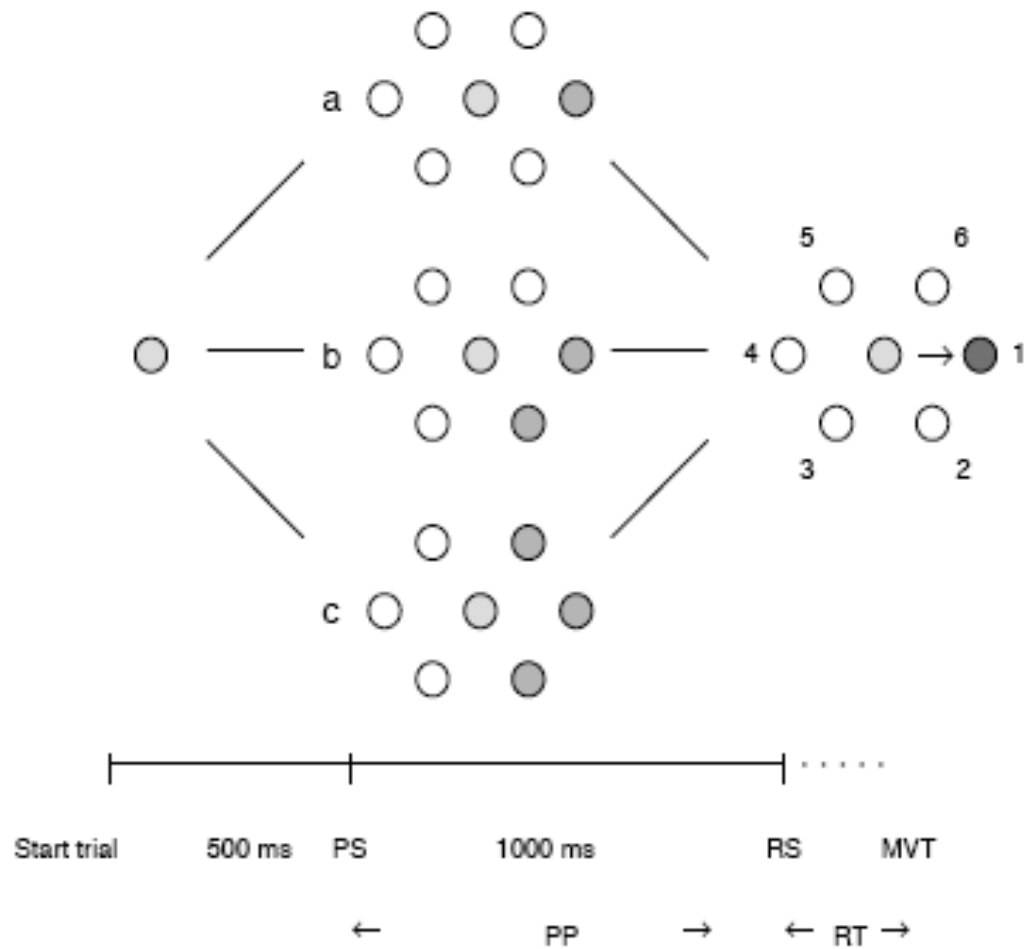


Grounding in neurophysiology

- activation within populations of neurons provides the best correlate with behavior

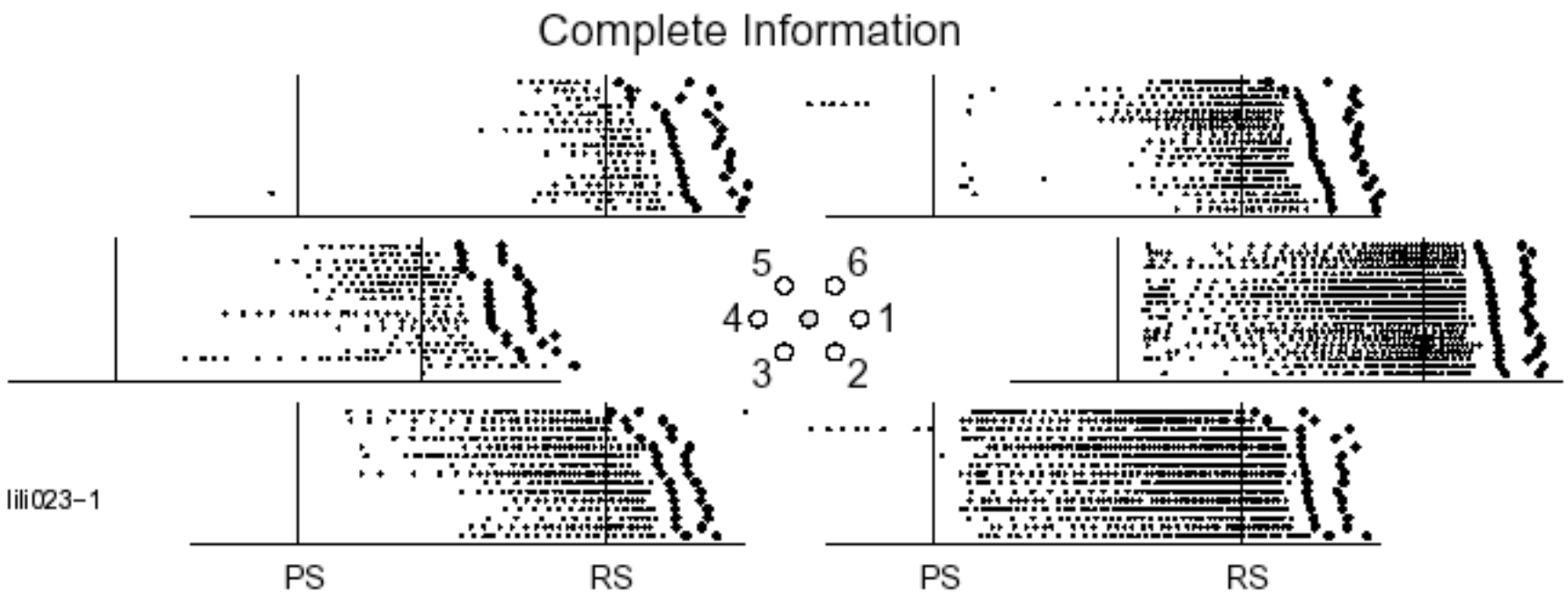
Neurophysiological grounding of DFT example: movement planning





Bastian, Riehle, Schöner, 2003

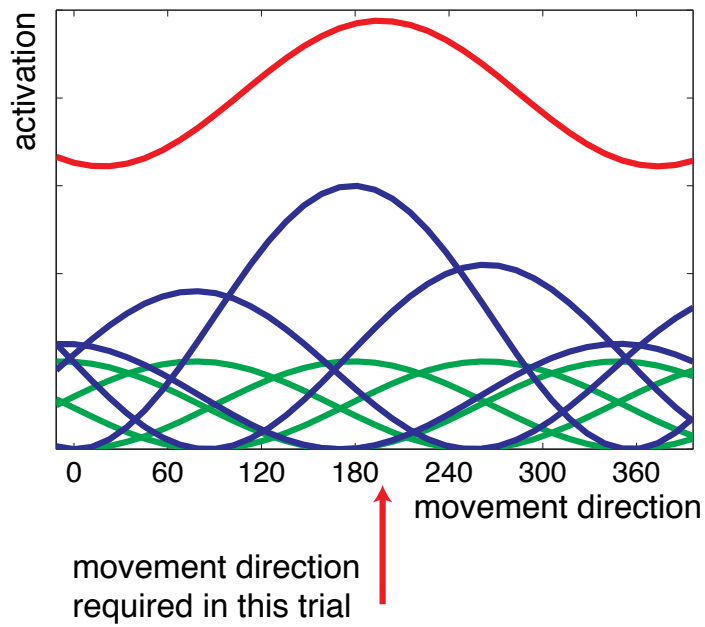
- tuning of cells in motor and premotor cortex to direction of end-effector movement path

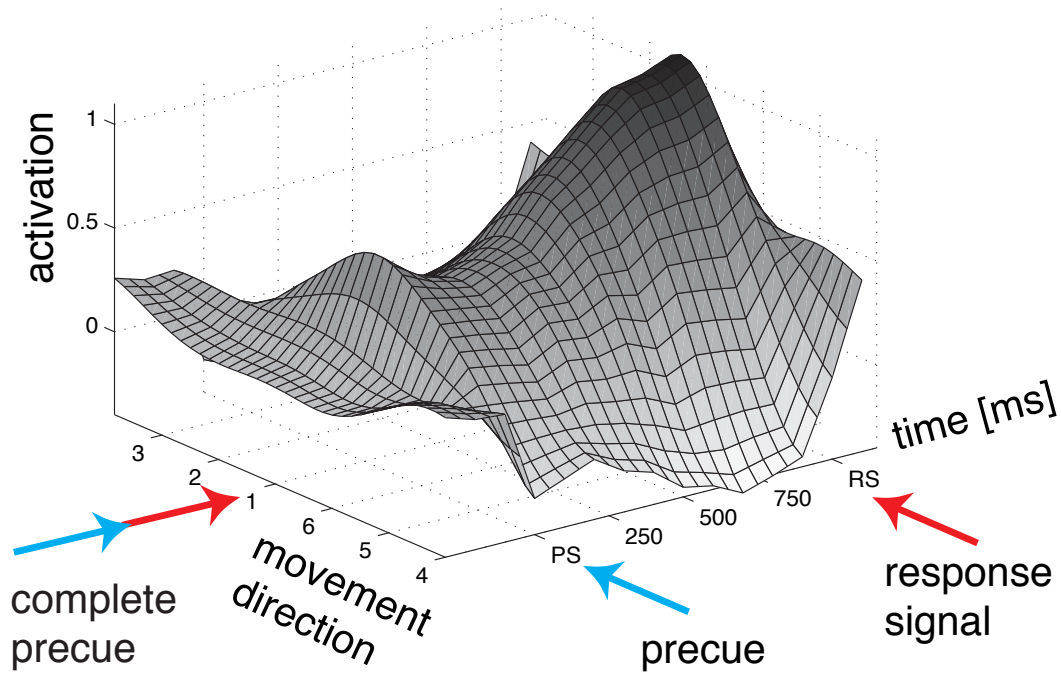


Distribution of Population Activation (DPA)

Distribution of population activation =

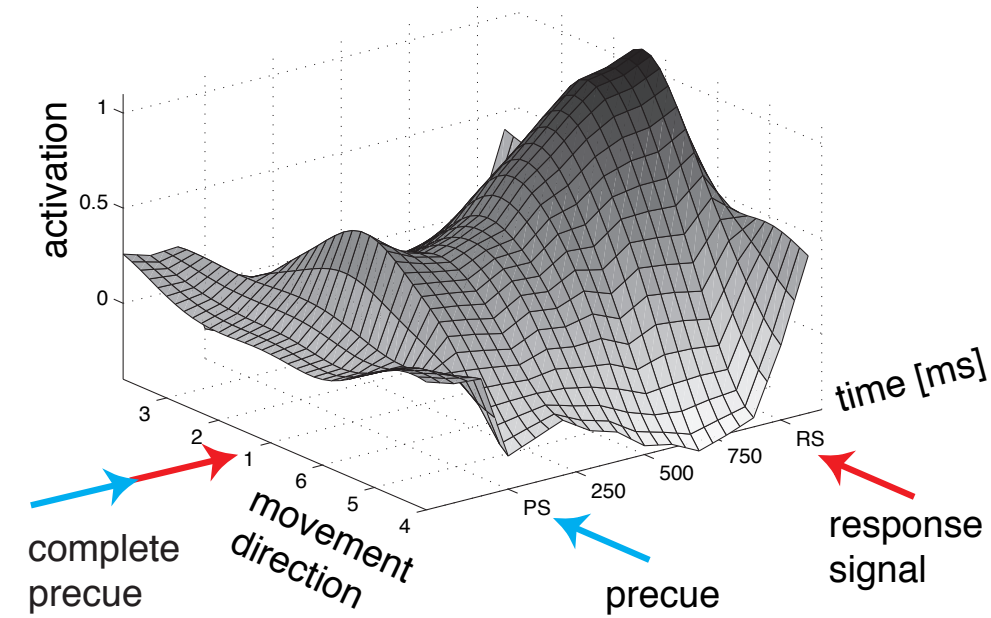
$\sum_{\text{neurons}}$ tuning curve * current firing rate

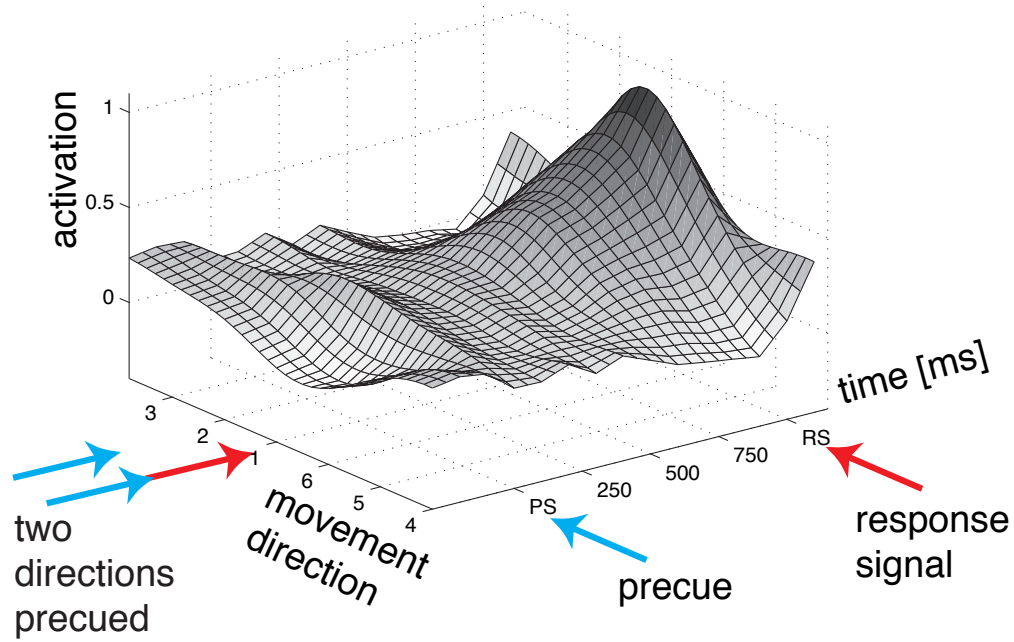




[Bastian, Riehle, Schöner, 2003]

- look at temporal evolution of DPA
- or DPAs in new conditions, here: DPA reflects prior information

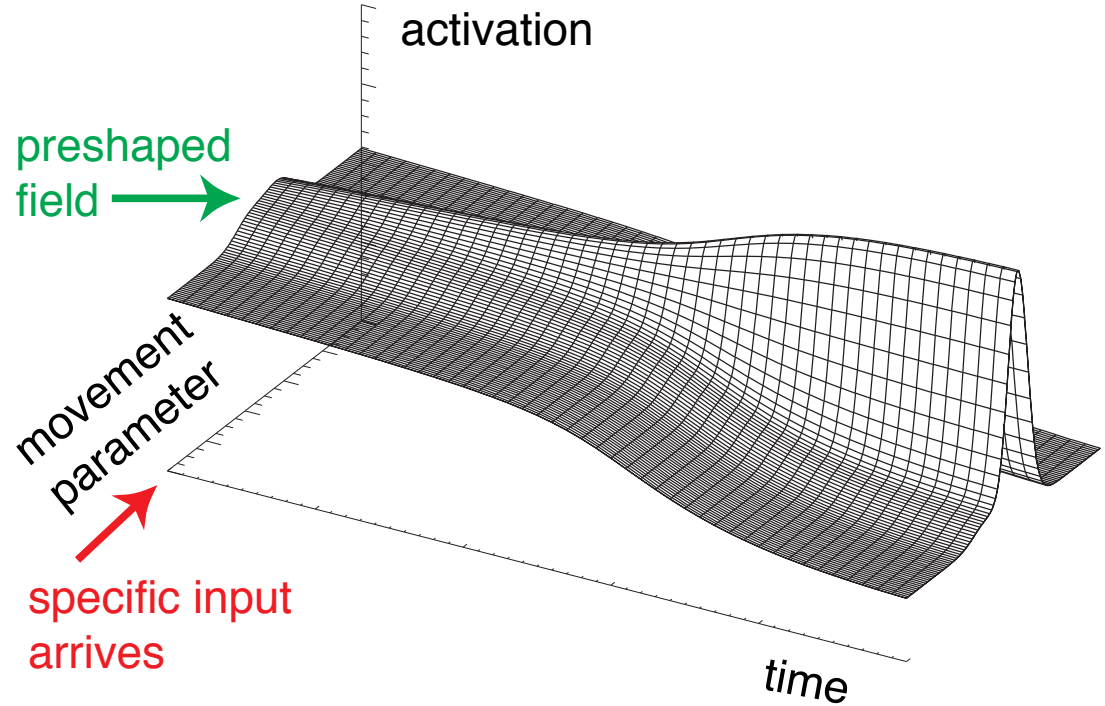


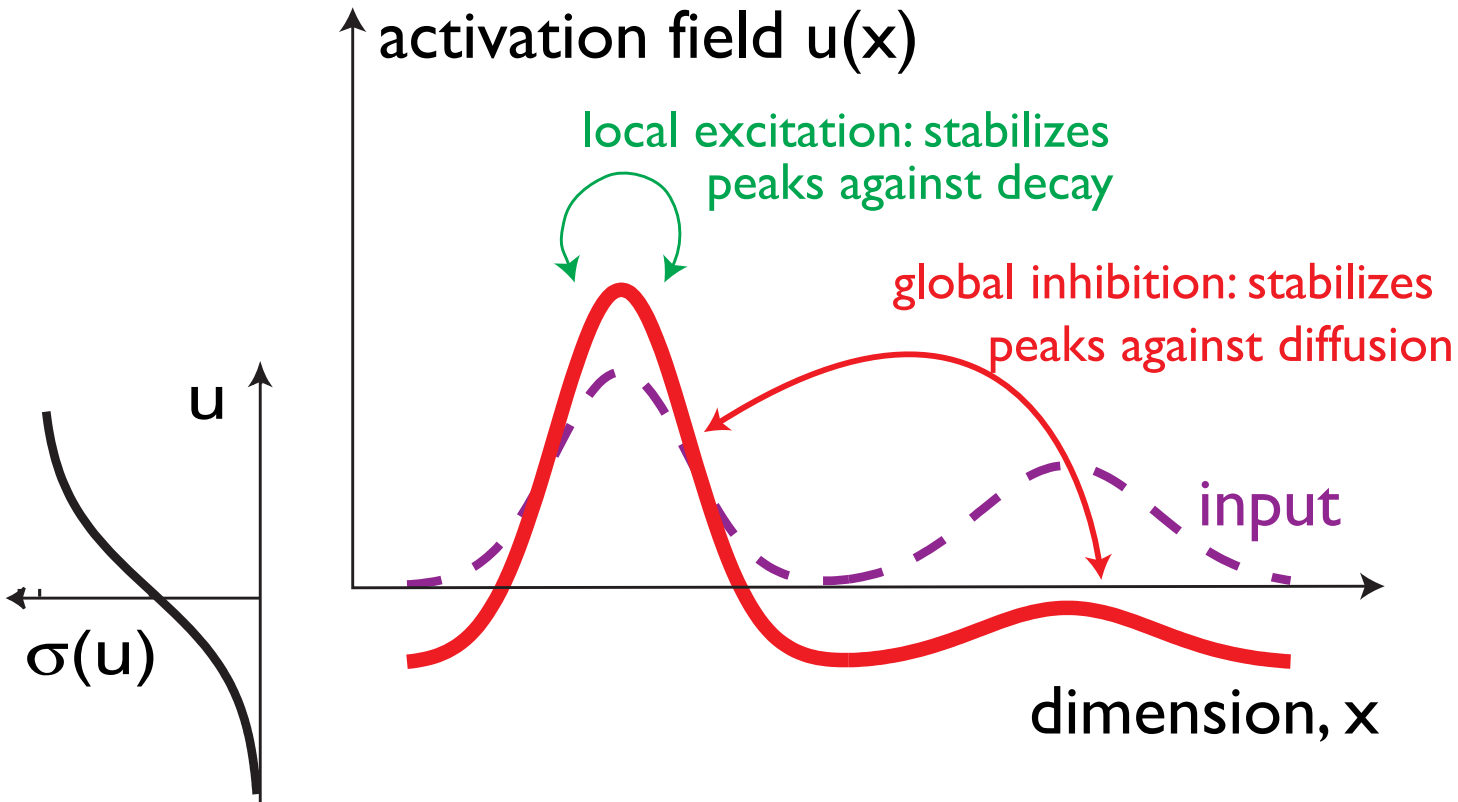


Distributions of Population Activation are abstract

- neurons are not localized within DPA!
- cortical neurons really are sensitive to many dimensions
  - motor: arm configuration, force direction
  - visual: many feature dimensions such as spatial frequency, orientation, direction...
- => DPA is a projection from that high-dimensional space onto a single dimension

Dynamics of activation fields in which localized peaks are attractors





mathematical formalization

Amari equation

$$\tau \dot{u}(x,t) = -u(x,t) + h + S(x,t) + \int w(x-x')\sigma(u(x',t))\ dx'$$

where

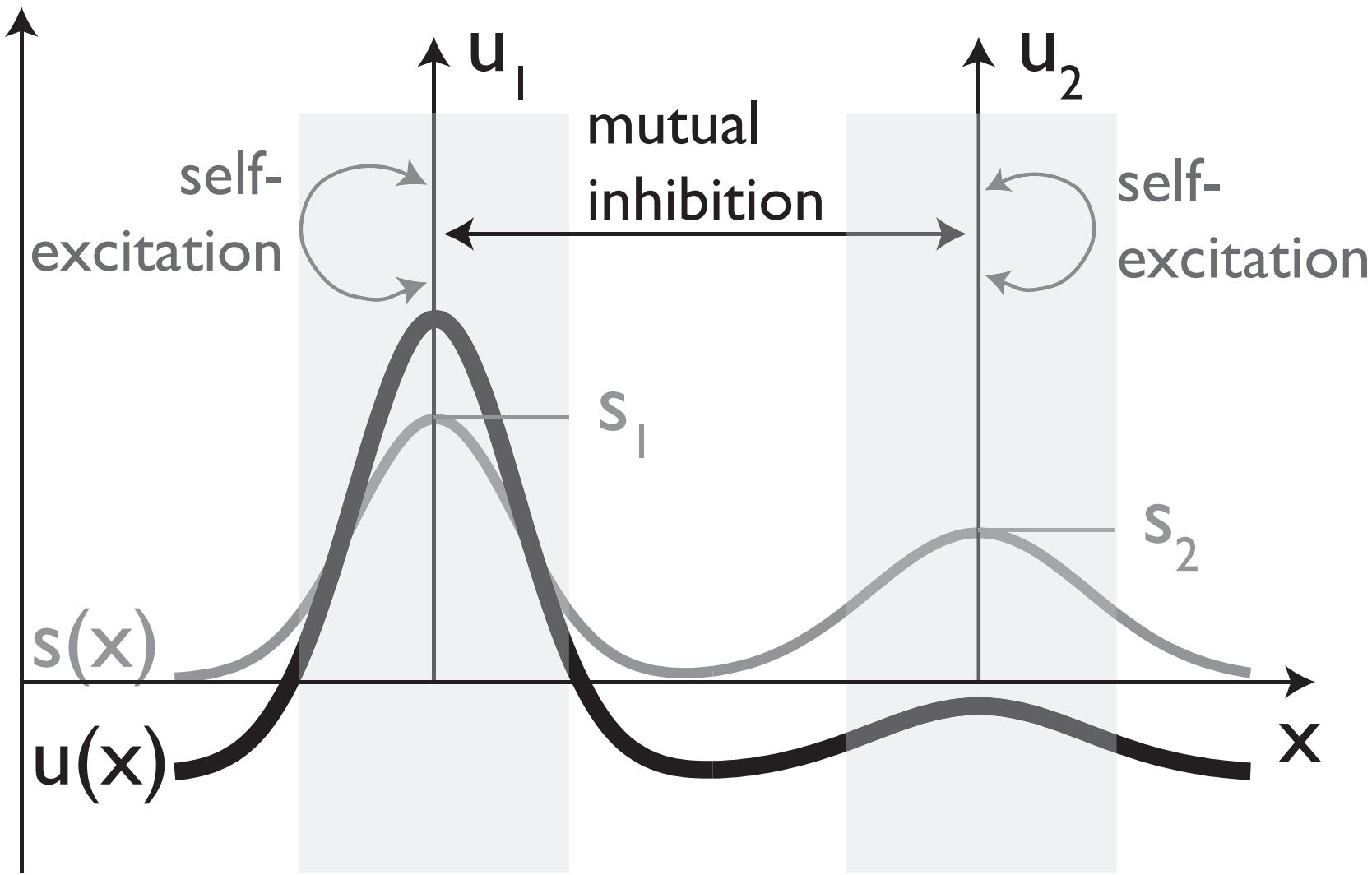
- time scale is τ
- resting level is $h < 0$
- input is $S(x,t)$
- interaction kernel is

$$w(x-x') = w_i + w_e \exp\left[-\frac{(x-x')^2}{2\sigma_i^2}\right]$$

- sigmoidal nonlinearity is

$$\sigma(u) = \frac{1}{1+\exp[-\beta(u-u_0)]}$$

Relationship to the dynamics of discrete activation variables



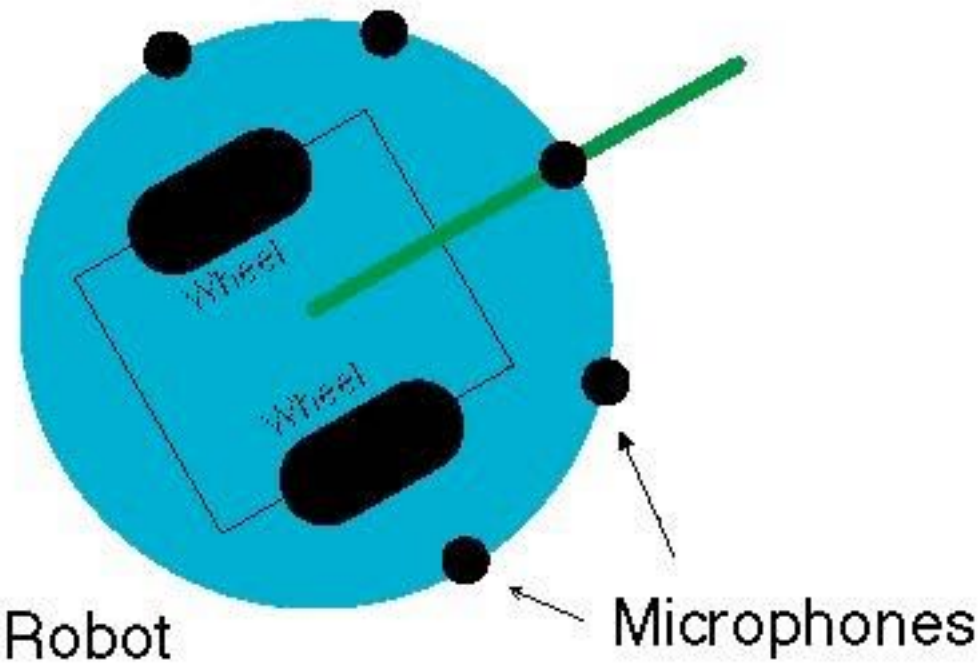
=> simulation

- Matlab code available at
- http://www.dynamicfieldtheory.org/cosivina
- or
- https://bitbucket.org/sschneegans/cosivina/

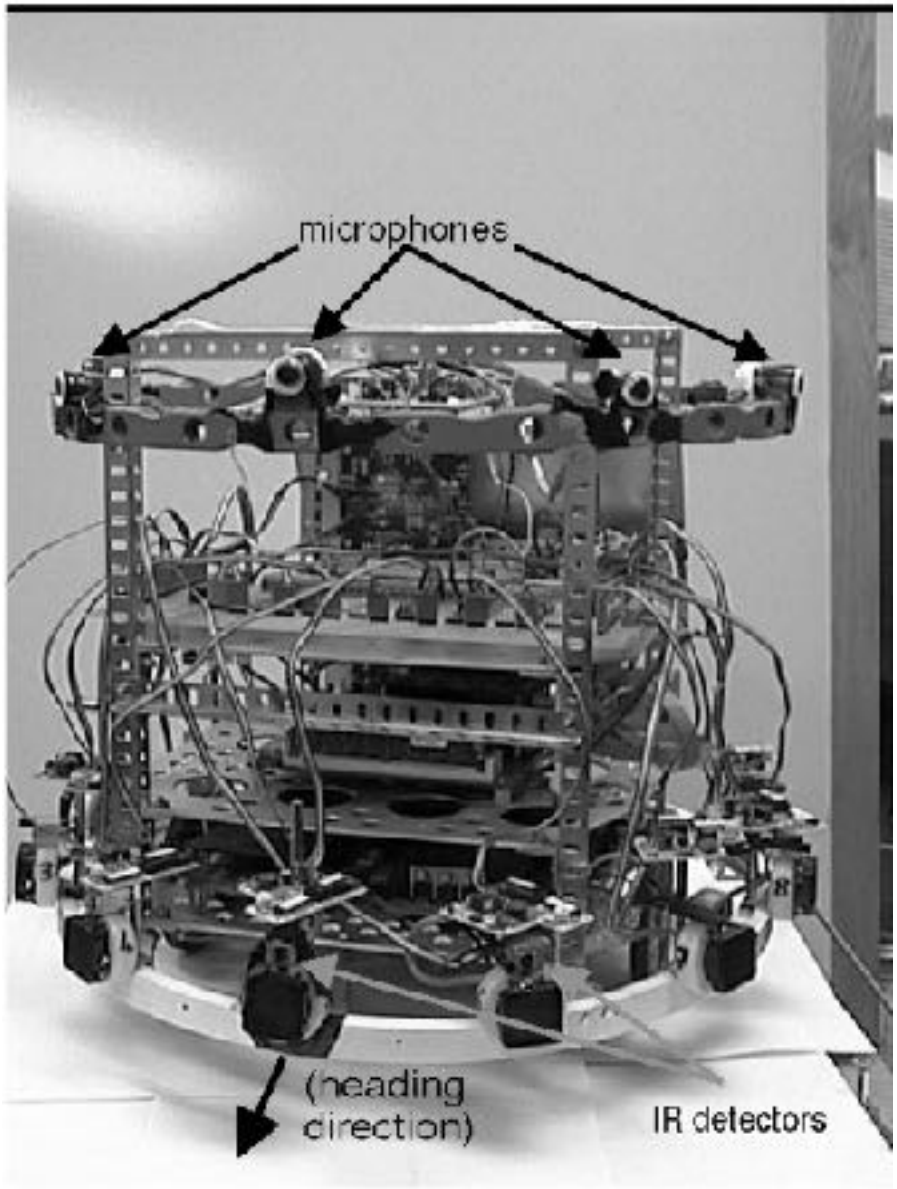
solutions and instabilities

- input driven solution (sub-threshold) vs. self-stabilized solution (peak, supra-threshold)
- detection instability
- reverse detection instability
- selection
- selection instability
- memory instability
- detection instability from boost

Illustration: DFT on a Braitenberg-like vehicle for target representation

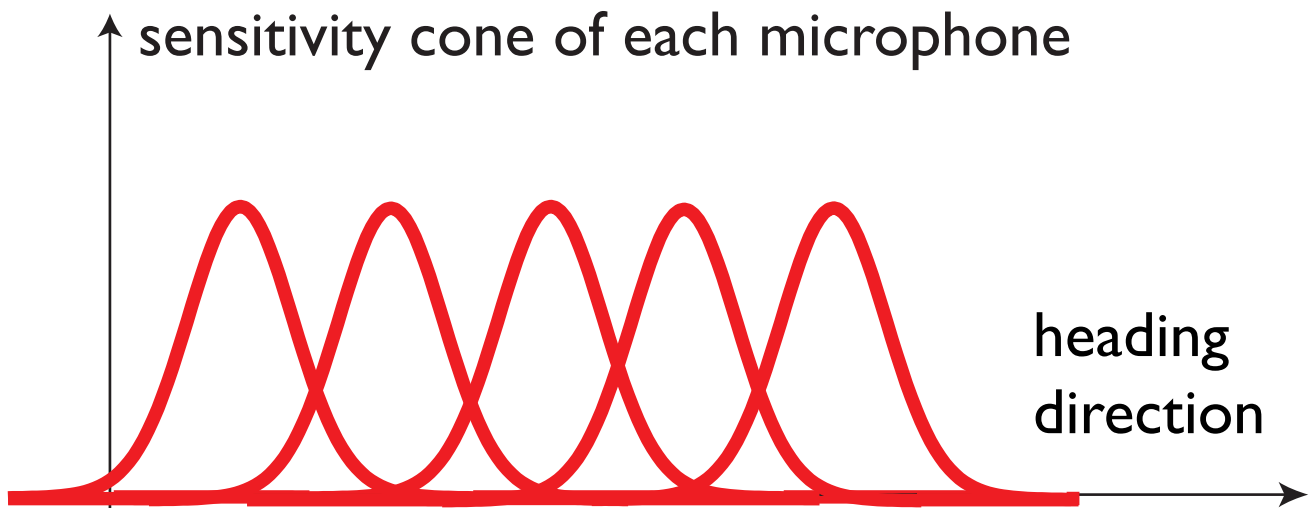


[from Bicho, Mallet, Schöner, Int J Rob Res,2000]

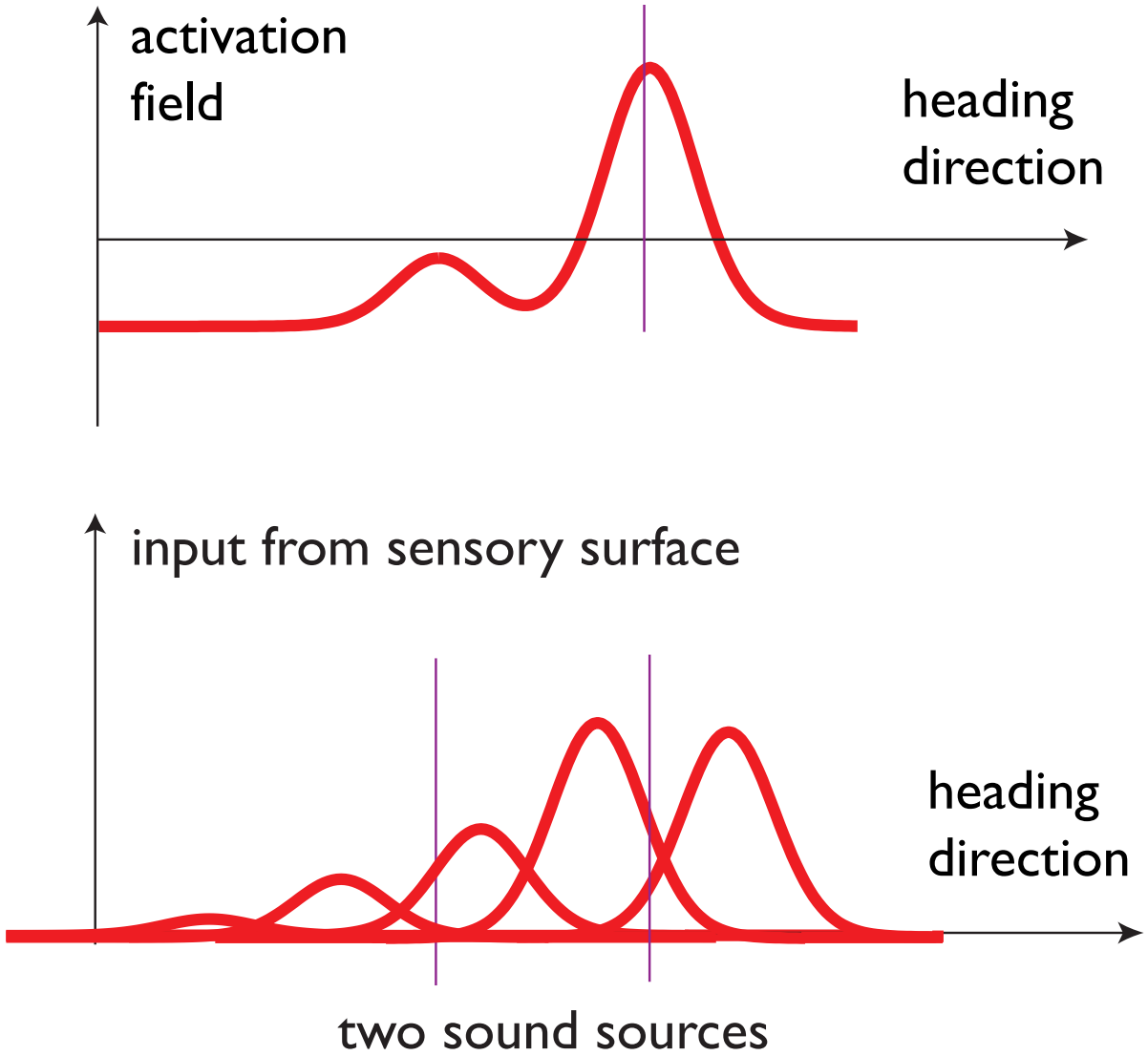


sensory surface

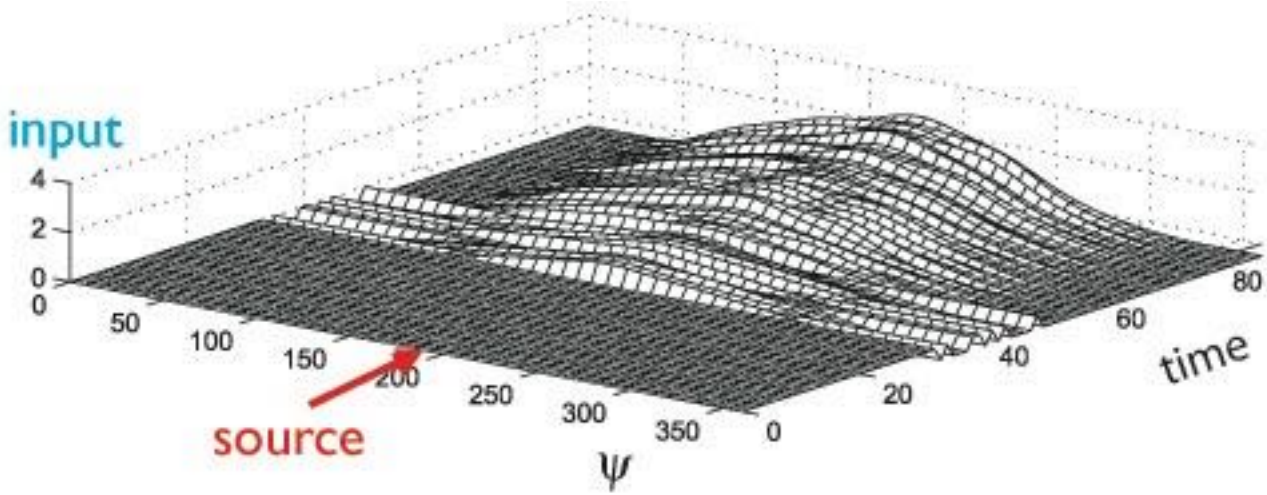
- each microphone samples heading direction

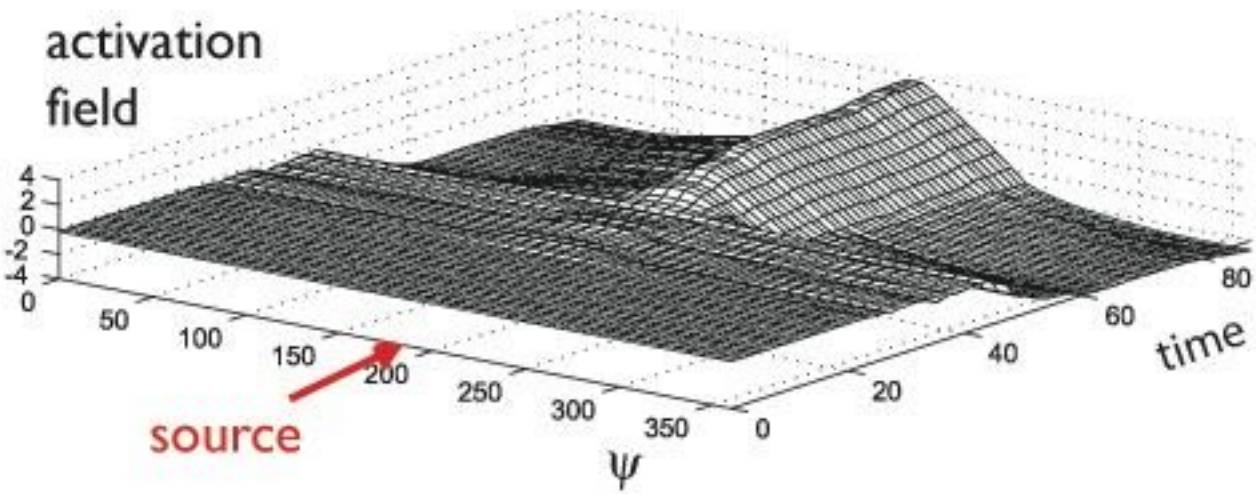


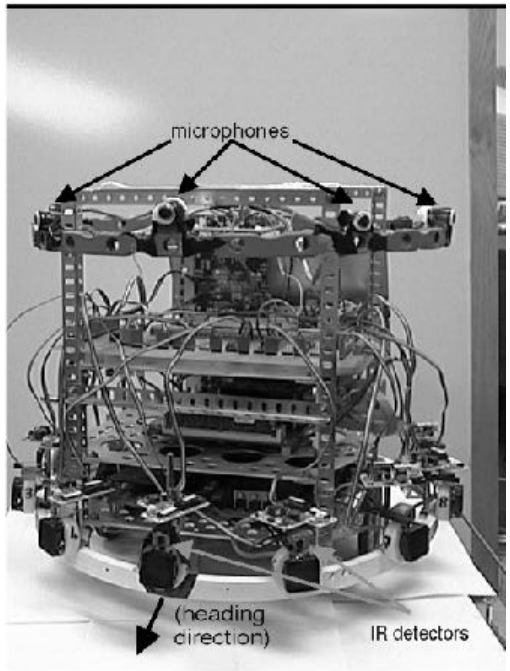
and provides input to the field



detection instability on a phonotaxis robot

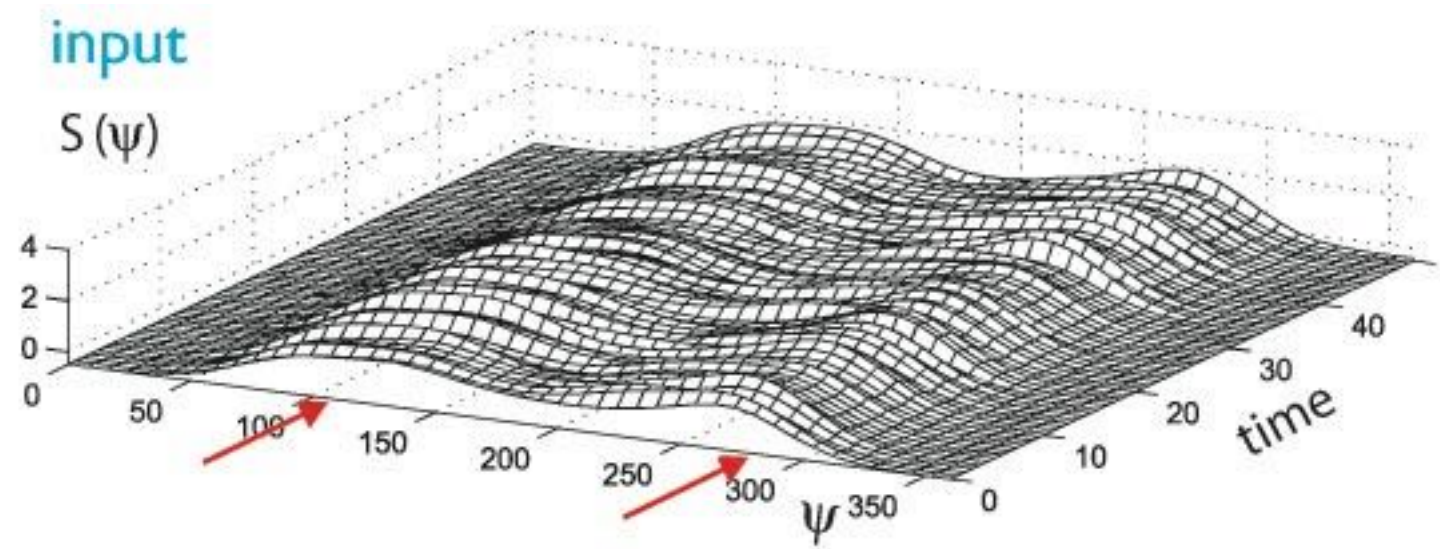


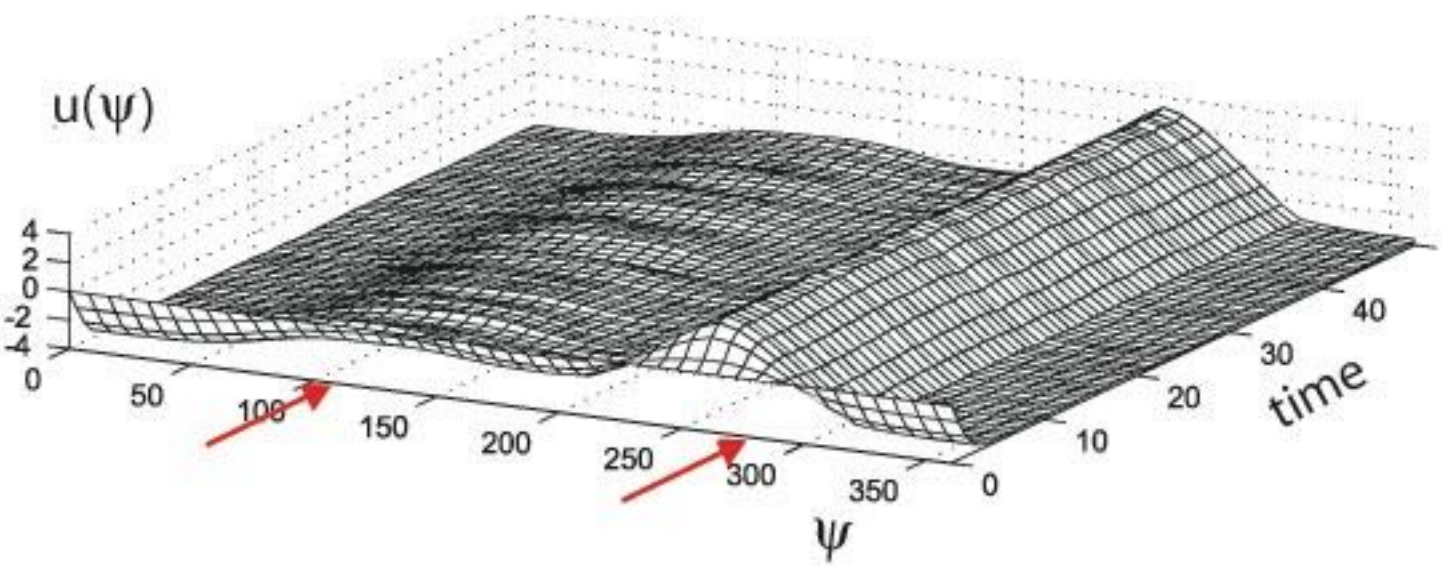


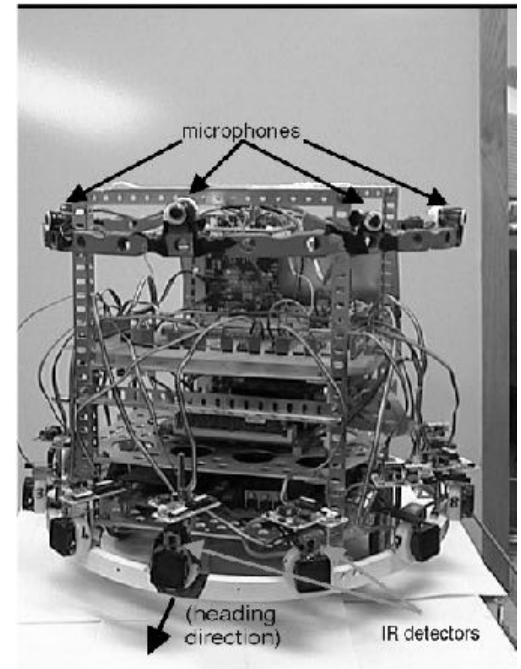


[from Bicho, Mallet, Schöner: Int. J. Rob. Res., 2000]

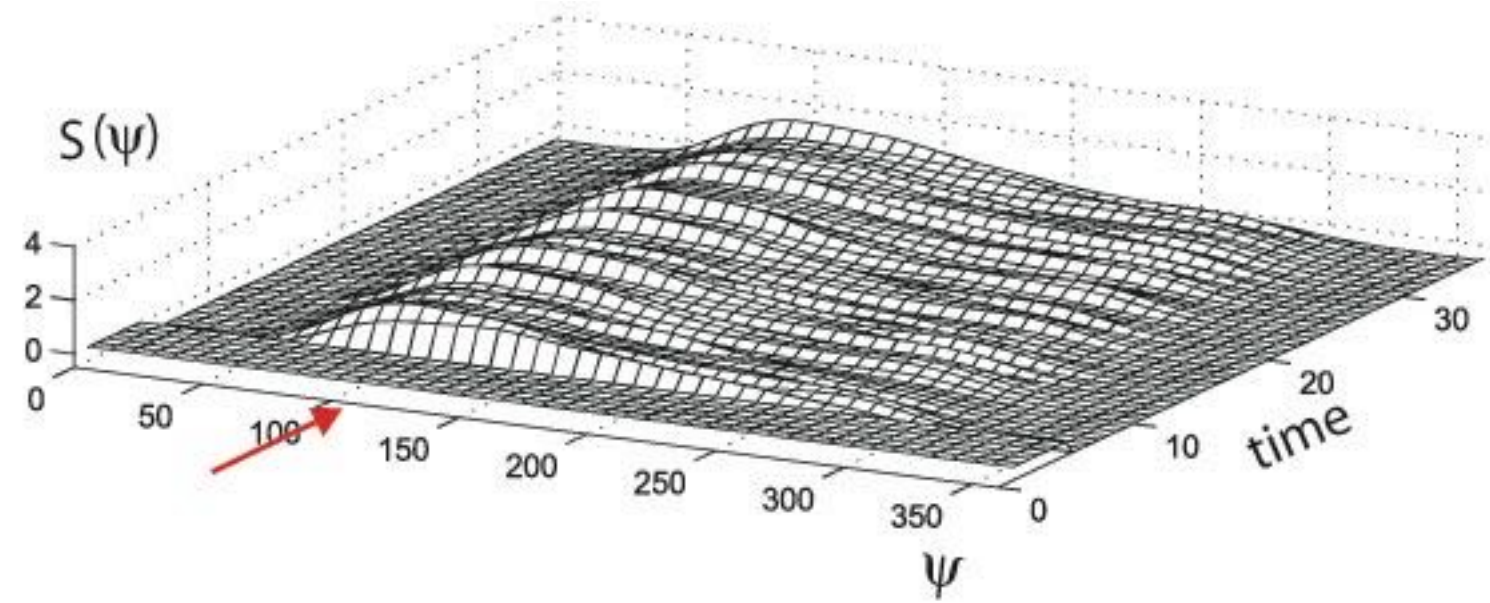
target selection on phonotaxis vehicle

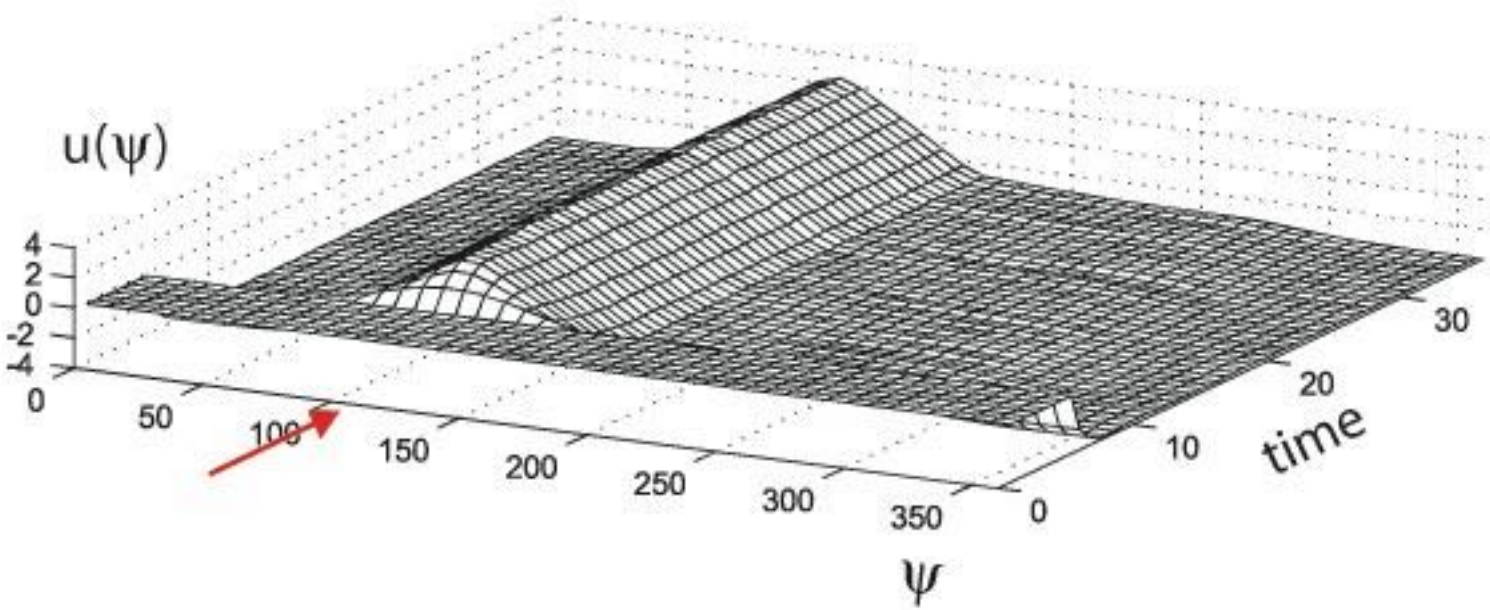




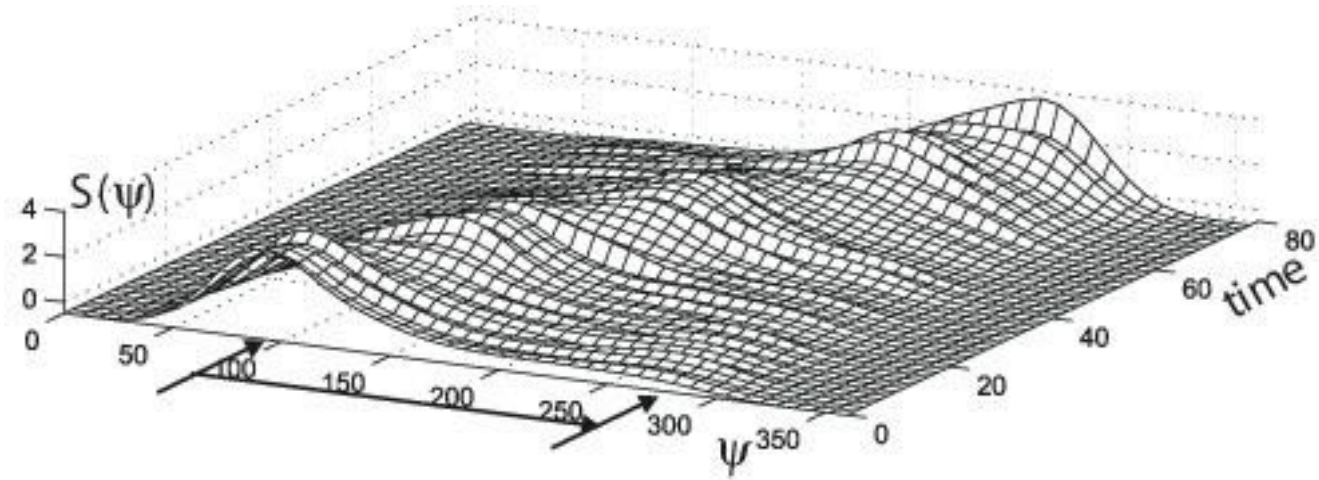


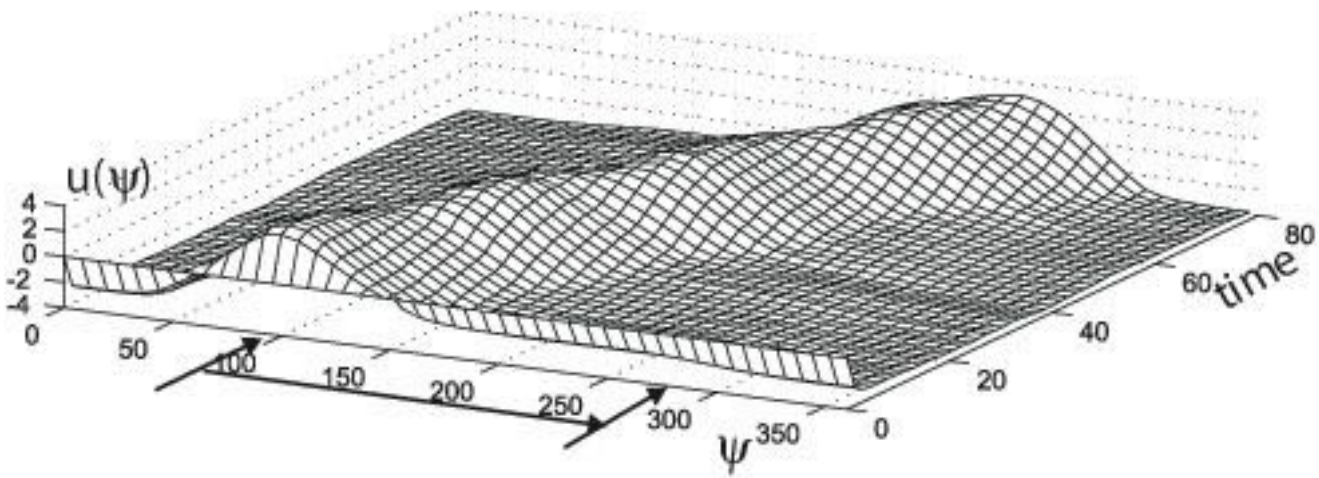
robust estimation



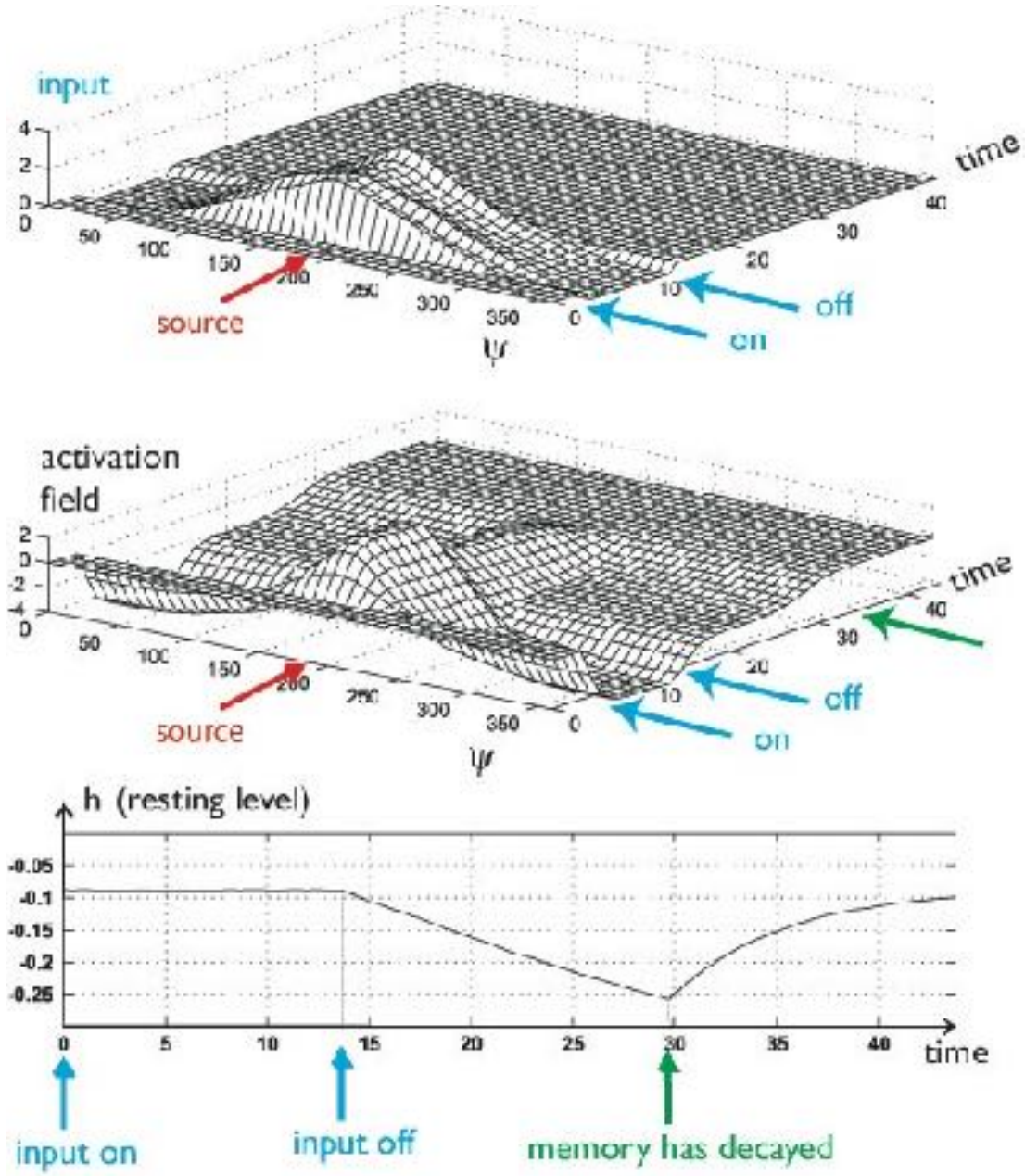


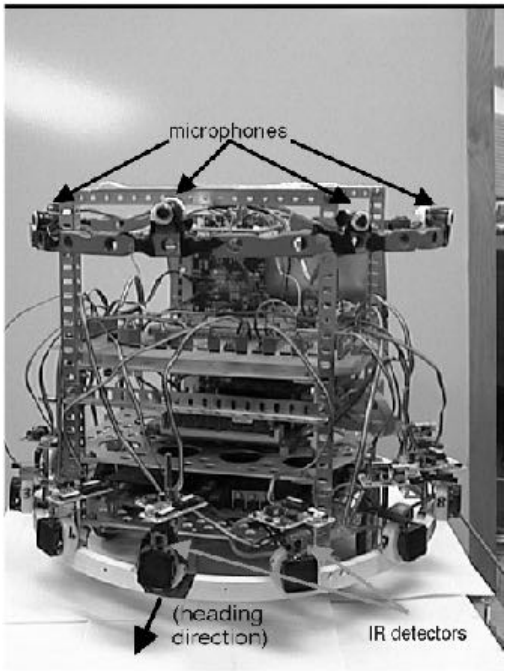
tracking


S(ψ)
4
2
0
0
50
100
150
200
250
300
350
ψ
0
20
40
60
80
time


u(ψ)
4
2
0
-2
-4
0
50
100
150
200
250
300
350
ψ
0
20
40
60
80
time

memory & forgetting on phonotaxis vehicle



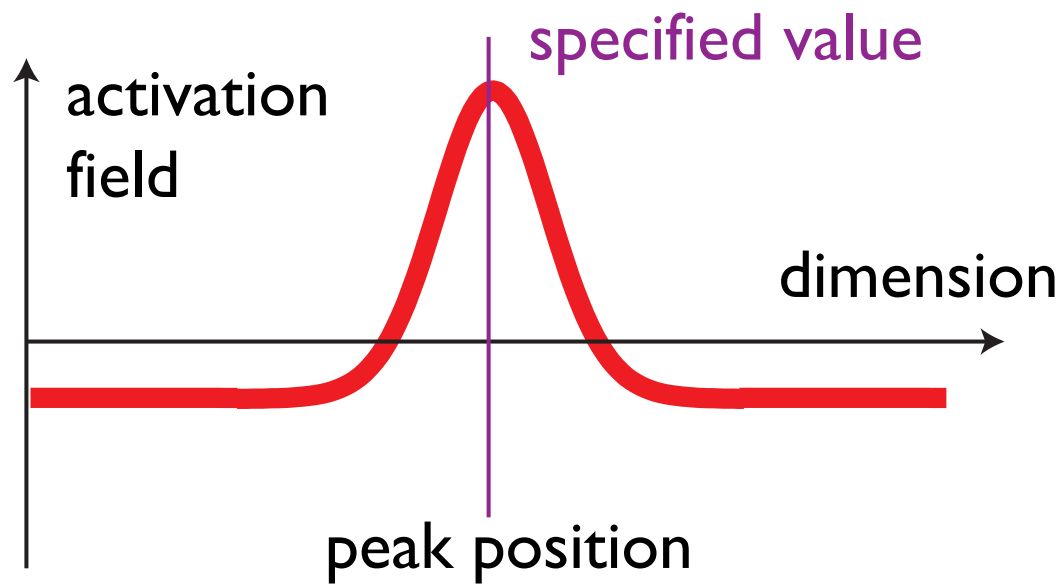


[from Bicho, Mallet, Schöner: Int J Rob Res 19:424(2000)]

a robotic demo of all of instabilities

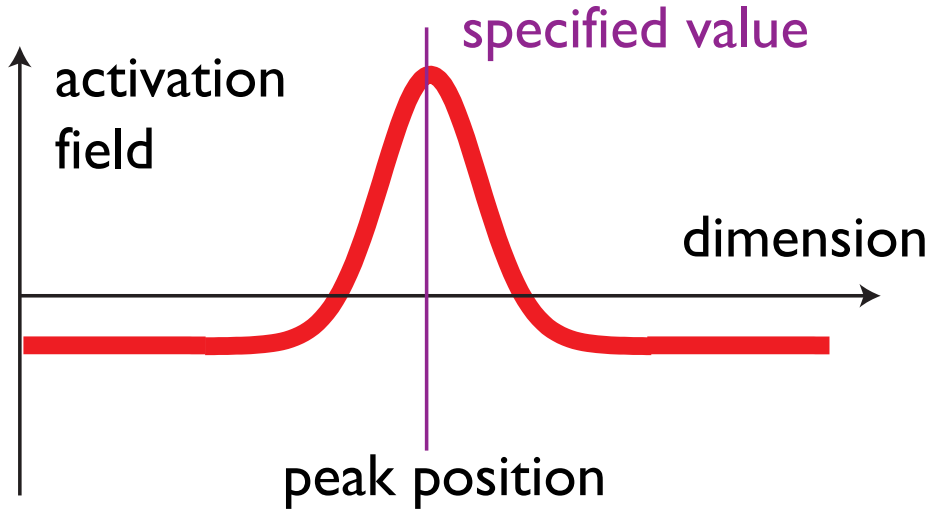
From fields to behavior

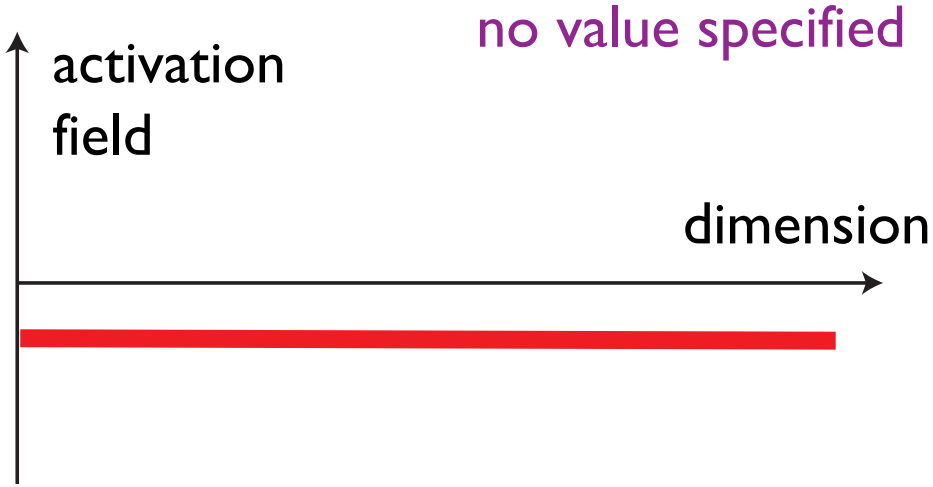
- peak specifies value for a dynamical variable that is congruent to the field dimension



From fields to behavior

- => treat supra-threshold activation as a probability density…
- but: need to normalize
- => problem when there is no peak: divide by zero!



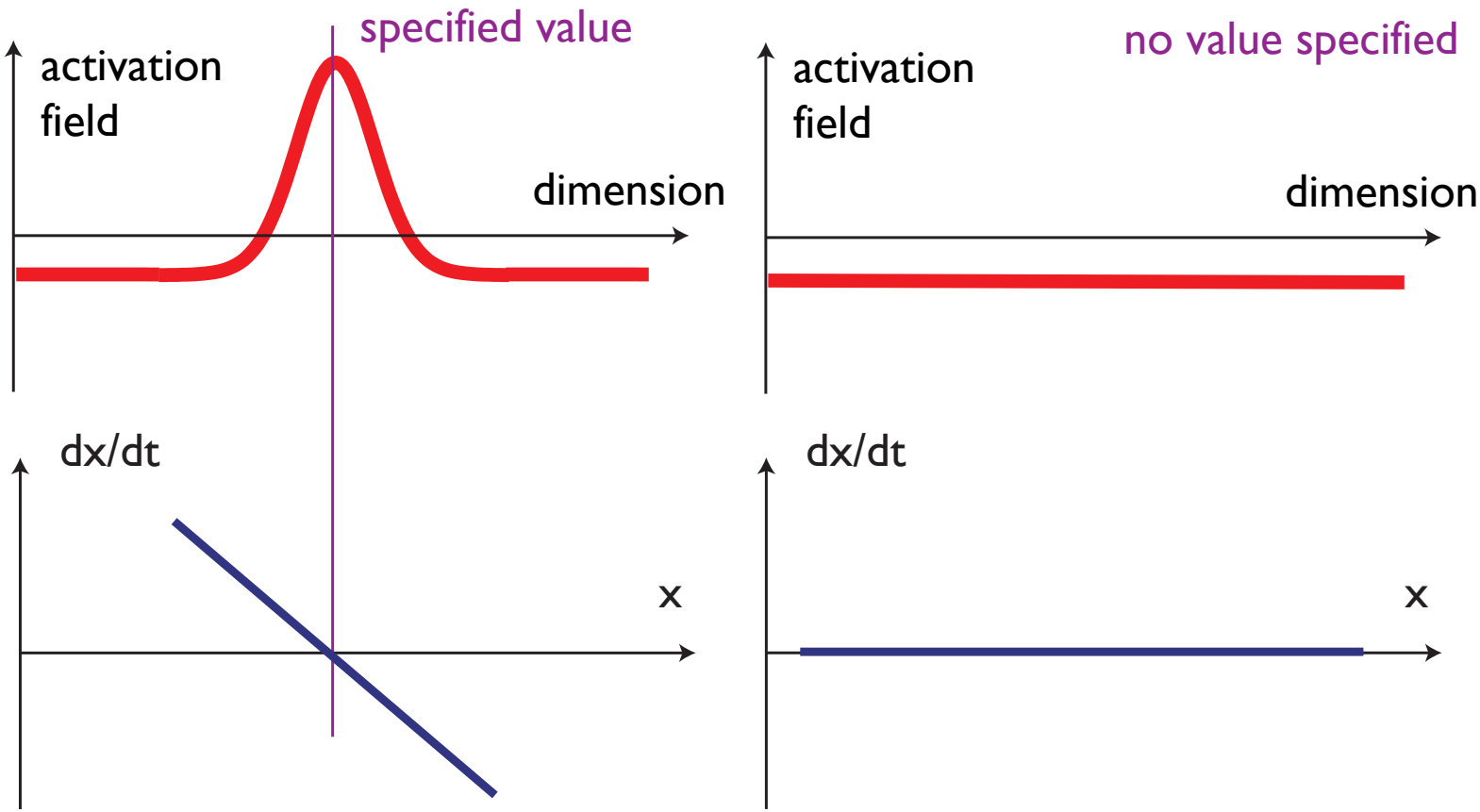


From fields to behavior

- solution: peak sets attractor
  - location of attractor: peak location
  - strength of attractor: summed supra-threshold activation

$$
\begin{aligned}
x_{\text{peak}} &= \frac{\int dx\ x\ \sigma(u(x,t))}{\int dx\ \sigma(u(x,t))} \\
\dot{x} &= -\left[\int dx\ \sigma(u(x,t))\right](x - x_{\text{peak}}) \\
\Rightarrow \dot{x} &= -\left[\int dx\ \sigma(u(x,t))\right]\ x + \left[\int dx\ x\ \sigma(u(x,t))\right]
\end{aligned}
$$

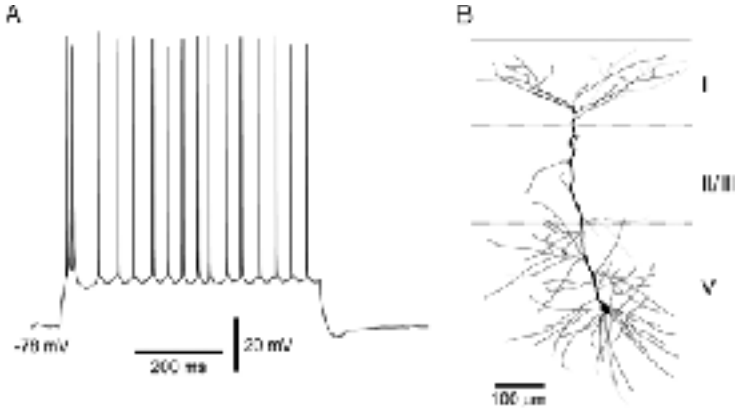
from DFT to DST



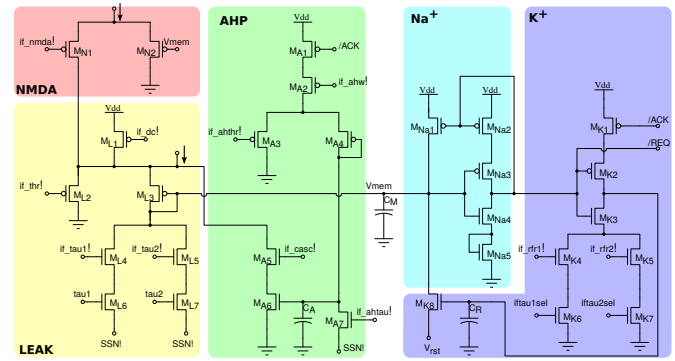
Neuromorphic implementation of DFT based vehicle

- Work of Yulia Sandamirskaya's at INI Zürich
- collaborating with Giacomo Indiveri
- Yulia was previously at INI Bochum, where she worked on sequence generation in DFT => second lecture

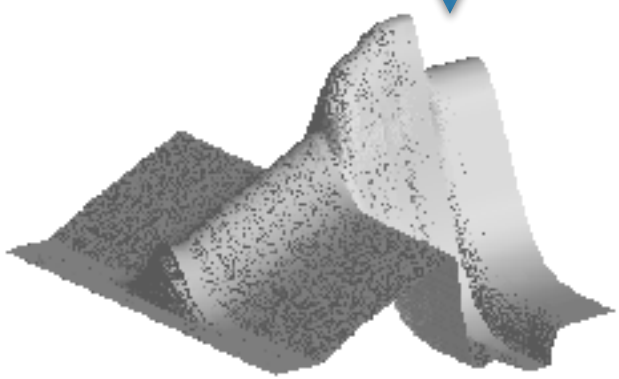
Neuromorphics



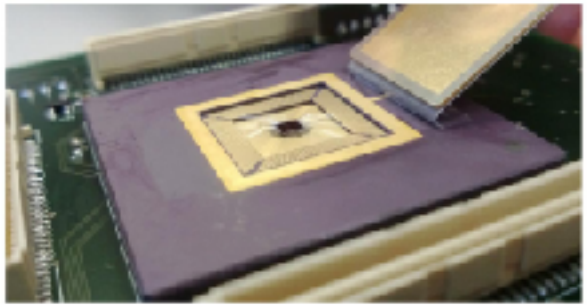
neuron



circuit of a neuron

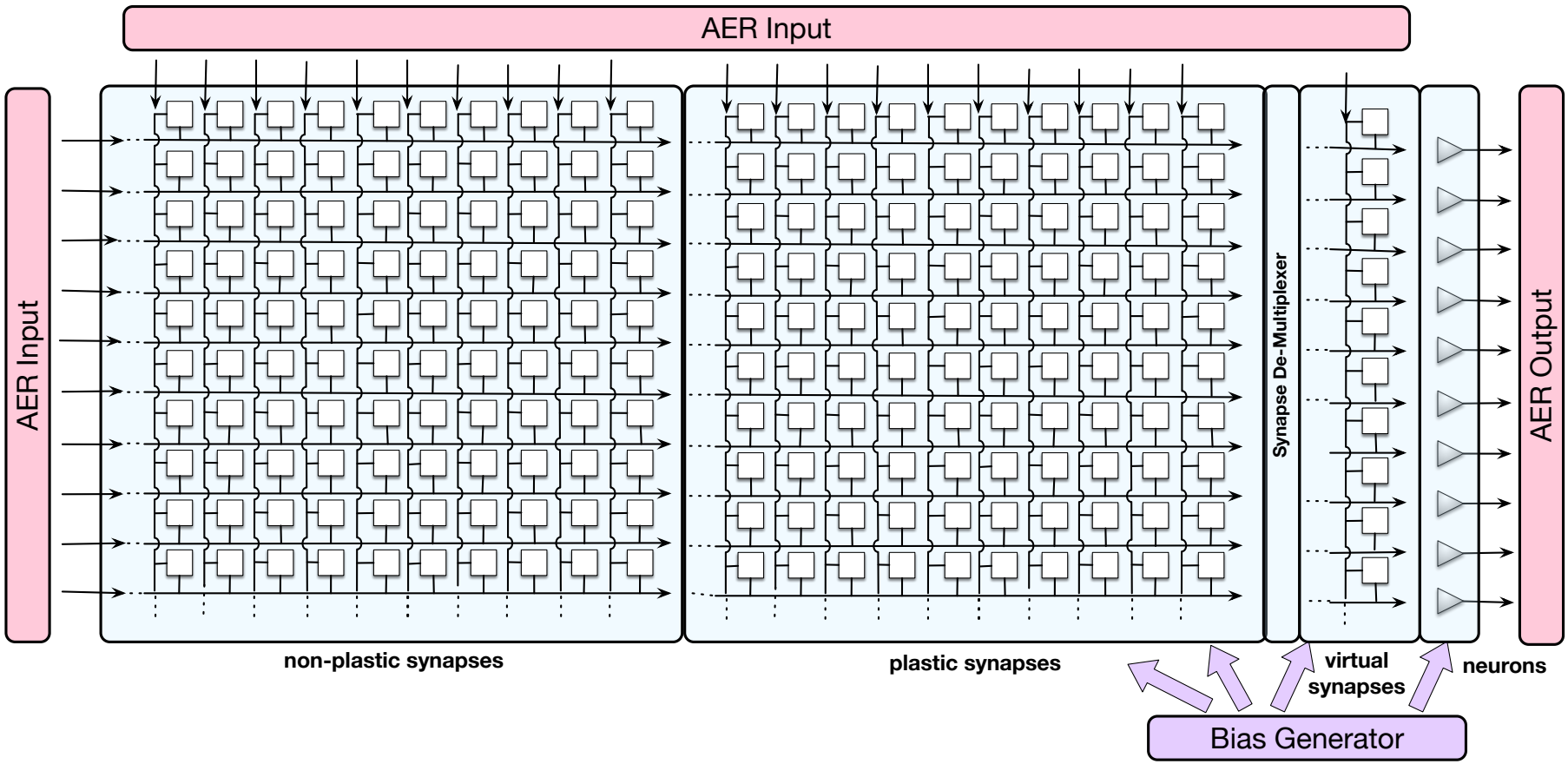


population dynamics



VLSI device
(ROLLS, CXQUAD)

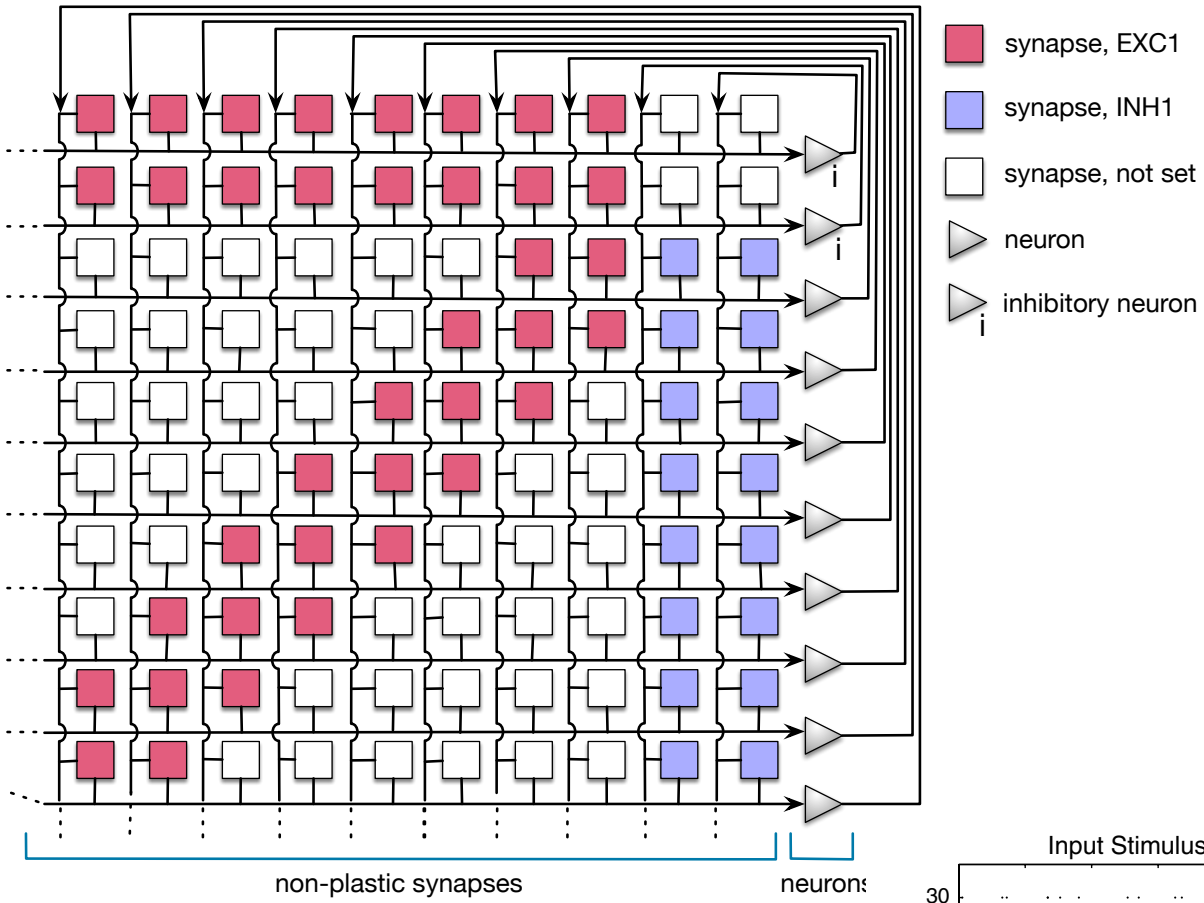
ROLLS: Reconfigurable Online-Leaning System

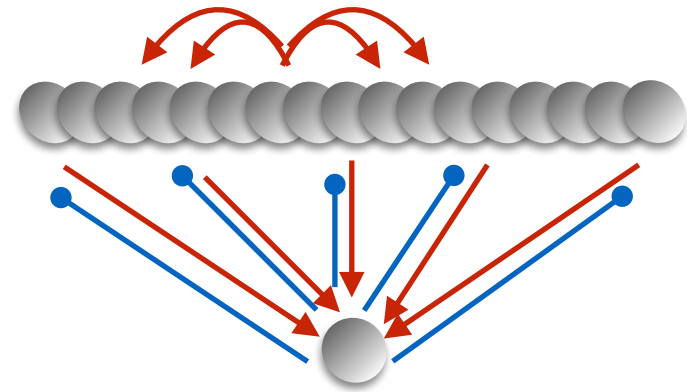


Qiao et al, 2015

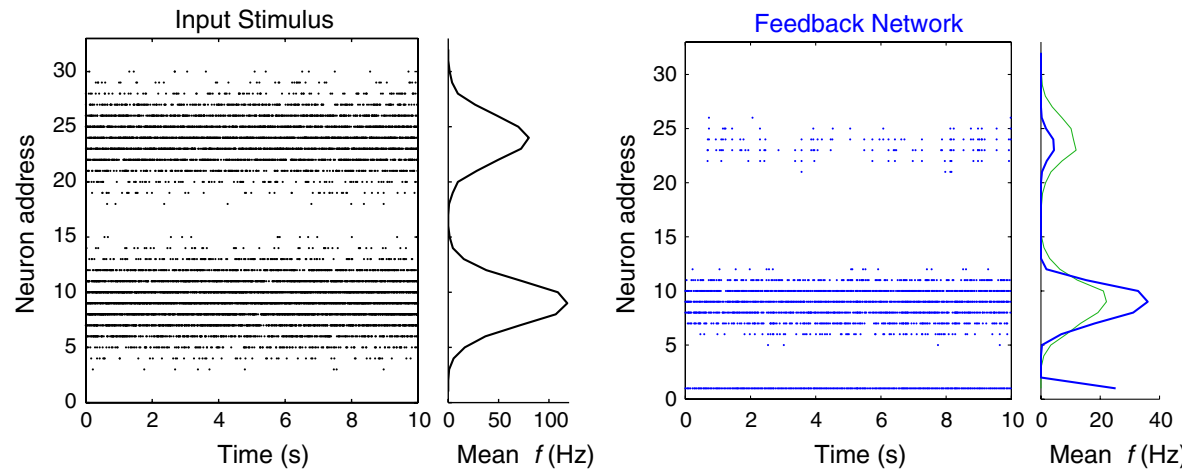
256 AE IF neurons
16K plastic and 16K non-plastic synapsis
analogue electronic circuits
digital controllers and AER communication

Dynamic Neural Field on ROLLS





Detection
Selection
Memory

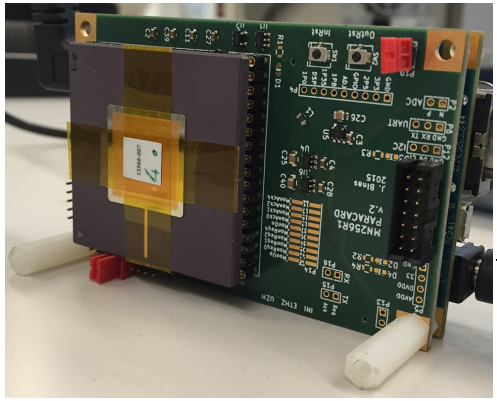


Indiveri et al, 2009; Chicca et al, 2014

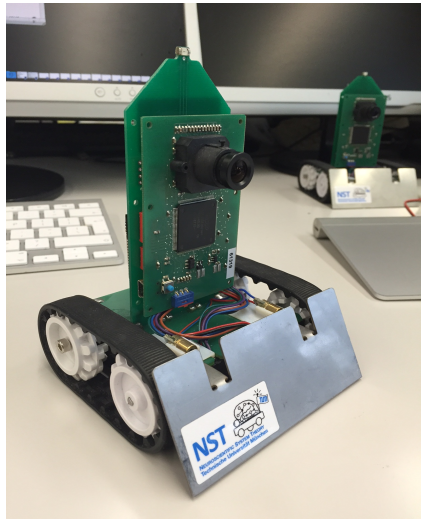
Neuromorphic architecture controlling a vehicle

- obstacle avoidance and target acquisition implemented on a PushBot (J Conradt)
- sensory input from a neuromorphic camera, DVS
- DFT on Rolls device

ROLLS device
on the parallella board

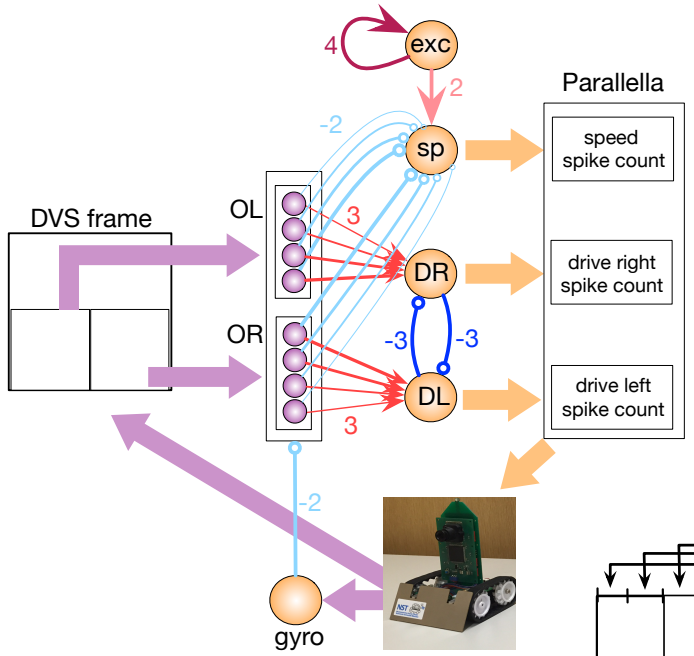


“PushBot” robot

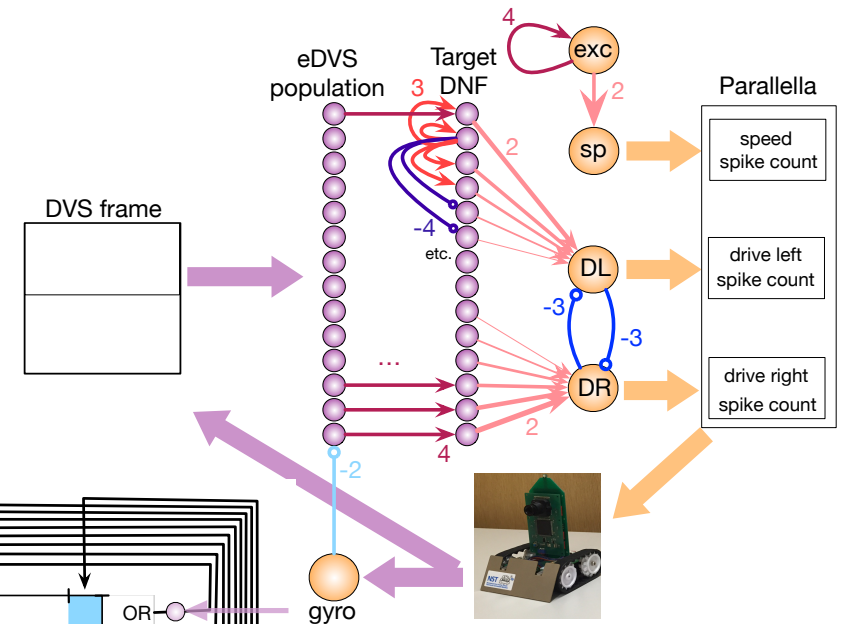


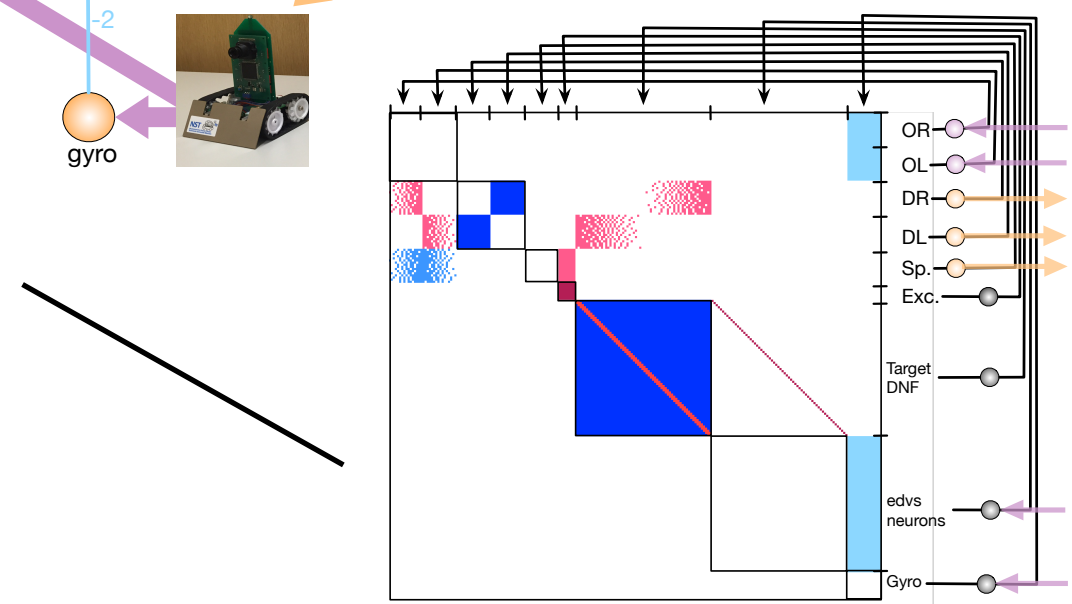
Milde, Dietmüller, Hermann Blum, Indiveri, Sandamirskaya ISCAS 2017

Obstacle avoidance



Target acquisition





connectivity matrix

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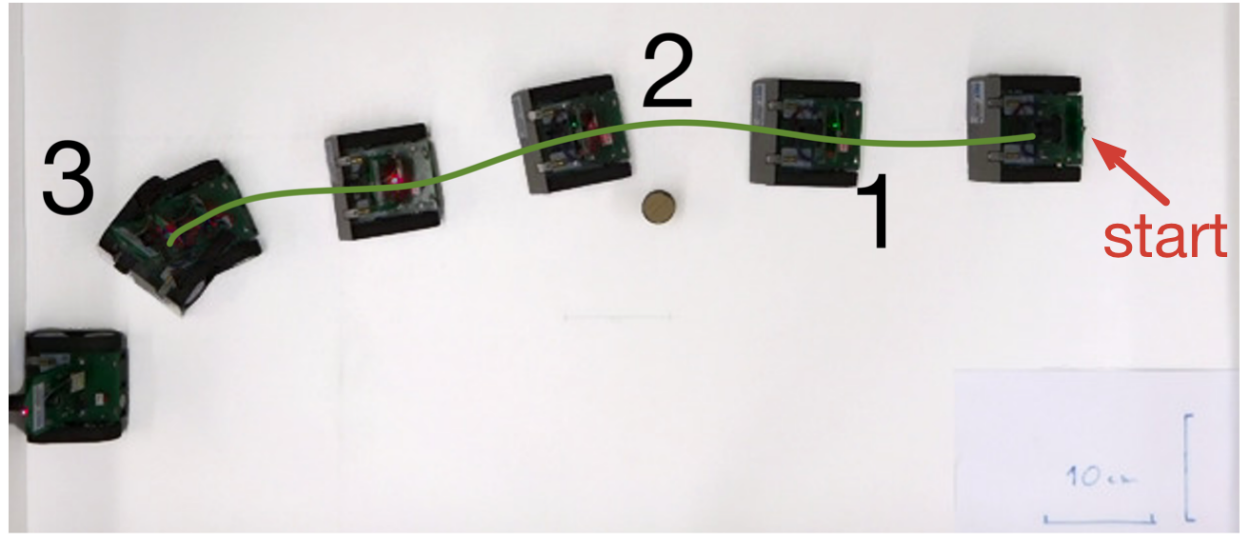

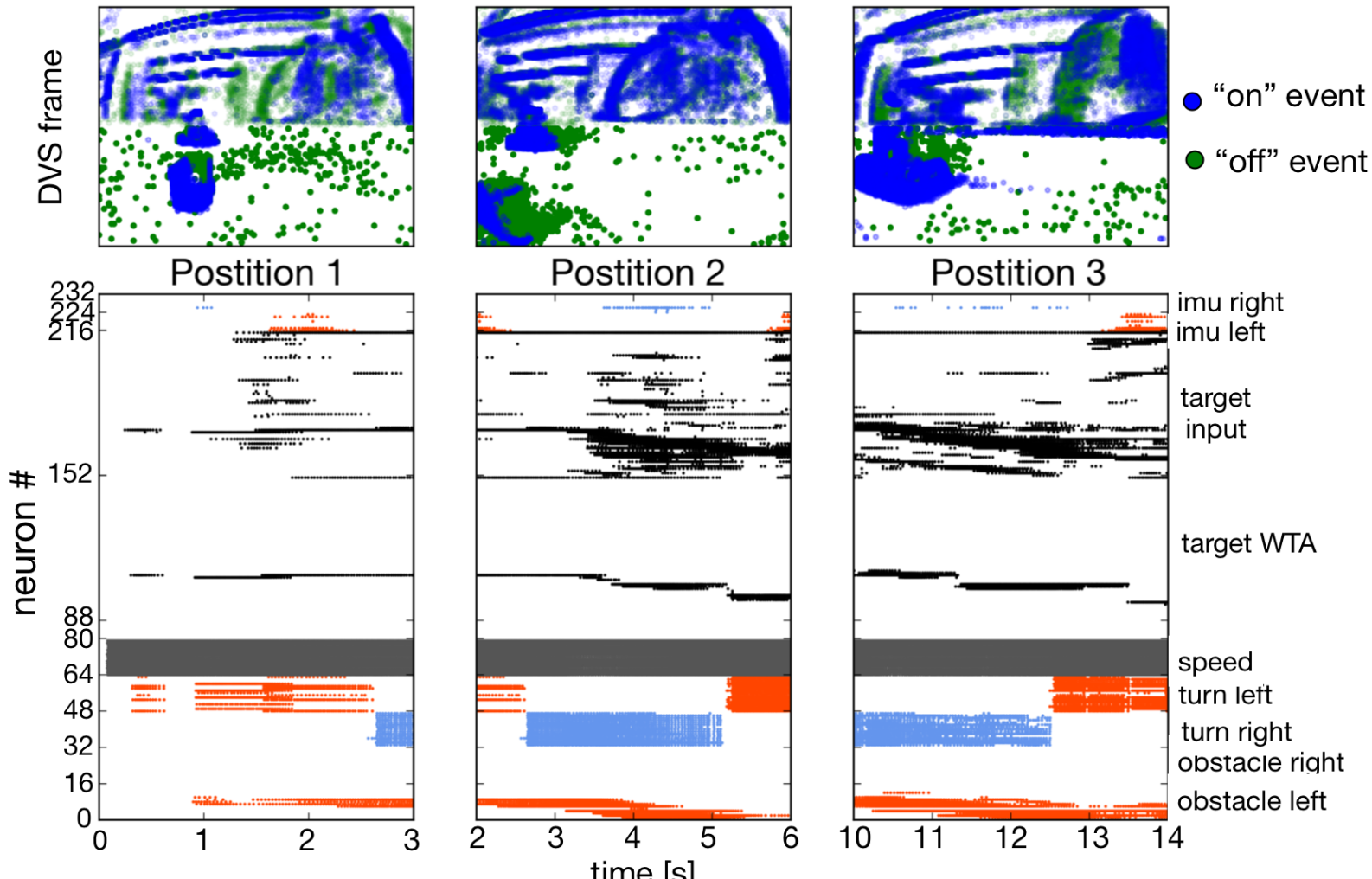

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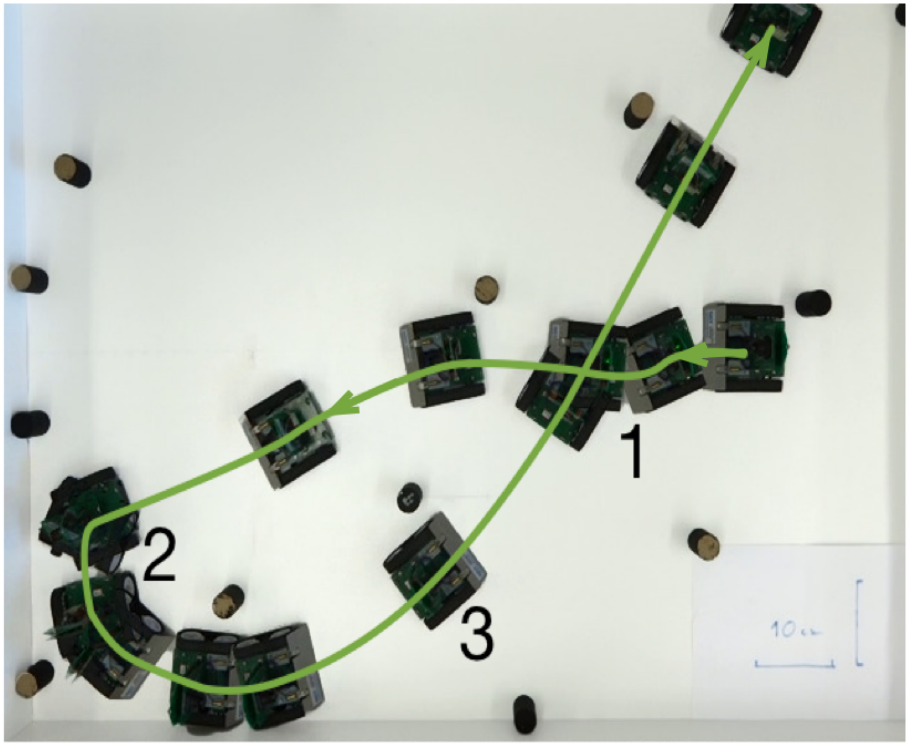

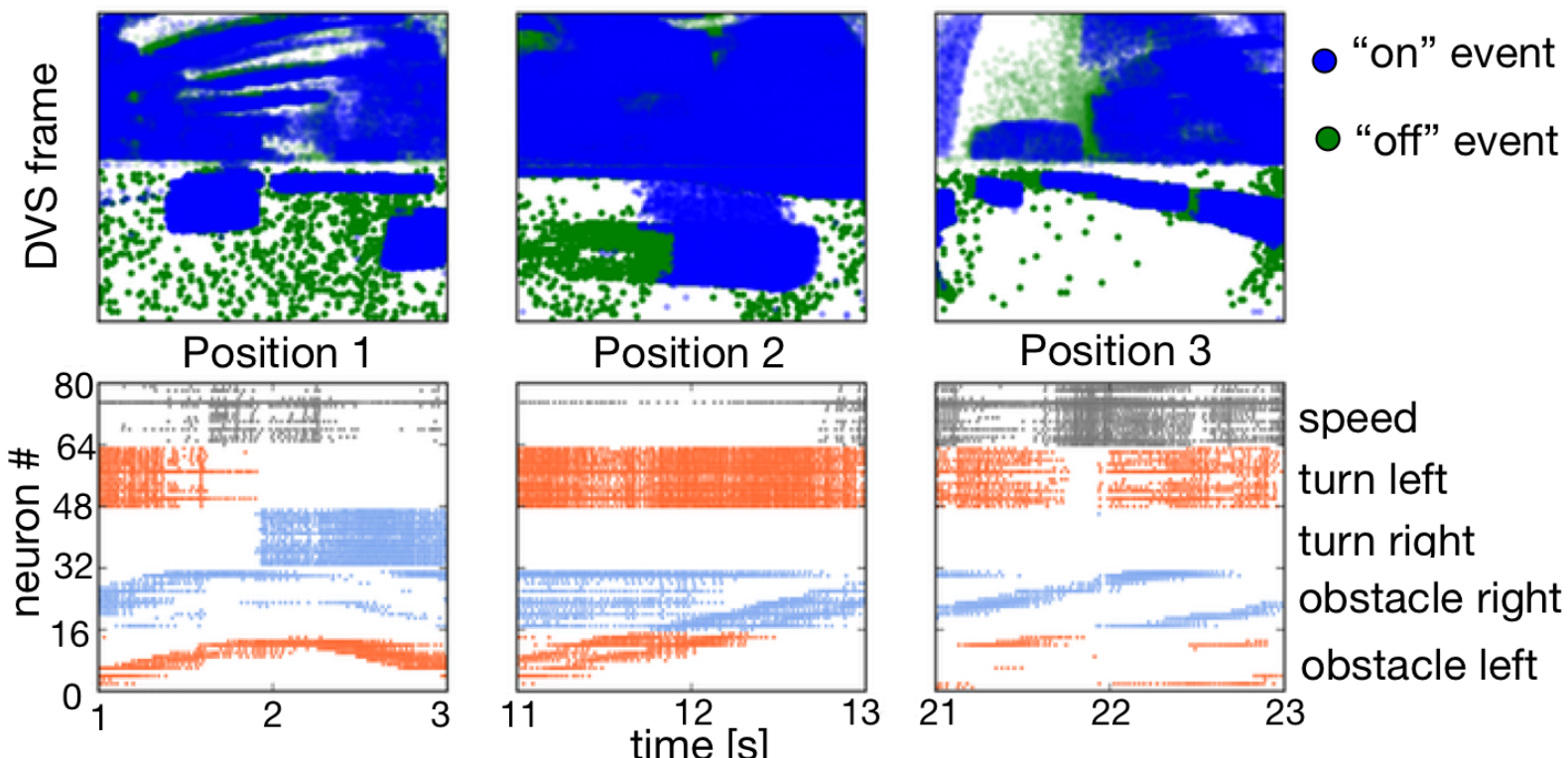

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Conclusion

- behavioral and neural dynamics endow embodied nervous systems with elementary forms of sensory-motor cognition