Summary

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Introduction

Cognition in the wild...

- attention/gaze
- active perception/working memory
- action plans/decisions/ sequences
- goal orientation
- motor control
- background knowledge
- learning from experience



=> implied properties of the underlying neural processes

- graded state
- continuous time
- continuous/intermittent link to the sensory and motor surfaces
- from which discrete events and categorical behavior emerge
- in closed loop
- => states must be stable



Embodiment hypothesis

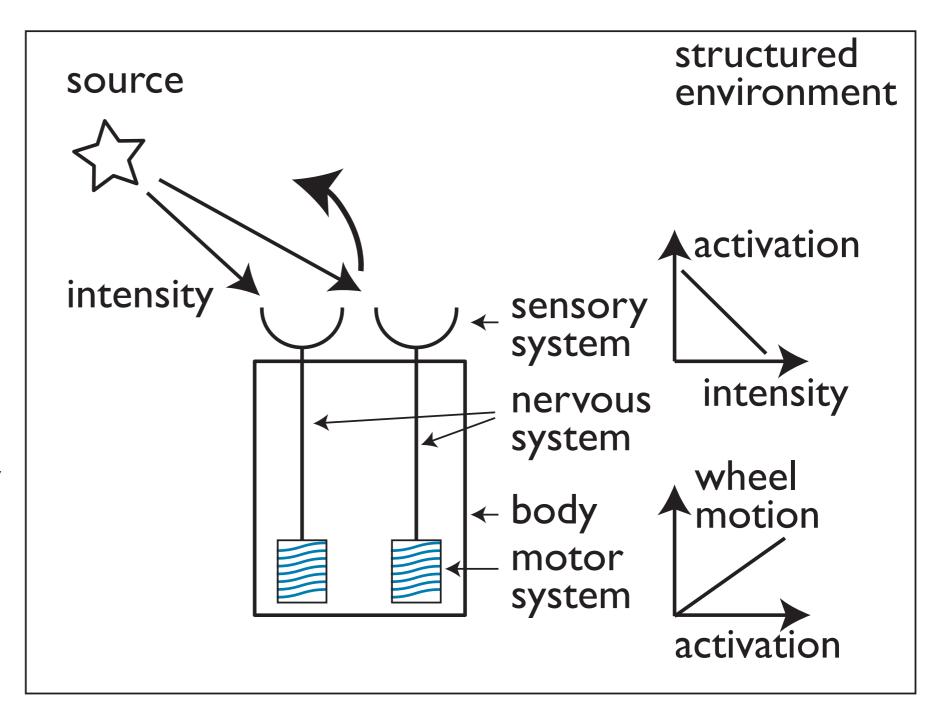
- all cognition is like soccer playing = has the properties of embodied cognition
- => there is no particular boundary up to which cognition is embodied and beyond which it is computational/symbolic



Braitenberg

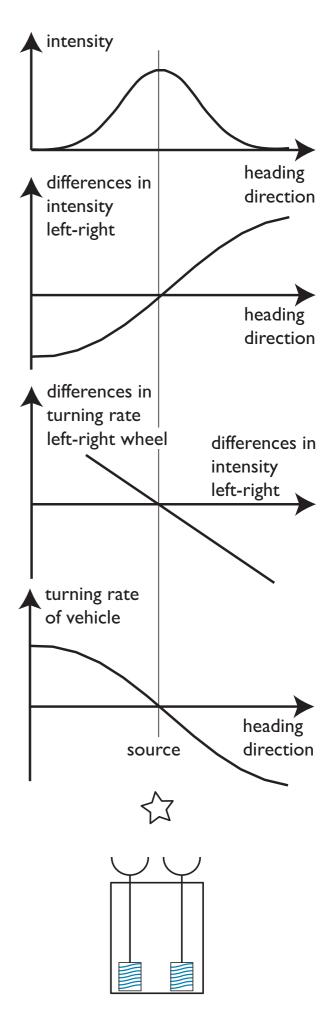
Five things needed to generate behavior

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



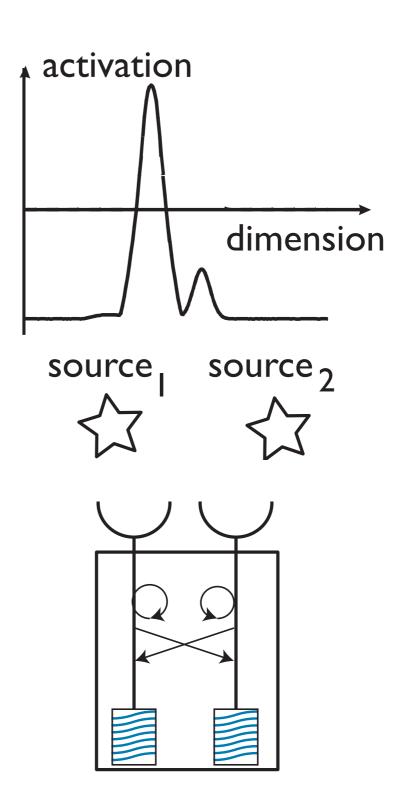
Emergent behavior: this is a dynamics

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



Emergent cognition from neural dynamics

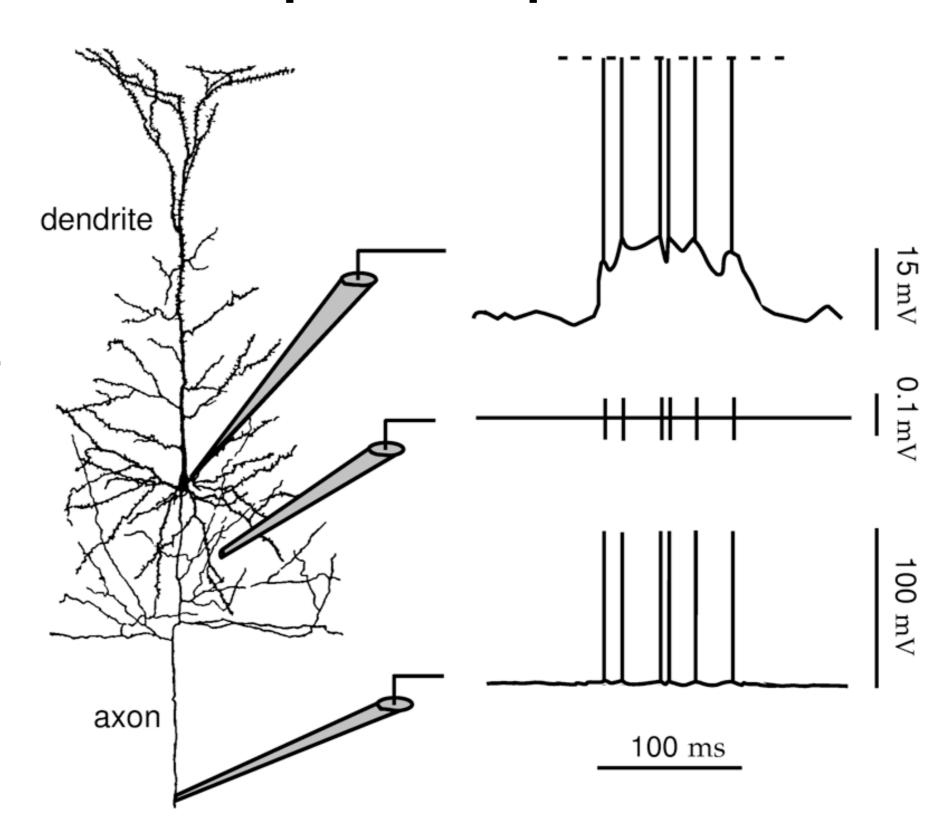
mental decisions, working memory..



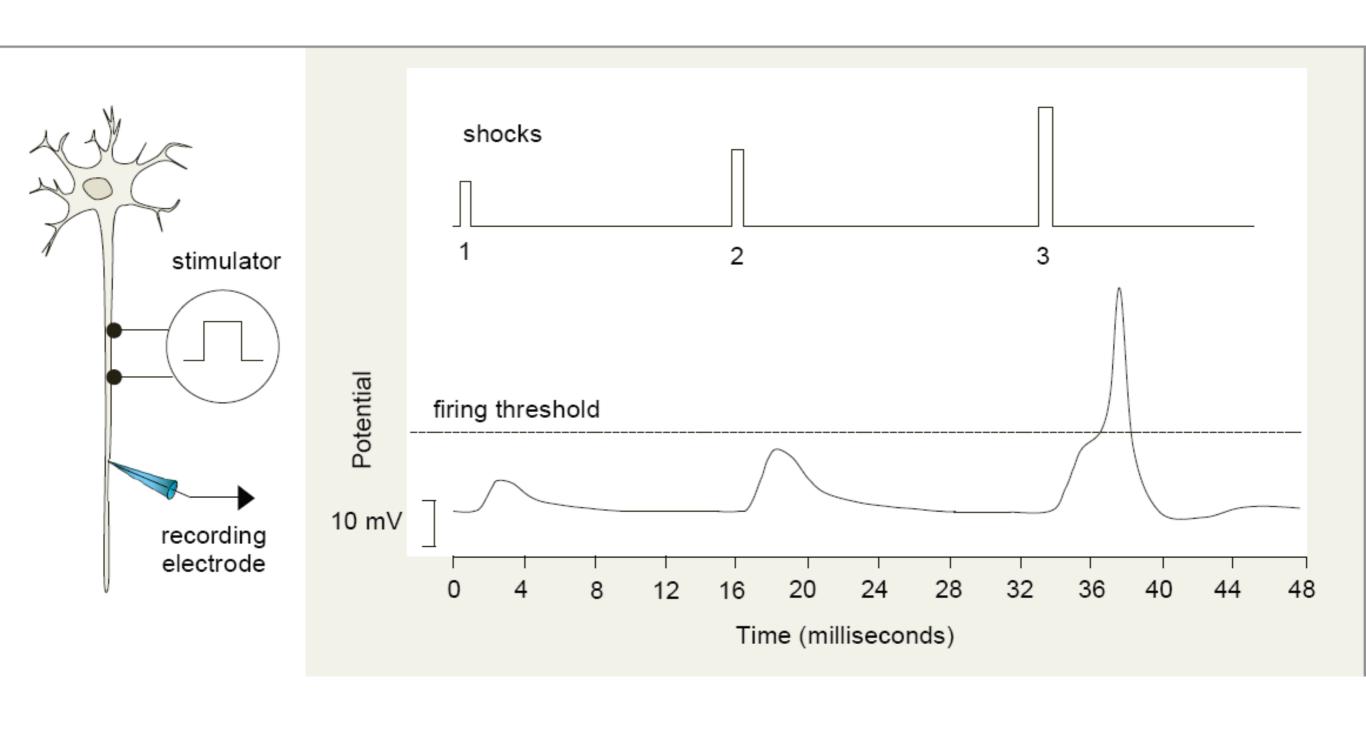
Neurophysics

Neurons as input-output units

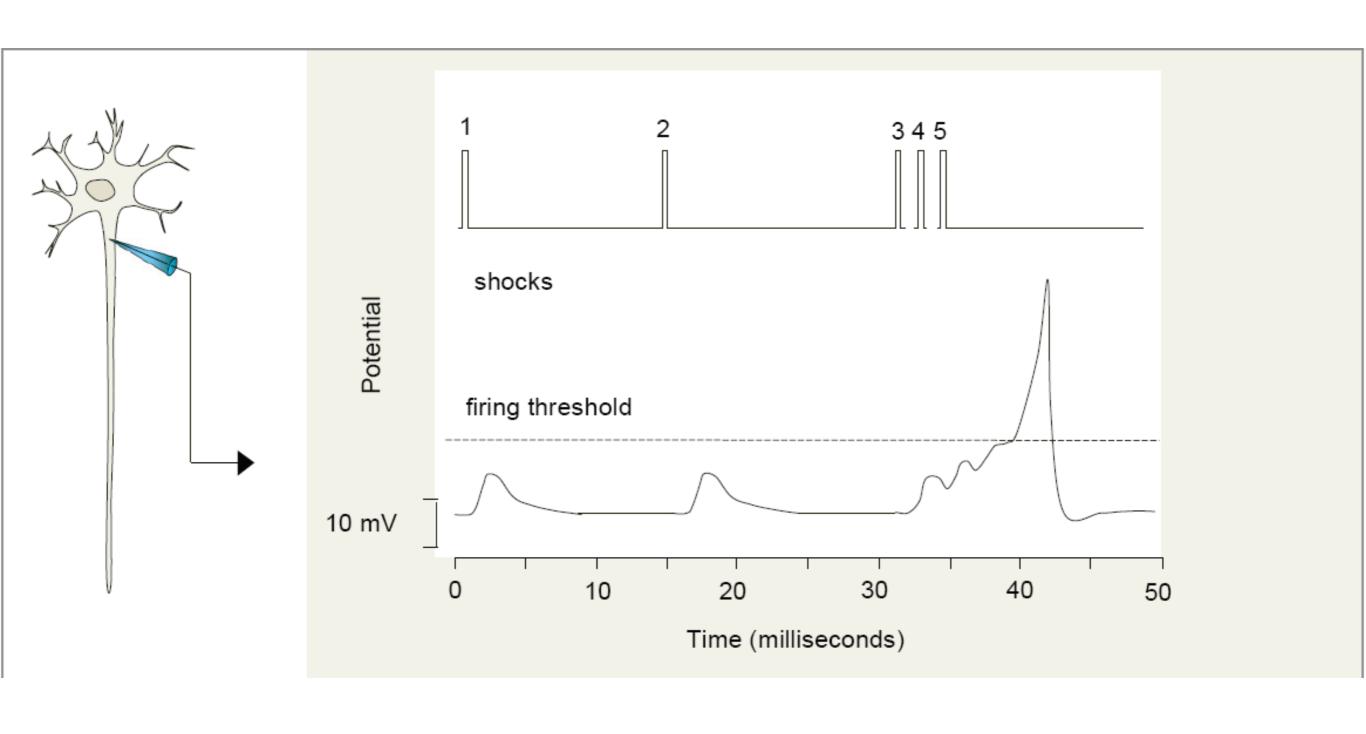
- inputs from dendrites
- spike formation at soma
- output at axon



threshold behavior

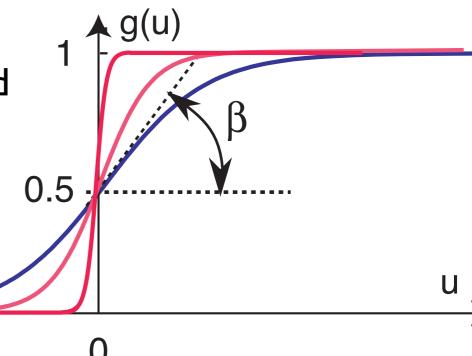


temporal summation



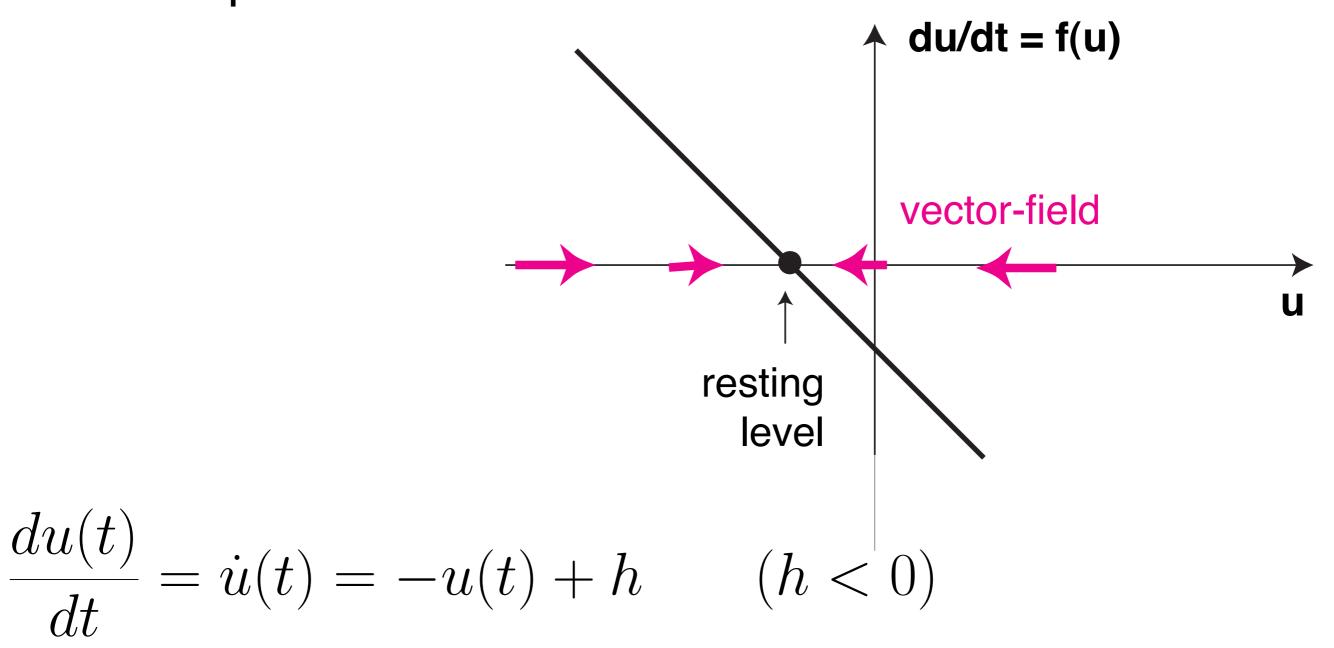
Neural dynamics

- replace spiking by a sigmoidal threshold function
- as an abstraction of the membrane potential
 - => low levels of activation are not transmitted (to other neural systems, to motor systems)
 - => high levels of activation are transmitted
 - threshold at zero (by definition)



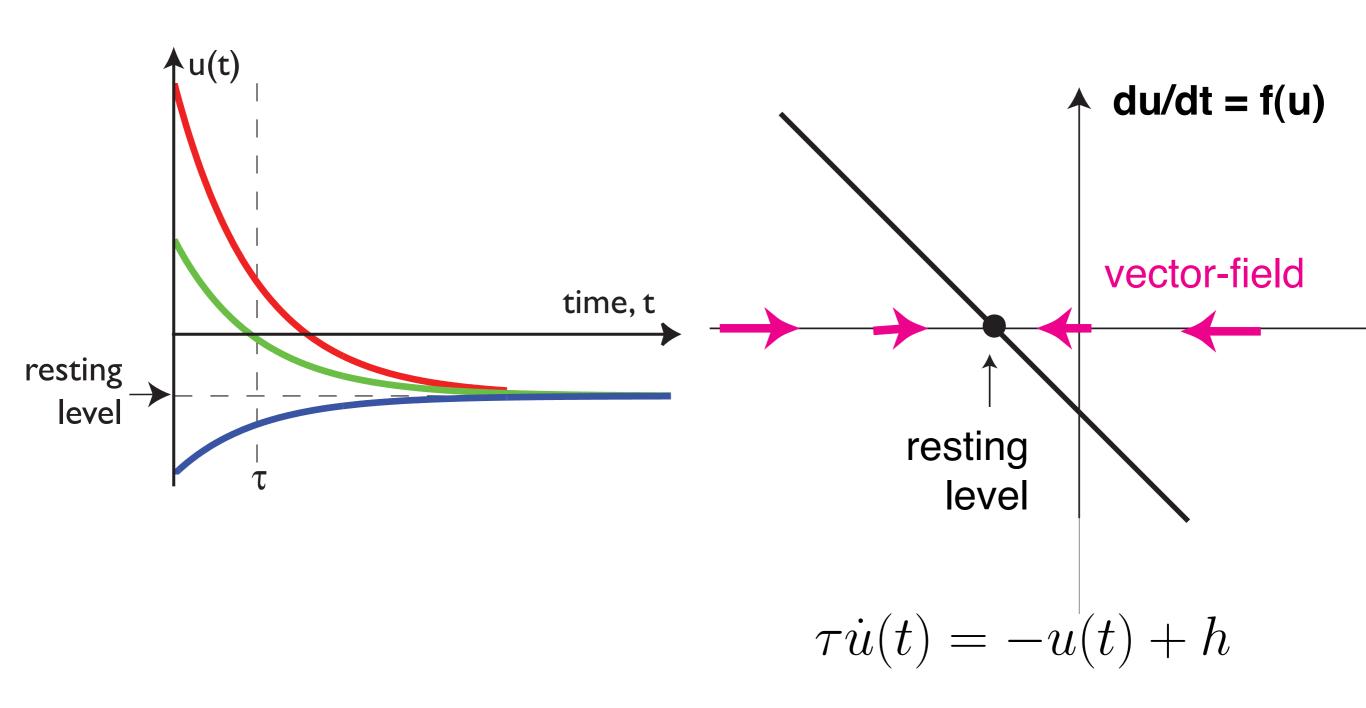
Neural dynamics

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



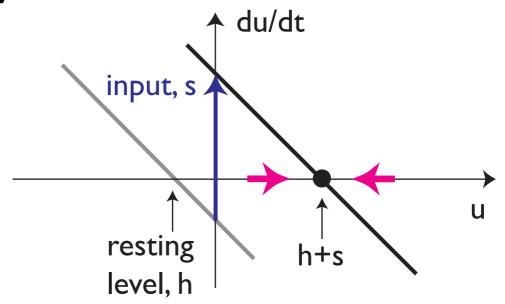
Neural dynamics

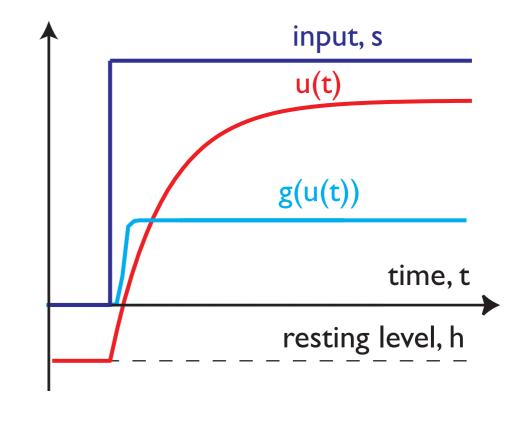
attractor structures ensemble of solutions=flow



Neuronal dynamics

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

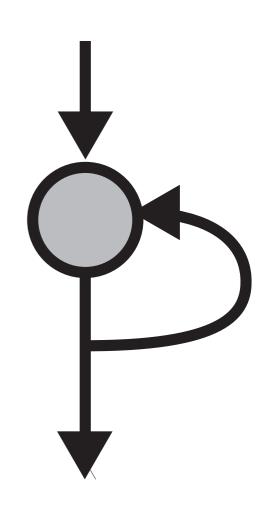




$$\tau \dot{u}(t) = -u(t) + h + inputs(t)$$

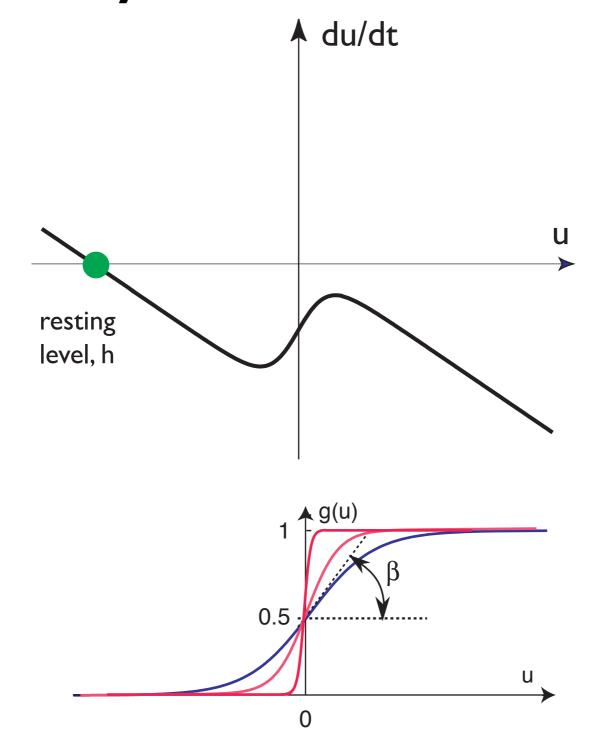
Neuronal dynamics with self-excitation

- single activation variable with selfexcitation
- representing a small population with excitatory coupling



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

Neuronal dynamics with self-excitation

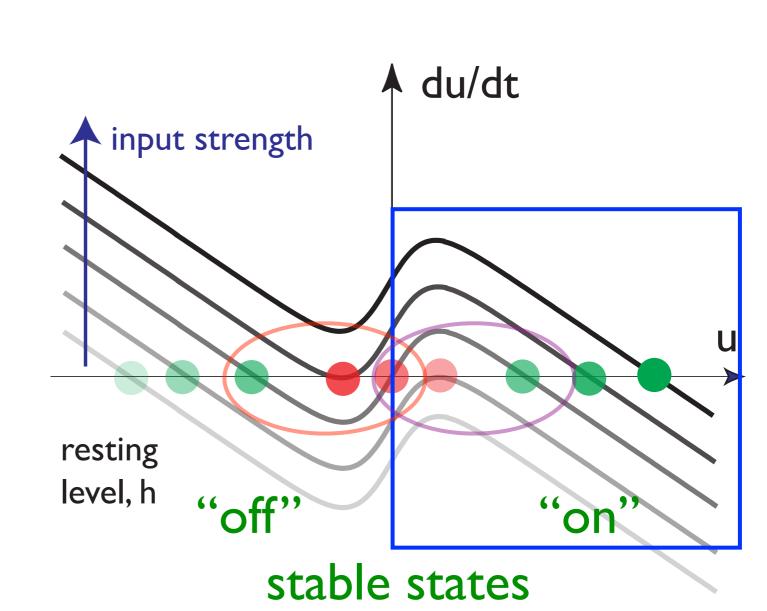


$$\tau \dot{u}(t) = -u(t) + h + S(t) + c\sigma(u(t))$$

Stability from neural dynamics

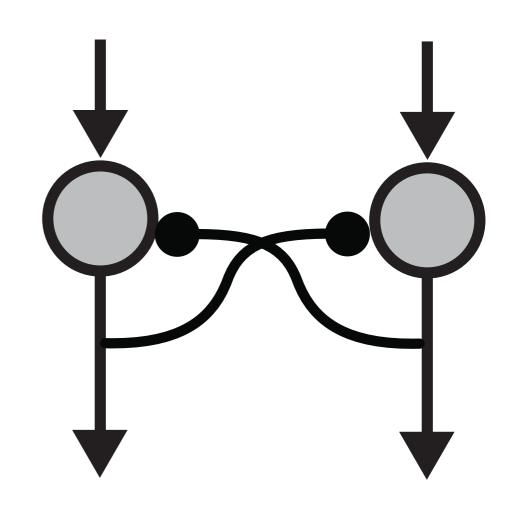
- autonomous activation from interaction
- $\dot{u}(t) = -u(t) + h + \text{input}(t) + \sigma(u(t))$

- detection instability
- working memory
- reverse detection instability



Neuronal dynamics with competition

- two activation variables with reciprocal inhibitory coupling
- representing two small populations that are inhibitorily coupled

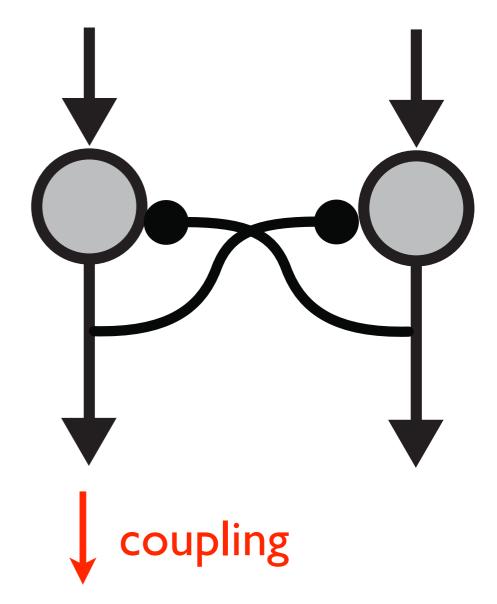


$$\tau \dot{u}_1(t) = -u_1(t) + h + s_1(t) - c_{12}\sigma(u_2(t))$$

$$\tau \dot{u}_2(t) = -u_2(t) + h + s_2(t) - c_{21}\sigma(u_1(t))$$

Neuronal dynamics with competition

Coupling: the rate of change of one activation variable depends on the level of activation of the other activation variable



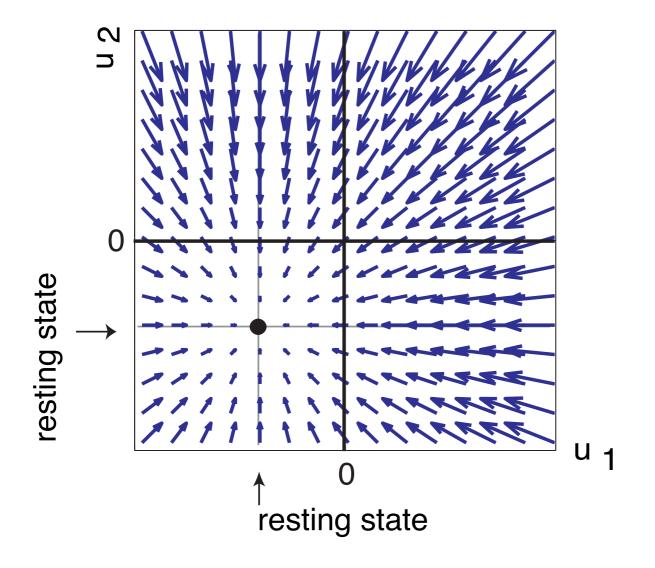
$$\tau \dot{u}_1(t) = -u_1(t) + h + s_1(t) - c_{12}\sigma(u_2(t))$$

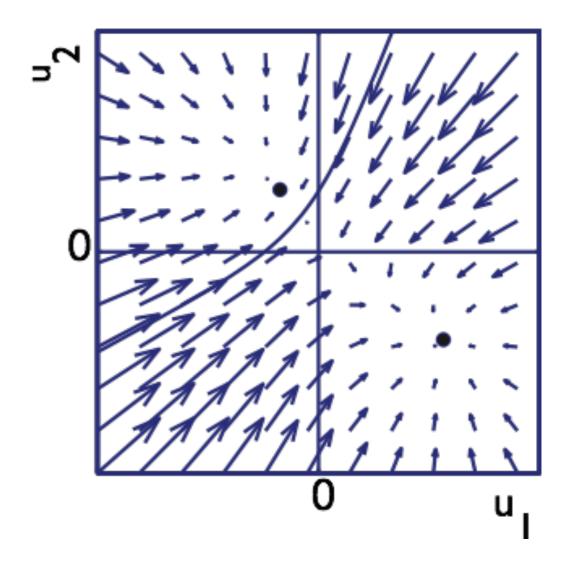
$$\tau \dot{u}_2(t) = -u_2(t) + h + s_2(t) - c_{21}\sigma(u_1(t))$$

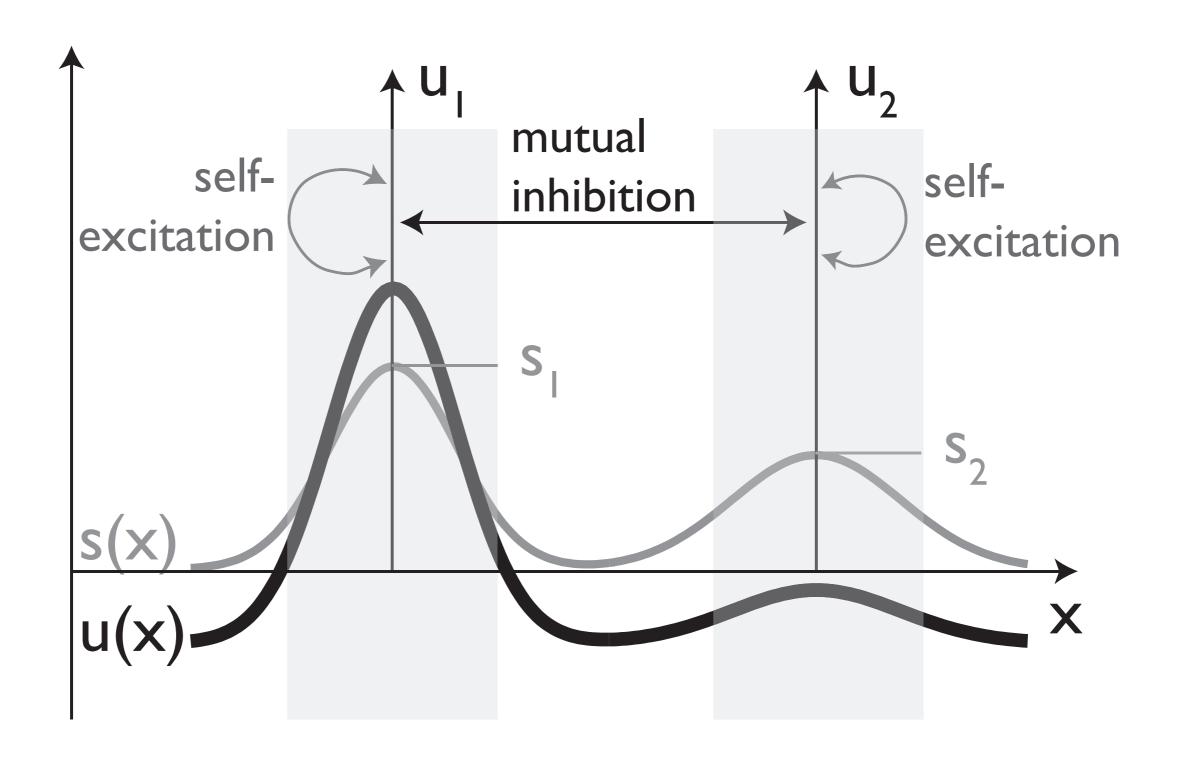
Neuronal dynamics with competition =>biased competition

before input is presented

after input is presented

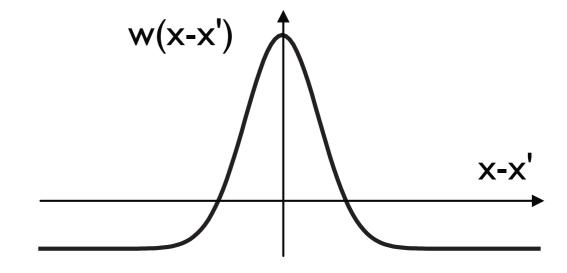




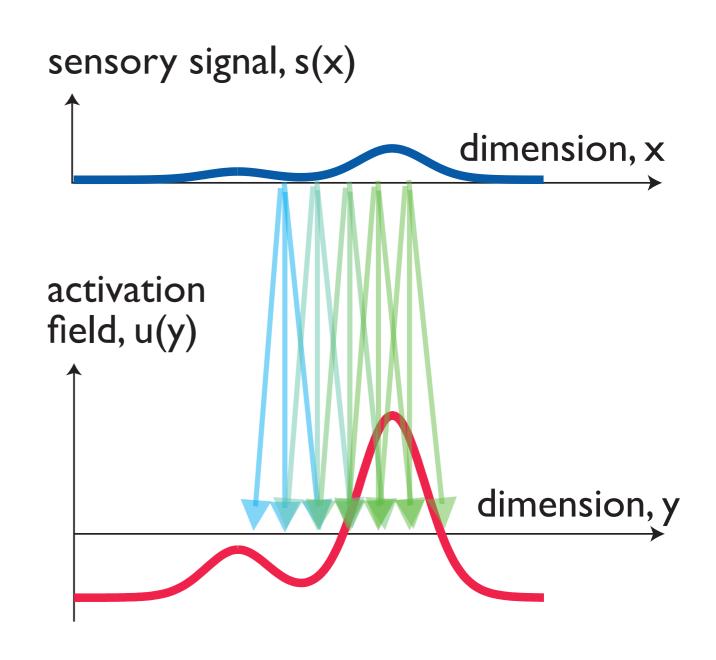


- the same underlying math
- coupling among continuously many activation variables
- local excitatory coupling ("self-excitation")
- global inhibitory coupling ("mutual inhibition")

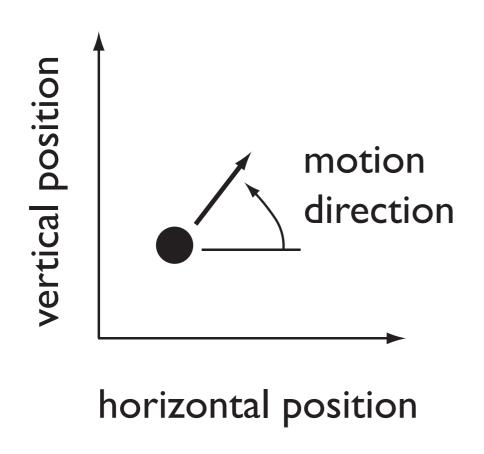
$$\tau \dot{u}(x,t) = -u(x,t) + h + s(x,t) + \int dx' w(x-x') \ \sigma(u(x',t))$$

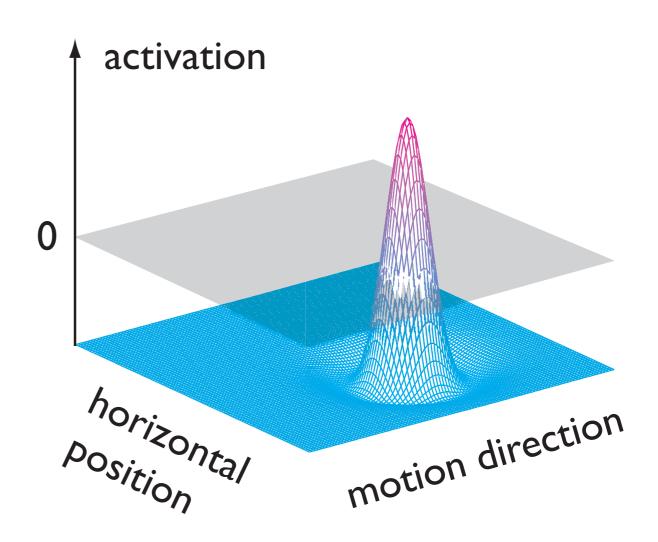


- forward connectivity thus generates a map from sensory surface to feature dimension
- neglect the sampling by individual neurons => activation fields



Example motion perception: space of possible percepts

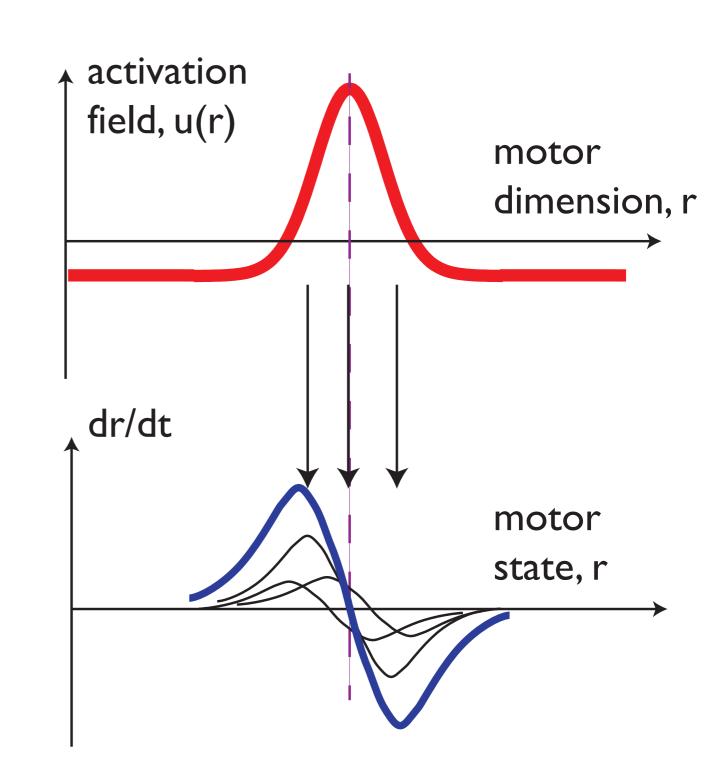




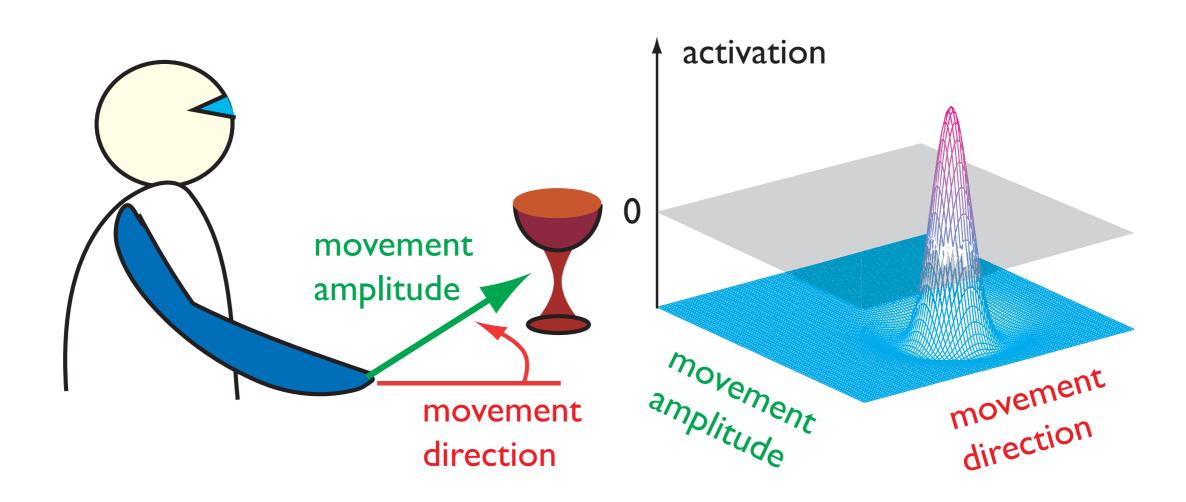
gous notion for rd connectivity to surfaces...

Ily involves ioral dynamics)

chrough neural oscillators eripheral reflex loops)



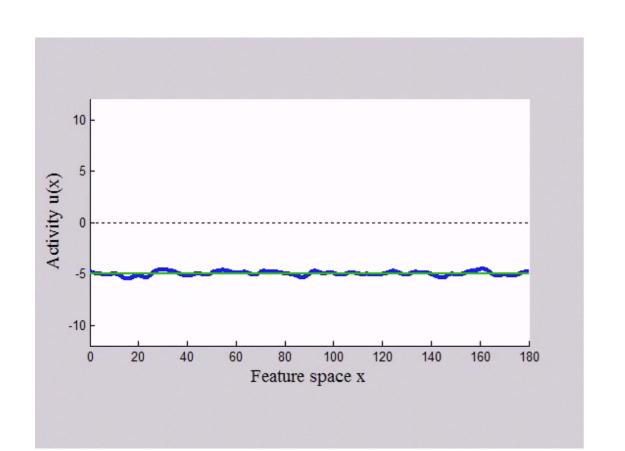
Example: movement planning: space of possible actions

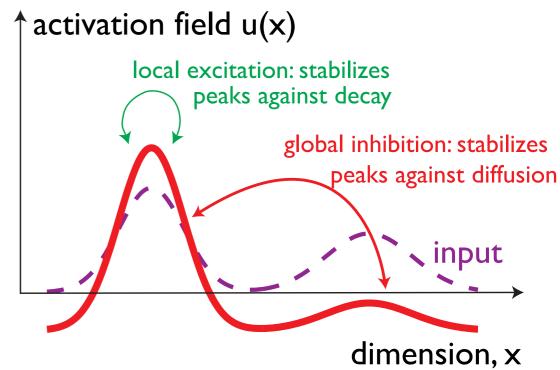




Dynamic of neural fields

- peaks as attractors
- detection instability
- working memory
- selection





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

$$+ \int dx' w(x - x') \ g(u(x',t))$$

$$\xrightarrow{w(x-x')}$$

Attractors and their instabilities

- input driven solution (subthreshold)
- self-stabilized solution (peak, supra-threshold)
- selection / selection instability
- working memory / memory instability
- boost-driven detection instability

detection instability

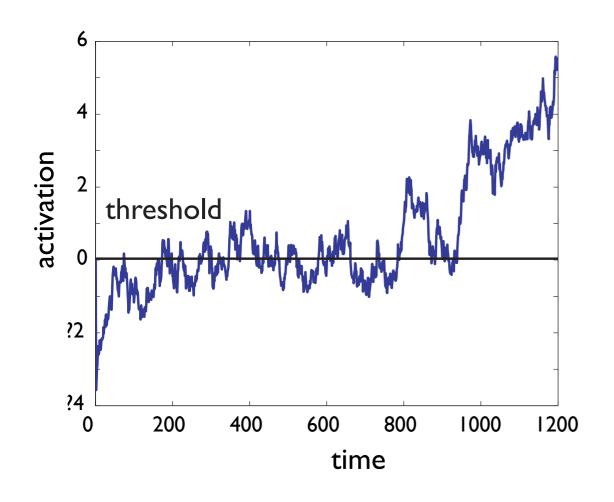
reverse detection instability

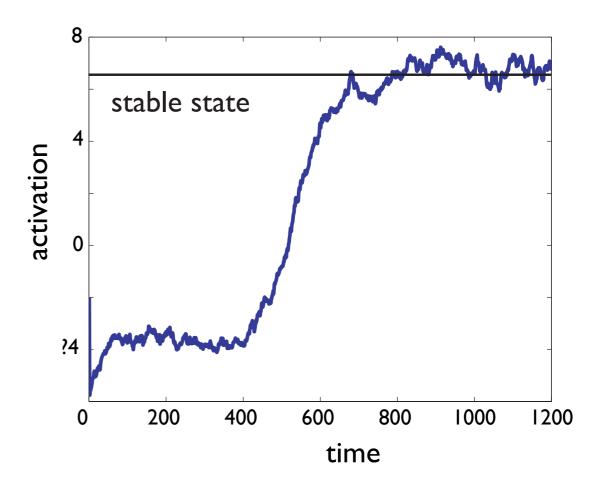
Noise is critical near instabilities

The detection instability stabilizes decisions

threshold piercing

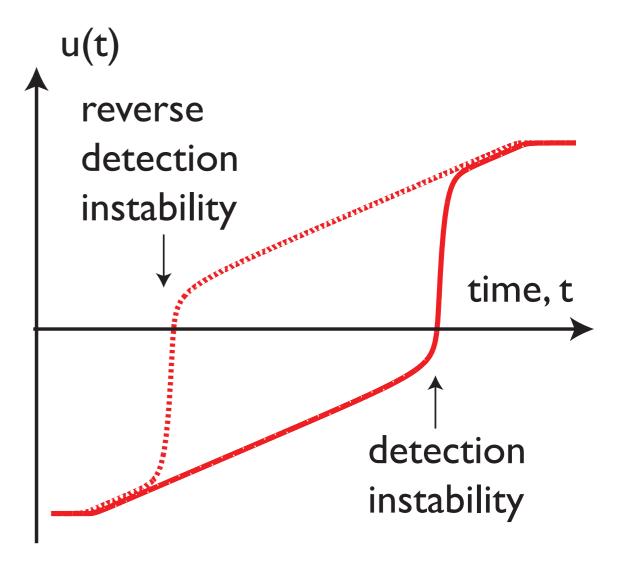
detection instability





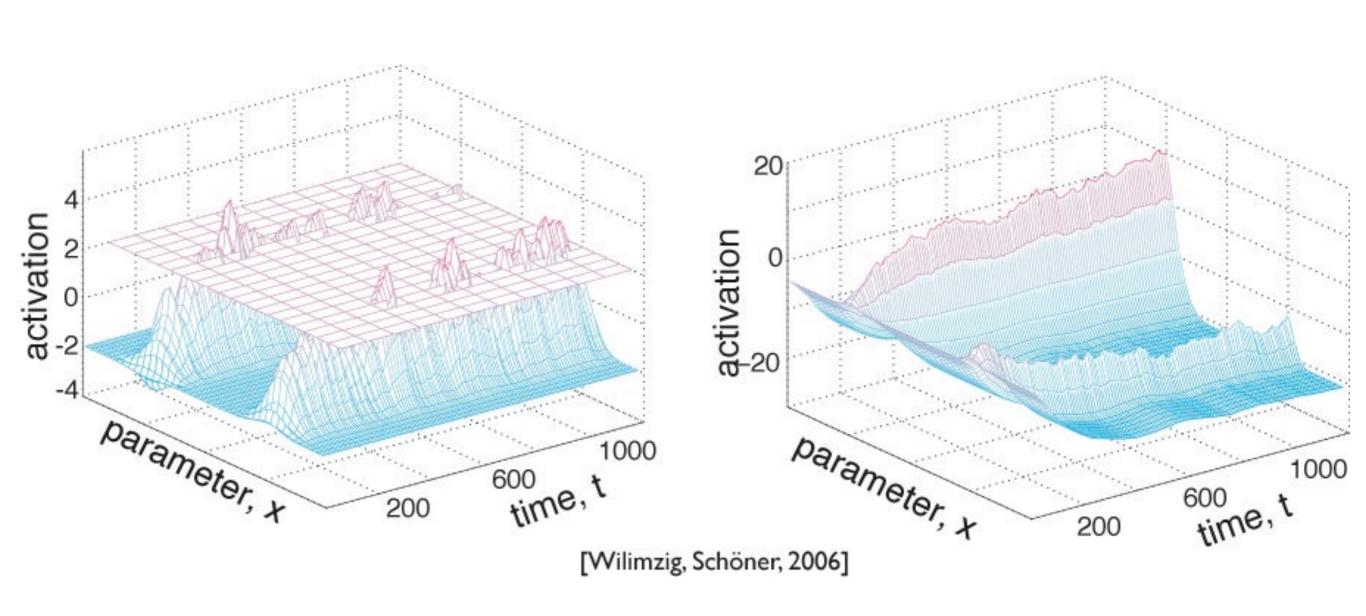
The detection instability leads to the emergence of events

the detection instability explains how a time-continuous neuronal dynamics may create macroscopic events at discrete moments in time

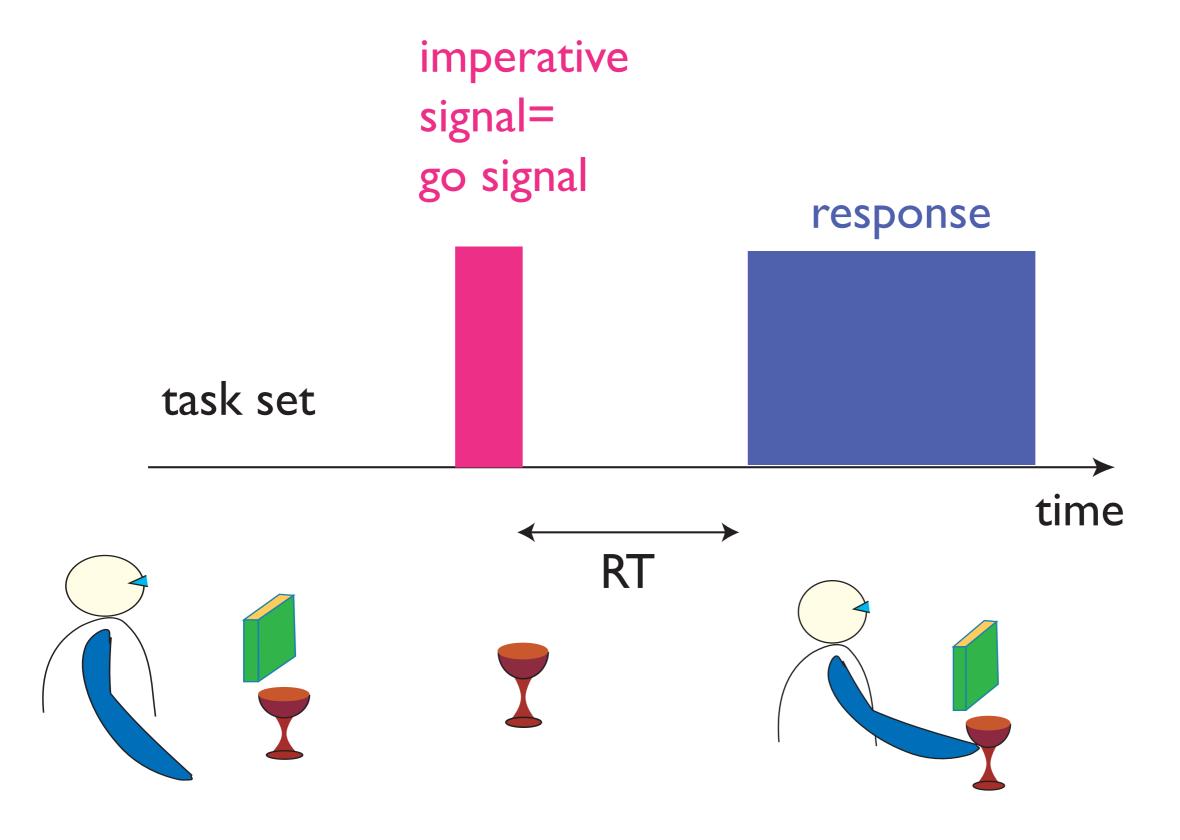




Selection decisions are stable

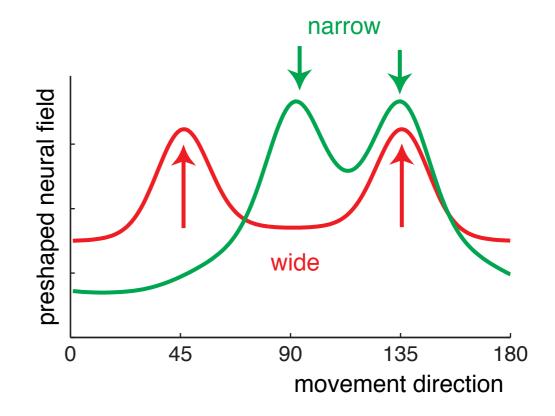


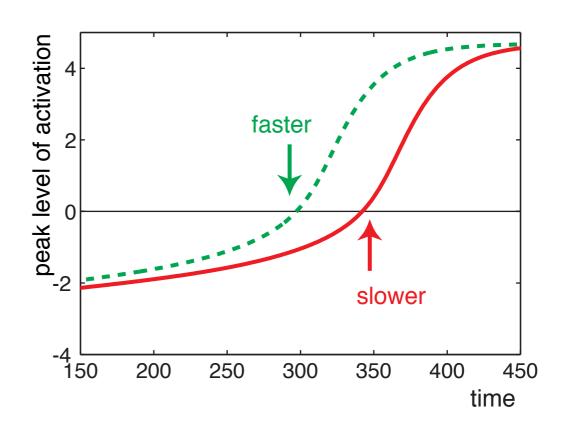
reaction time (RT) paradigm



metric effect

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





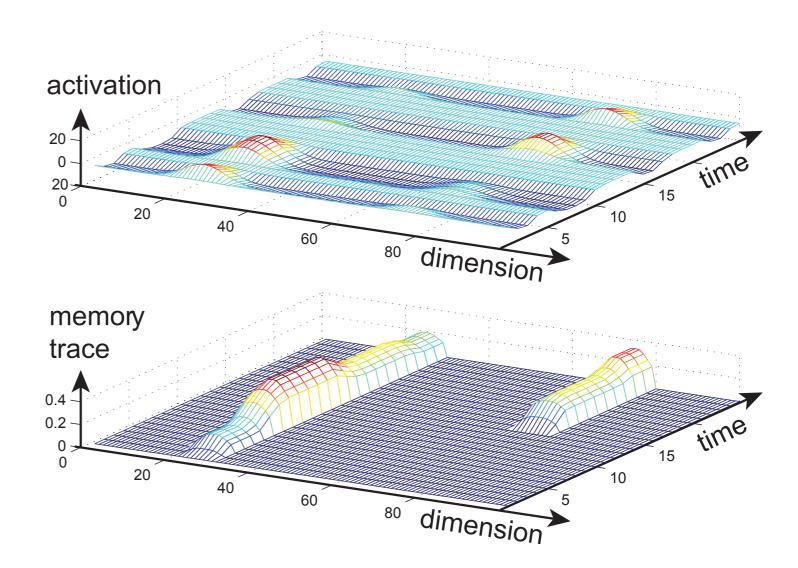
[from Schöner, Kopecz, Erlhagen, 1997]



The memory trace

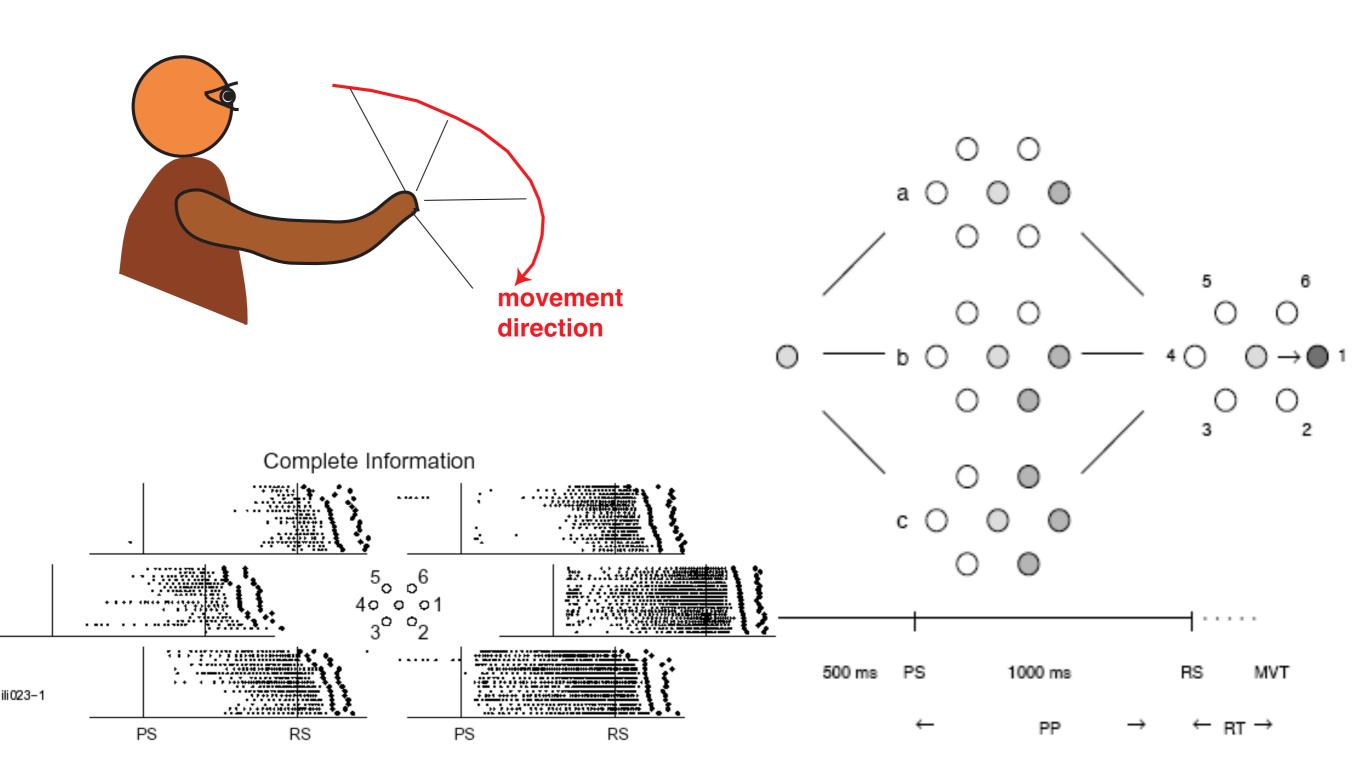
activation leaves a trace that may influence the activation dynamics later... in a simplest form of learning, the "bias" term of NN

powerful in DFT because the detection instability may amplify the induced into peaks of activation



Neural grounding

Tuning of neurons

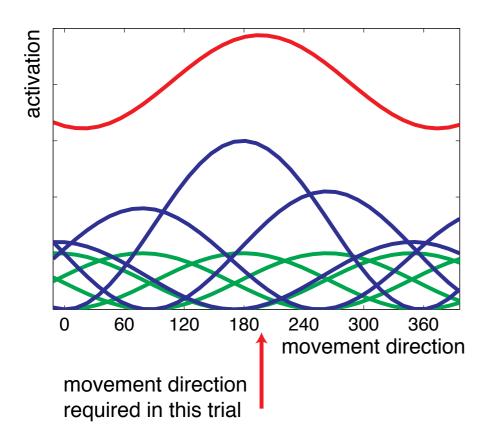


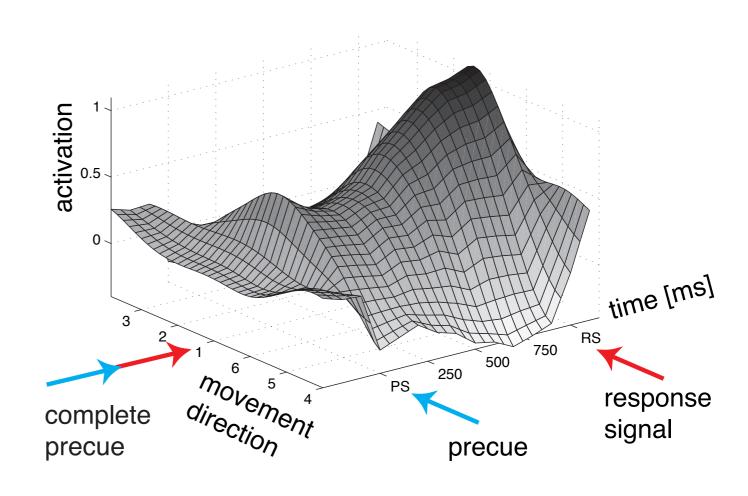
Bastian, Riehle, Schöner, 2003

Distribution of Population Activation (DPA) <=> neural field

Distribution of population activation =

Σ tuning curve * current firing rate

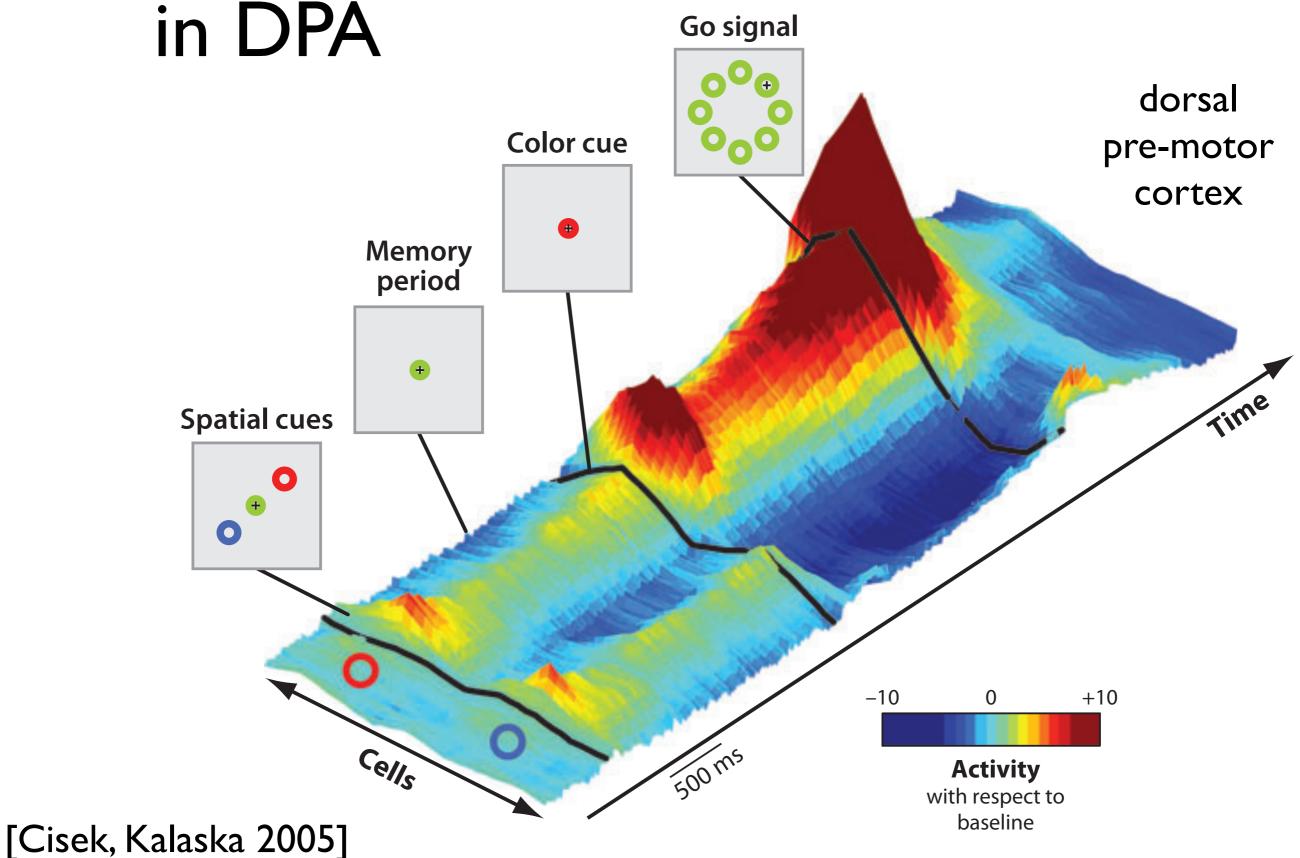




note: neurons are not localized within DPA!

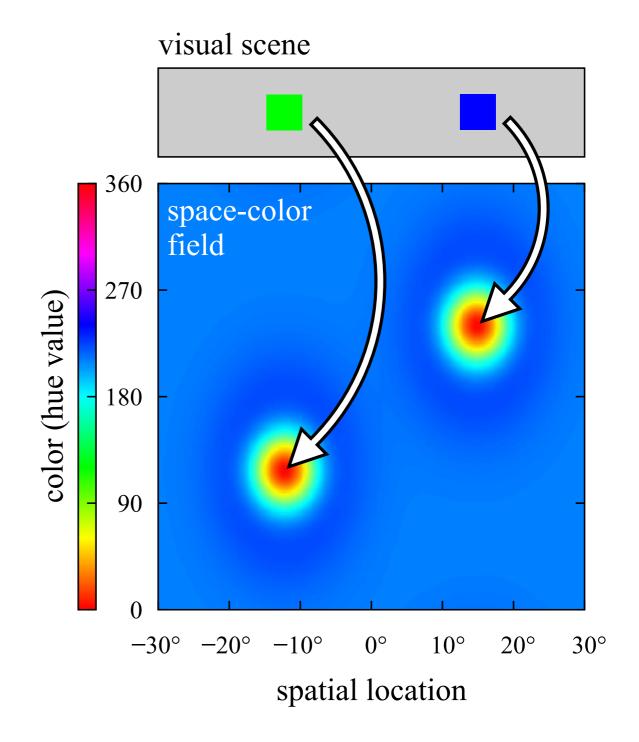
[Bastian, Riehle, Schöner, 2003]

Decision making in DPA



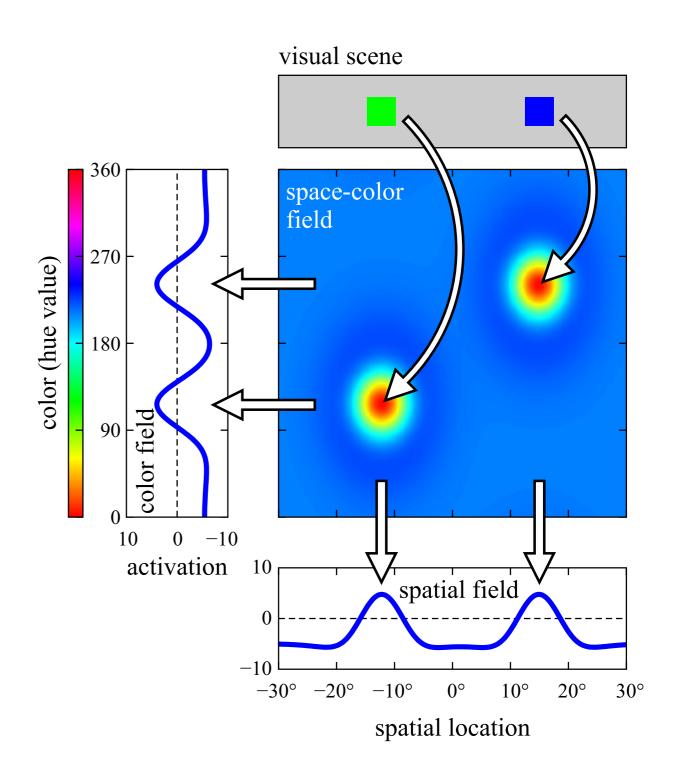
Joint representations

- "anatomical" binding
- example: a joint representation of color and visual space "binds" these two dimensions



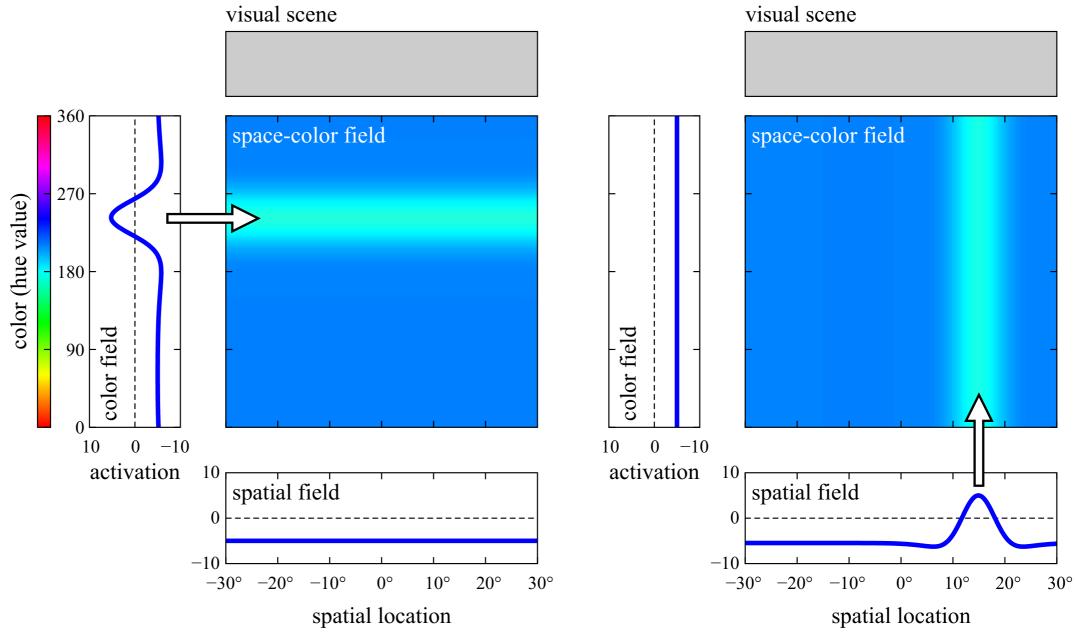
Extract the bound features

- project to lowerdimensional fields
- by summing along the marginalized dimensions
- (or by taking the softmax)



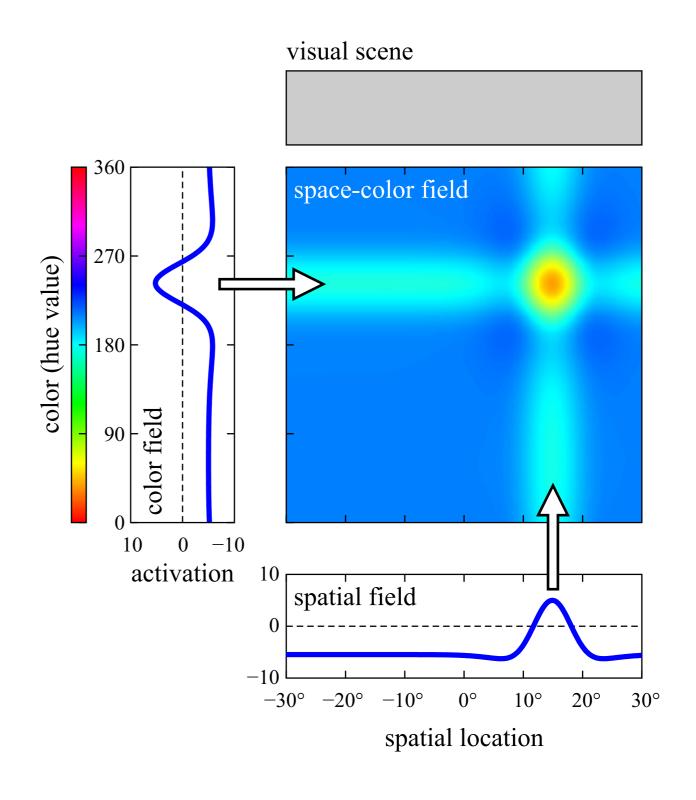
Assemble bound representations

project lower-dimension field onto higherdimensional field as "ridge input"



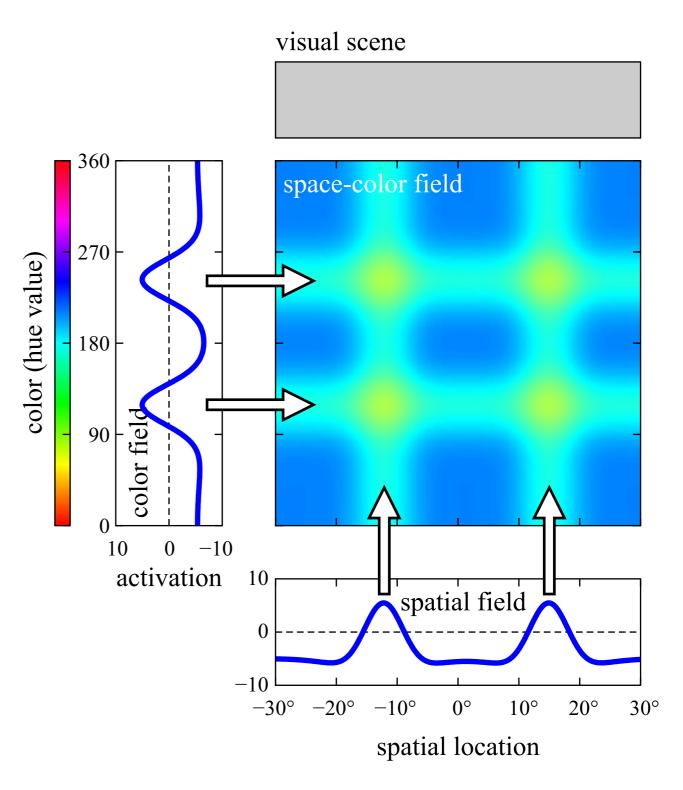
[Schneegans et al., Ch 5 of DFT Primer, 2016]

Assemble bound representations



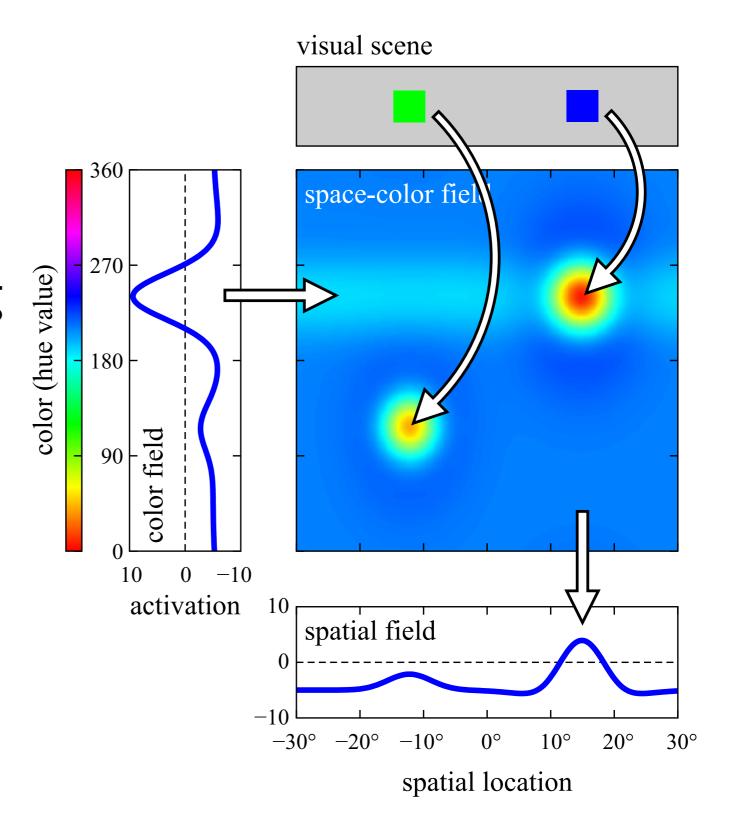
Assemble bound representations

- binding problem: multiple ridges along lower-dimensional space lead to a correspondence problem
- => assemble one object at a time...
- => sequentiality bottleneck!

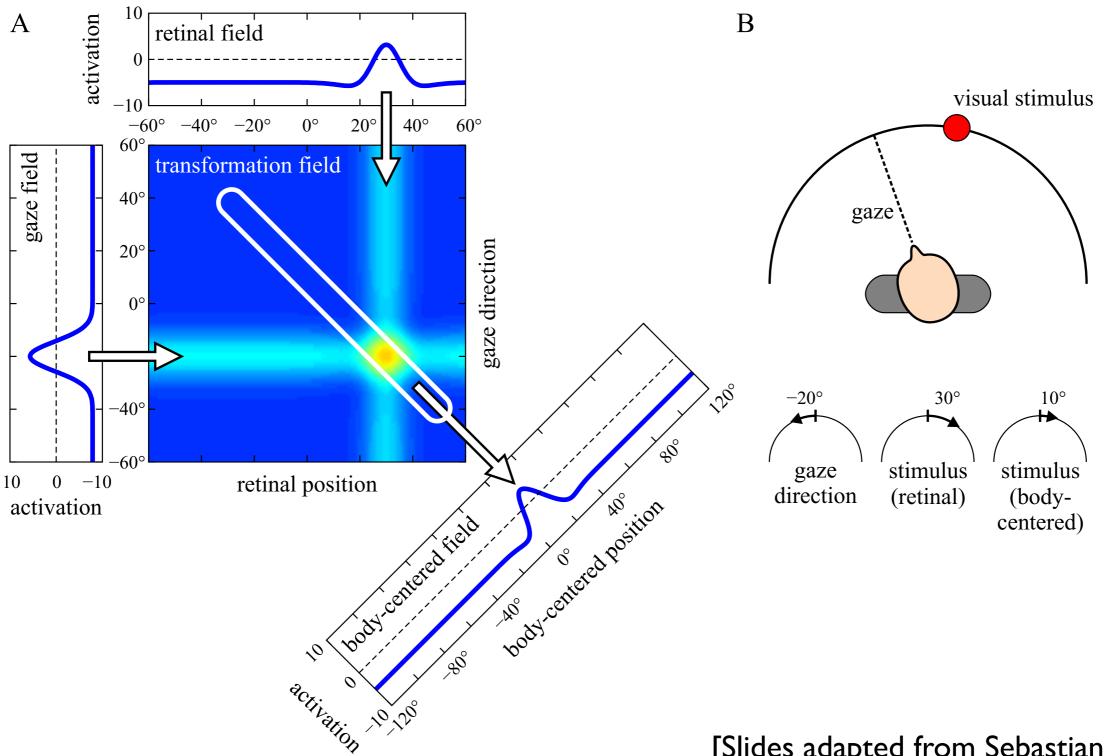


Search

- ridge input along one dimension extracts from bound representation matching objects
- other dimensions of those objects can then be extracted
- e.g. visual search



Coordinate transforms



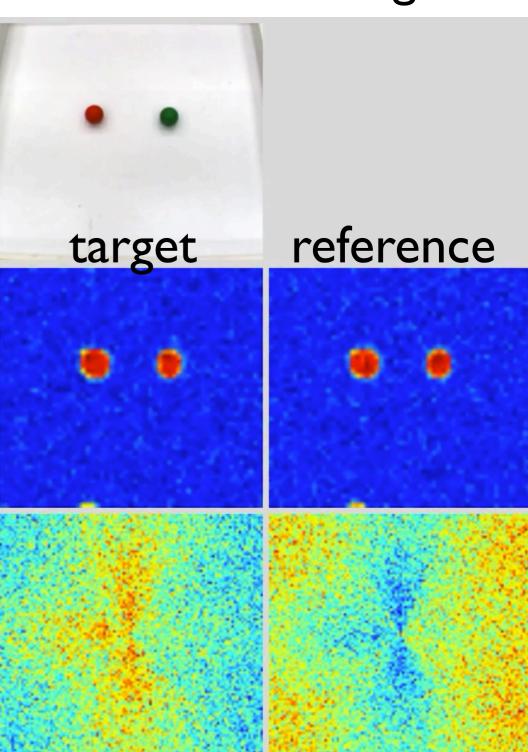
[Slides adapted from Sebastian Schneegans, see Schneegans, Chapter 7 of Dynamic Field Theory-A Primer, OUP, 2015]

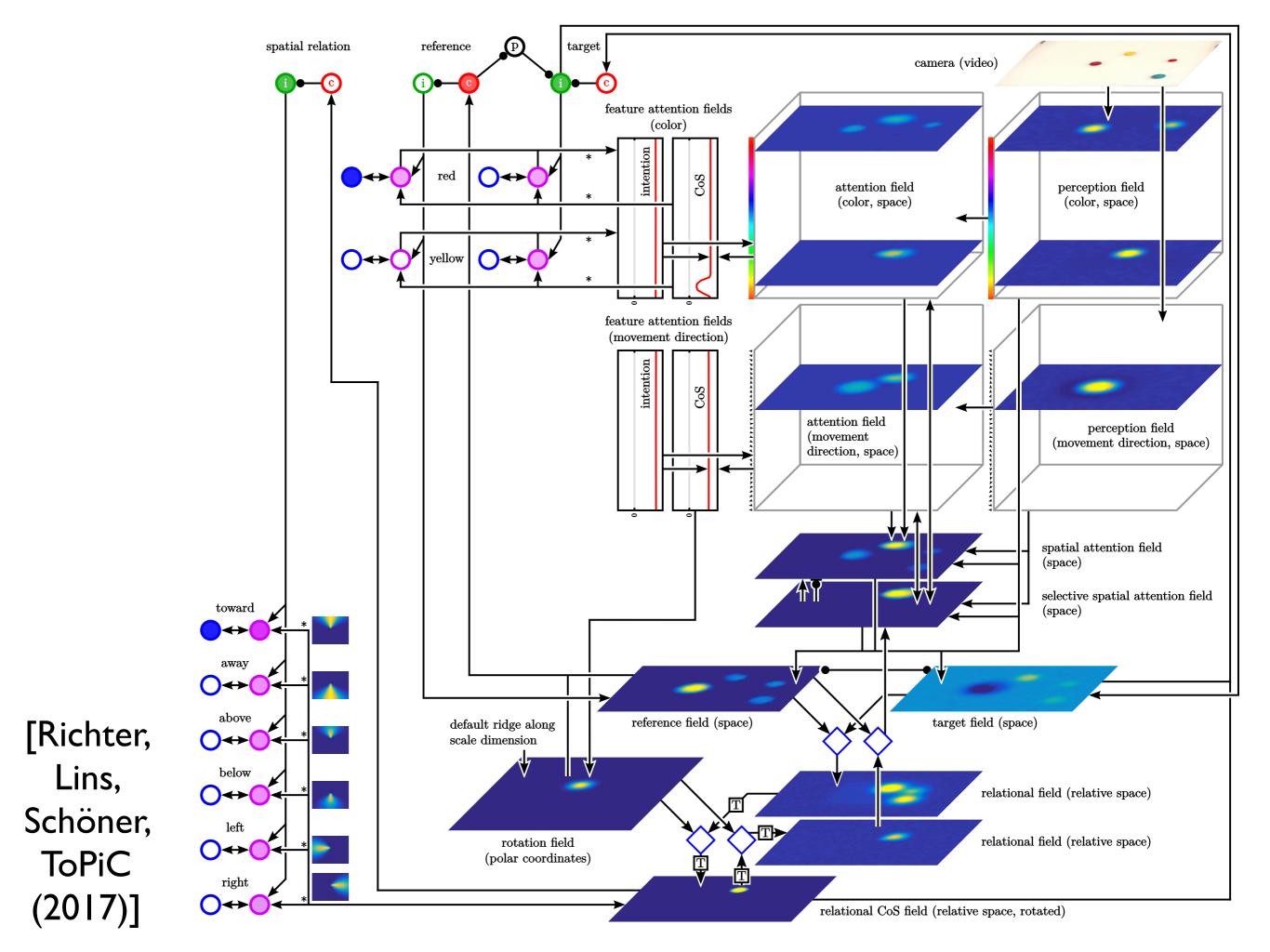
Perceptual grounding of concepts

Perceptual grounding of a relation: bringing the target object into the attentional foreground

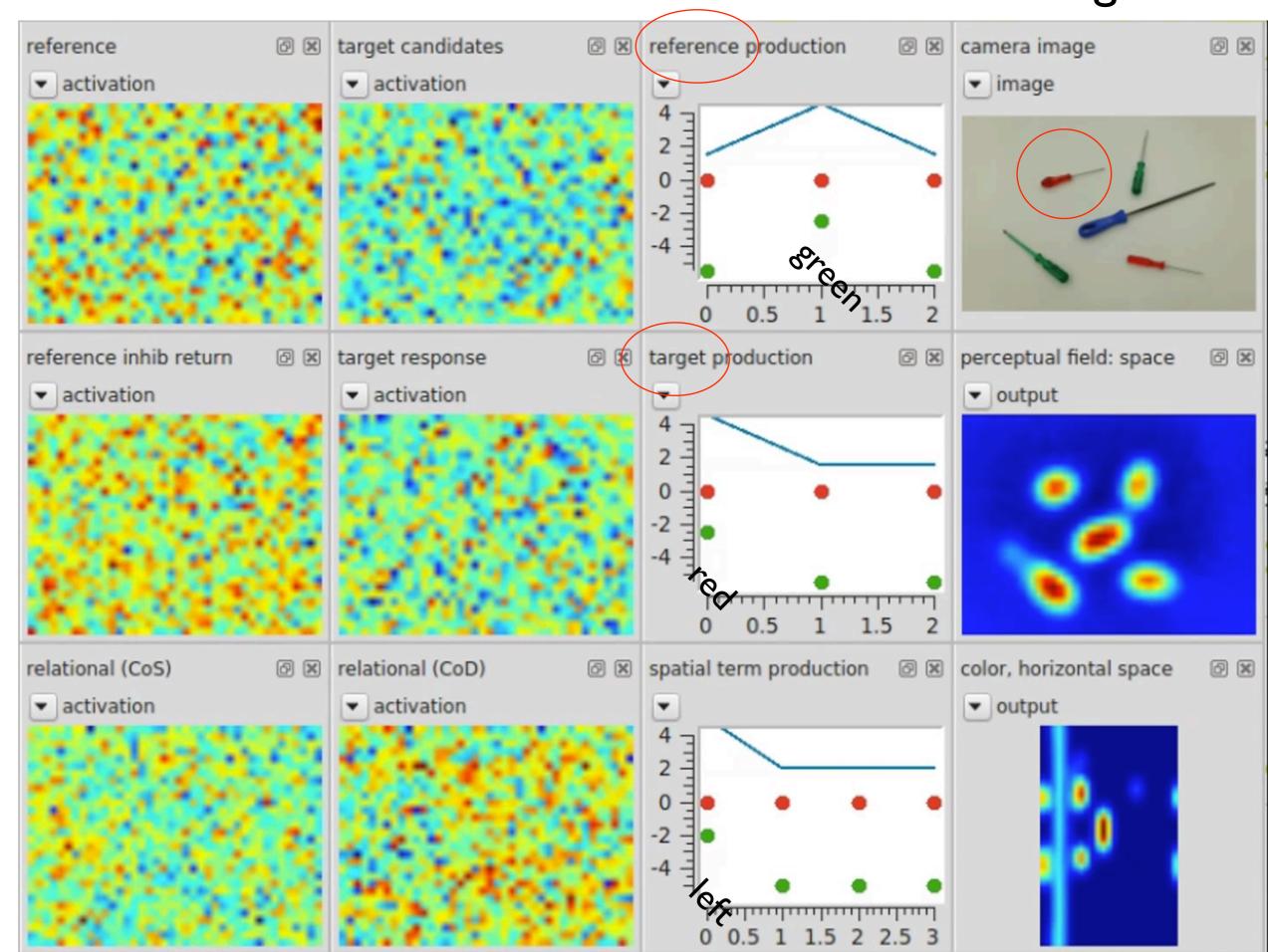
[Lipinski, Sandamirskaya, Schöner 2009 ... Richter, Lins, Schöner, *Topics* 2017]

"red to the left of green"





"red to the left of green"



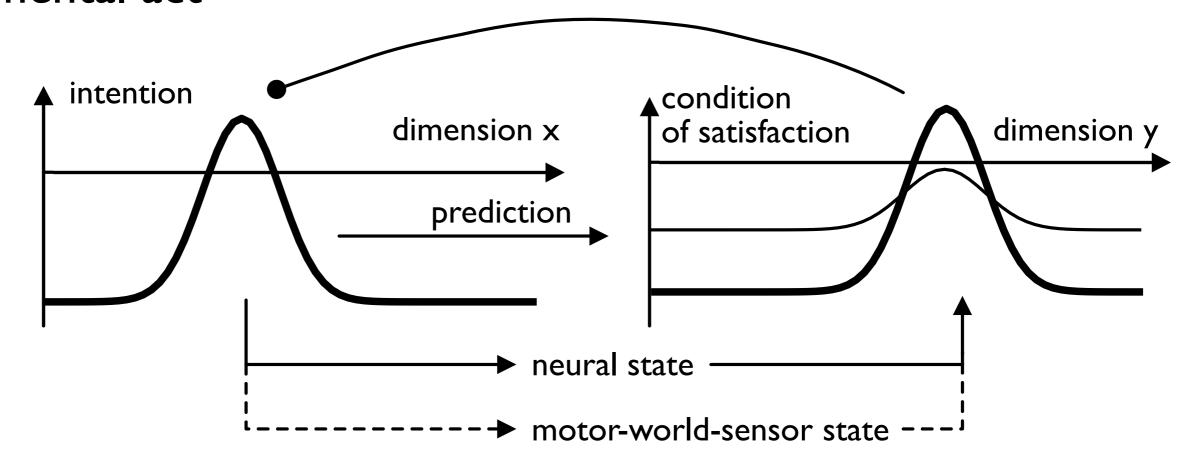
Sequence generation

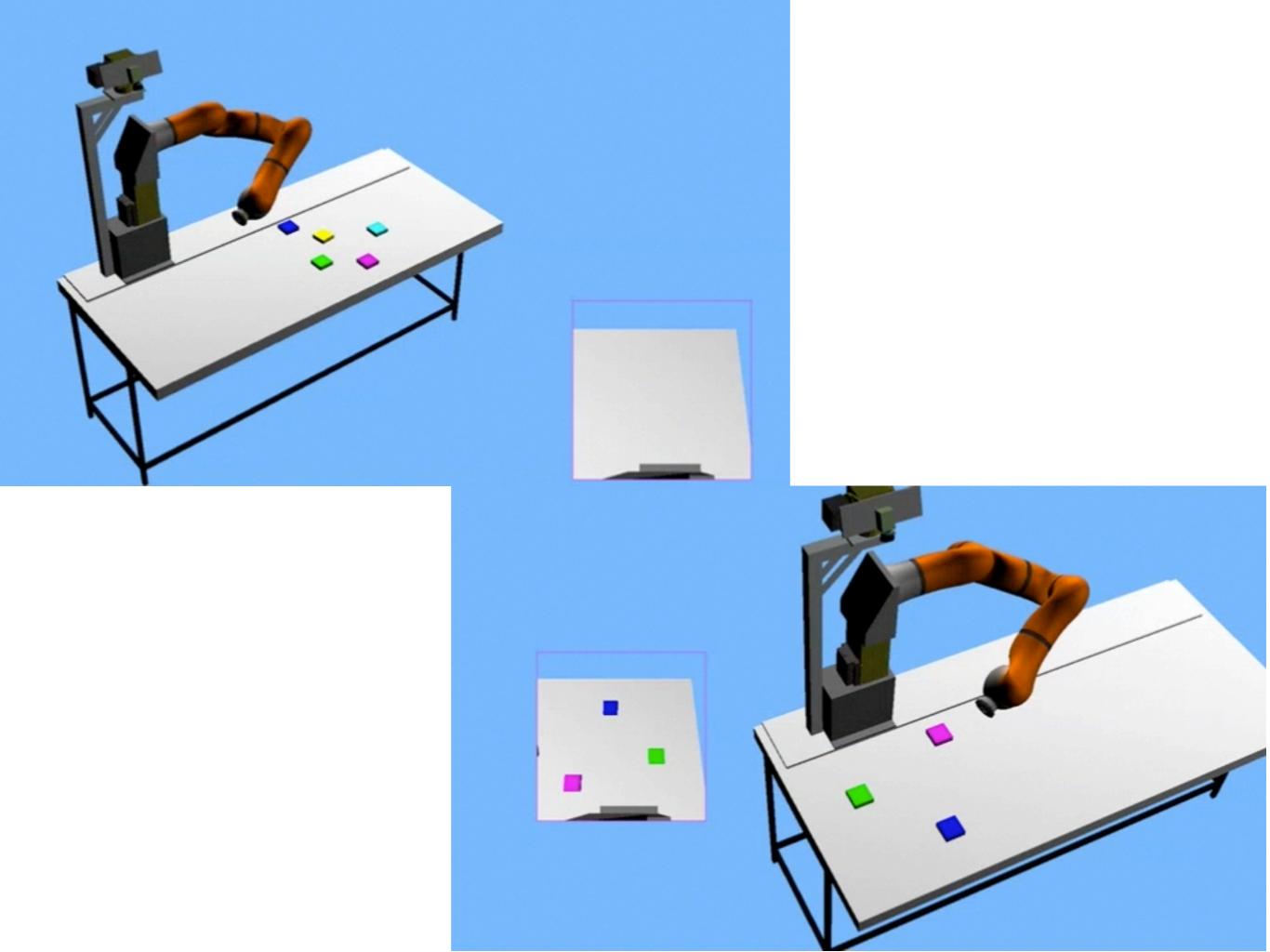
Sequential behaviors or mental acts

- behaviors/mental states are attractors
- that resist change...
- to induce change in sequential behavior/ thinking: induce an instability

Sequence generation

- the CoS organizes the transition away from on ongoing behavior/mental state
- based on a signal from perception or from an inner state of a neural architecture that is predicted to be indicative of successful completion of the behavior/ mental act





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