Dynamic Field Theory: Detection decisions

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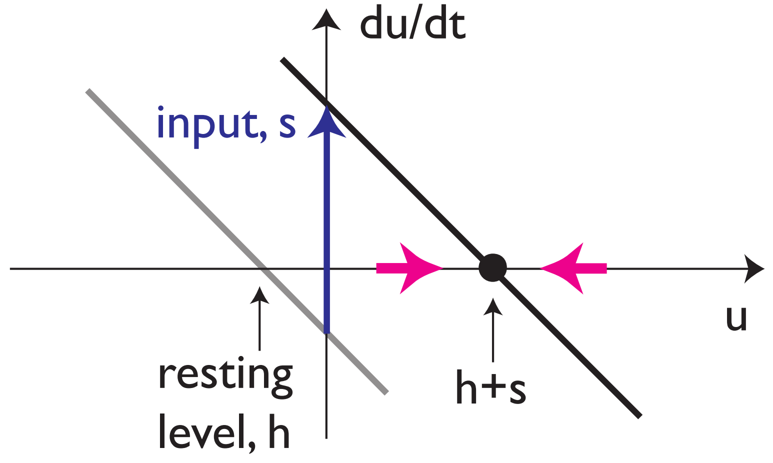
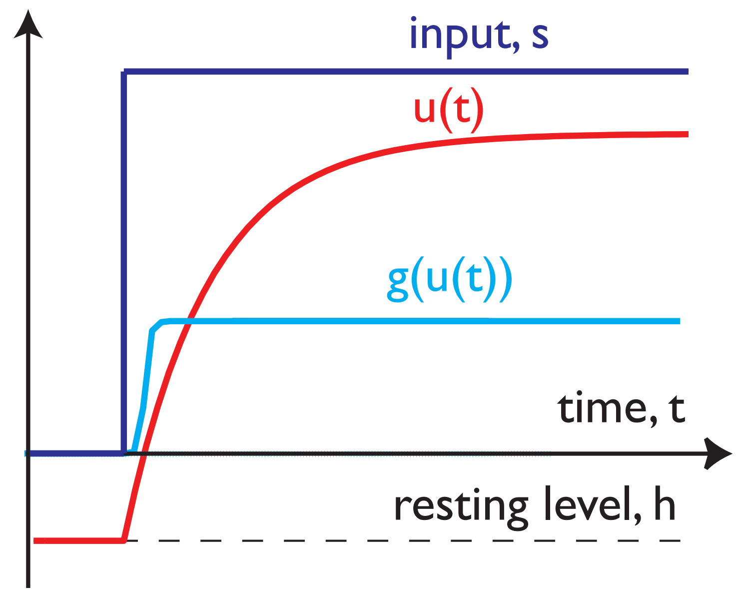
Recall: neural dynamics



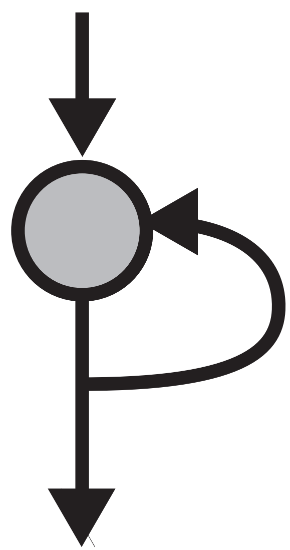
- activation dynamics of individual "neurons"

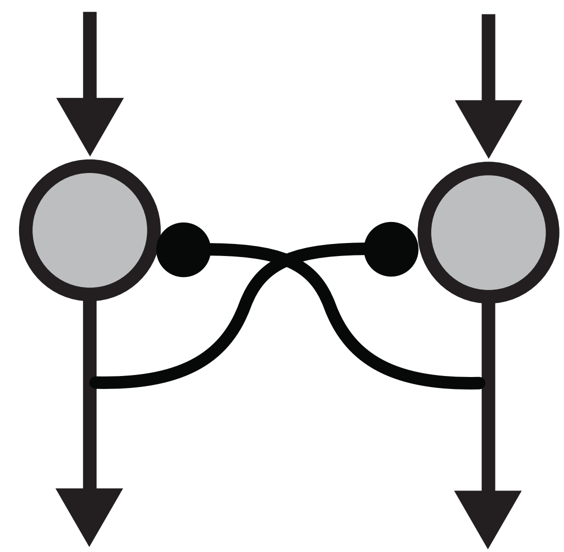


$$\tau \dot{u}(t) = -u(t) + h + \text{ inputs(t)}$$

Neural Dynamics

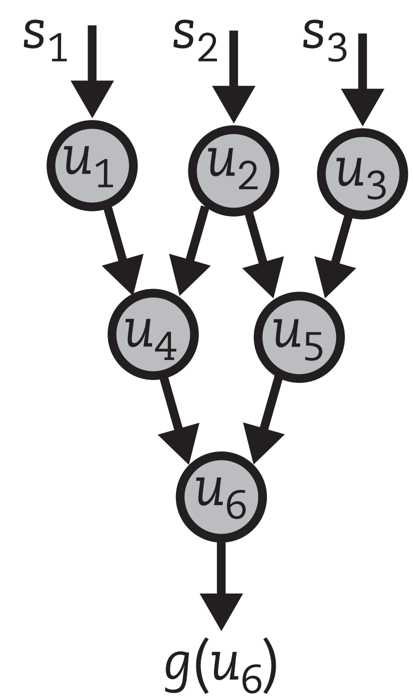
- dynamic neural “networks” consisting of one or two neurons

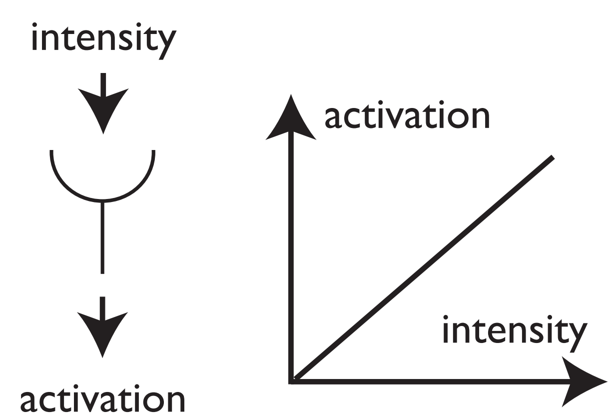




Neural dynamic networks

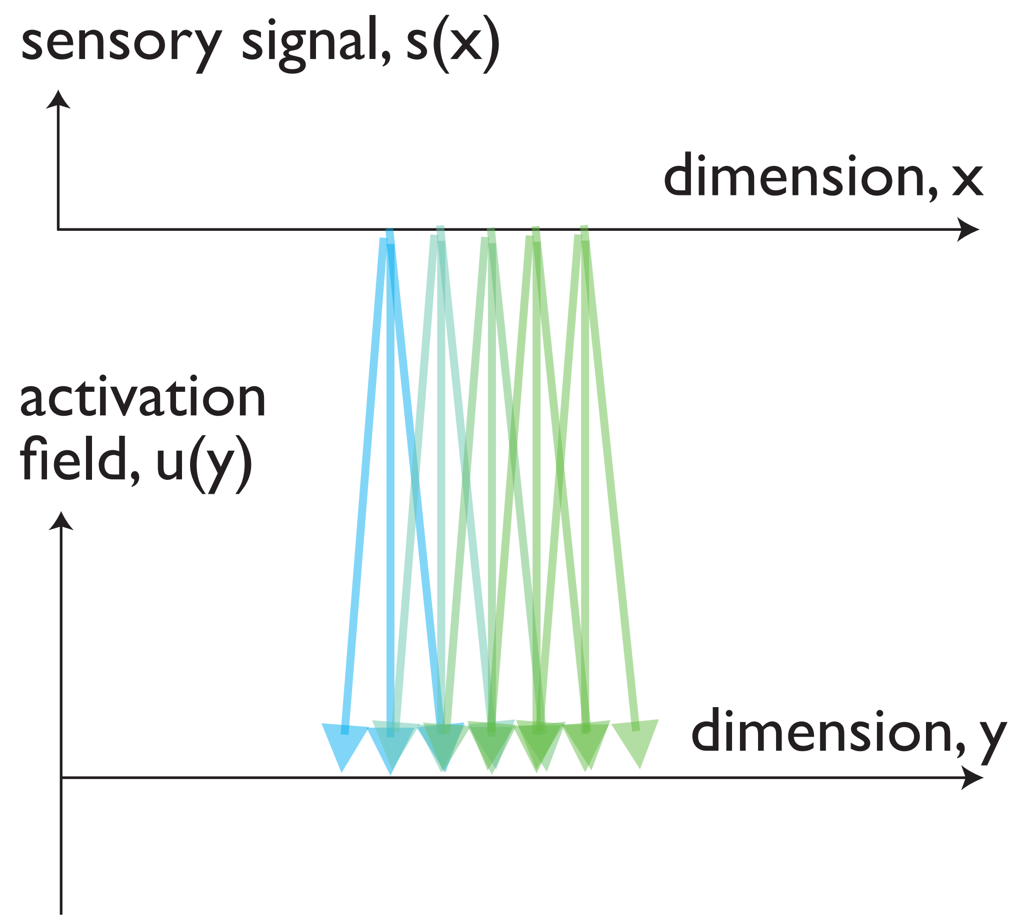
- in networks neural activation variables, the forward connectivity determines "what a neuron stands for"
- = space code (or labelled line code)
- in rate code, the activation level "stands for" something, e.g. a sensed intensity
- generic neural networks combine both codes





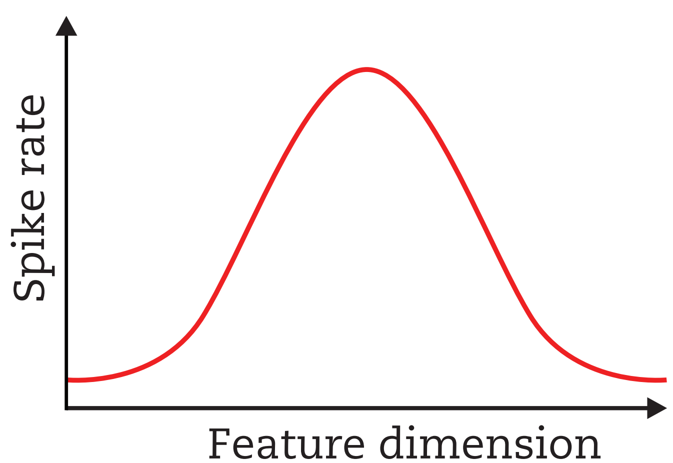
Neural fields

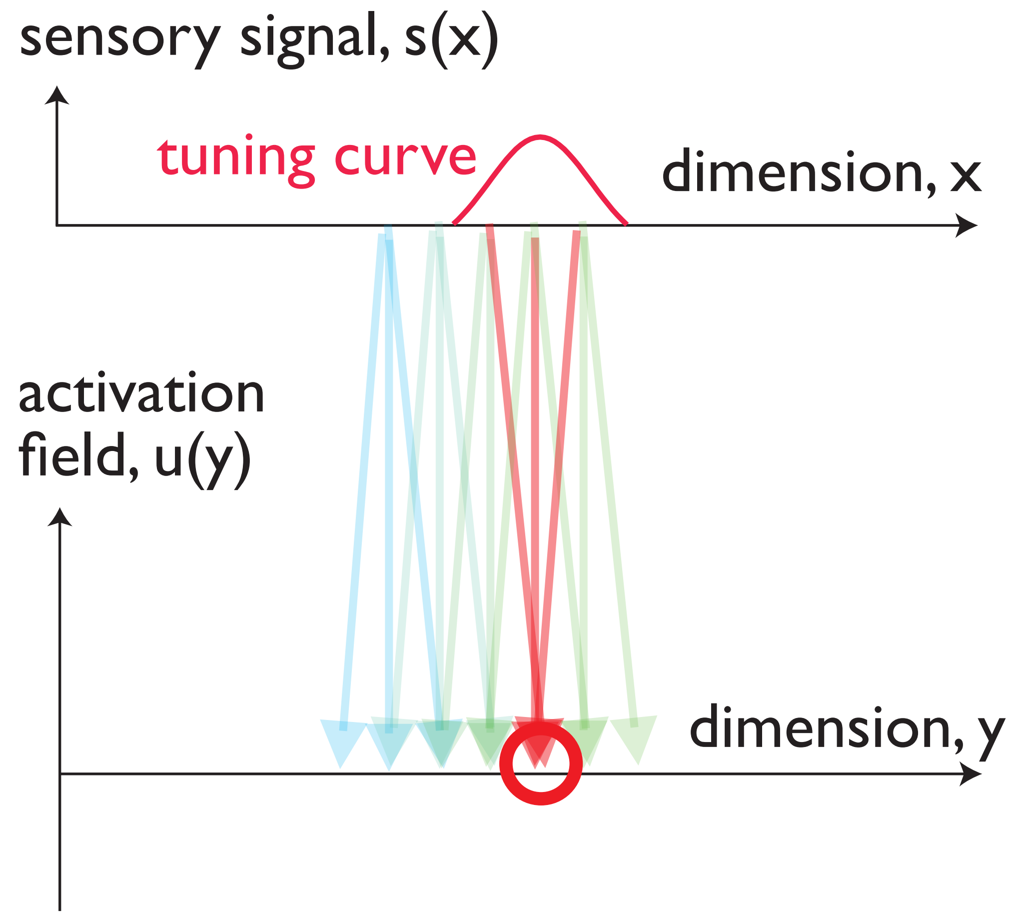
- forward connectivity from the sensory surface extracts perceptual feature dimension



Neural fields

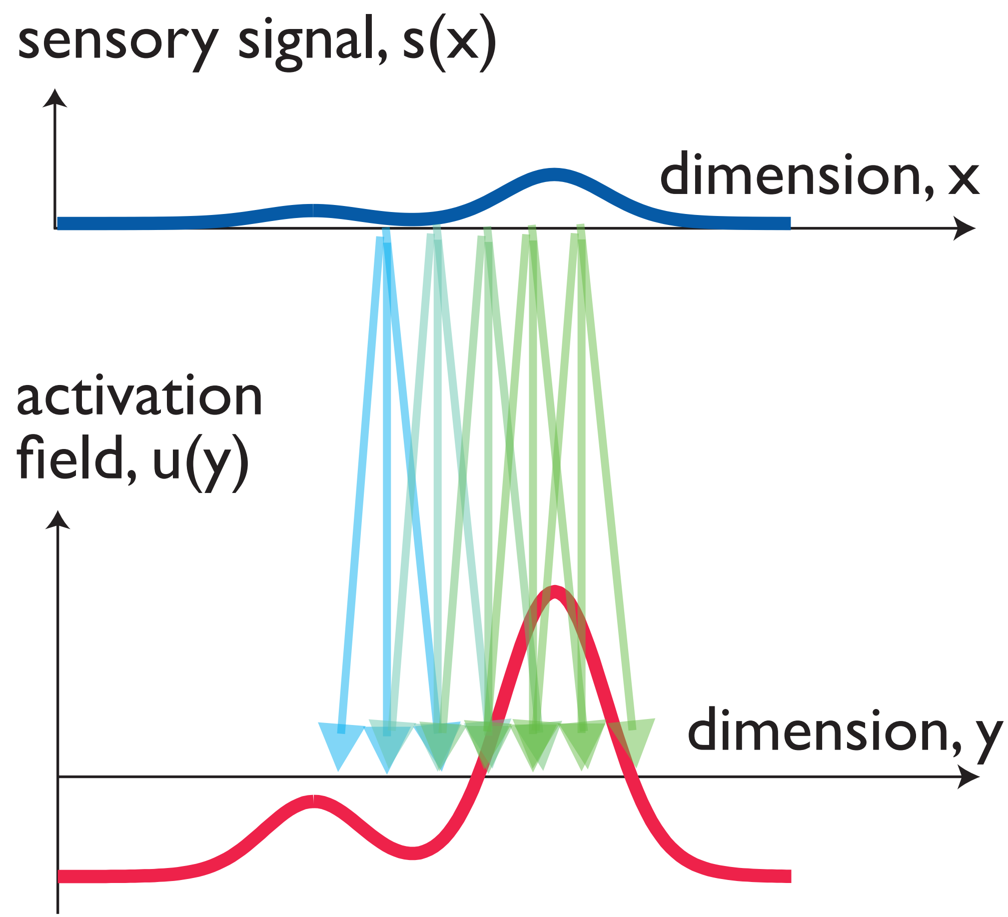
- forward connectivity predicts/models tuning curves





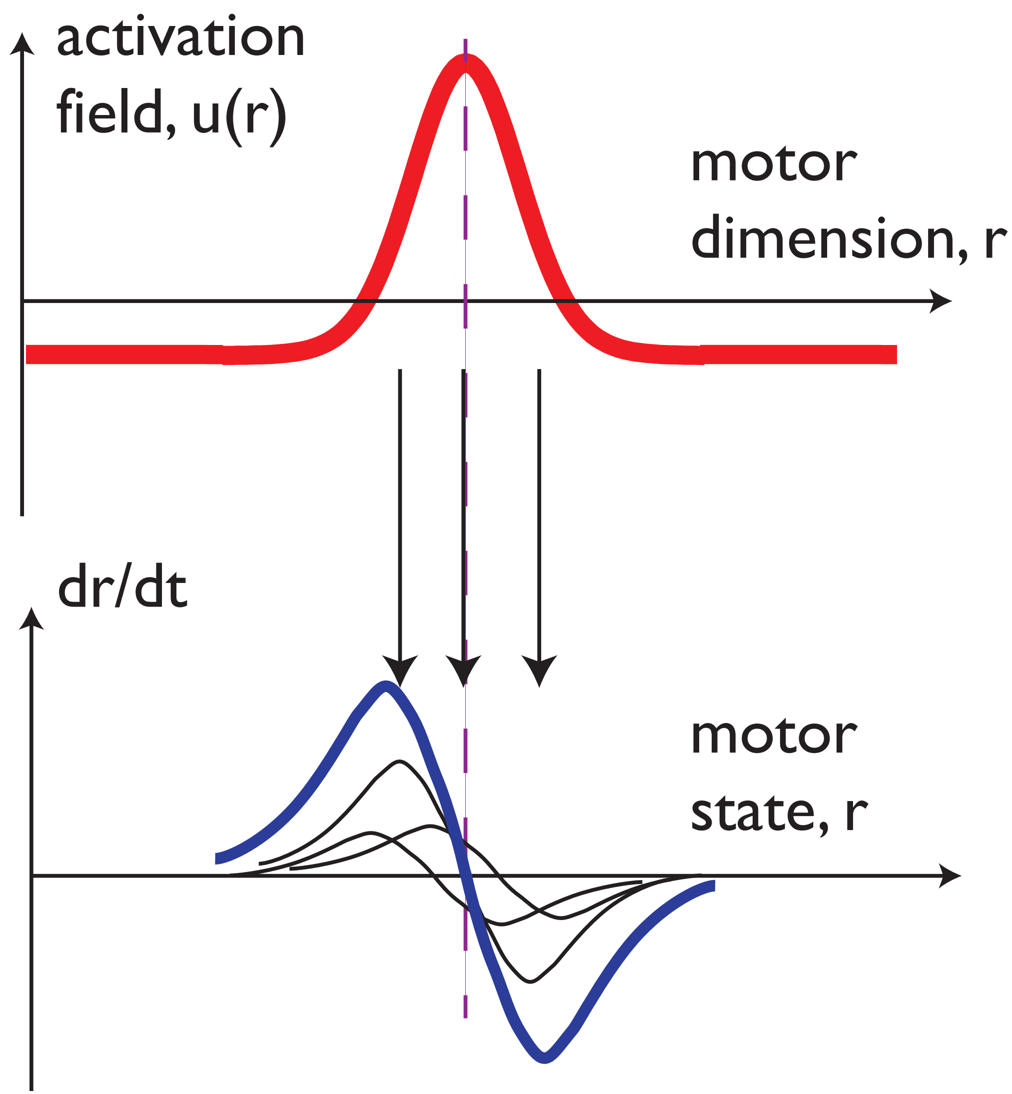
Neural fields

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

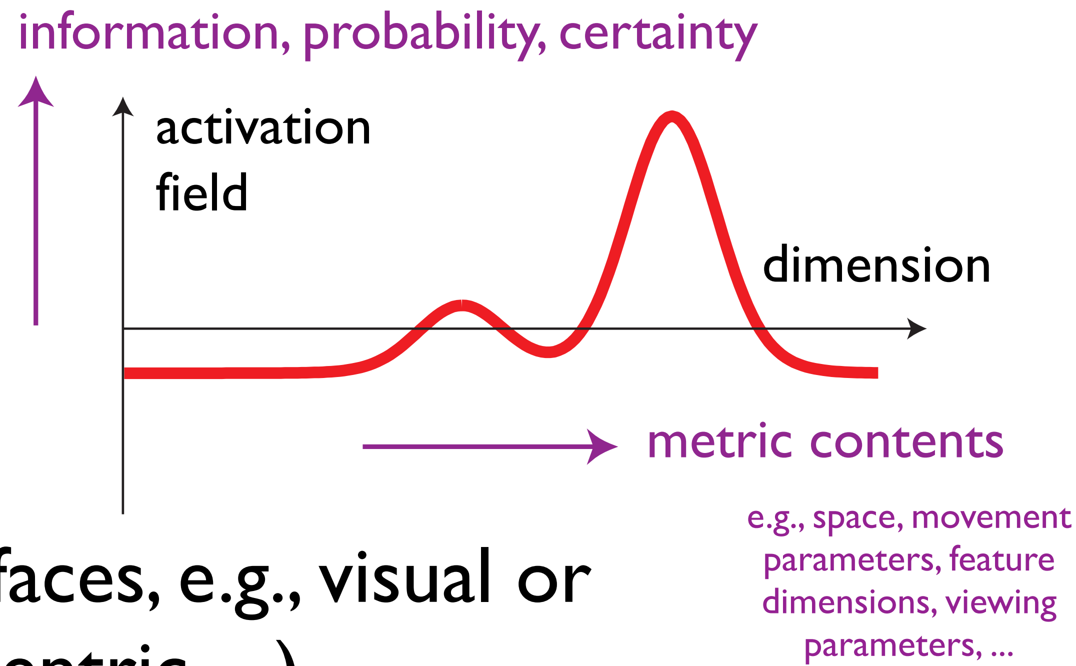


Neural fields

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

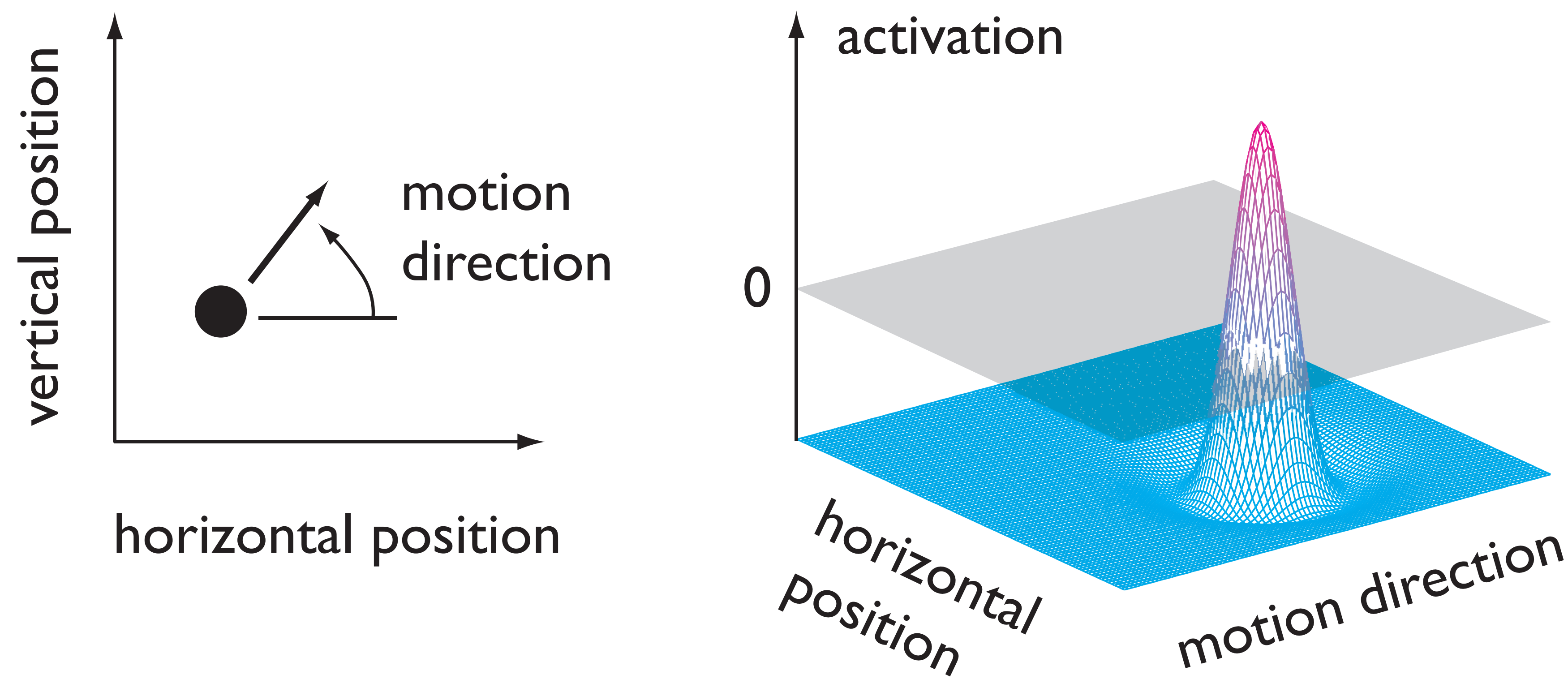


fields defined over continuous spaces

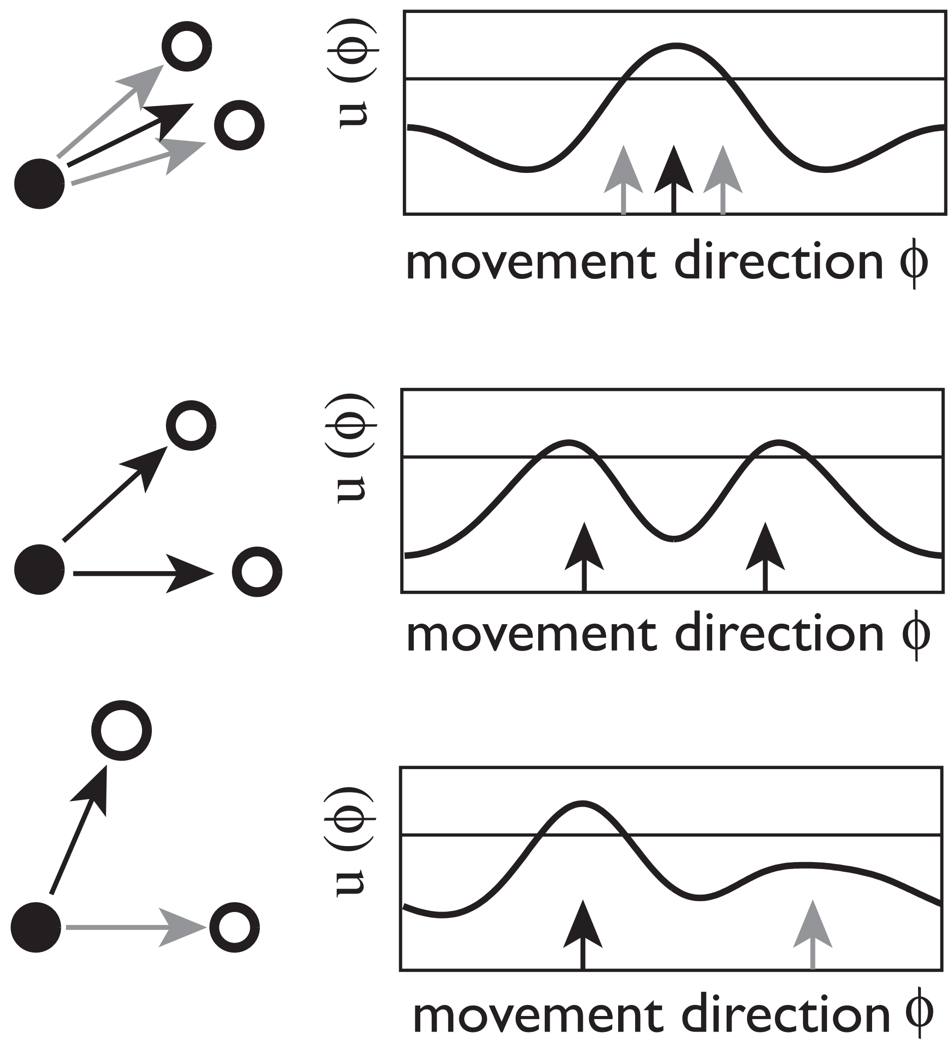


- homologous to sensory surfaces, e.g., visual or auditory space (retinal, allocentric, ...)
- homologous to motor surfaces, e.g., saccadic end-points or direction of movement of the end-effector in outer space
- feature spaces, e.g., localized visual orientations, color, impedance, ...
- abstract spaces,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

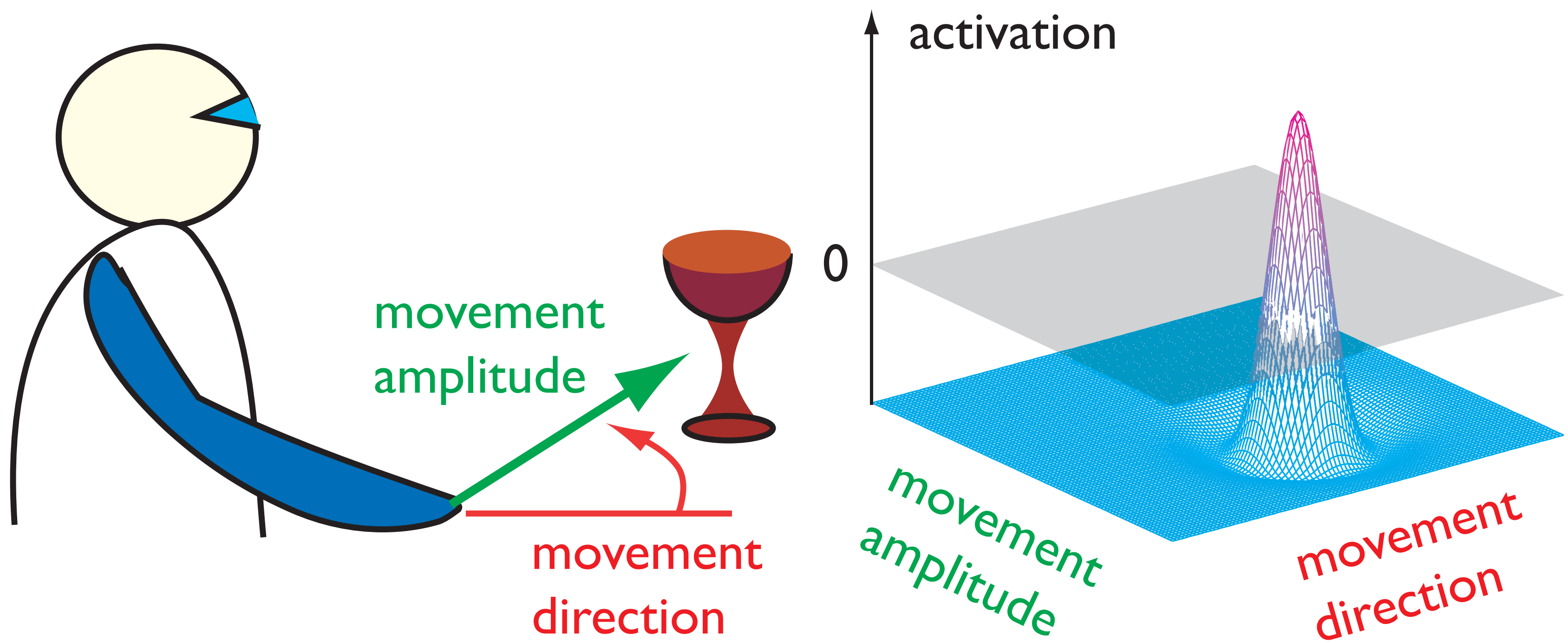
Example motion perception: space of possible percepts



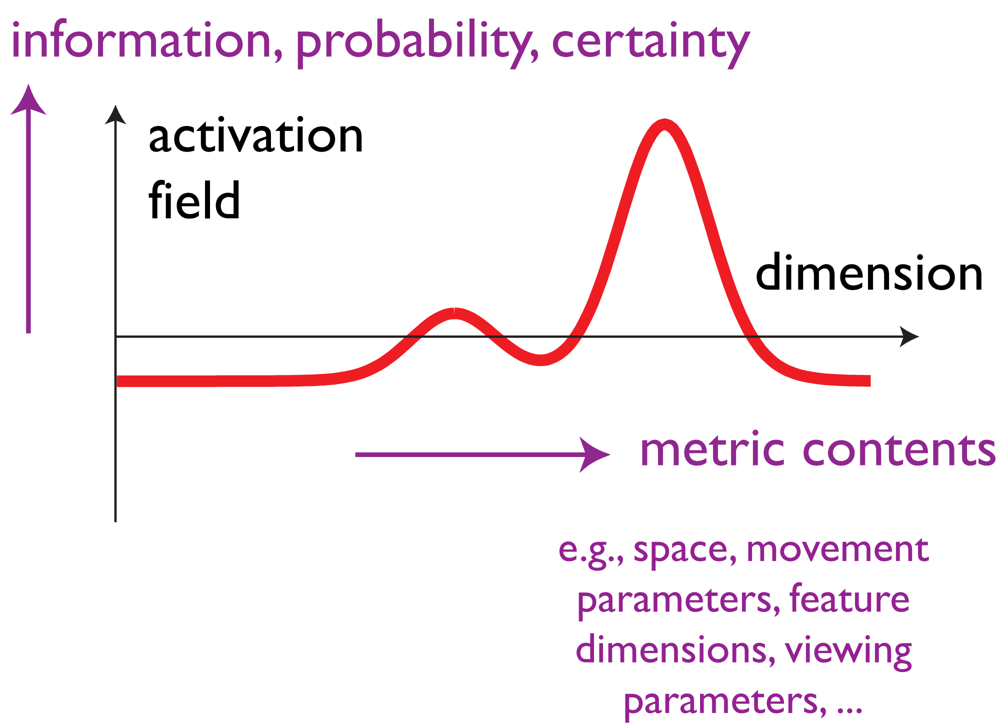
Activation patterns representing different percepts

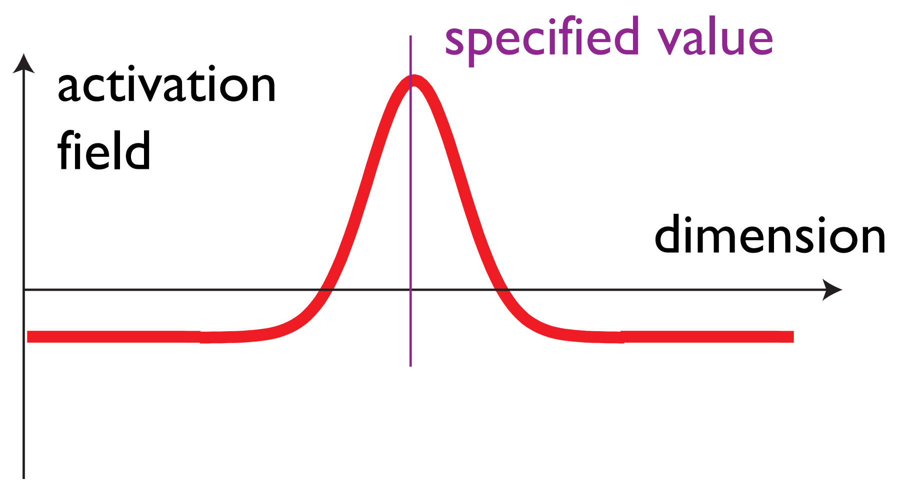


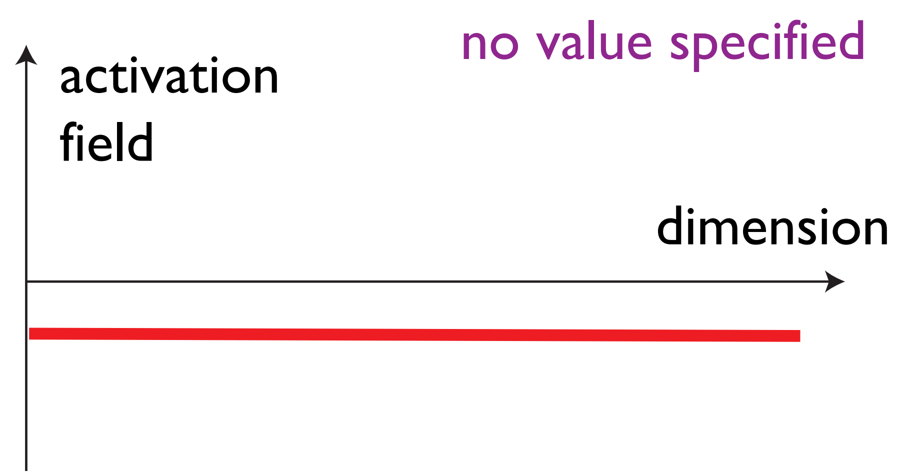
Example: movement planning: space of possible actions



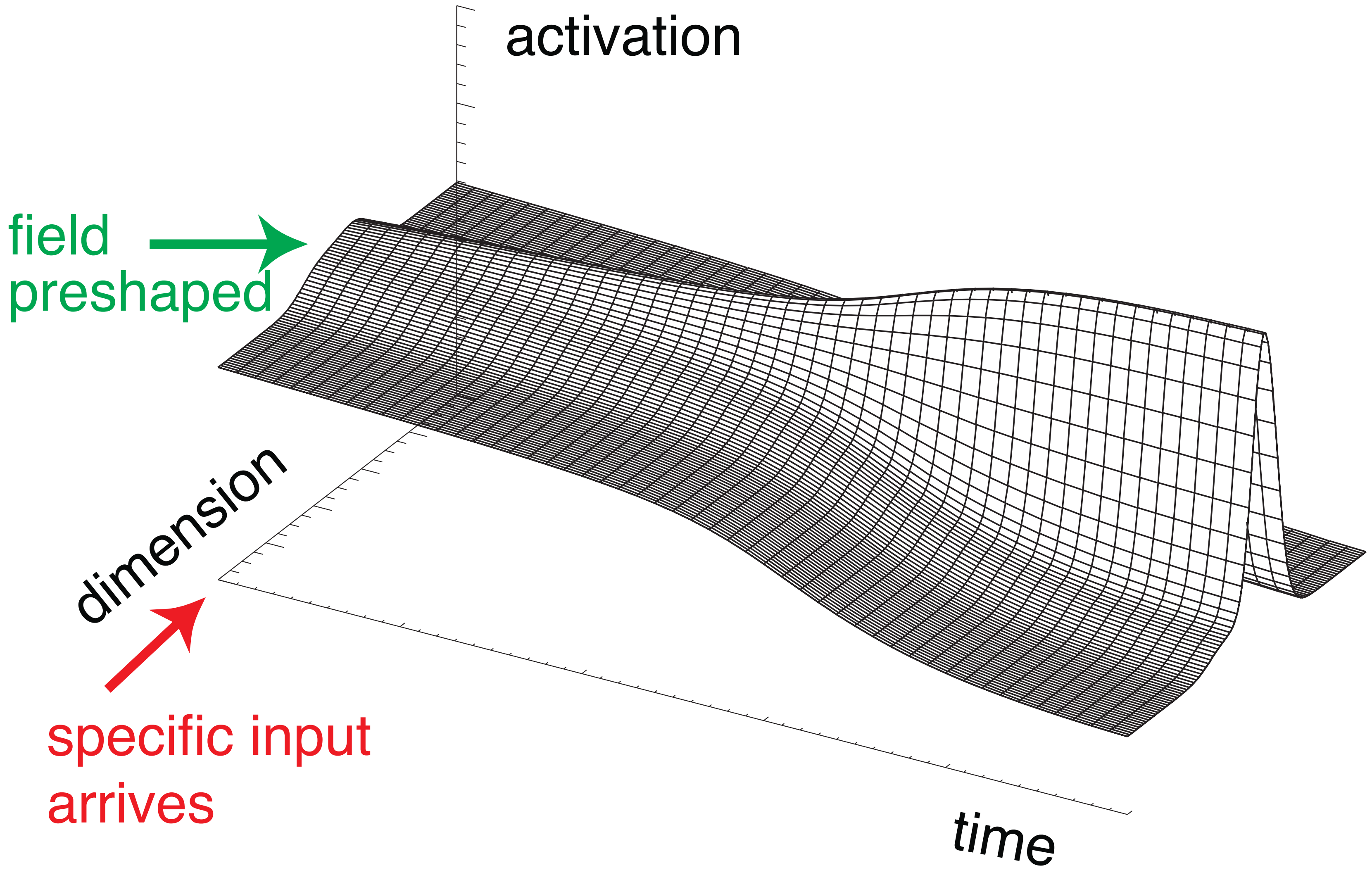
Activation fields... peaks as units of representation





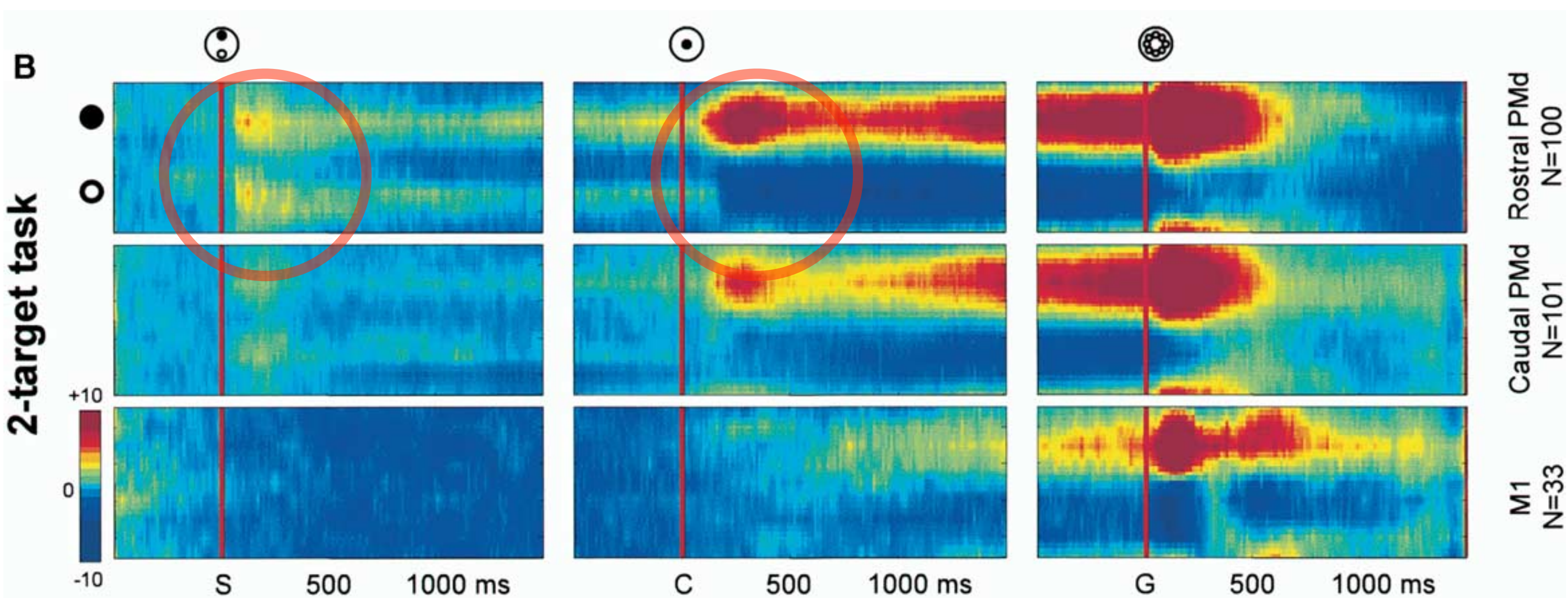


Time courses of activation fields



Activation patterns representing states of motor decision making

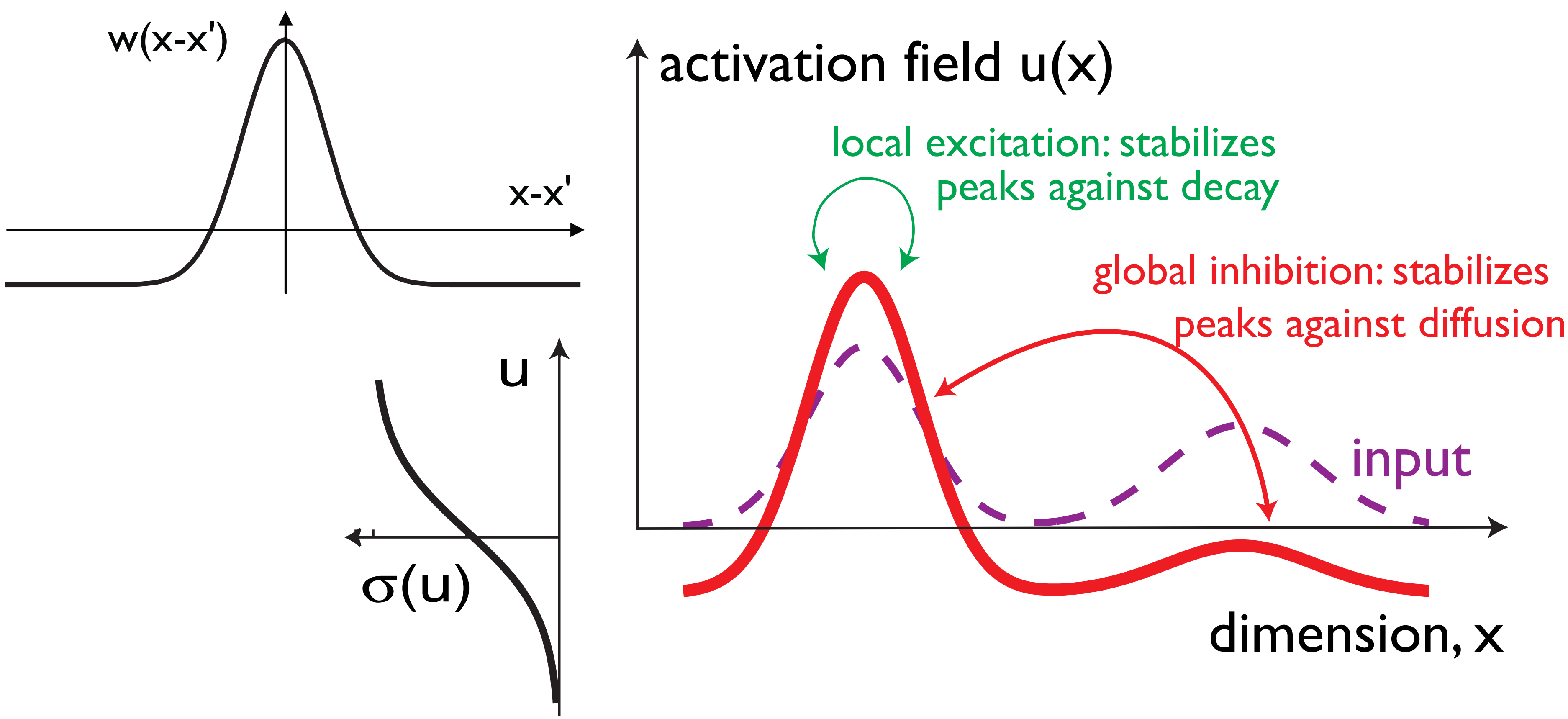
- bi-modal distribution of activation over movement direction in pre-motor cortex before a selection decision is made
- mono-modal distribution once the decision is made



[Cisek, Kalaska: Neuron 2005]

Neural dynamics of fields

- Peaks as stable states =attractors
- from intra-field interaction: local excitation/global inhibition



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

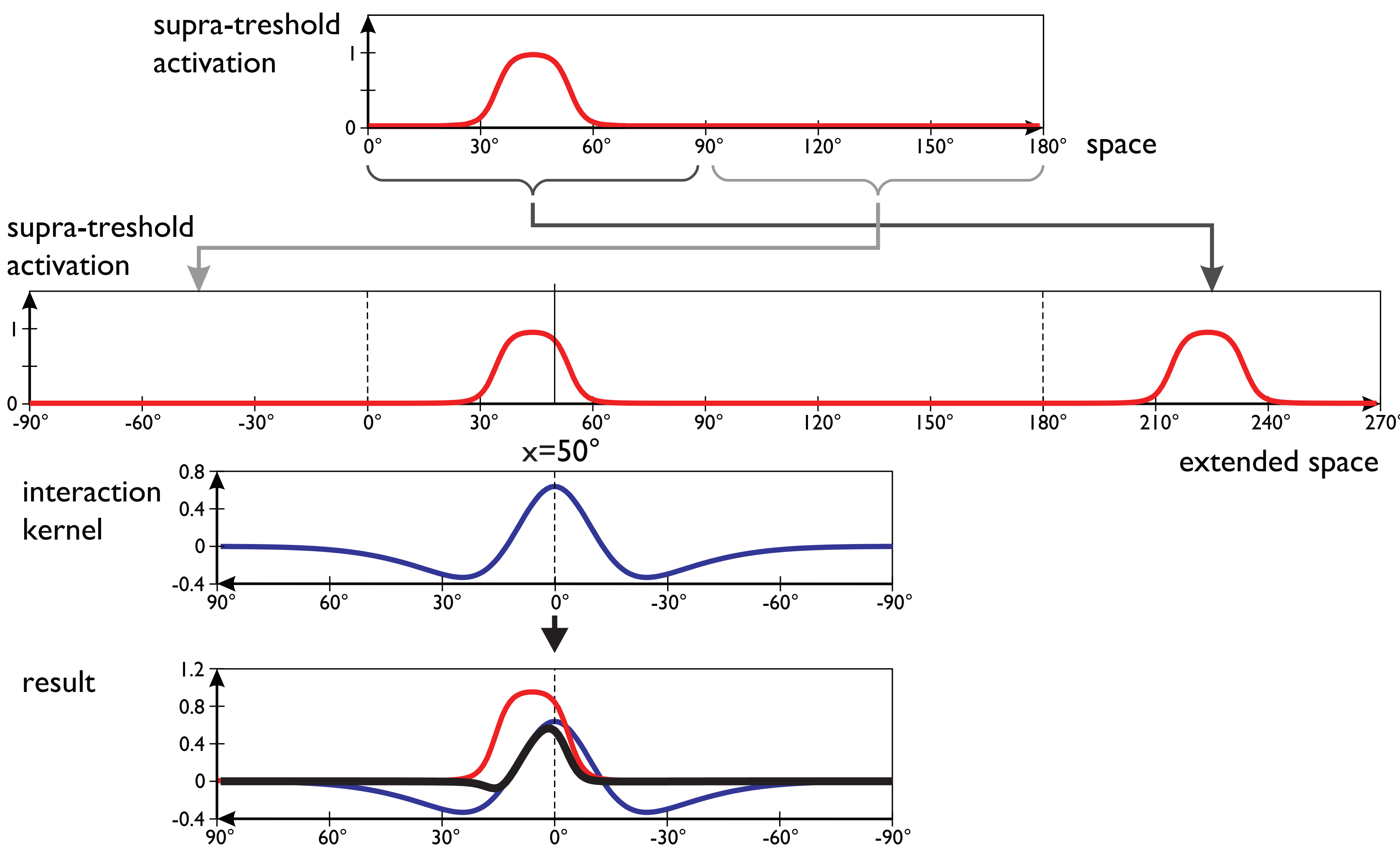
- time scale is τ
- resting level is $h < 0$
- input is $S(x,t)$
- interaction kernel is

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

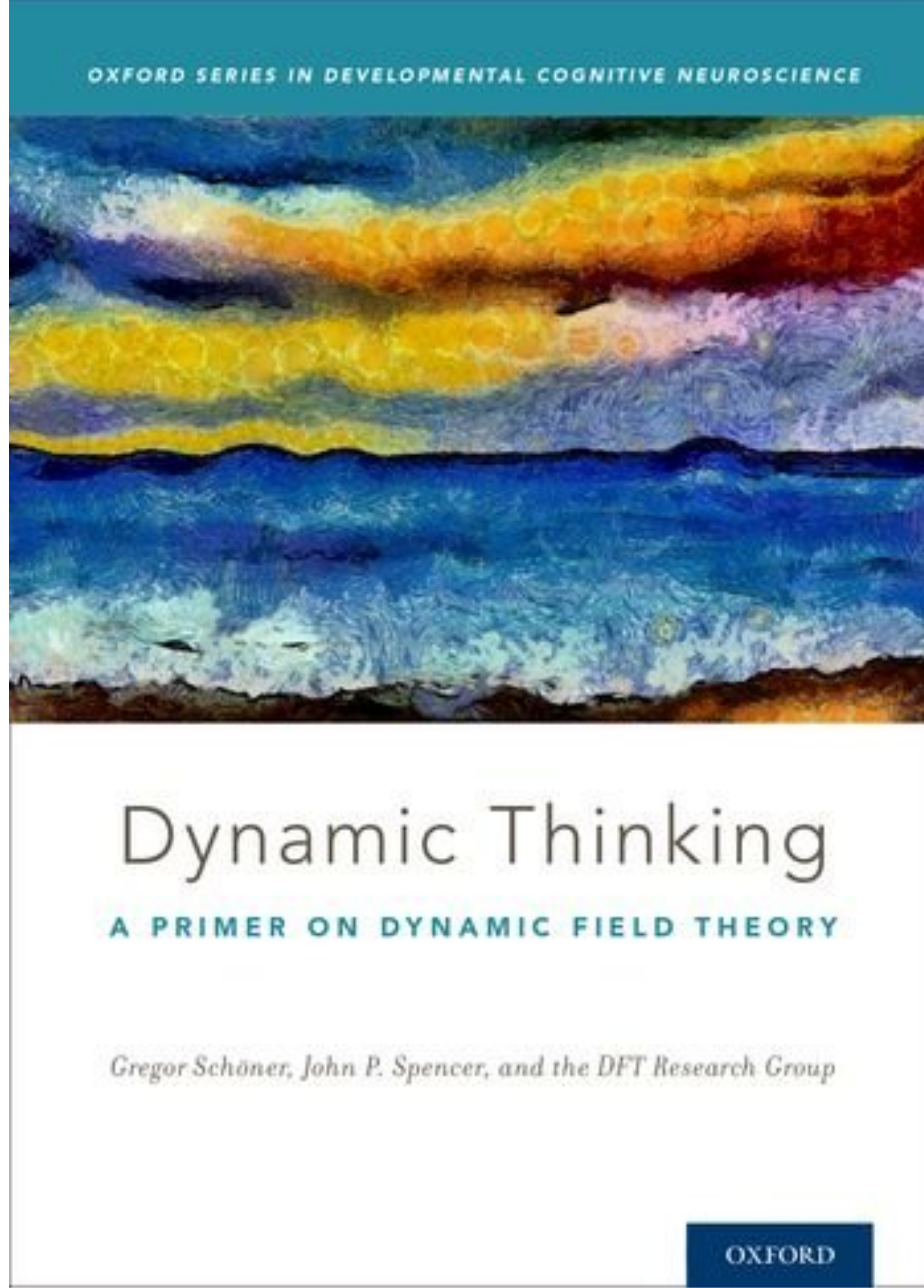
- sigmoidal nonlinearity is

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

Interaction: convolution



- dynamicfieldtheory.org



=> simulation

Attractors and their instabilities

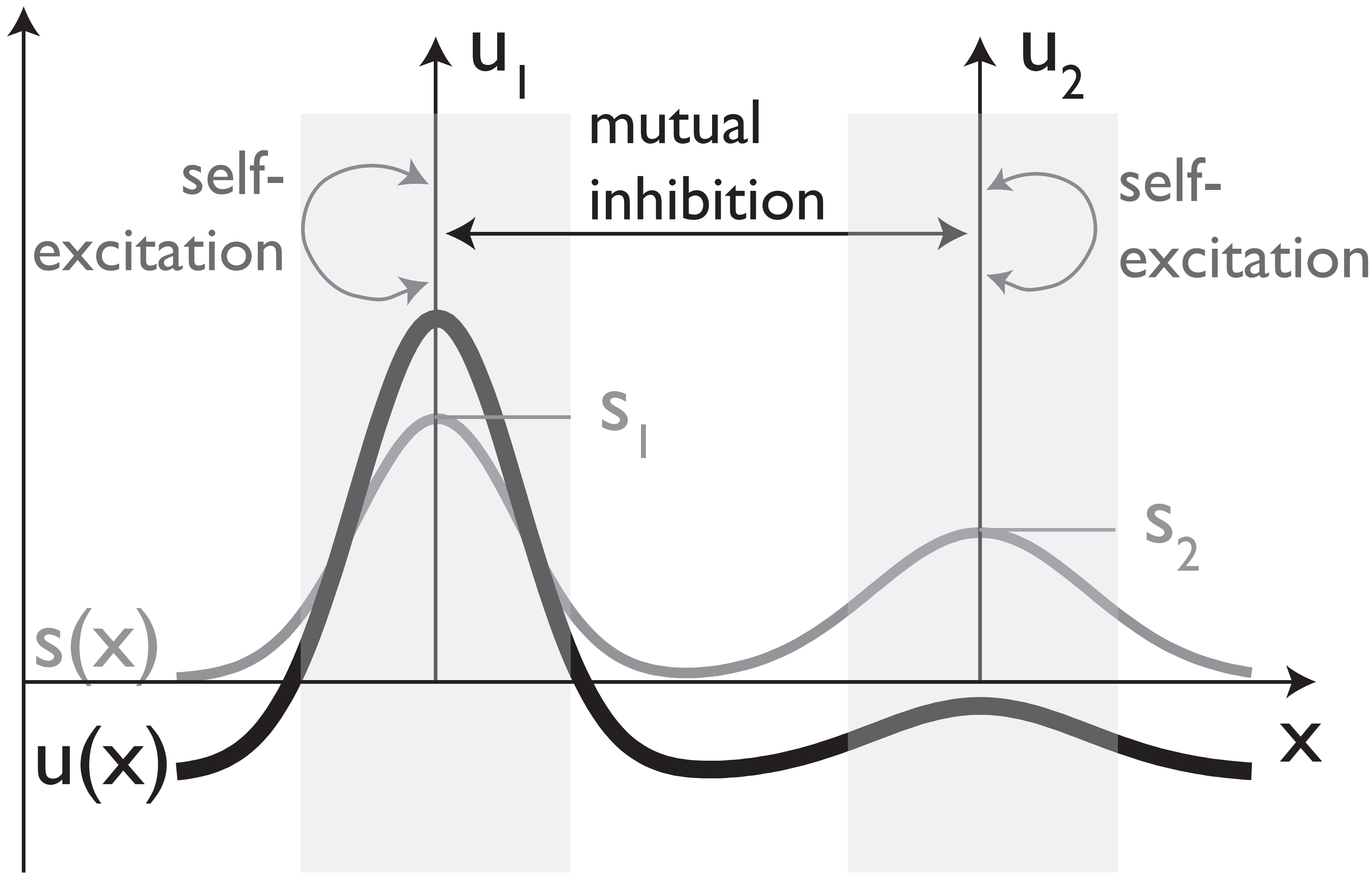
- input driven solution (sub-threshold)
- self-stabilized solution (peak, supra-threshold)
- selection / selection instability
- working memory / memory instability
- boost-driven detection instability

↓ detection instability

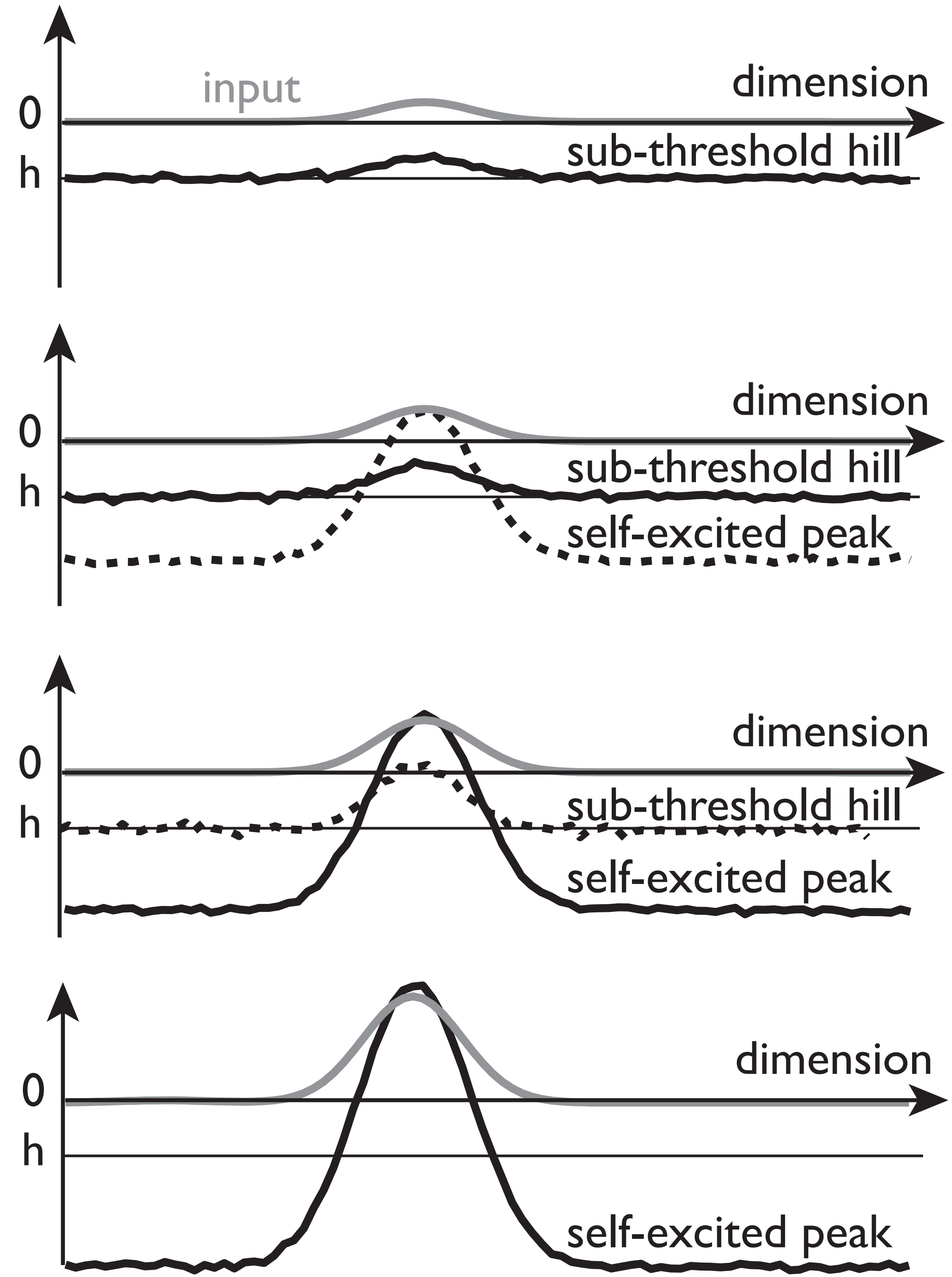
↑ reverse detection instability

Noise is critical near instabilities

Relationship to the dynamics of discrete activation variables

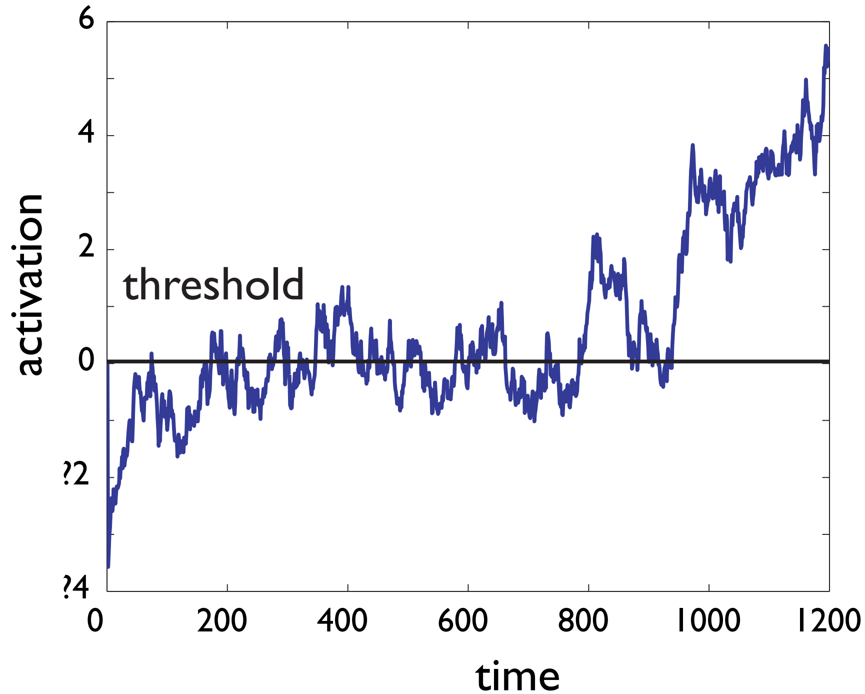


Detection instability

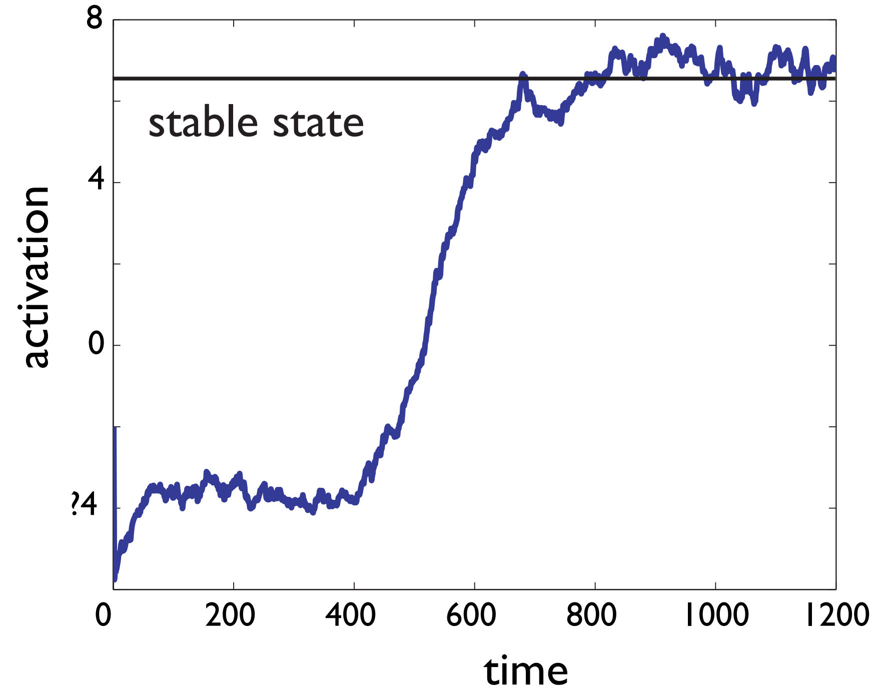


The detection instability stabilizes decisions

threshold piercing



detection instability

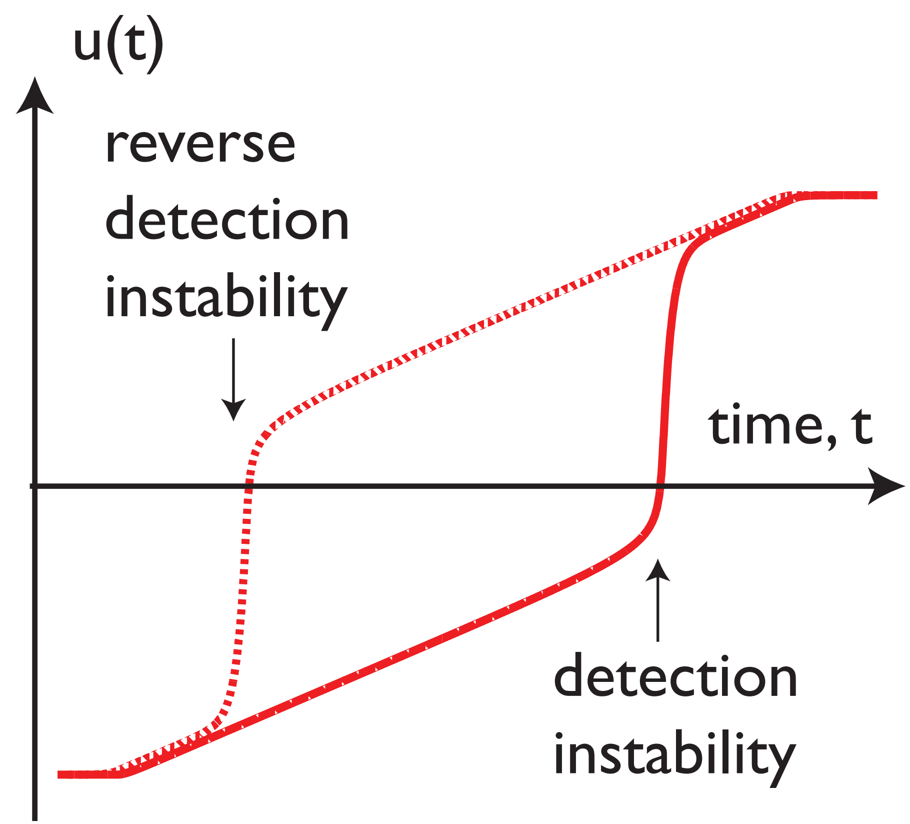


The detection instability stabilizes detection decisions

- self-stabilized peaks are macroscopic neuronal states, capable of impacting on down-stream neuronal systems
- (unlike the microscopic neuronal activation that just exceeds a threshold)

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

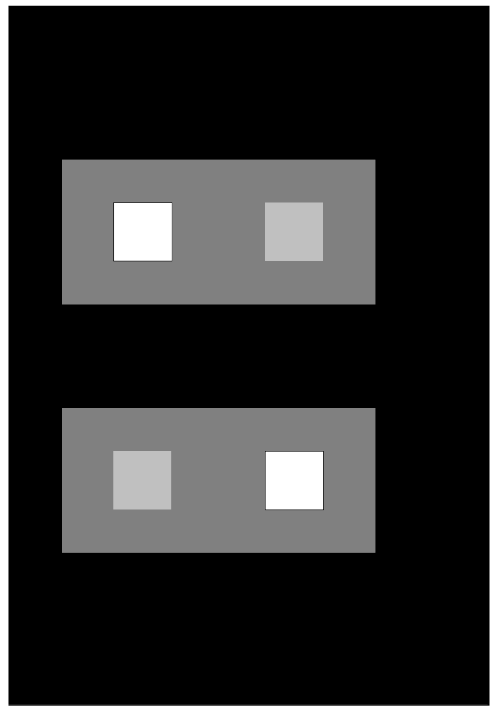


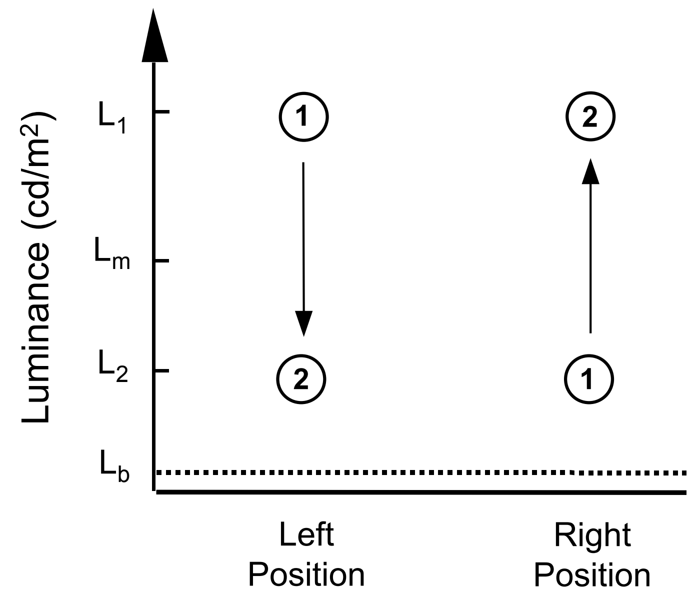
behavioral signatures of detection decisions

- detection in psychophysical paradigms is rife with hysteresis
- but: minimize response bias

Detection instability

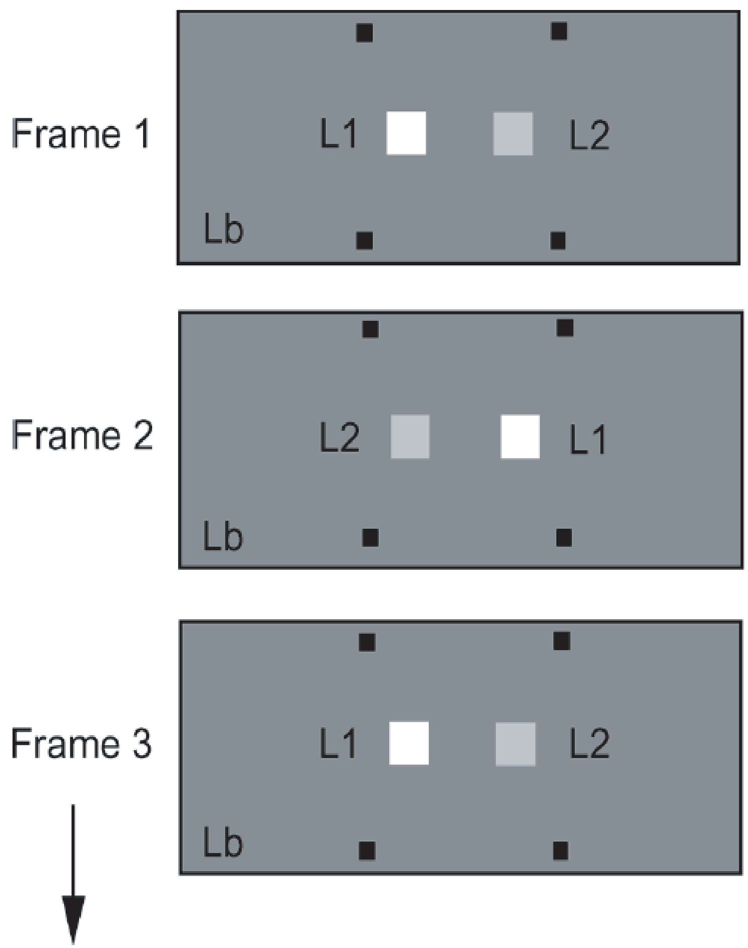
- in the detection of Generalized Apparent Motion





Detection instability

- varying BRLC



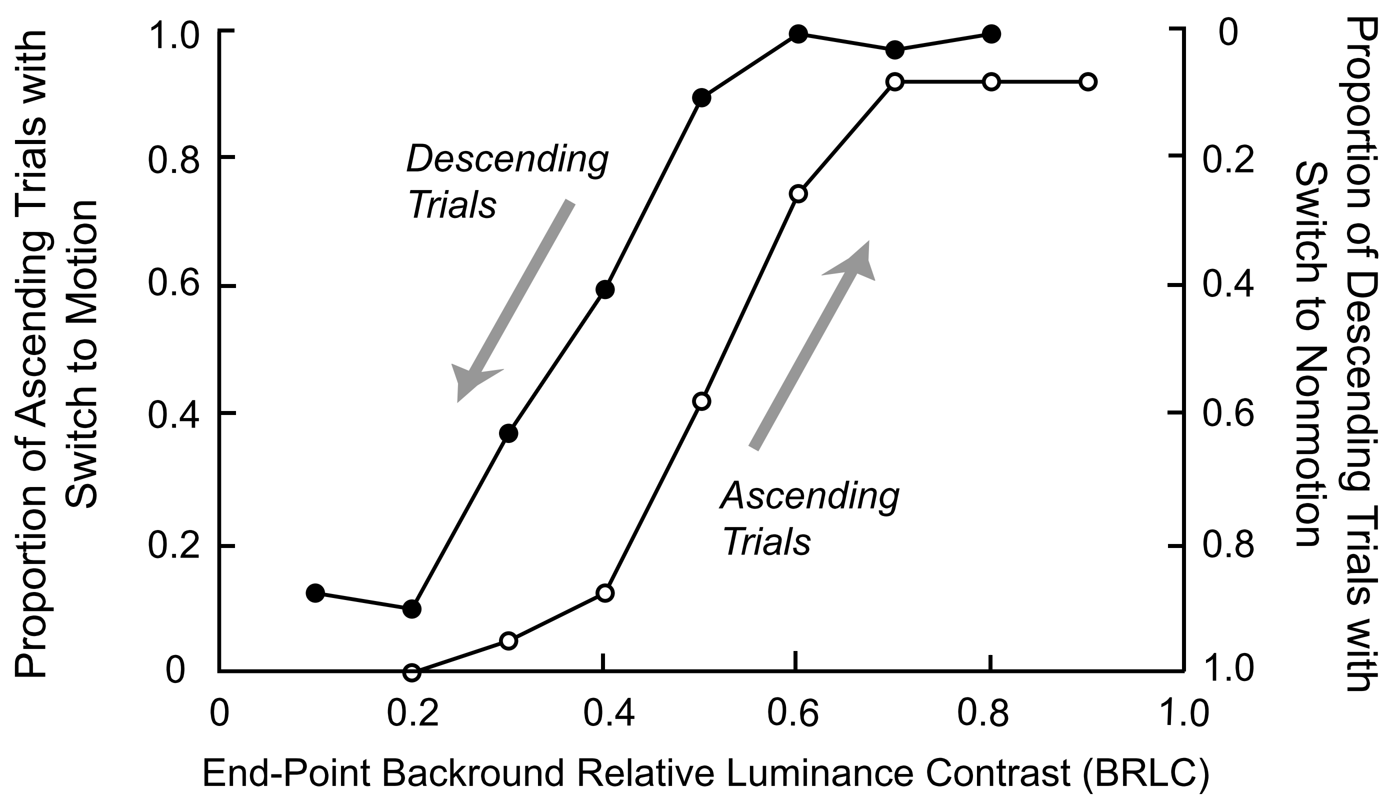
$$Lm = \frac{L1 + L2}{2}$$

$$\text{Background-Relative Luminance Change (BRLC)} = \frac{L1 - L2}{Lm - Lb}$$

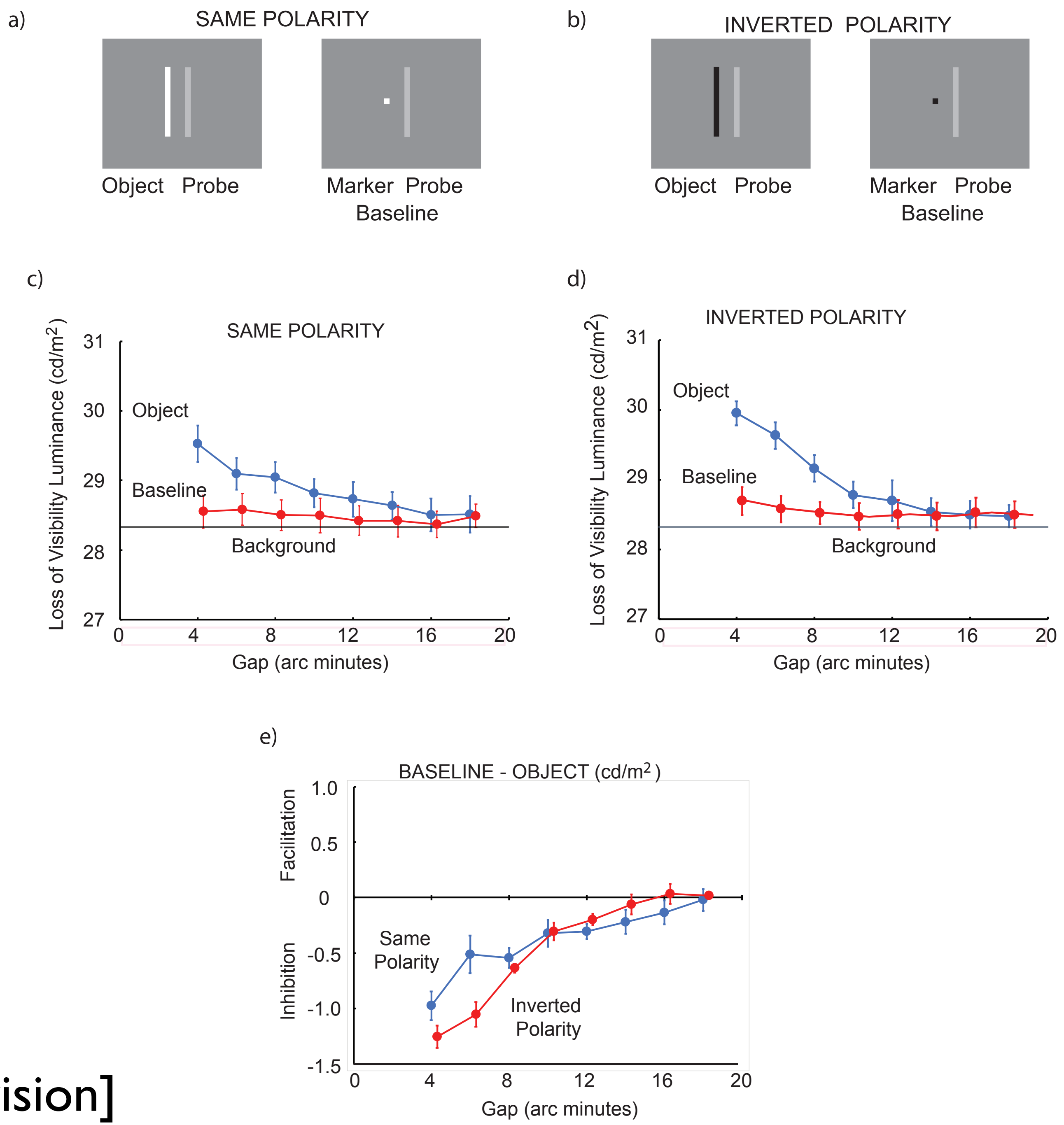
Detection instability

- hysteresis of motion detection as BRLC is varied
- (while response bias is minimized)

H. S. Hock, G. Schöner / Seeing and Perceiving 23 (2010) 173–195



Contrast detection

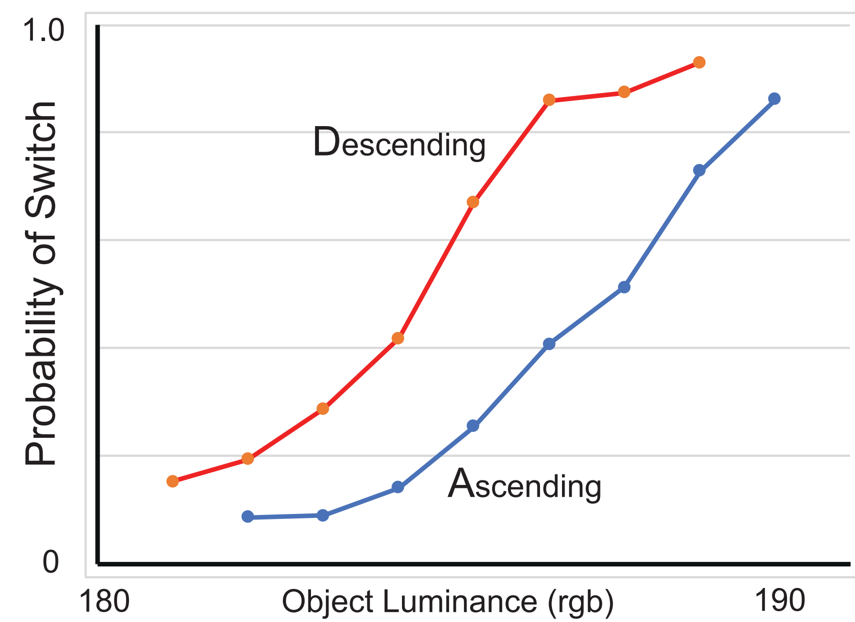


[Hock, Schöner, under revision]

Hysteresis in contrast detection

- ascending trials: increase luminance in steps, ending unpredictably… report contrast or not
- descending trials: decrease luminance in steps, ending unpredictably
- report change over initial percept (modified method of limits)

- object a 4 minutes distance suppresses probe detection at lowest luminance
- also helps to localize attention!
- between presentations, the object/probe pair jumps around on the screen unpredictably by < 1 deg



[Hock, Schöner, under revision]

Conclusion

- even the simplest of decisions=detection in the simplest settings (contrast) is state dependent…
- consistent with the notion of a detection instability at the basis of perception