# Building neural processing accounts of higher cognition in Dynamic Field Theory

Gregor Schöner
Aaron Buss

# How the tutorial works

- mix of video and life Zoom talks
  - my two longer tutorials are life, all other talks are videos
- discussions are life, audio/video encouraged
- you can also submit questions in the chat dialogue, will be addressed in discussions
  - useful during video lectures as speakers can read questions ahead of time
- tutorials vs. case studies

# Program

- 9:00/15:00 *Gregor Schöner* Tutorial: Foundational concepts of DFT [40 life+15 disc]
- 10:10/16:00 *Sophie Aerdker* Case study: A DFT model of motor habituation [20 video+5]
- 10:30/16:30 *Gregor Schöner* Tutorial: Advanced concepts of DFT [40 life+15]
- 11:30/17:30 *Mathis Richter* Tutorial: Introduction to *cedar* [25 video+5]
- 12:00/18:00 Lunch/Dinner break [30 free]

# Program

- 12:30/18:30 *Jan Tekülve* Tutorial: Sequence generation [30 video+10]
- 1:15/19:15 *Raul Grieben* Case study: Visual search and scene memory [20 video+5]
- 1:45/19:45 *Mathis Richter* Tutorial: Grounding in DFT [30 video+10]
- 2:30/20:30 *Aaron Buss* Tutorial: Cognitive control [40 video+15]
- 3:30/21:30 Discussion and outlook [10 disc]
- 3:40/21:40 End

# Foundational Concepts of DFT

Gregor Schöner
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# What DFT is about… how cognition emerges from sensory-motor processes

# There is much cognition in real action

- 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

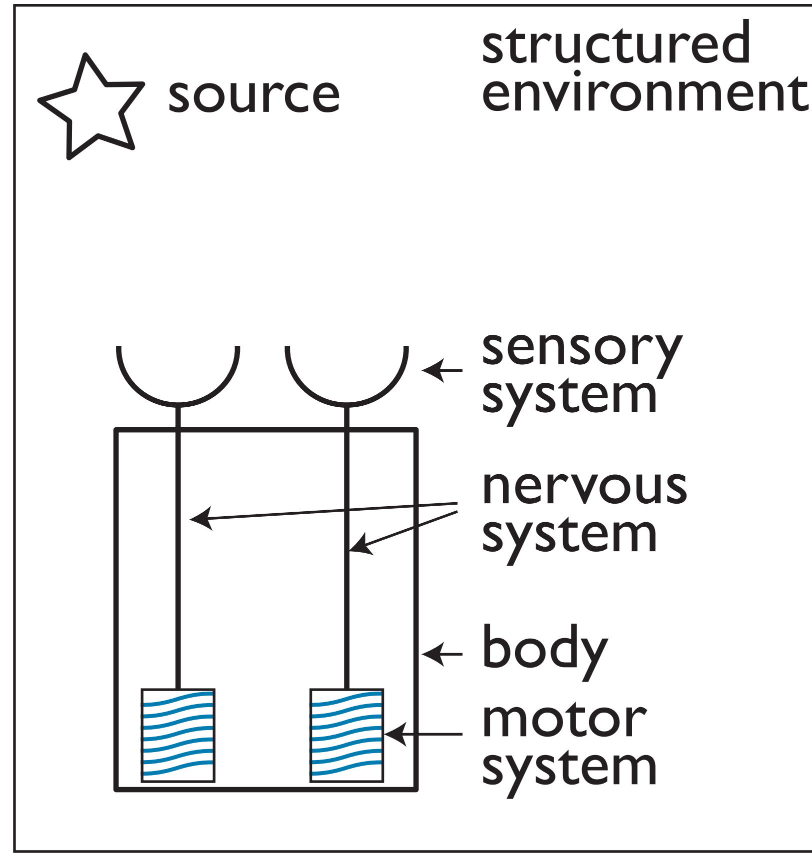
- graded state
- continuous time
- continuous/intermittent link to the sensory and motor surfaces
- from which discrete events and categorical behavior emerge
- in closed loop
- => states must be stable

# Embodiment hypothesis

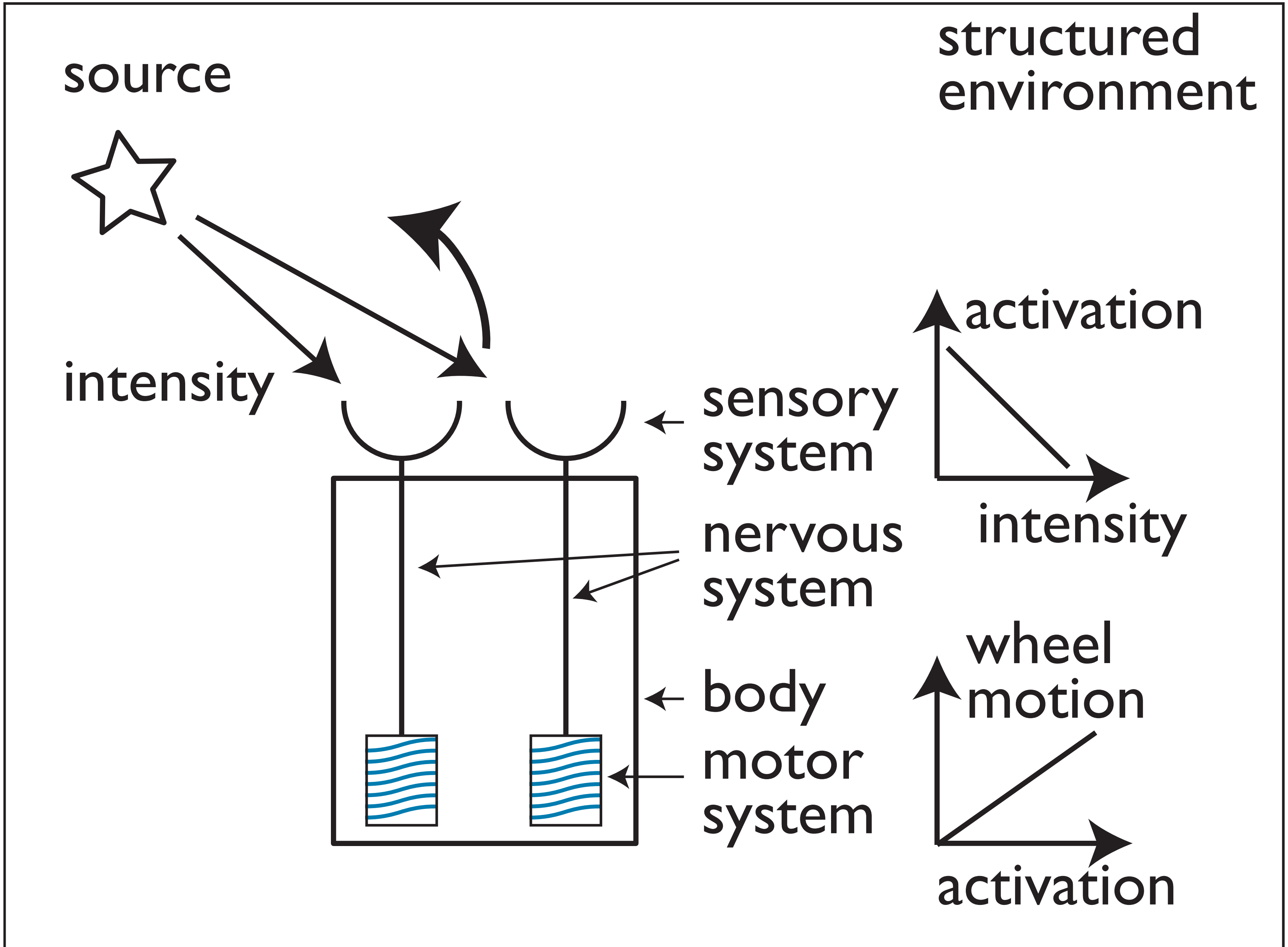
- cognition inherits the properties of embodied cognition
- stability, internal closed loops => dynamics.. neural dynamics
- NOT: cognition necessarily involves movement
- this workshop: explore neural dynamic principles in higher cognition

# Braitenberg vehicles

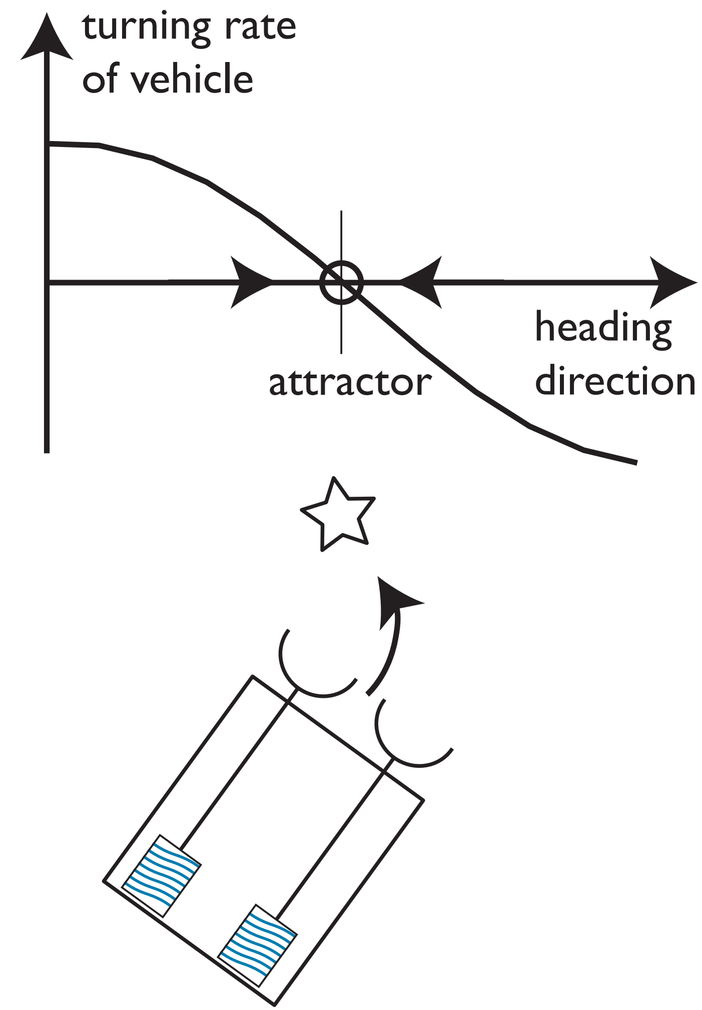
- =embodied nervous systems with:
  - effectors
  - sensors
  - a nervous system
  - a body
- + situated in a structured environment
- => behavior emerges



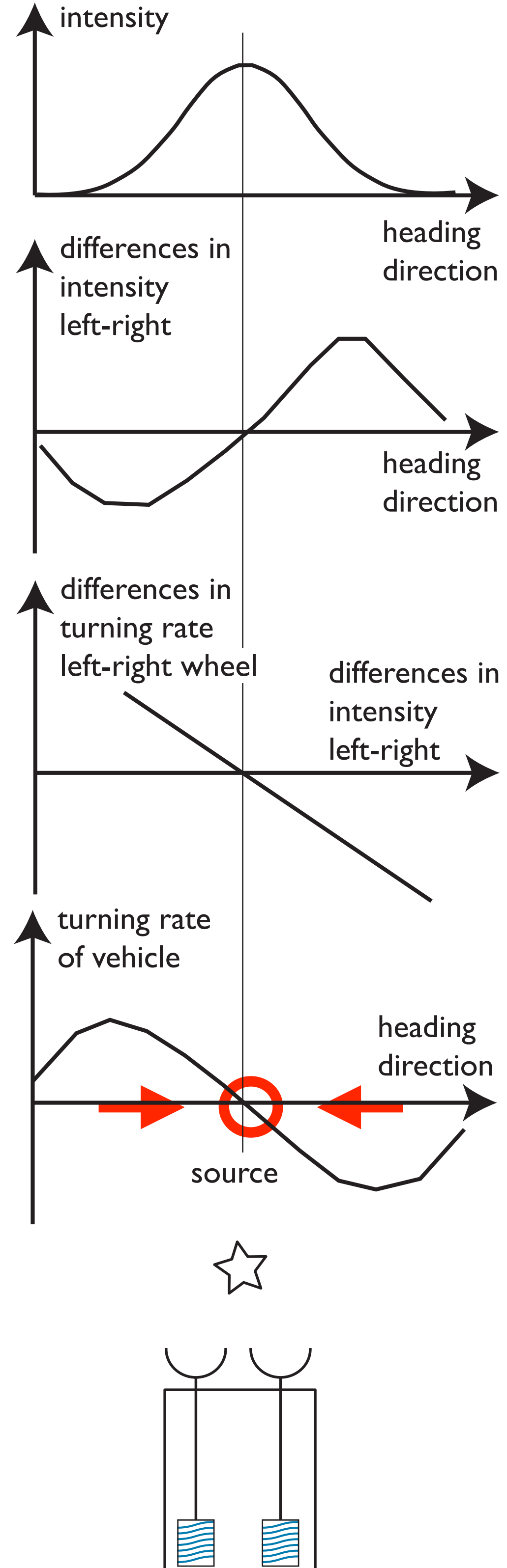
# Emergent behavior: taxis



# Behavior emerges from the attractor of a dynamical system

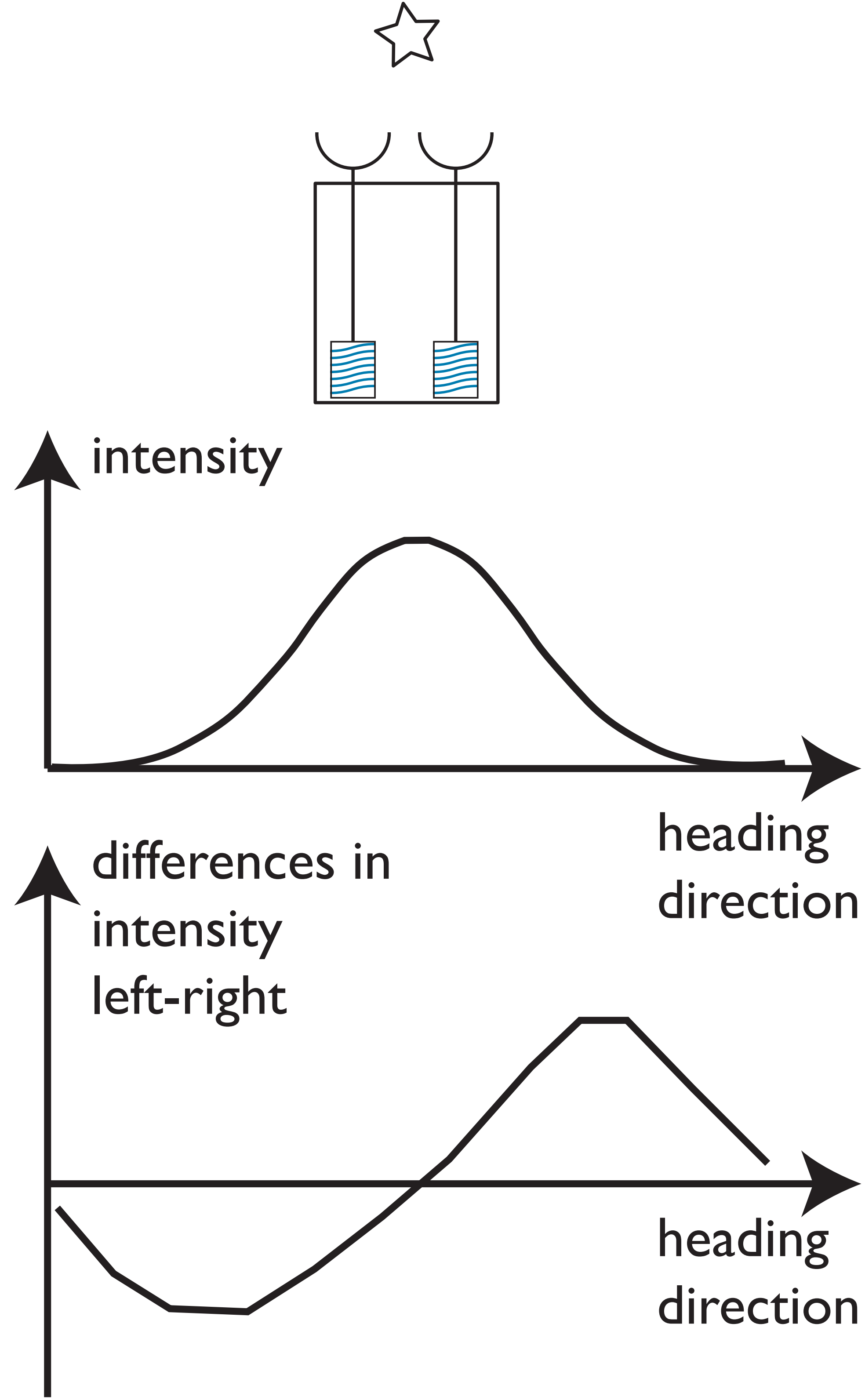


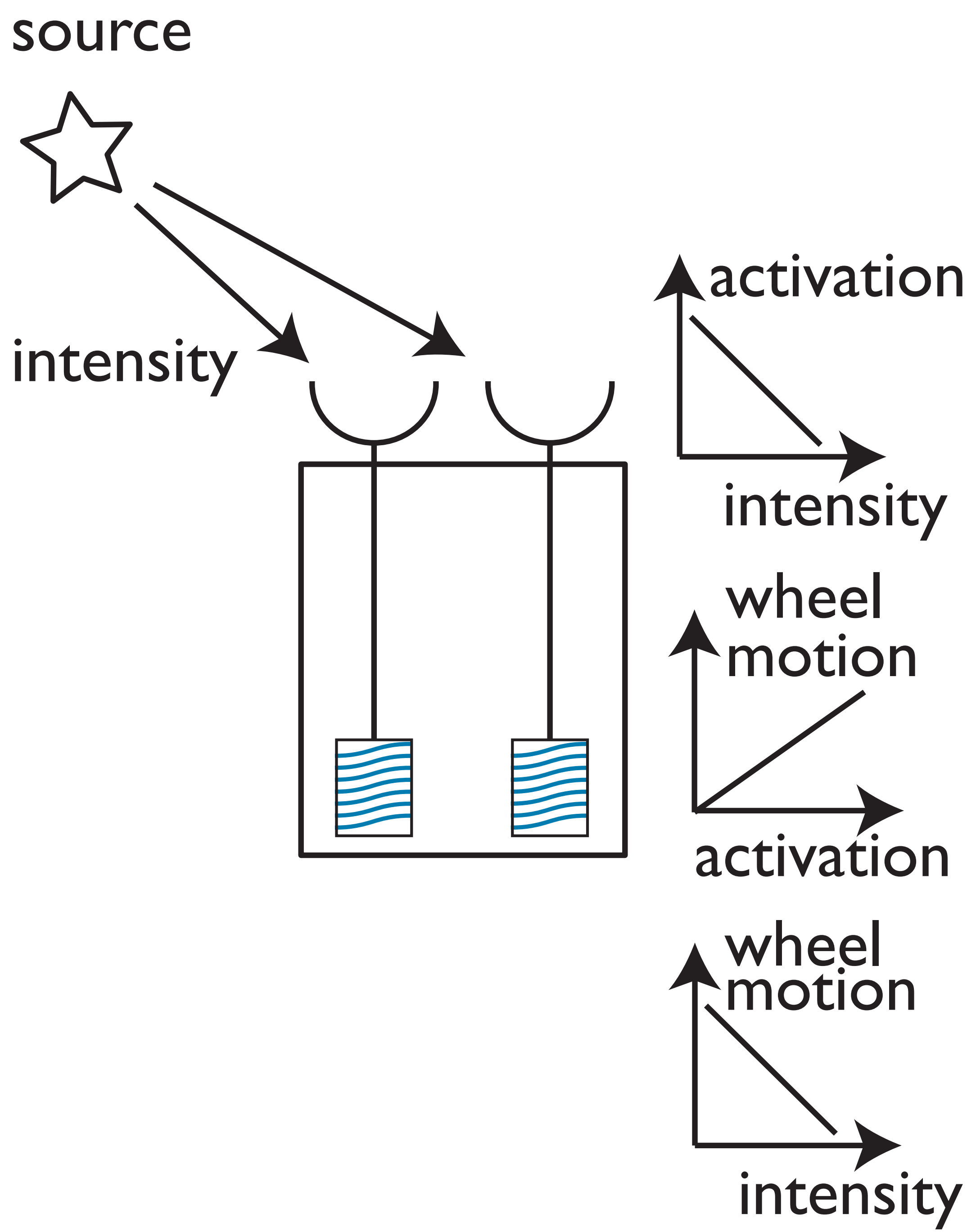
# [proof



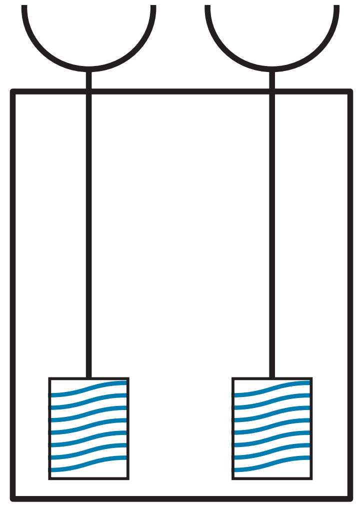
intensity
heading direction
differences in intensity left-right
heading direction
differences in turning rate left-right wheel
differences in intensity left-right
turning rate of vehicle
heading direction
source

# model of environment





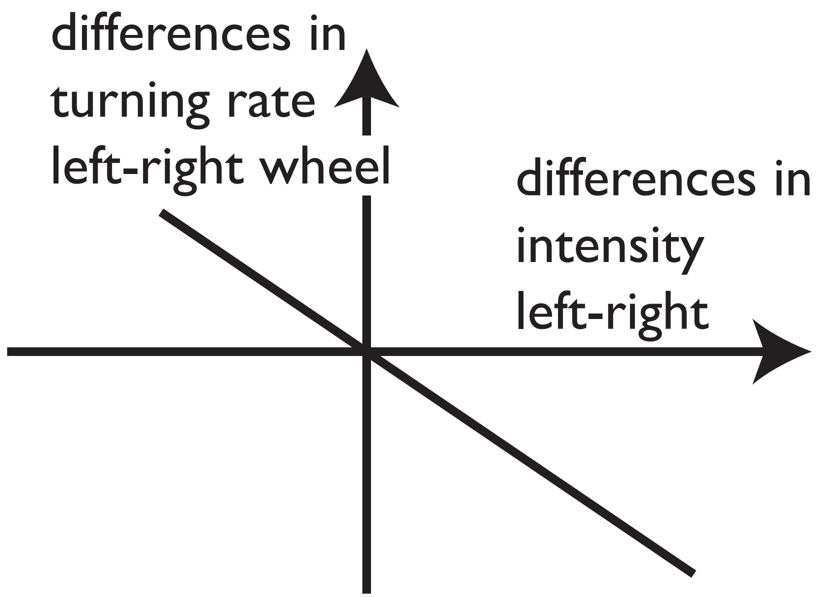
source
intensity
activation
intensity
wheel
motion
activation
wheel
motion
intensity



$$\omega_l = \omega_0 - cI_l$$


$$\omega_r = \omega_0 - cI_r$$

$$\Delta\omega = -\,c\Delta I$$



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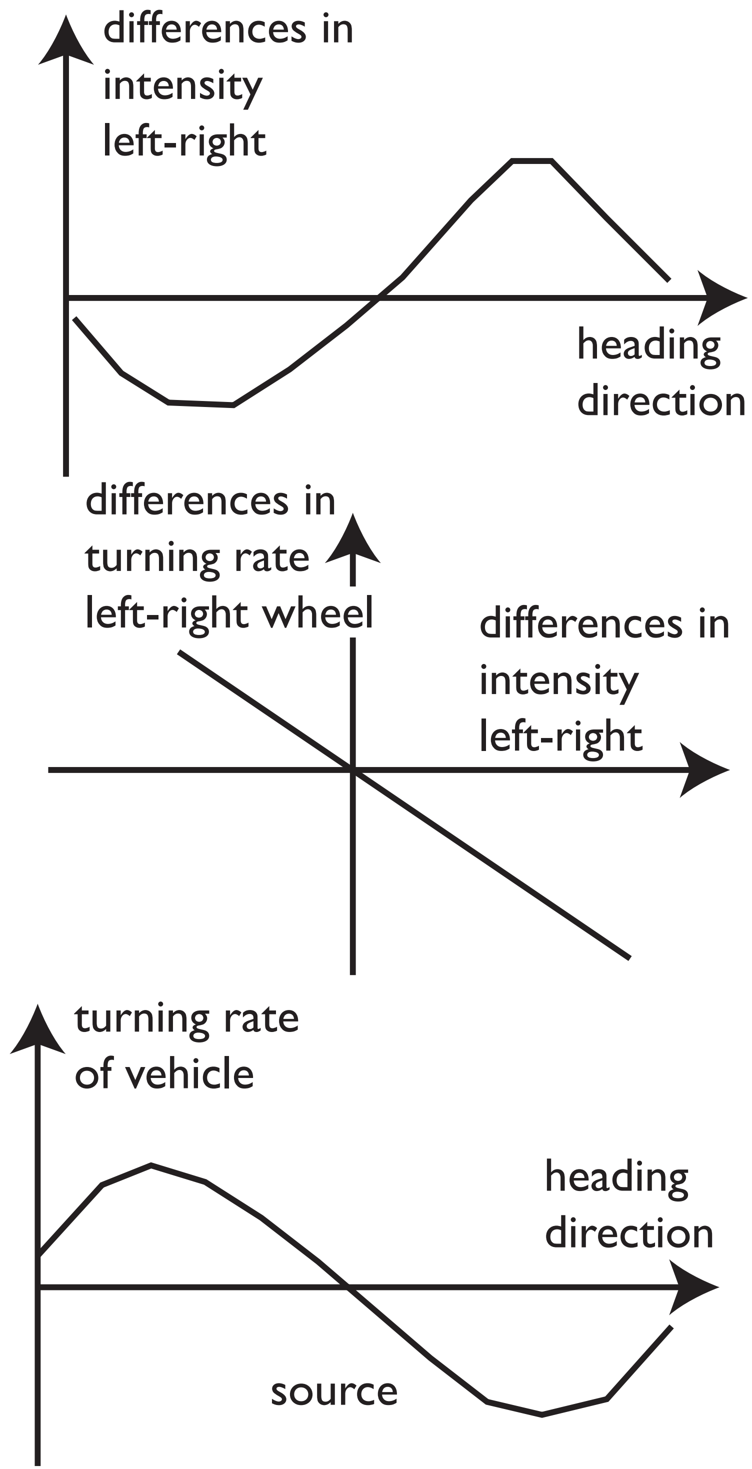
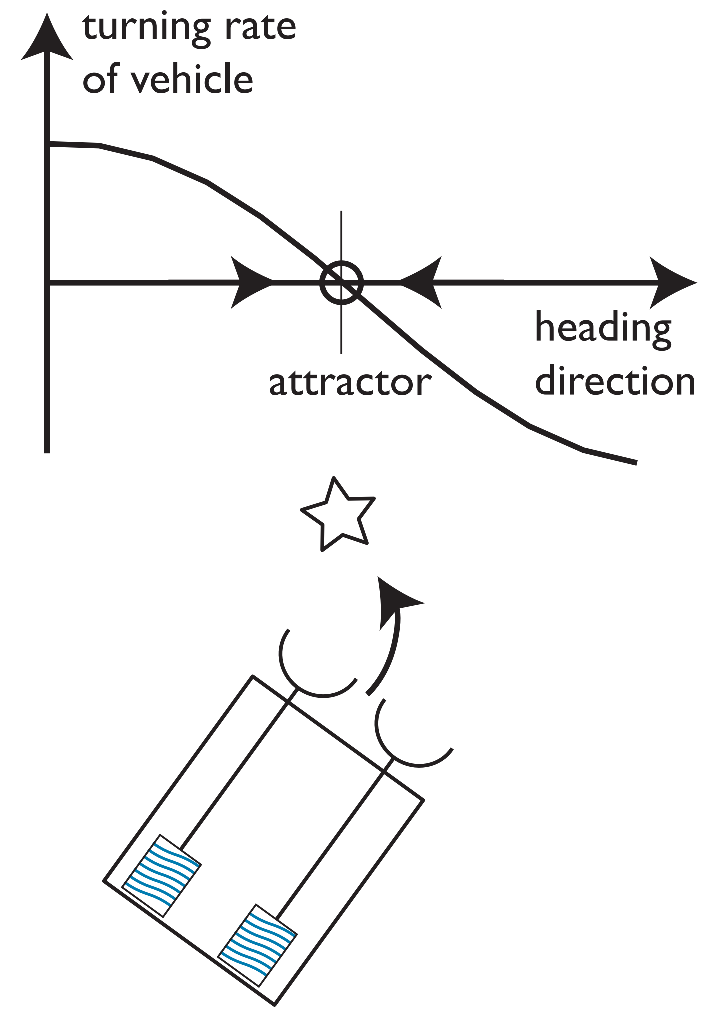
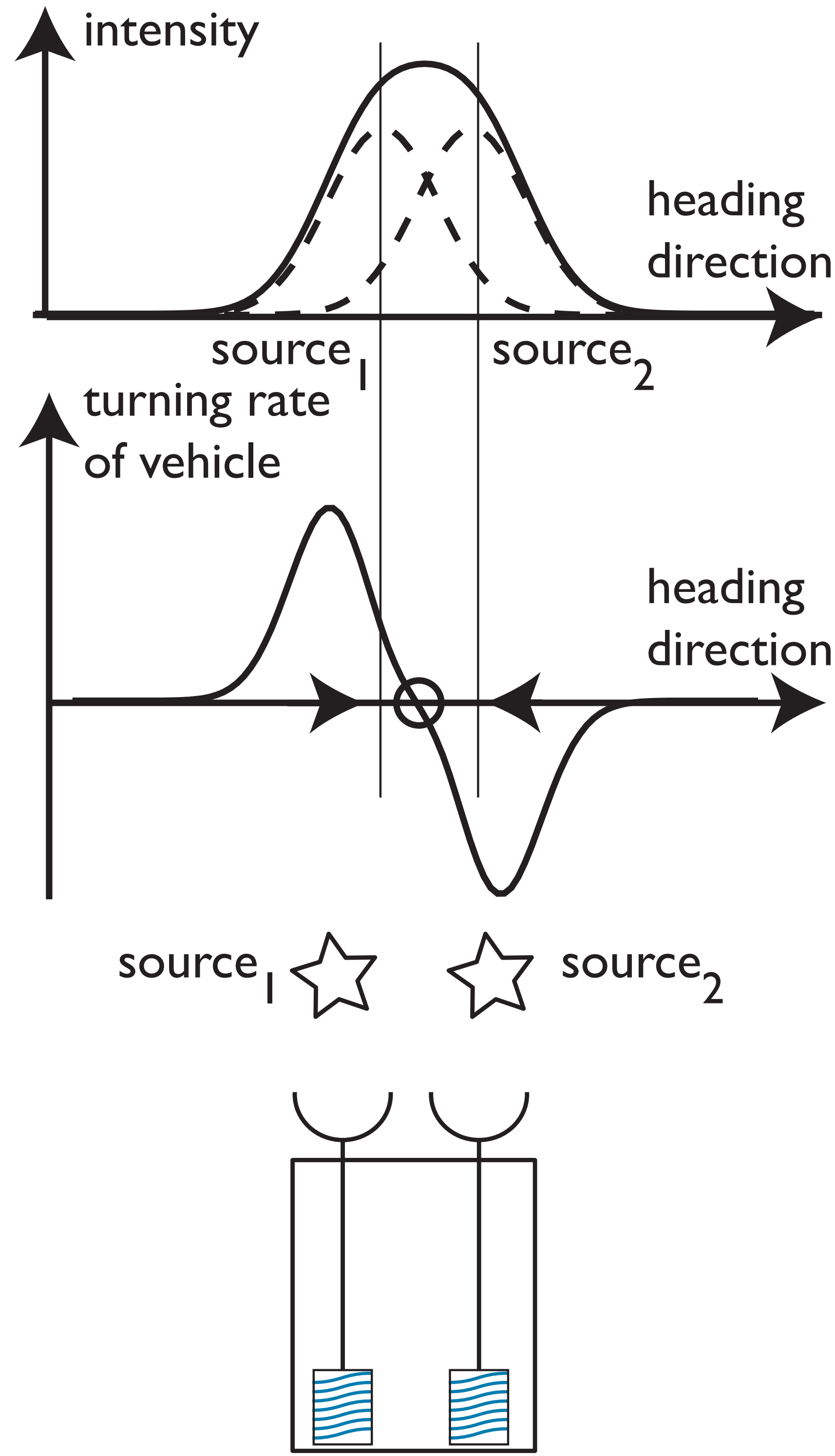

differences in
intensity
left-right
heading
direction
differences in
turning rate
left-right wheel
differences in
intensity
left-right
turning rate
of vehicle
heading
direction
source

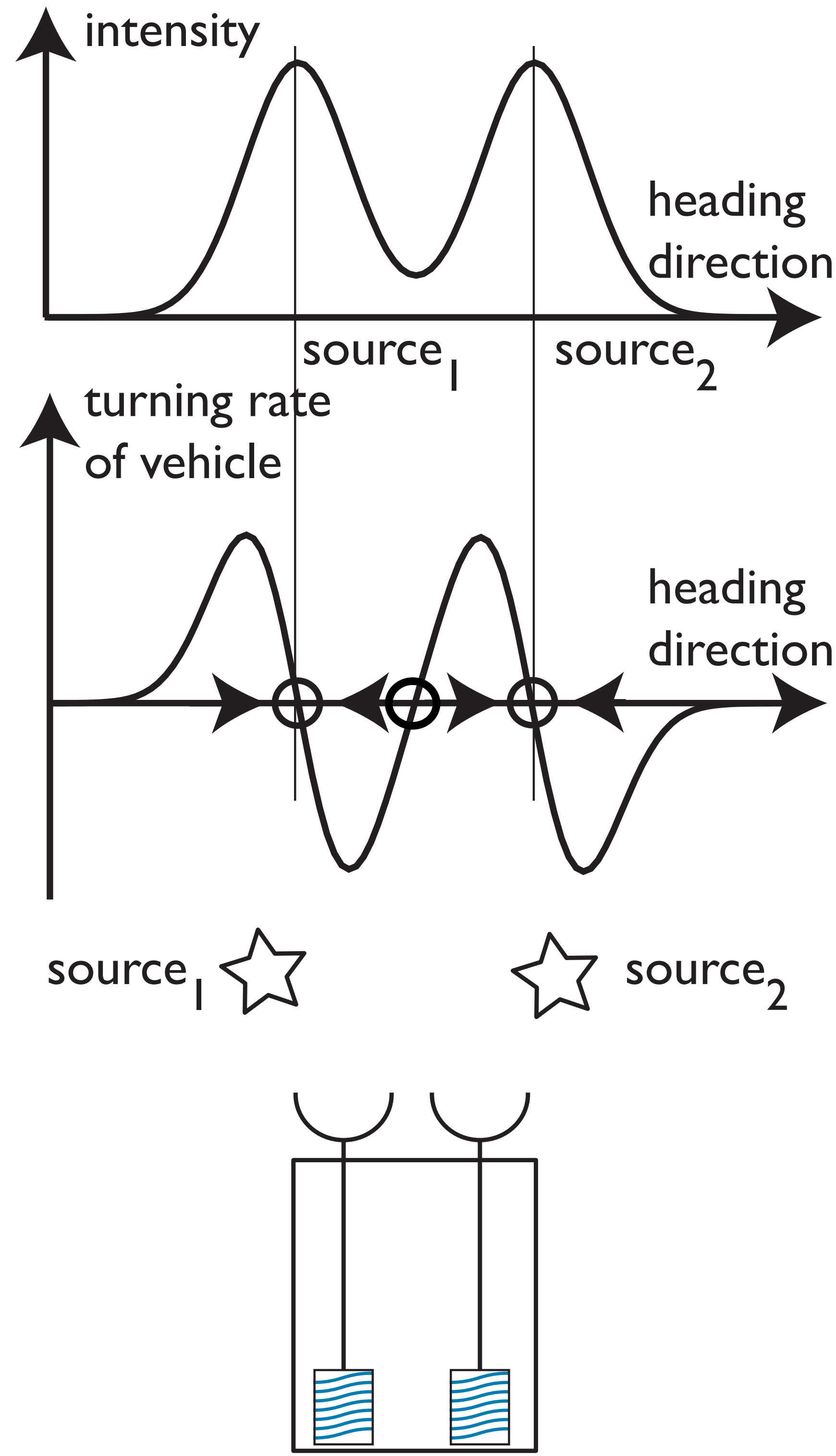
- feedforward nervous system
- + closed loop through environment
- => (behavioral) dynamics

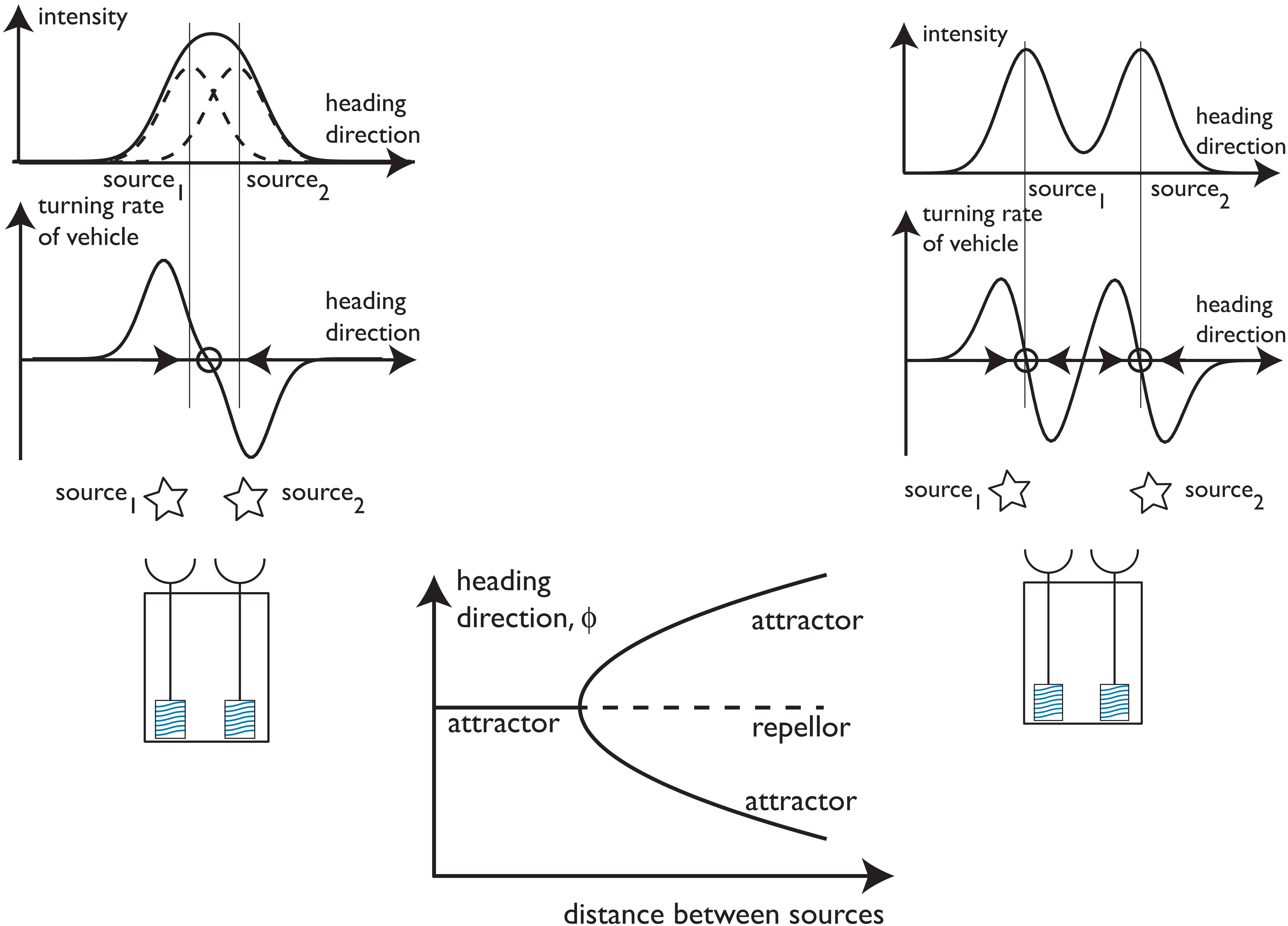


- two sources
- mono-modal distribution
- => monostable dynamics

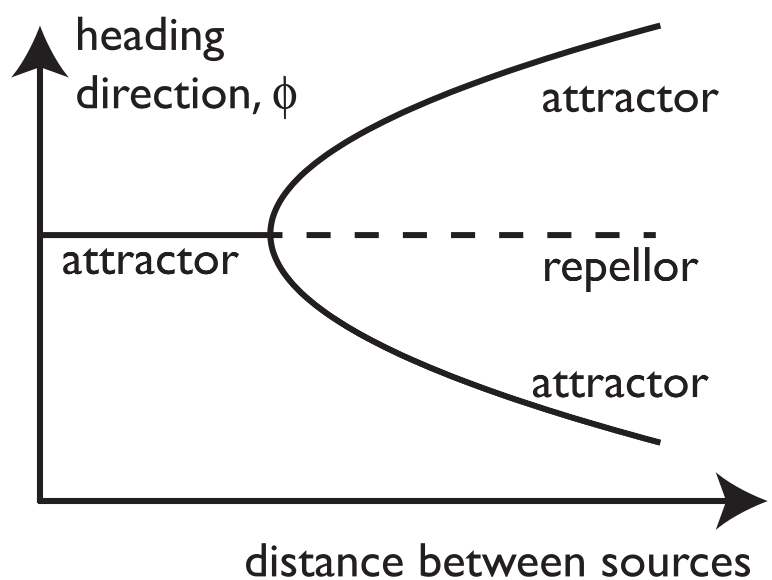


- two sources
- bimodal distribution
- => bistable dynamics
- => selection decision

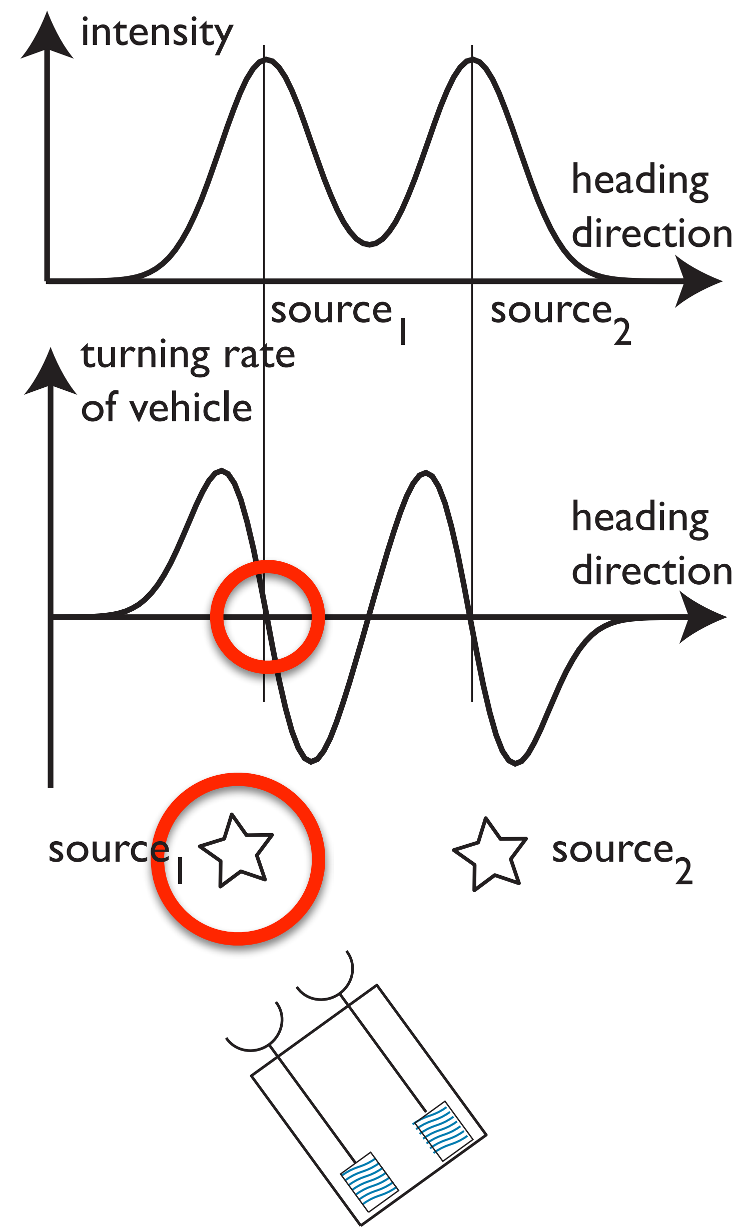



intensity
heading
direction
source
1
source
2
turning rate
of vehicle
heading
direction
source
1
source
2
intensity
heading
direction
source
1
source
2
turning rate
of vehicle
heading
direction
source
1
source
2
heading
direction, ϕ
attractor
attractor
repellor
attractor
distance between sources

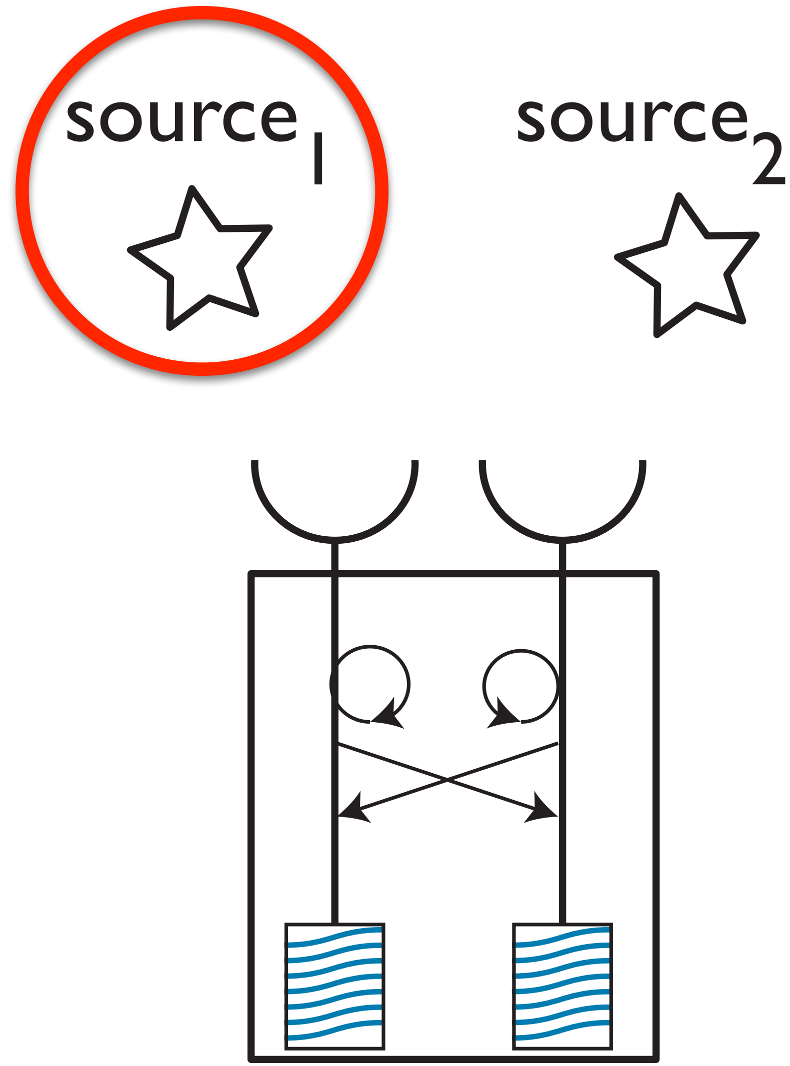
- capacity to make selection decisions = qualitative change of behavior
- => emerges from an instability



- “overt” decision stored in the vehicle’s physical state

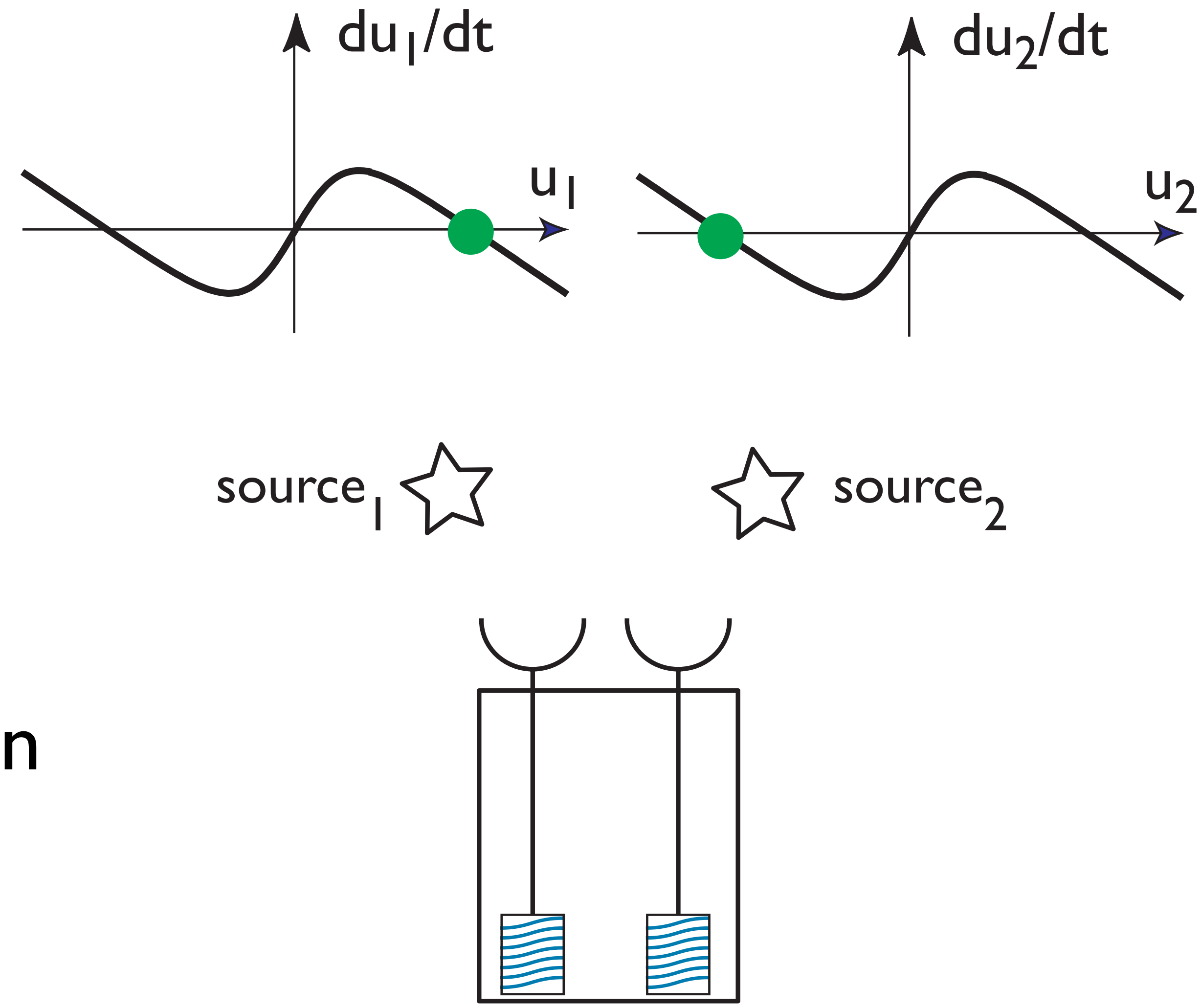


- “covert” decision?
- =>“store” the state of that decision in an inner=neural state



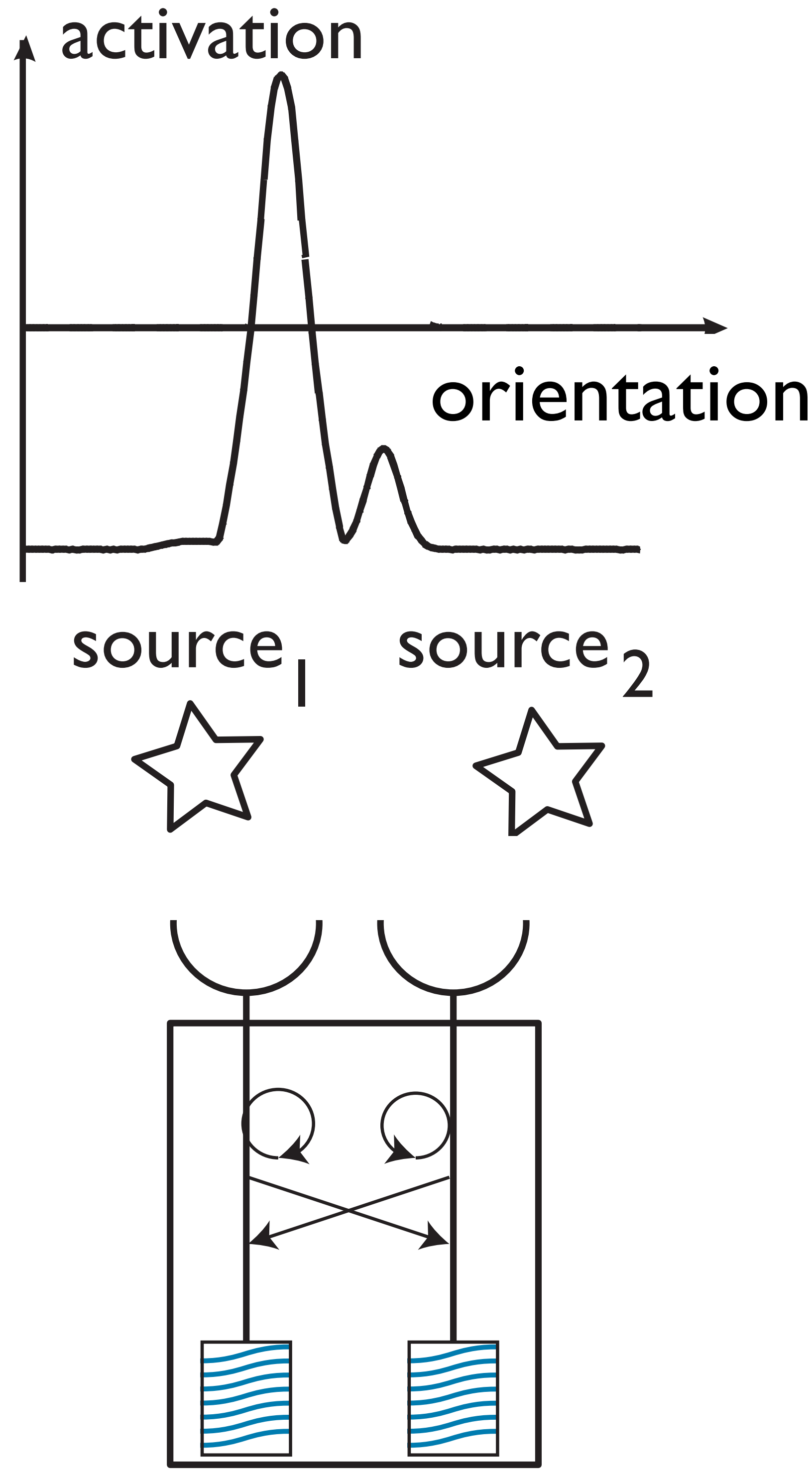
# => neural dynamics

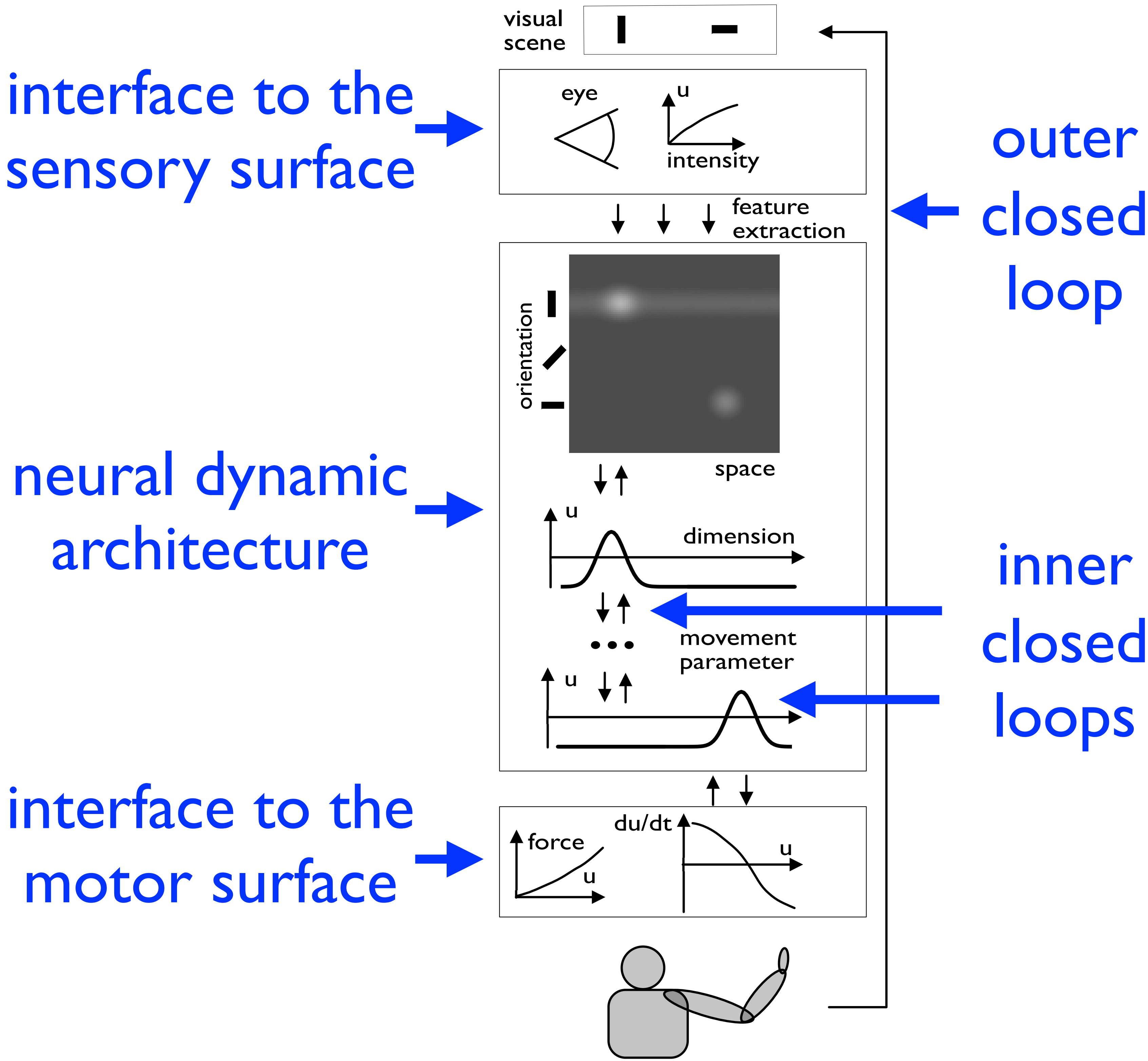
- neural state: activation
- activation dynamics
- competition/ inhibition=> selection



# neural fields

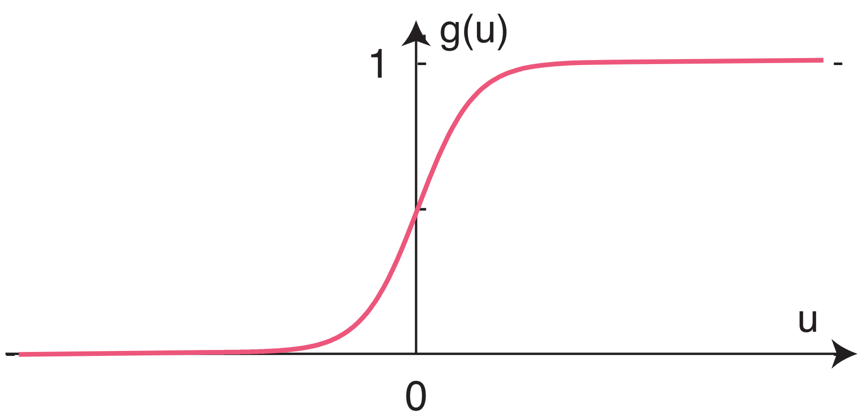
- neural activation field represents the continuum of possible orientations

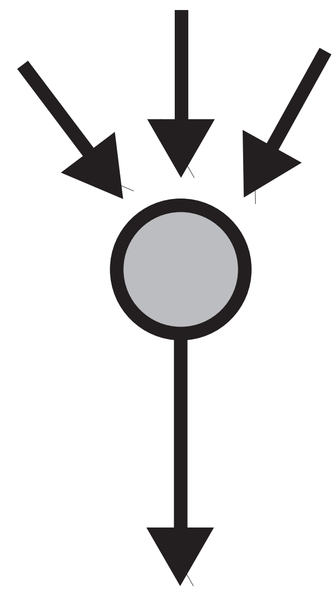


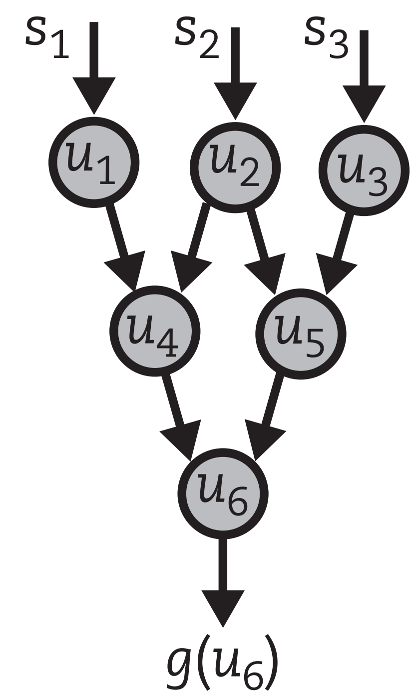

interface to the sensory surface
neural dynamic architecture
interface to the motor surface
outer closed loop
inner closed loops
visual scene
eye
u
intensity
feature extraction
orientation
space
u
dimension
movement parameter
u
force
u
du/dt
u

# Neural activation in the connectionist abstraction

- activation state (membrane potential or spiking rate)
- summing inputs and generating output through a sigmoidal threshold function



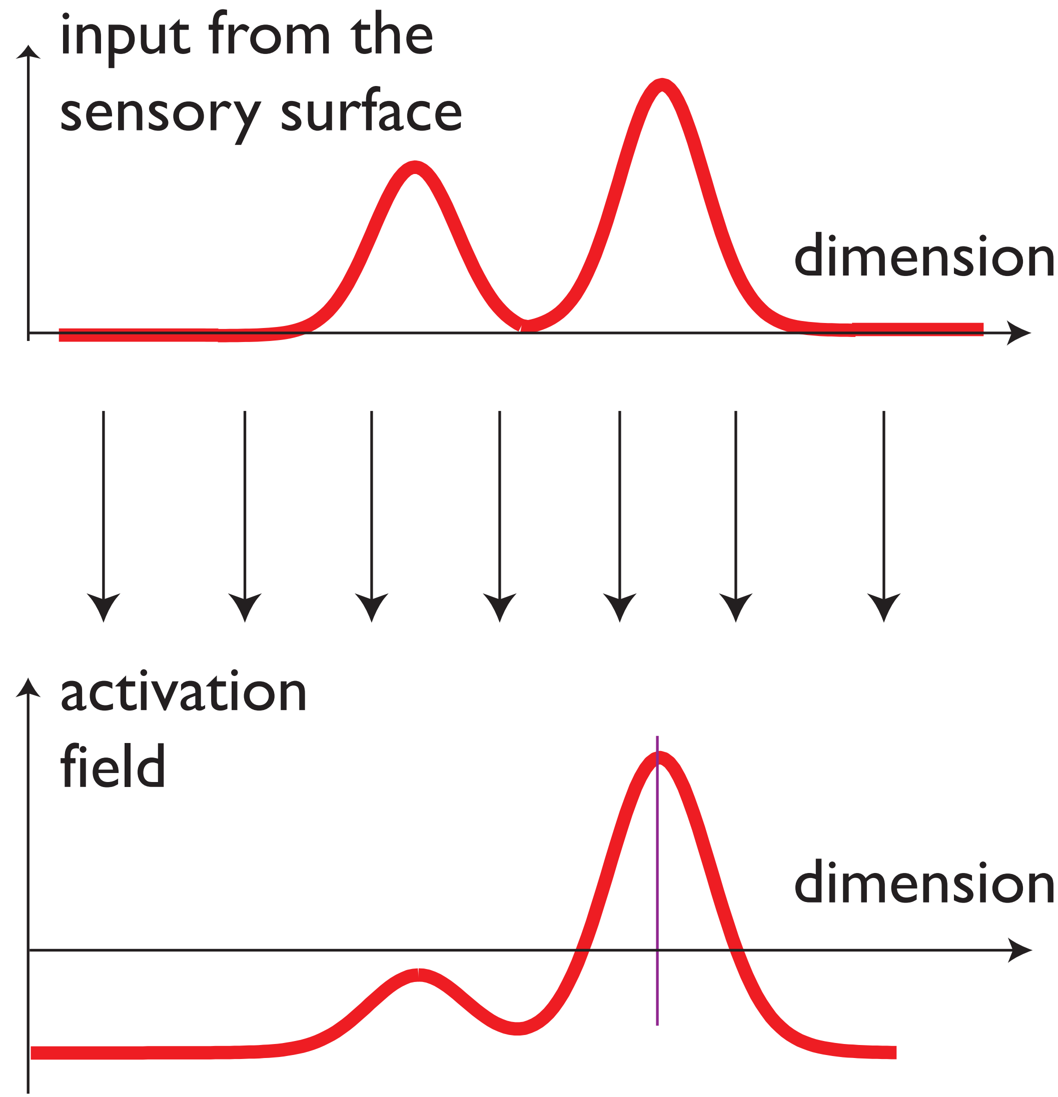




$$\text{output} = g\left(\sum(\text{inputs})\right)$$

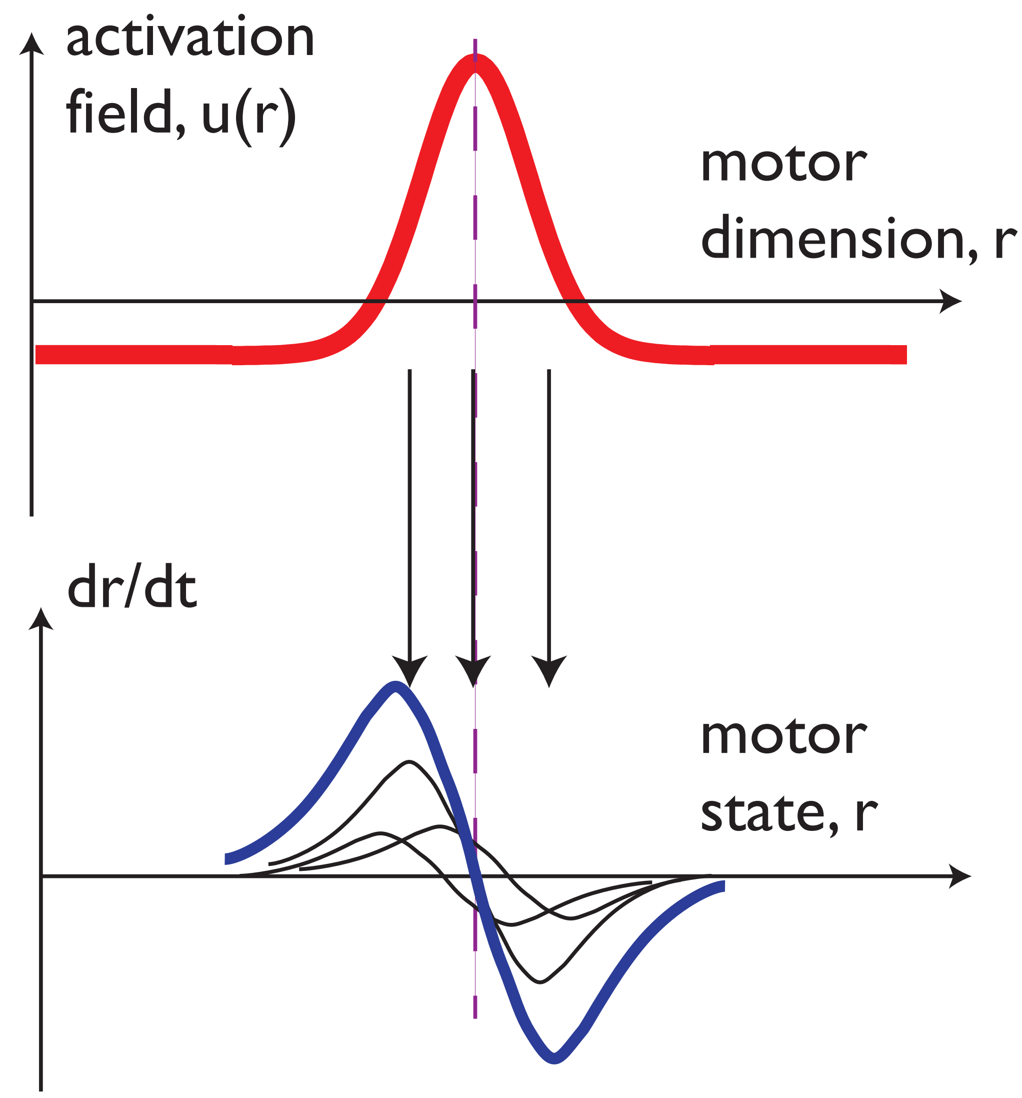
# Neural fields

- neurons represent perceptual dimensions by virtue of the forward connectivity from the sensory surface
  - e.g., feature maps…
- the discrete sampling by neurons does not matter: activation fields

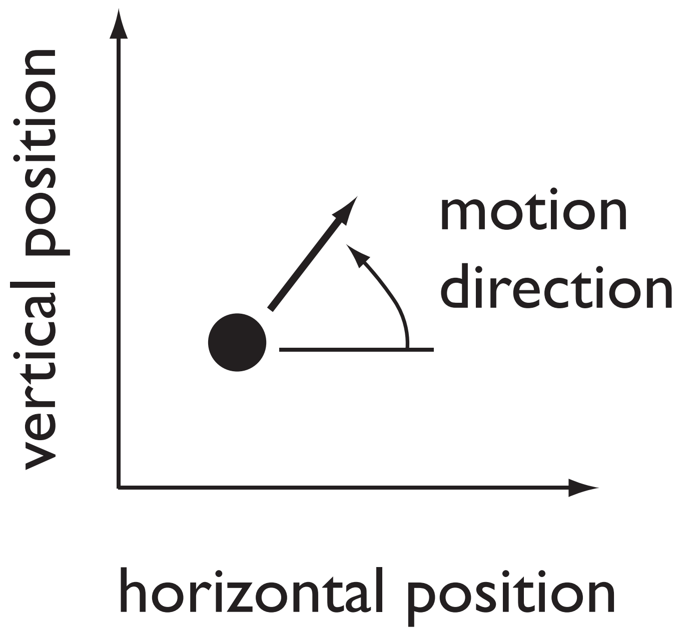


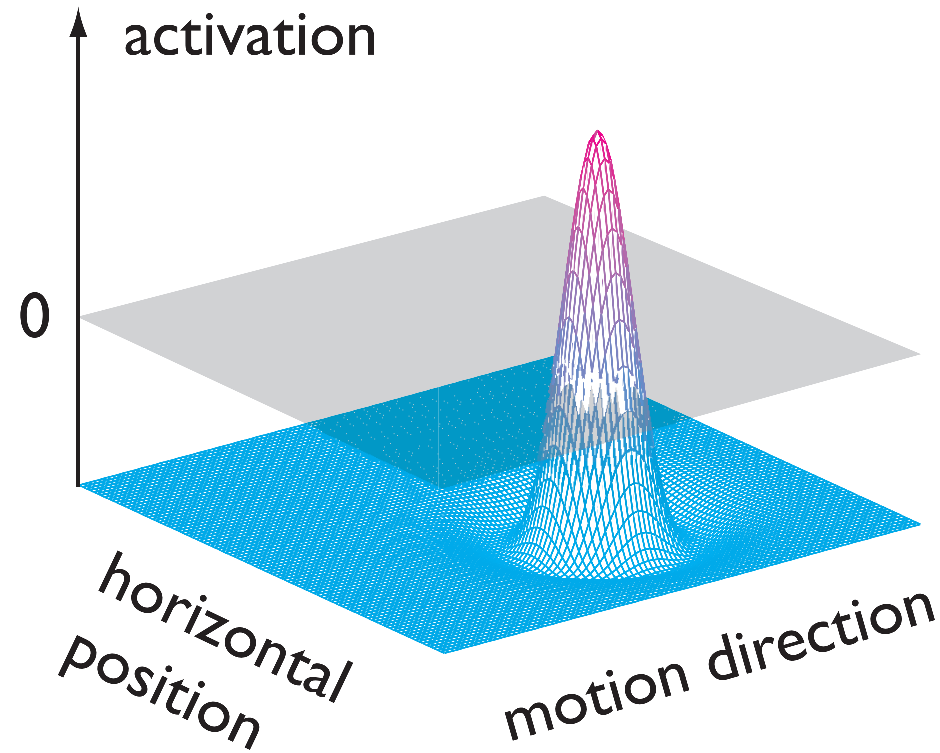
# Neural fields

- neural fields represent motor dimensions by virtue of their output connectivity to motor surfaces… => behavioral dynamics
  - e.g., through peripheral reflex loops

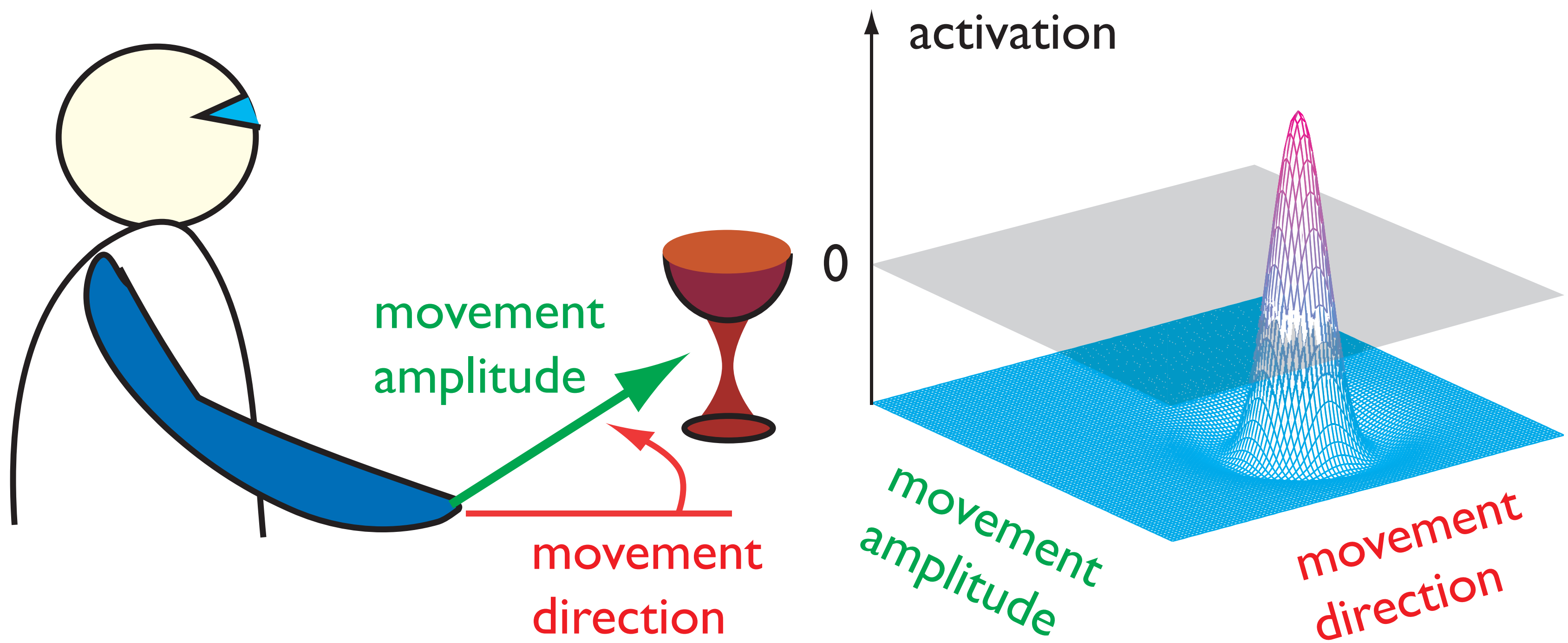


# Peaks of activation may represent perceptual objects

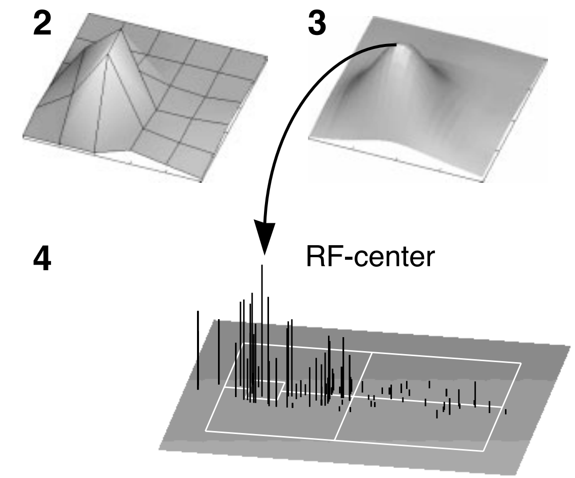


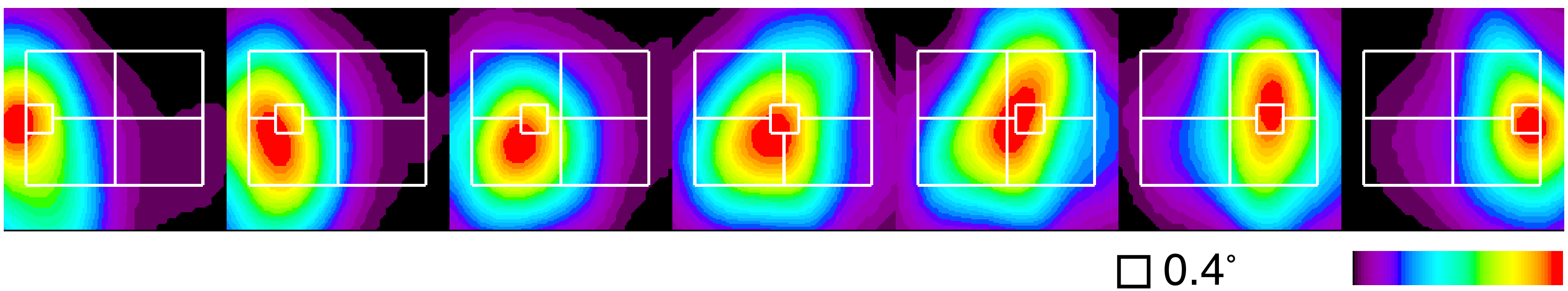
# Peaks of activation may represent motor plans

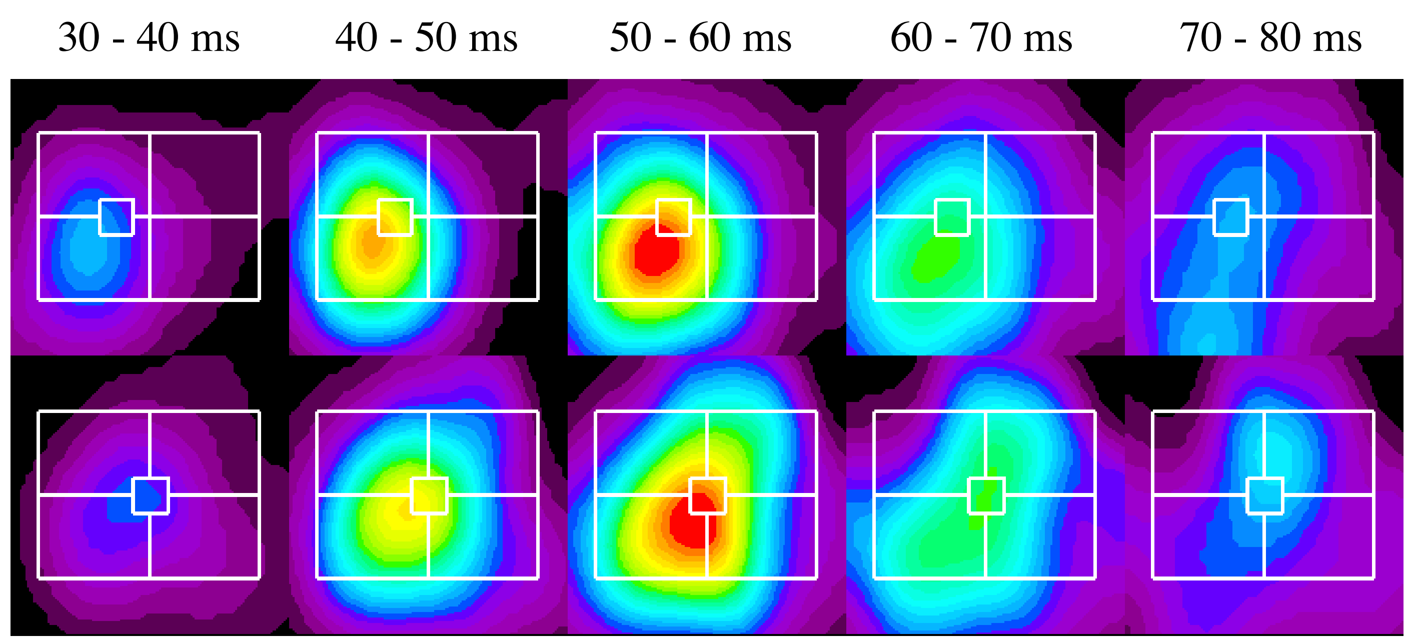


# Neural fields: Distributions of population activation



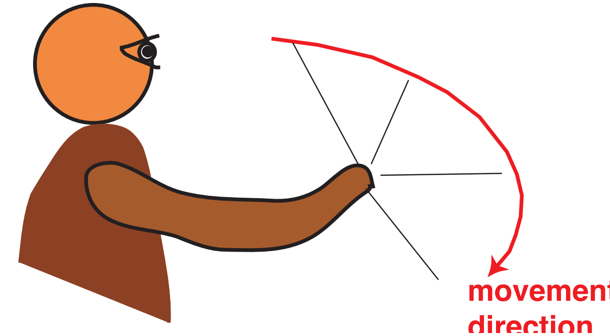

- primary visual cortex



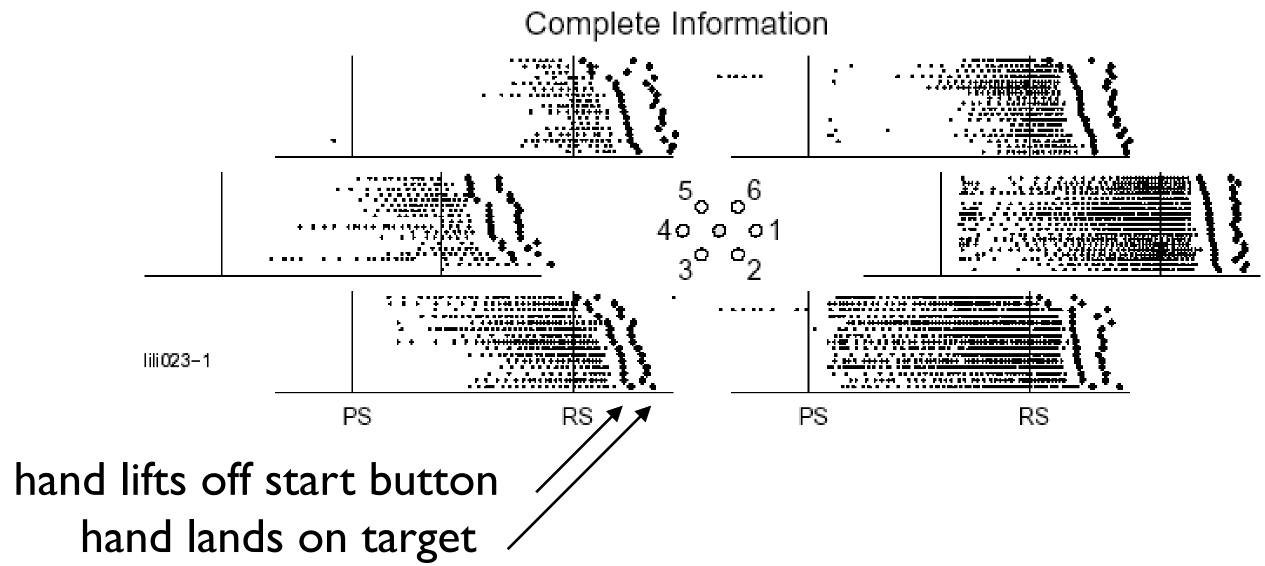




[Jancke et al, J. Neurosci 1999]

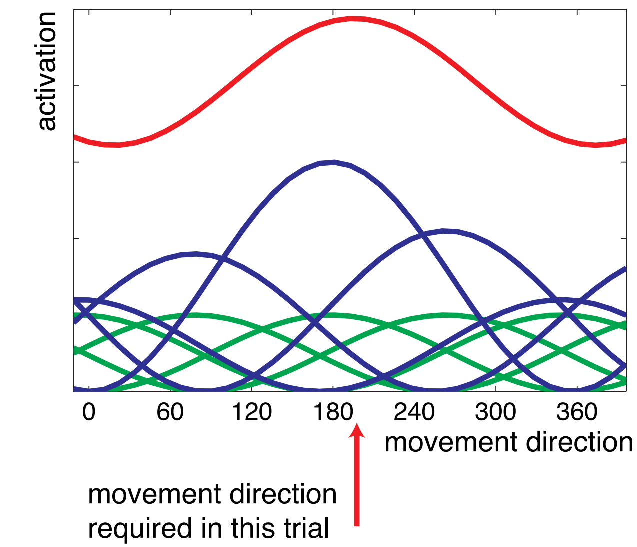
# Neural fields: Distributions of population activation

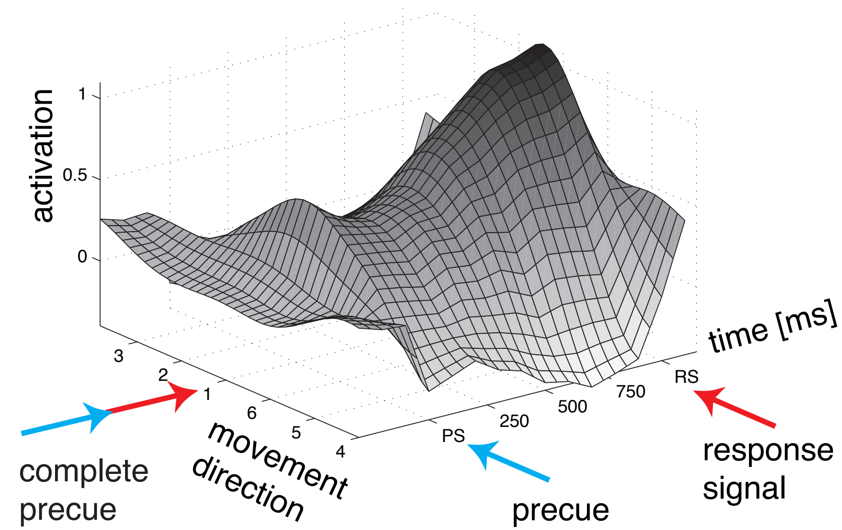



- motor cortex




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

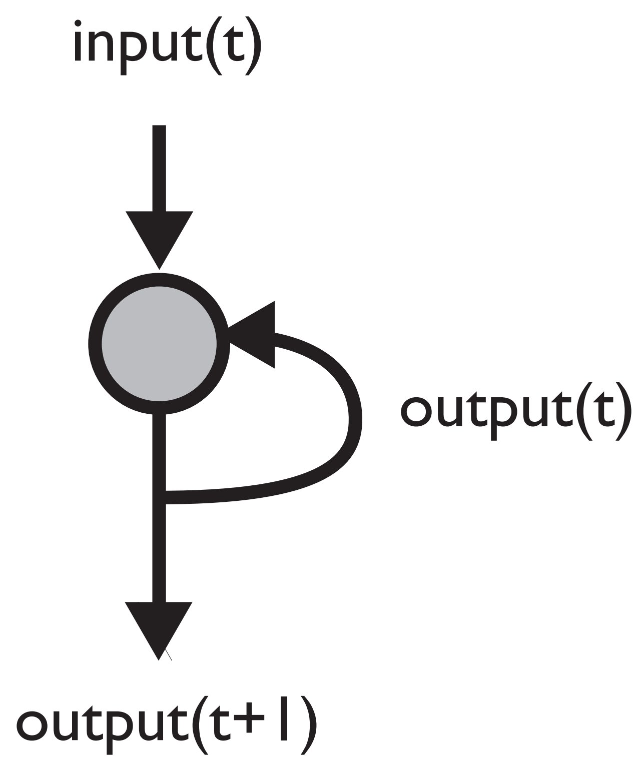



[Bastian et al, Europ J. Neurosci 2003]

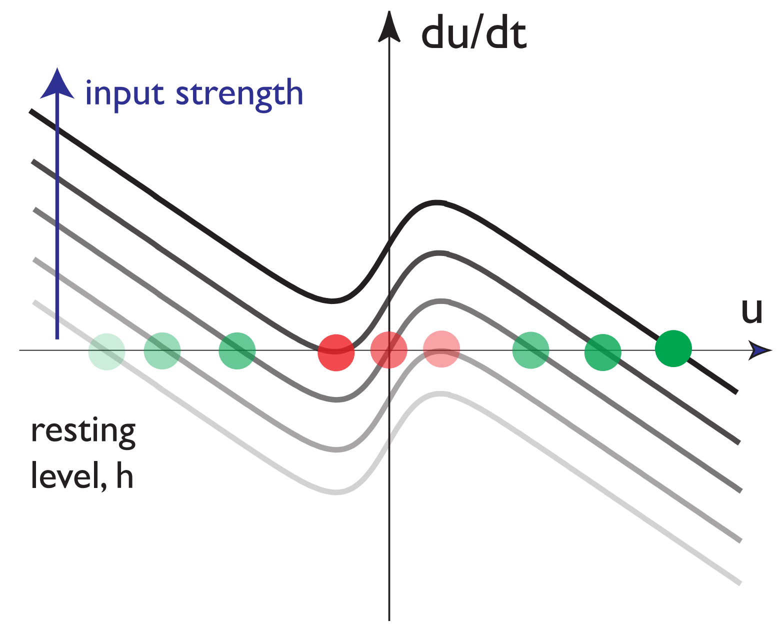
# Autonomous generation of activation

- activation that arises or persists in the absence of input
  - e.g. during movement generation
  - e.g. in working memory
  - e.g. in sequences generation
- => requires (strong) recurrence
- => implies time



# Neural dynamics

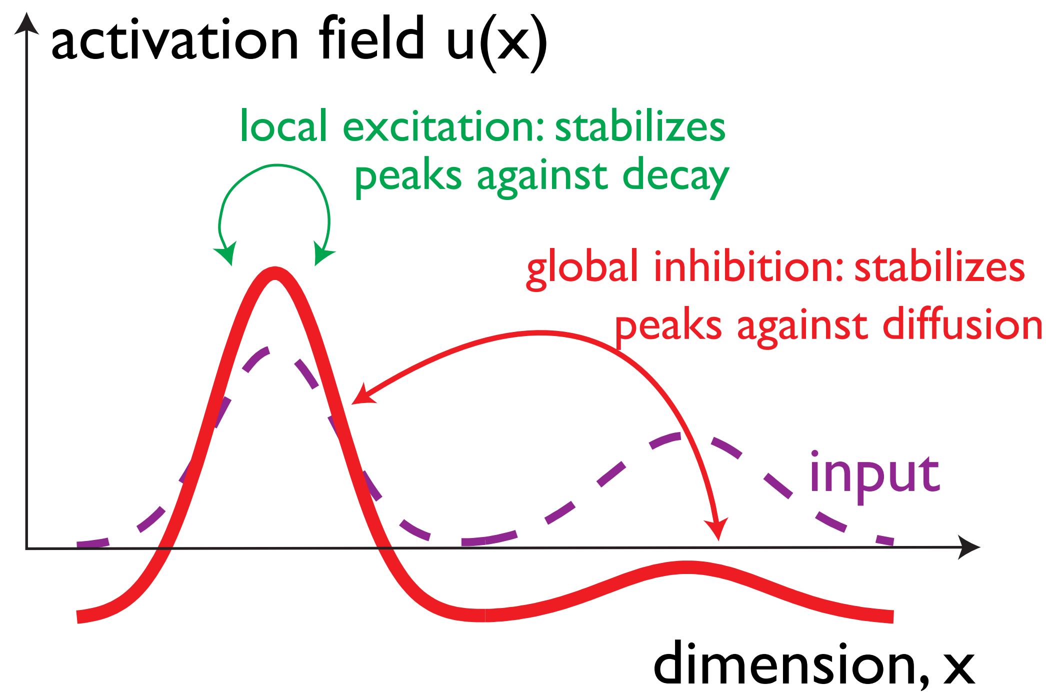
- time is not discrete (spiking is asynchronous)
- => neural dynamics… of the activation state, u
- "-u" term inherited from membrane dynamics: source of stability



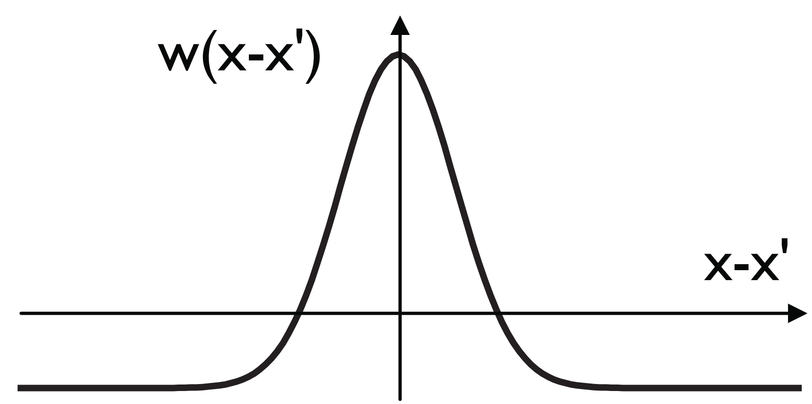

$$\dot{u}(t) = -u(t) + h + \text{input}(t) + g(u(t))$$

# Neural dynamics of fields

- Localized peaks of activation as stable states
- from regular pattern of within-field connectivity=interaction
- local excitation/global inhibition stabilize peaks
- peaks arise/disappear in dynamic instabilities

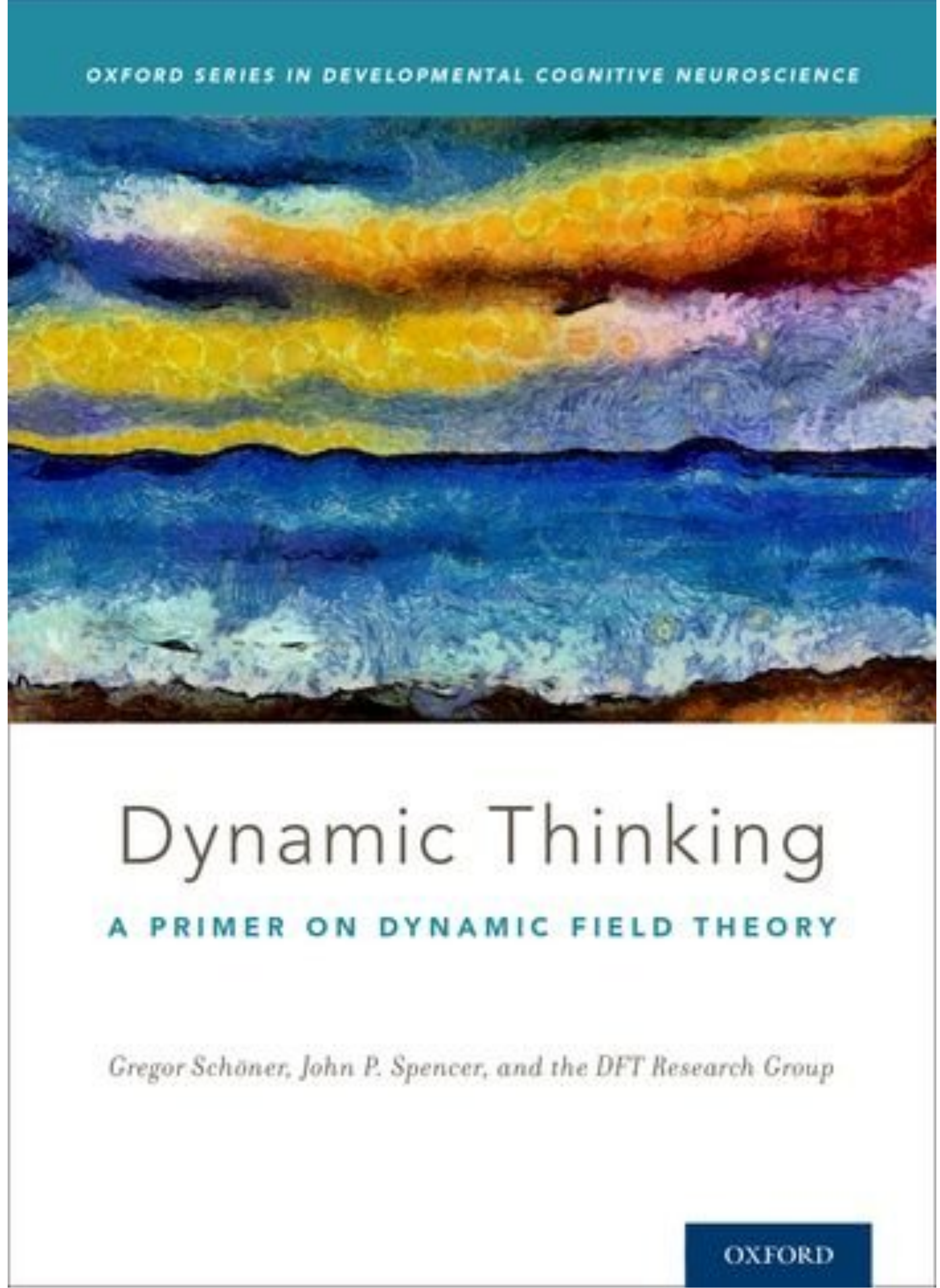



$$\tau \dot{u}(x,t) = -u(x,t) + h + s(x,t) + \int dx' w(x-x')\ g(u(x',t))$$



# => Dynamic Field Theory

- dynamicfieldtheory.org



# Attractors and their instabilities

- input driven solution (sub-threshold)
- 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

# Learning in DFT

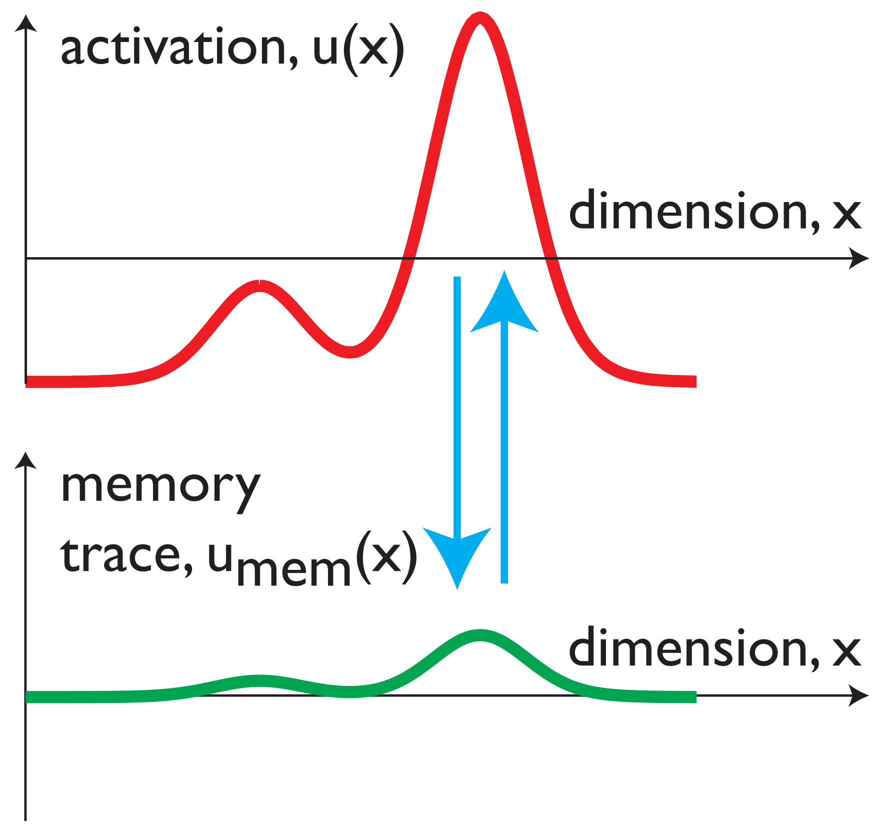
- Learning is change of behavior based on experience
  - experience is driven by activation patterns
  - behavior is generated by neural dynamics
- => Learning is change of the neural dynamics driven by activation patterns

# Sensitization and habituation

- simplest non-associative learning in simple stimulus-induced responses
  - sensitization: experience lowers the threshold for eliciting a behavior
  - habituation: experience increases the threshold for eliciting a behavior
- => Sophie Aerdker's case study

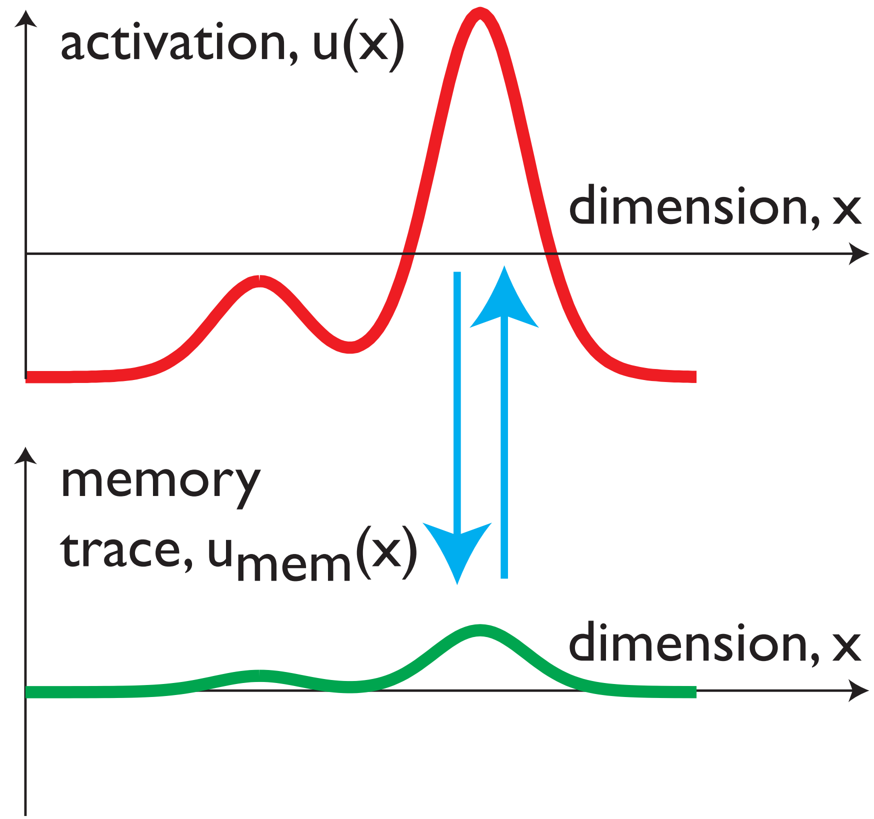
# The memory trace

- facilitatory trace of patterns of activation
- in excitatory field: leads to sensitization
- in inhibitory field: leads to habituation



# The memory trace

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

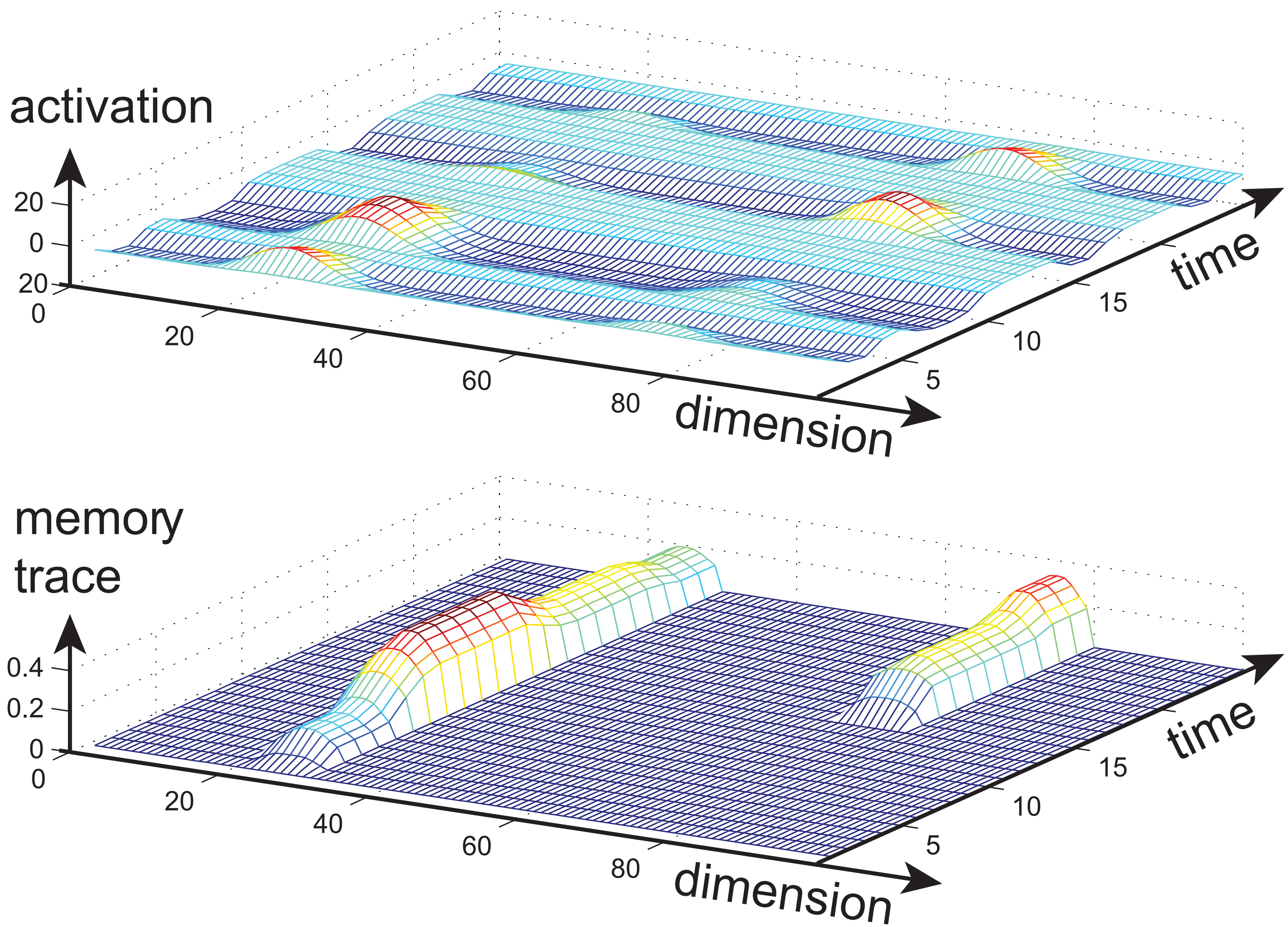



$$\tau_{\text{mem}}\dot{u}_{\text{mem}}(x,t) = -u_{\text{mem}}(x,t) + g(u(x,t))$$

$$\tau_{\text{mem}}\dot{u}_{\text{mem}}(x,t) = 0$$

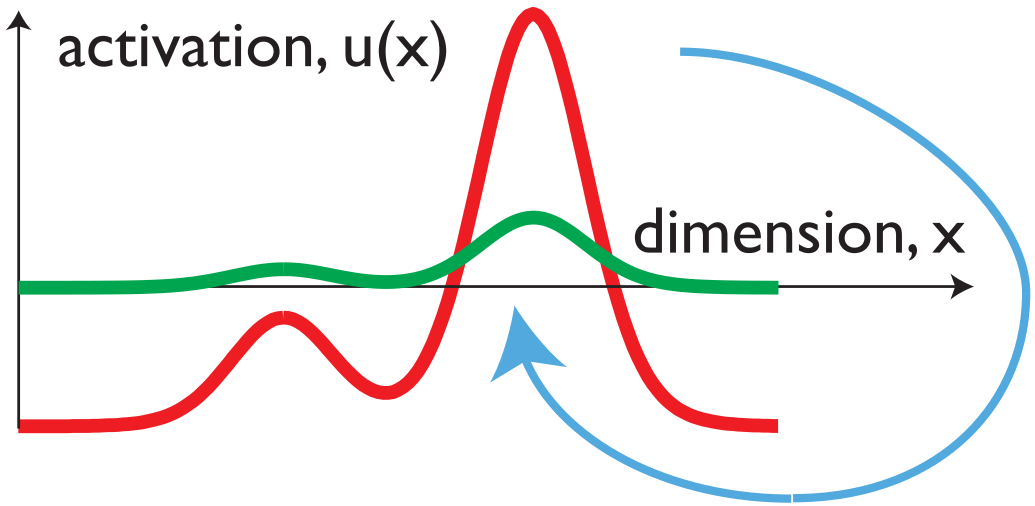
if there is no supra-threshold activation anywhere in the field

# => the memory trace reflects the history of detection decisions



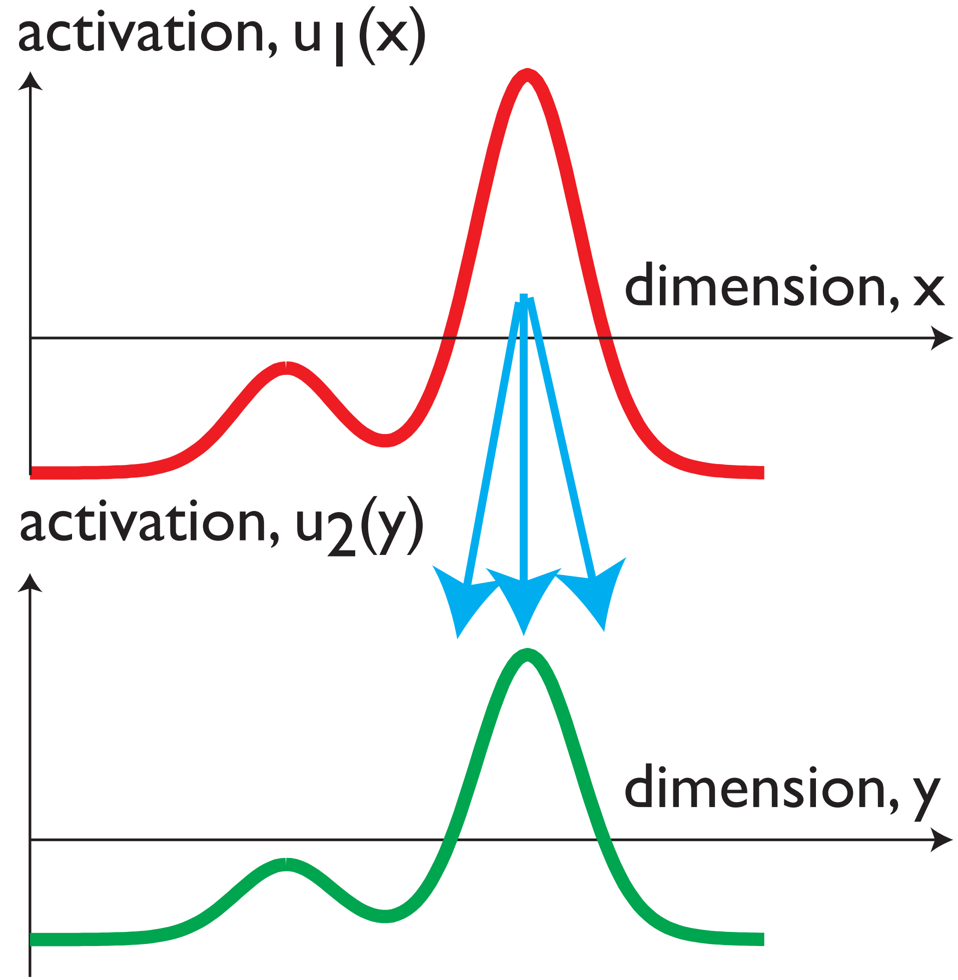
# Memory trace ~ first-order Hebbian learning

- increases local resting level at activated locations
- ~ the bias input in NN
- boost-driven detection instability amplifies small bias => important role in DFT



# Regular (second-order) Hebbian learning

- projections among fields (or from sensory input to field) evolve according to the Hebb rule

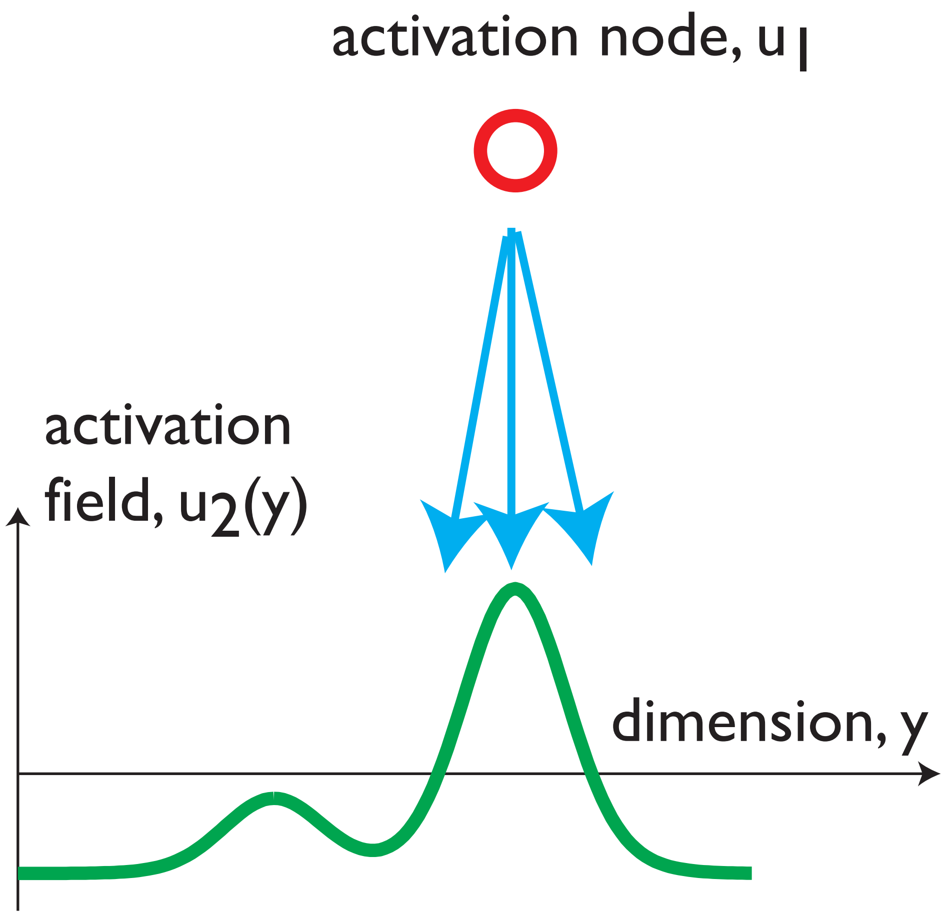



$$\tau \dot{W}(x, y, t) = \epsilon(t)\Big( - W(x, y, t) + f(u_1(x, t)) \times f(u_2(y, t))\Big)$$

[Sandamirskaya, Frontiers Neurosci 2014]

# Regular second-order Hebbian learning

- important in DFT for projections from zero-dimensional nodes to fields
- => concepts

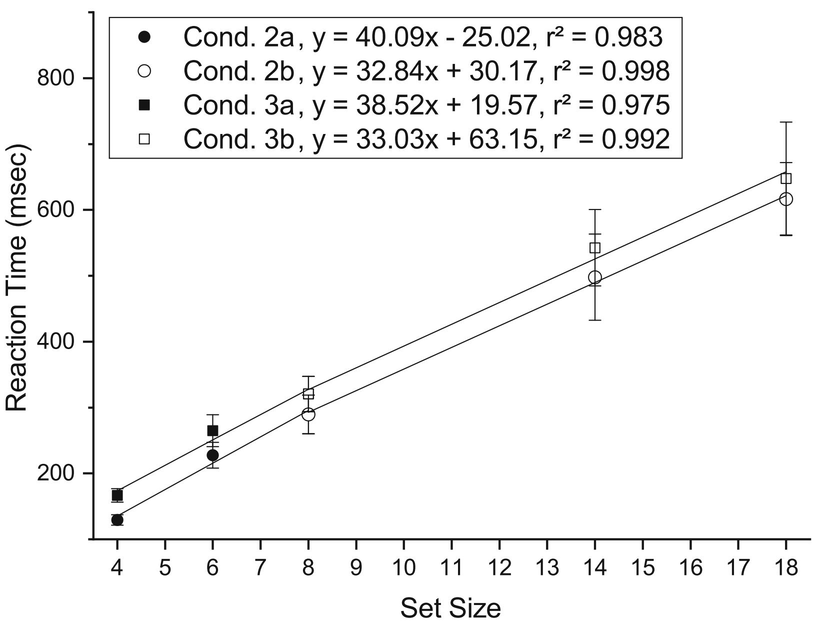


# DFT models

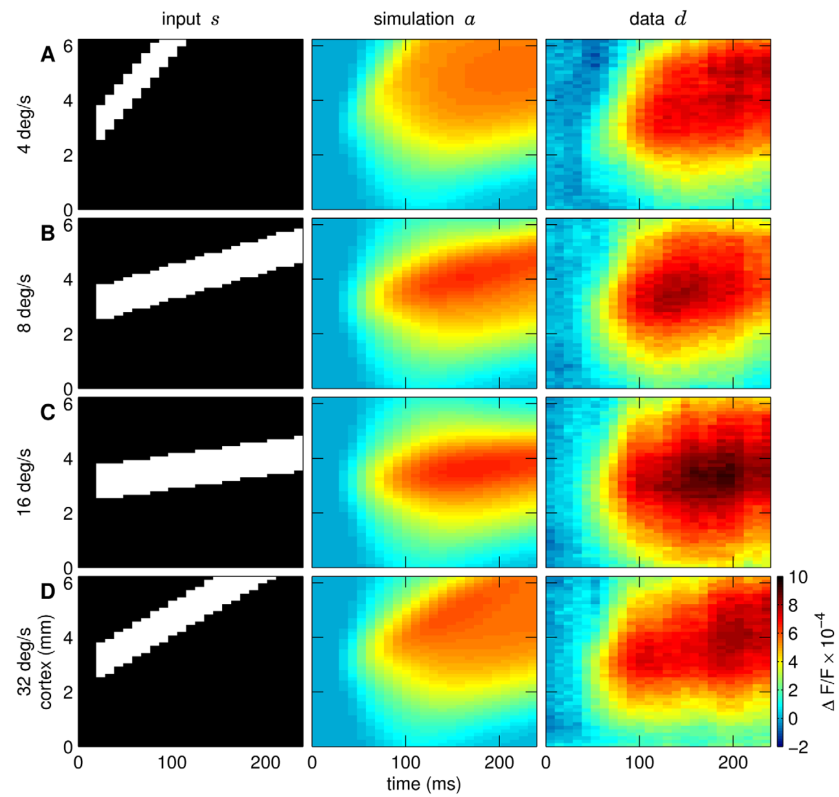
- as neural process models of  cognition
- vary in how complete the link to the sensory motor surfaces is

# DFT models that account for behavioral or neural data

- by mapping states of the model onto behavioral or neural responses



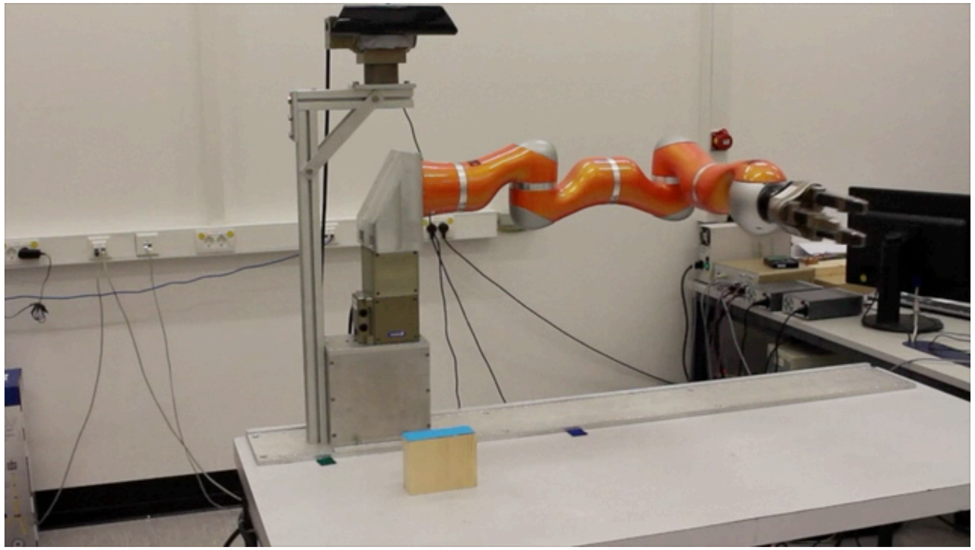

[Grieben et al. Attention, Perception & Psychophysics (2020)]

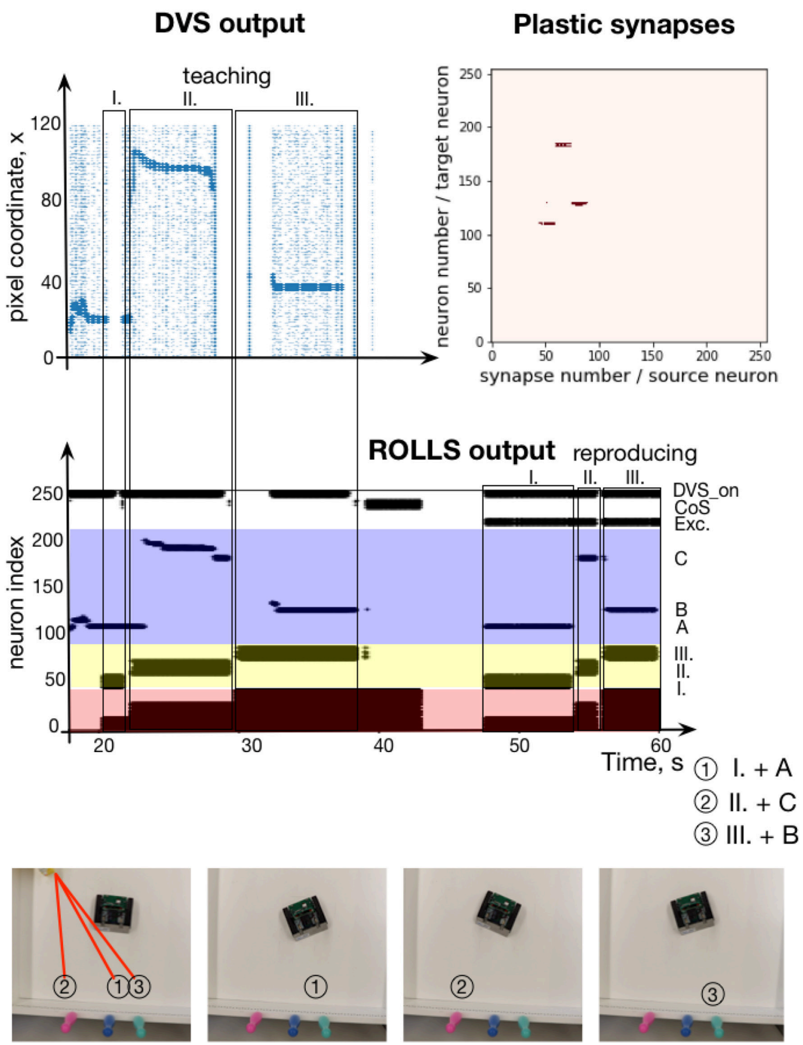



[Markounikau et al, PLoS Comp Biol (2010)]

# DFT models in robotic demonstration

neuro-morphic implementation!






[Knips et al., Frontiers Neurorobotics (2017)]

[Kreiser et al., Frontiers Neuroscience (2018)]

# DFT models

- Sophie Aerdker/Aaron Buss: field states are mapped onto perceptual/motor states
- Raul Grieben/Mathis Richter: sensor generates input
- Jan Tekülve: activation drives motor system