Summary

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Embodied cognition

- Properties of sensorimotor processes
  - continuous link to the sensory and motor surfaces
  - temporal continuity in state
  - stabilization of states against sensor and motor noise
  - unfolding of processes in closed loop with the environment
  - sensitive to the structure of the environment

Embodied cognition

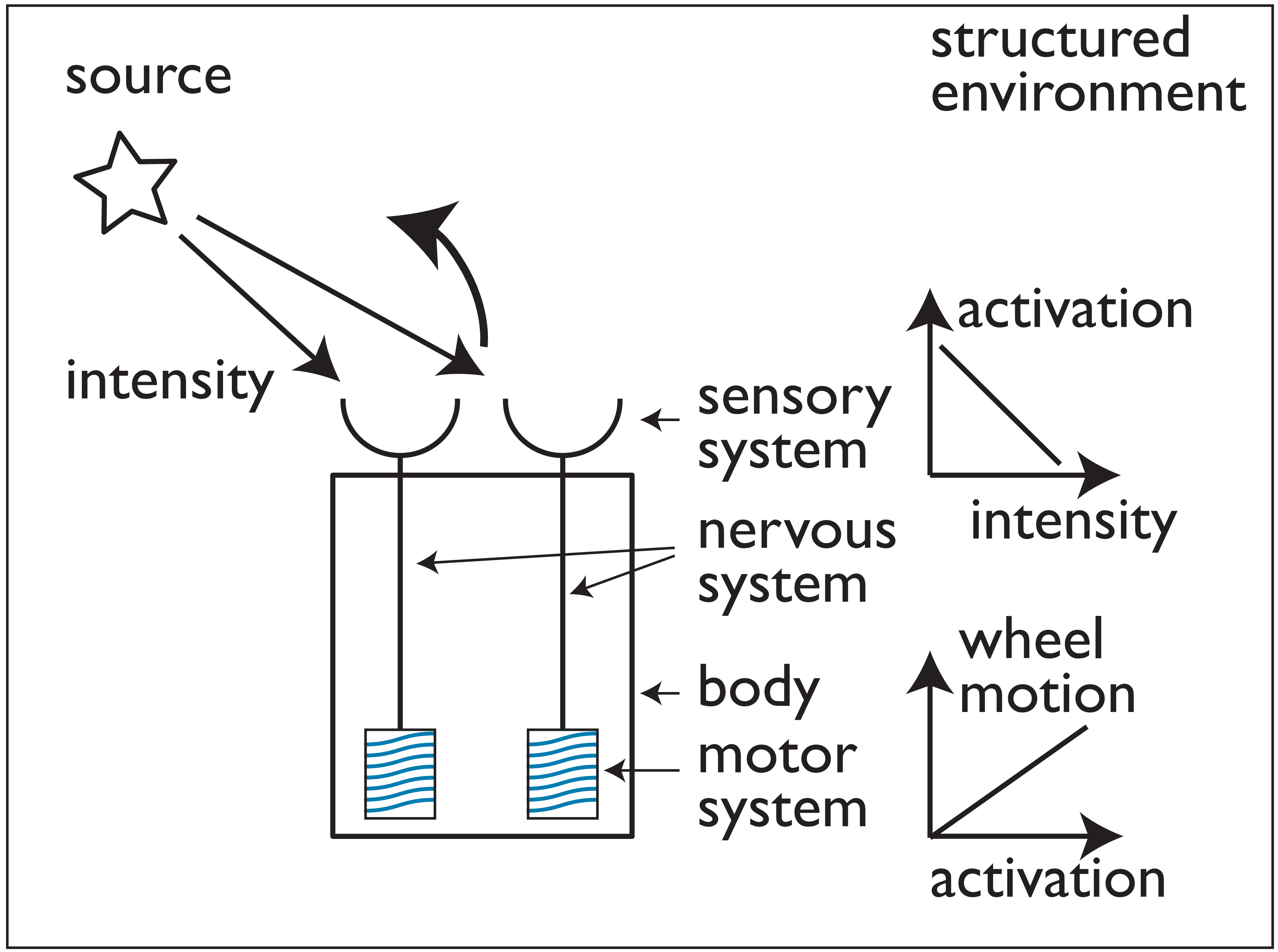
- Embodied cognition emerges from sensorimotor processes
    - through decision making
    - working memory
    - autonomous sequence generation
    - achieving invariance through coordinate transforms

Neural dynamics hypothesis

- embodied cognition
  - unfolds continuously in time
  - with internal closed loops: prediction/planning
  - in closed loops with the environment
- => embodied cognition requires stability
- embodied cognitive processes must be characterized as dynamical systems
  - behavioral dynamics
  - neural dynamics

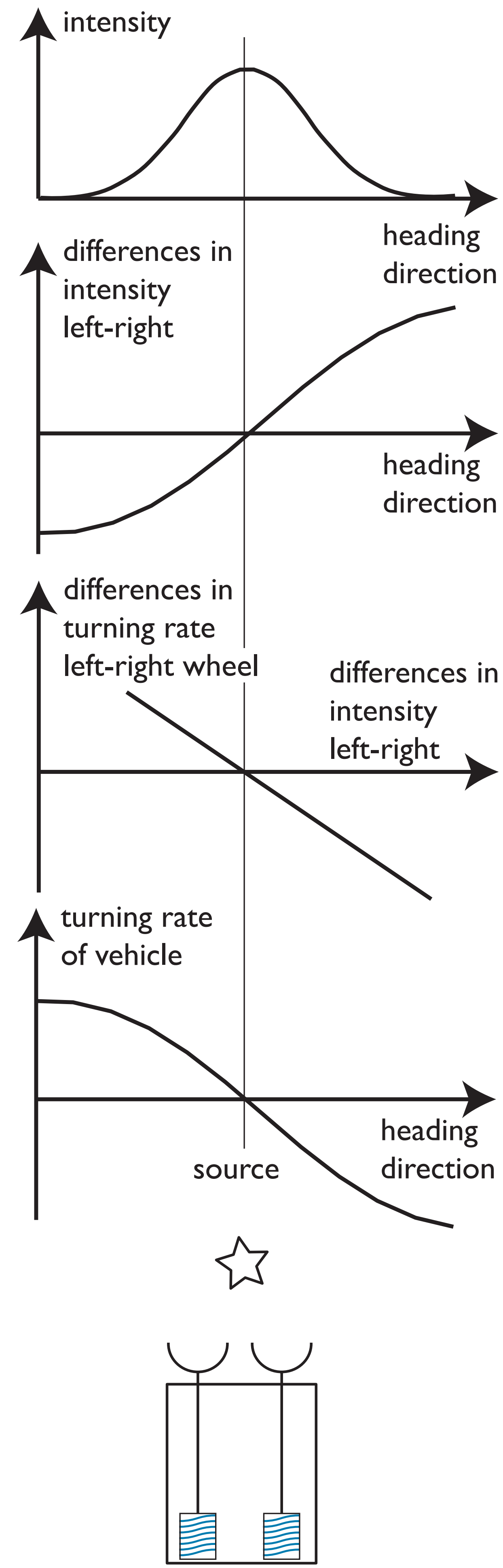
Five things needed to generate behavior

- sensors
- motors
- linked by a nervous system
- linked physically by a body
- an appropriately structured environment



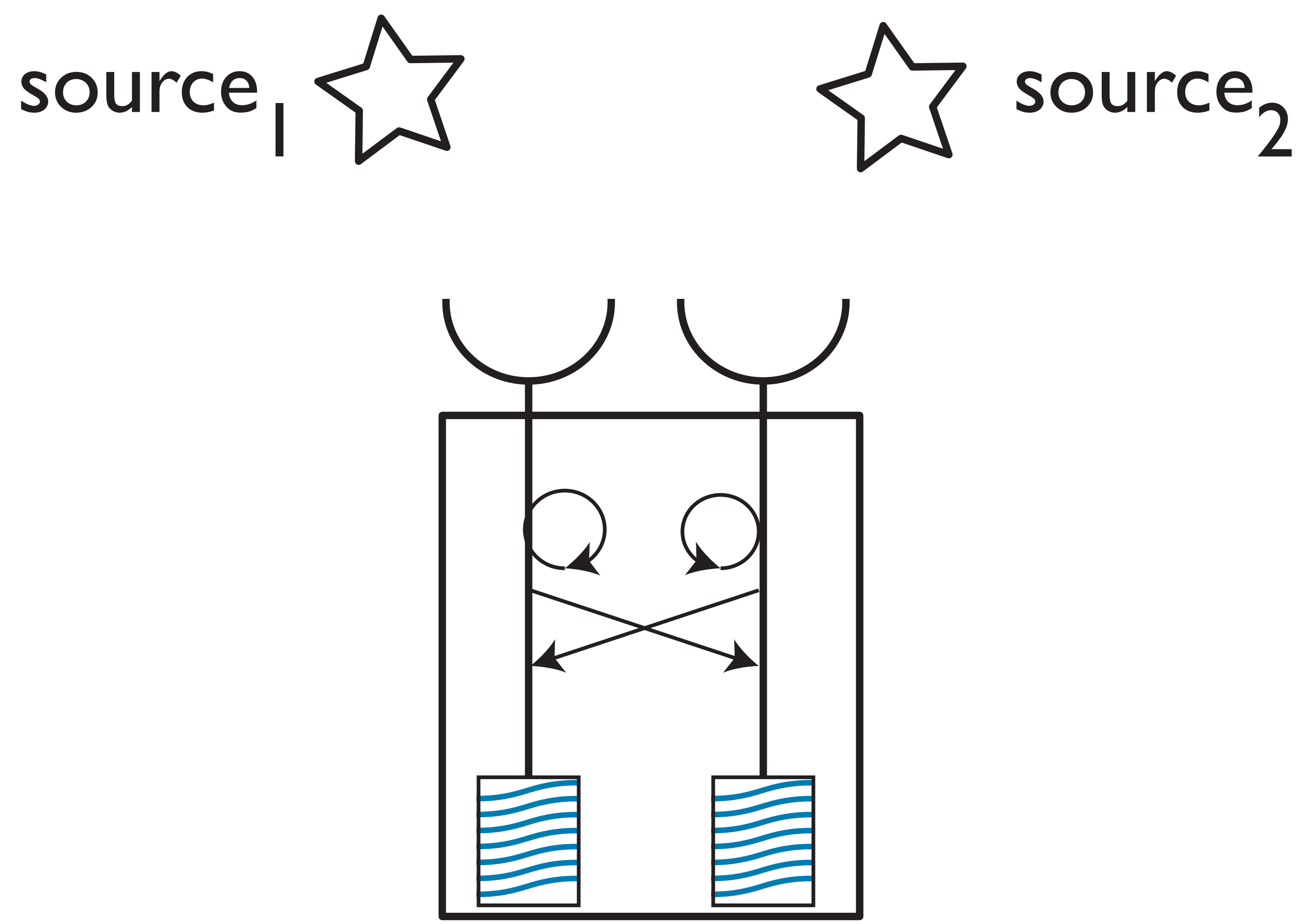
Emergent behavior: this is a dynamics

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



Internal loops generate neural dynamics

- that generate cognition: internal decisions…
- bifurcations => different cognitive regimes

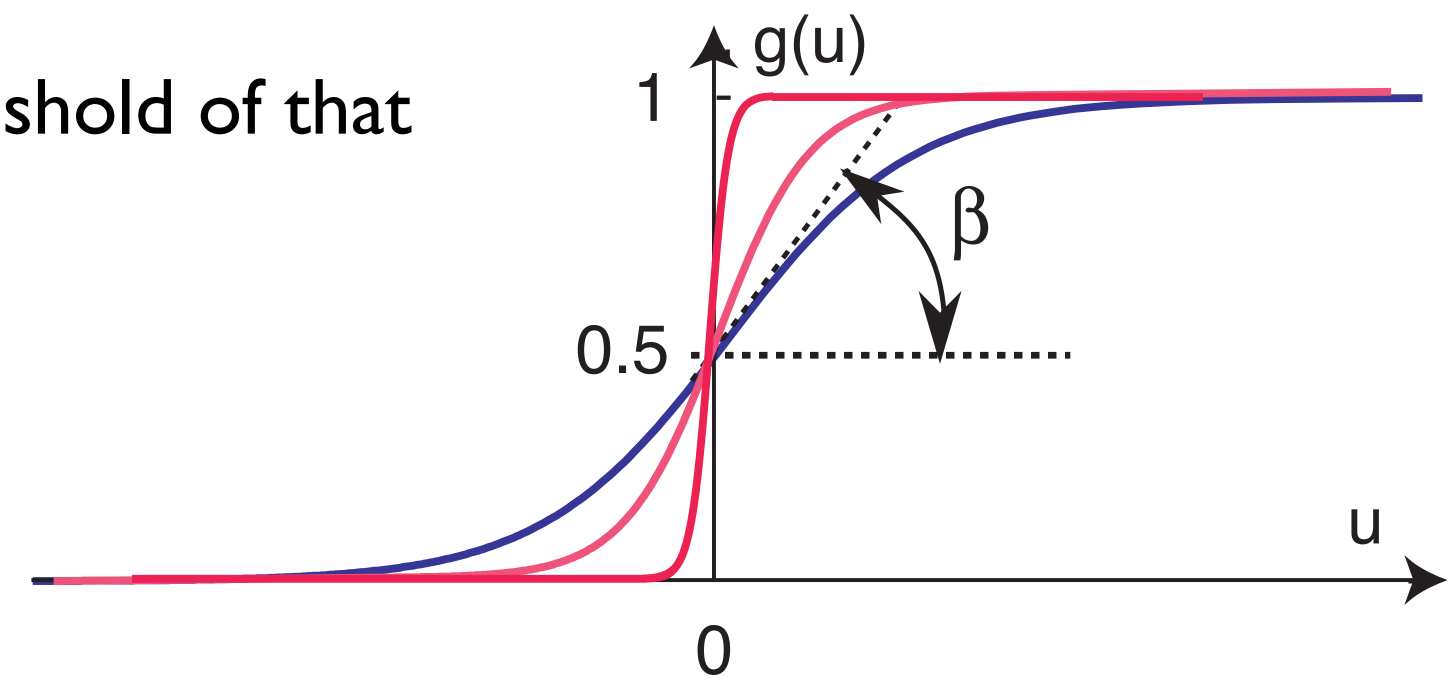


Activation

- neural state variable activation
  - linked to membrane potential of neurons in some accounts
  - linked to spiking rate in our account
  - through: population activation... (later)

Activation

- activation as a real number, abstracting 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

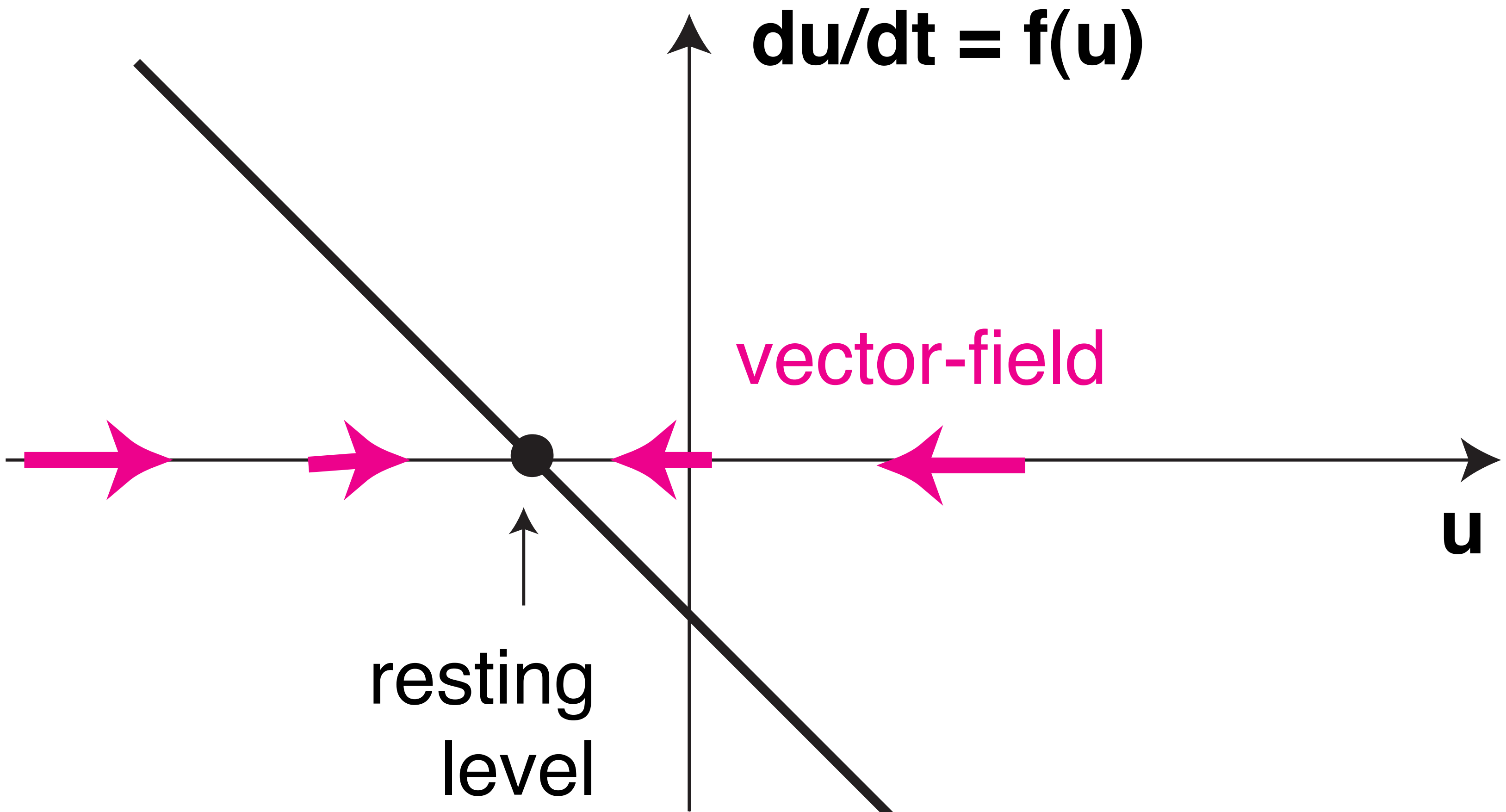


Activation dynamics

- activation evolves in continuous time
  - no evidence for a discretization of time, for spike timing to matter for behavior

Neural dynamics

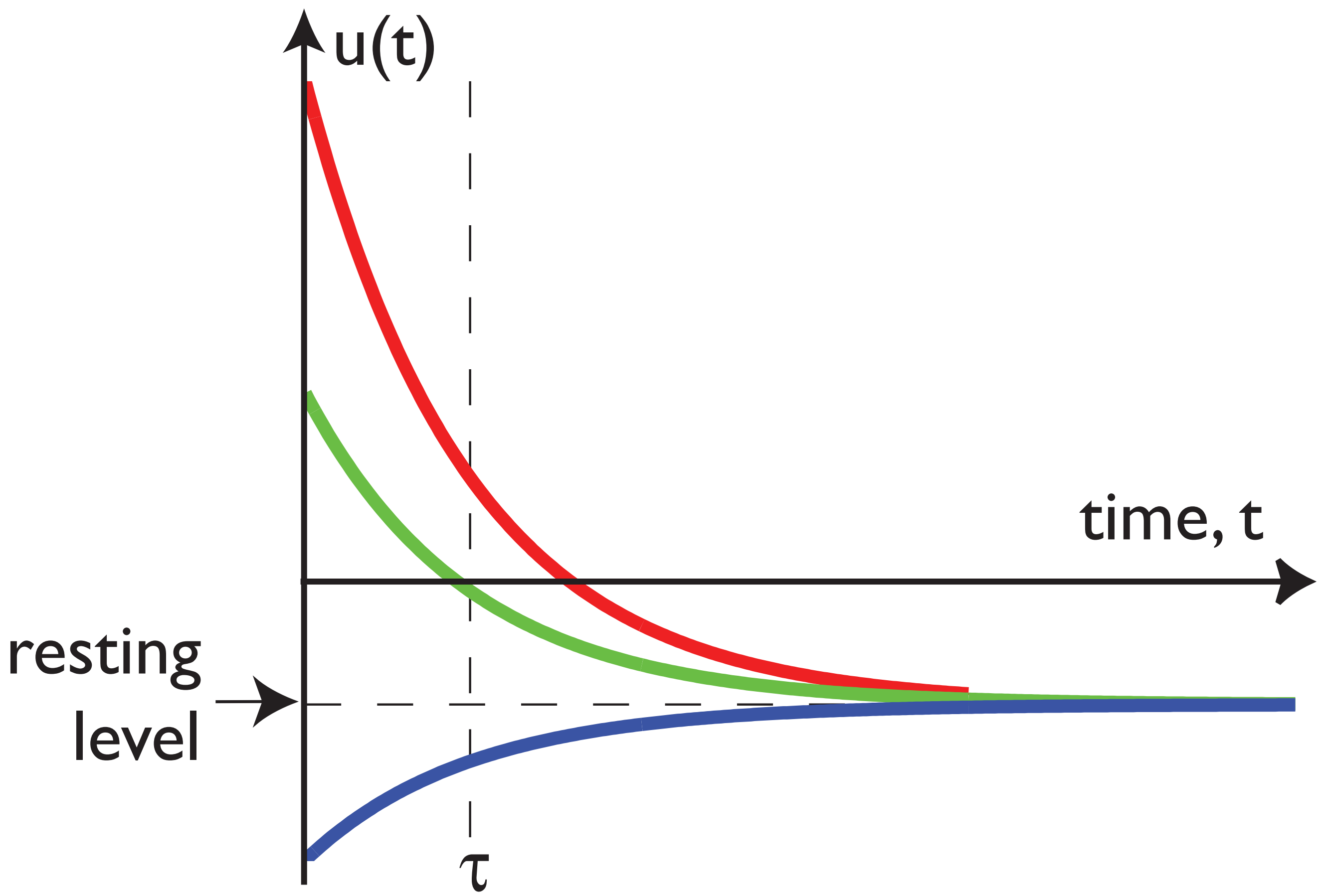
- stationary state=fixed point= constant solution
- stable fixed point: nearby solutions converge to the fixed point=attractor

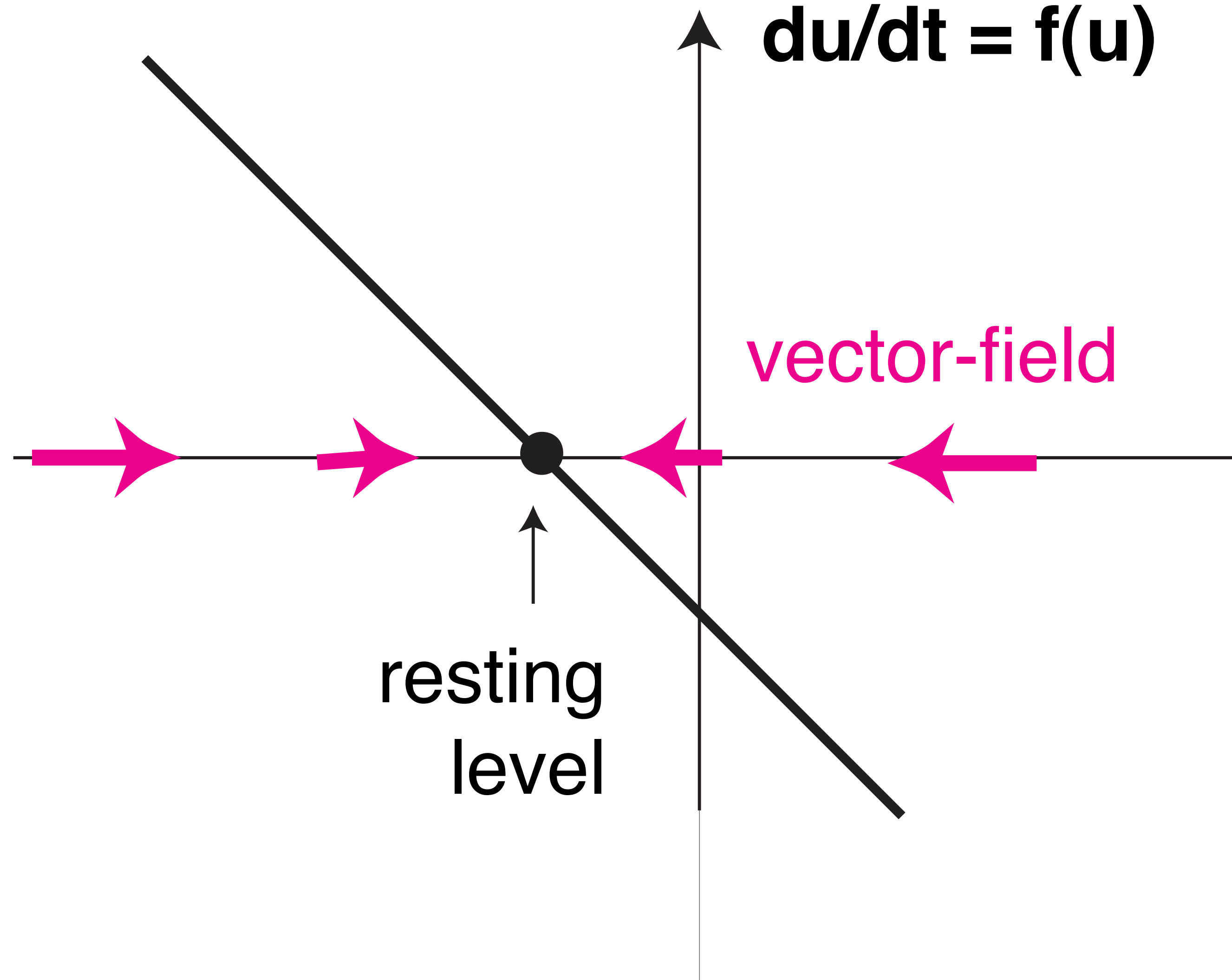


$$\frac{du(t)}{dt} = \dot{u}(t) = -u(t) + h \qquad (h < 0)$$

Neural dynamics

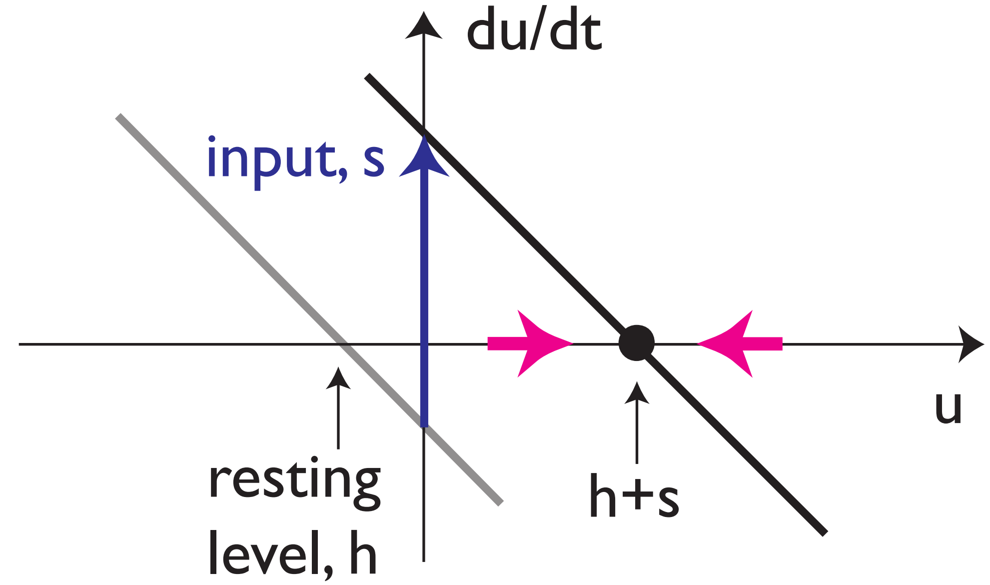
- attractor structures ensemble of solutions=flow



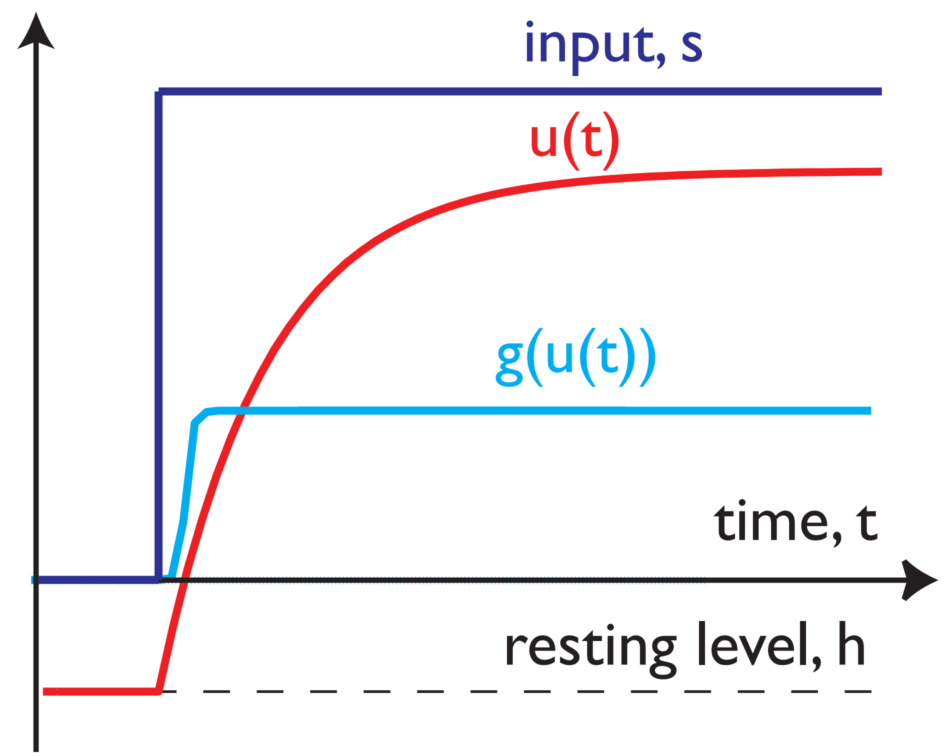


$$\tau \dot{u}(t) = -u(t) + h$$

Neuronal dynamics

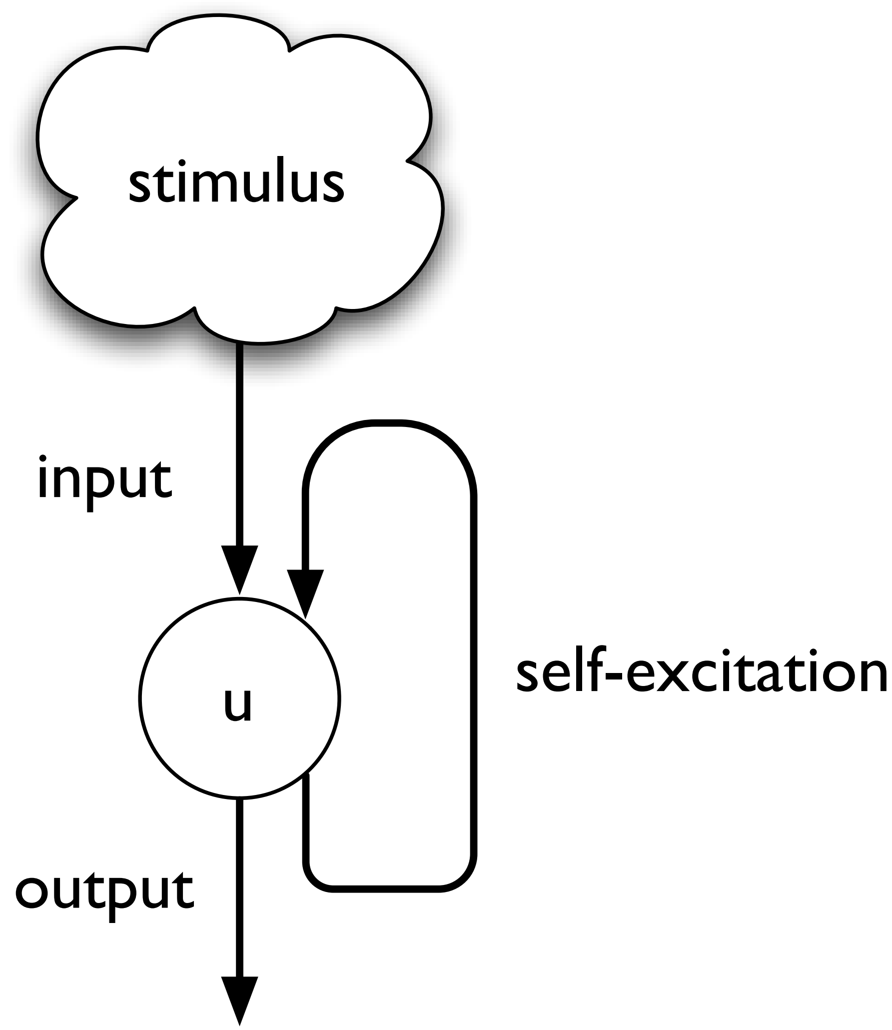


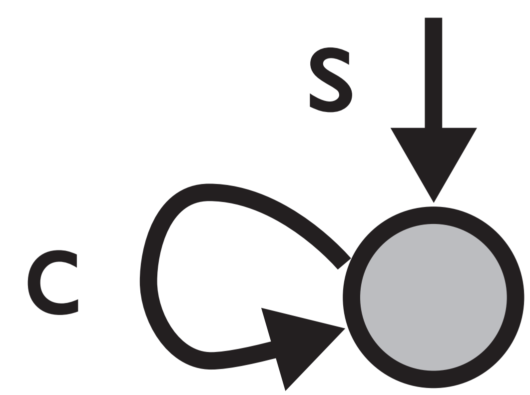
- inputs=contributions to the rate of change
  - positive: excitatory
  - negative: inhibitory
- => shifts the attractor
- activation tracks this shift (stability)



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

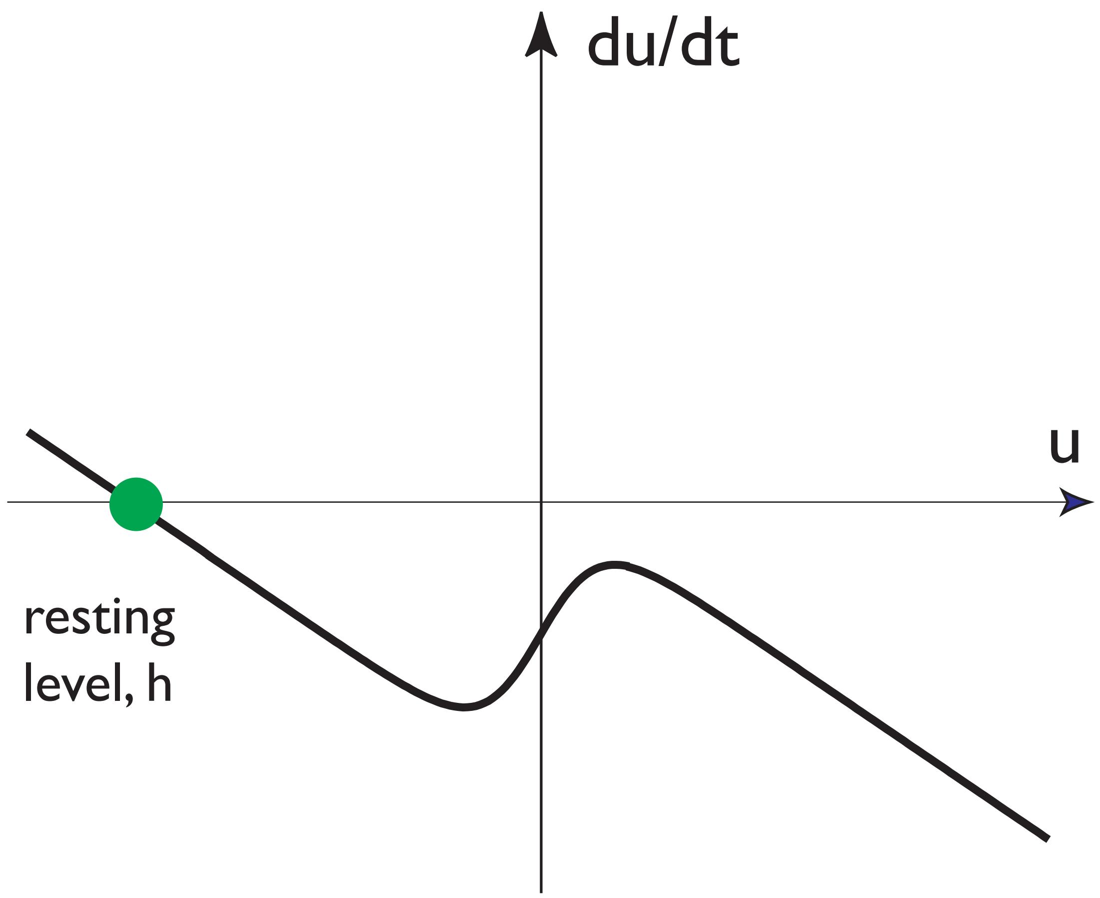
Neuronal dynamics with self-excitation

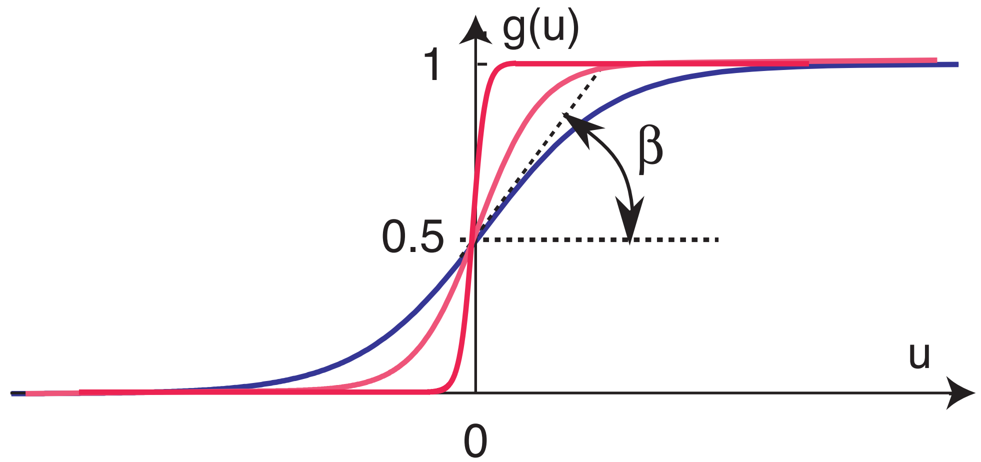




$$\tau \dot{u}(t) = -u(t) + h + S(t) + c\sigma(u(t))$$

Neuronal dynamics with self-excitation

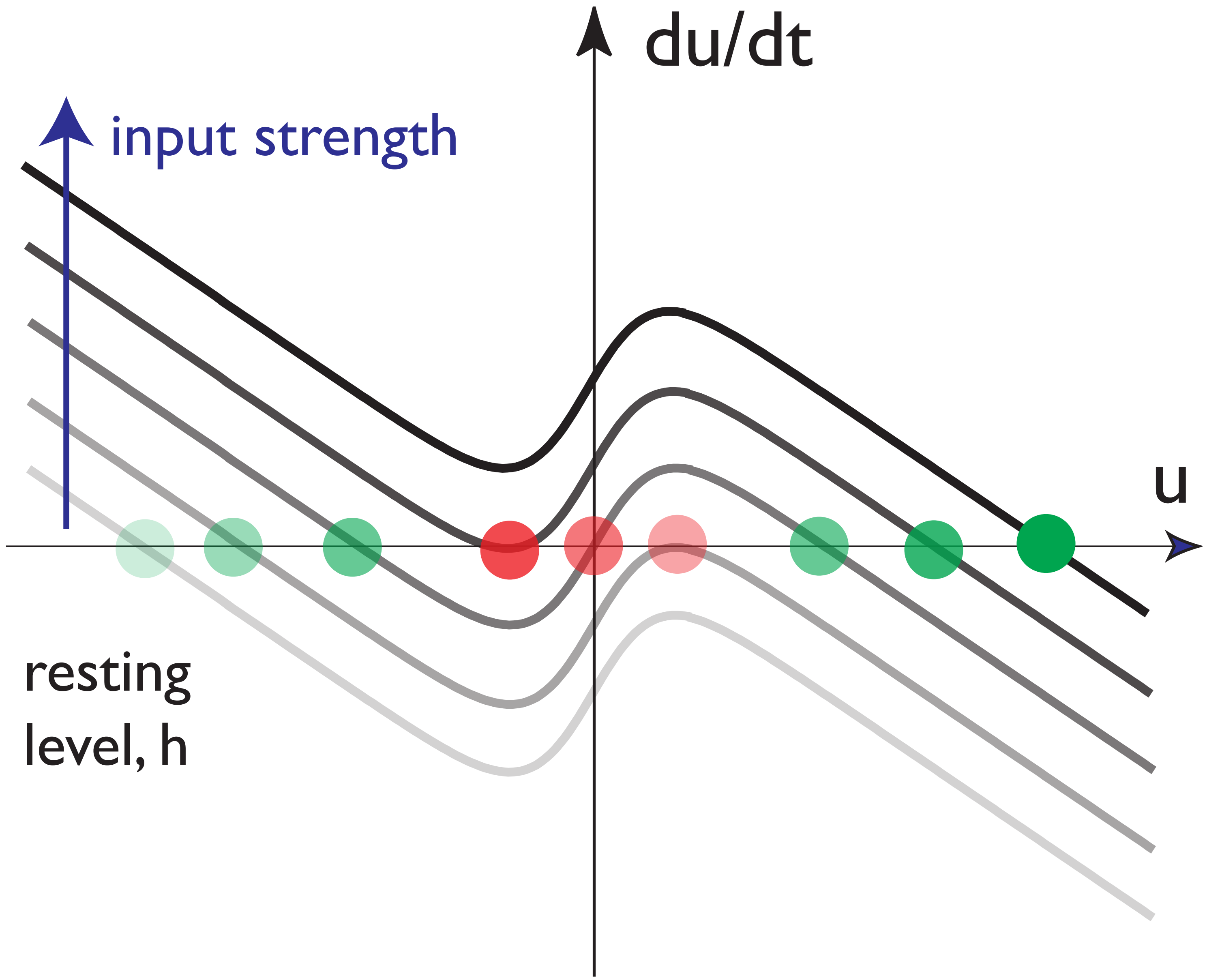




$$\tau\dot{u}(t) = -u(t) + h + S(t) + c\sigma(u(t))$$

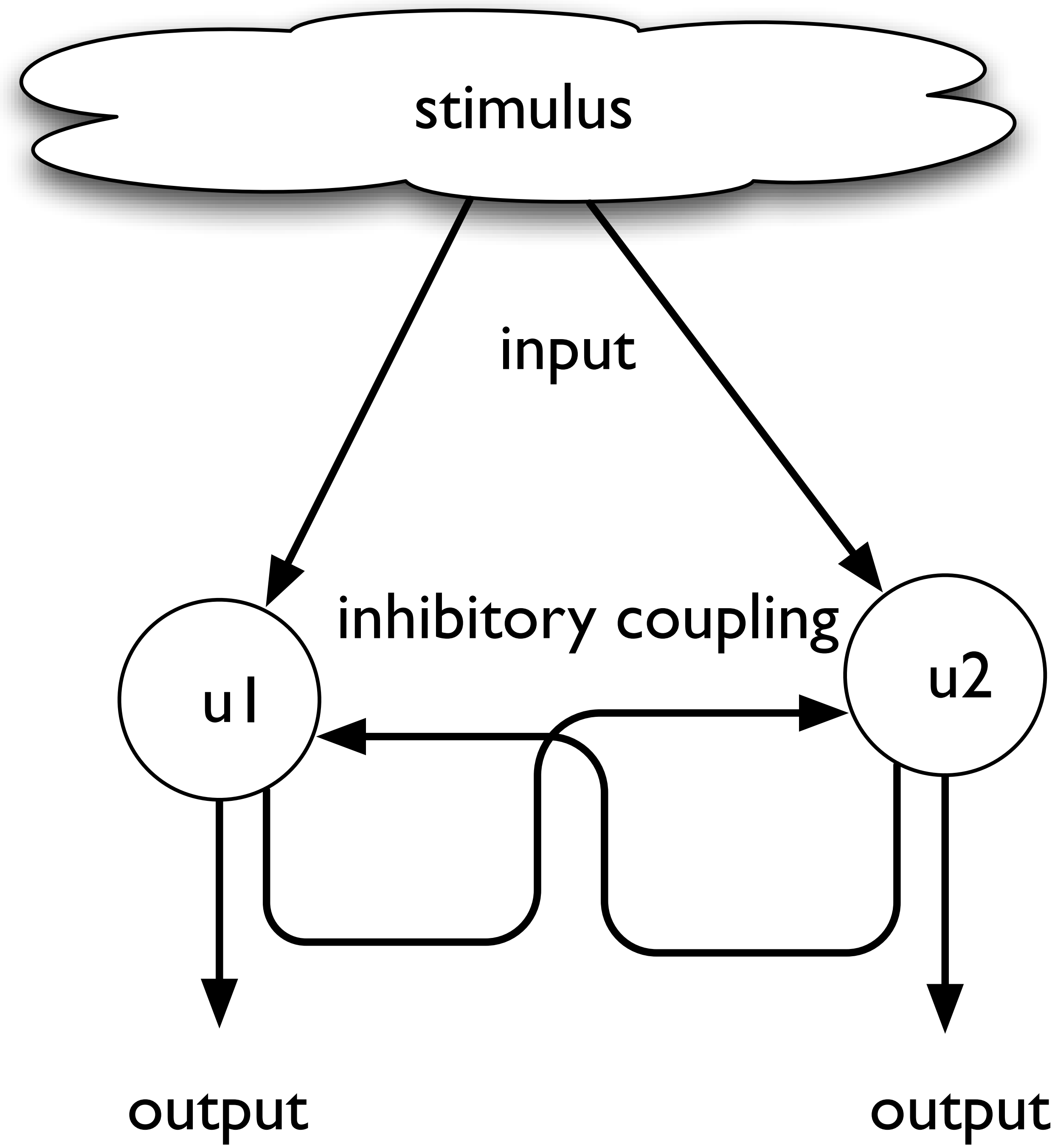
Neuronal dynamics with self-excitation

- stimulus input



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

Neuronal dynamics with competition

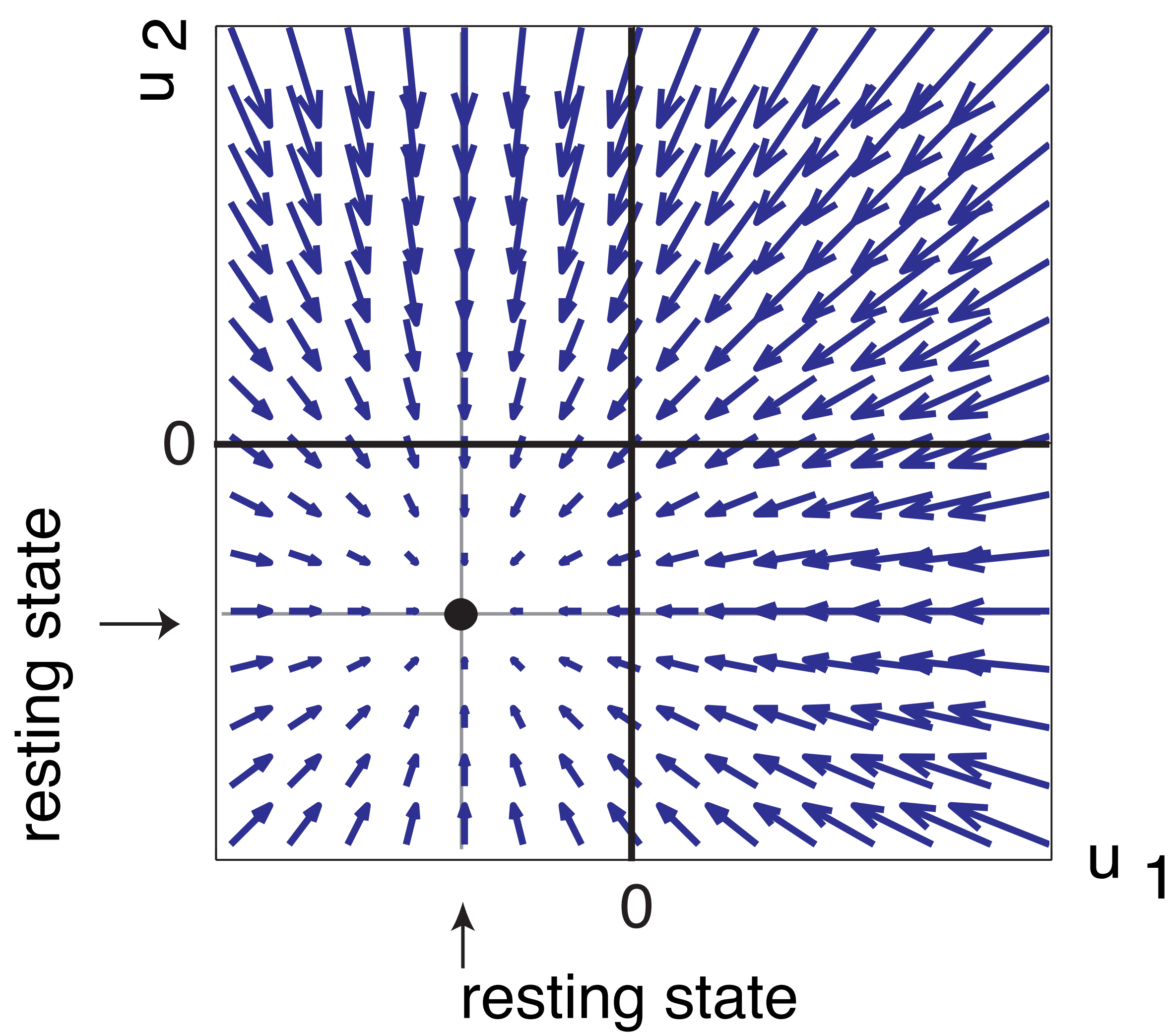


$$\tau \dot{u}_1(t) = -u_1(t) + h - \sigma(u_2(t)) + S_1$$
$$\tau \dot{u}_2(t) = -u_2(t) + h - \sigma(u_1(t)) + S_2$$

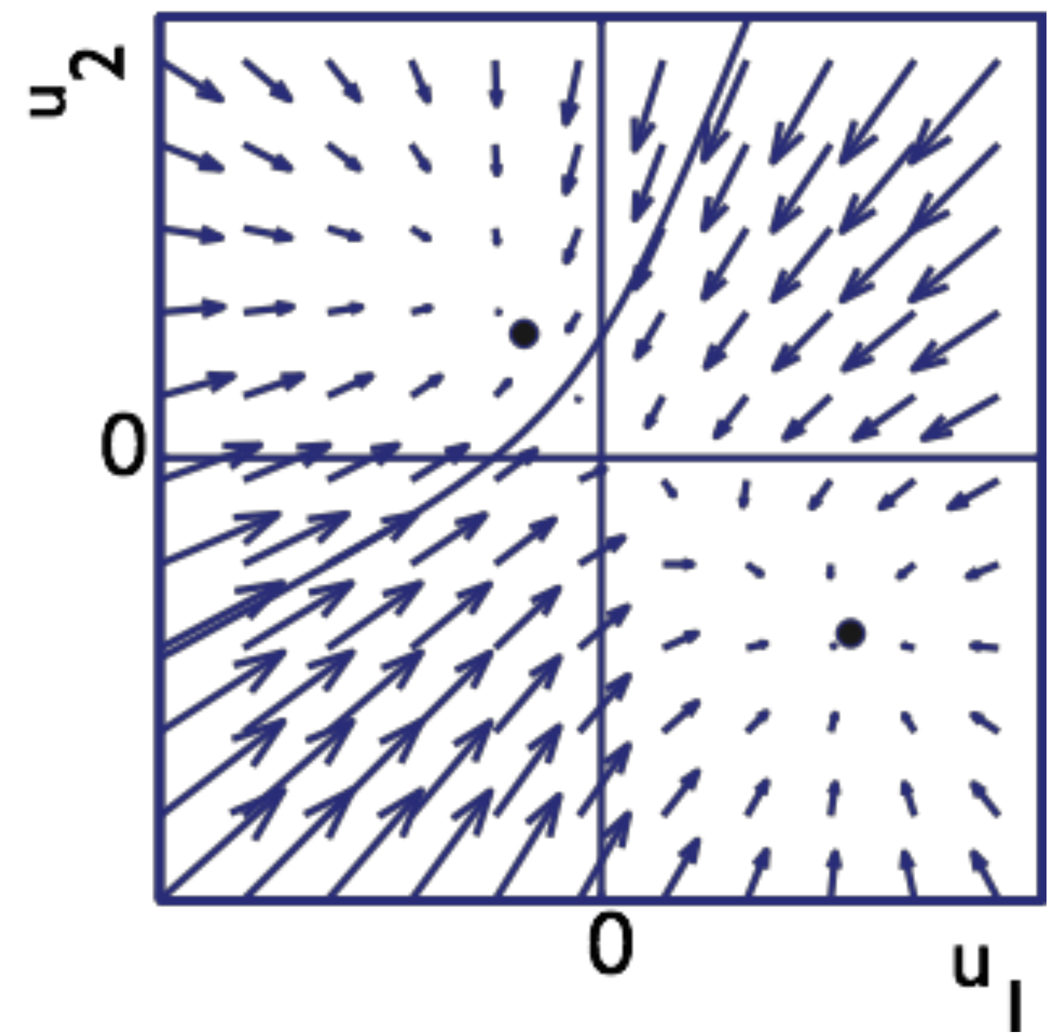
Neuronal dynamics with competition

=>biased competition

before input is presented

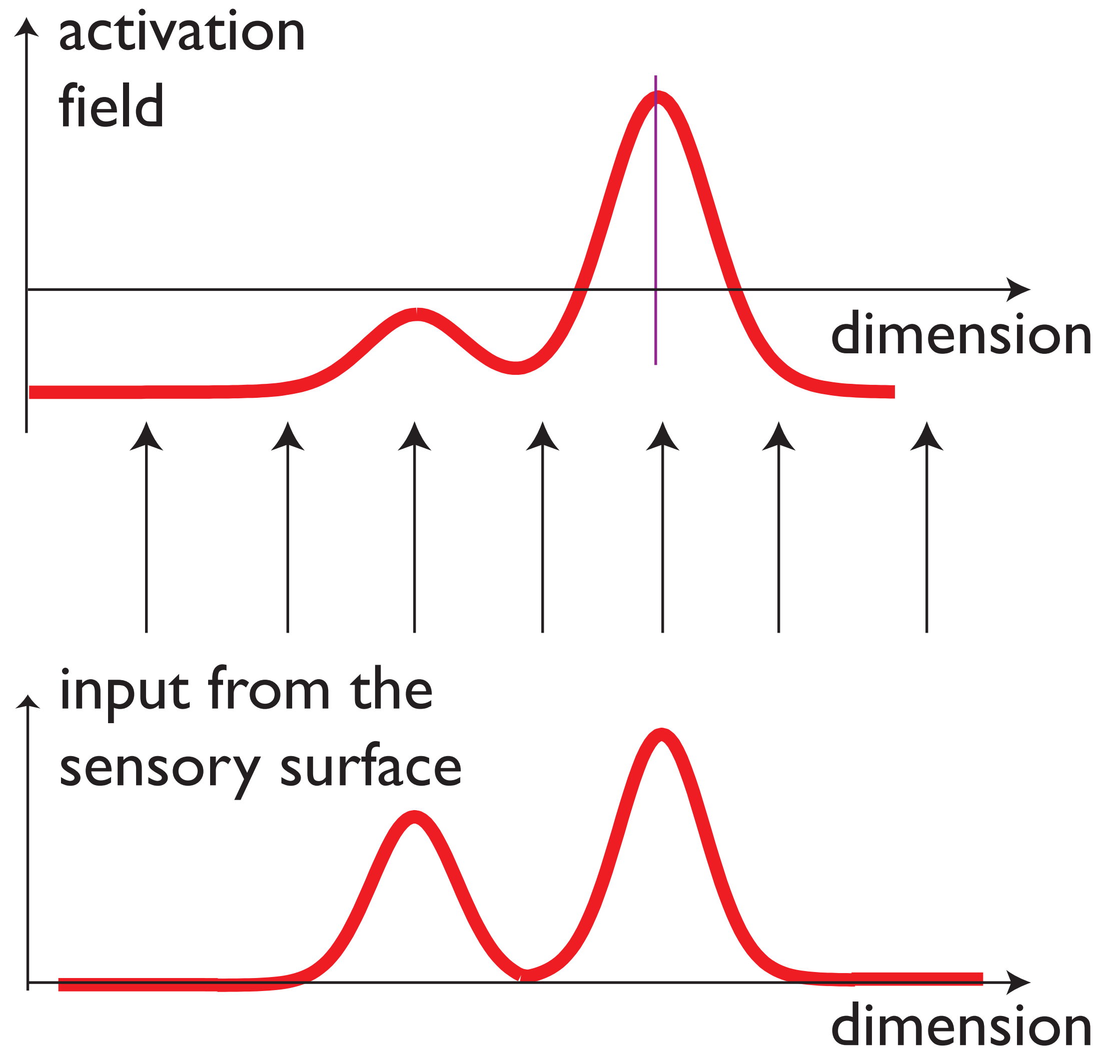


after input is presented

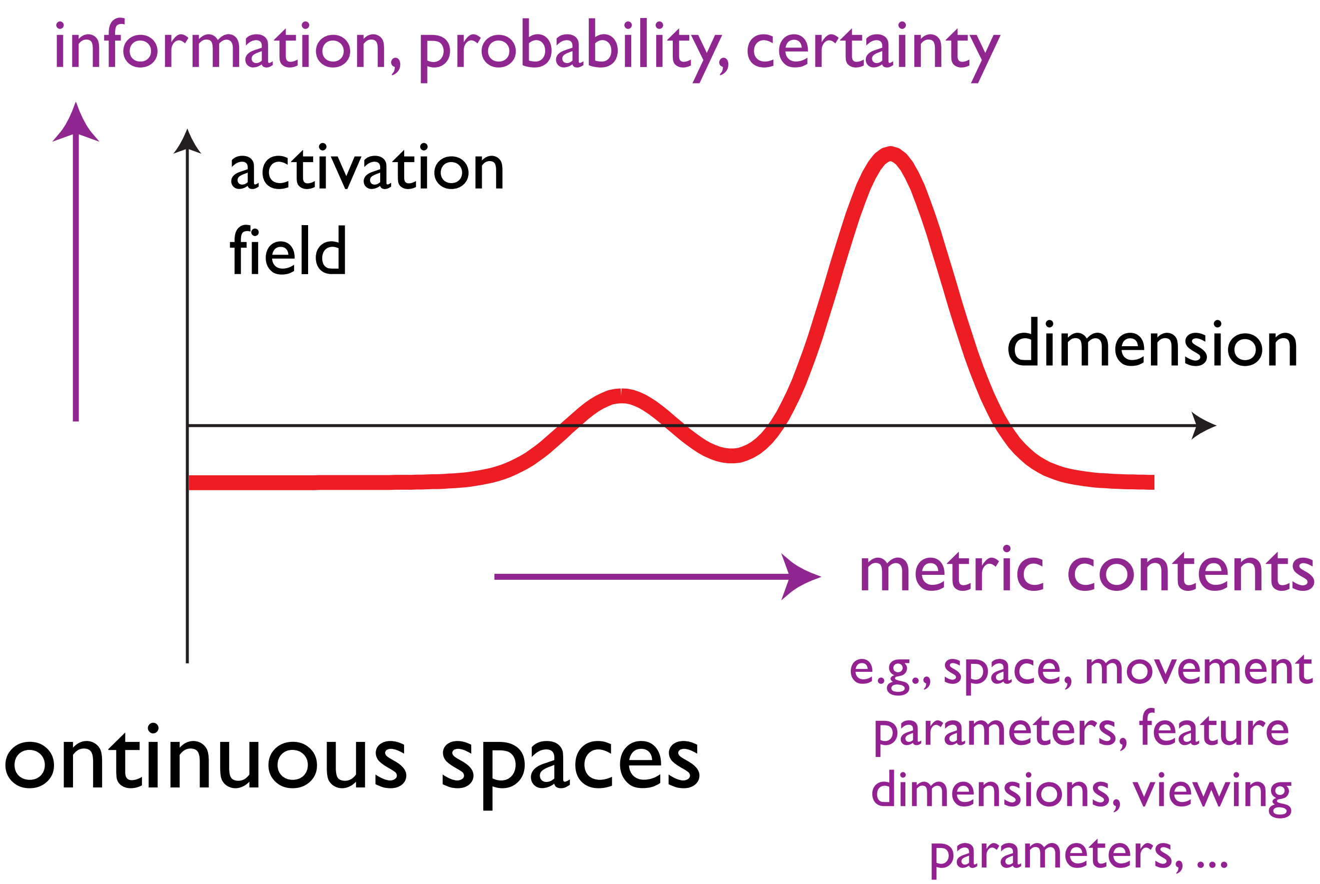


… toward fields

- define field is over the continuous stimulus dimension
- … as dictated by input/output connectivity…

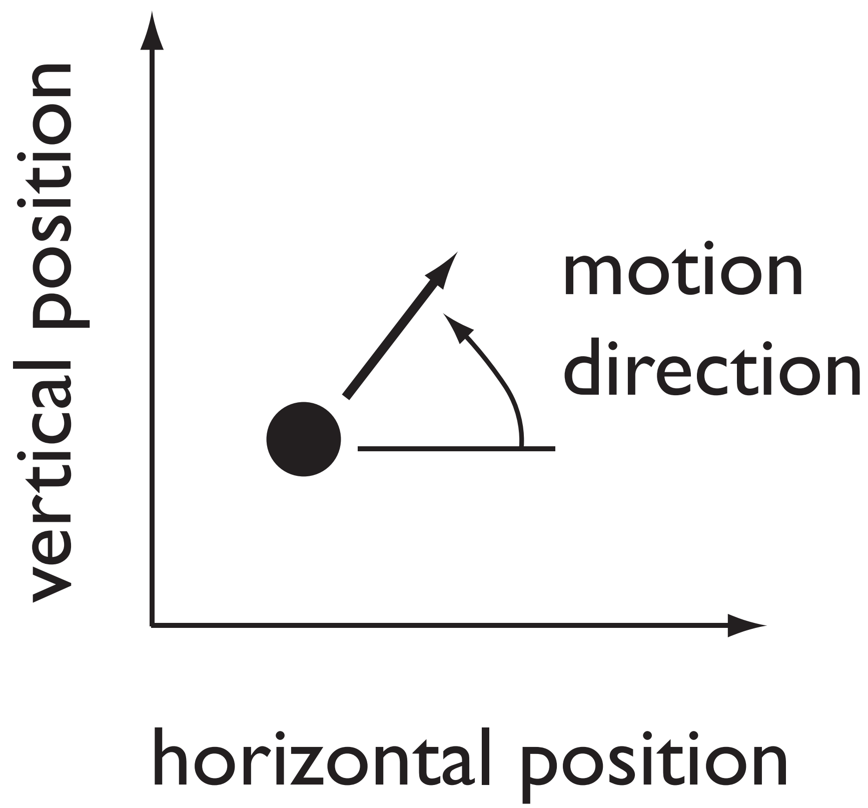


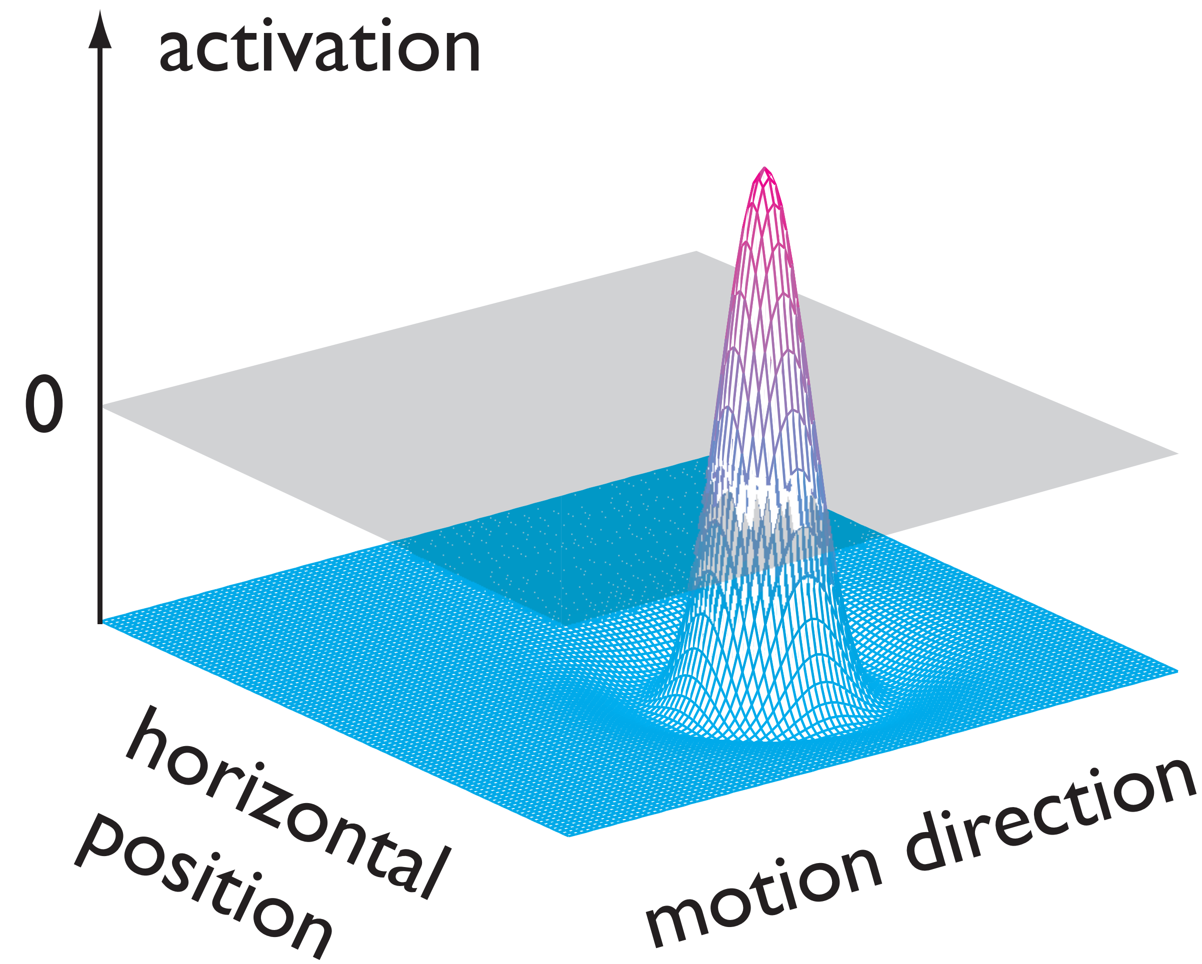
activation fields



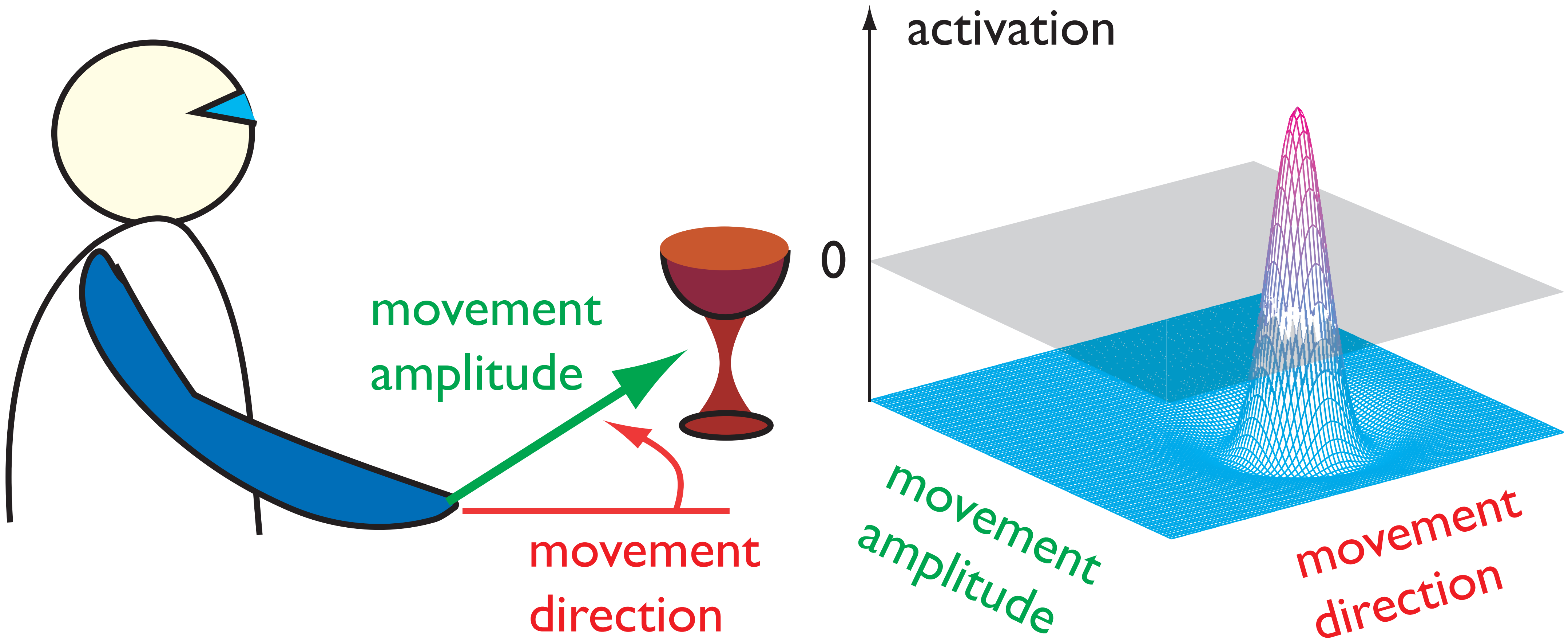
- define activation fields over continuous spaces
  - homologous to sensory surfaces, e.g., visual or auditory space (retinal, allocentric, ...)
  - homologous to motor surfaces, e.g., saccadic end-points or direction of movement of the end-effector in outer space
  - feature spaces, e.g., localized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

Example motion perception: space of possible percepts



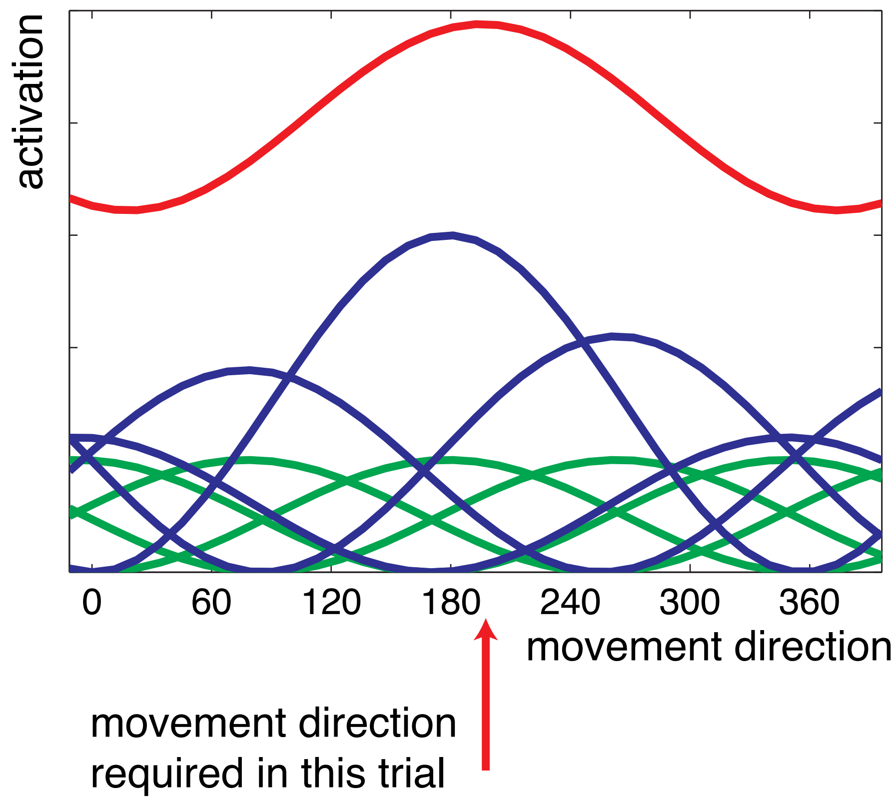


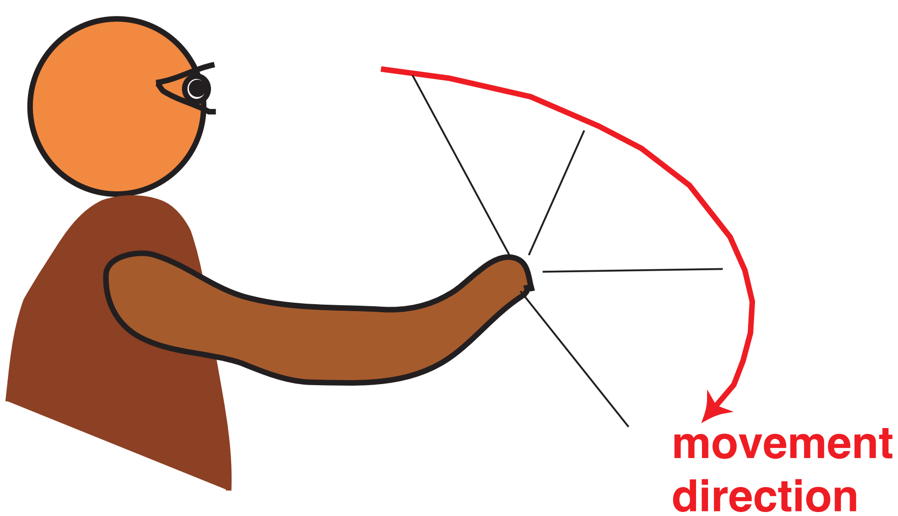
Example: movement planning: space of possible actions

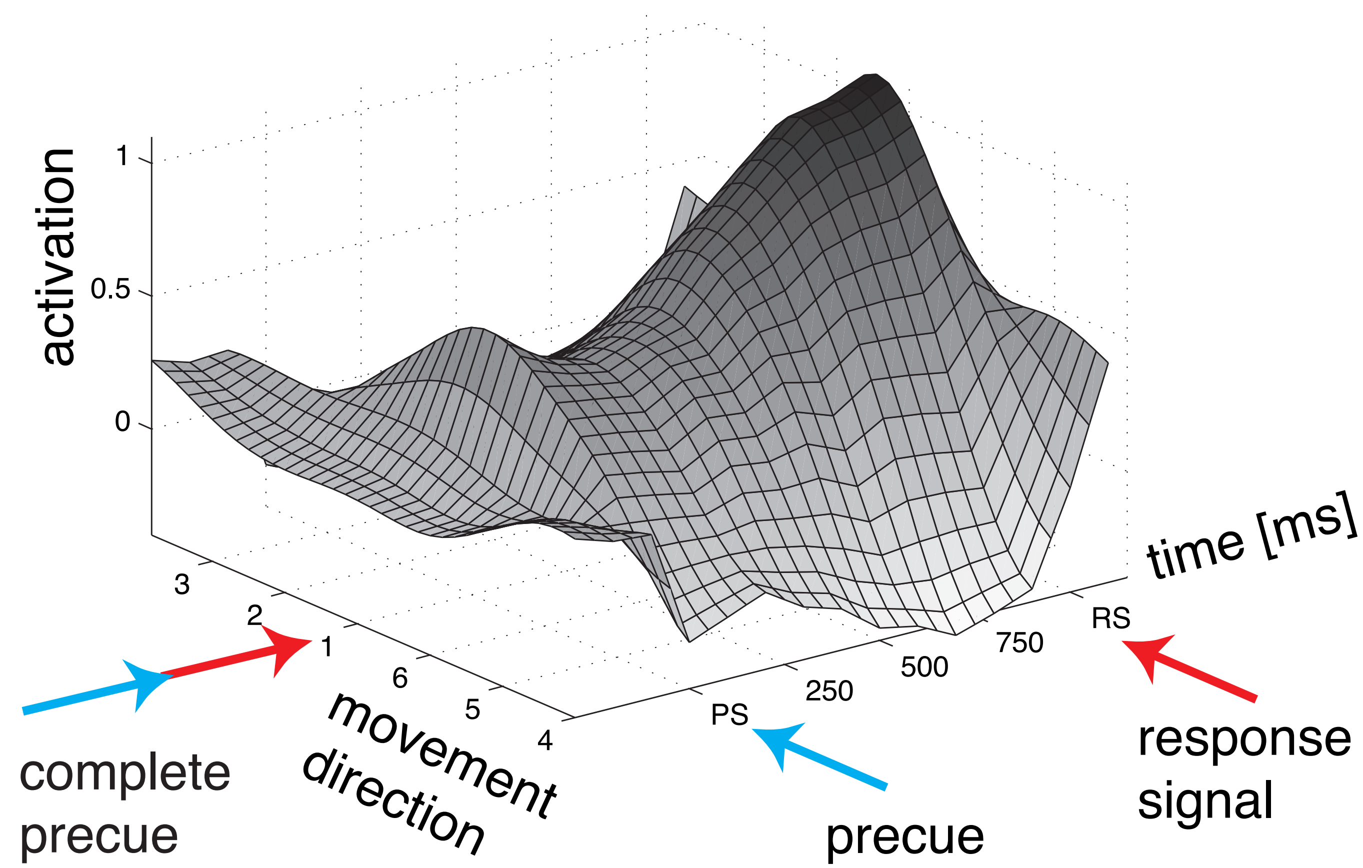


Distribution of Population Activation (DPA)

Distribution of population activation = $\sum_{\text{neurons}}$ tuning curve * current firing rate

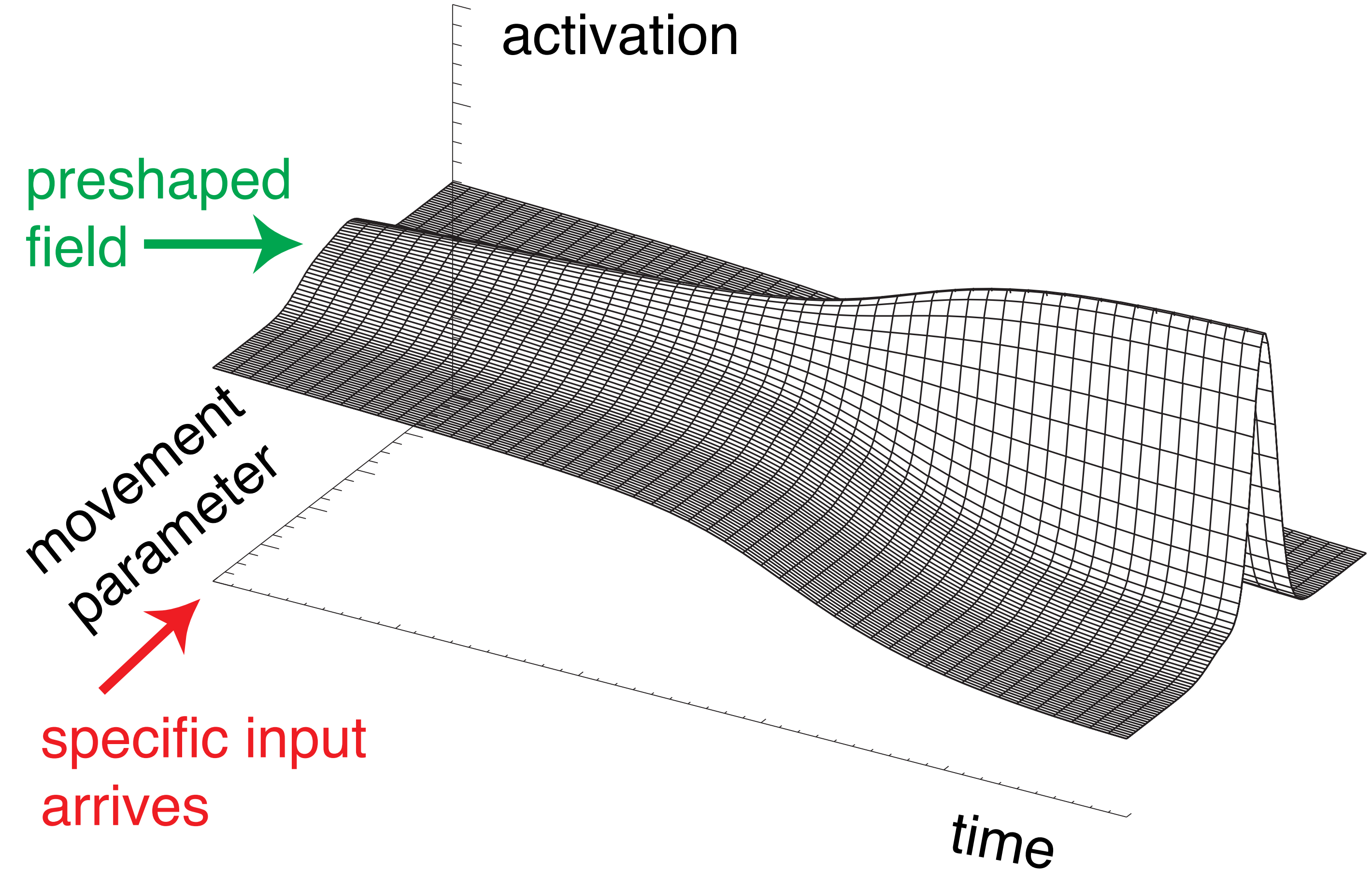


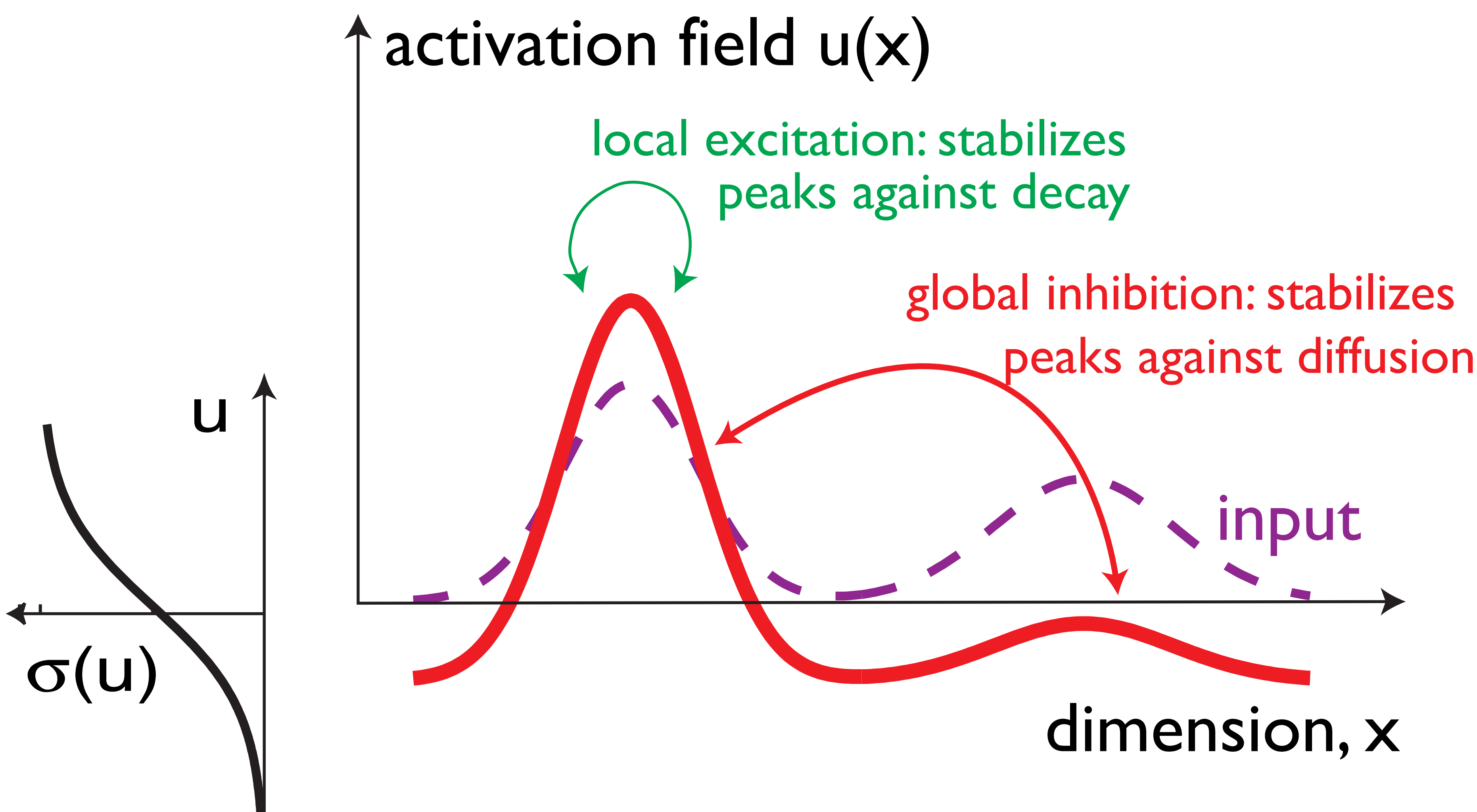




[Bastian, Riehle, Schöner, 2003]

Neural dynamics of activation fields is structured so that 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

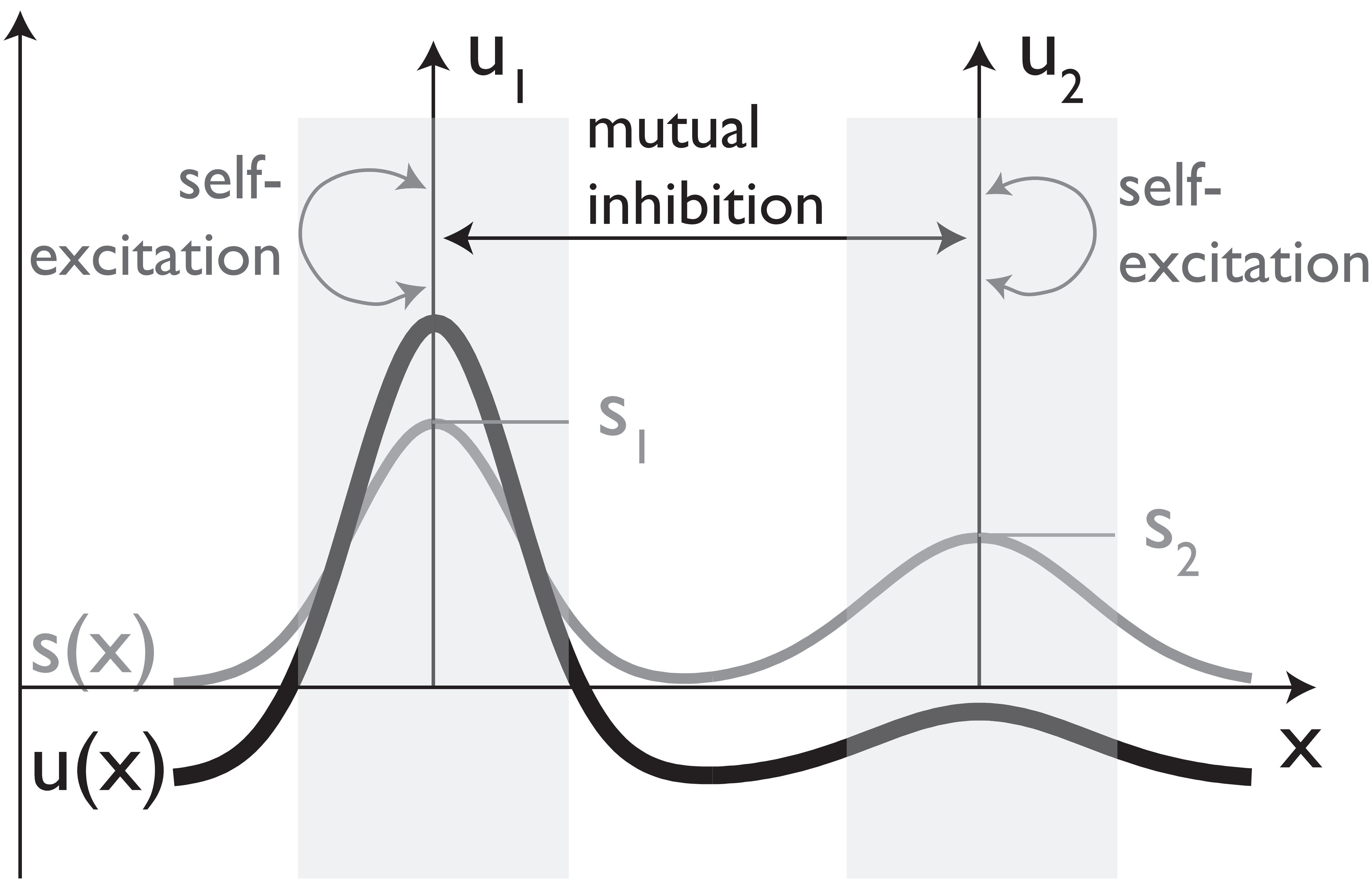
- time scale is τ
- resting level is $h < 0$
- input is $S(x,t)$
- interaction kernel is

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

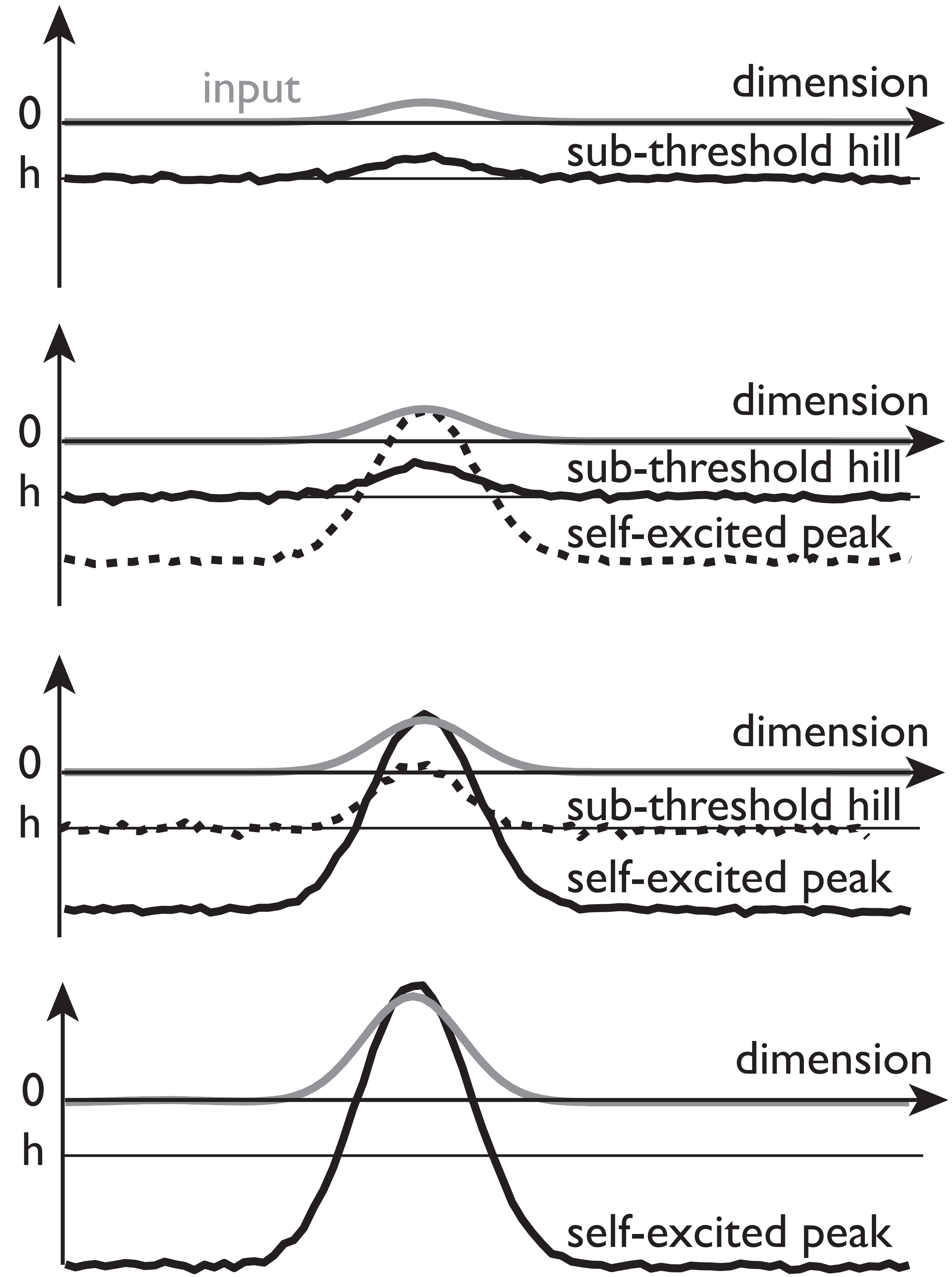
- sigmoidal nonlinearity is

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

Relationship to the dynamics of discrete activation variables

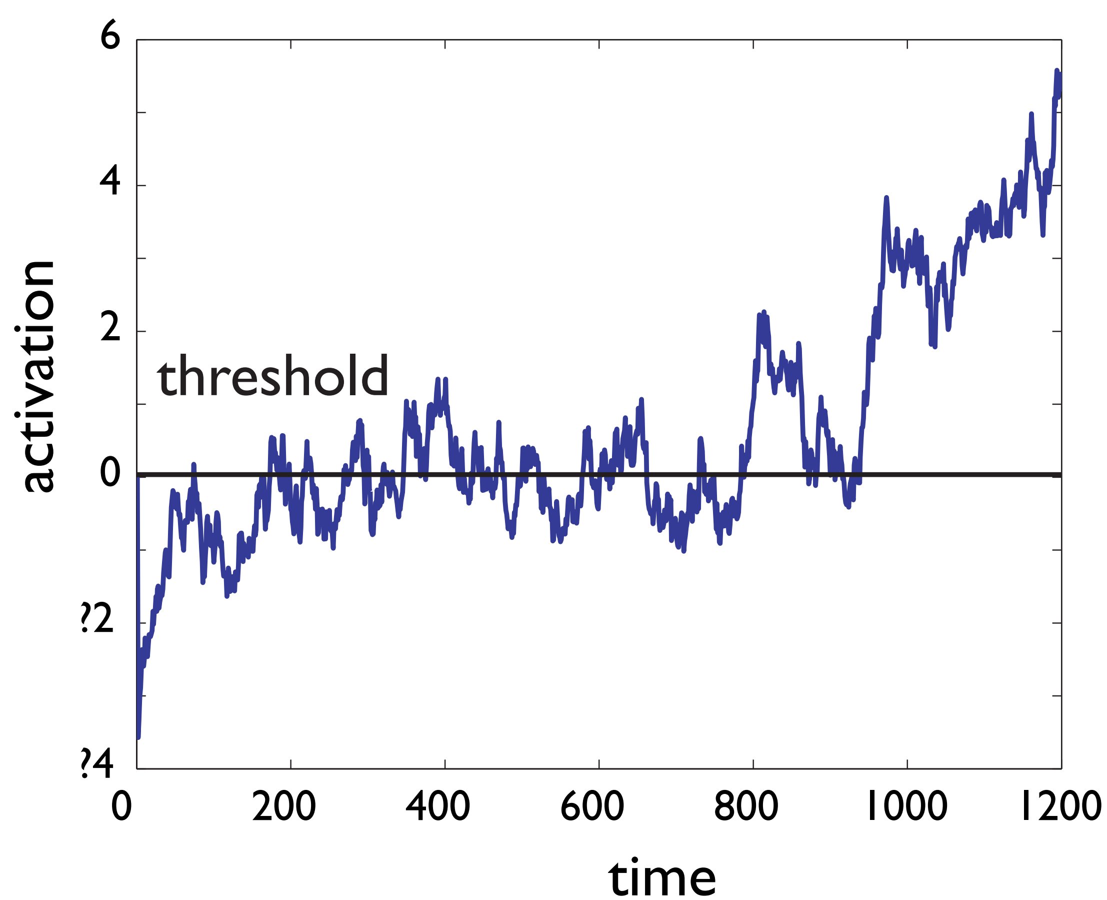


Detection instability

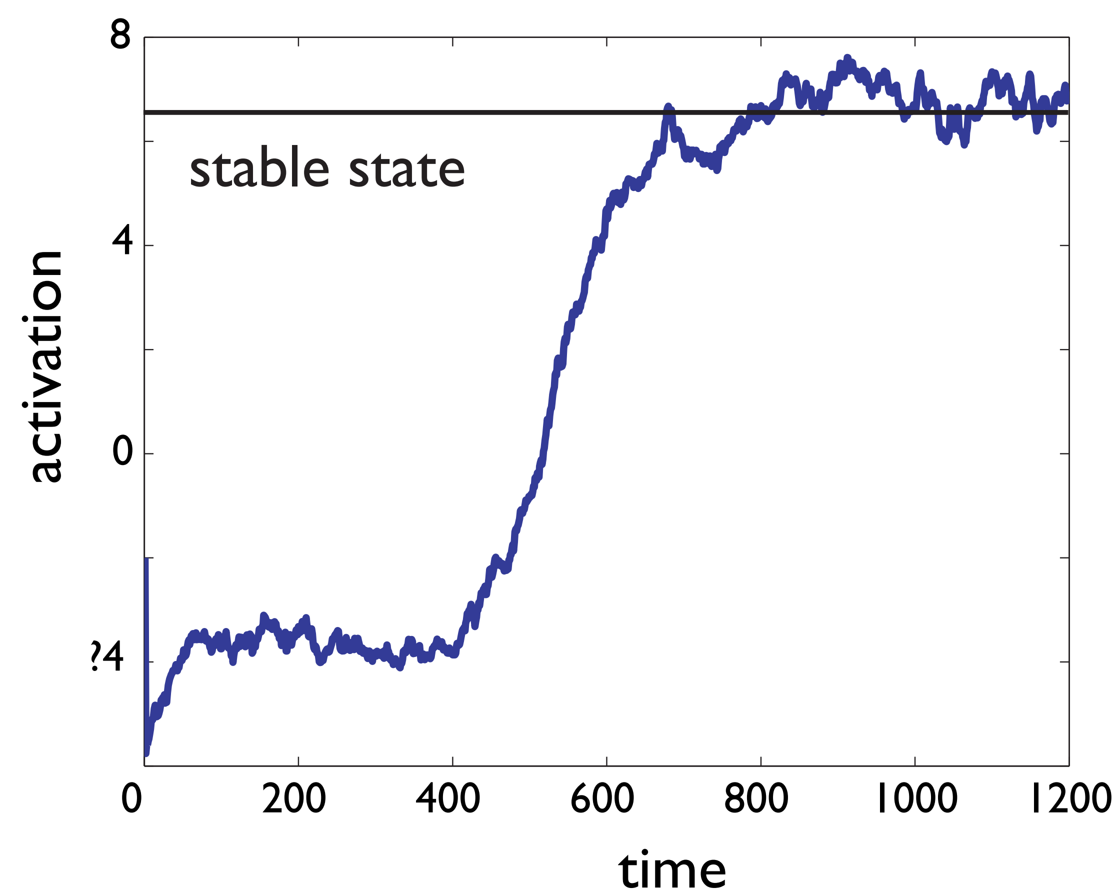


the detection instability helps stabilize decisions

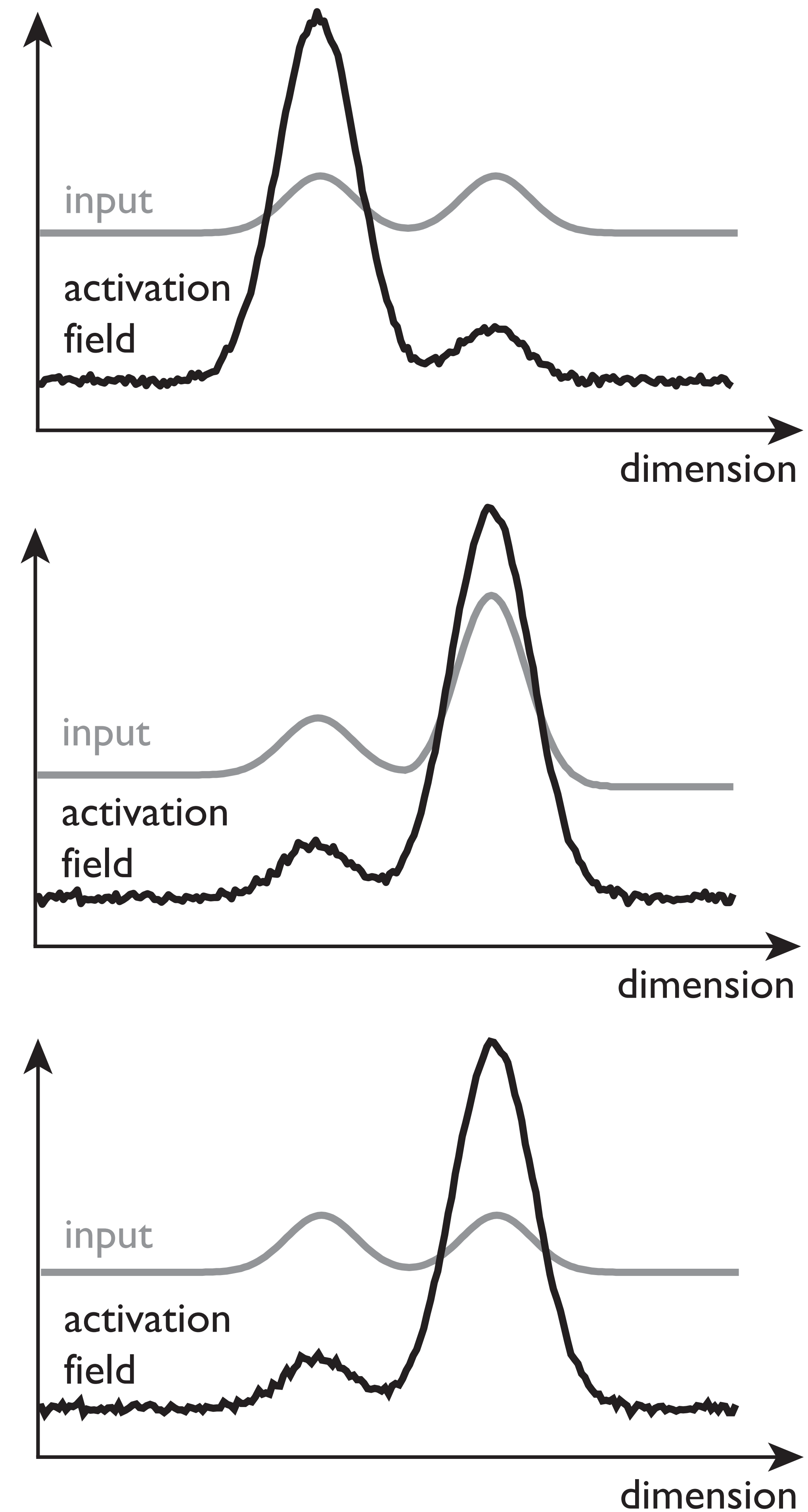
threshold piercing



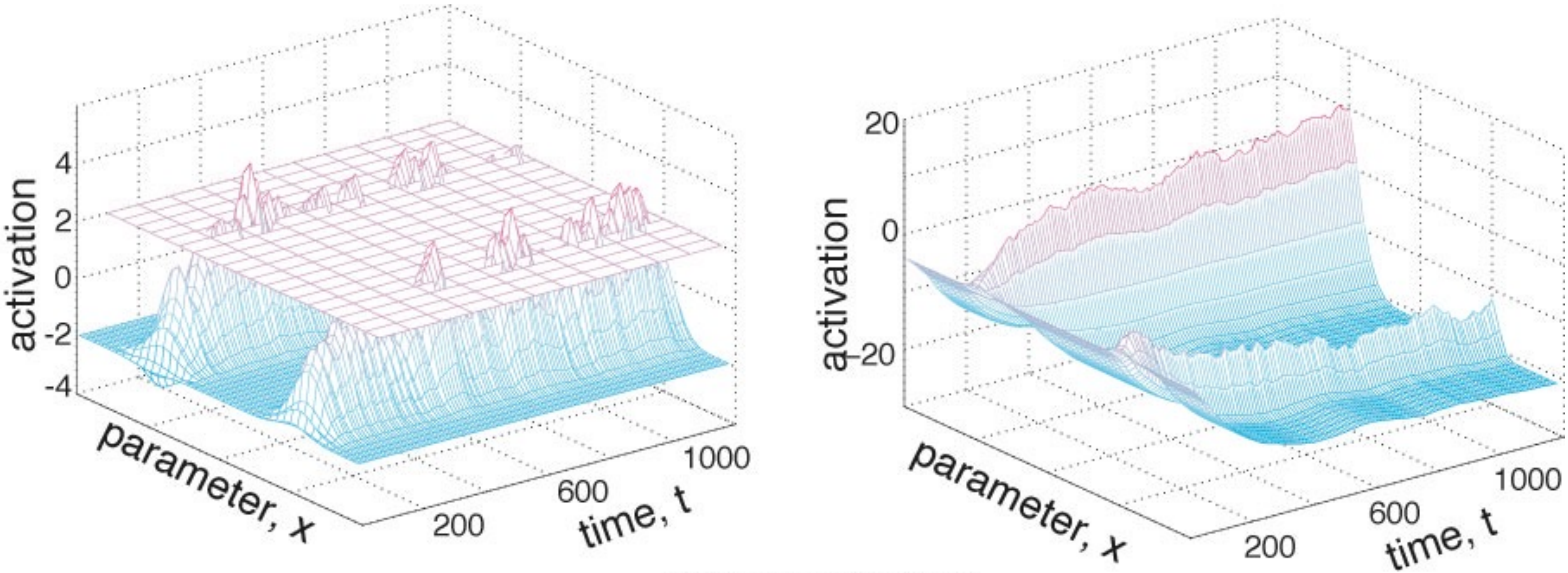
detection instability



selection instability

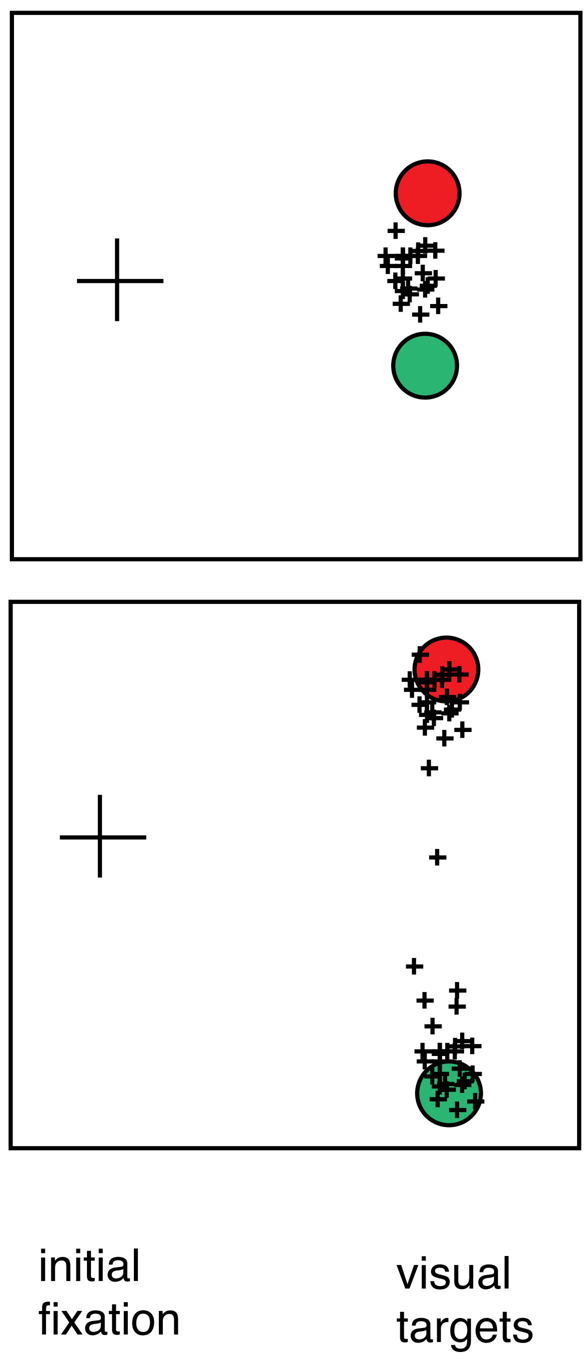


stabilizing selection decisions

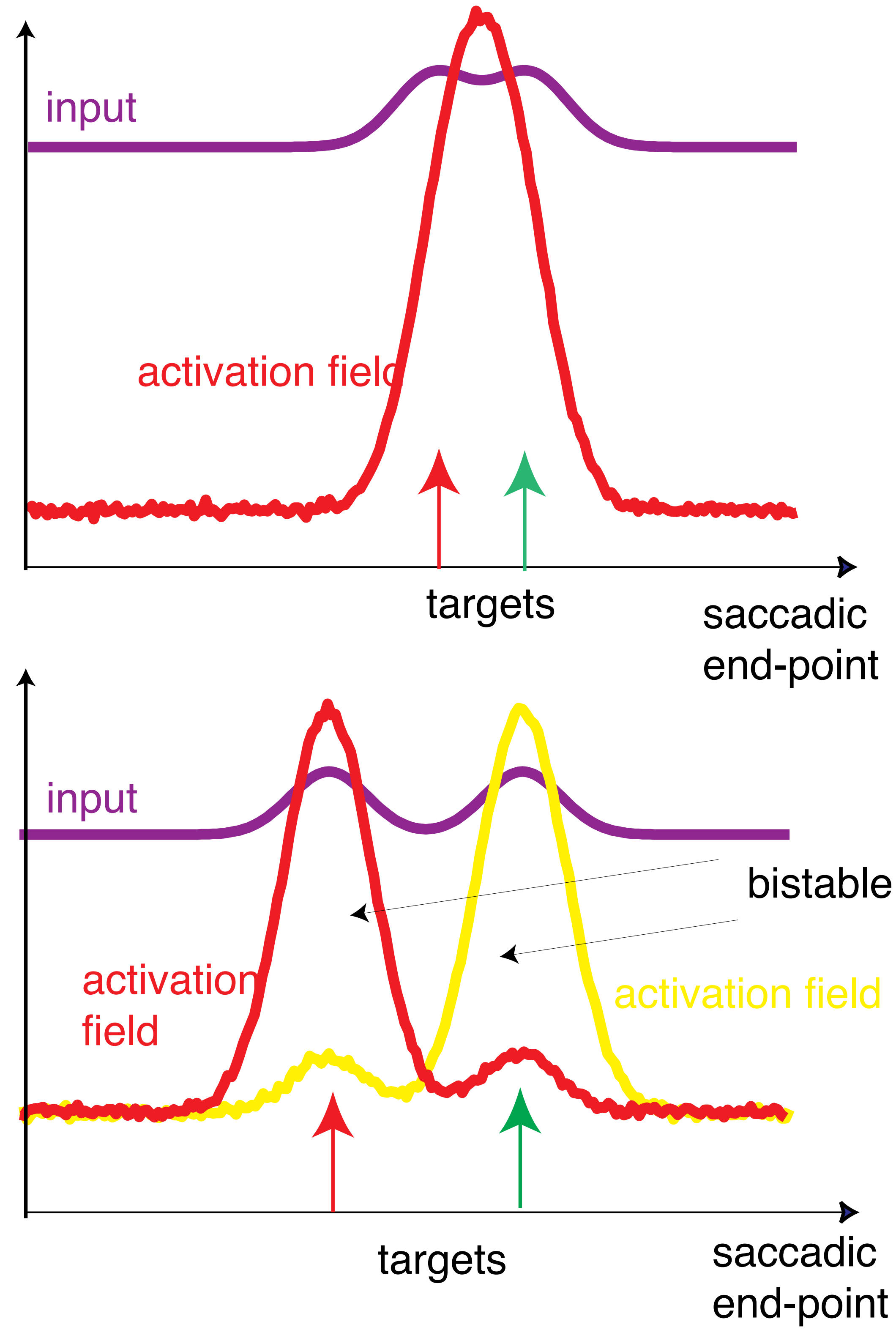


[Wilimzig, Schöner, 2006]

saccade generation

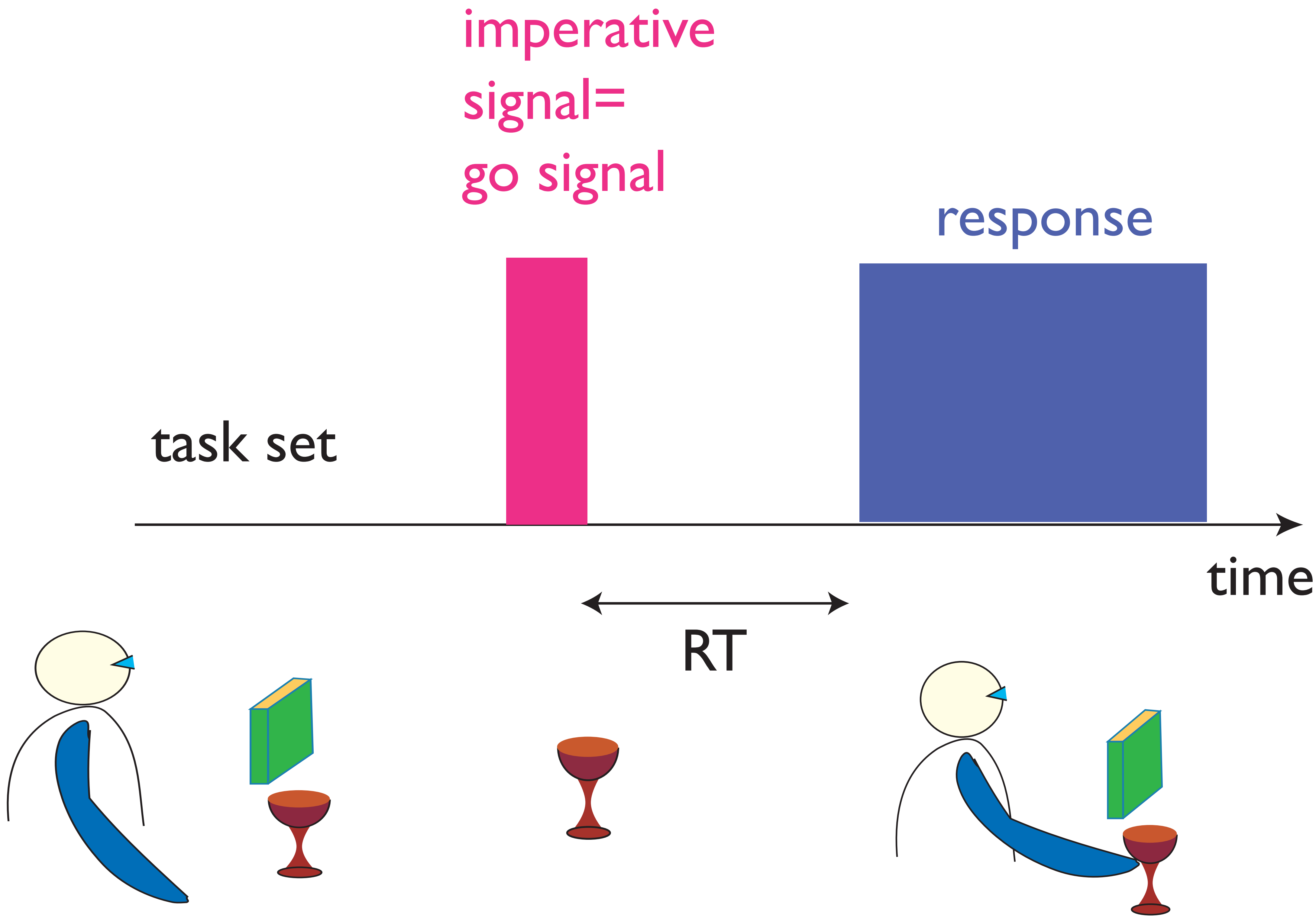


[after: Ottes et al., Vis. Res. 25:825 (85)]

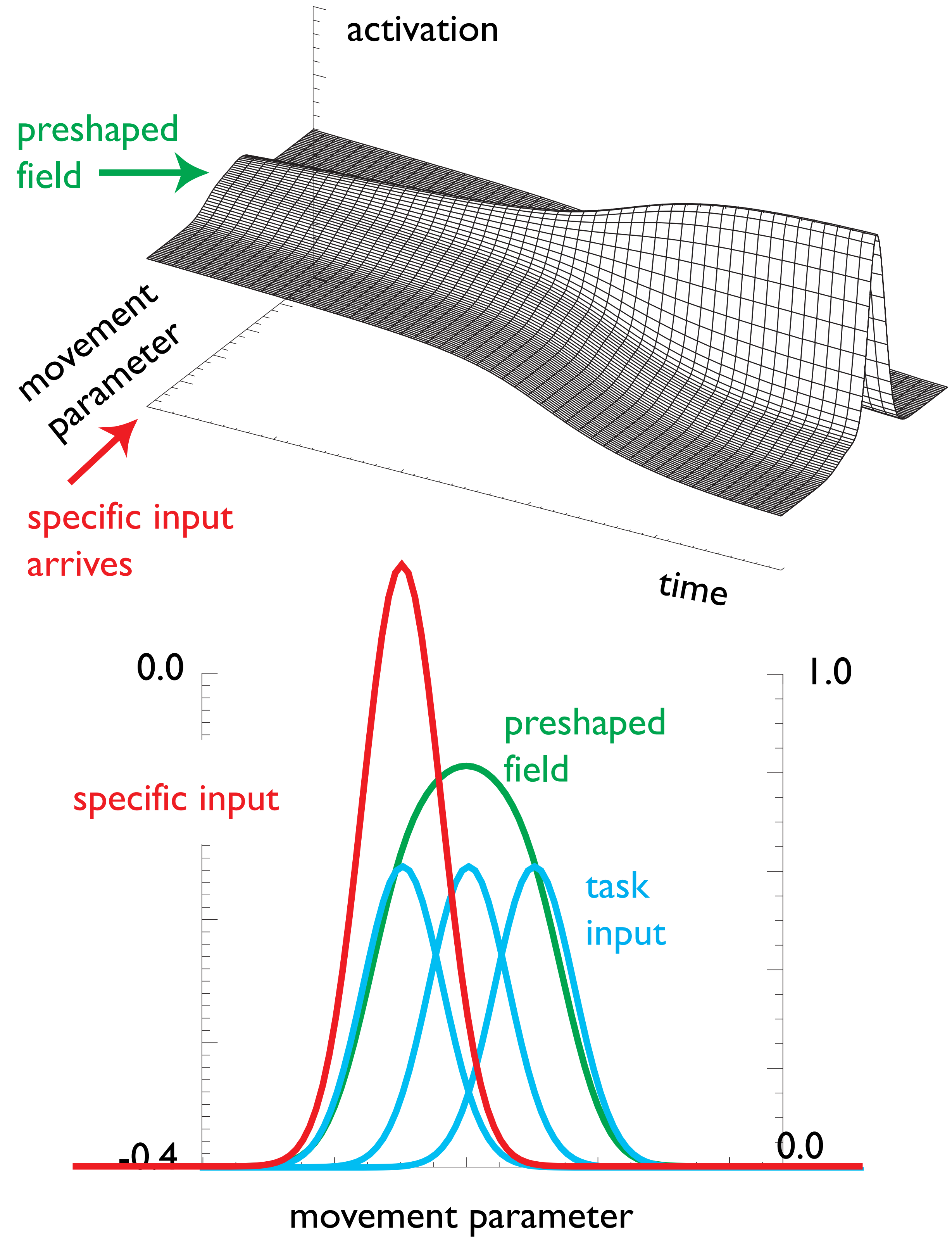


[after Kopecz, Schöner: Biol Cybern 73:49 (95)]

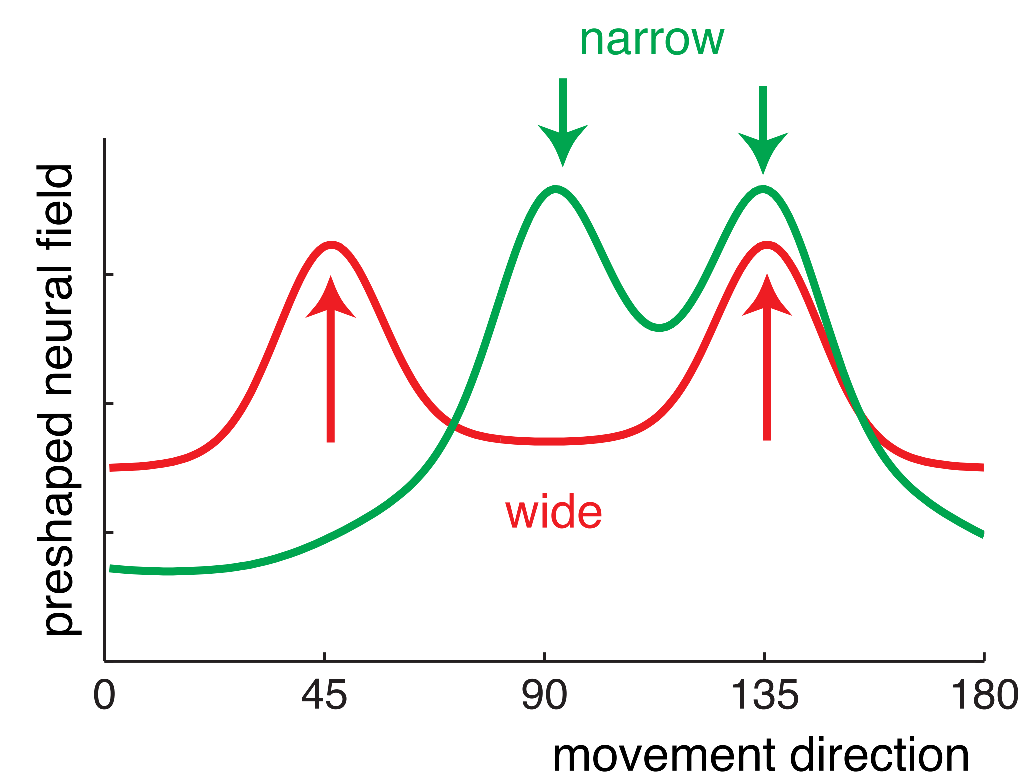
reaction time (RT) paradigm



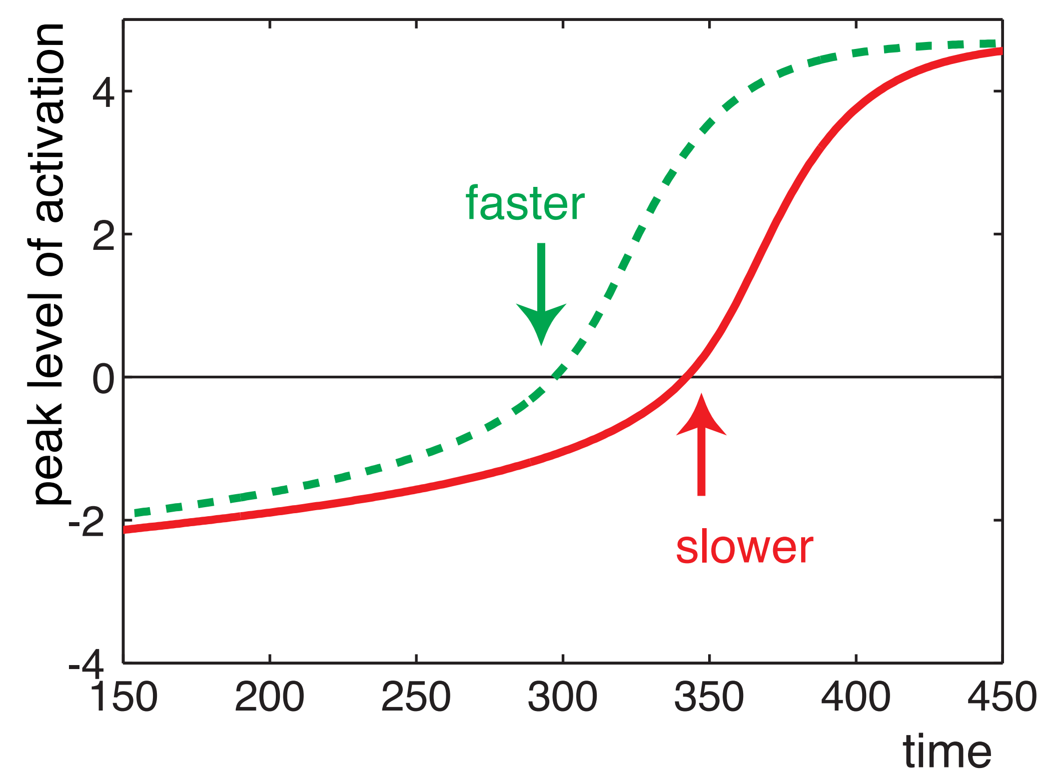
notion of preshape



metric effect

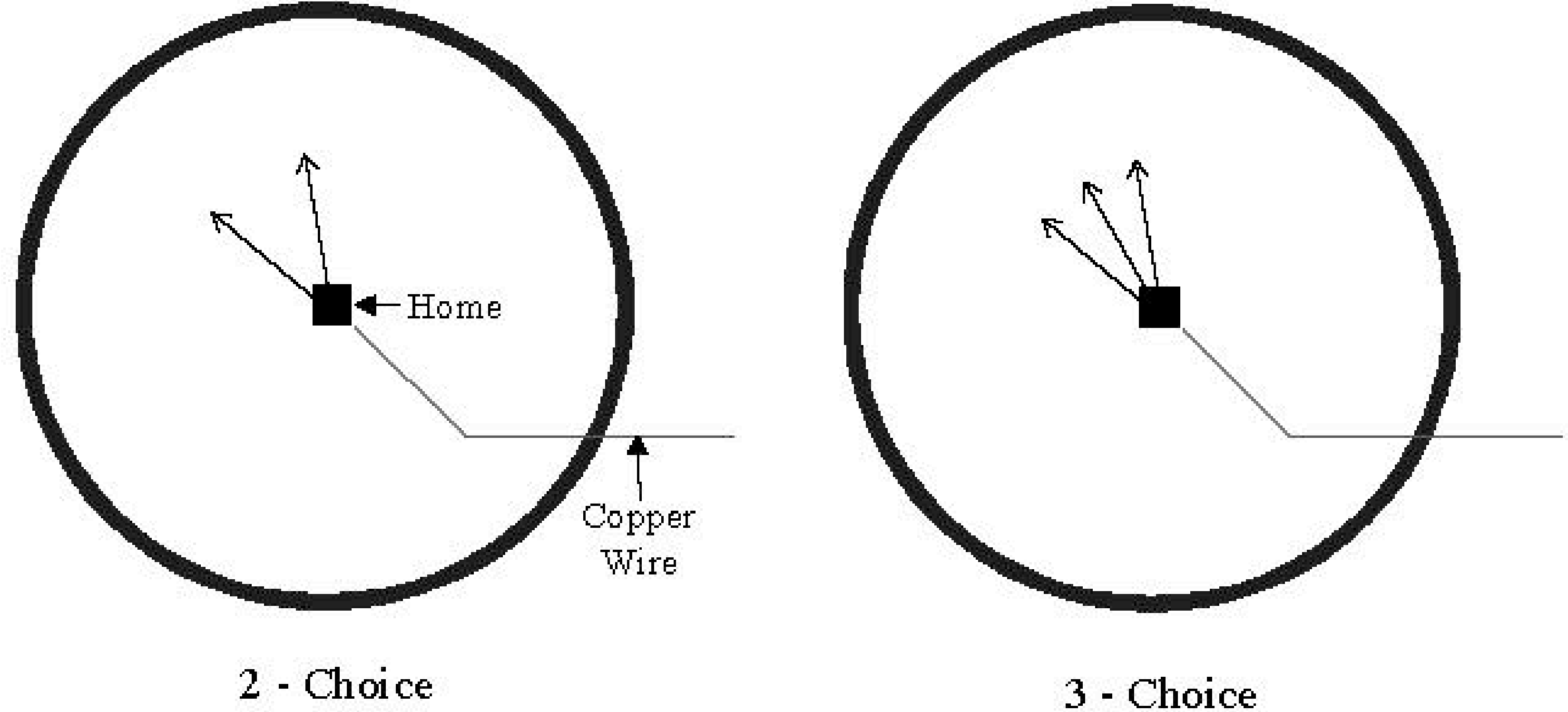


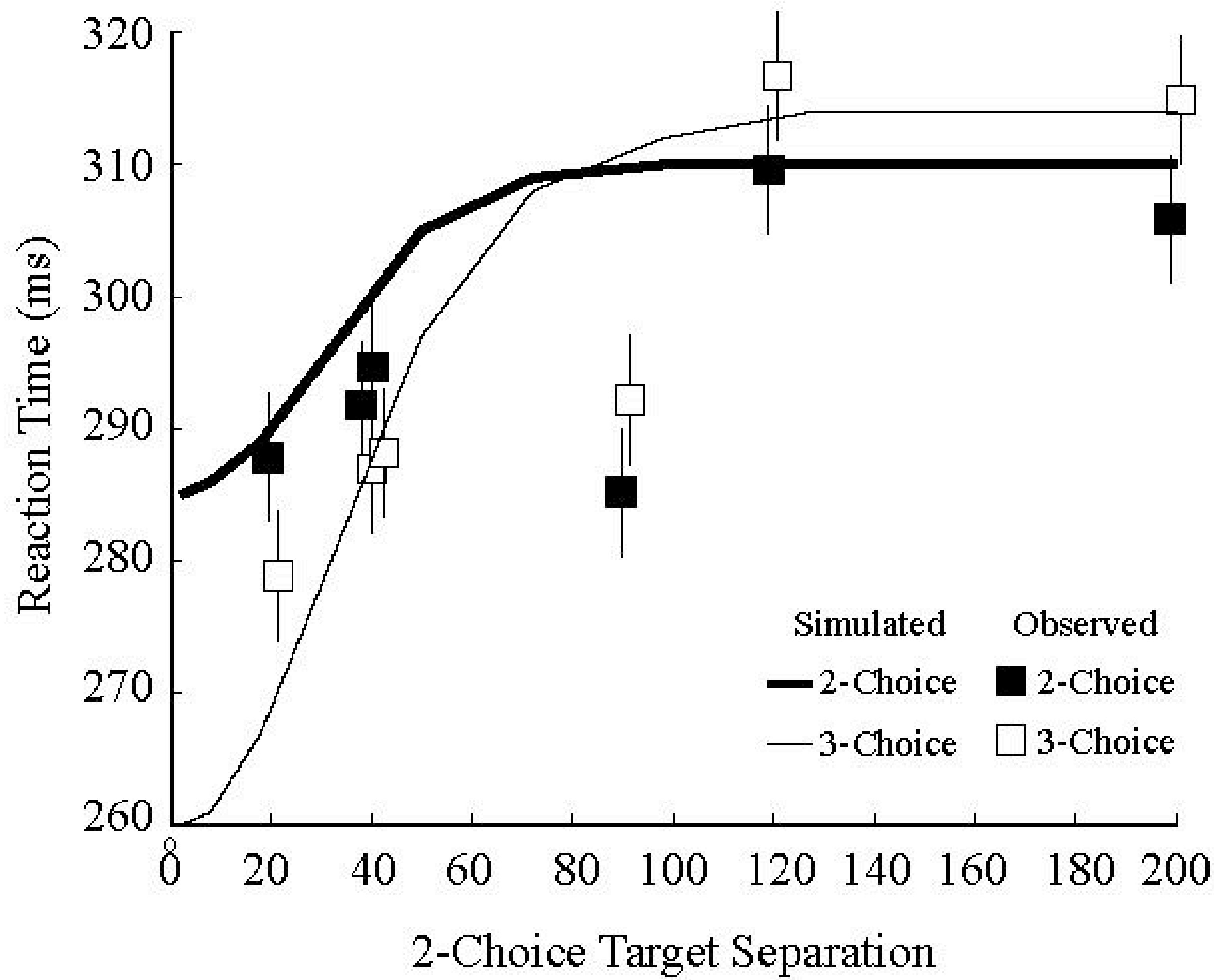
- predict faster response times for metrically close than for metrically far choices



[from Schöner, Kopecz, Erlhagen, 1997]

experiment: metric effect

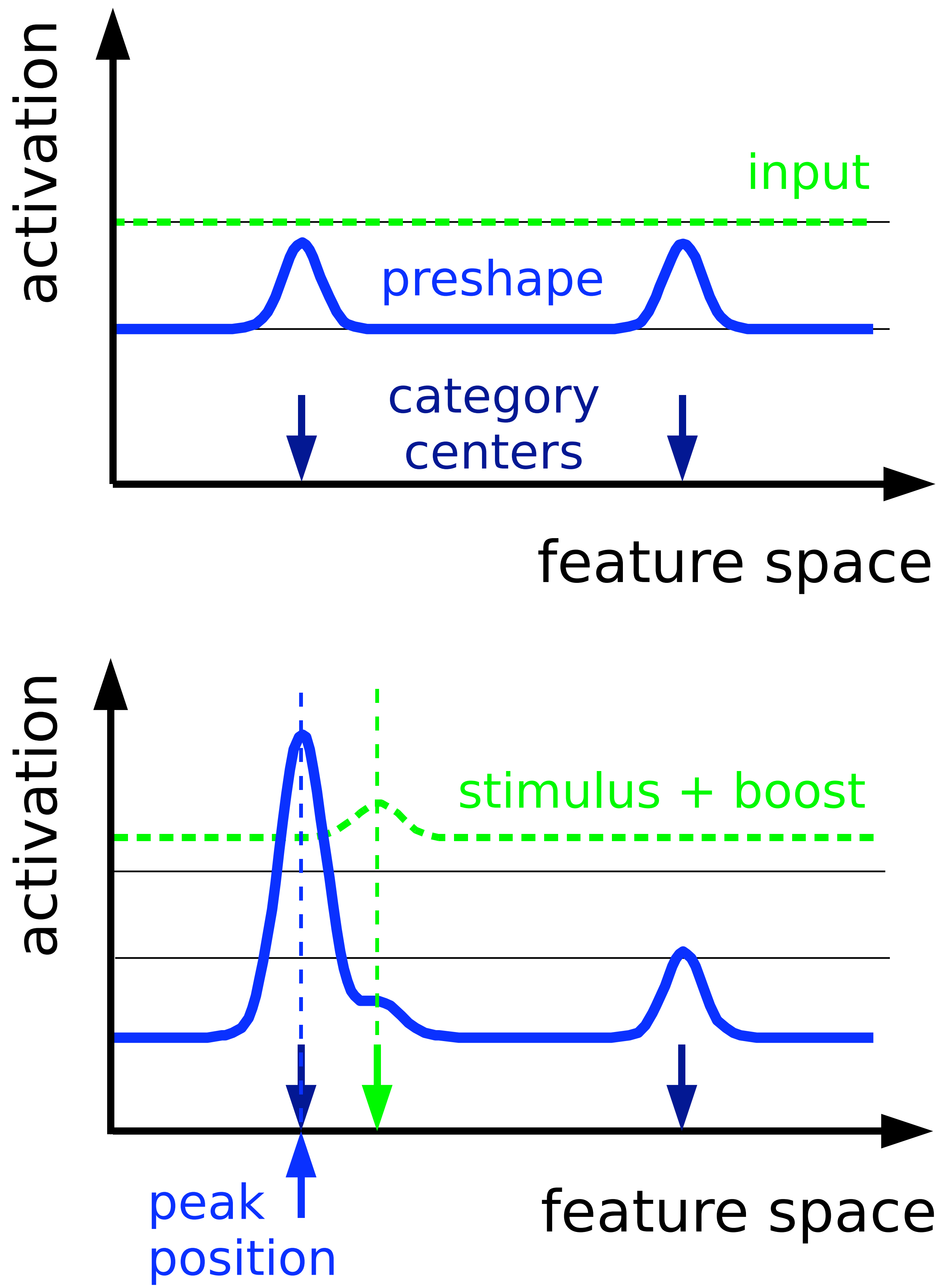




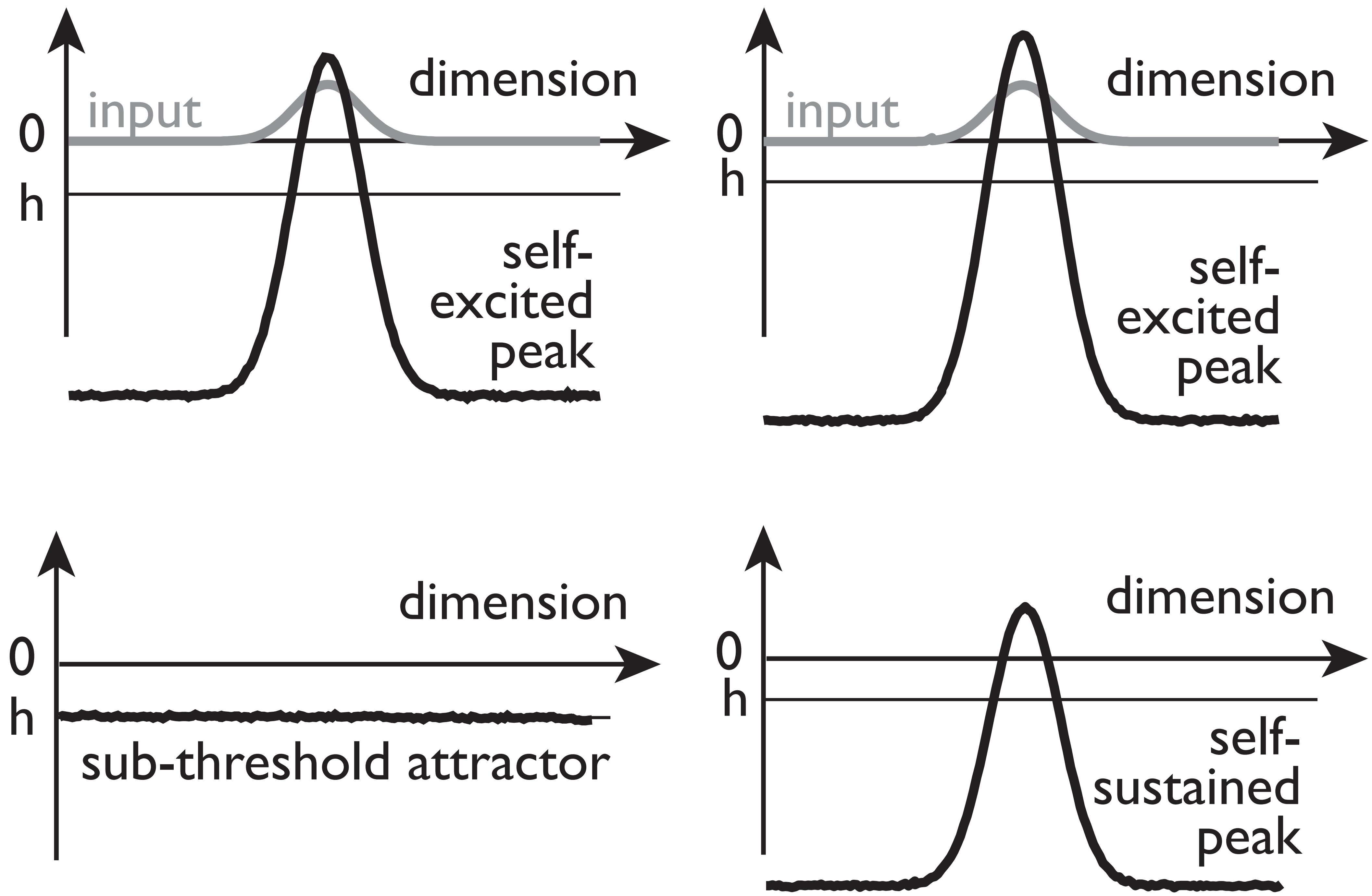
[McDowell, Jeka, Schöner]

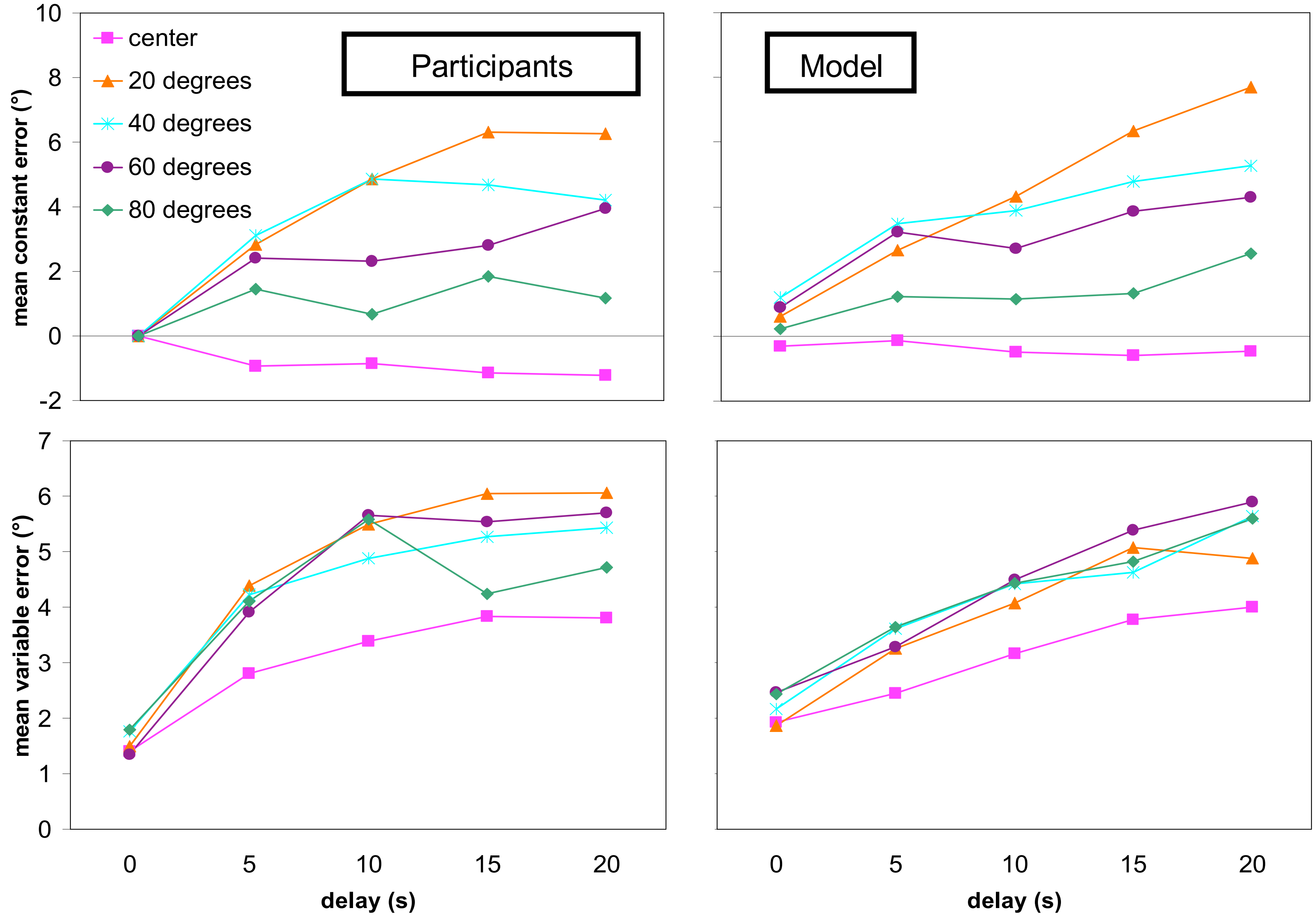
categorical responding

- based on strong preshape and boost-driven detection instability

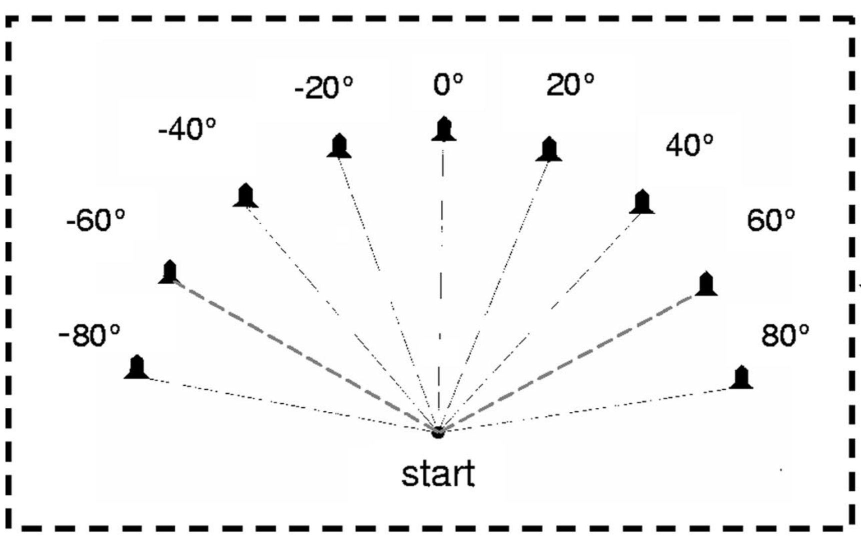


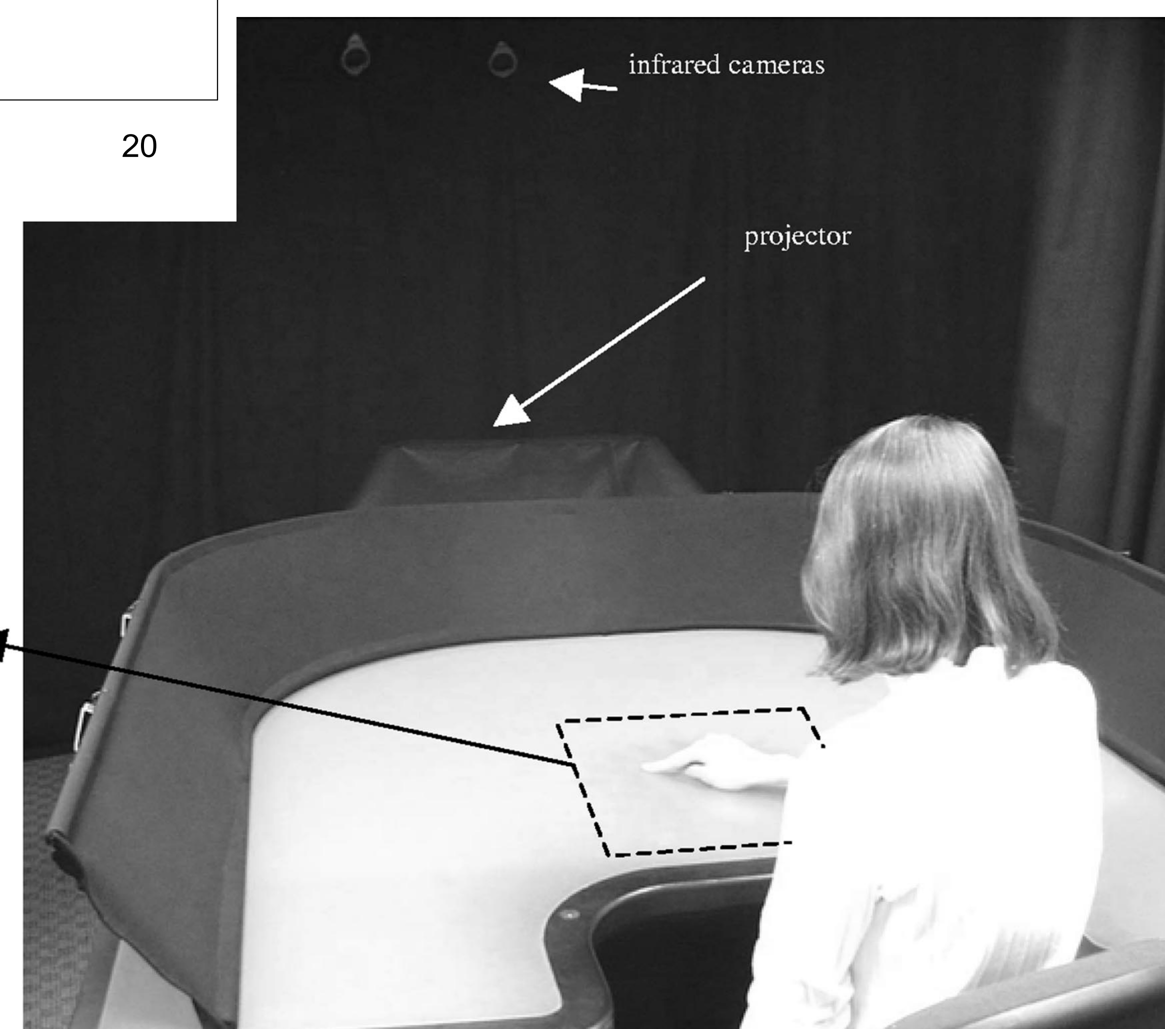
Memory instability





repulsion from mid-line

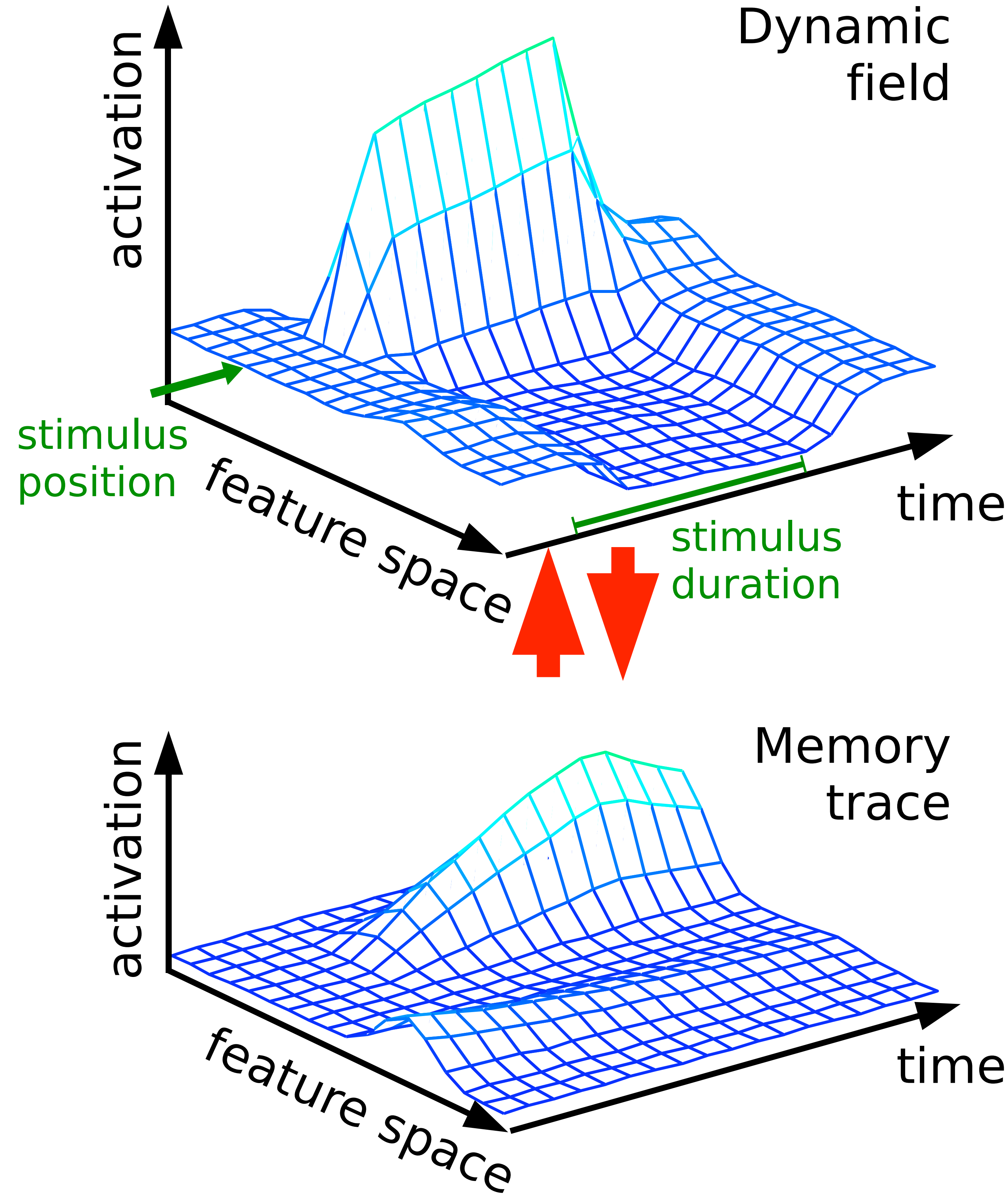




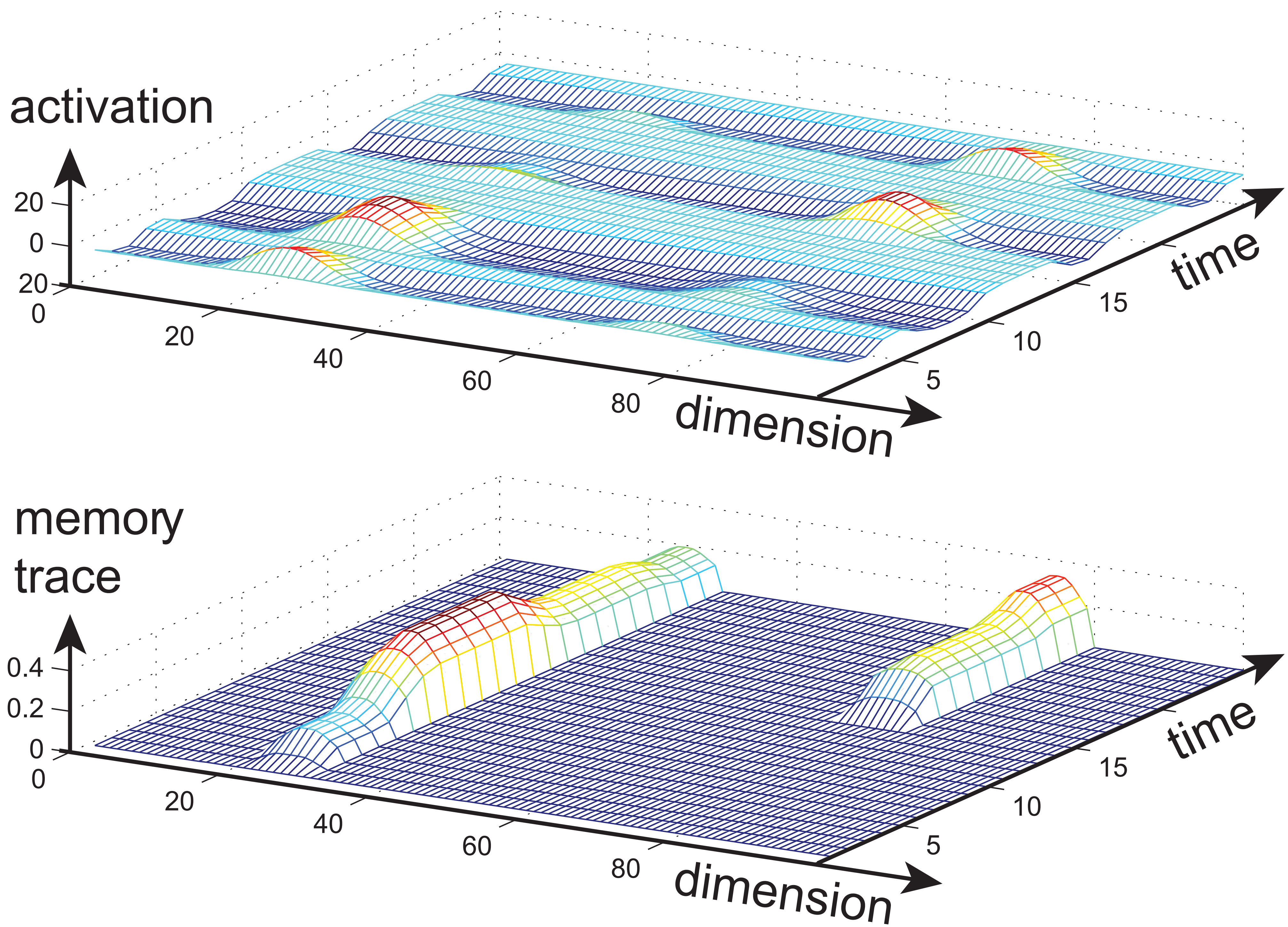
[Spencer, Schöner, 2006]

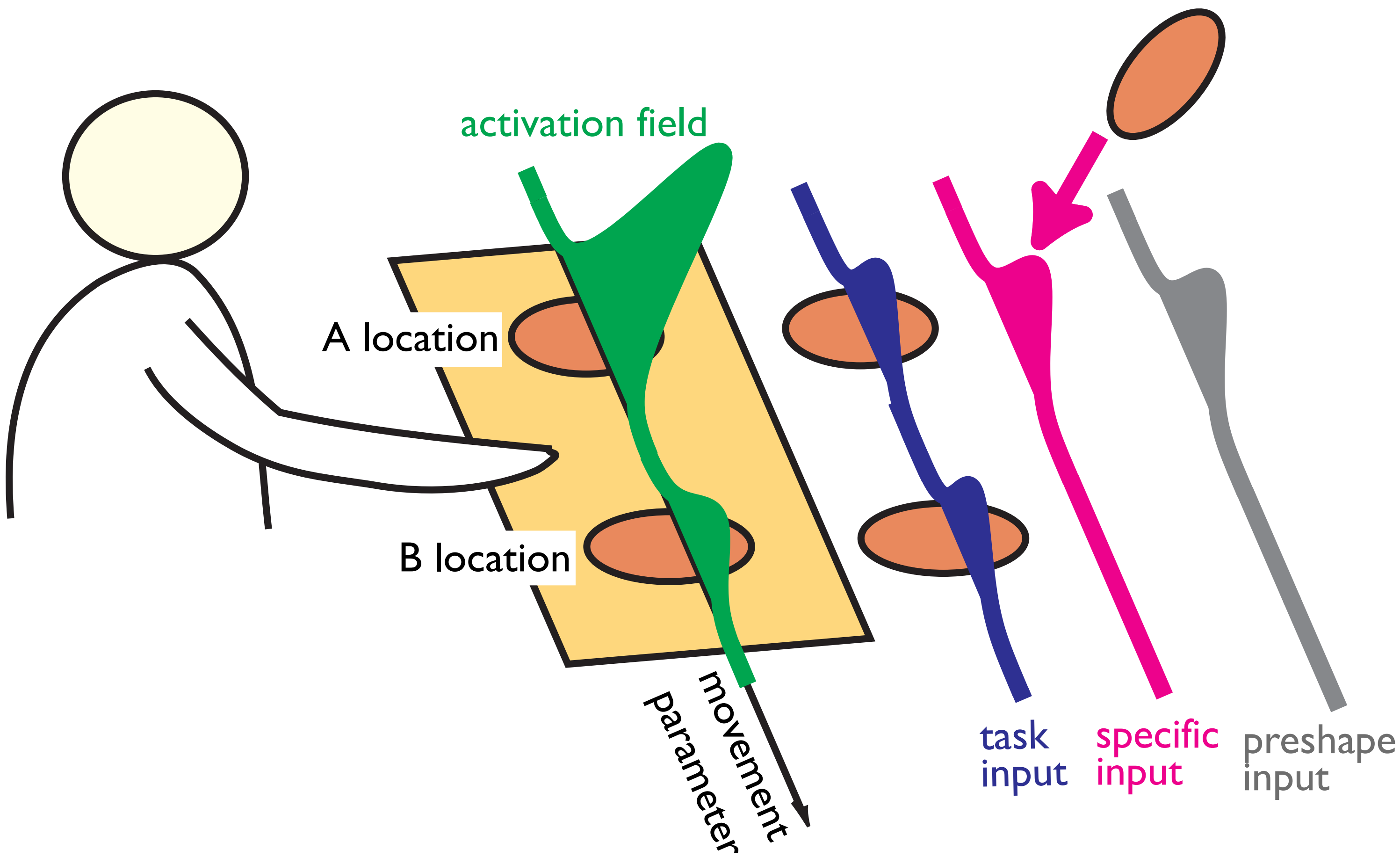
The memory trace

- activation leaves a trace that may influence the activation dynamics later…
- a simplest form of learning
- relevant in DFT because the detection instability may amplify the slightly inhomogeneous activation patterns induced by the memory trace into peaks of activation

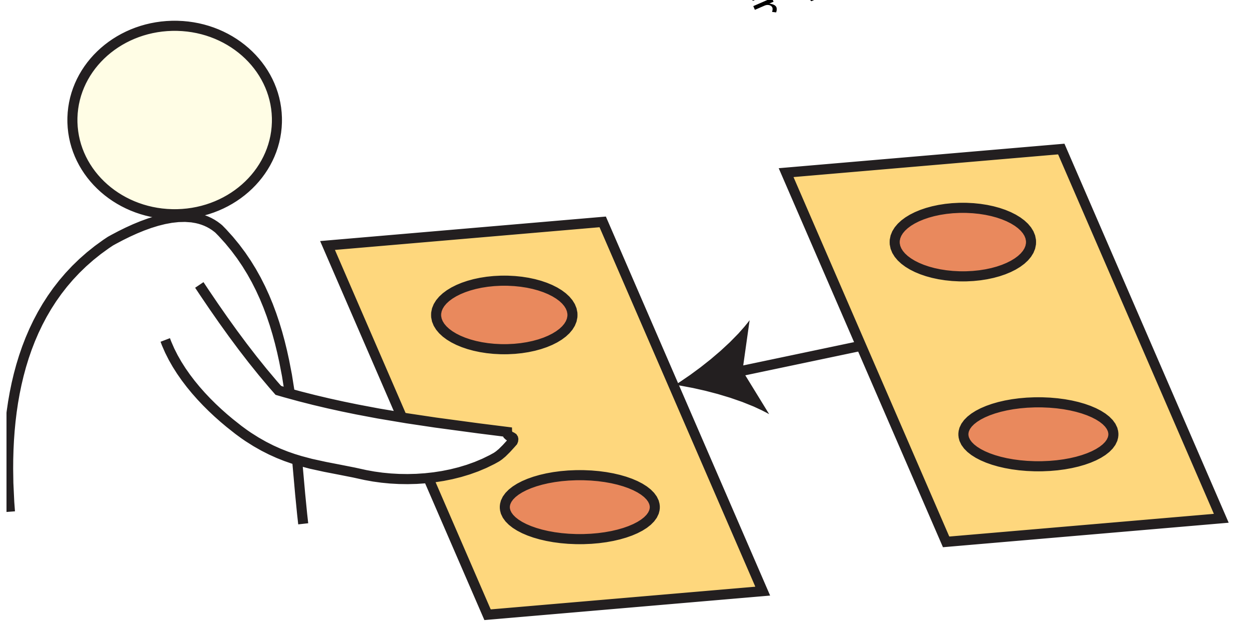


memory trace reflects history of decisions formation





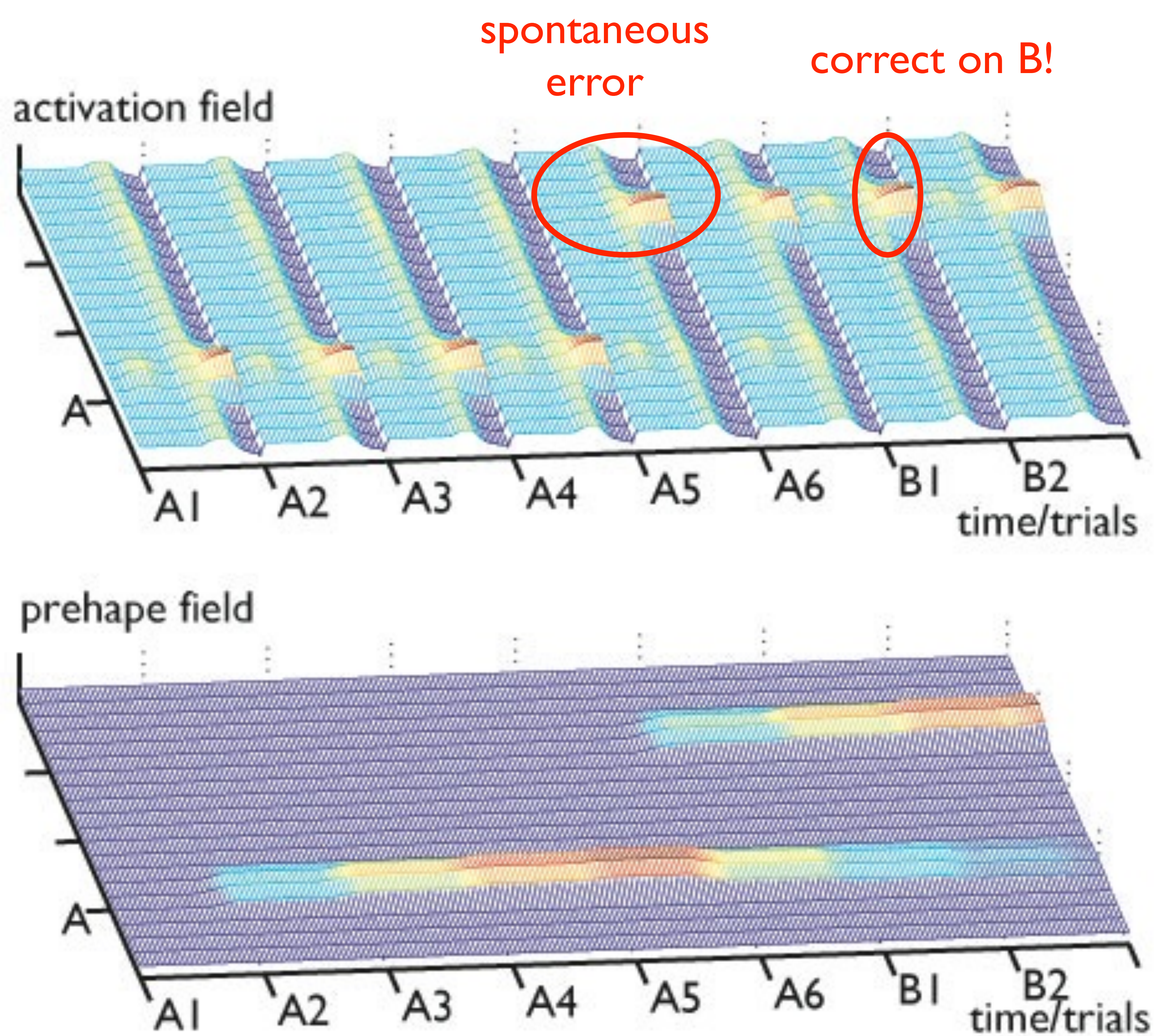
[Thelen, et al., BBS (2001)]



[Dinveva, Schöner, Dev. Science 2007]

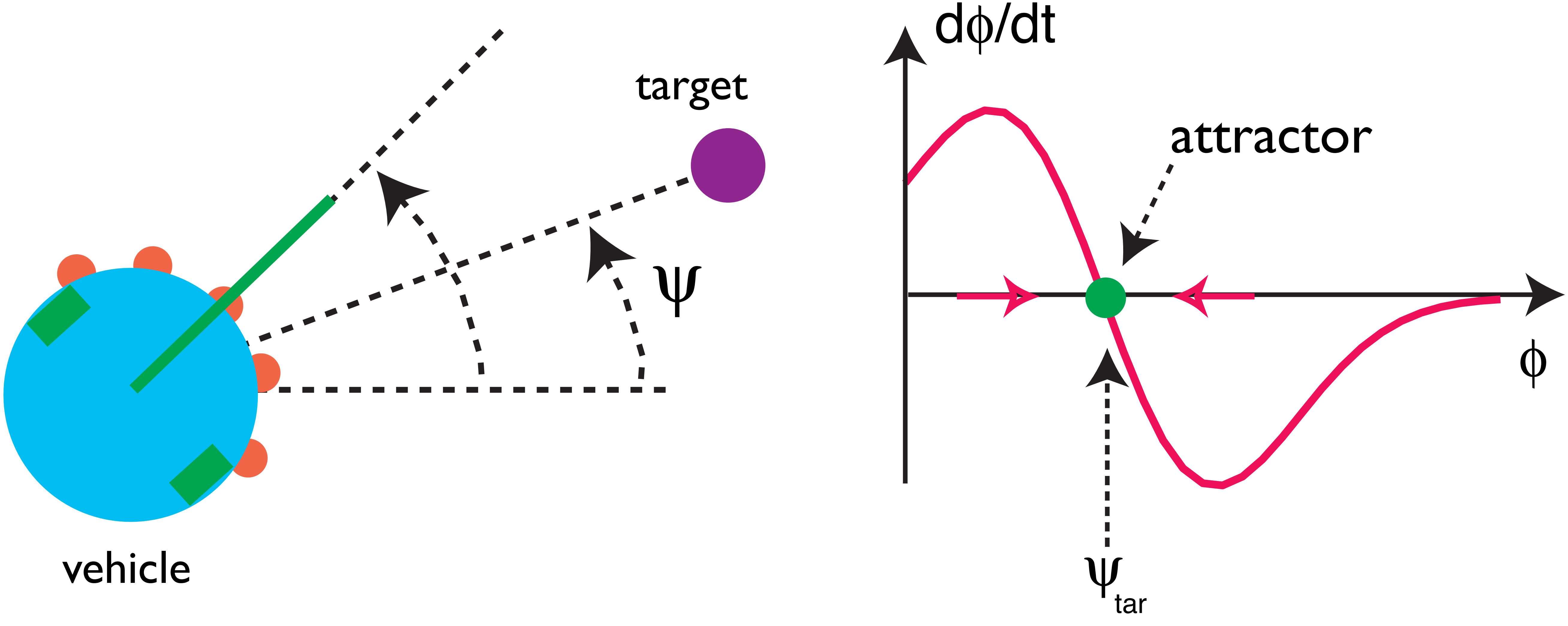
DFT of infant perseverative reaching

- that is because reaches to B on A trials leave memory trace at B

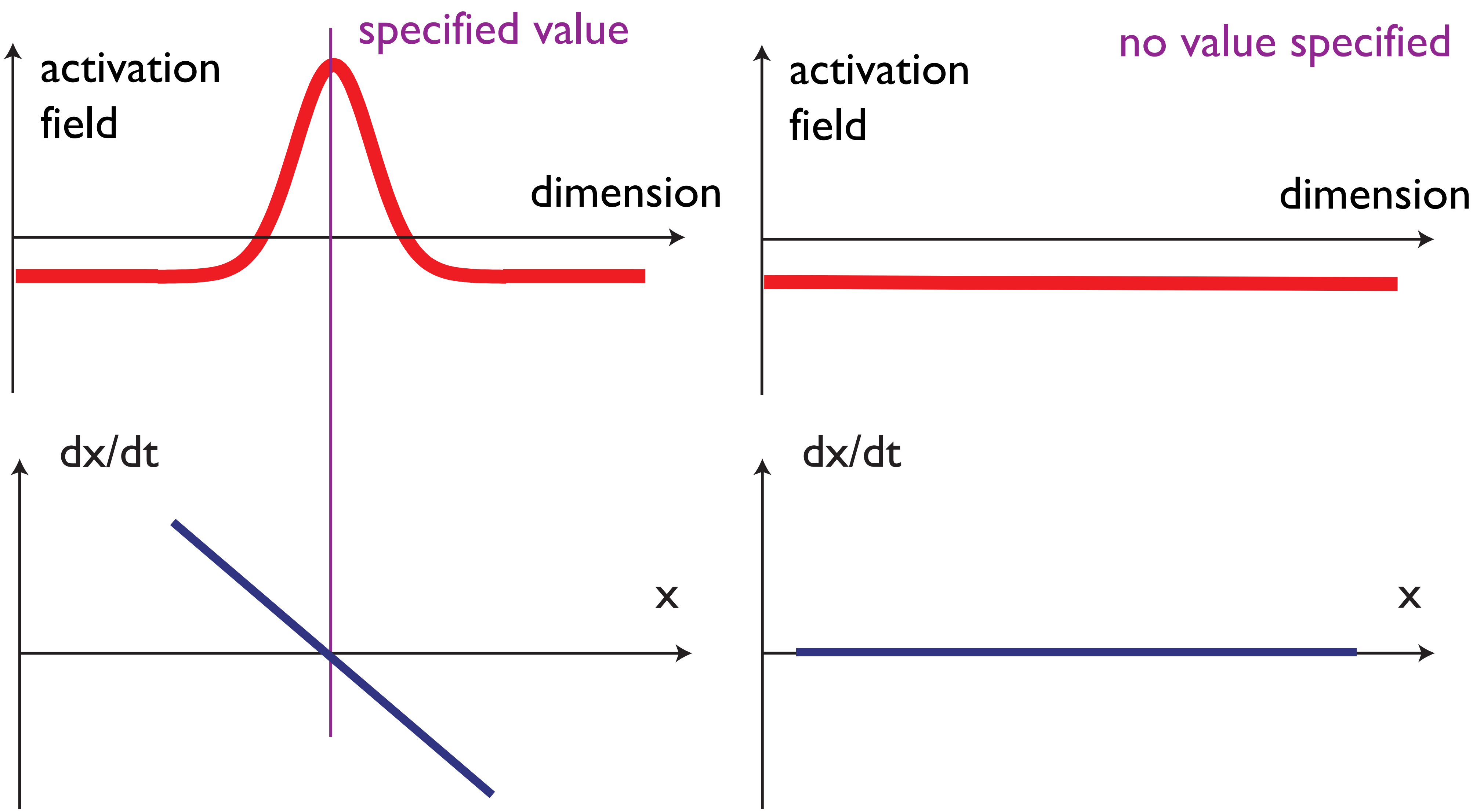


[Dinveva, Schöner, Dev. Science 2007]

From neural to behavioral dynamics



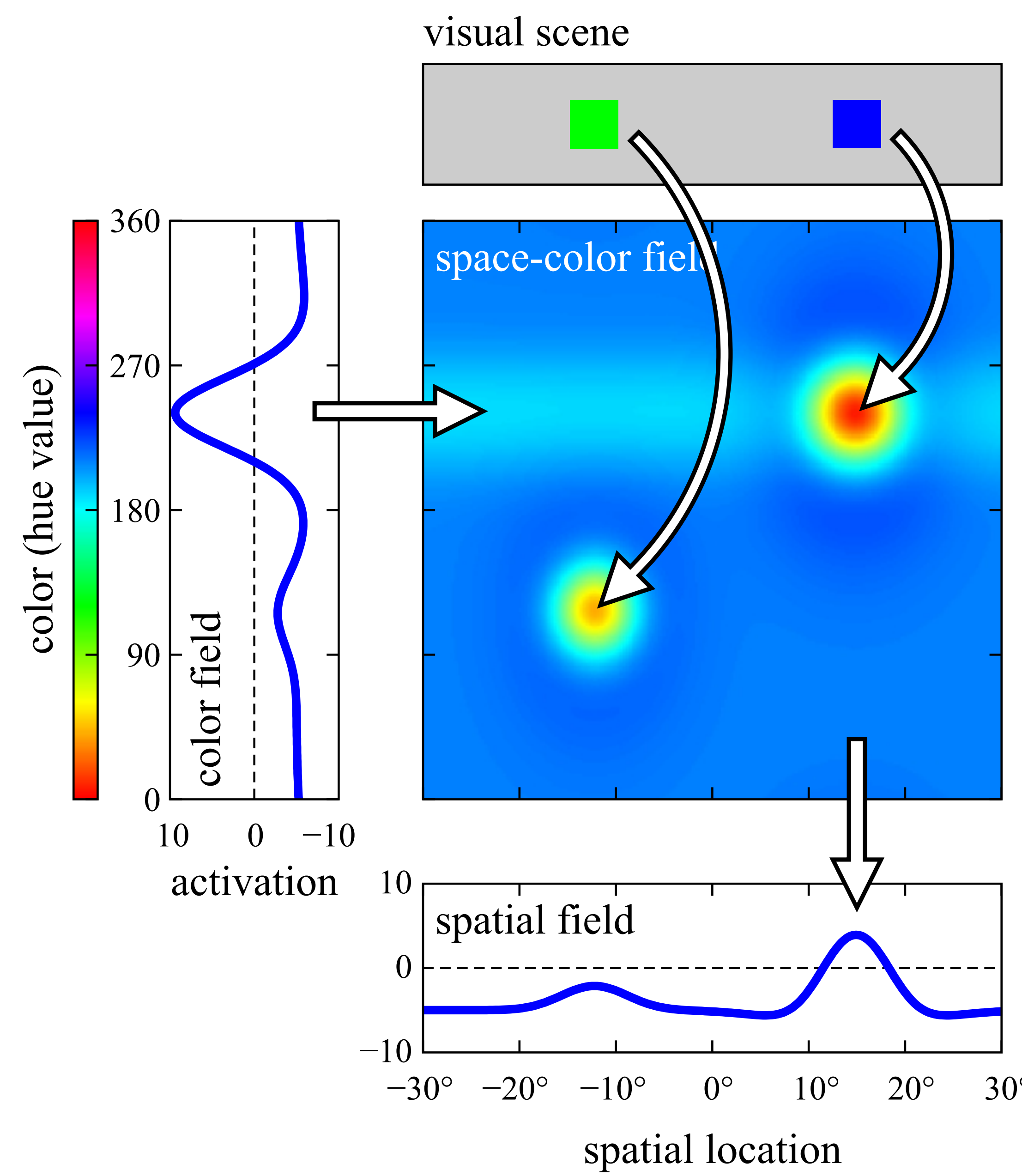
From neural to behavioral dynamics



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

New functions from higher-dimensional fields

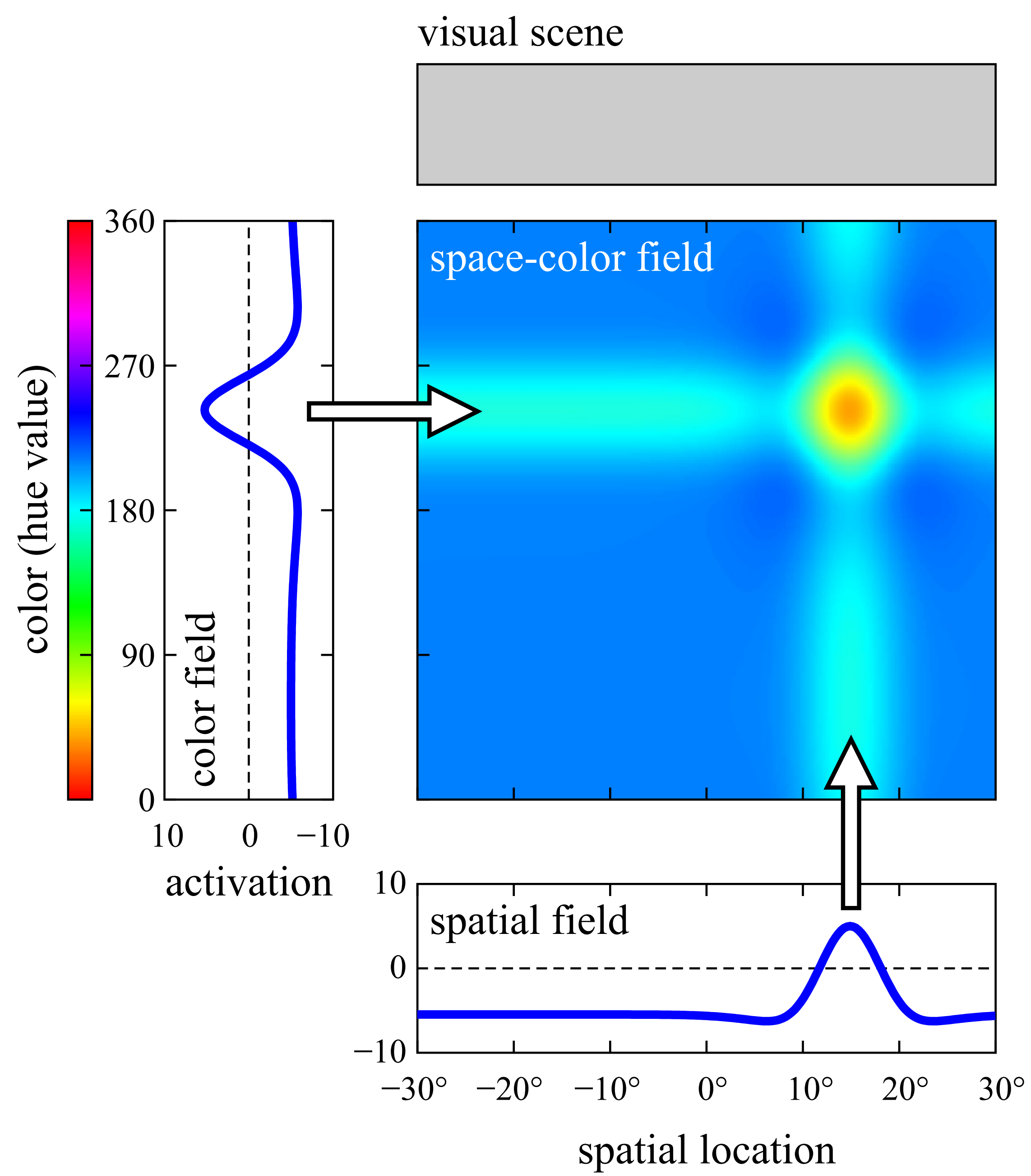
- visual search: combine ridge input with 2D input..



[Slides adapted from Sebastian Schneegans,
see Schneegans, Lins, Spencer, Chapter 5 of Dynamic Field Theory-A Primer, OUP, 2015]

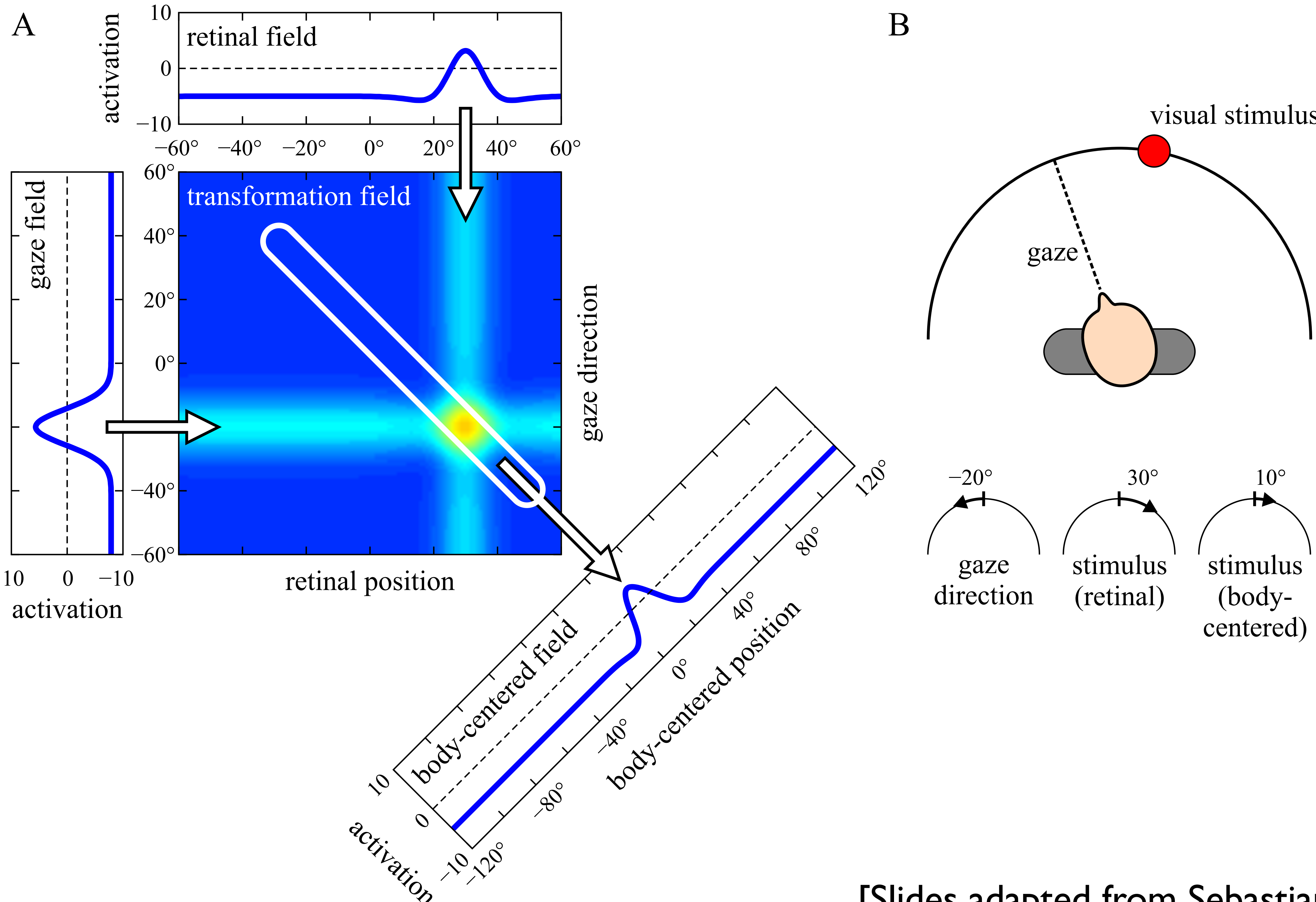
New functions from higher-dimensional fields

- peaks at intersections of ridges: bind two dimensions



[Slides adapted from Sebastian Schneegans,
see Schneegans, Lins, Spencer, Chapter 5 of Dynamic Field Theory-A Primer, OUP, 2015]

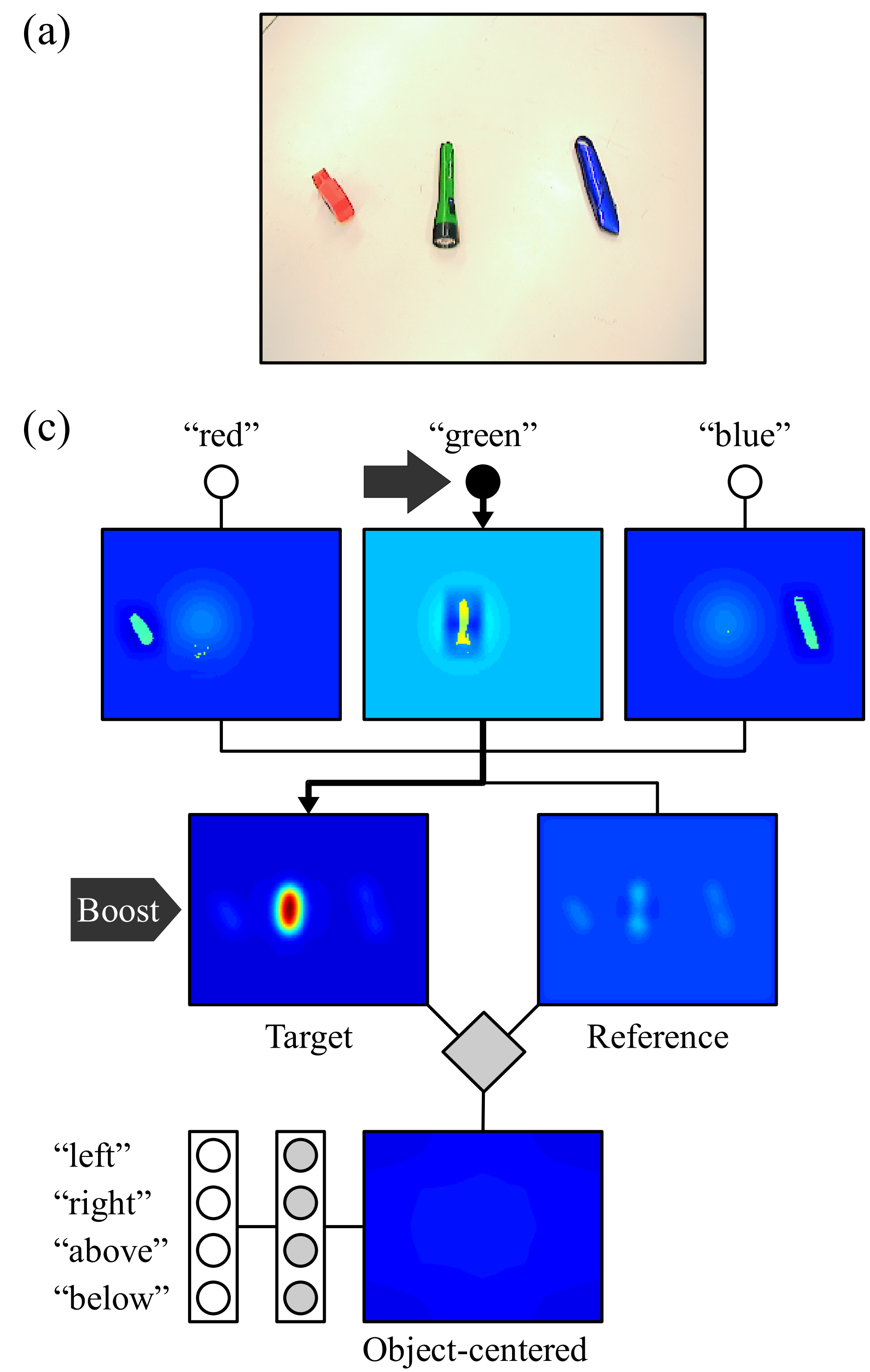
New functions from higher-dimensional fields: coordinate transforms



[Slides adapted from Sebastian Schneegans,
see Schneegans, Chapter 7 of Dynamic Field Theory-A Primer, OUP, 2015]

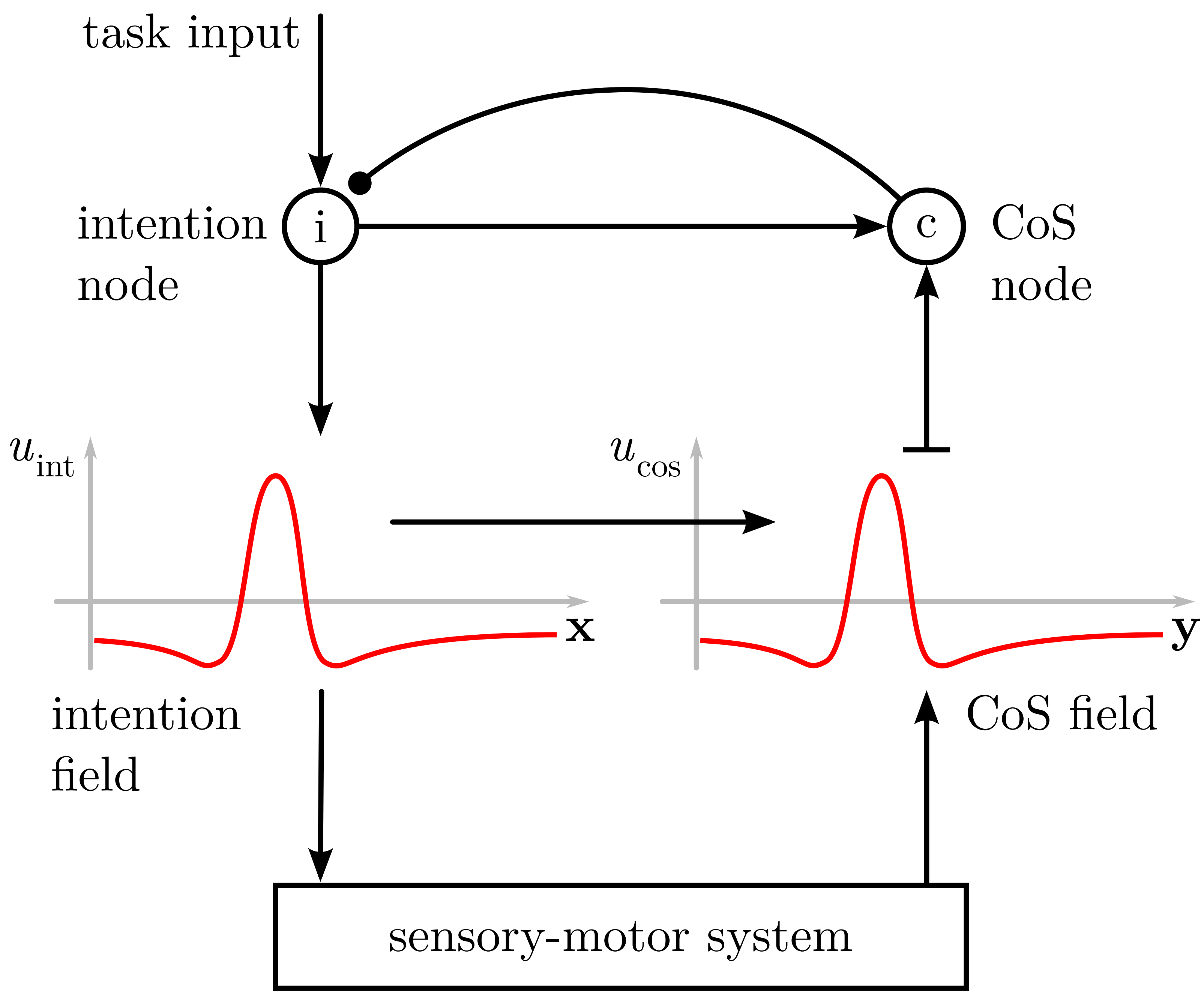
Toward higher cognition: Grounding spatial concepts

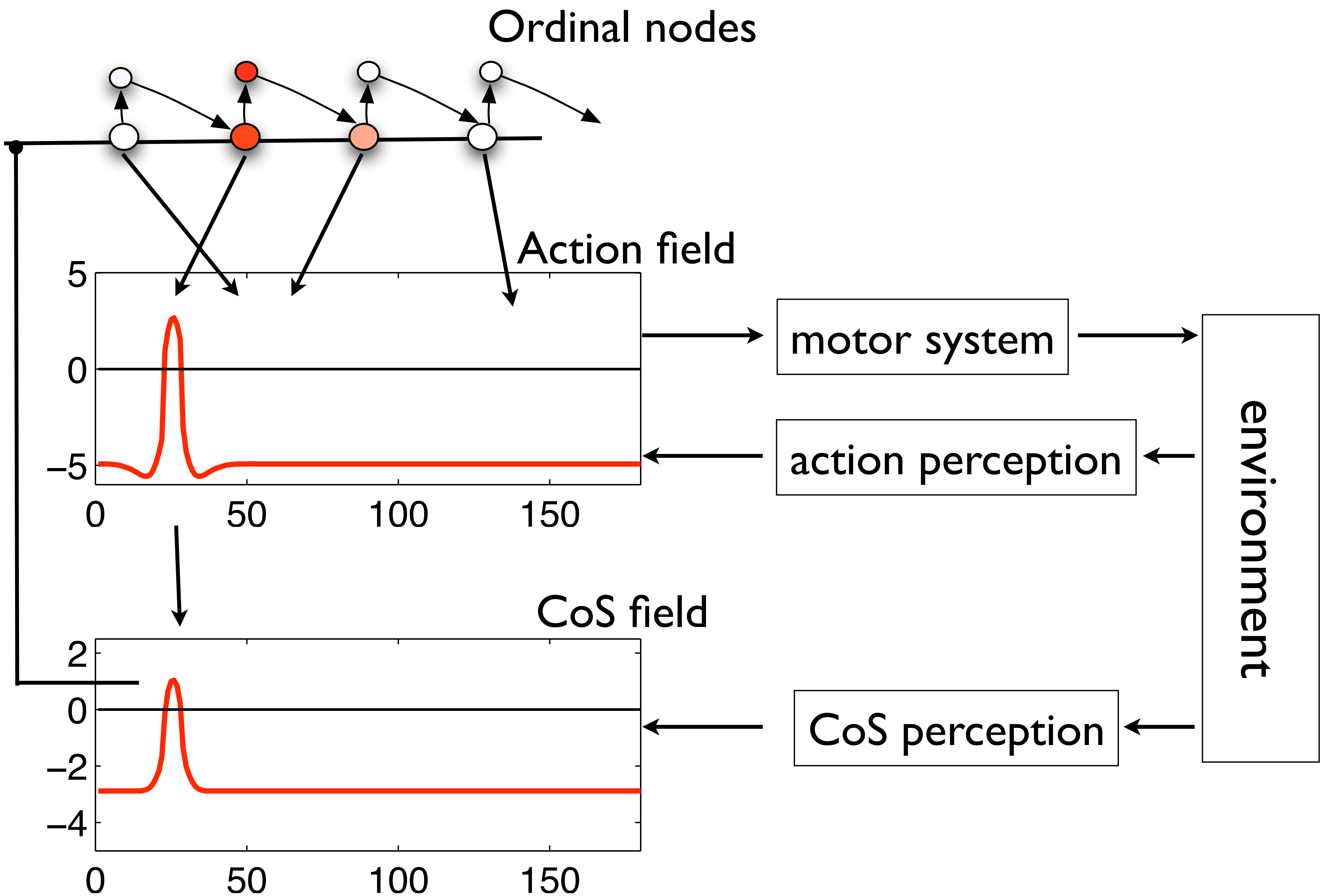
- bring objects into foreground
- make coordinate transformation
- apply comparison operators



[Lipinski et al: JEP:LMC (2011)]

Sequences: Condition of Satisfaction

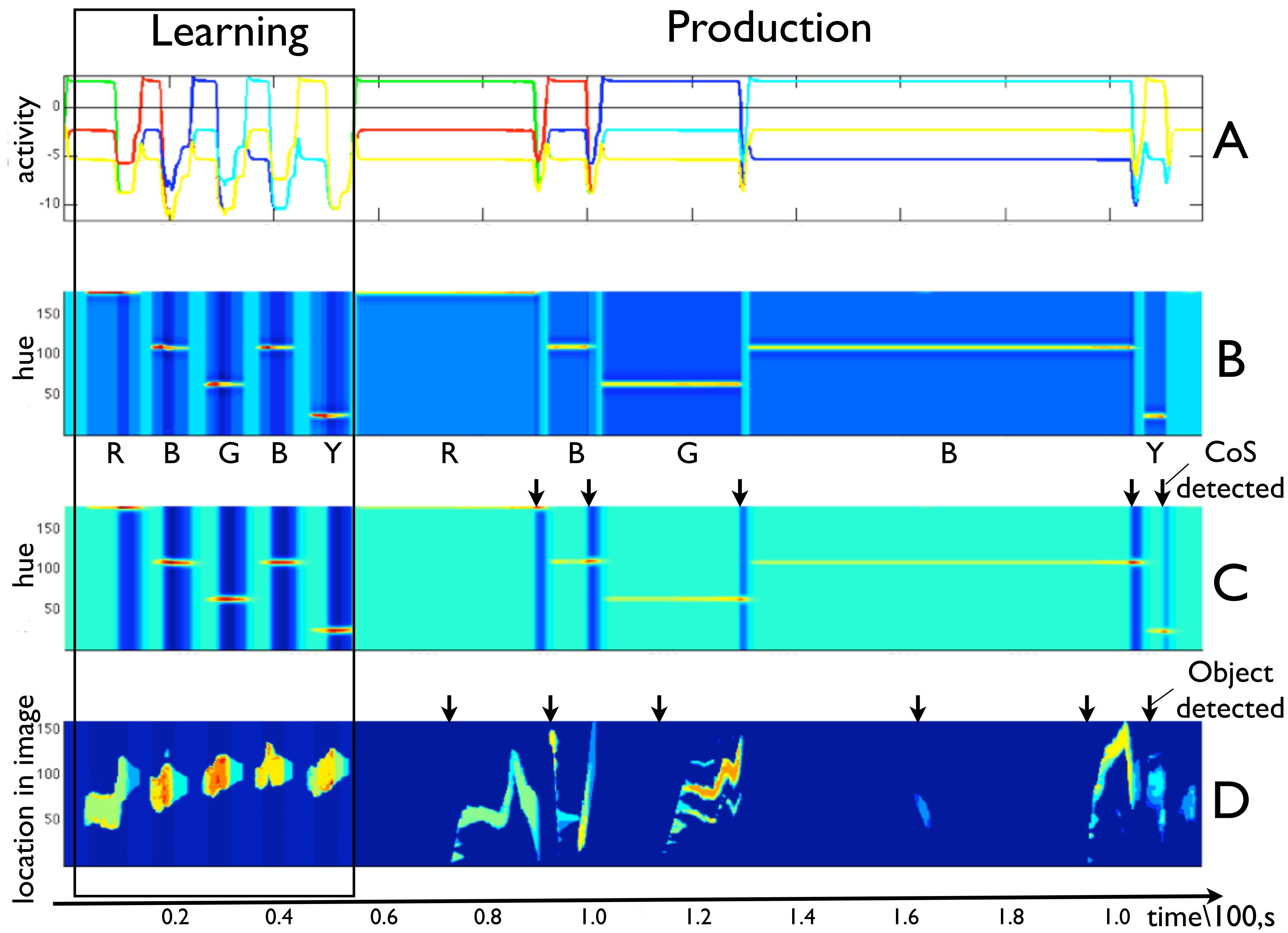




[Sandamirskaya, Schöner: Neural Networks 23:1163 (2010)]

Autonomous sequence generation

- discrete events in time are autonomously generated
- when the world matches the intention condition of satisfaction



[Sandamirskaya, Schöner: Neural Networks 23:1163 (2010)]

What skills do you learn?

- academic skills
  - read and understand scientific texts
  - write technical texts, using mathematical concepts and illustrations

What skills do you learn?

- mathematical skills
  - conceptual understanding of dynamical systems
  - capacity to read differential equations and illustrate them
  - perform “mental simulation” of differential equations
  - use numerical simulation to test ideas about an equation

What skills do you learn?

- interdisciplinary skills
  - handle concepts from a different discipline
  - handle things that you don’t understand
  - sharpen sense of what you understand and what not

- … any joy?