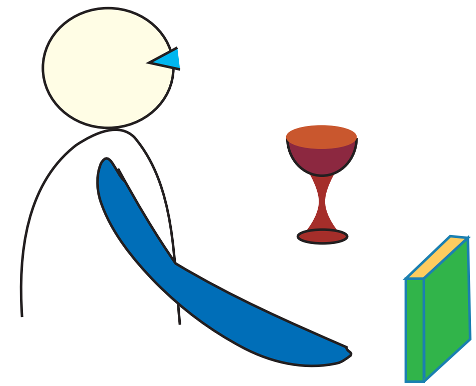


Dynamic Field Theory: embodied cognition

Gregor Schöner
Institute for Neural Computation (INI)
Ruhr-University Bochum, Germany
dynamicfieldtheory.org
gregor.schoener@rub.de

Roadmap

Neural dynamics

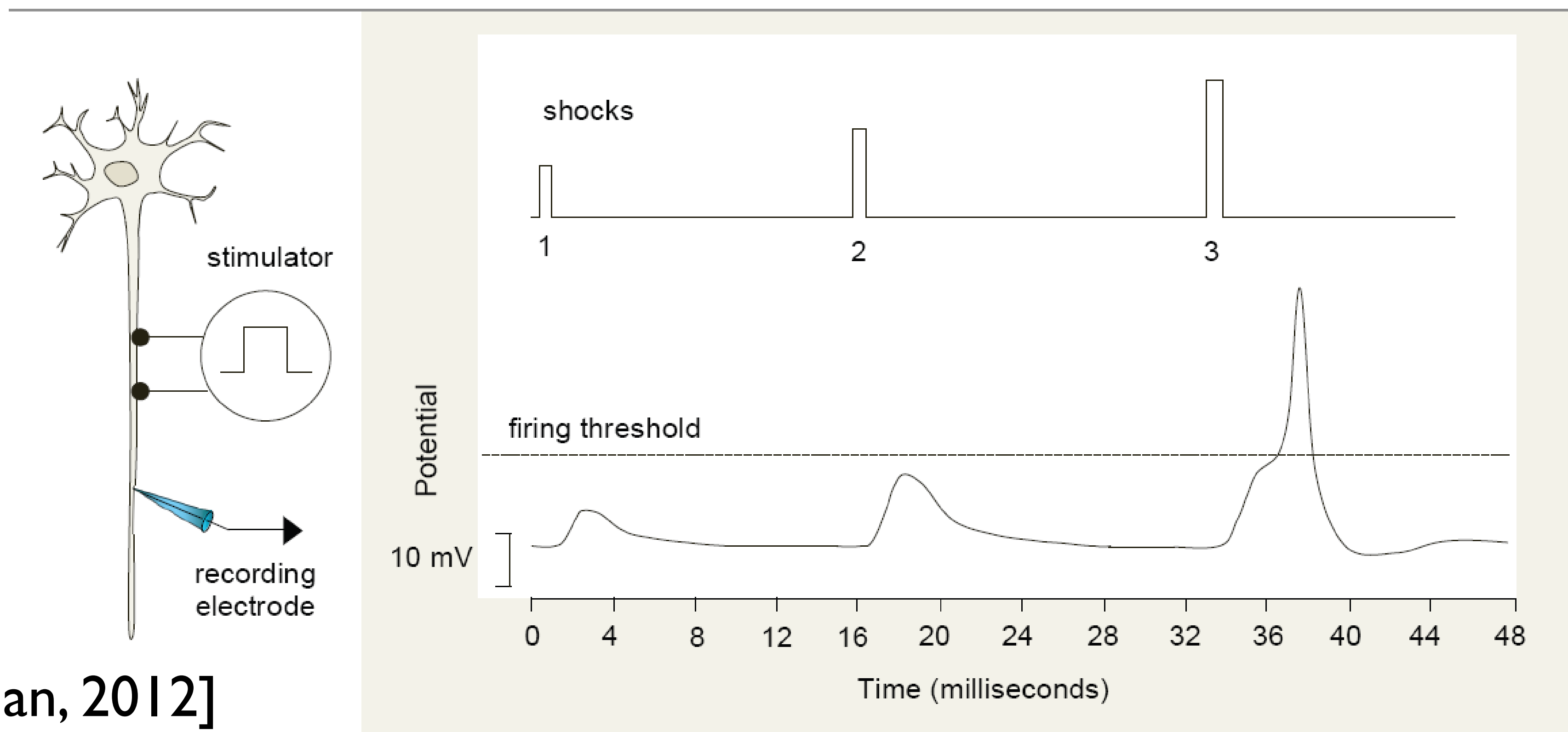
- Neuro-physics
  - $\tau \dot{u} = -u + h + \text{inputs}$ ~integrate and fire…
  - spiking mechanism replaced by the sigmoid threshold function in population picture
- attractor dynamics
  - $-u$ term is the source of the stability of neural states
- this dynamics as a low-pass filter of input

Neuro-physics

- membrane potential, $u(t)$, evolves as a dynamical system

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

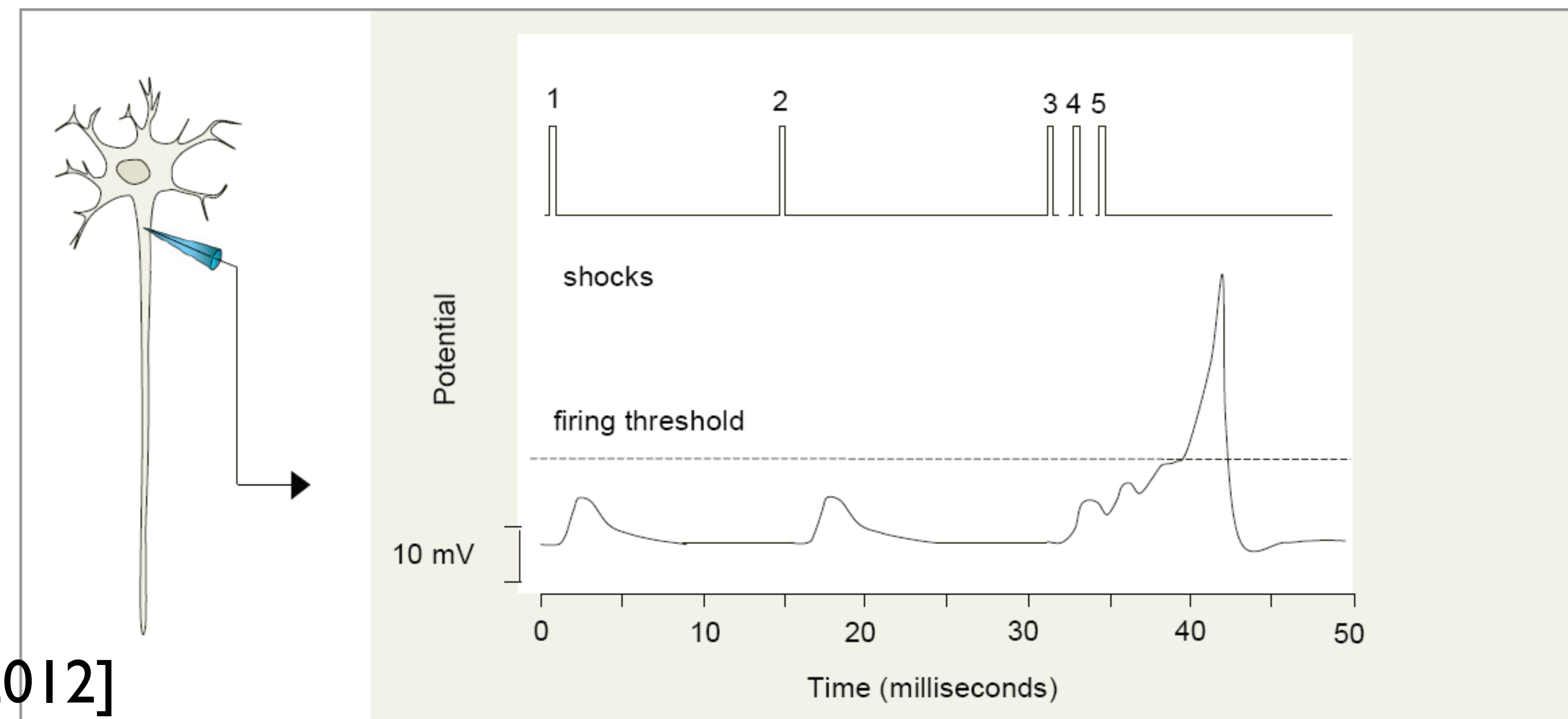
- time scale, $\tau \approx 10$ ms



[from: Tresilian, 2012]

Neuro-physics

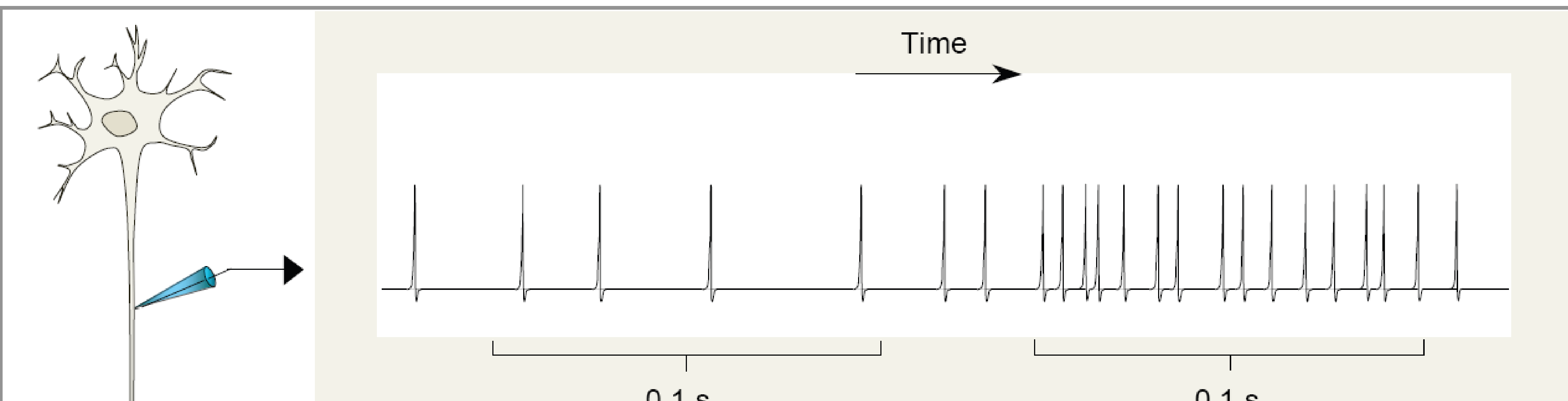
- spikes when membrane potential exceeds threshold…. and only spikes are transmitted to downstream neurons



[from: Tresilian, 2012]

Neuro-physics

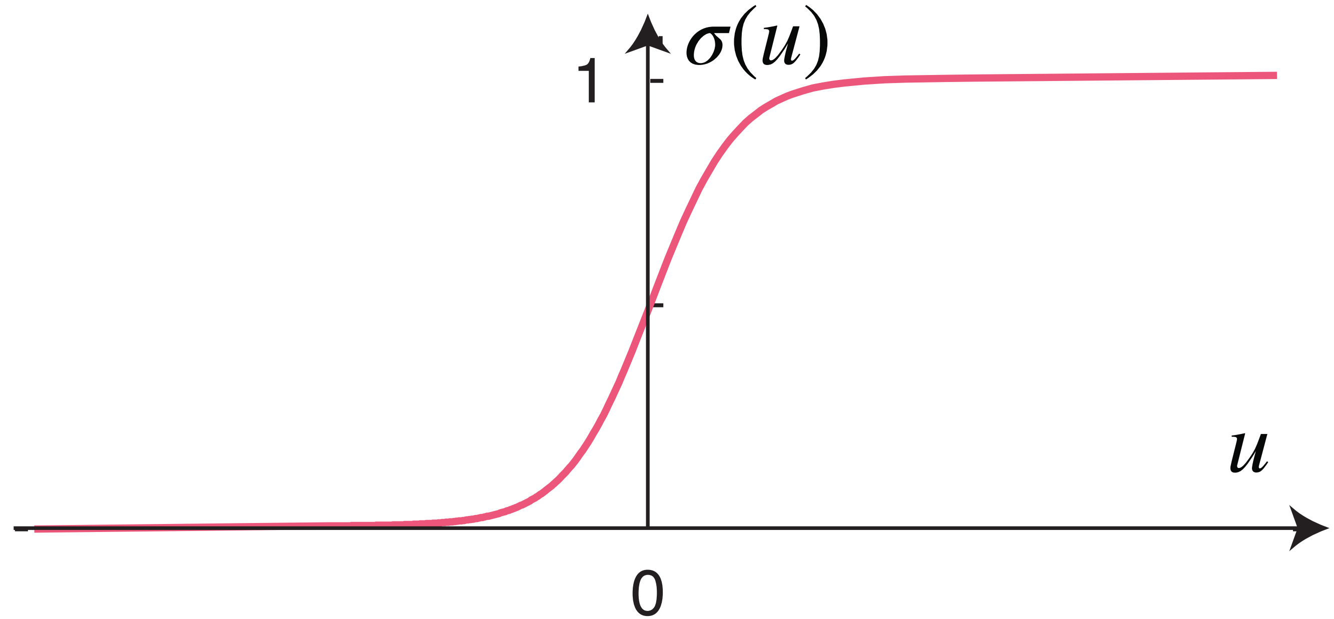
- firing rate reflects level of input…



[from: Tresilian, 2012]

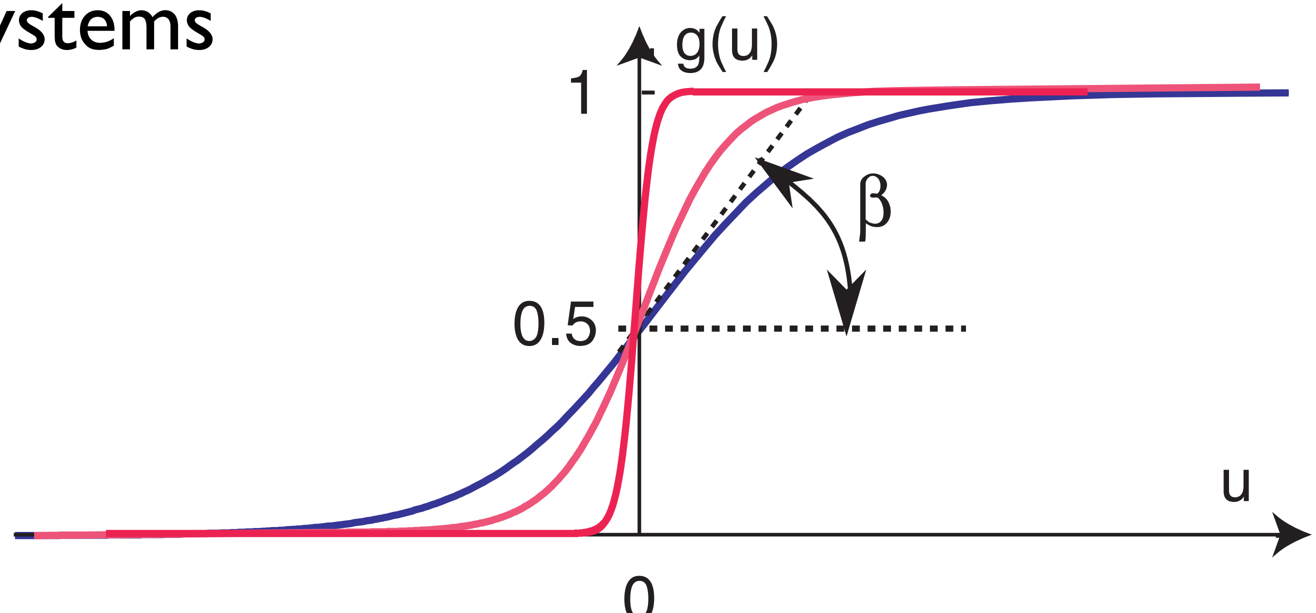
Neural dynamics

- spiking mechanism replaced by a threshold function
- that captures the effective transmission of spikes in populations



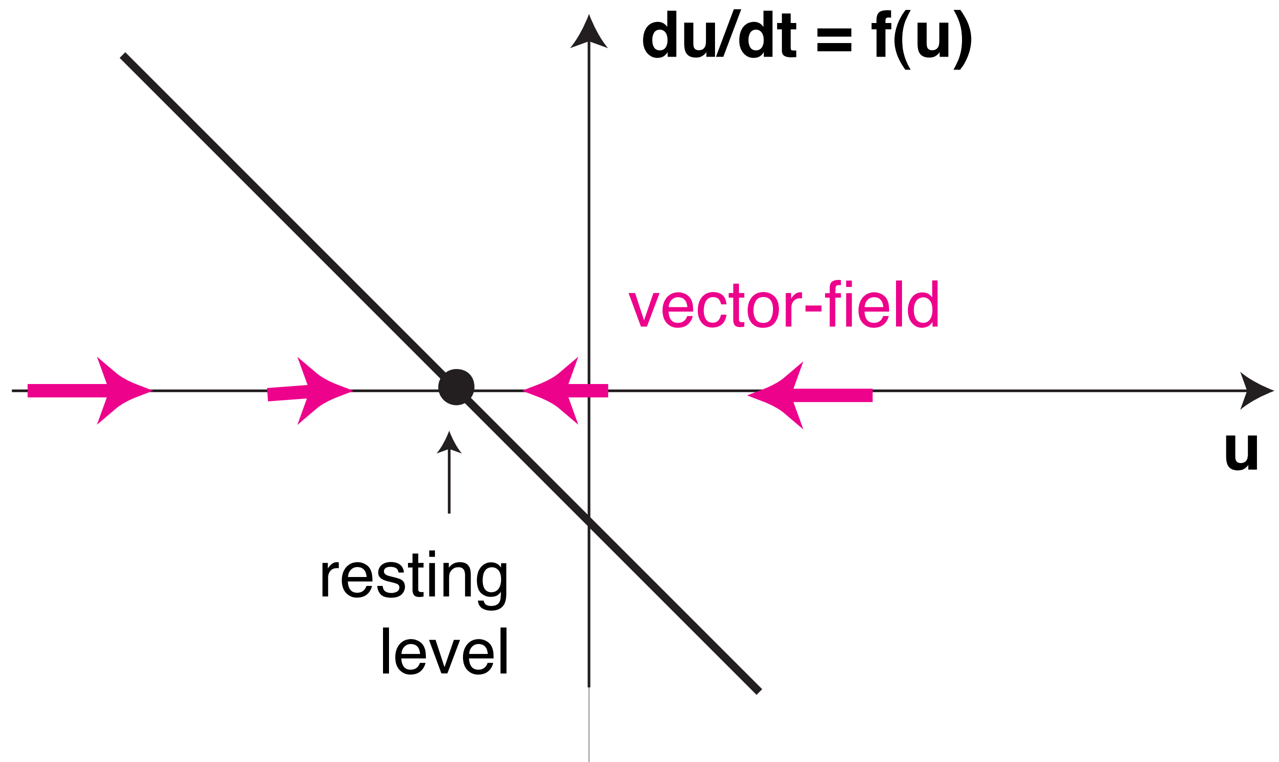
Neural dynamics

- activation as a real number with threshold at zero, abstracting from biophysical details ~ population level membrane potential
- low levels of activation: not transmitted to downstream systems (including motor systems)
- high levels of activation: transmitted to downstream systems



Neural dynamics

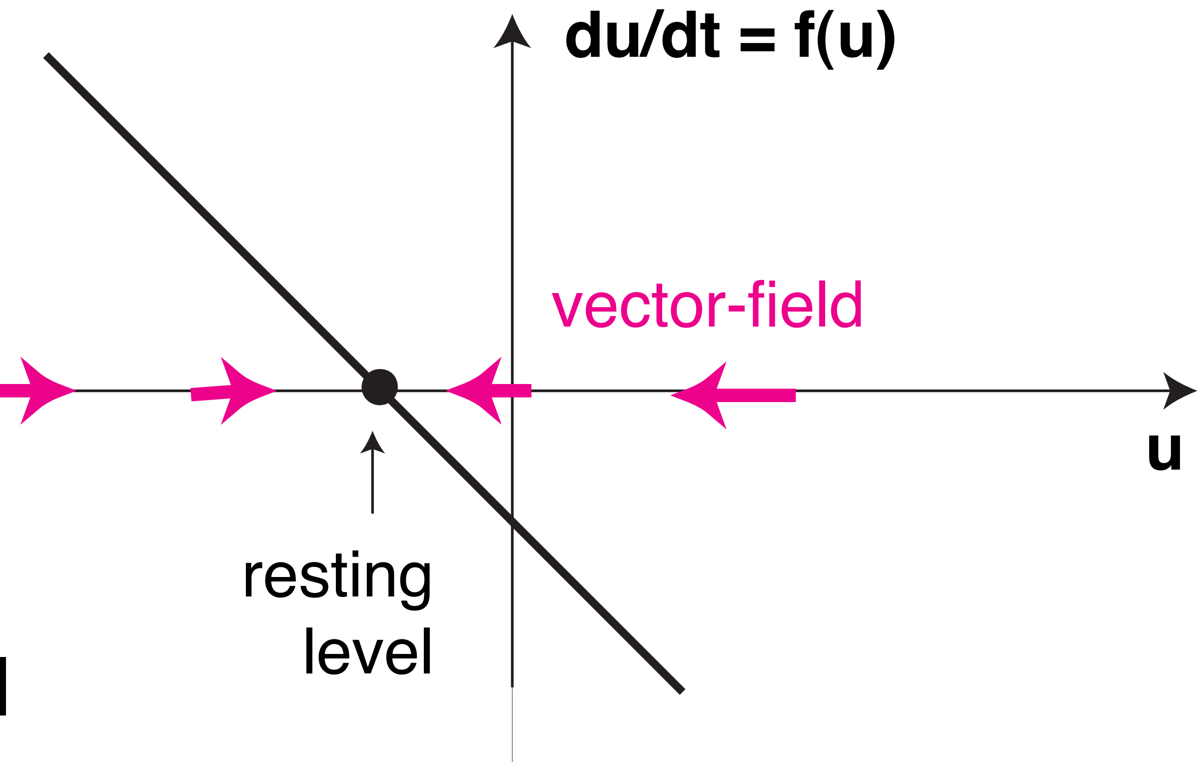
- dynamical system: the present state predicts the future evolution of the state
- => given an initial level of activation, $u(0)$, the time course of activation, $u(t)$, for $t > 0$ is uniquely determined



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

Neural dynamics

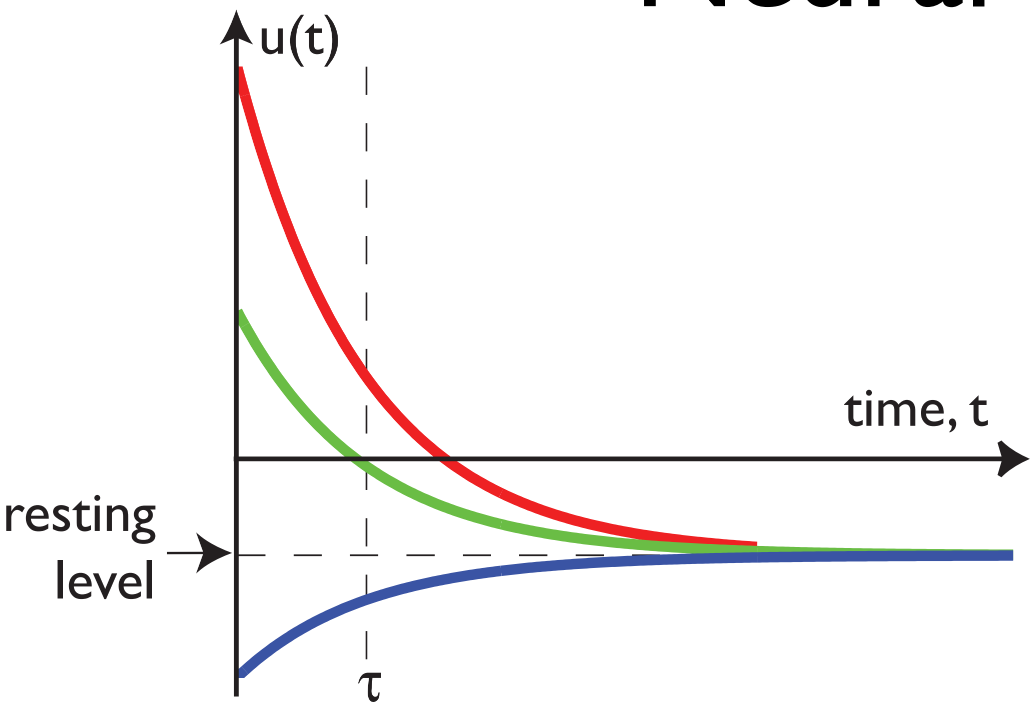
- fixed point = constant solution (stationary state)
- stable fixed point = attractor: nearby solutions converge to the fixed point



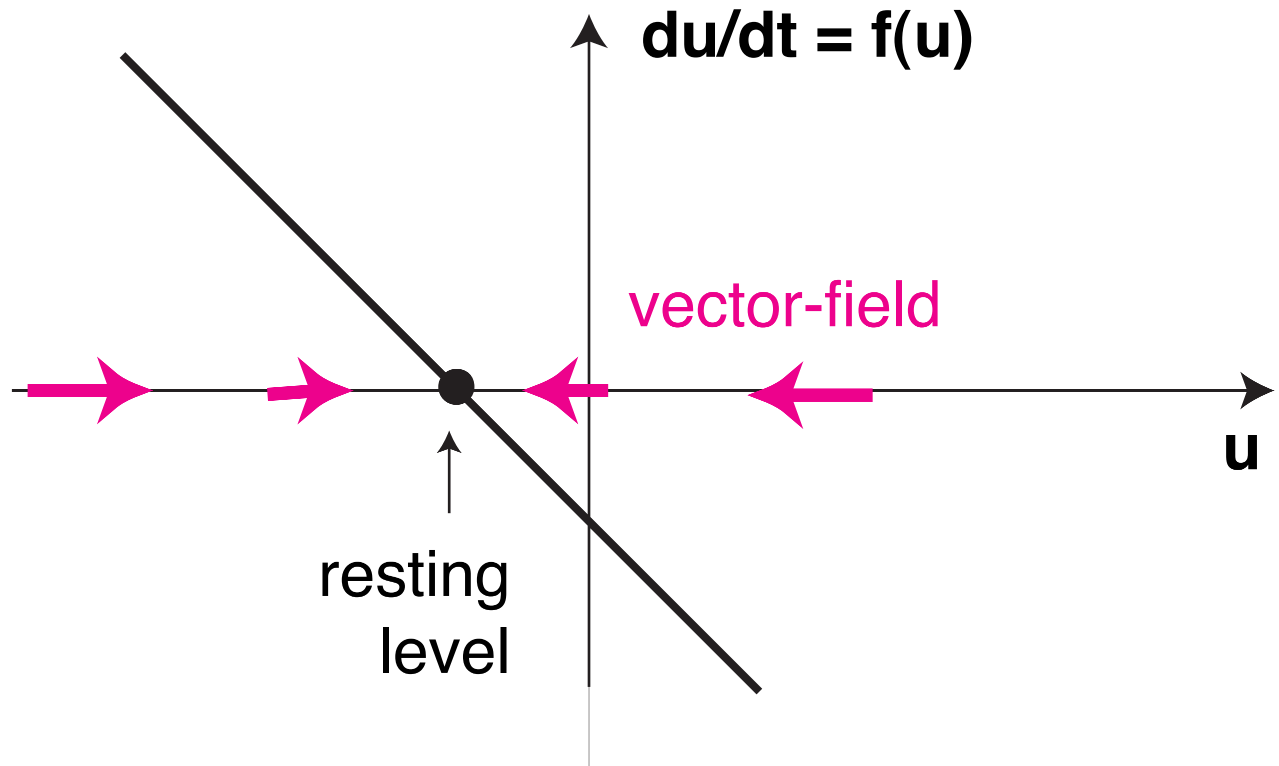
$$\tau \dot{u}_{\mathrm{fp}} = -u_{\mathrm{fp}} + h = 0$$

$\Rightarrow u_{\mathrm{fp}} = h$ resting level

Neural dynamics



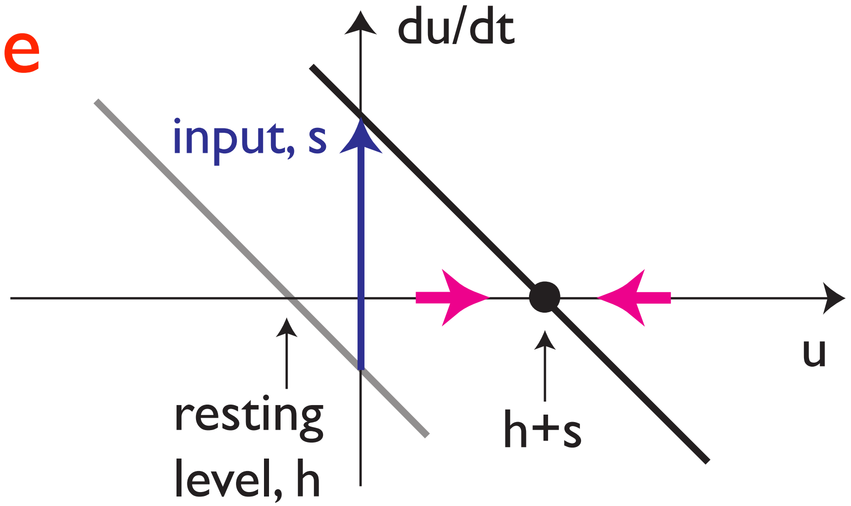
- attractors structure the ensemble of solutions (from all initial conditions) = flow



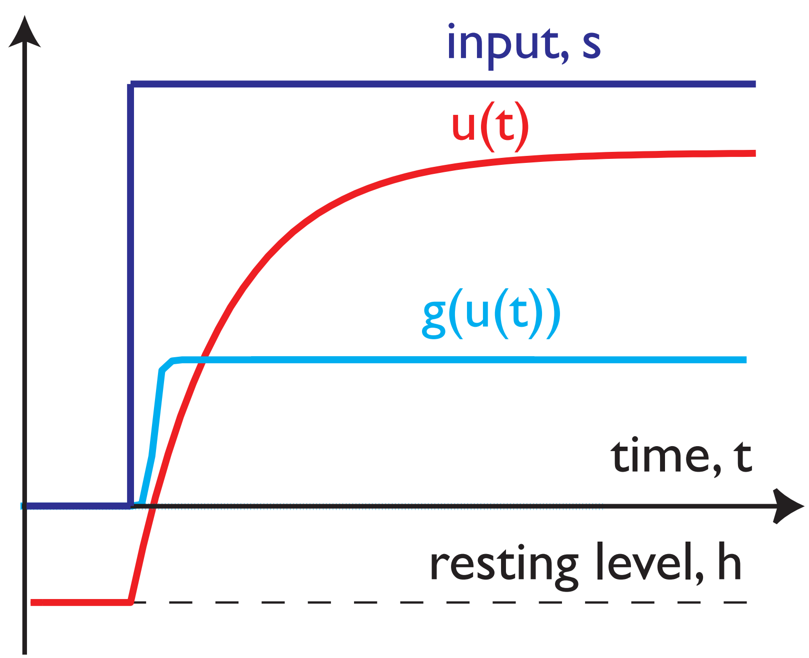
$$\tau \dot{u}(t) = -u(t) + h$$

Neuronal dynamics

- inputs are contributions to the rate of change of activation
  - positive: excitatory
  - negative: inhibitory



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



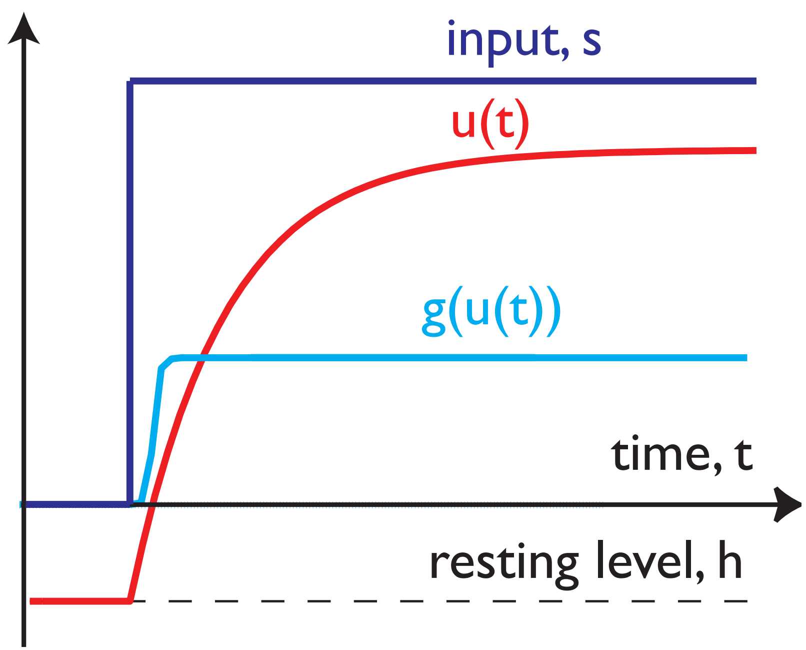
- => input shifts the attractor
- => activation tracks this shift due to stability

Neuronal dynamics

- transmitted to down-stream neurons/motor systems: $\sigma(u(t))$
- [we use $\sigma(u)$ and $g(u)$ interchangeably in some papers/the DFT book]

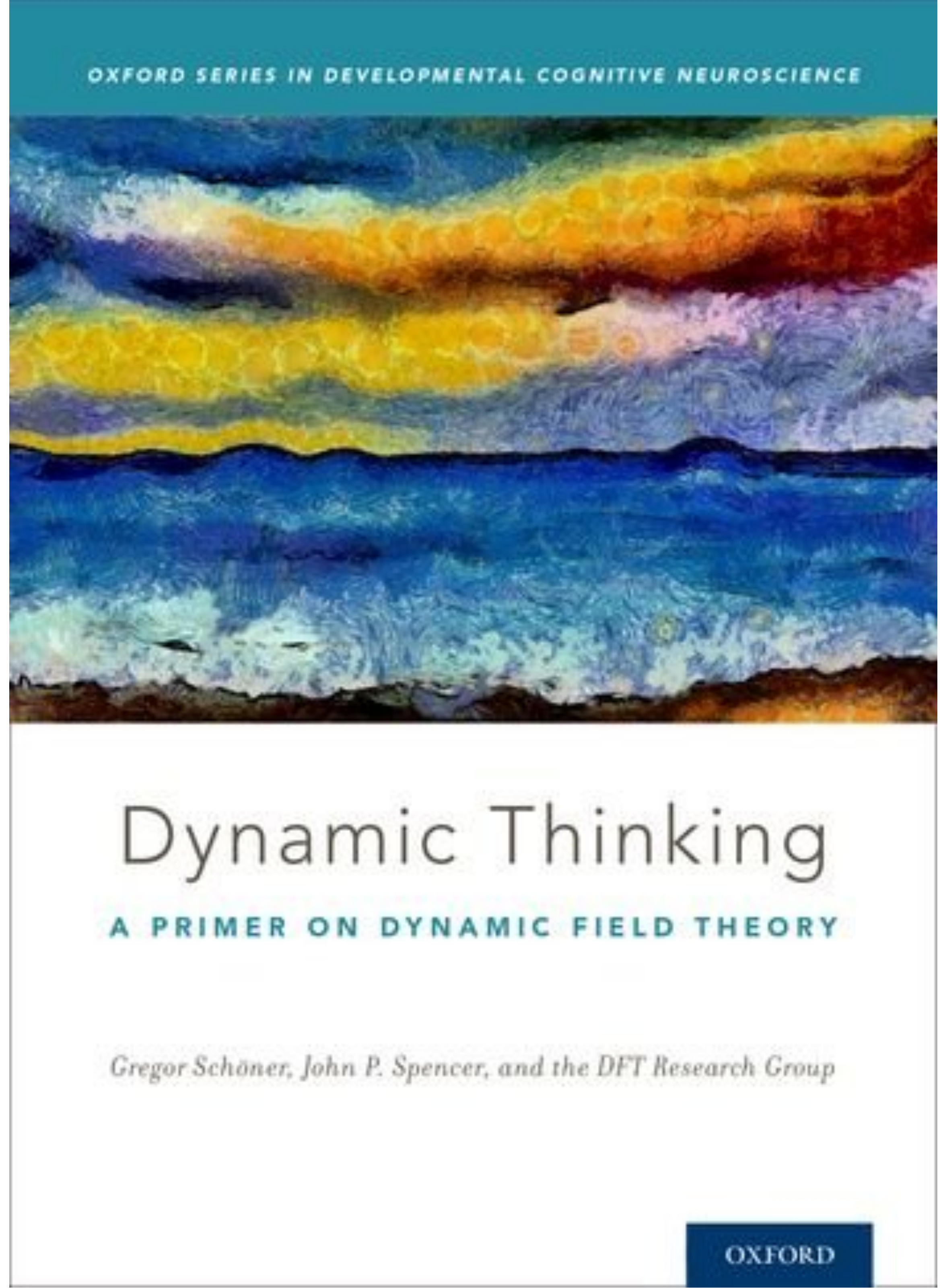
- => the "input-driven solution" of the neural dynamics low-pass filters time varying input

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



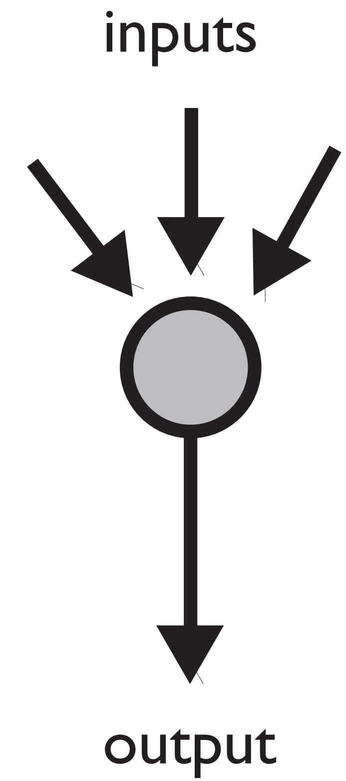
=> simulation

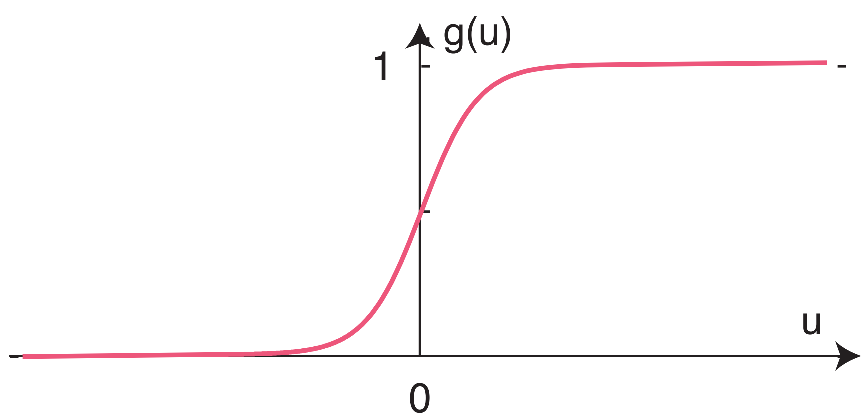
- dynamicfieldtheory.org



Connectionism: similar abstraction

- neurons sum input activations and pass them through a sigmoidal threshold function
- some connectionist models neglect the low-pass filtering/ time delaying properties of the neural membrane dynamics





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

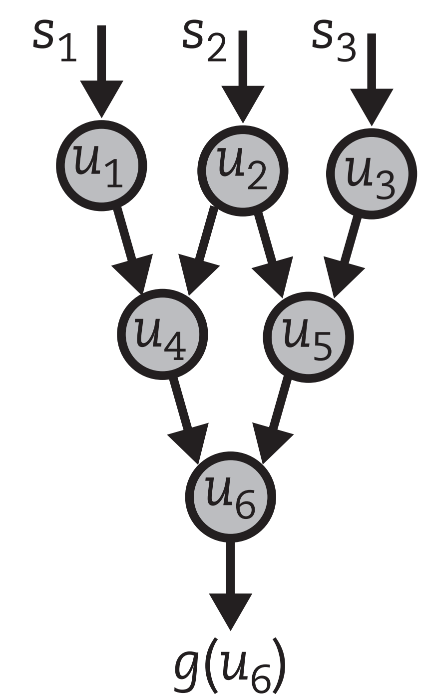
Roadmap

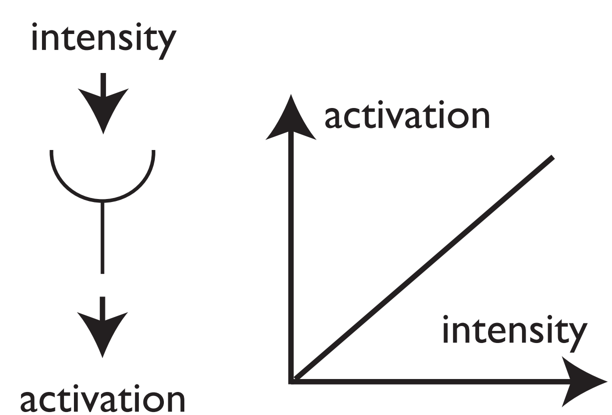
Neural field

- defined by pattern of forward connectivity to sensory/motor surfaces
  - as described by tuning curves/receptive fields
  - analogous to forward NN …
- neglect sampling by discrete neurons => neural fields
- notion of feature spaces that are represented in neural fields

Neural dynamic networks

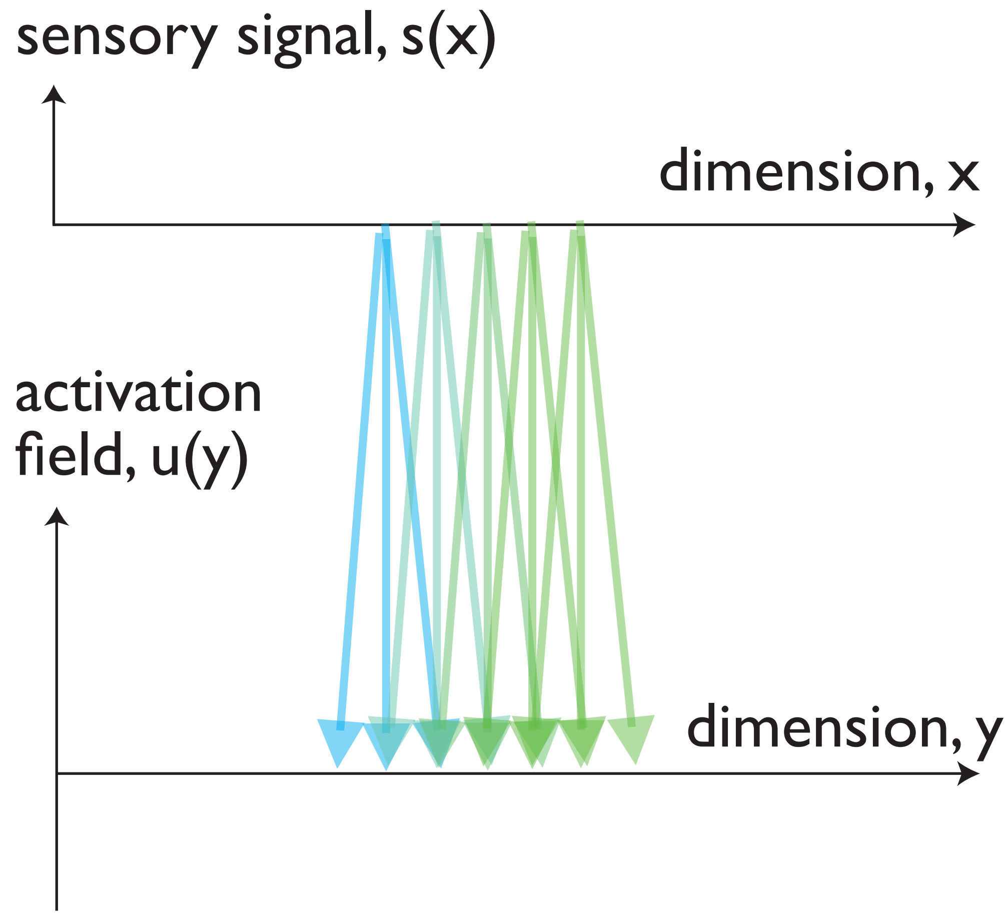
- in networks neural activation variables, the forward connectivity determines "what a neuron stands for"
- = space code (or labelled line code)
- in rate code, the activation level "stands for" something, e.g. a sensed intensity
- generic neural networks combine both codes





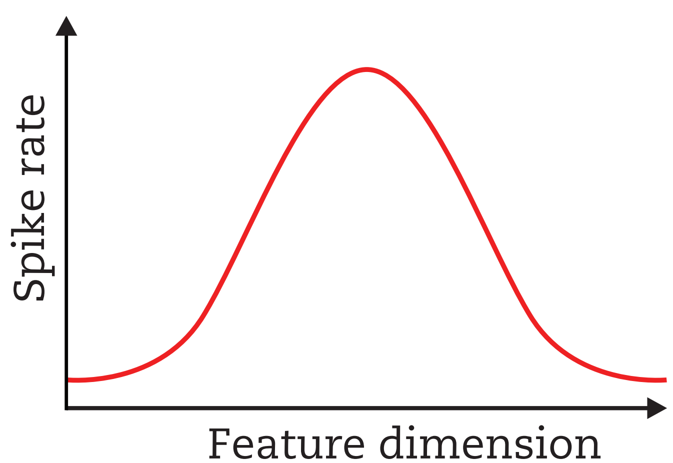
Neural fields

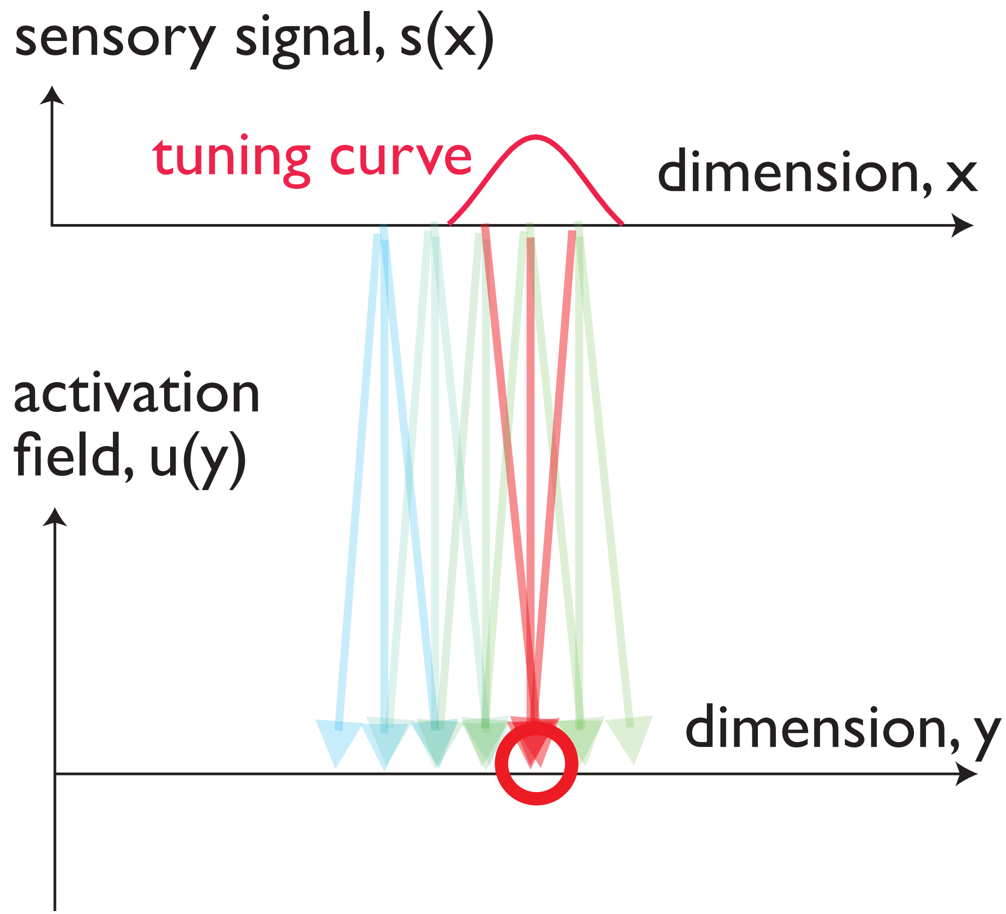
- forward connectivity from the sensory surface extracts perceptual feature dimension



Neural fields

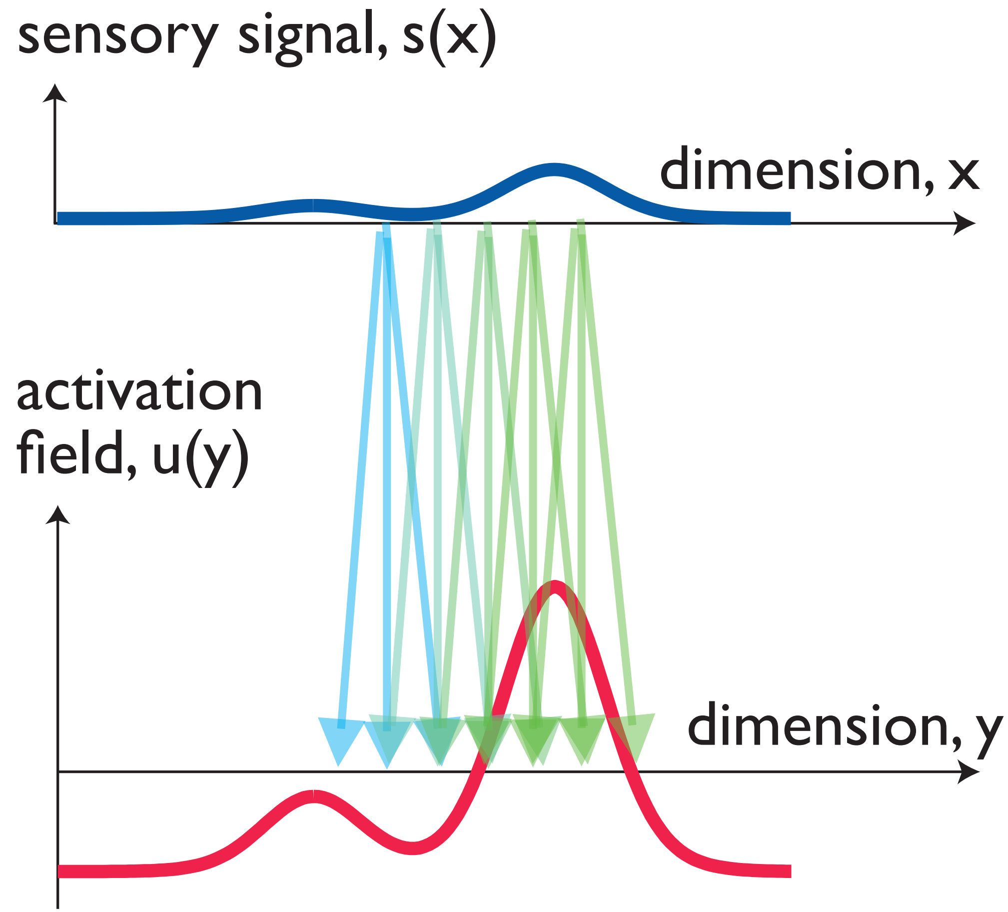
- forward connectivity predicts/models tuning curves





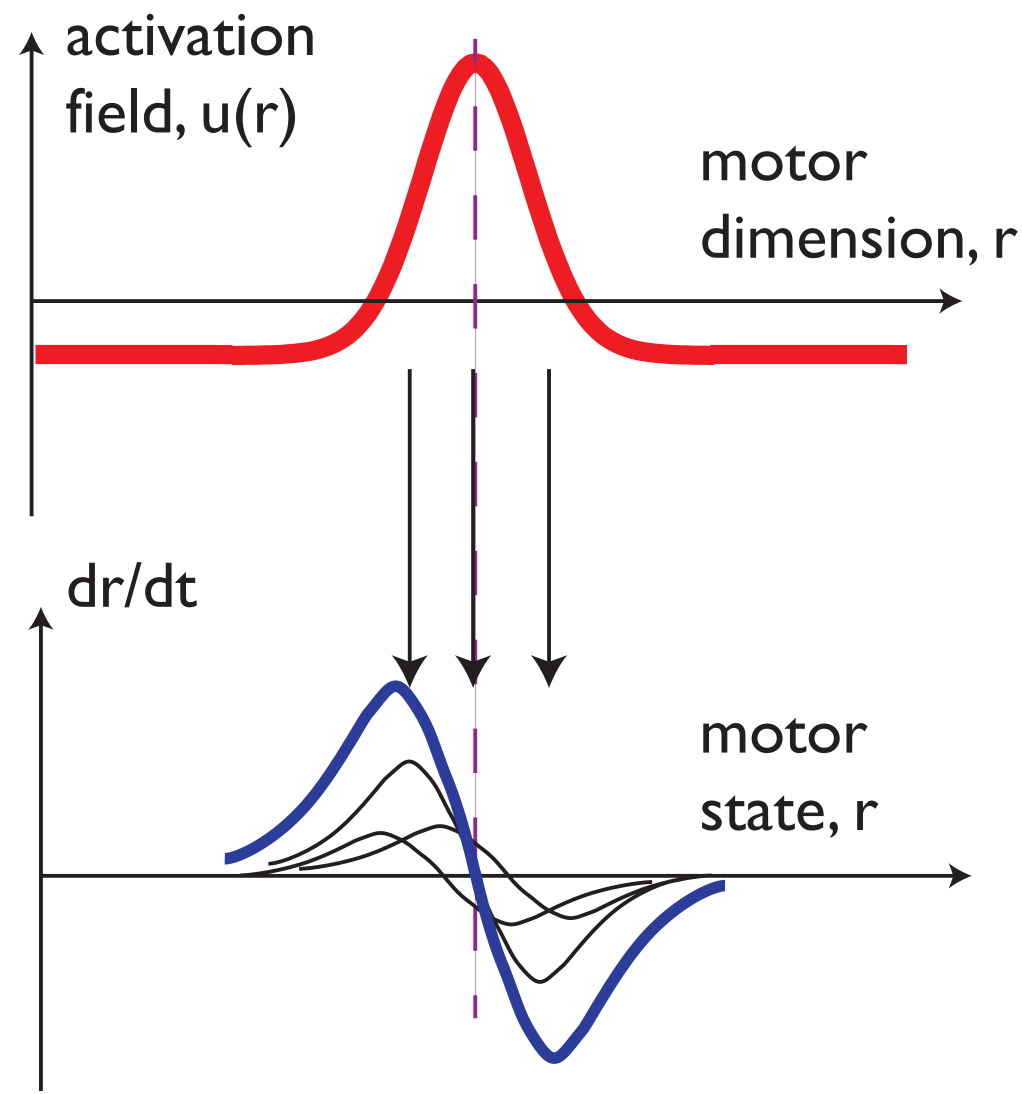
Neural fields

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



Neural fields

- analogous notion for forward connectivity to motor surfaces…
- (actually involves behavioral dynamics)
  - (e.g., through neural oscillators and peripheral reflex loops)

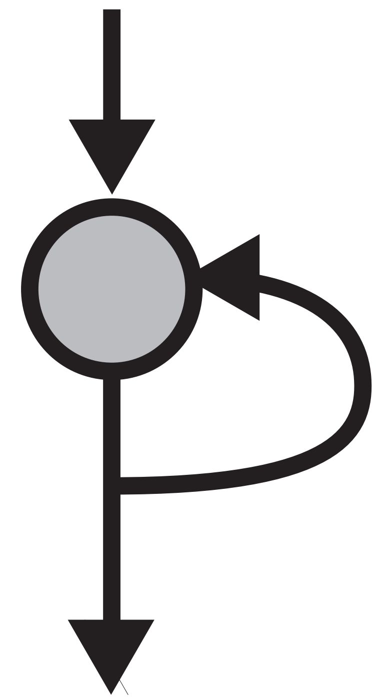


Neural dynamics: state

- neural activation that is not entirely determined by input…but depends on the activation state
- this originates from recurrent connectivity (“interaction” or “coupling”) that is organized to keep activation states stable
- detection instability
- selection/competition
- => dynamic regimes/instabilities

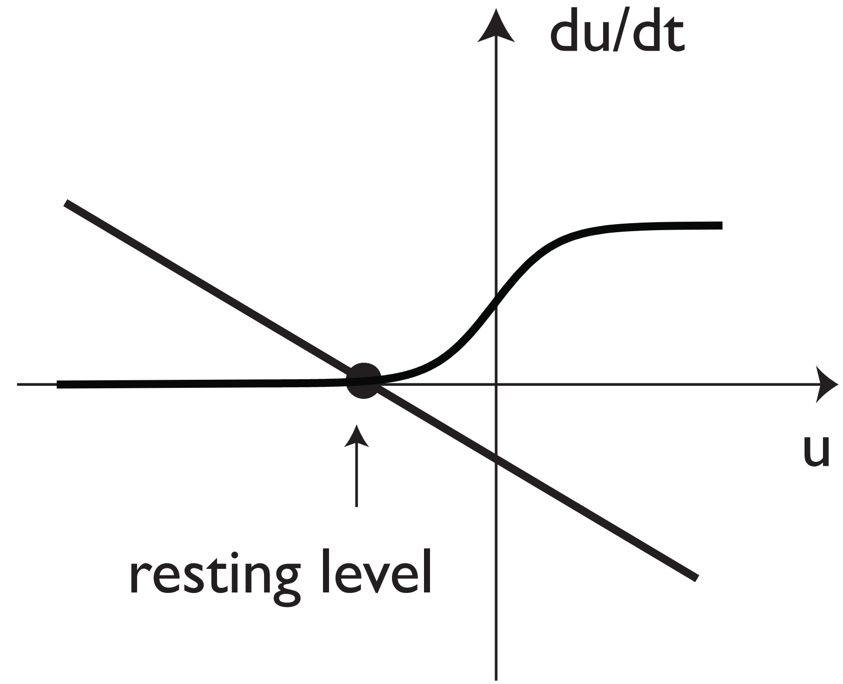
Neuronal dynamics with self-excitation

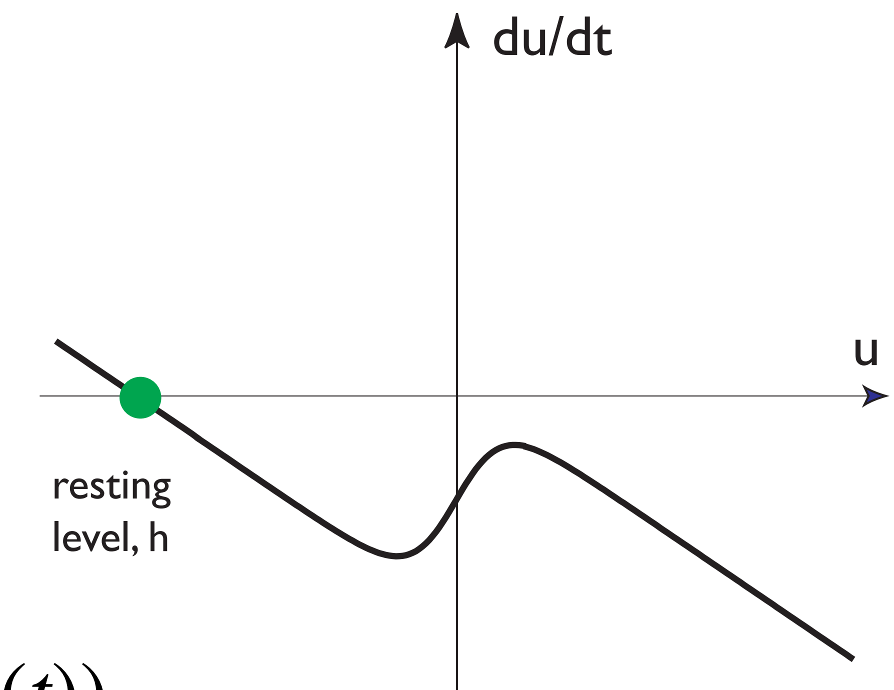
- single activation variable with self-excitation
- (representing a small population with excitatory coupling)



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

Neuronal dynamics with self-excitation



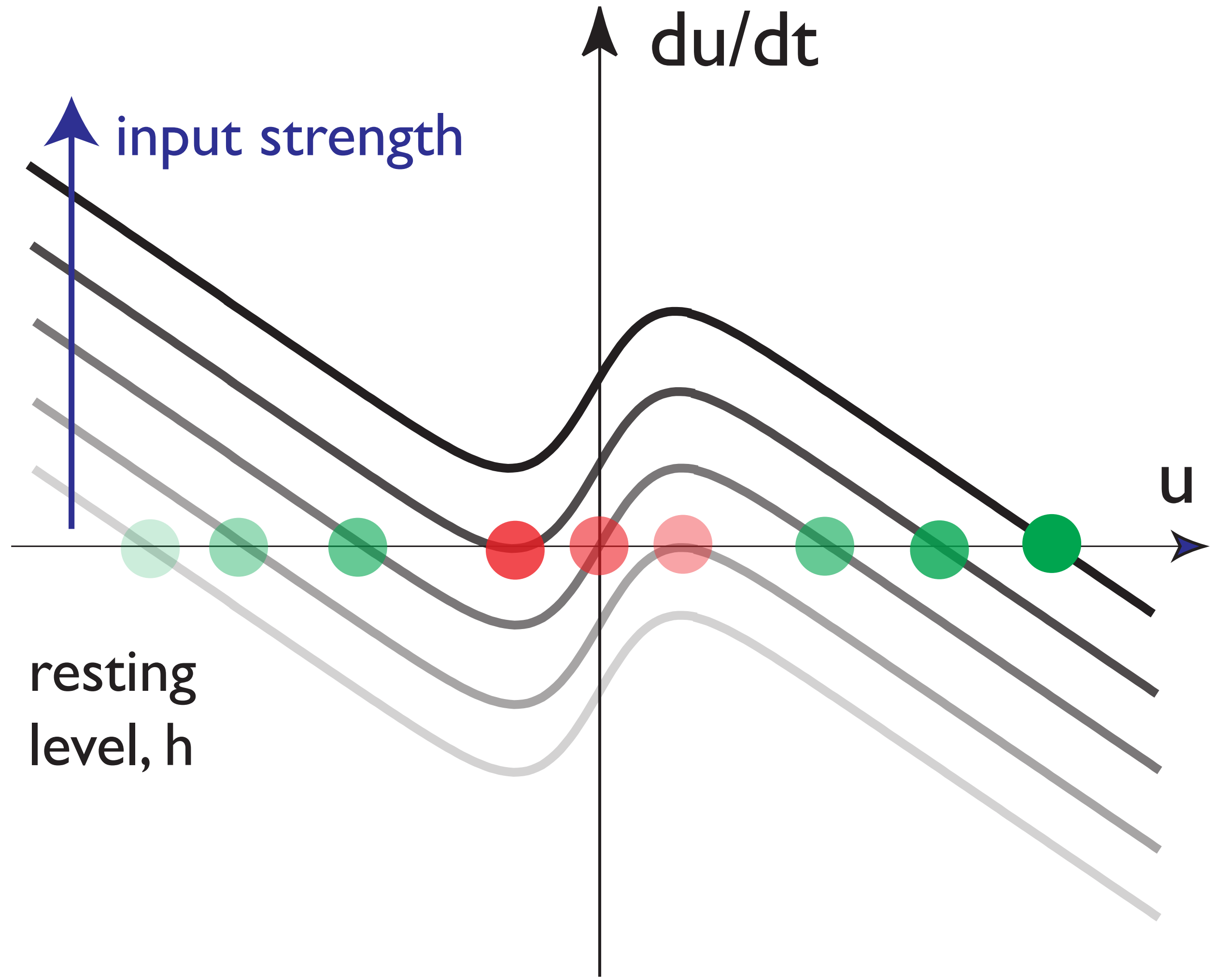


- => nonlinear dynamics!

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

Neuronal dynamics with self-excitation

varying input



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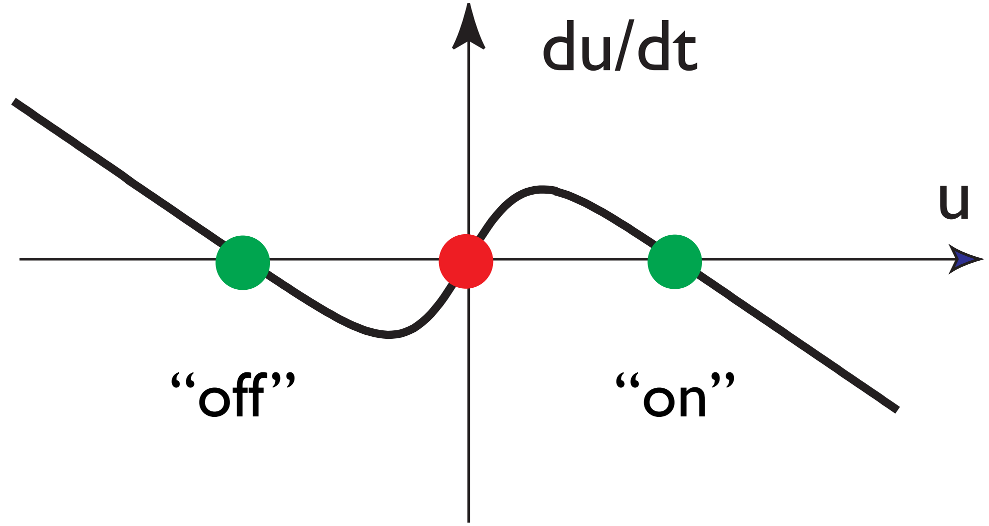
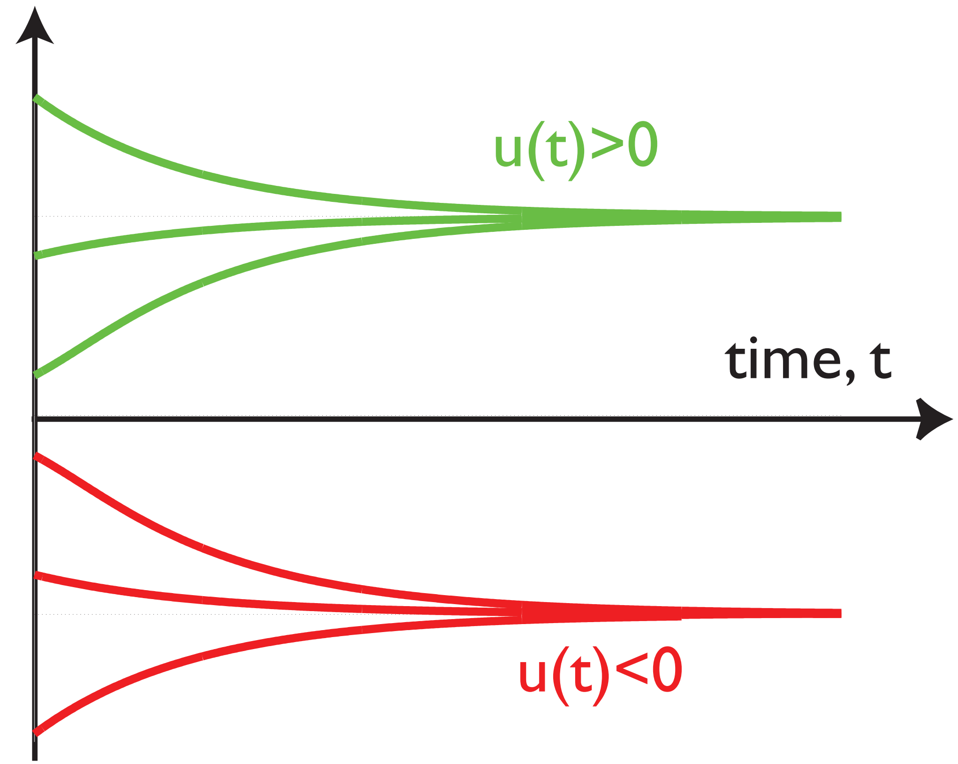
Neuronal dynamics with self-excitation



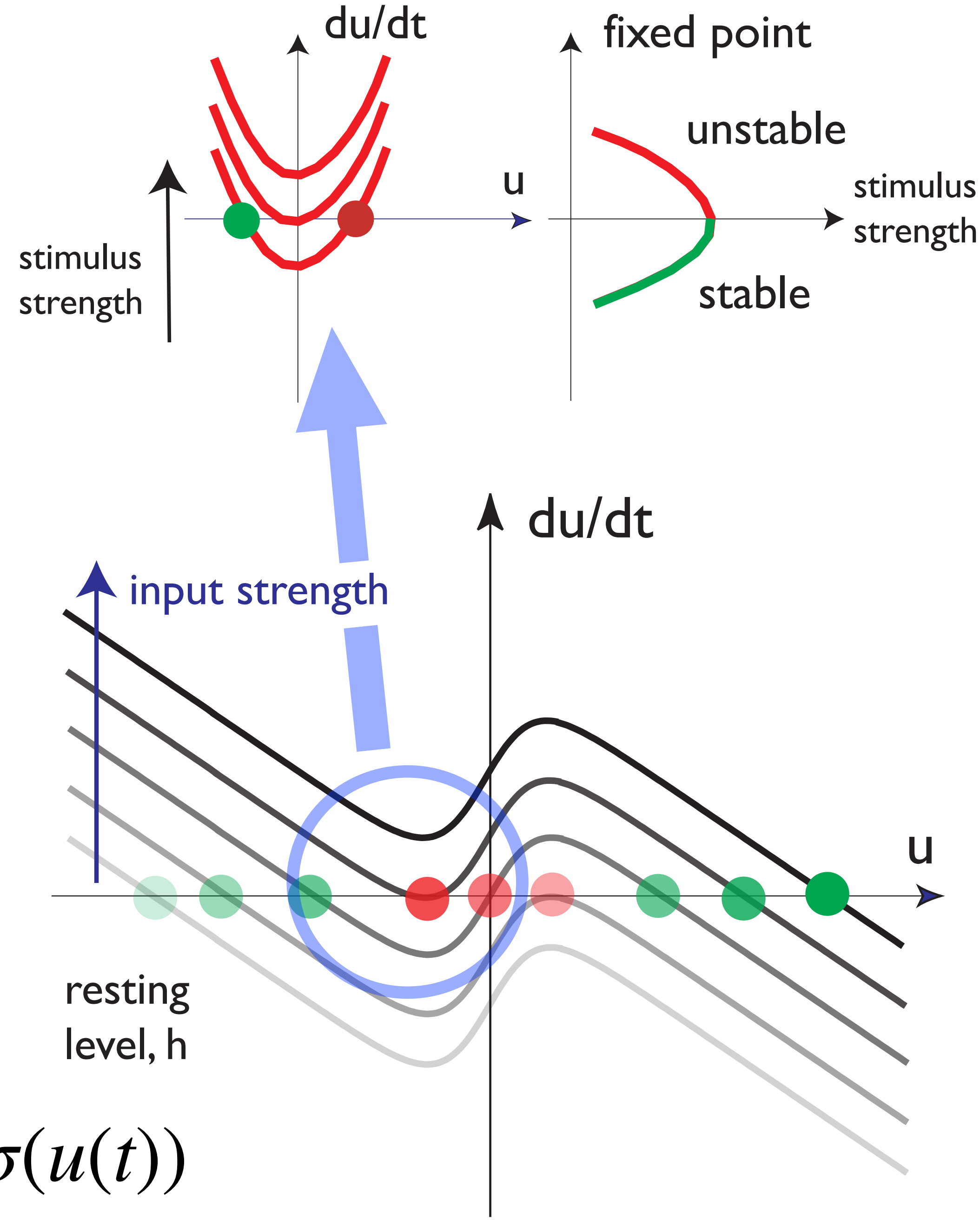


- for some inputs: bistable dynamics
- “on” vs “off” state

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

Neuronal dynamics with self-excitation

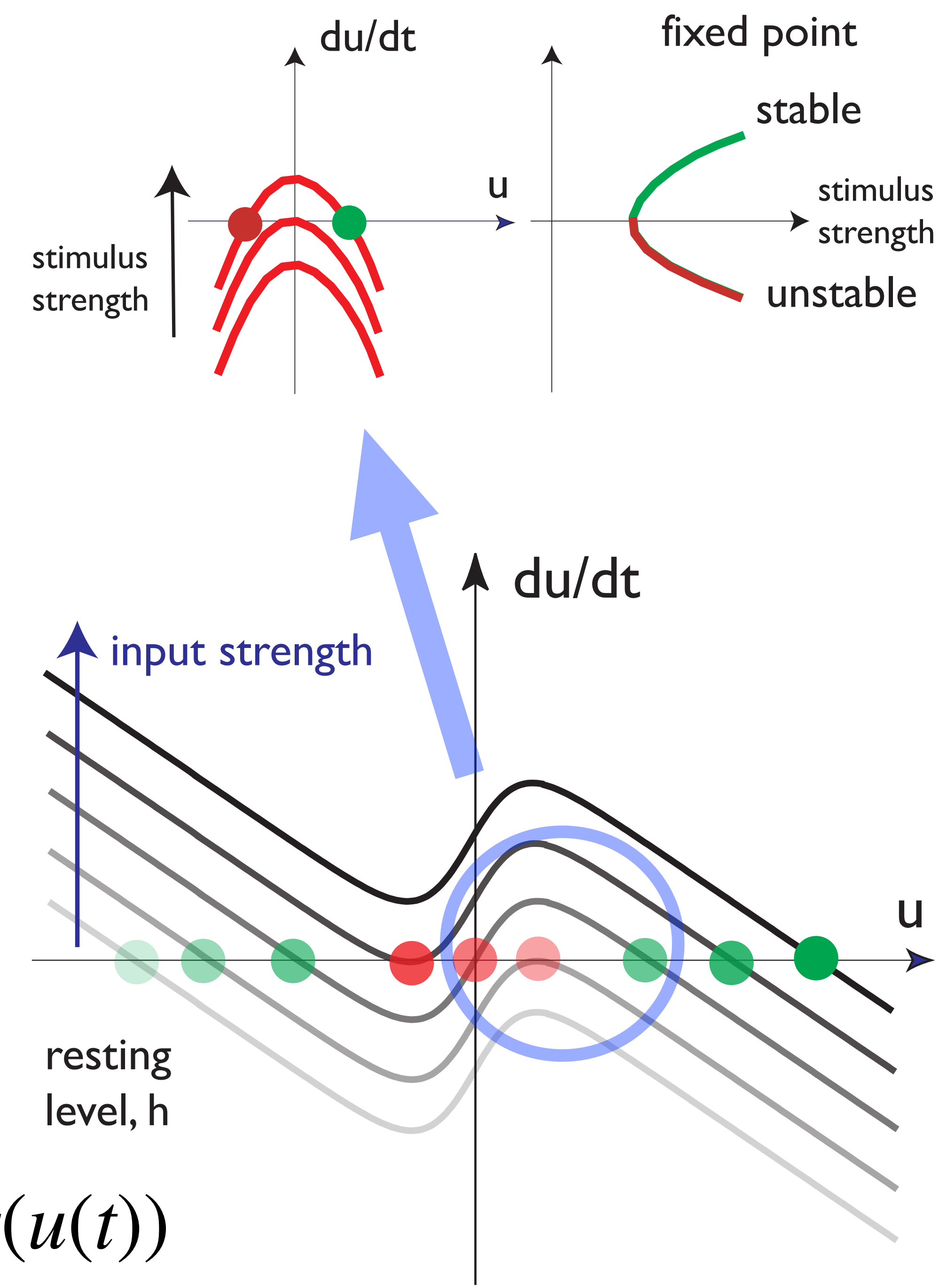
- increasing input strength => detection instability



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

Neuronal dynamics with self-excitation

- decreasing input strength => reverse detection instability



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

=> simulation

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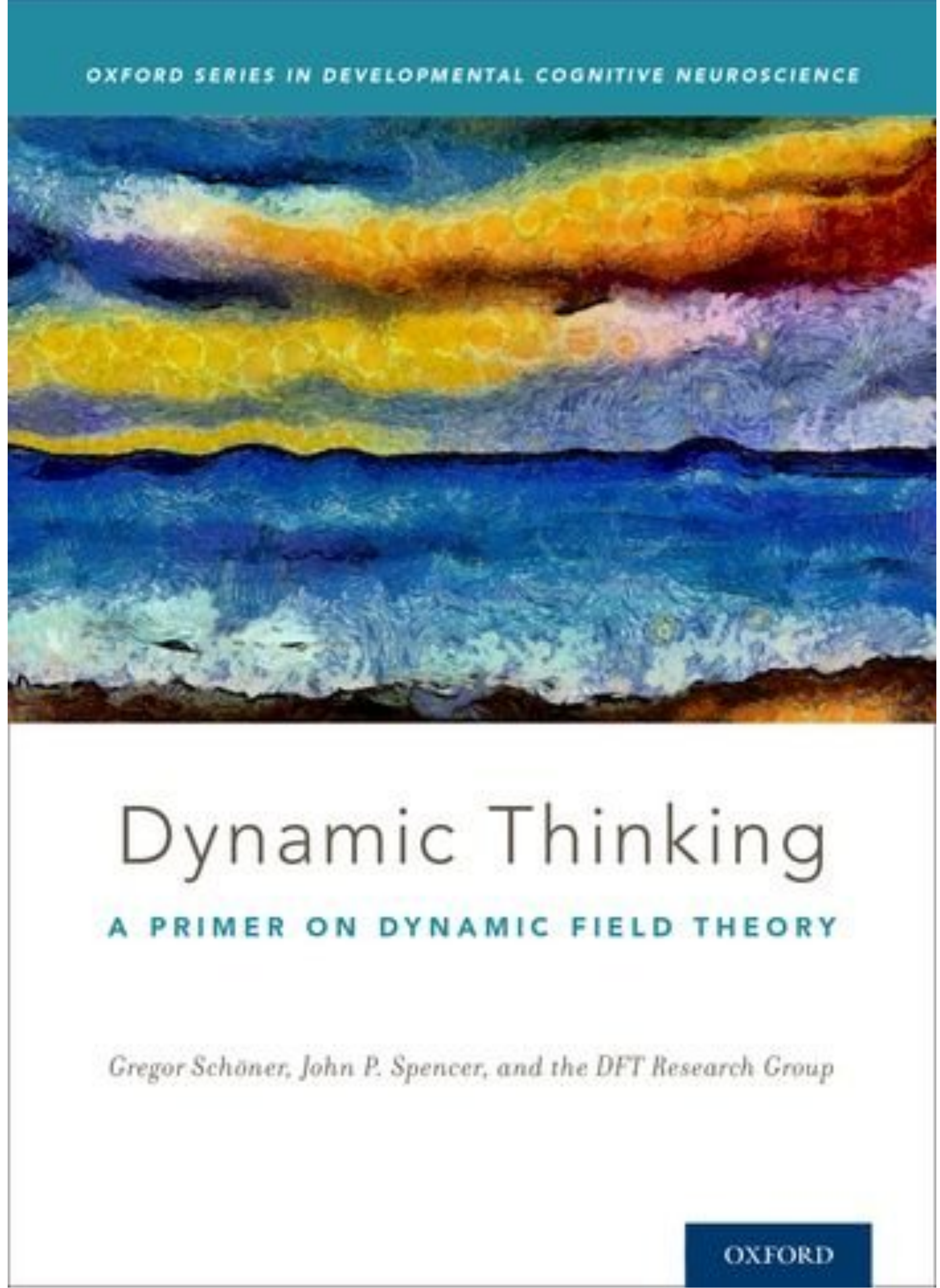
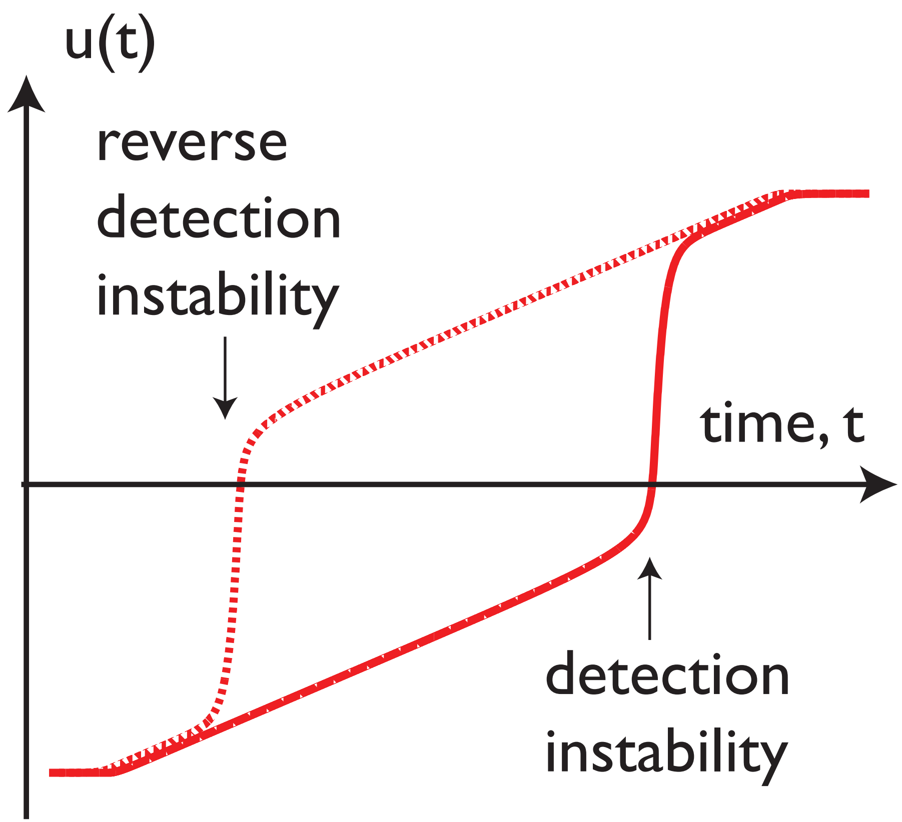


Neuronal dynamics with self-excitation

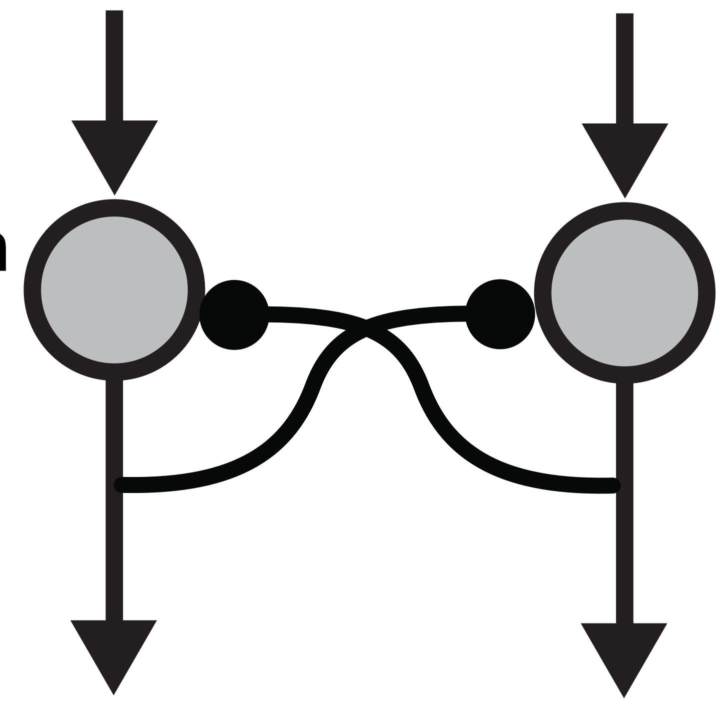
- the detection and its reverse => create discrete events from time-continuous changes



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

Neuronal dynamics with competition

- two activation variables with reciprocal inhibitory connection
- (representing two small populations with inhibitory connections)

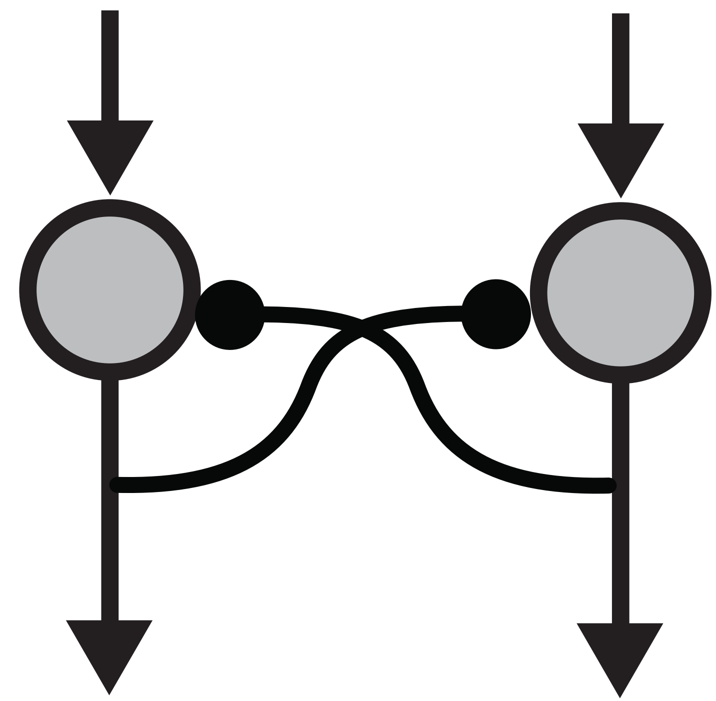


$$\tau \dot{u}_1(t) = -u_1(t) + h + s_1(t) - c_{12}\sigma(u_2(t))$$

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

Neuronal dynamics with competition

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



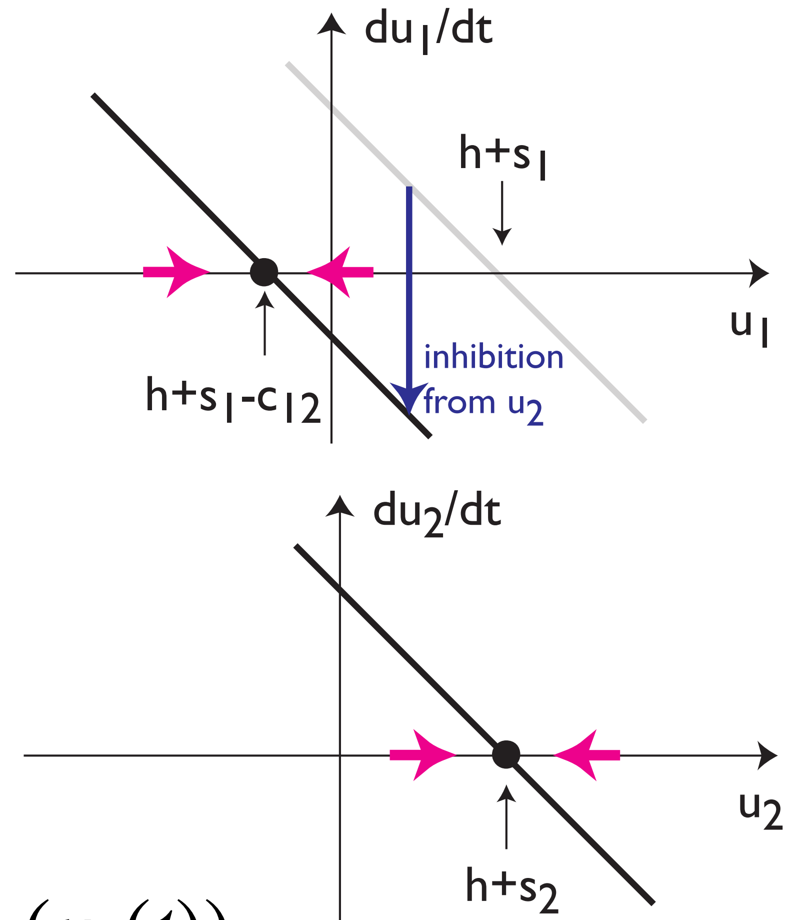
coupling/interaction

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

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

Neuronal dynamics with competition

- assume $u_2 > 0$ => u_2 inhibits u_1
- => attractor for $u_1 < 0$
- => u_1 does not inhibit u_2



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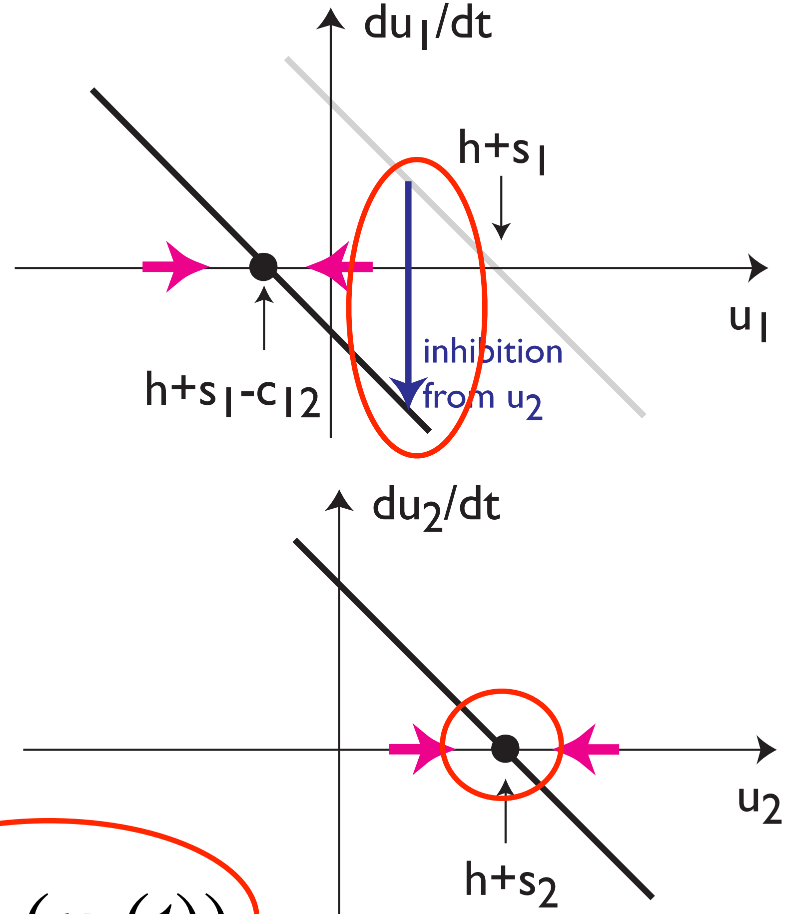

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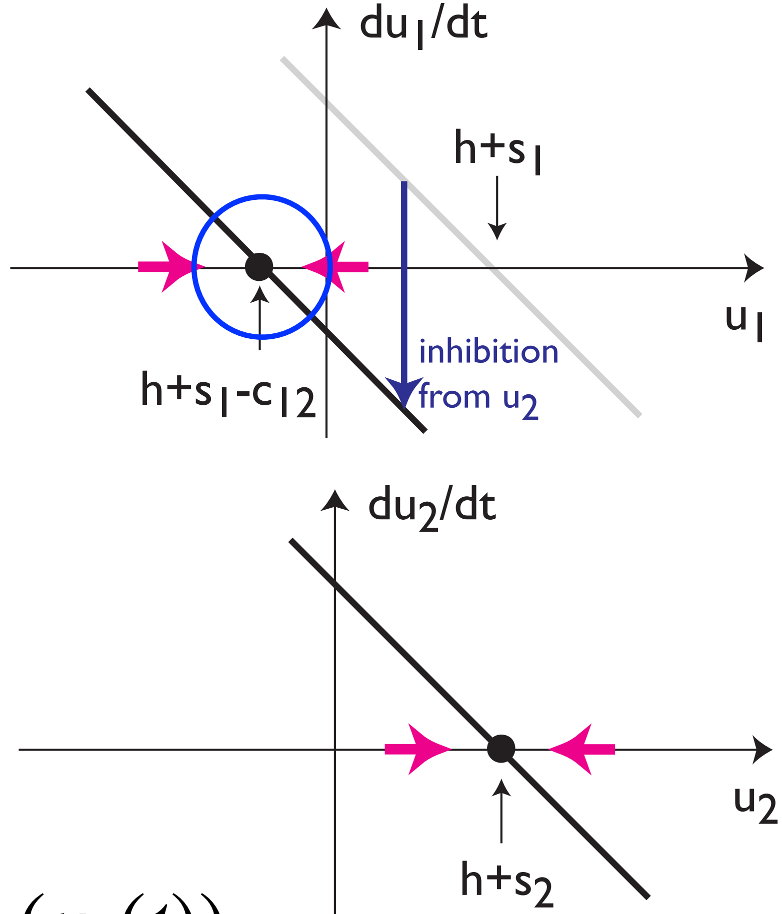

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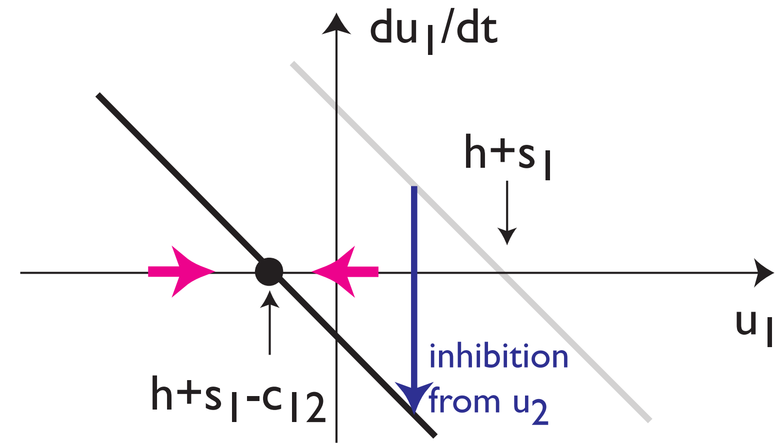

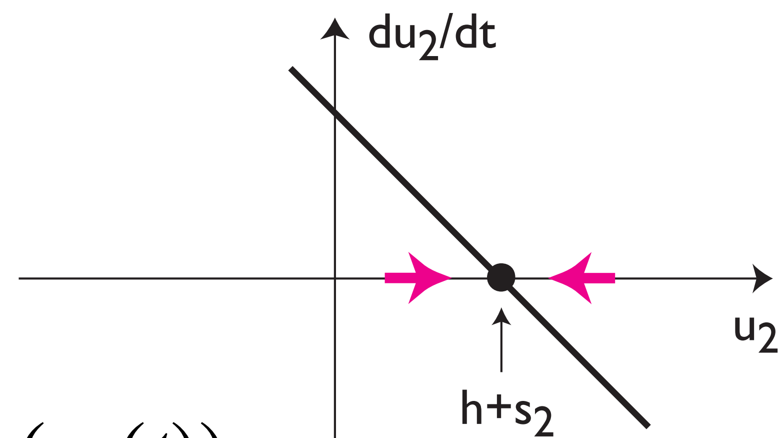

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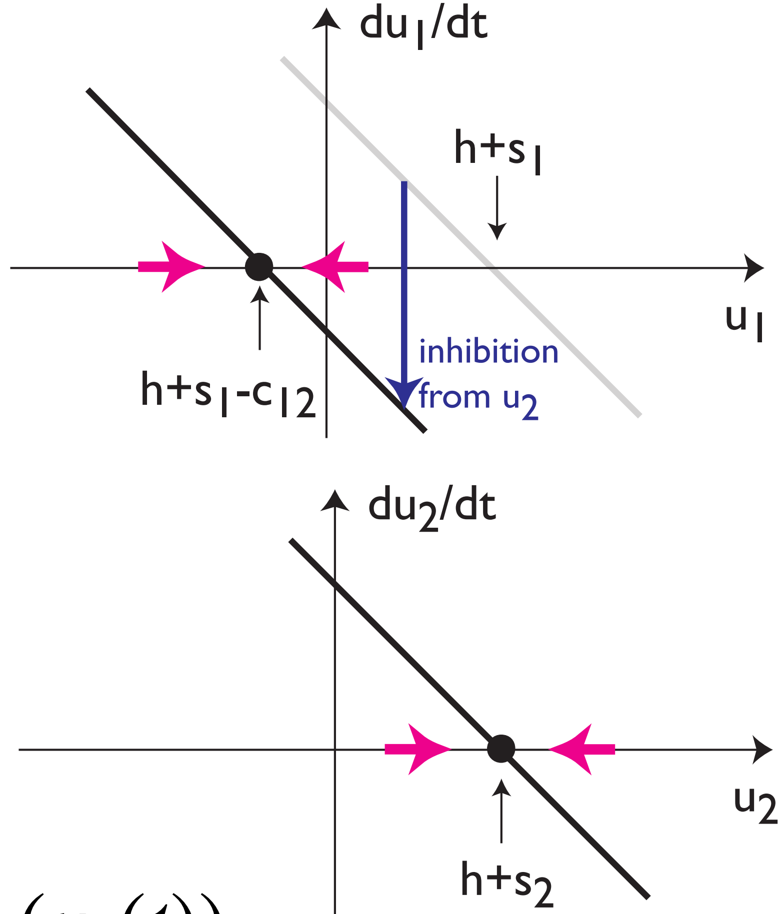
$$\tau \dot{u}_2(t) = -u_2(t) + h + s_2(t) - c_{21}\sigma(u_1(t))$$

Neuronal dynamics with competition

- $u_2 > 0$ and $u_1 < 0$
- symmetry: $u_2 < 0$ and $u_1 > 0$
- => competition/selection



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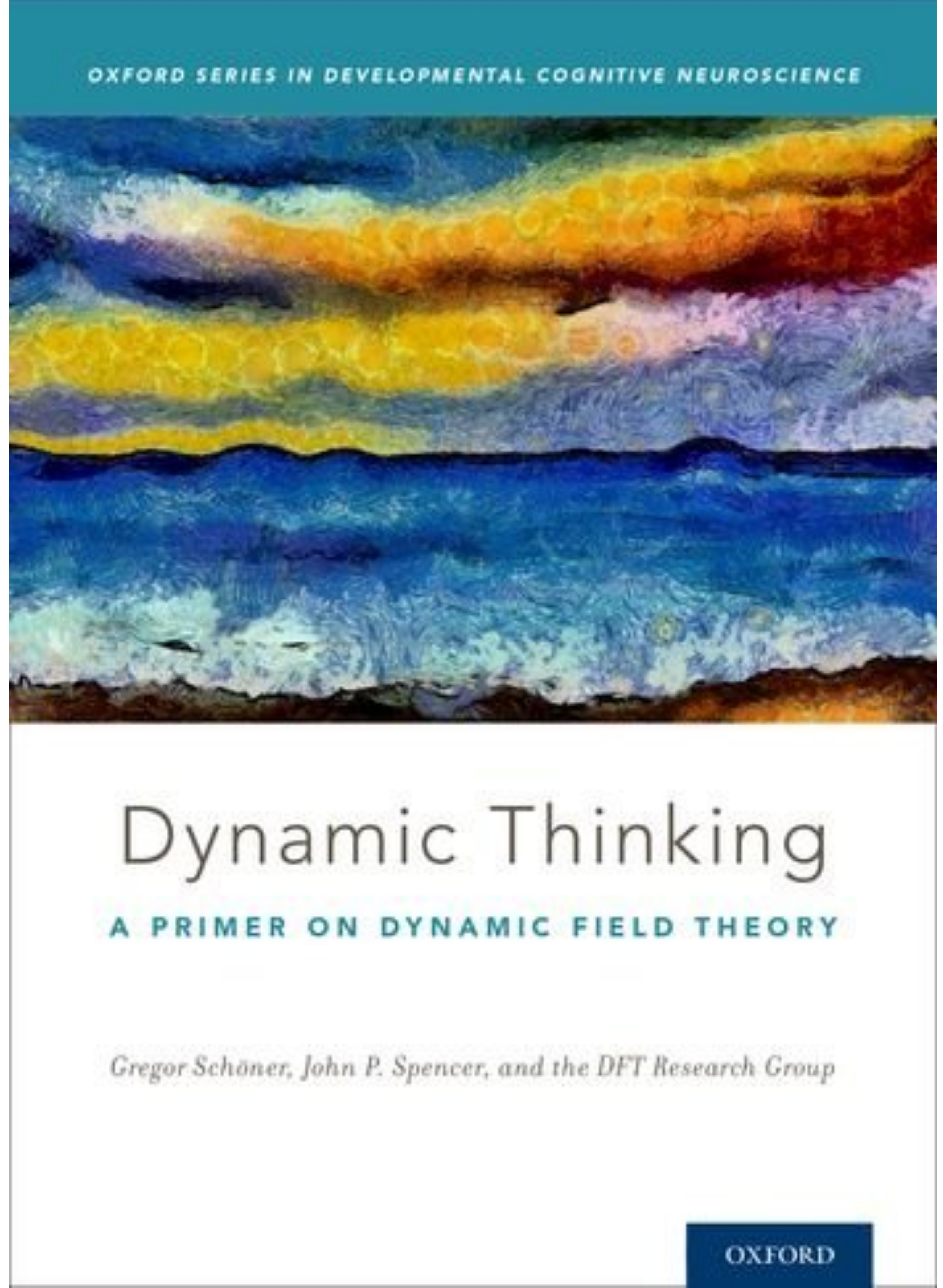
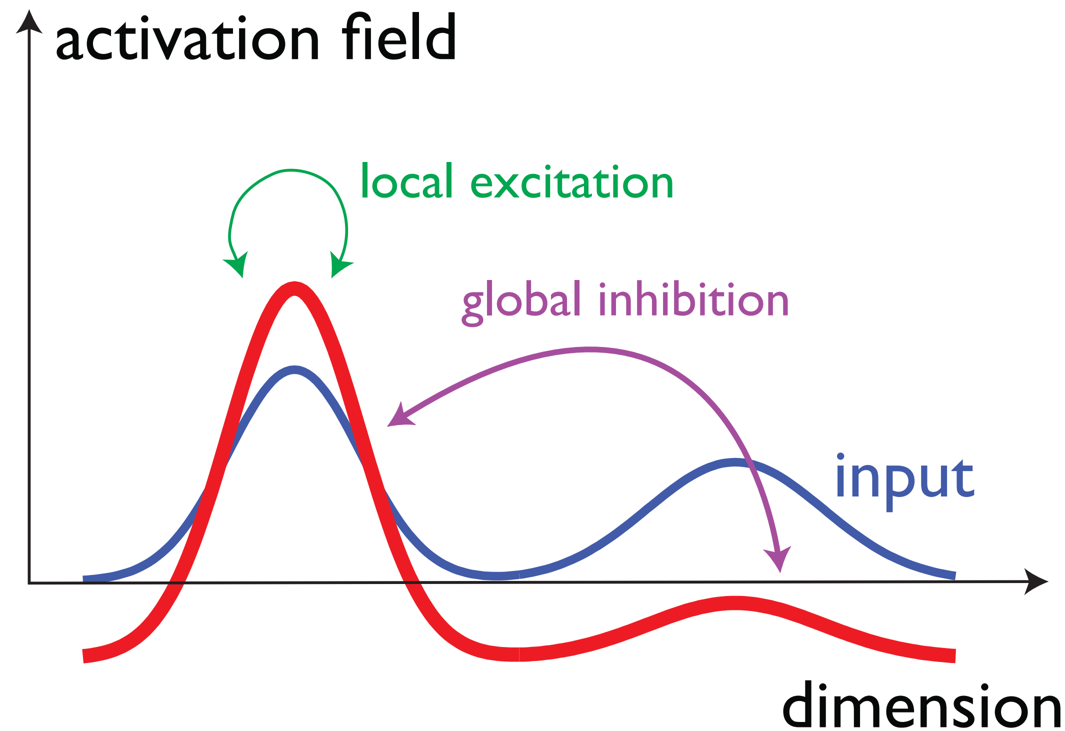
=> simulation

- dynamicfieldtheory.org

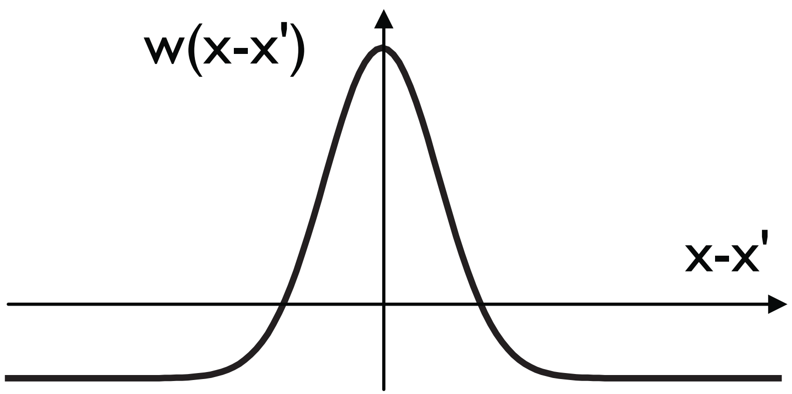


Neural dynamics of fields

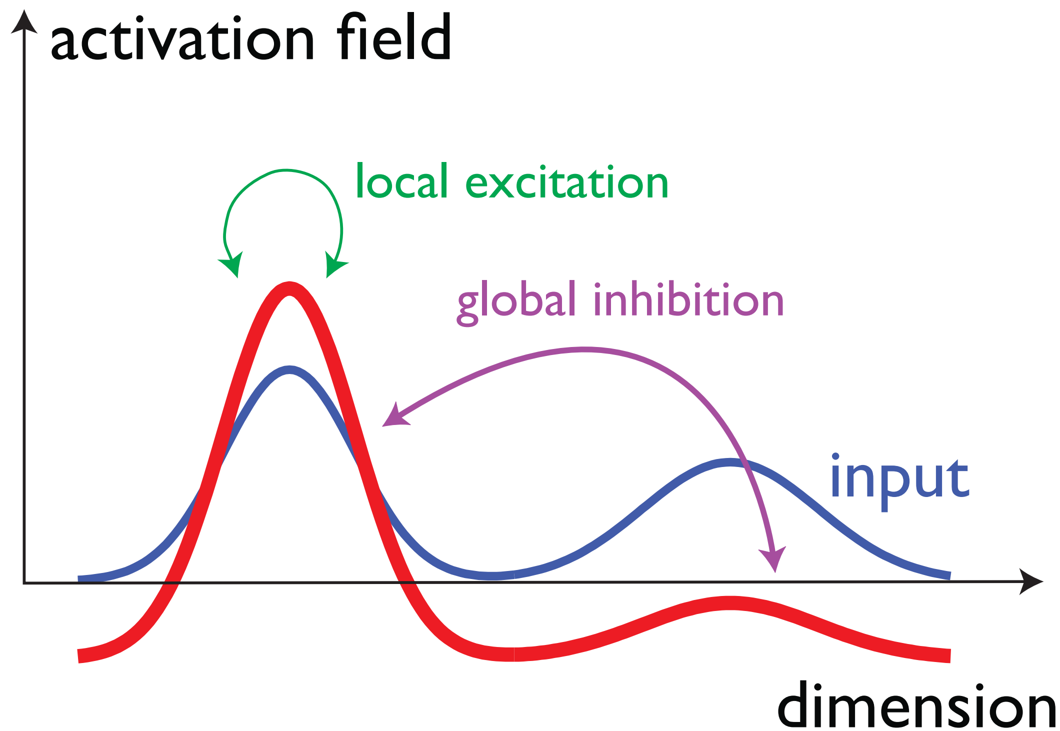
- combine detection with selection
- => local excitation/ global inhibition



Neural dynamics of fields

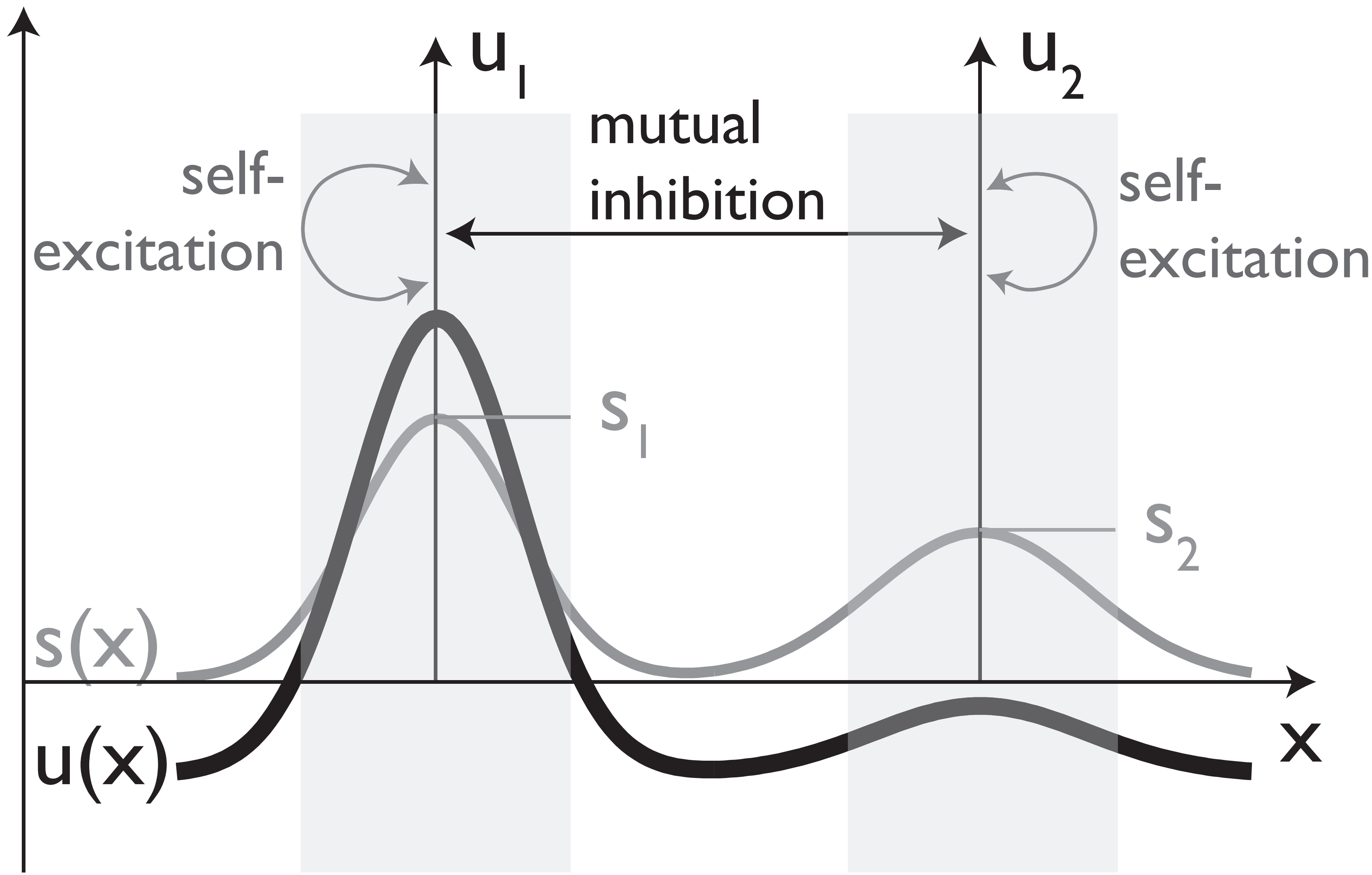


$$w(x-x') = w_{\text{exc}} e^{-\frac{(x-x')^2}{2\sigma^2}} - w_{\text{inh}}$$



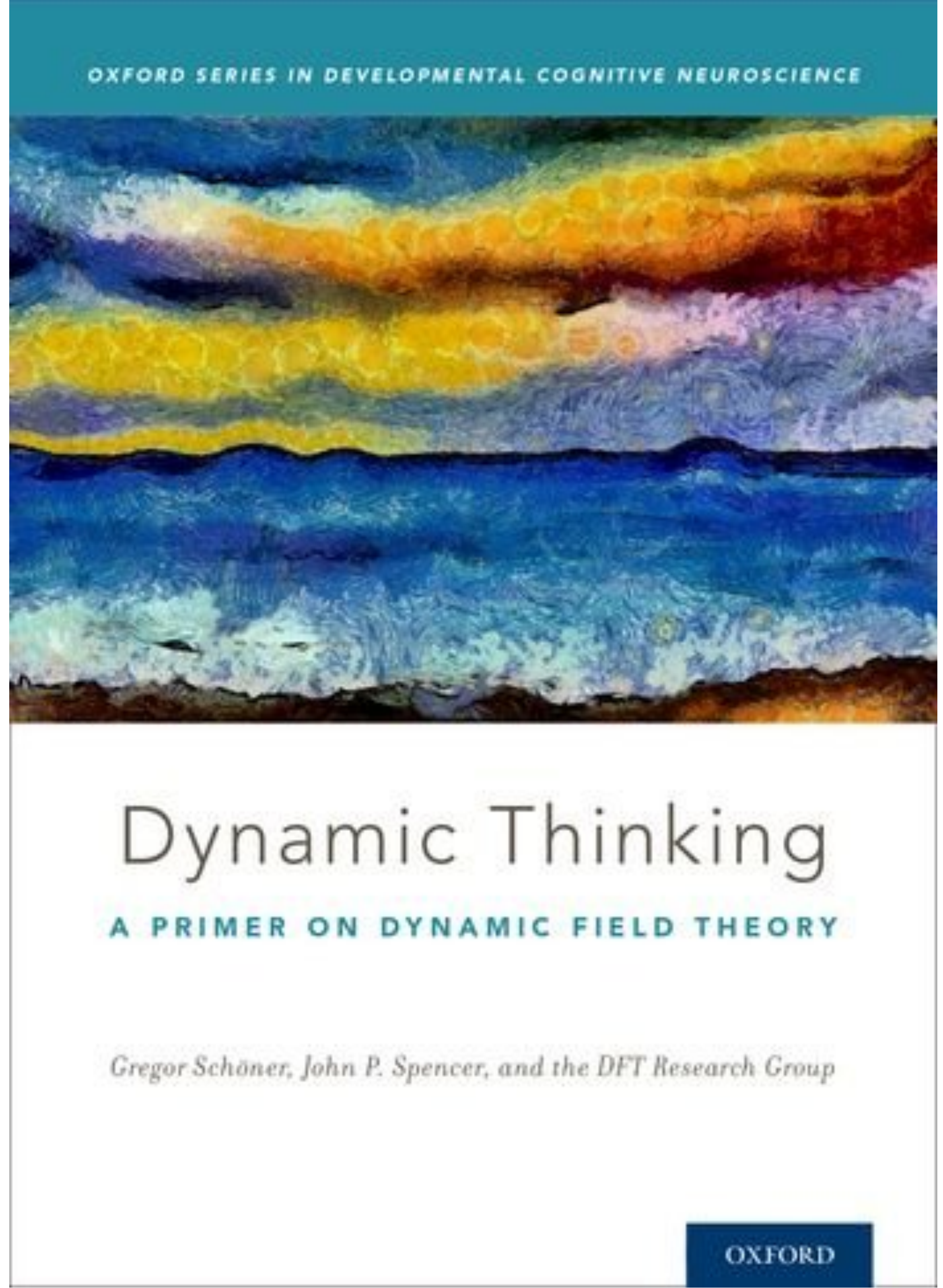
$$\tau \dot{u}(x,t) = -u(x,t) + h + s(x,t) + \int dx' \; w(x-x') \; \sigma(u(x'))$$

Relationship to the dynamics of discrete activation variables



=> simulation

- 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

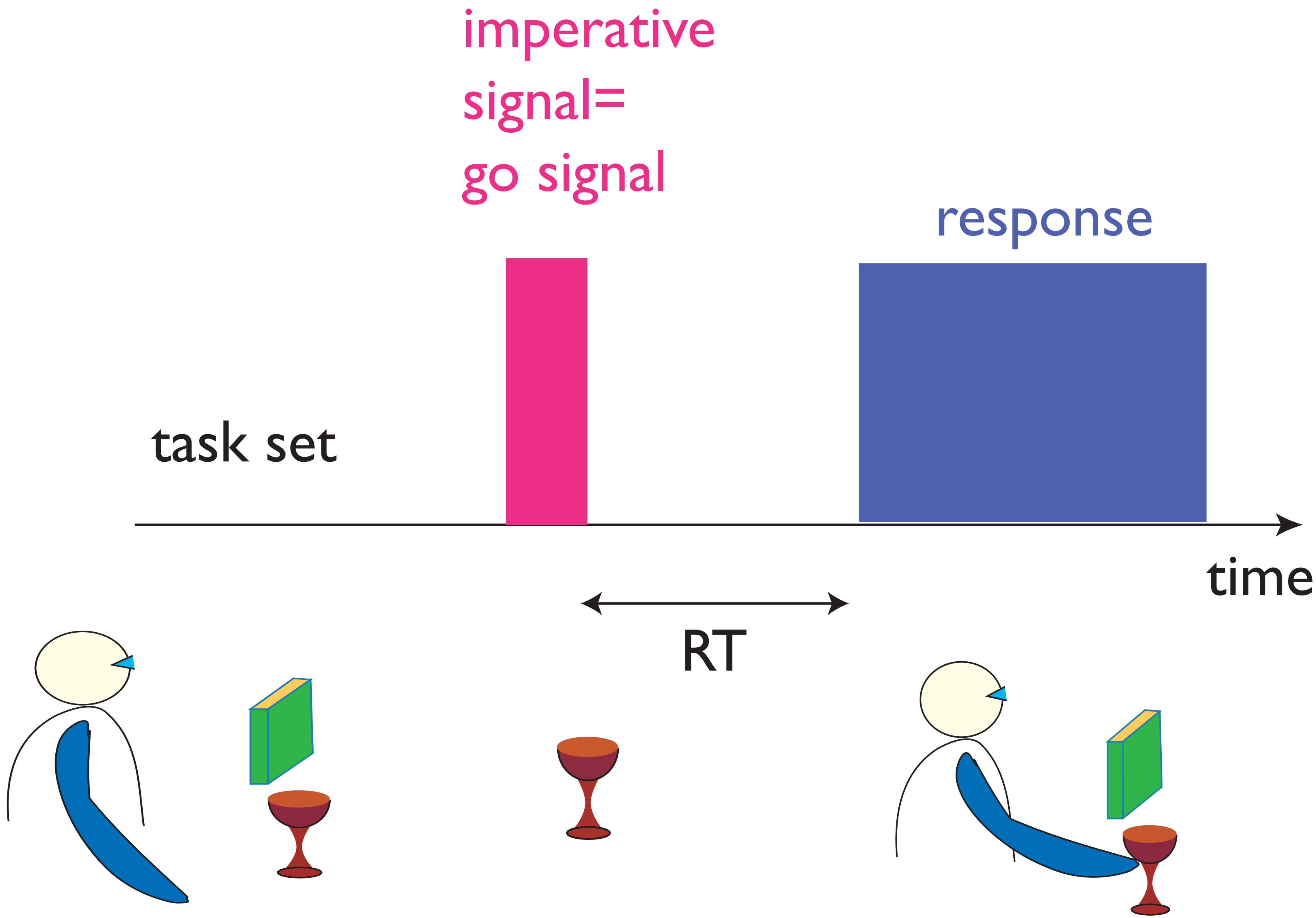
Dynamic regimes

- which attractors and instabilities arise as input patterns are varied
- examples
  - "perceptual regime": mono-stable sub-threshold => bistable sub-threshold/peak => mono-table peak..
  - "working memory regime" bistable sub-threshold/peak => mono-table peak.. without mono-stable sub-threshold
  - single ("selective") vs. multi-peak regime

Case study: DFT account of sensory-motor decision making

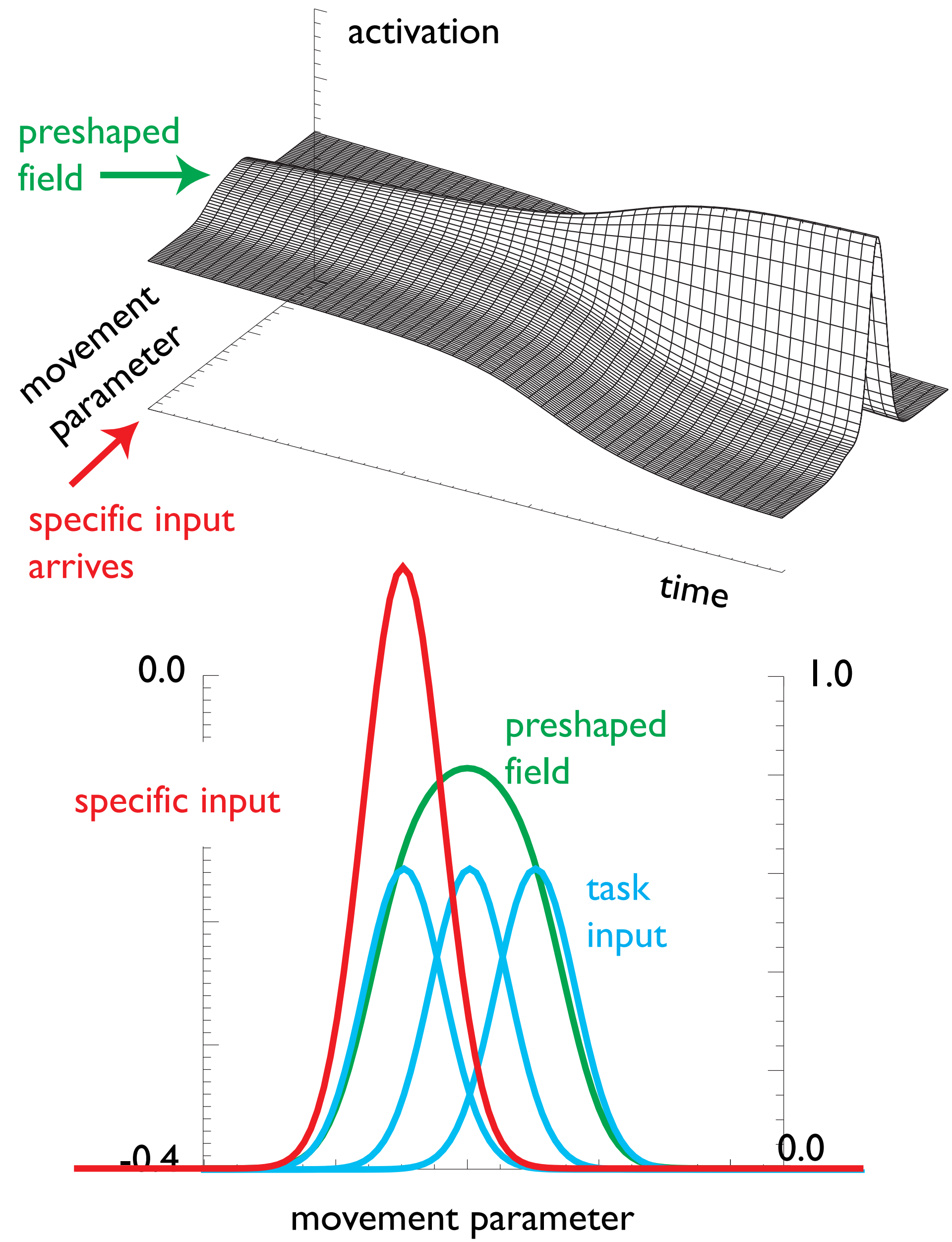
- assessed in reaction-time tasks
- information processing: how much information is processed…
- DFT: contents of task matters… embodiment
- DFT: decisions evolve continuously in time and metric space

Reaction time (RT) paradigm

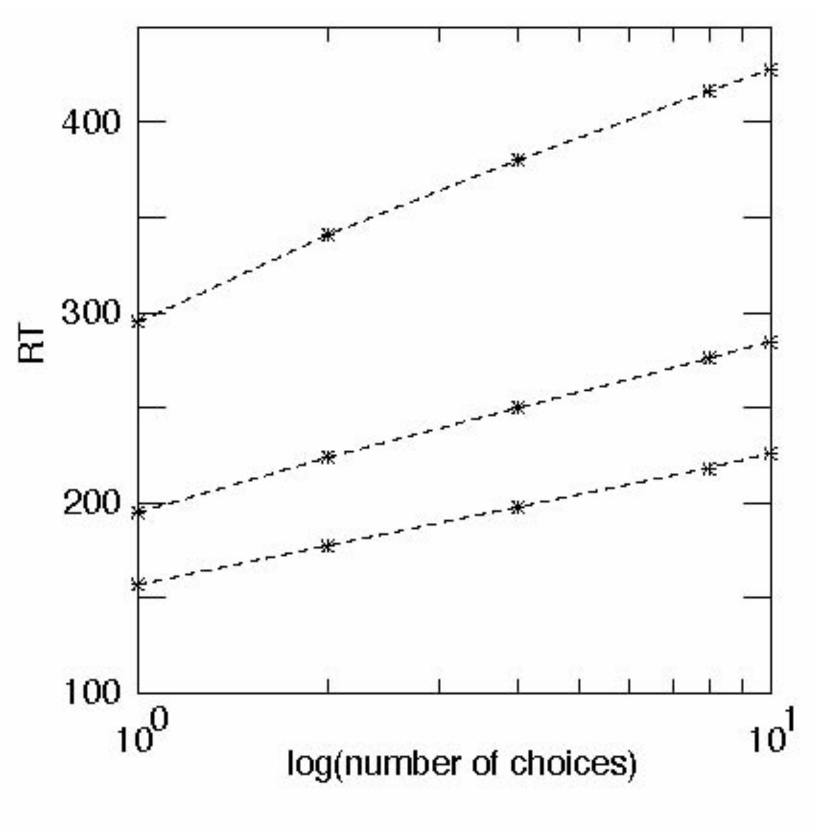


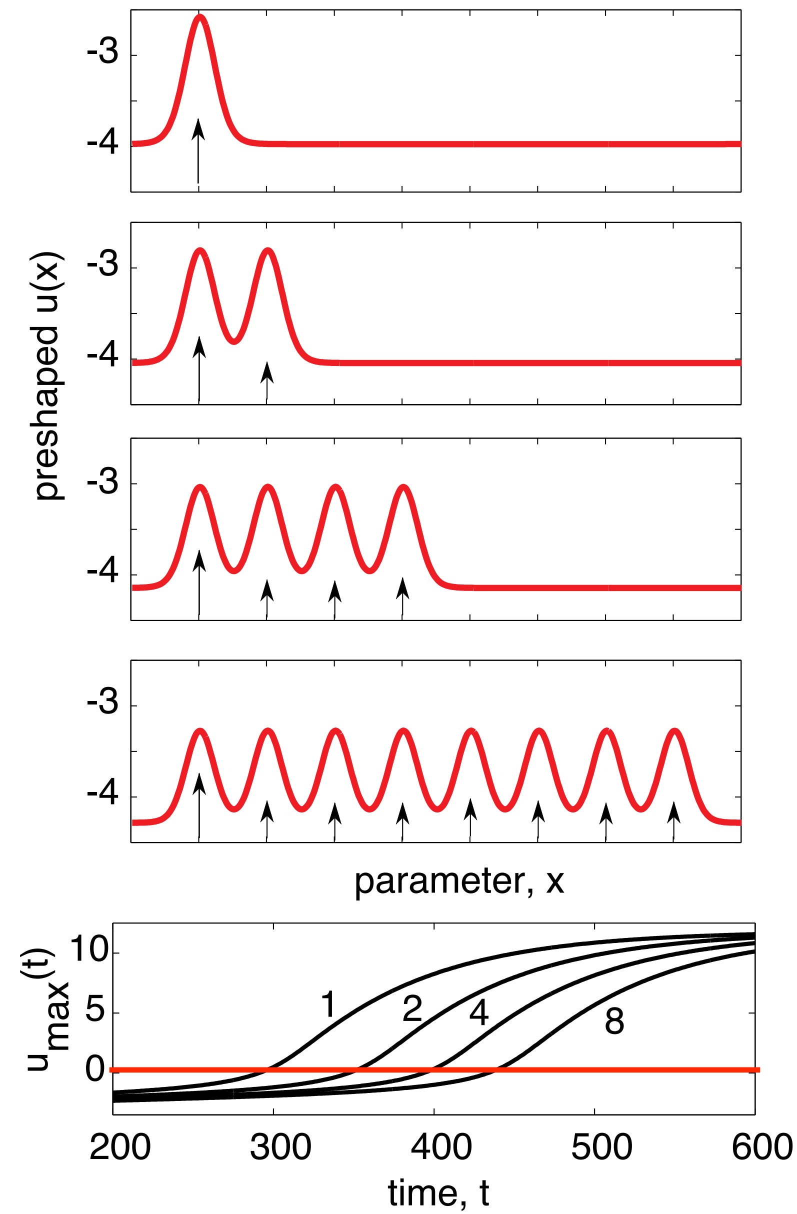
Model the task set by preshape

- which choices are available
  - how many, how probable
  - how different from each other
  - how easy to recognize/perform
- choices known to the participant before the imperative signal comes
- => preshape the field



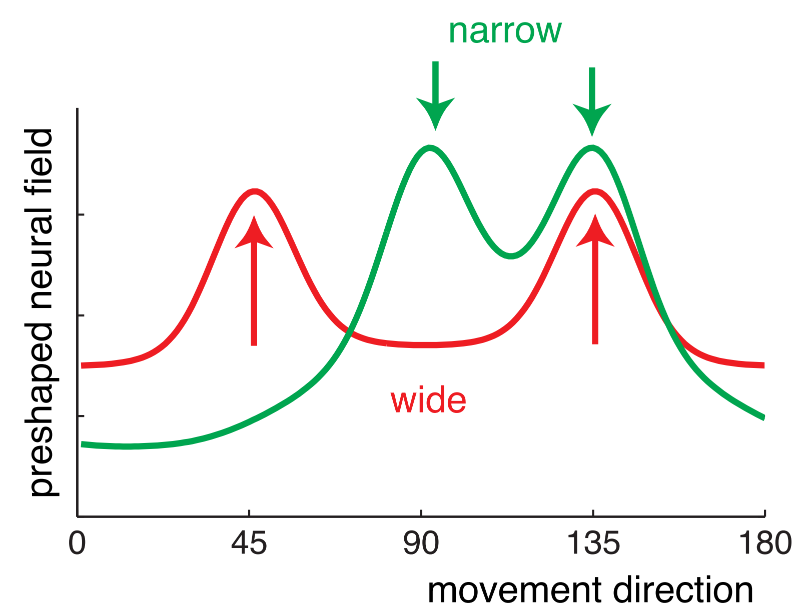
Hick's law: RT increases with # choices



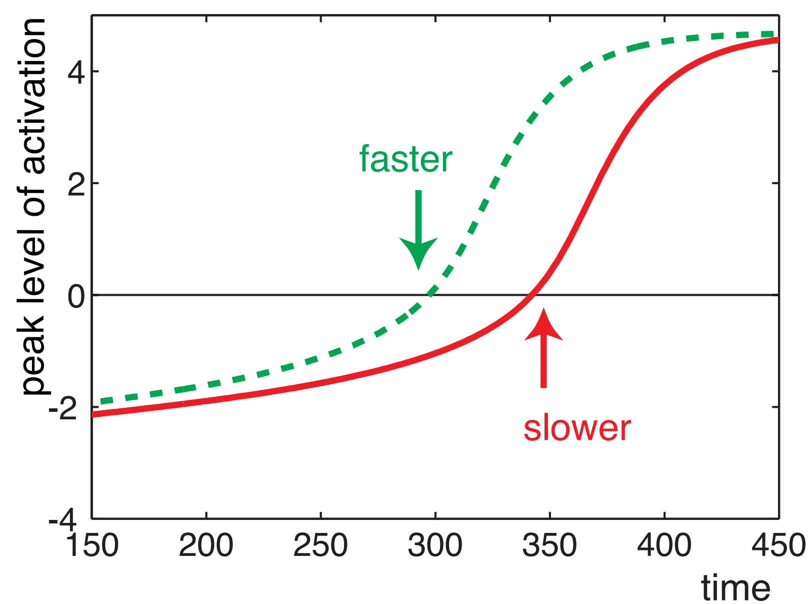


[Erlhagen, Schöner, Psych Rev 2002]

Metric effect

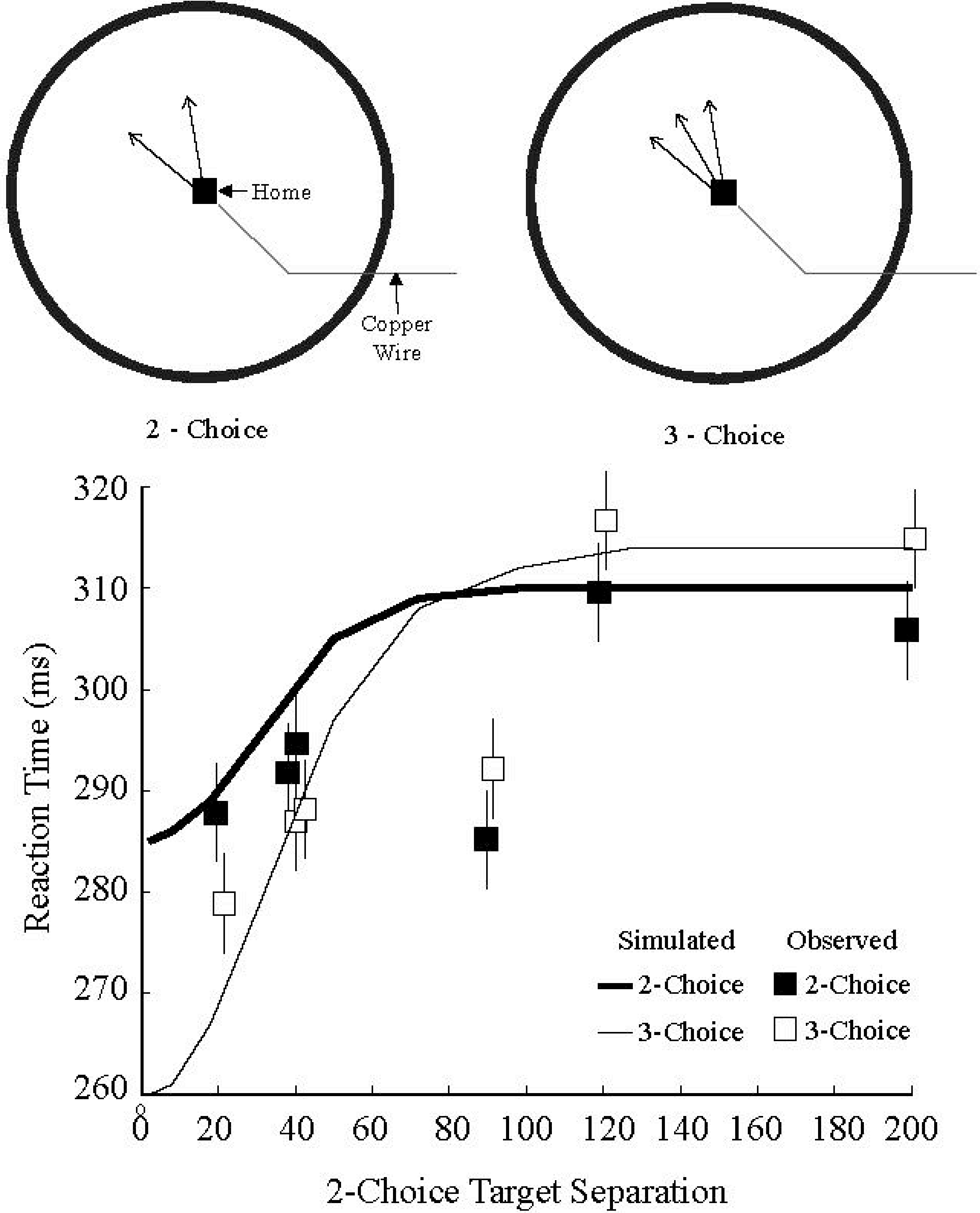


- predict faster response times for metrically close than for metrically far choices

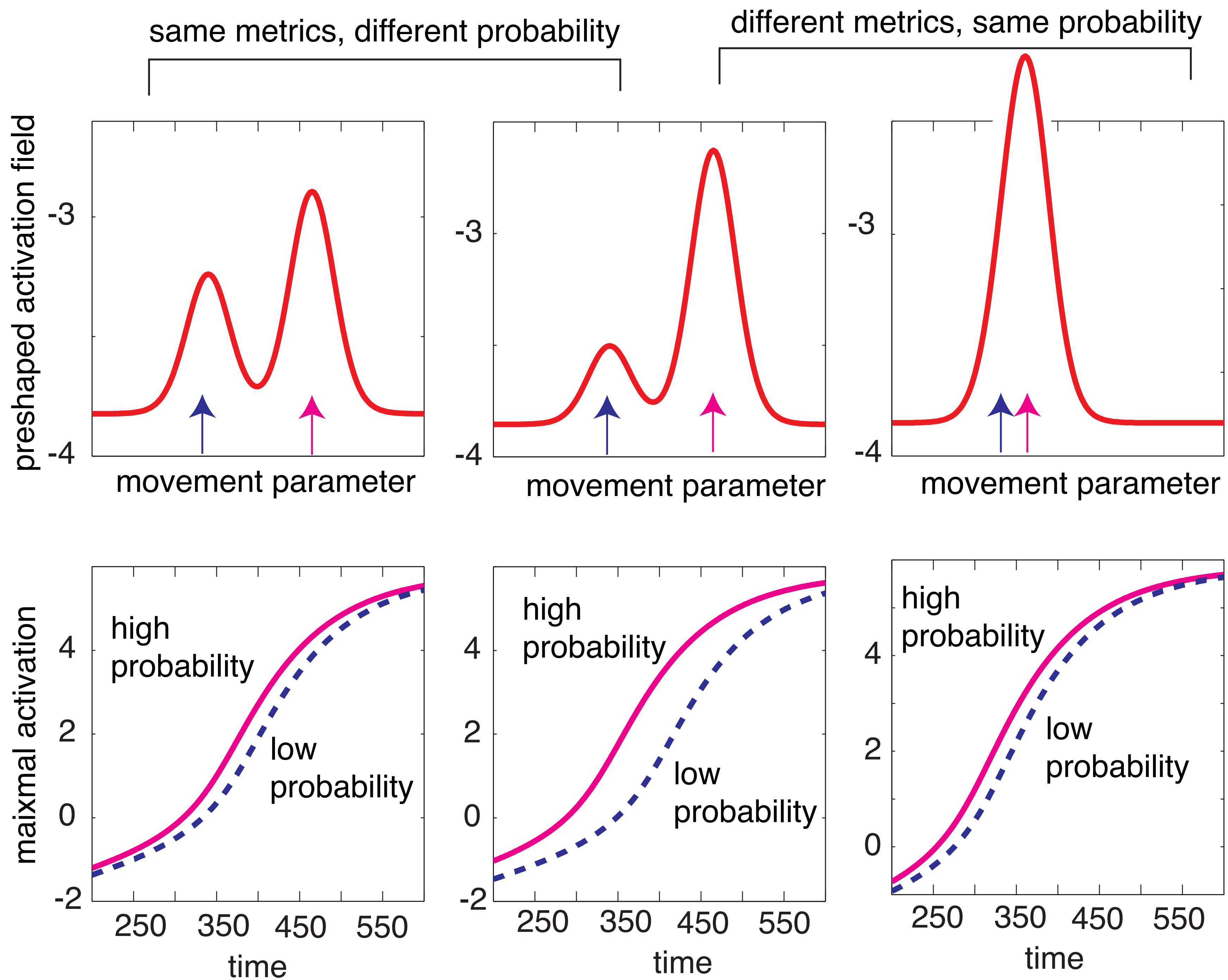


[from Schöner, Kopecz, Erlhagen, 1997]

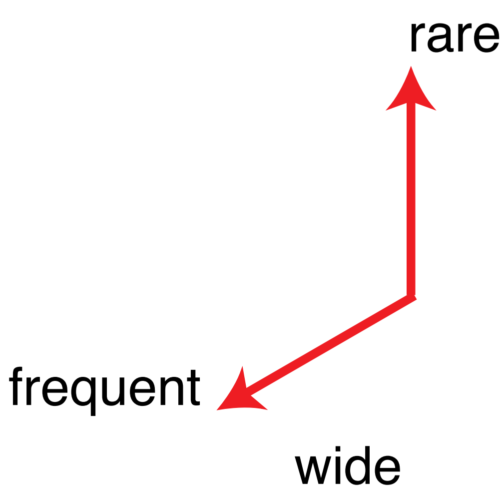
Metric effect: experiment

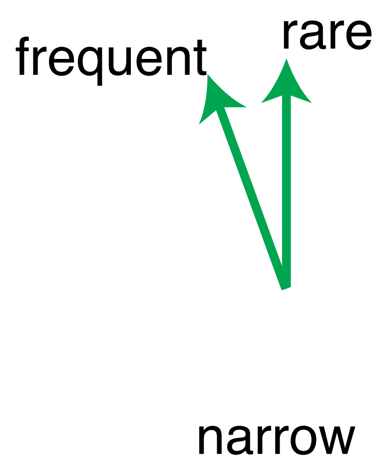


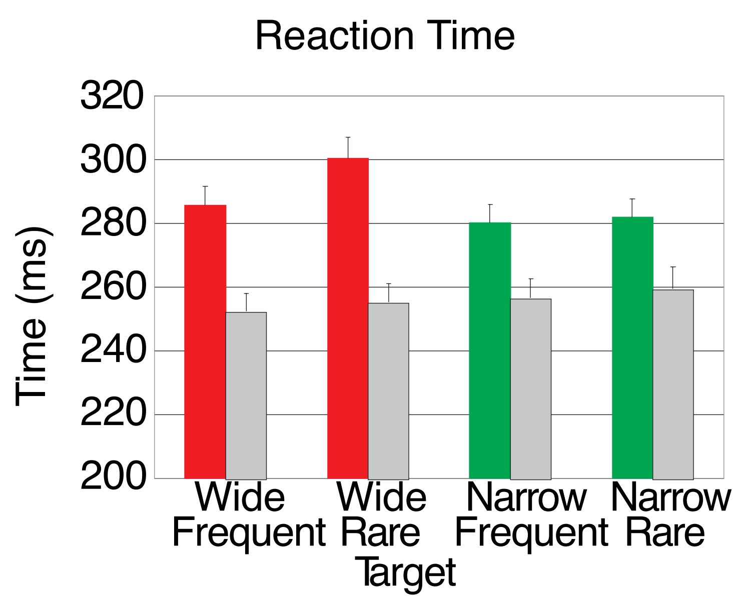
[McDowell, Jeka, Schöner]

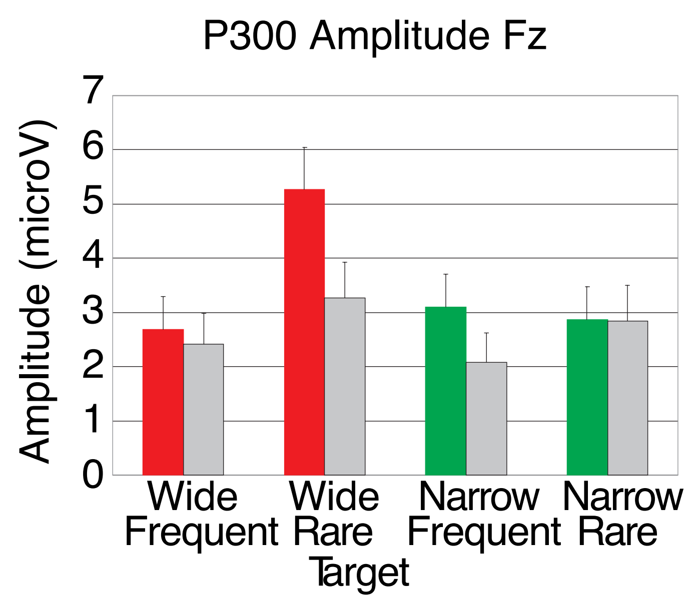


[from Erlhagen, Schöner: Psych. Rev. 2002]





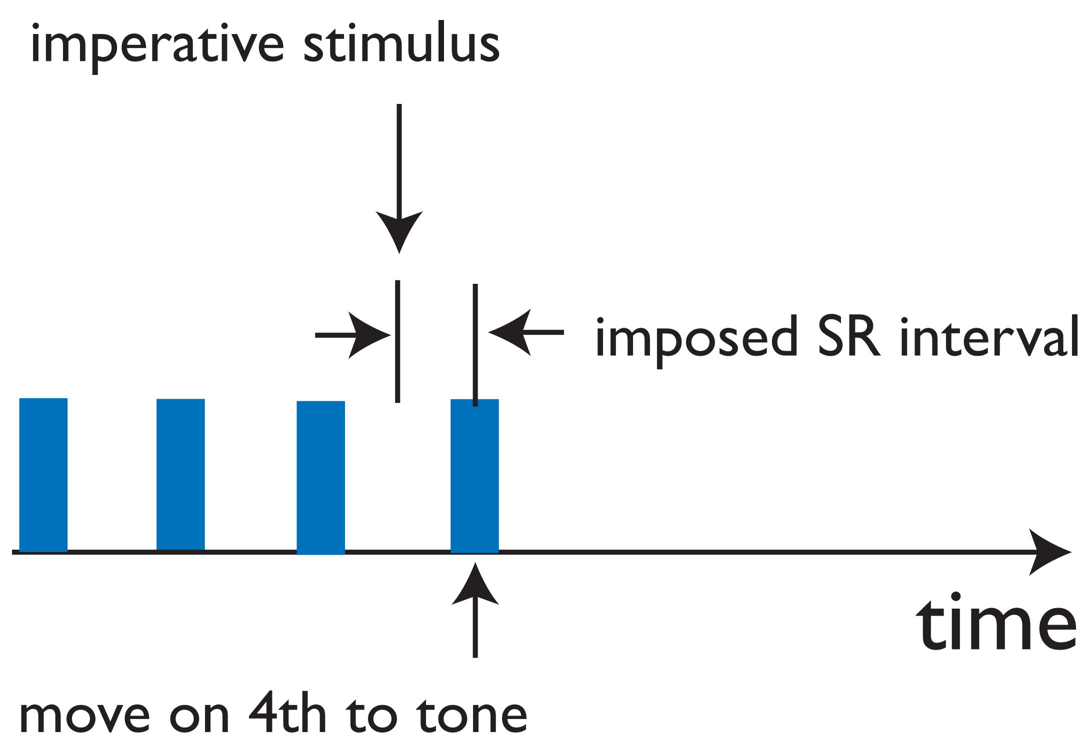




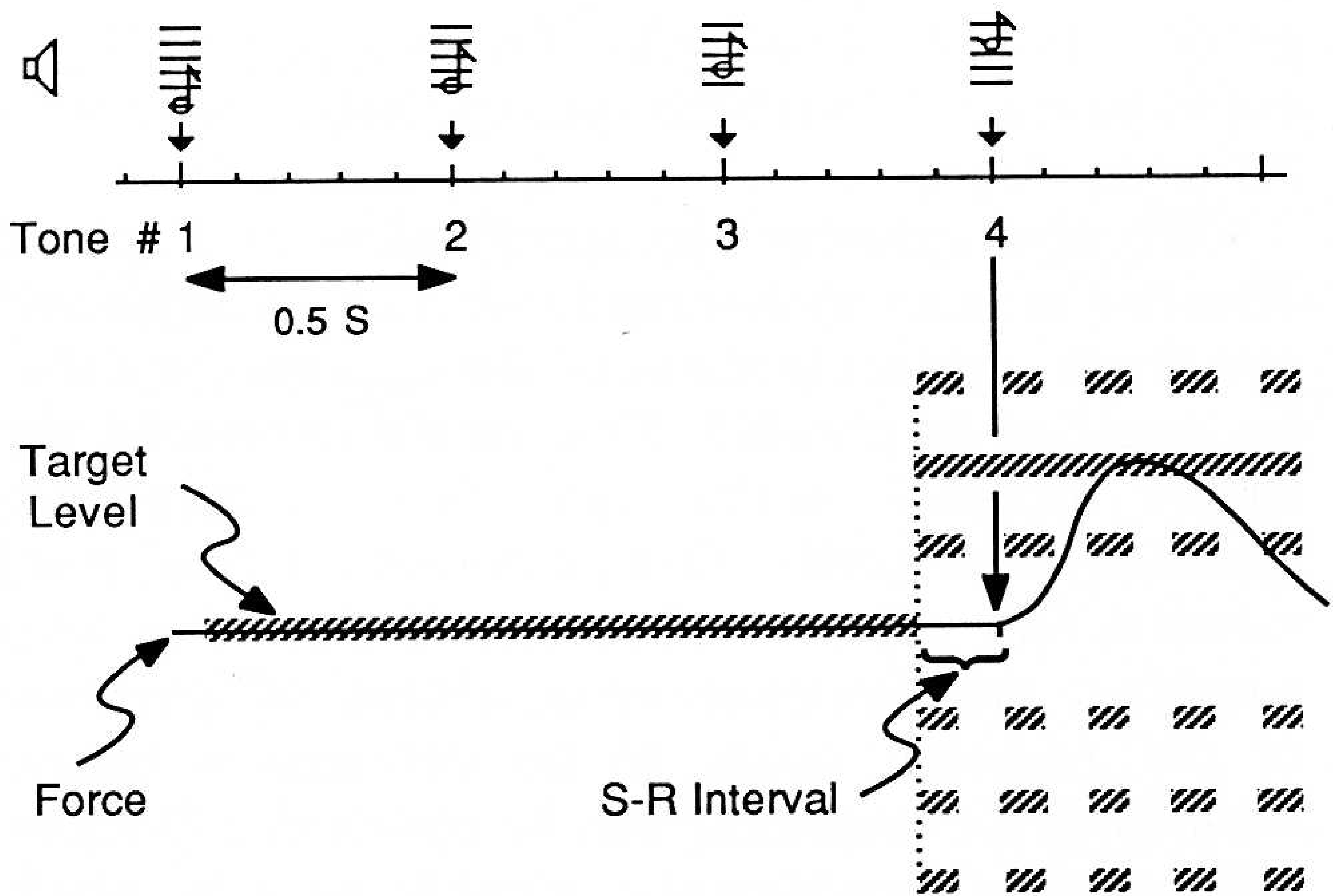
[from McDowell, Jeka, Schöner, Hatfield, 2002]

Continuous evolution of sensory-motor decisions

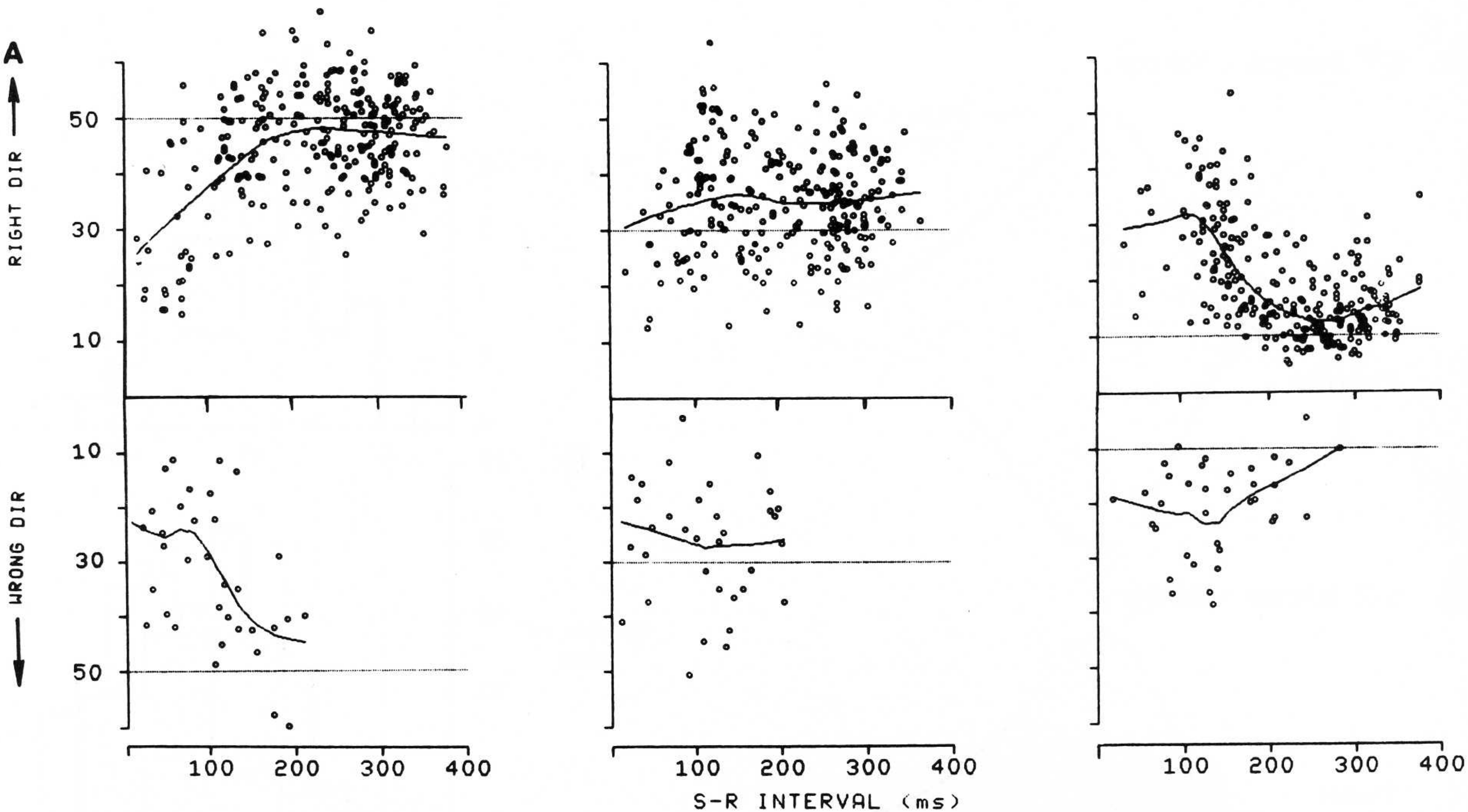
- timed movement initiation paradigm



[Ghez and colleagues, 1988 to 1990's]

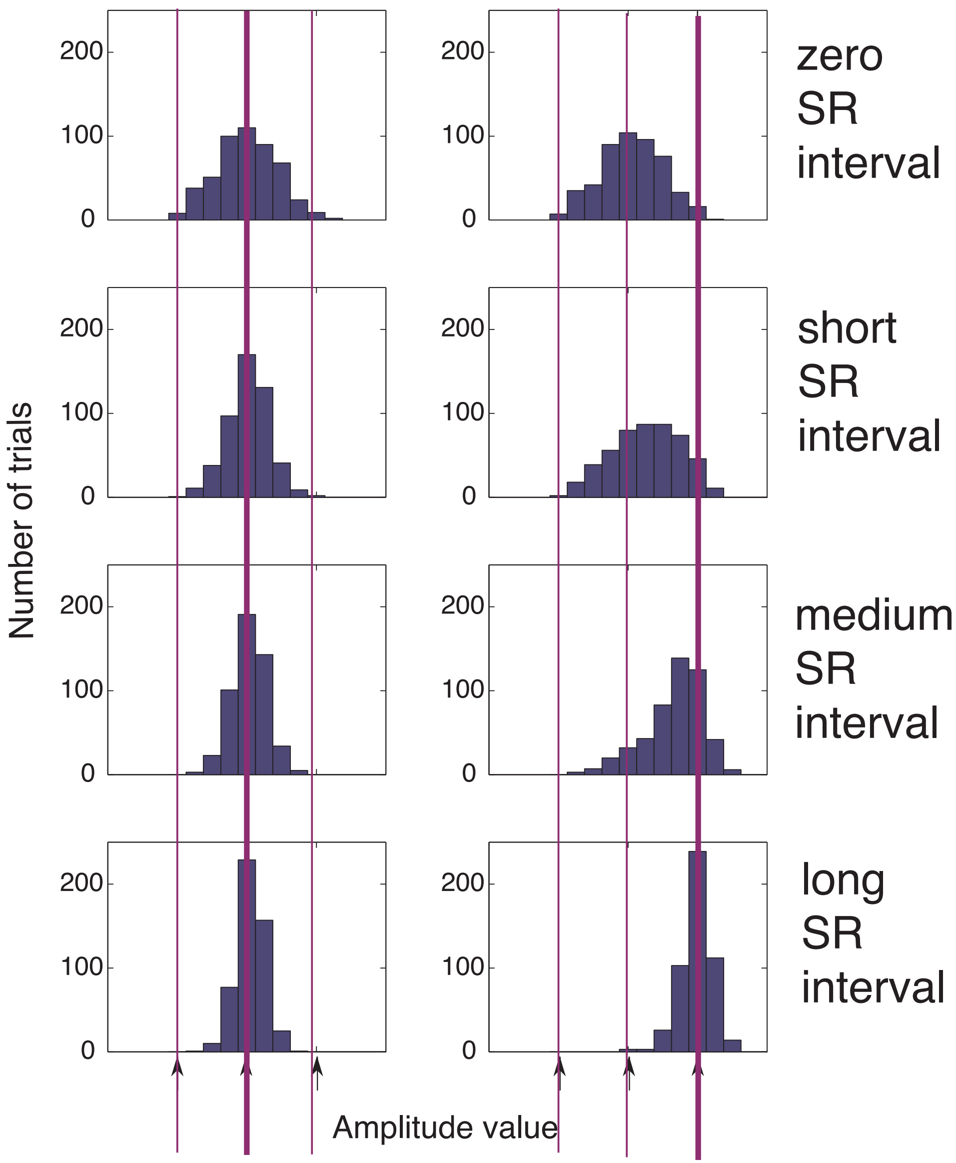


[Favilla et al. 1989]

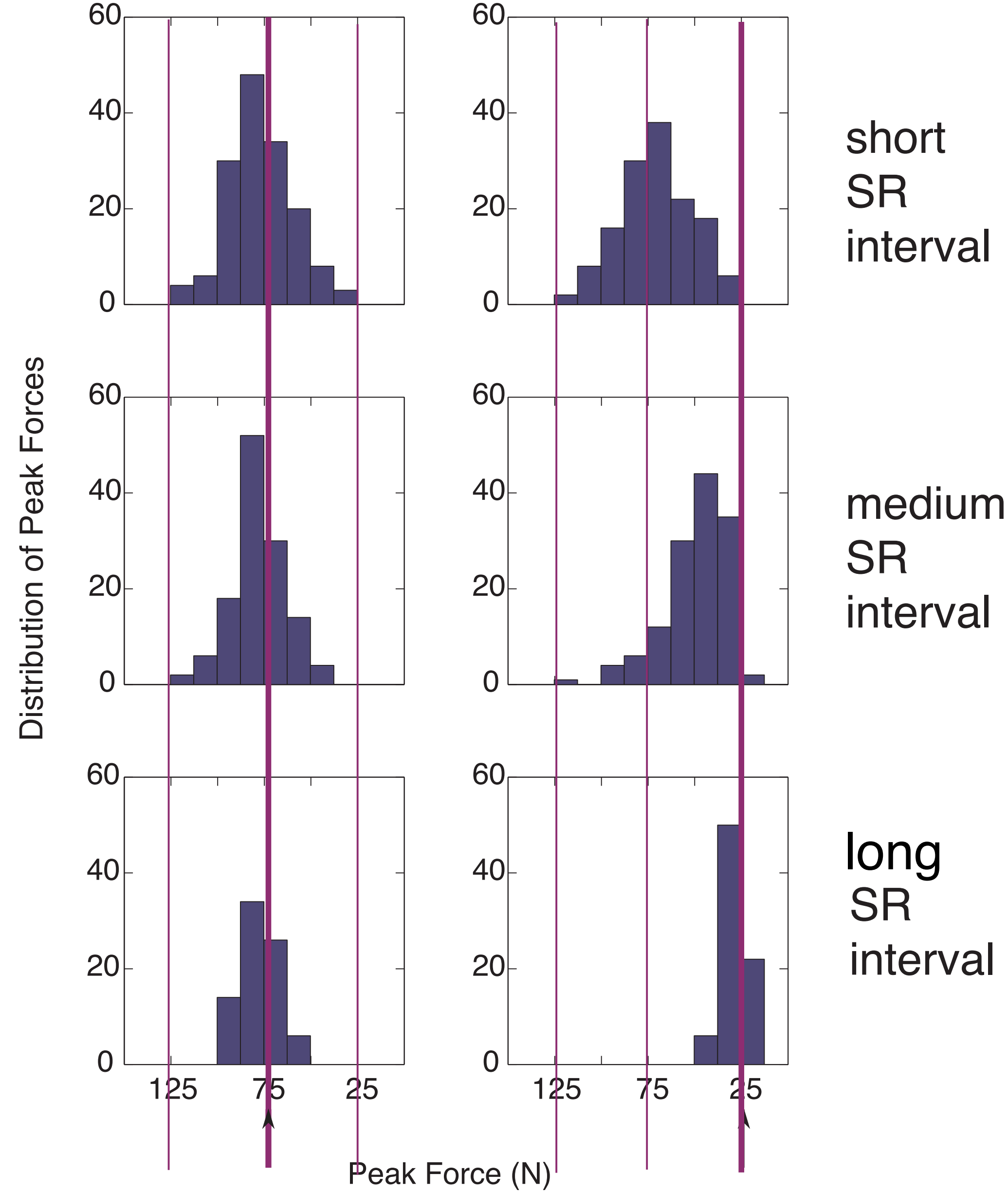


[Favilla et al. 1989]

theoretical account for Henig et al.



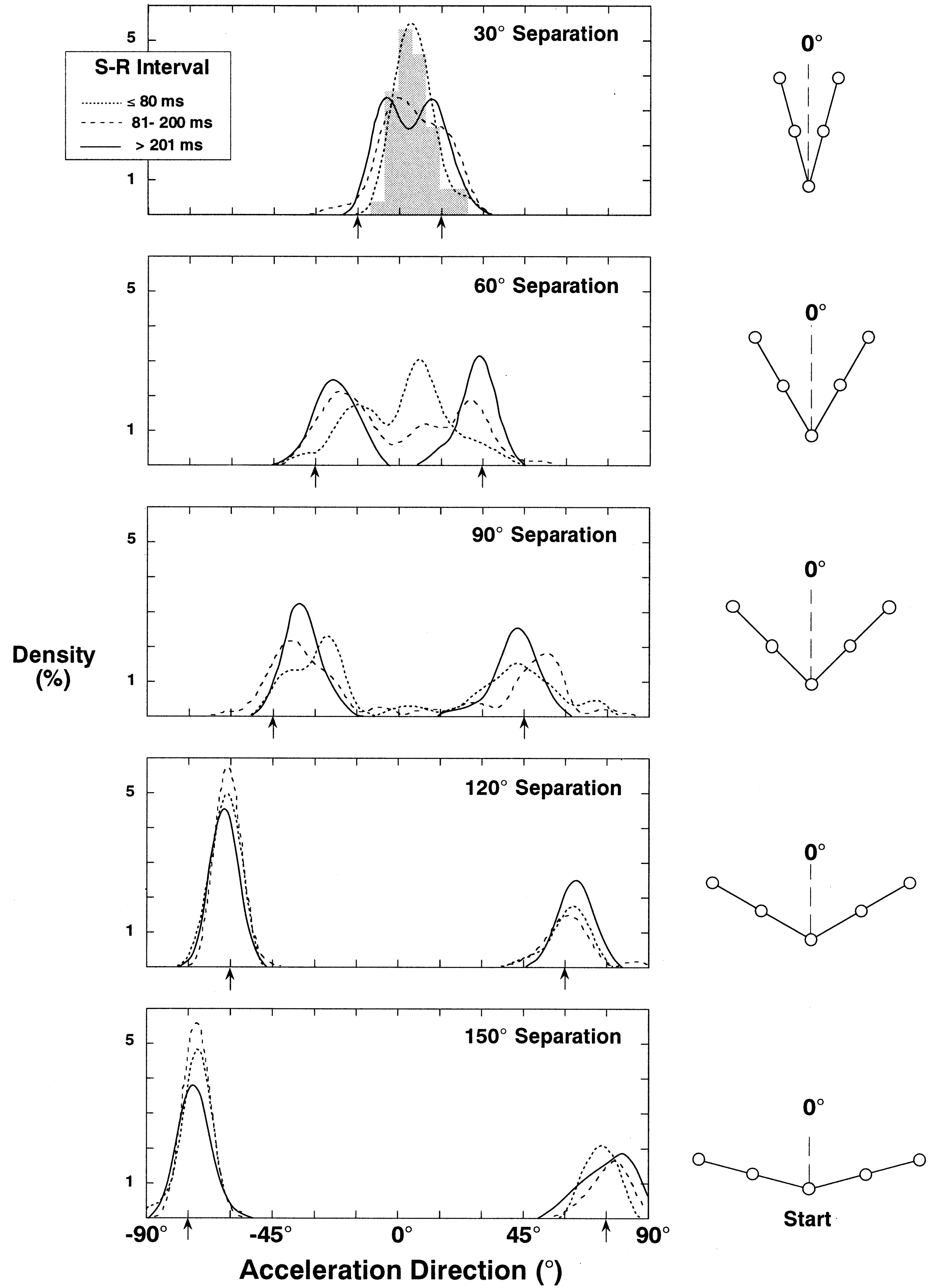
Experimental results of Henig et al



[Erlhagen, Schöner: Psychological Review 109, 545–572 (2002)]

Metric effect

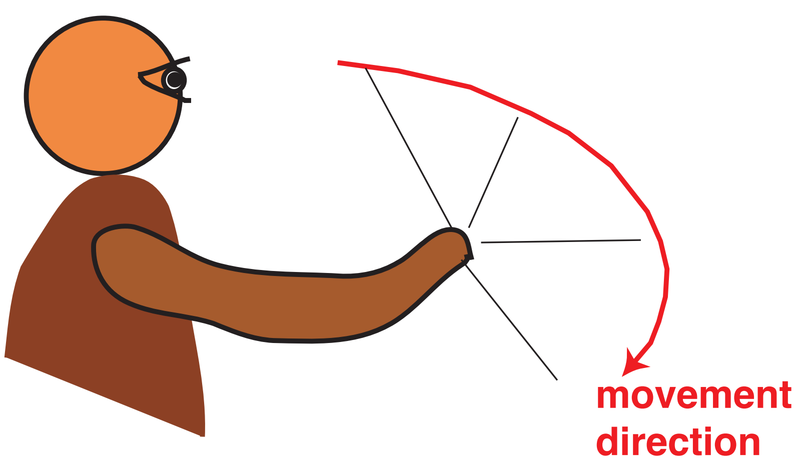
- directly observe the preshaped field …
- and infer the width of preshape peaks

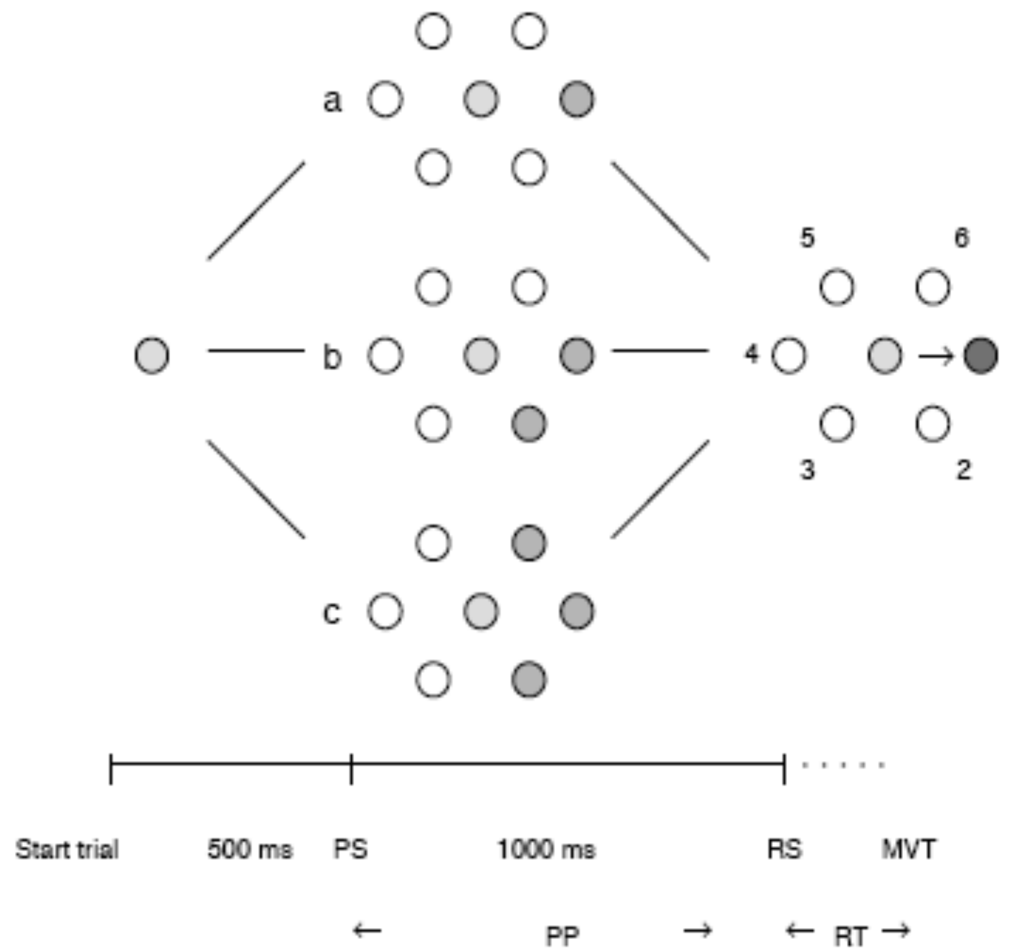


[Ghez et al 1997]

Neural observation of field

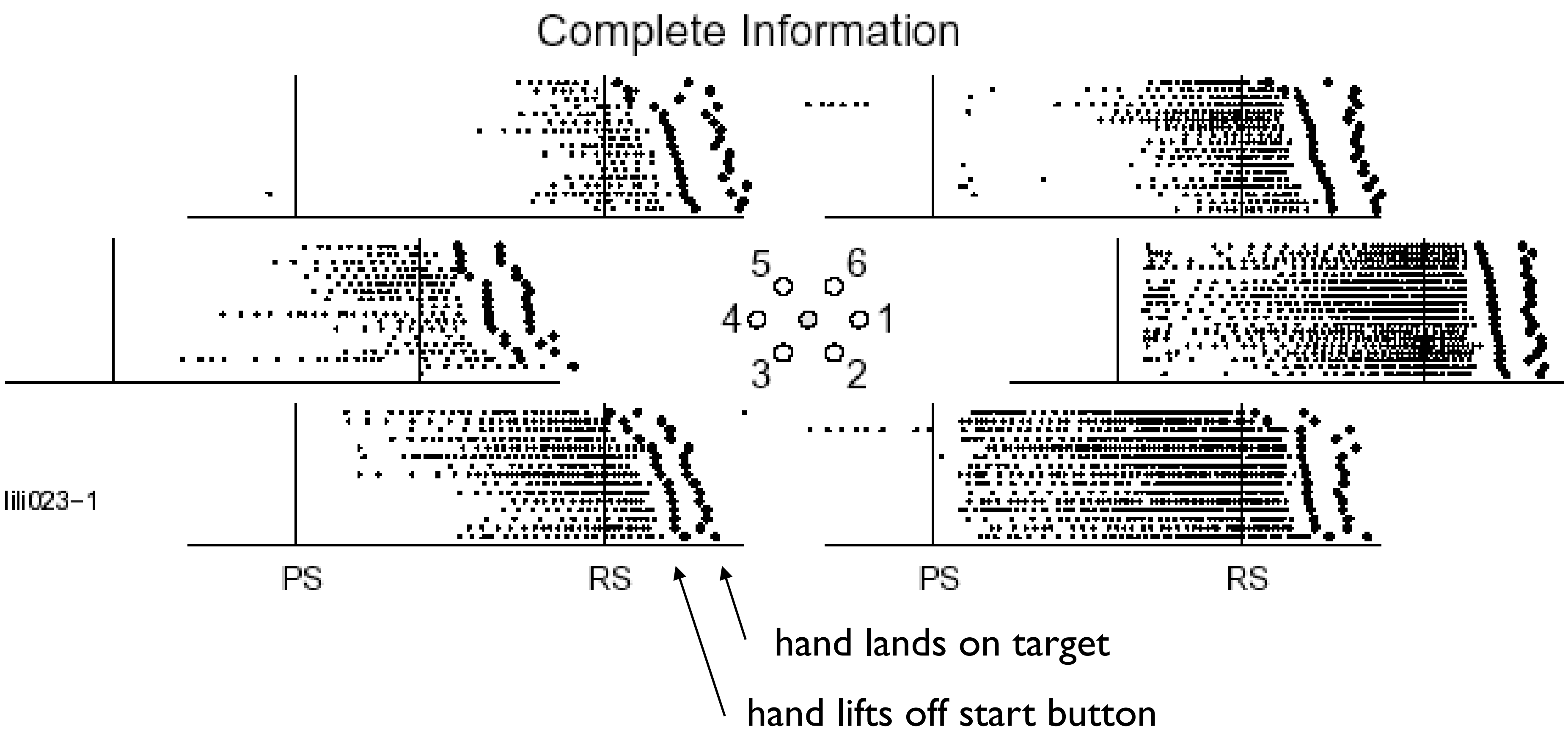
- center-out sensori-motor selection task
- varying prior information
- macaque





Bastian, Riehle, Schöner, 2003

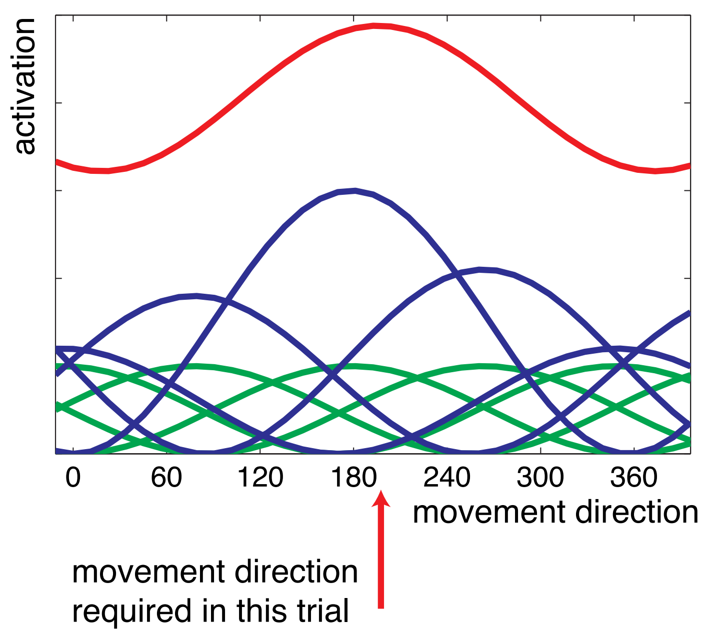
Tuning of neurons in MI to movement direction

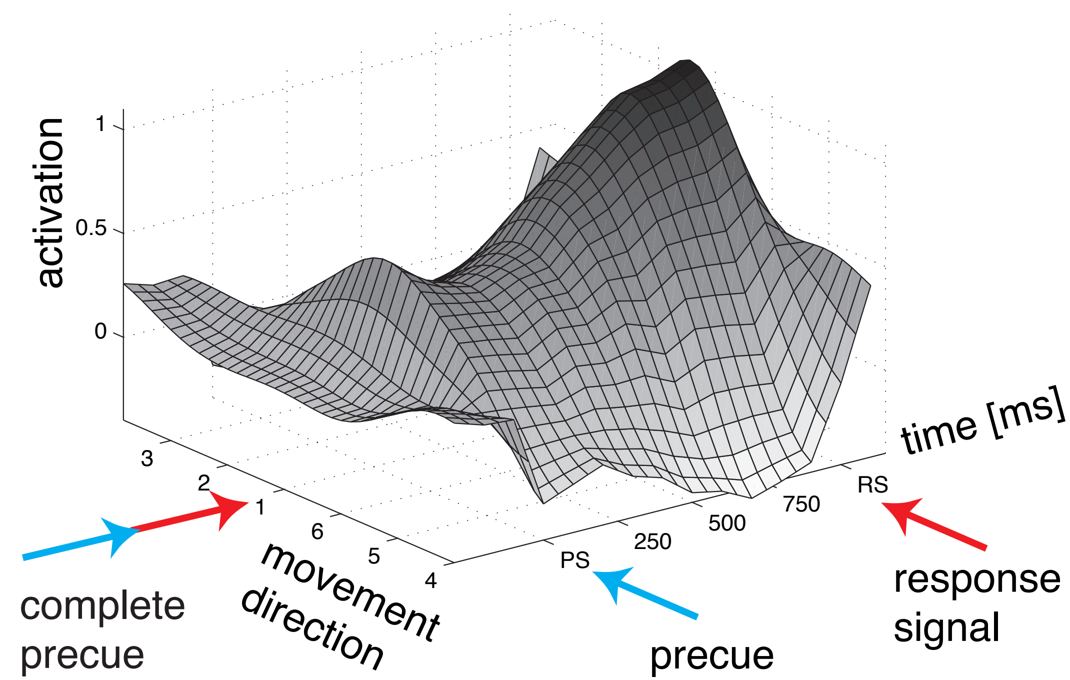


Distribution of Population Activation (DPA) <=> neural field

Distribution of population activation =

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





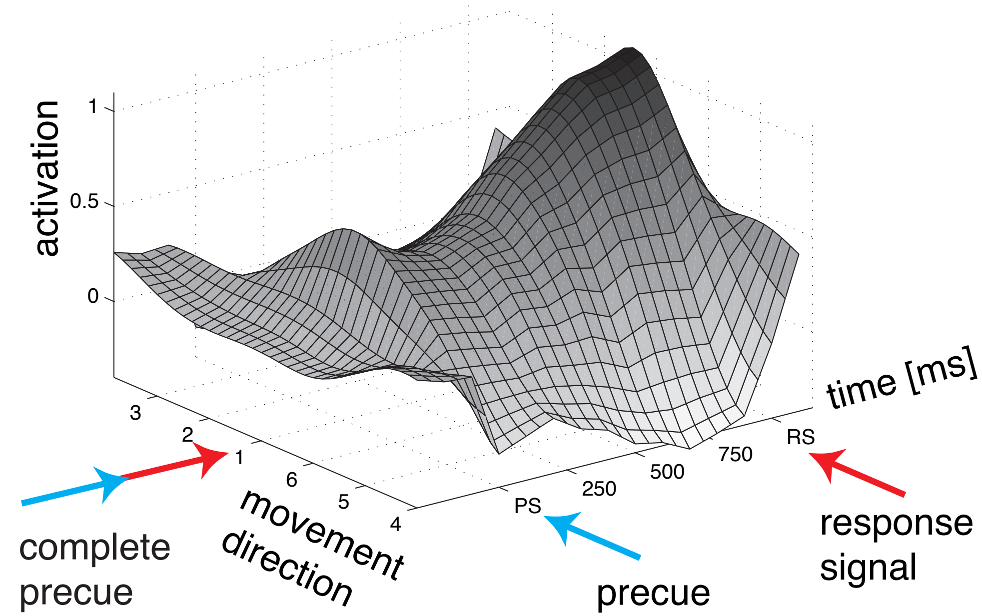
- note: neurons are not localized within DPA!

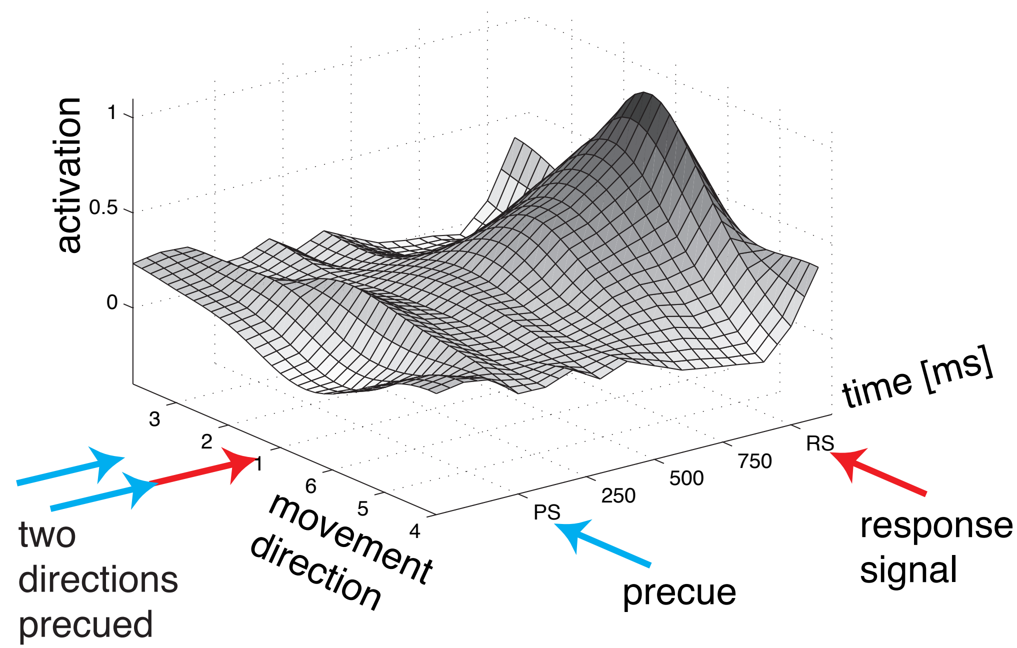
[Bastian, Riehle, Schöner, 2003]

DPA

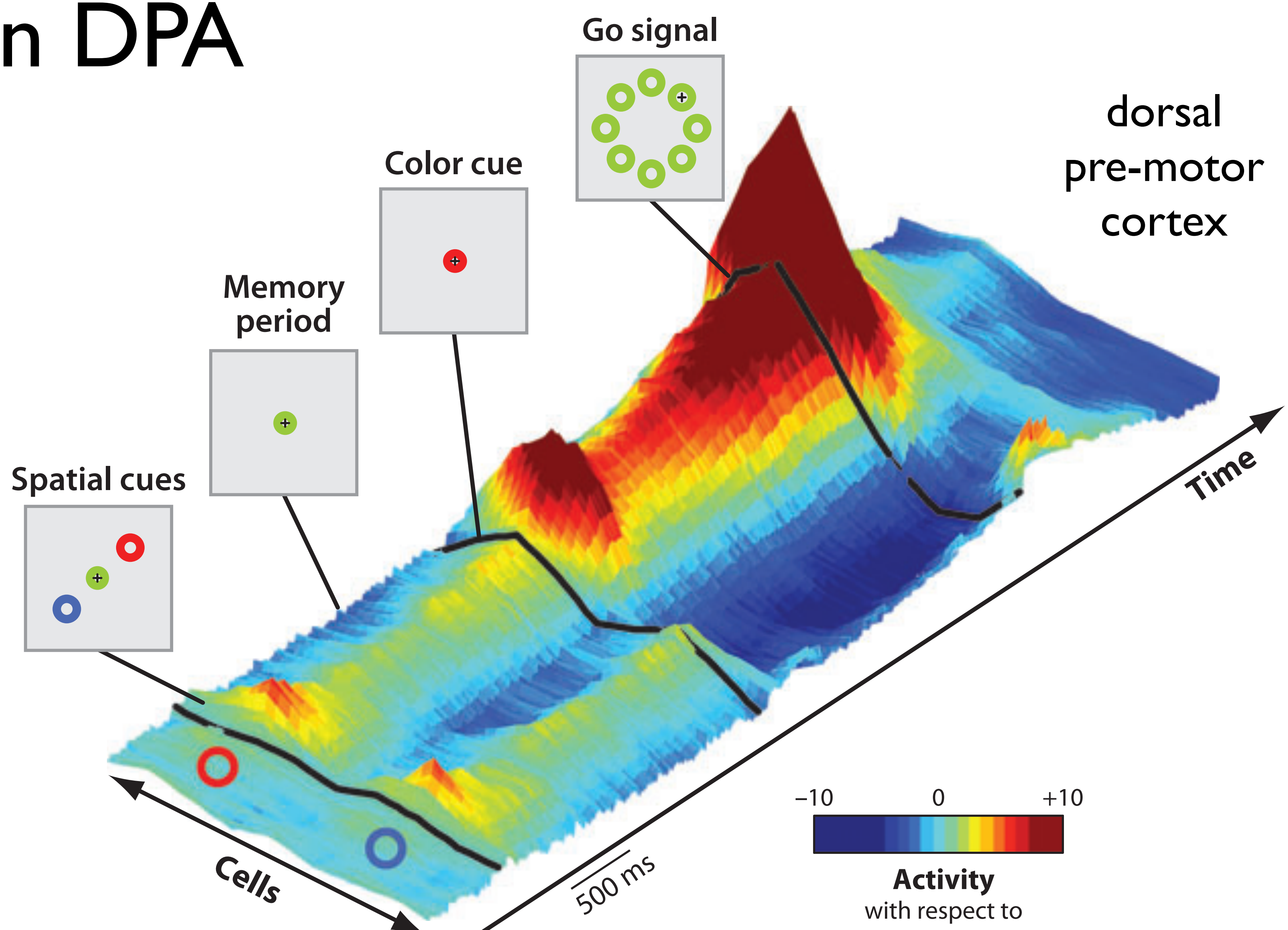
- note: neurons are not localized within DPA!
- [notion of projection cortical neurons really are sensitive to many dimensions
  - motor: arm configuration, force direction
  - visual: many feature dimensions such as spatial frequency, orientation, direction...
- => DPA is a projection from that high-dimensional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

DPA pre-shaped by pre-cue





Decision making in DPA



dorsal pre-motor cortex

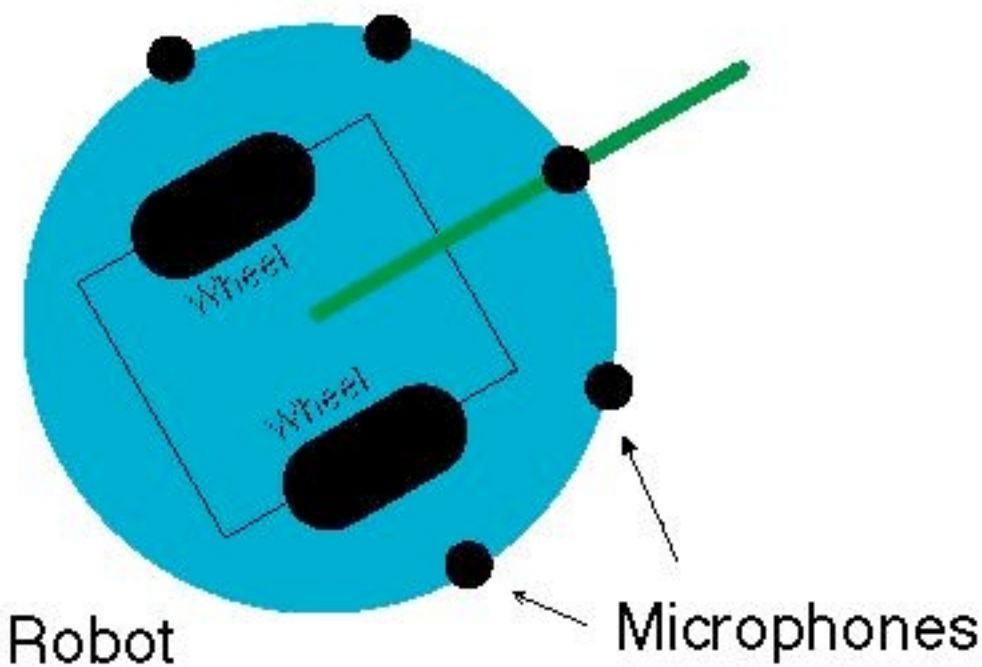
[Cisek, Kalaska 2005]

Case study: embodiment

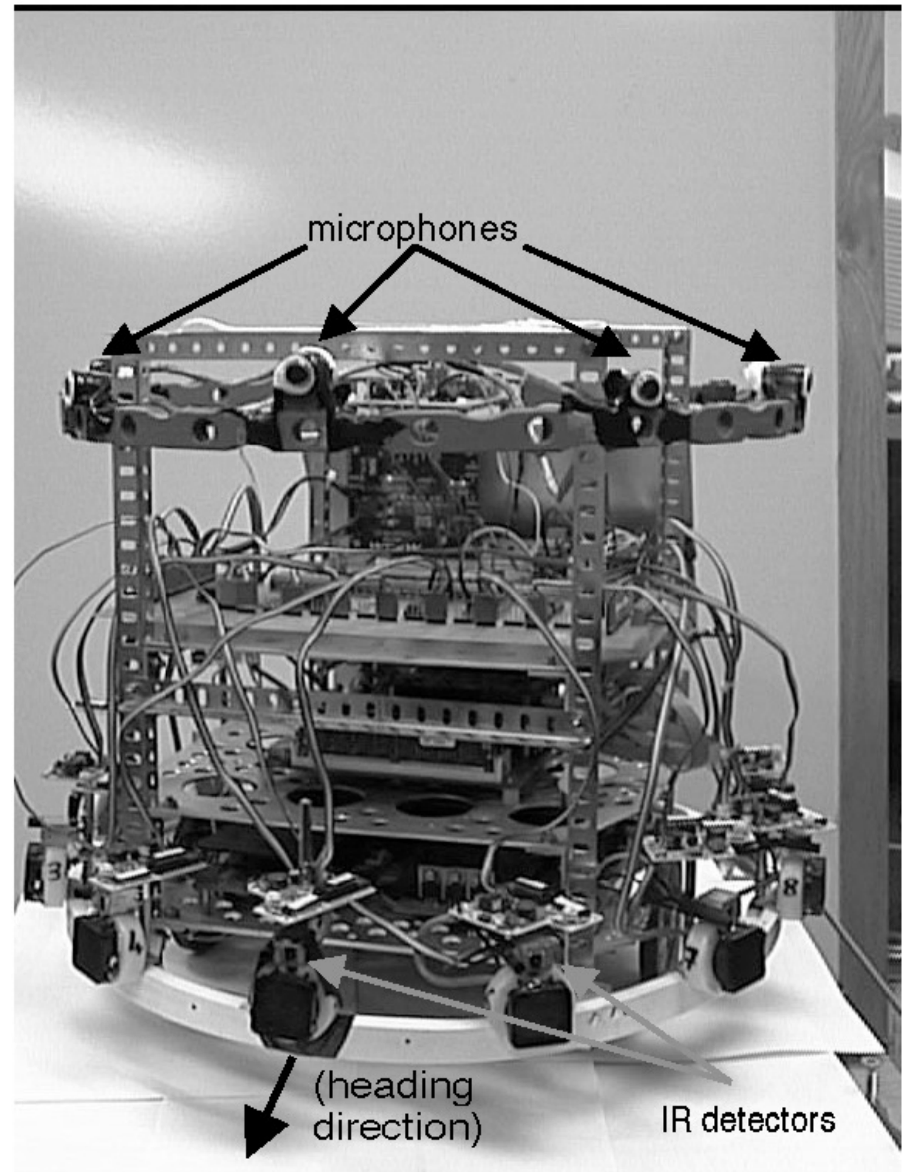
- neural dynamic fields can be linked to time-varying sensory inputs and can control motor systems in closed loop

Driving fields from sensory signals

- robot that orients toward sound sources

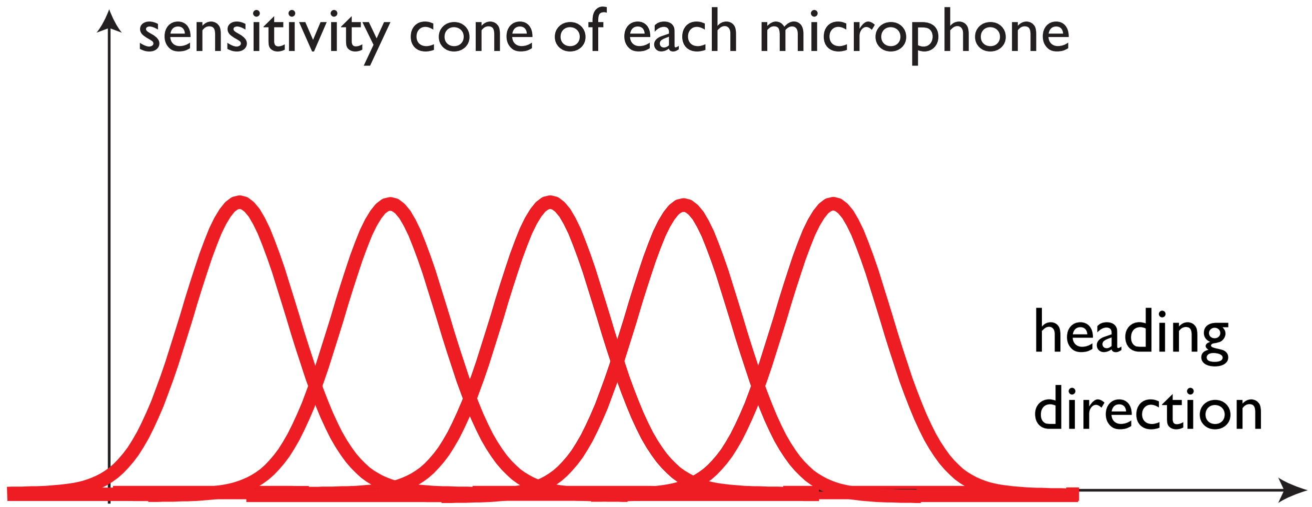


[from Bicho, Mallet, Schöner, Int J Rob Res,2000]



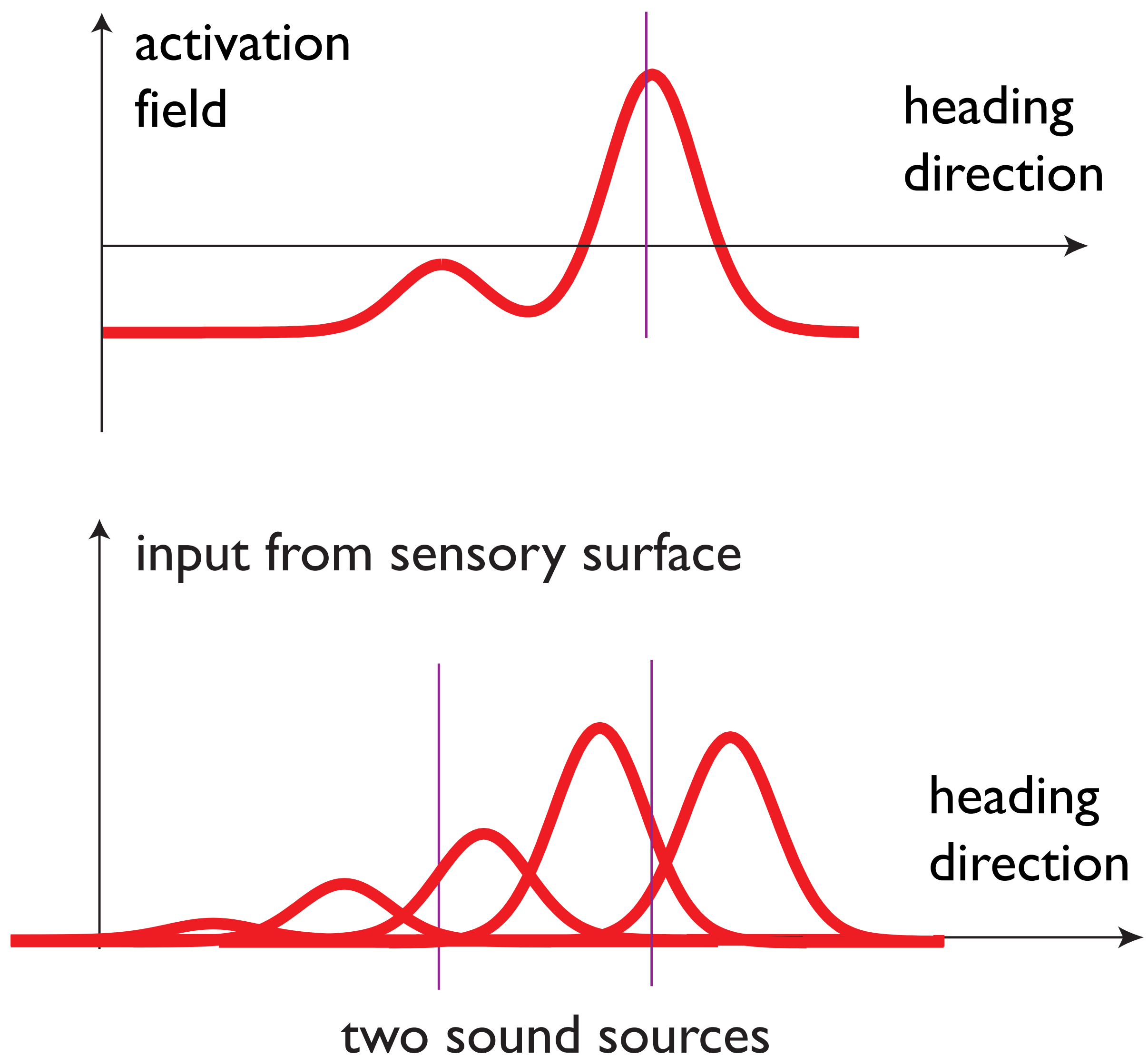
Sensory surface

- each microphone samples heading direction

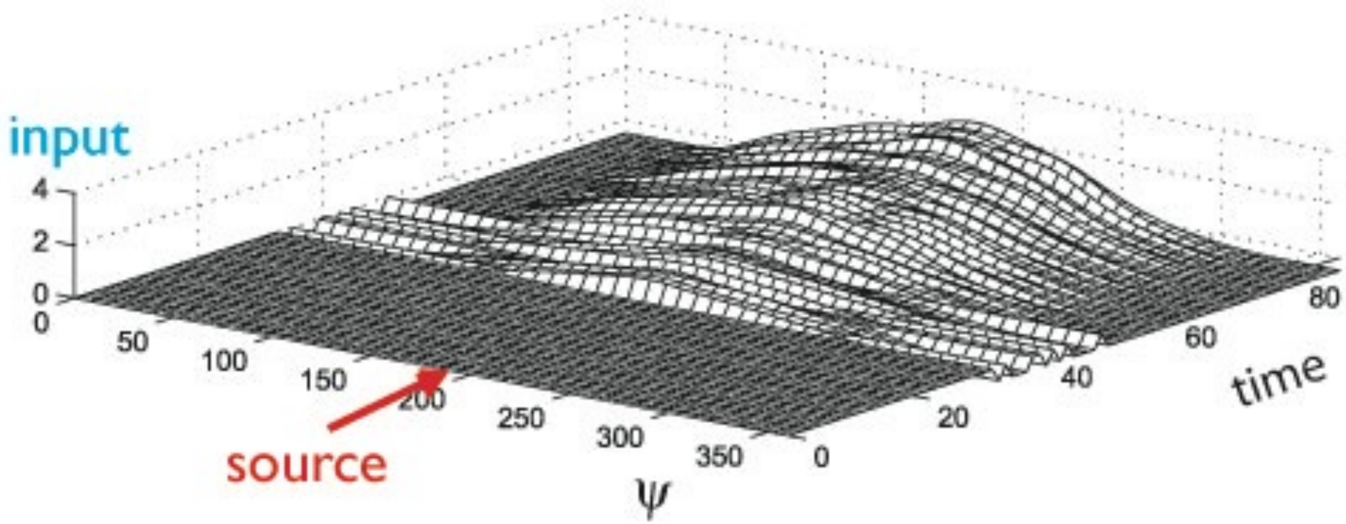


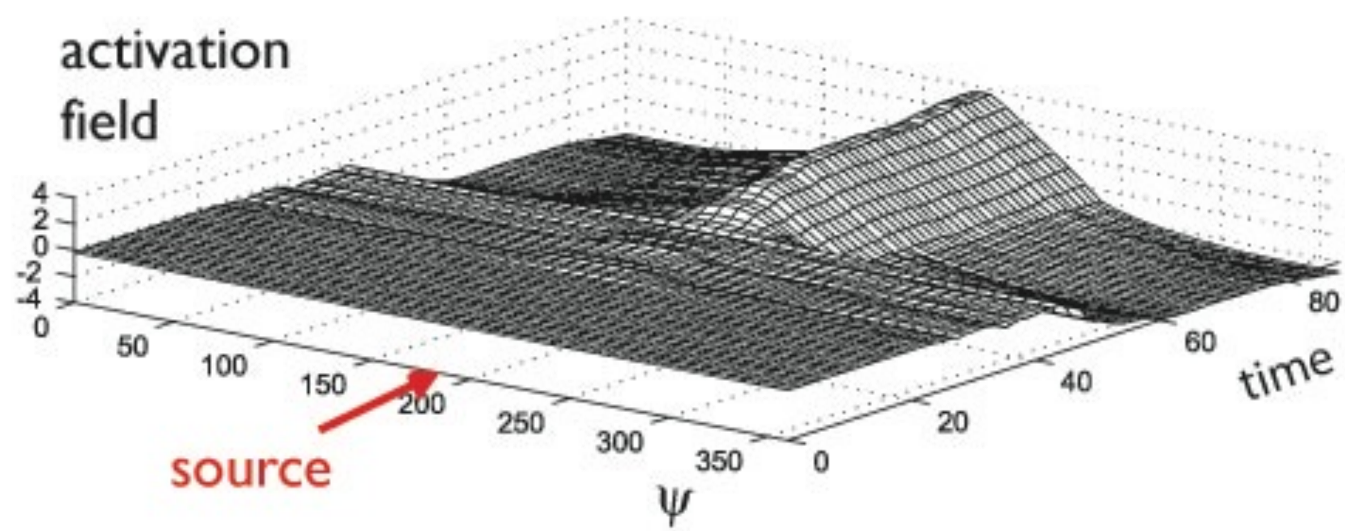
Sensory input

- each microphone provides input to the field = loudness * sensitivity cone

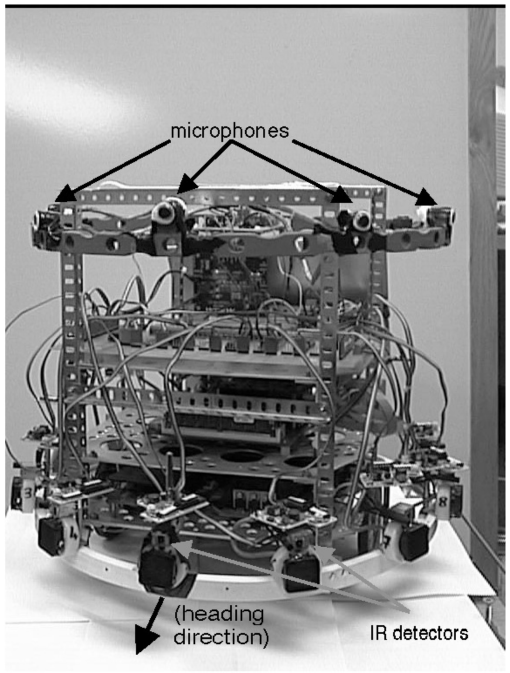


Detection instability as intensity of sound source increases

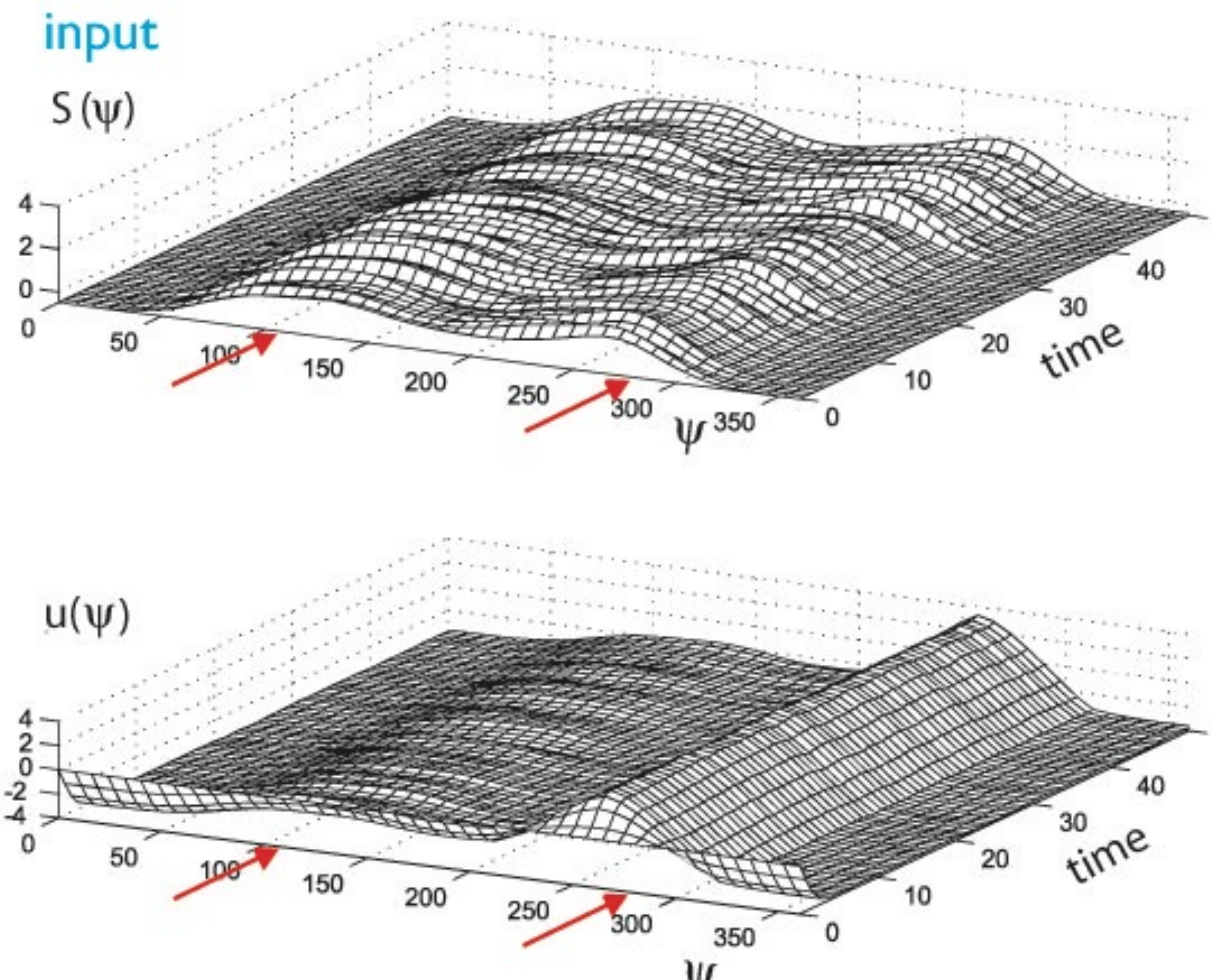




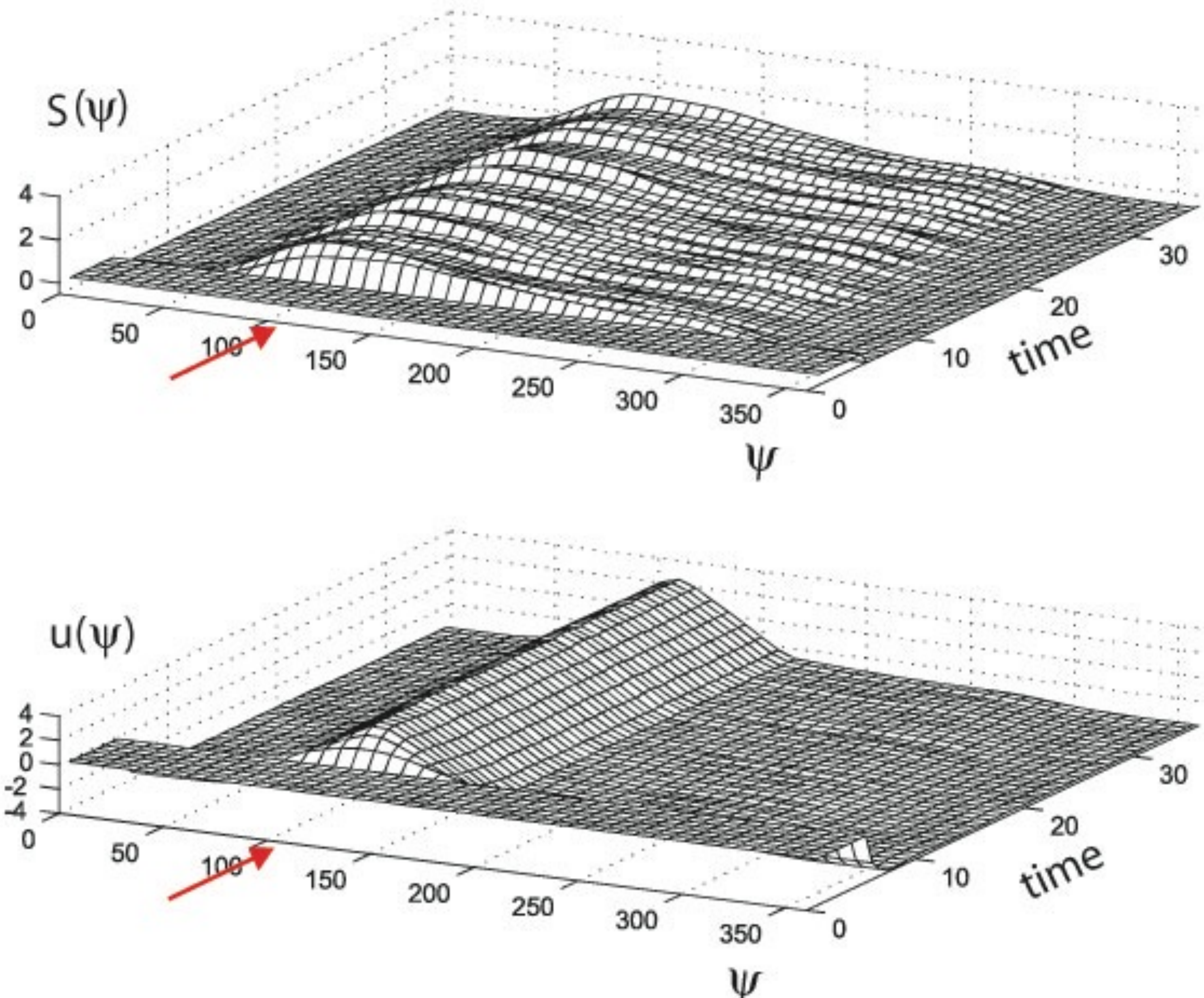
[from Bicho, Mallet, Schöner: Int. J. Rob. Res., 2000]



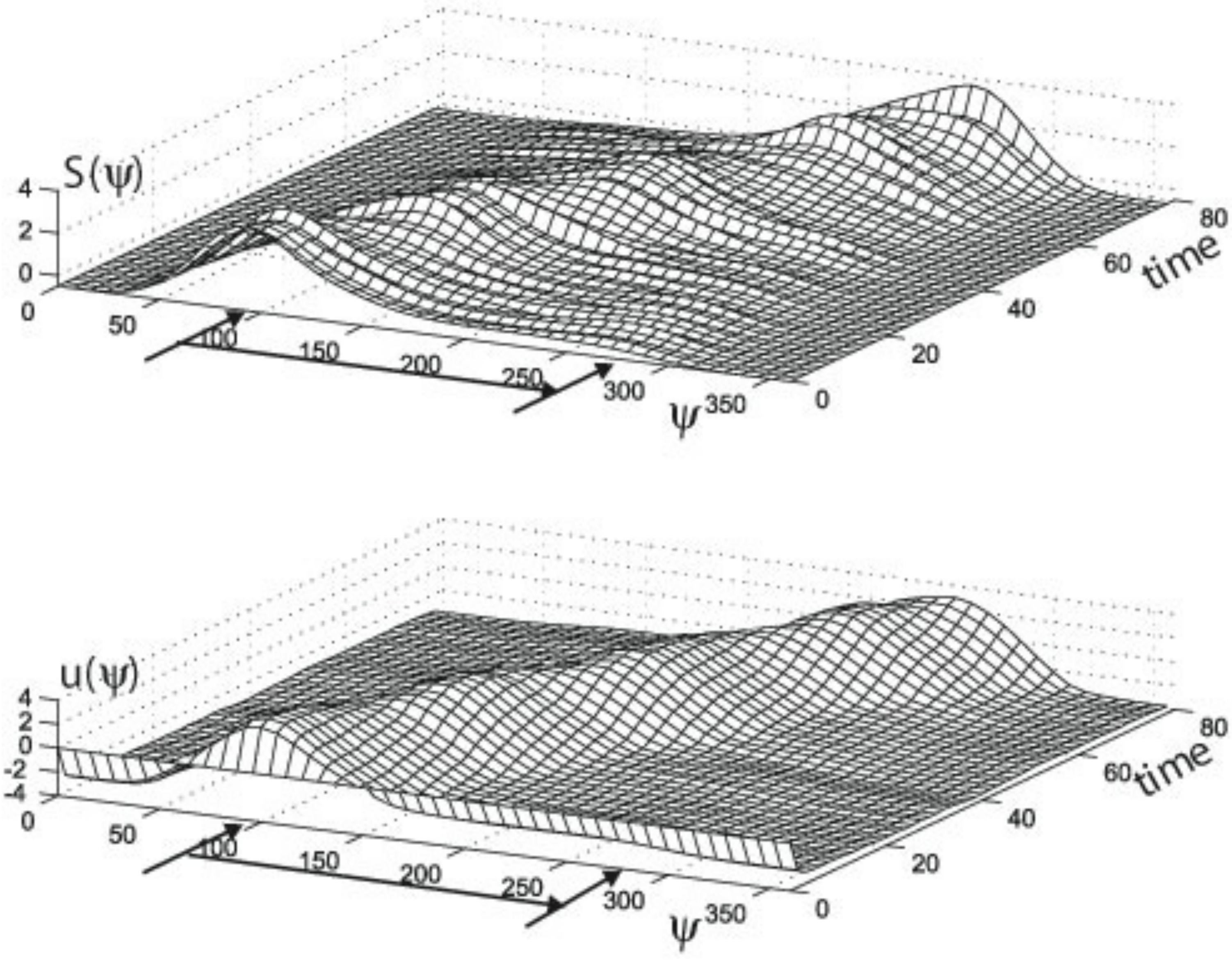
Target selection in the presence of two sources



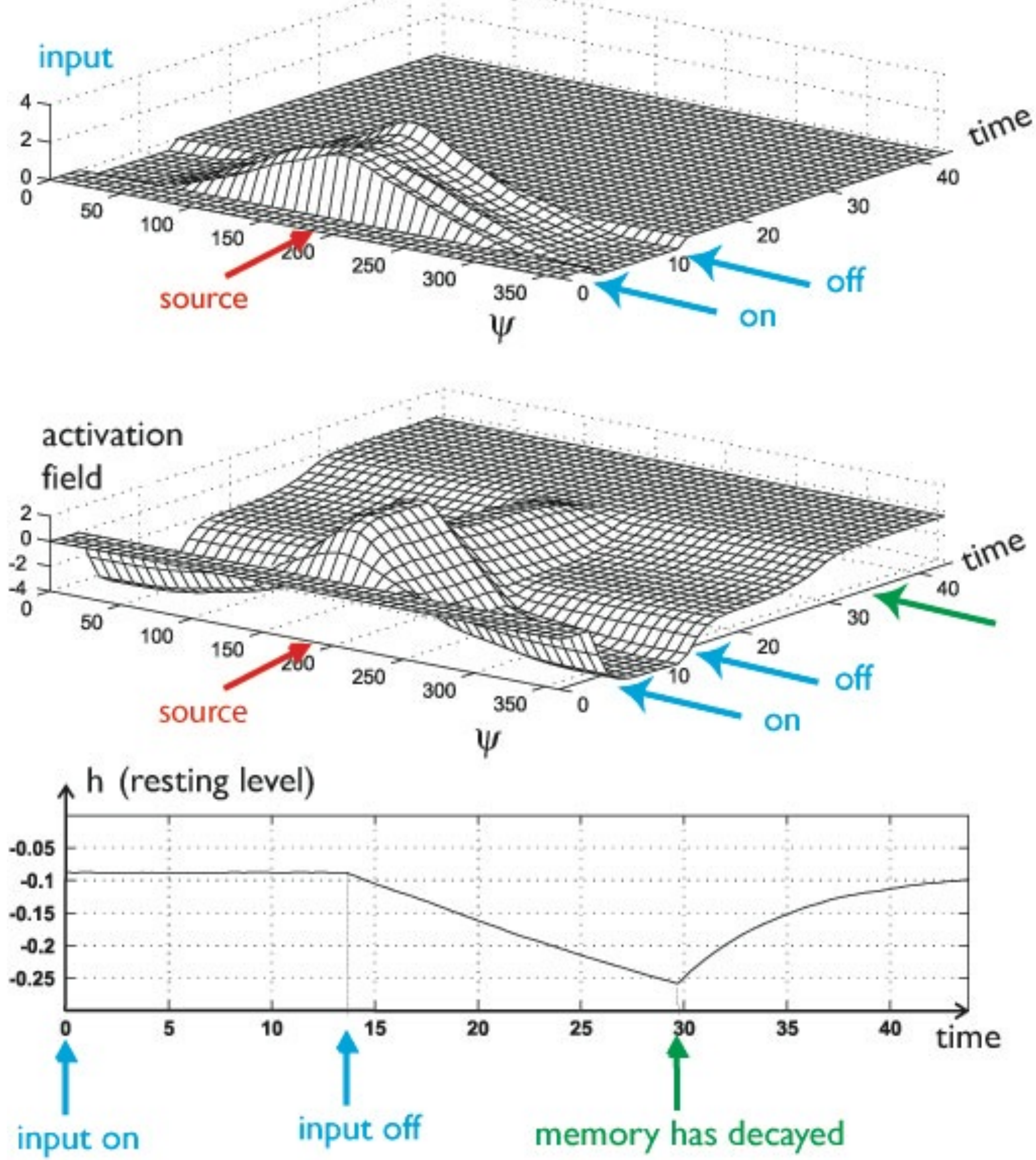
Robust estimation in the presence of outliers



Tracking moving sound source



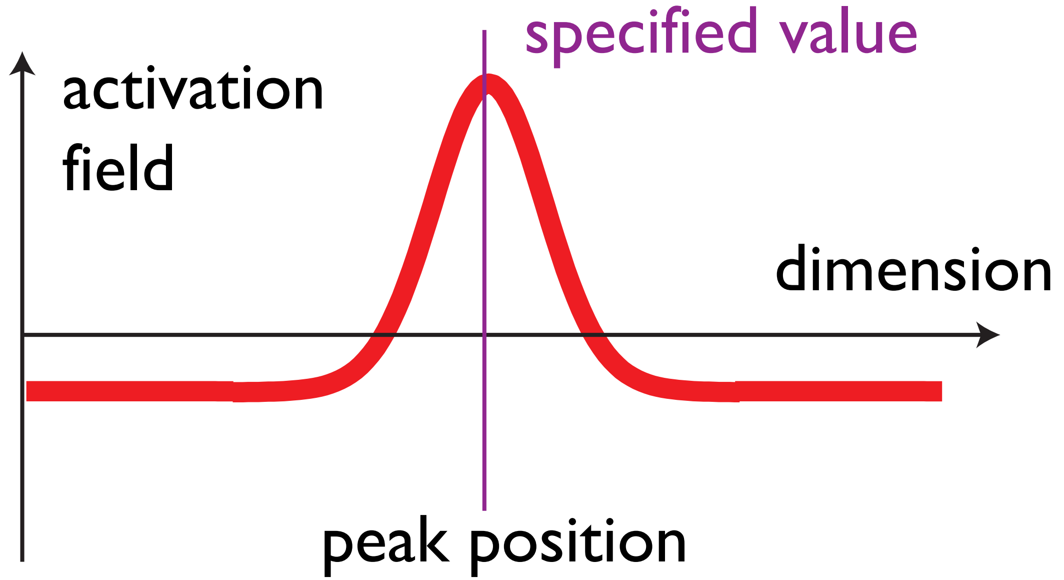
Working memory



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

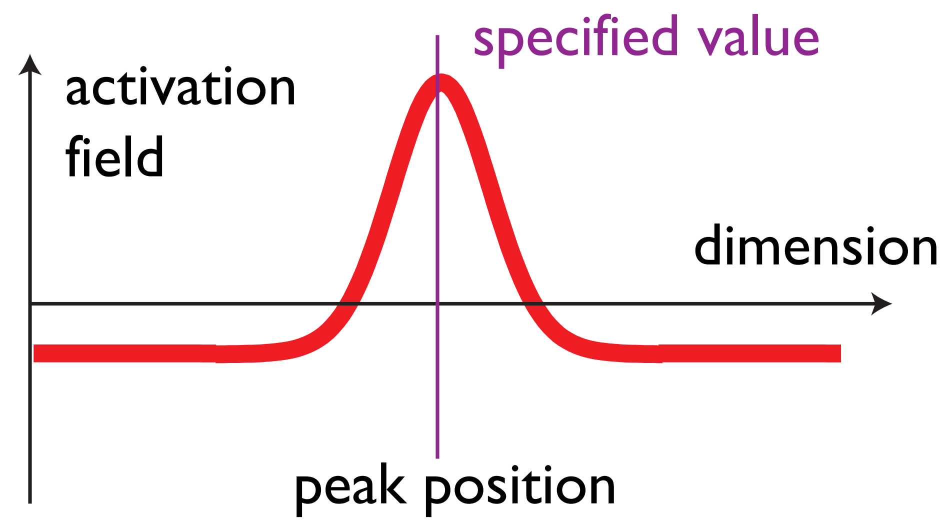
How to generate the behavior?

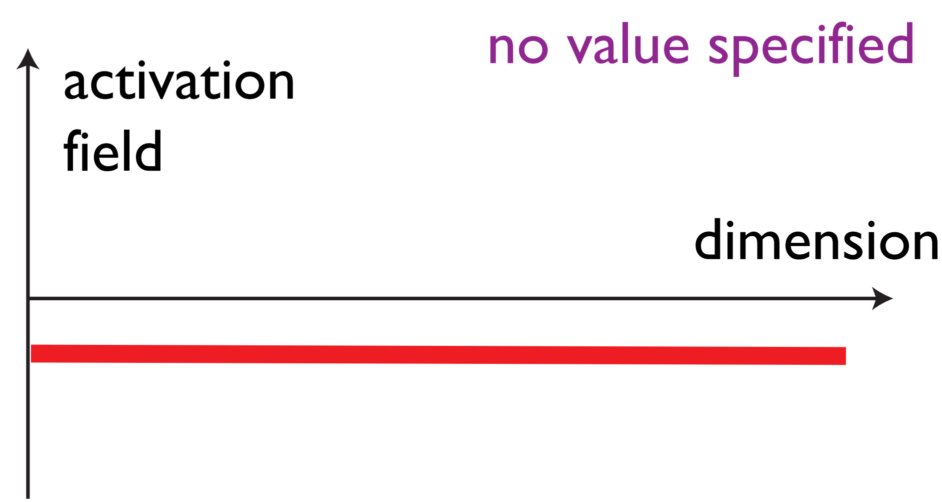
- “reading out” the peak location to specify heading?



"Reading out" from a neural field?

- standard idea: $\sigma(u)$~ probability density
- but: normalization!
- => problem when there is no peak: divide by zero!

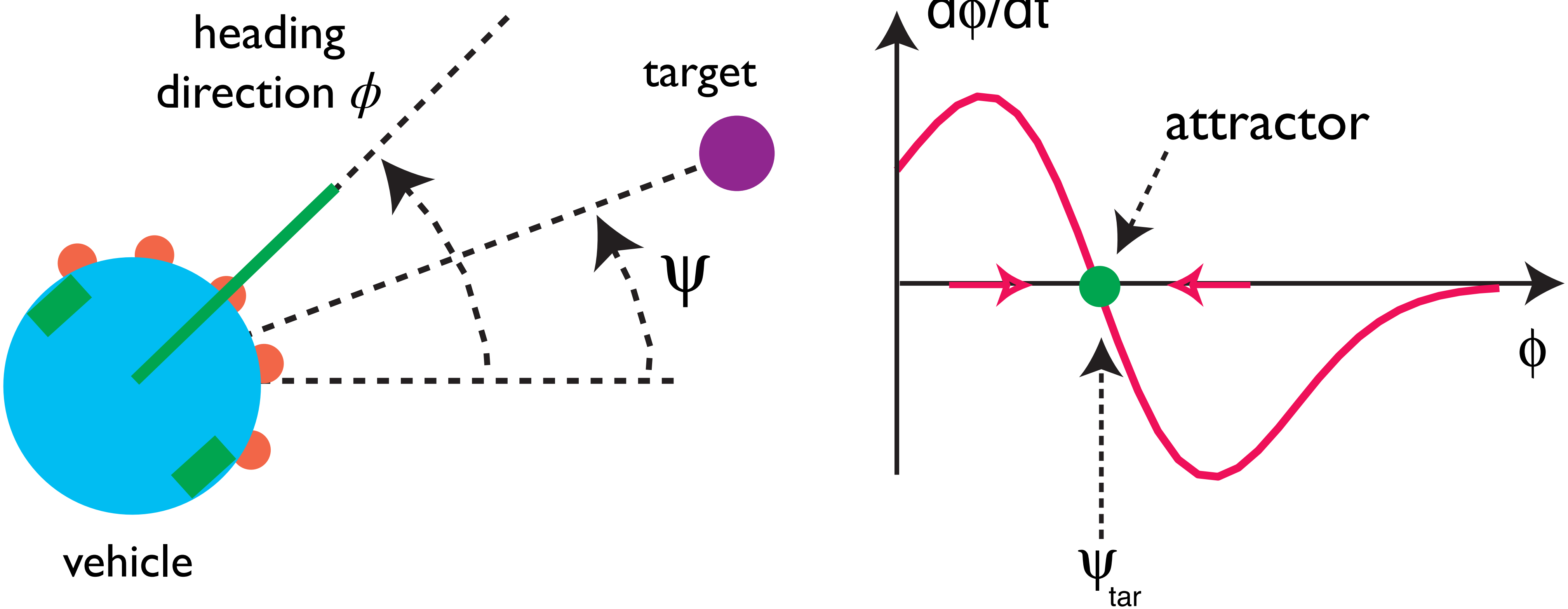




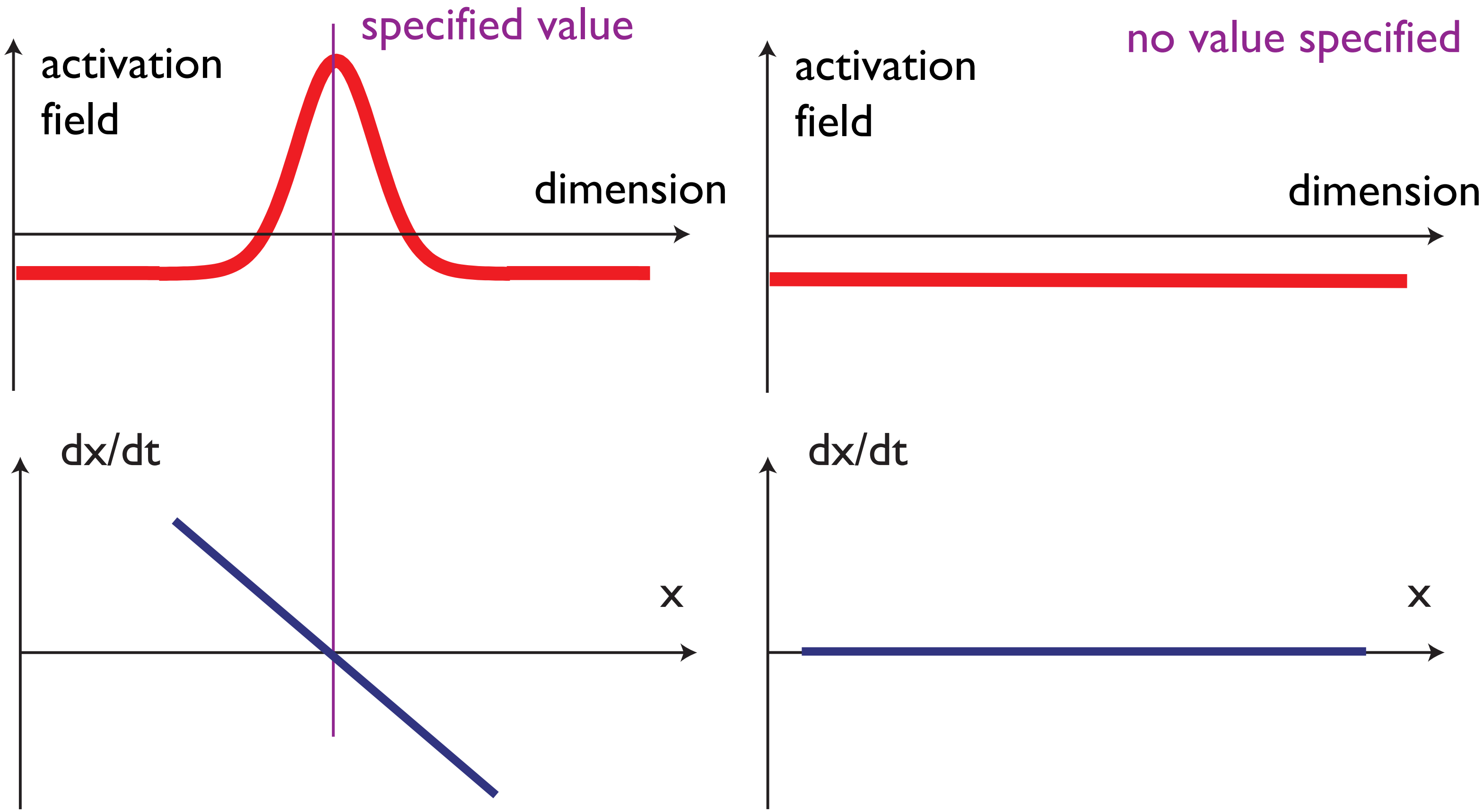
$$\phi_{\text{peak}} = \frac{\int d\phi \; \phi \; \sigma(u(\phi, t))}{\int d\phi' \; \sigma(u(\phi', t))}$$

Generating behavior actually entails dynamics

- behavioral dynamics with attractor at desired heading



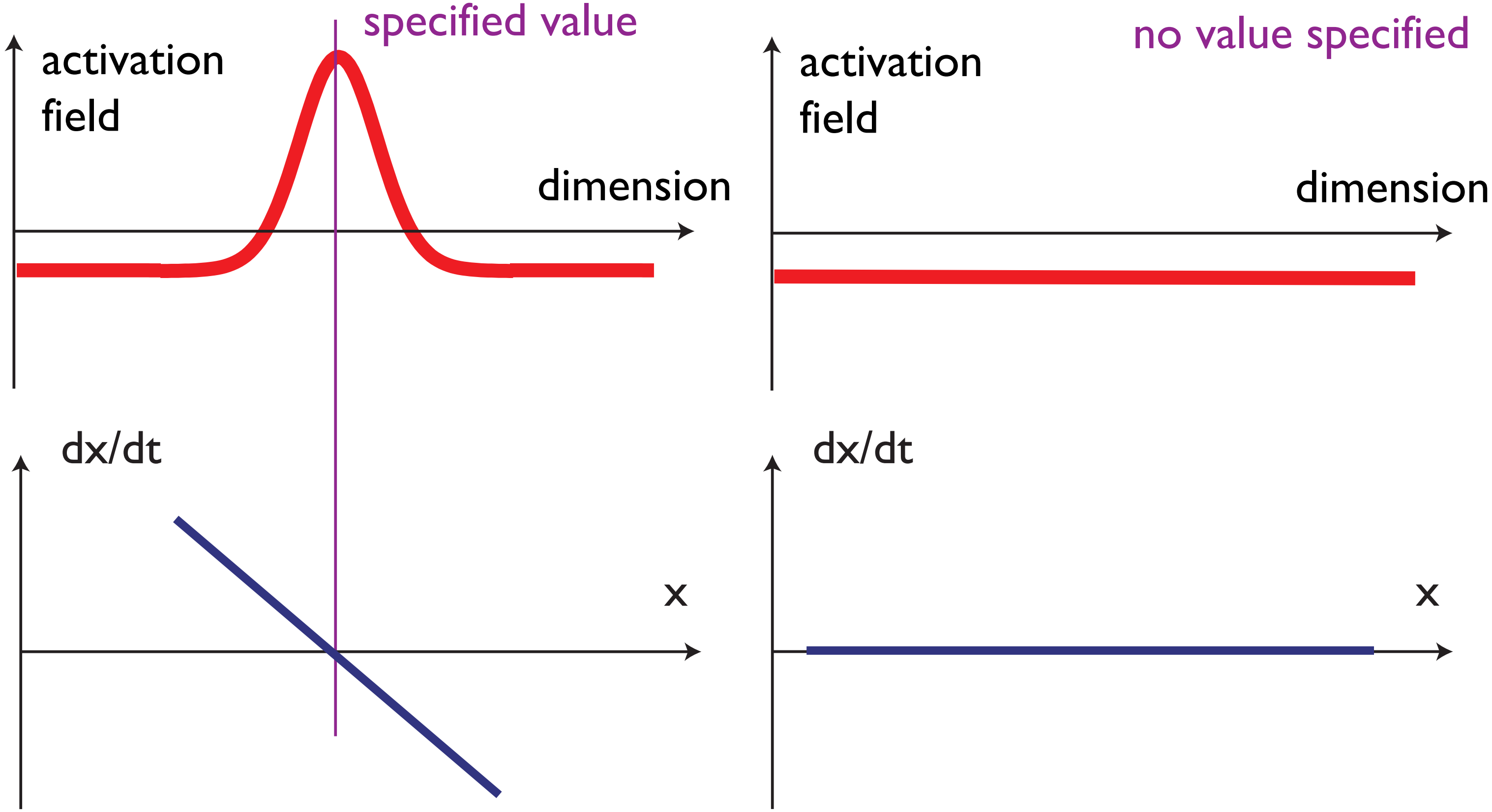
“Reading out” => erect an attractor!



“Read out” => erect an attractor!

$$\dot{\phi} = -\left[\int d\phi' \sigma(u(\phi',t))\right](\phi - \phi_{\text{peak}})$$

$$= -\int d\phi' \; (\phi - \phi') \; \sigma(u(\phi',t))$$



Conclusion

- sensory-motor cognition from neural dynamic fields that are coupled to sensory surfaces and act on the motor surfaces (through behavioral dynamics)
- instabilities make decisions
  - detection
  - selection
  - working memory

Outlook

- how do we go from sensory-motor cognition to “real” cognition?