Dynamic Field Theory: Part 3: the dynamic instabilities

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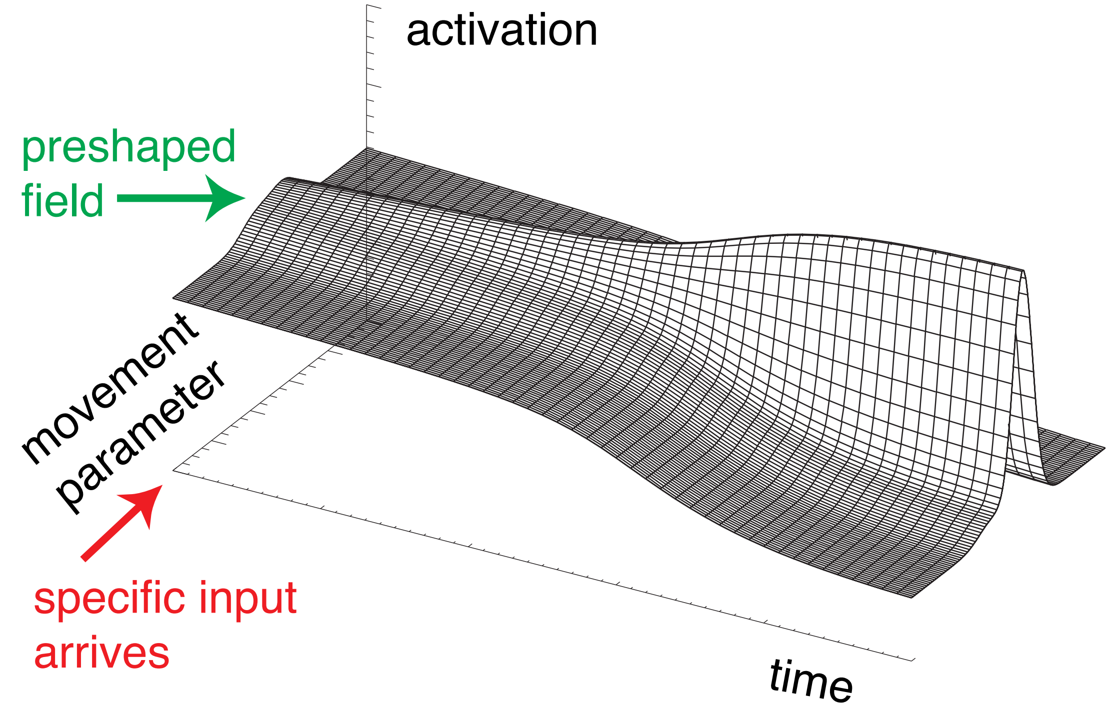
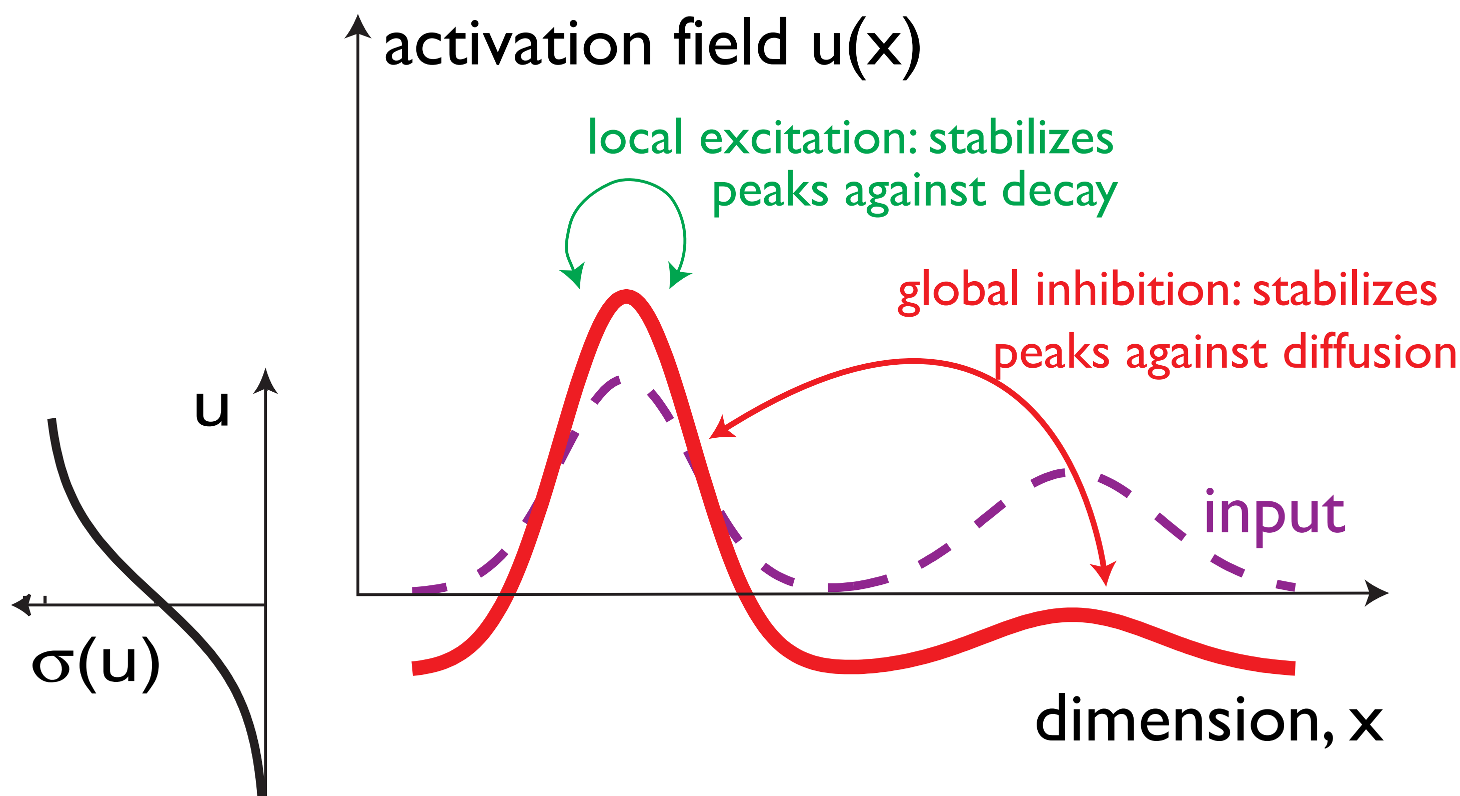
the dynamics such activation fields is structured so that localized peaks emerge as attractor solutions

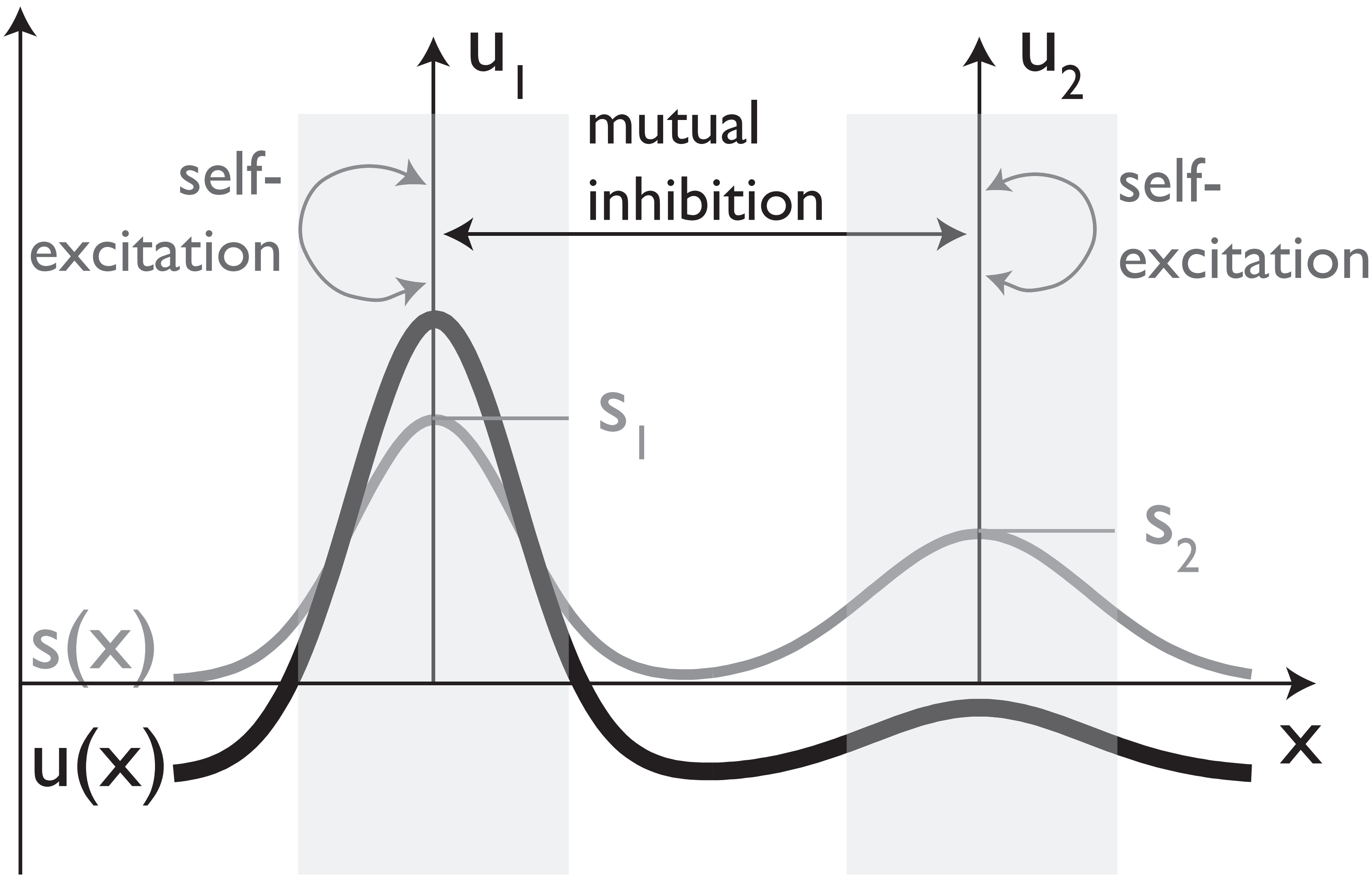




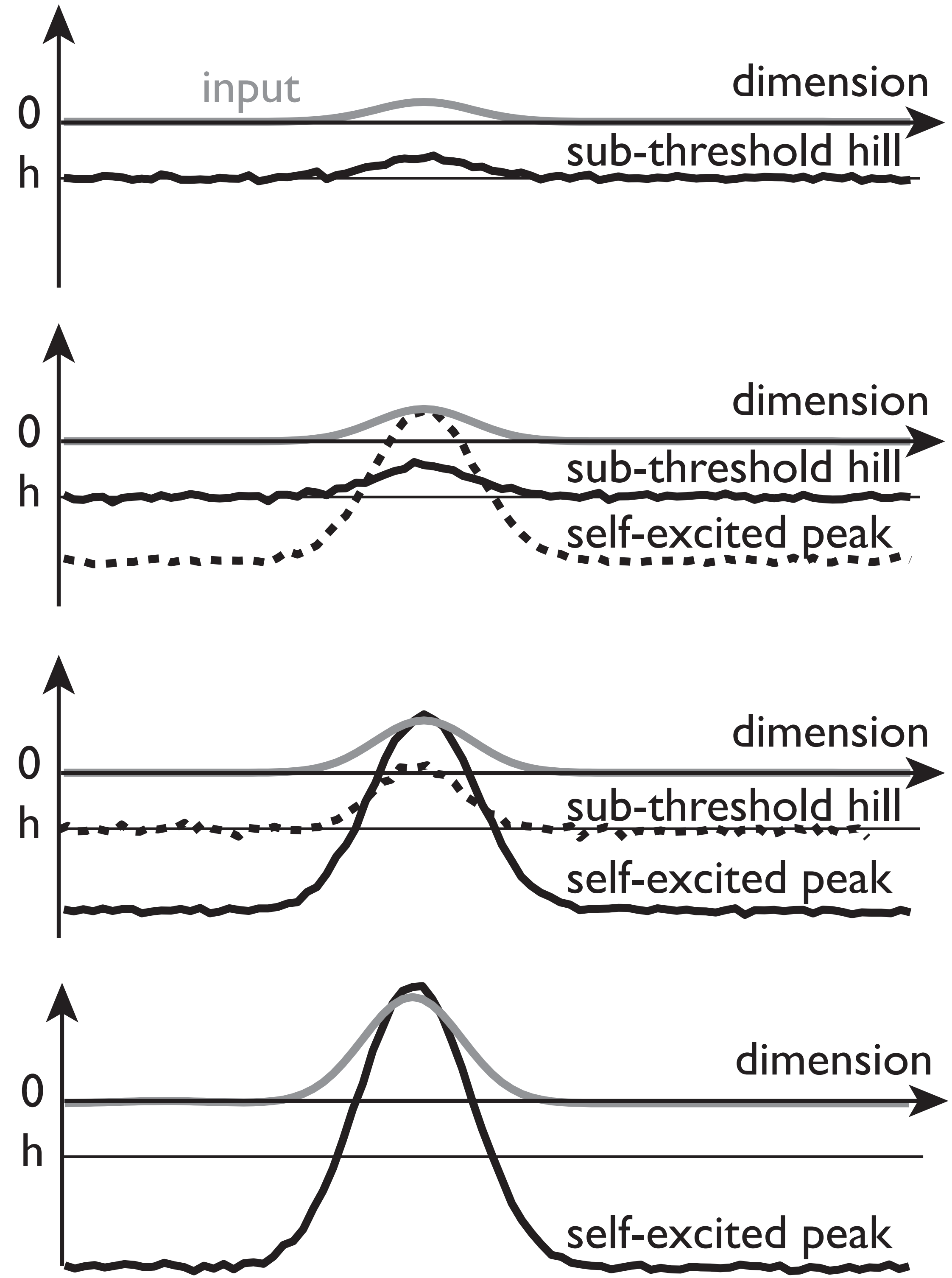
solutions and instabilities

- input driven solution (sub-threshold) vs. self-stabilized solution (peak, supra-threshold)
- detection instability
- reverse detection instability
- selection
- selection instability
- memory instability
- detection instability from boost

Relationship to the dynamics of discrete activation variables

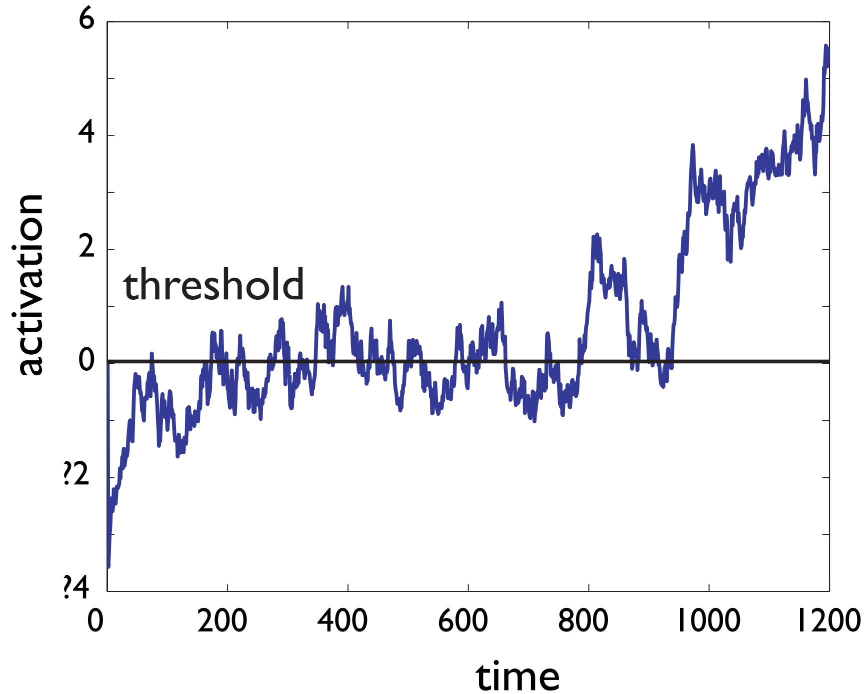


Detection instability

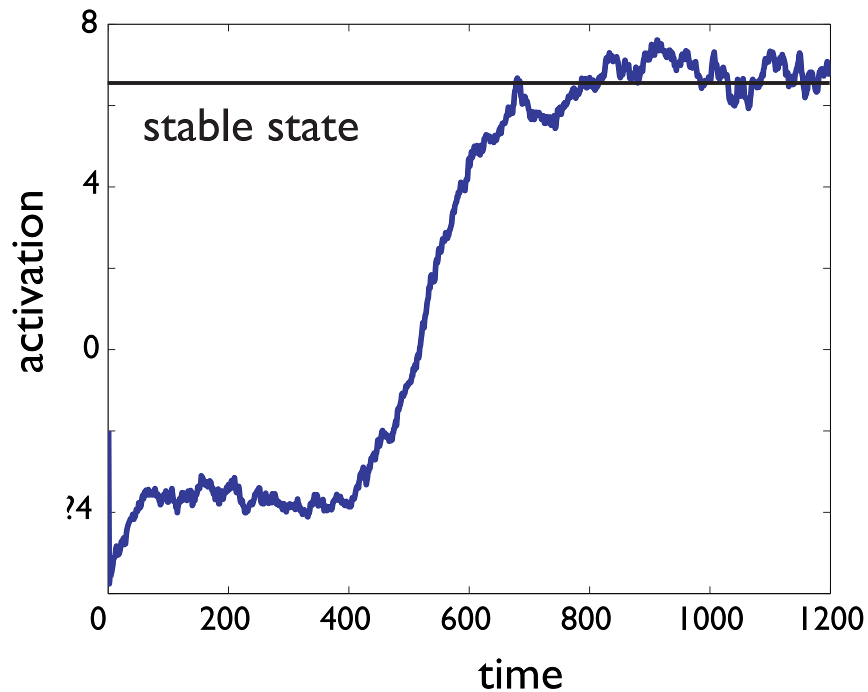


the detection instability helps stabilize decisions

threshold piercing



detection instability



the detection instability helps stabilize 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)

emergence of time-discrete events

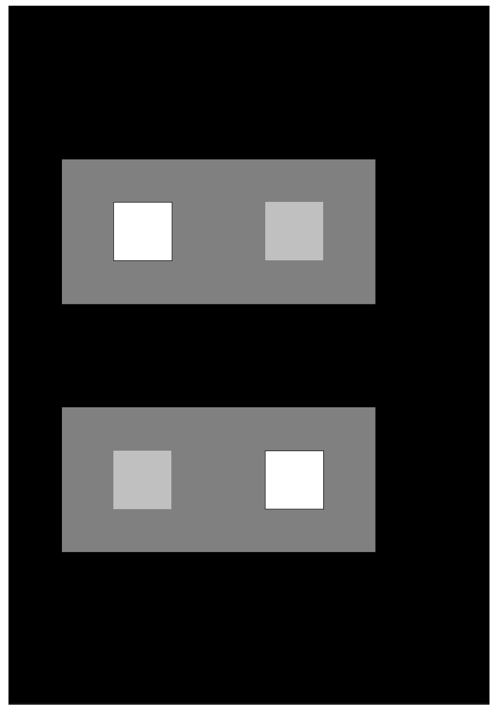
- the detection instability also explains how a time-continuous neuronal dynamics may create macroscopic, time-discrete events

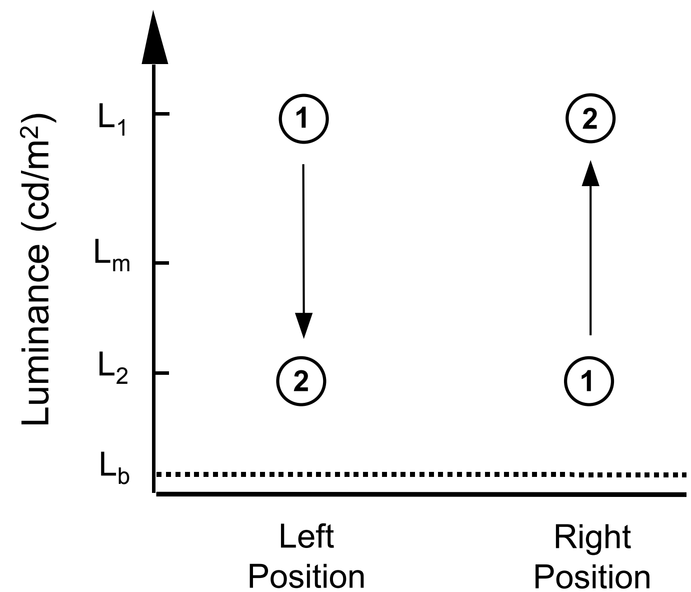
behavioral signatures of detection decisions

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

Detection instability

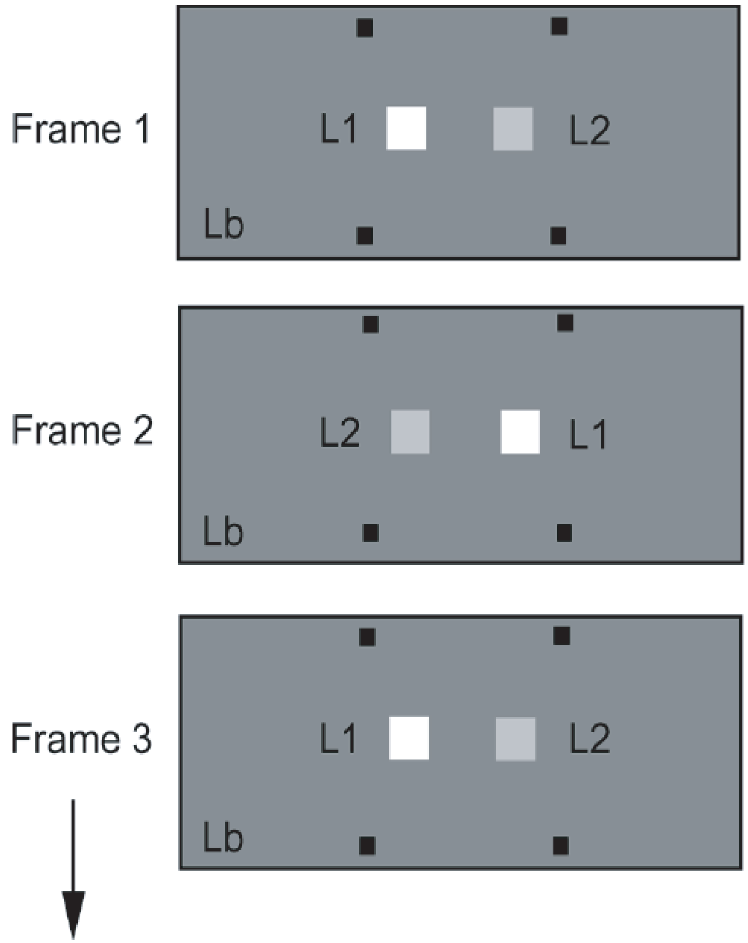
- in the detection of Generalized Apparent Motion





Detection instability

- varying BRLC



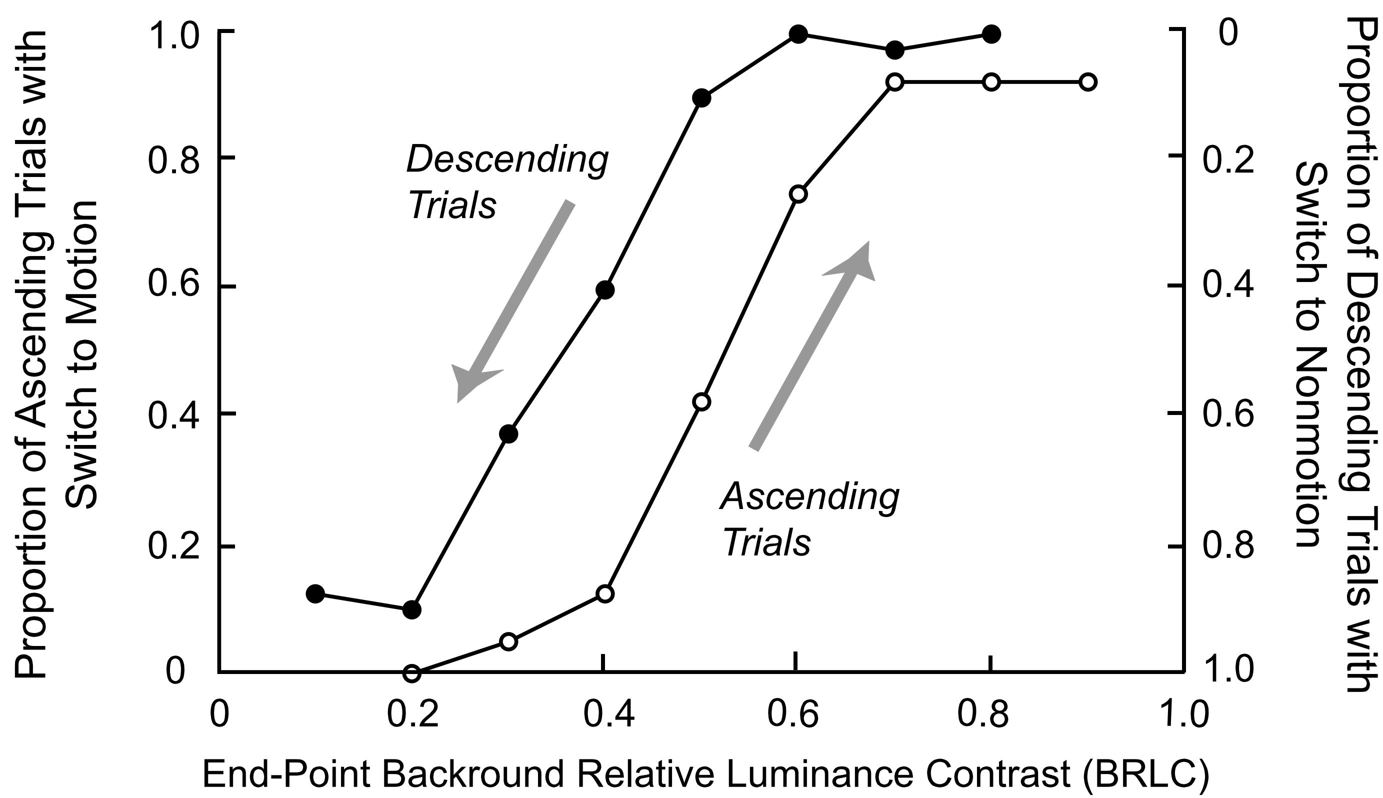
$$Lm = \frac{L1 + L2}{2}$$

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

Detection instability

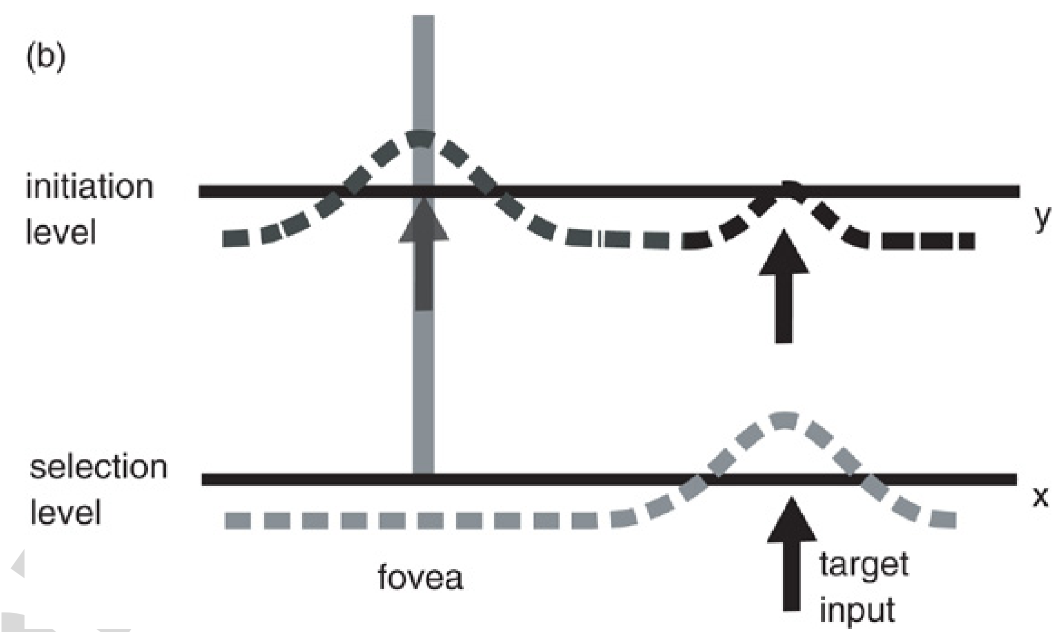
- hysteresis of motion detection as BRLC is varied
- (while response bias is minimized)

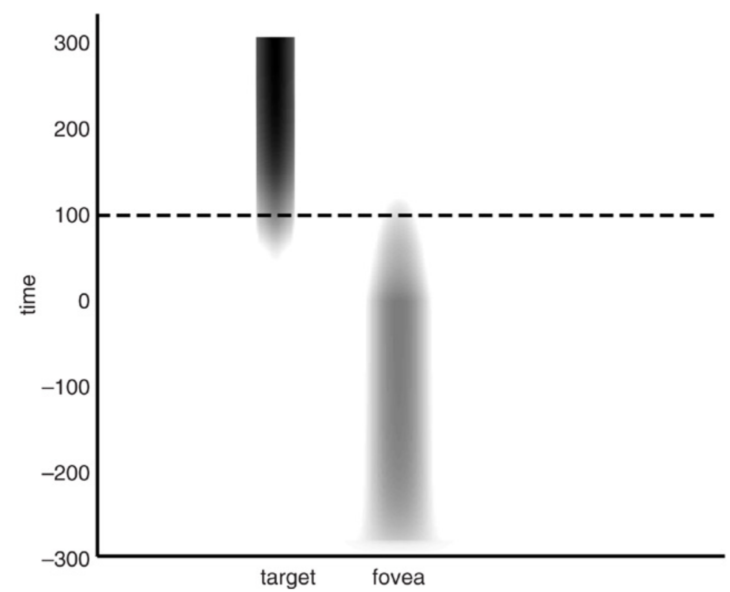
H. S. Hock, G. Schöner / Seeing and Perceiving 23 (2010) 173–195



overcoming fixation

- detection can be like selection: initiating an action means terminating the non-action=fixation or posture
- example: saccade initiation

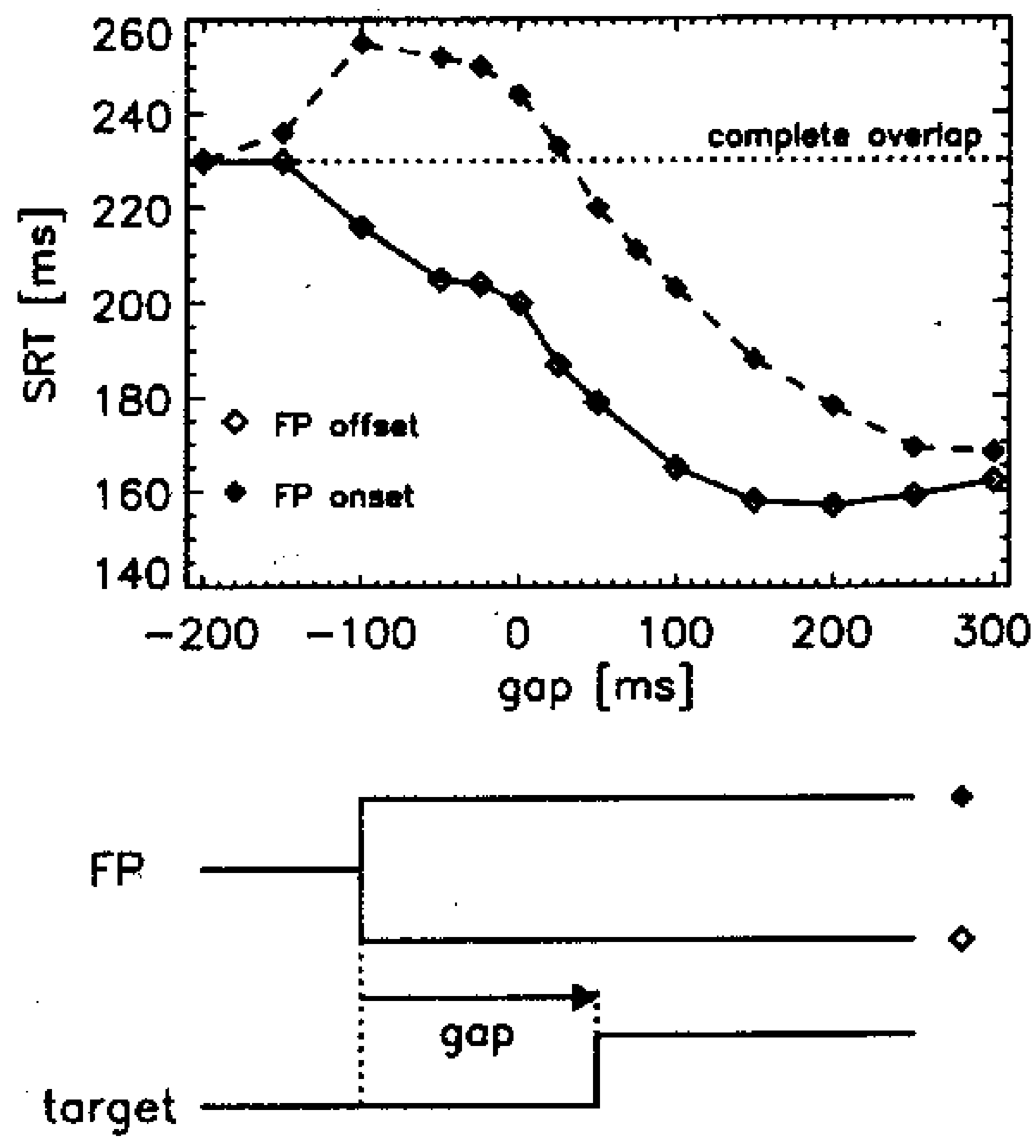




[Wilimzig, Schneider, Schöner, 2006]

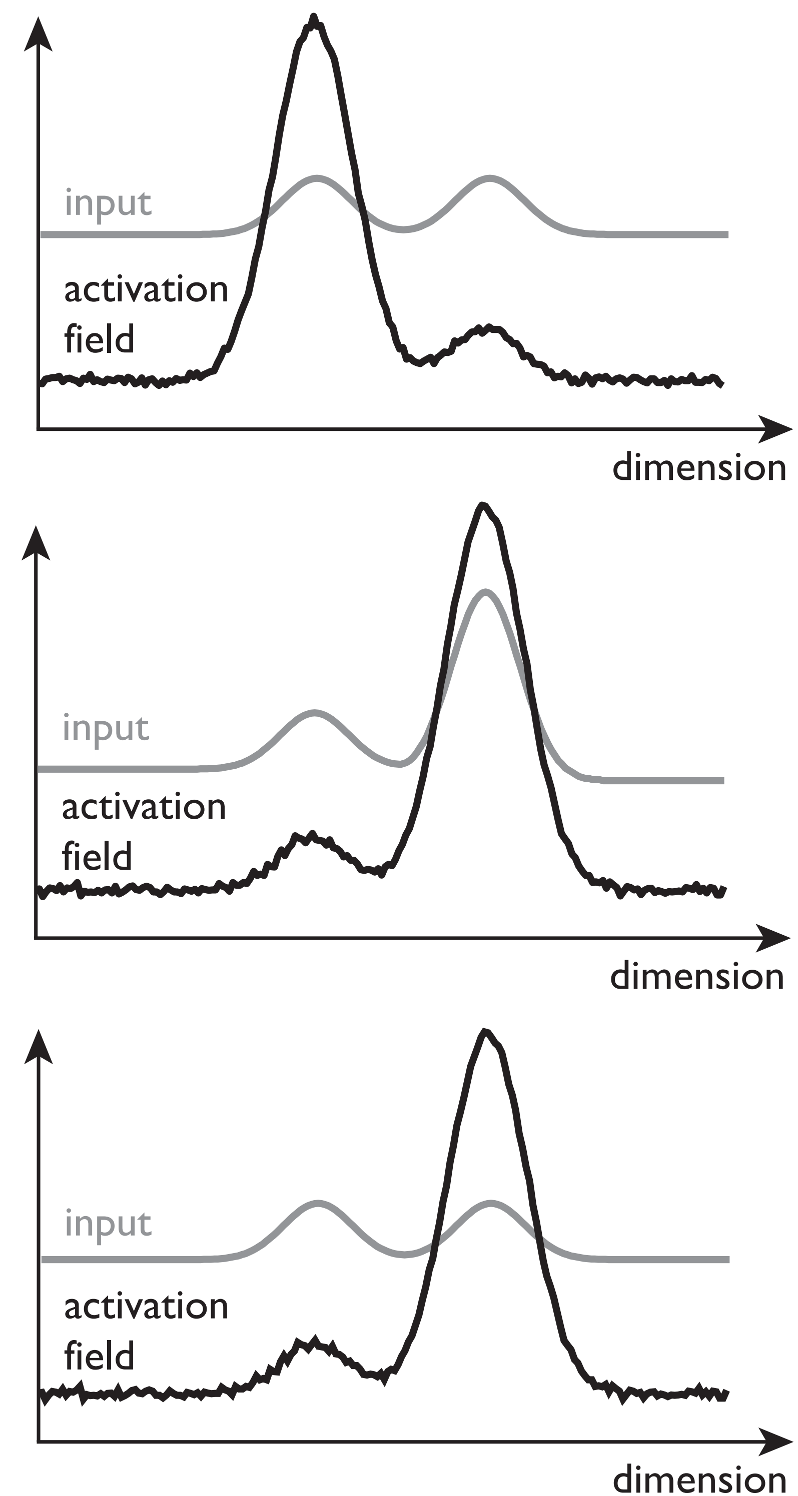
initiation vs. fixation

- such models account for the gap-step-overlap effect

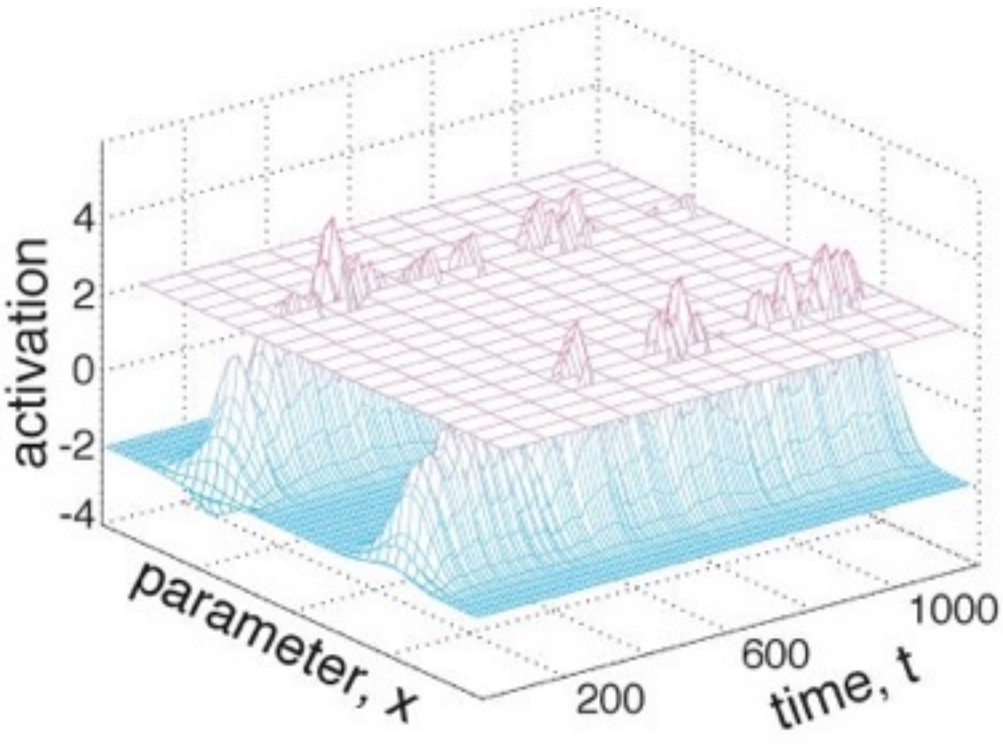


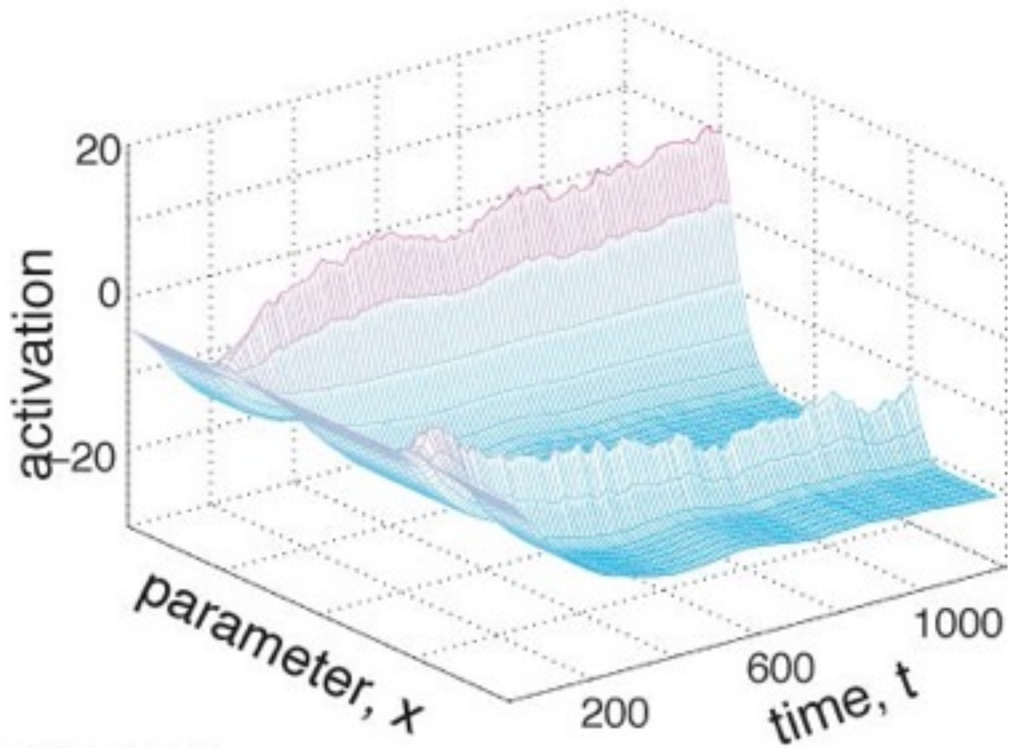
[Kopecz, 95]

selection instability



stabilizing selection decisions





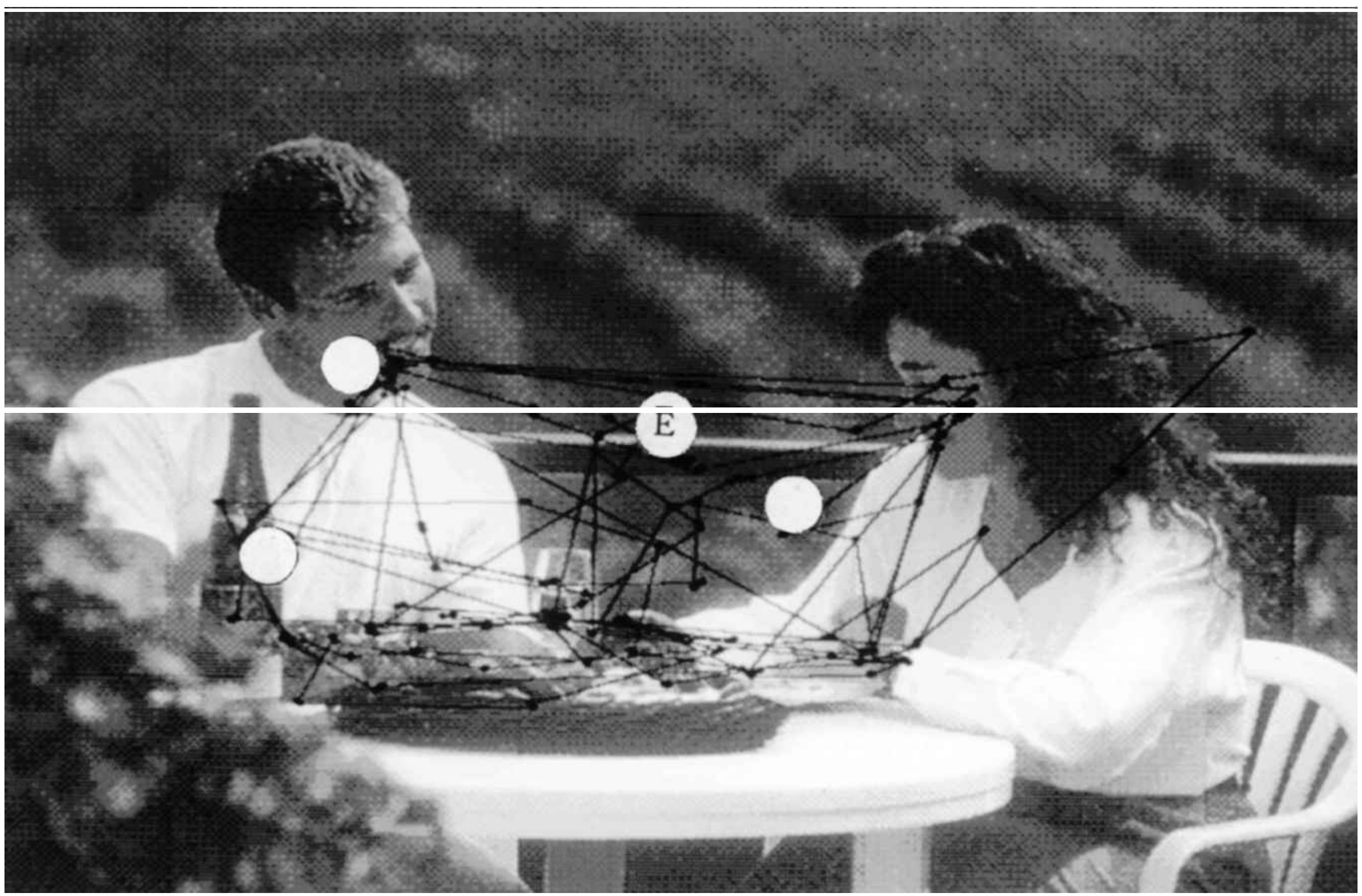
[Wilimzig, Schöner, 2006]

behavioral signatures of selection decisions

- in most experimental situations, the correct selection decision is cued by an "imperative signal" leaving no actual freedom of "choice" to the participant (only the freedom of "error")
- reasons are experimental
- when performance approaches chance level, then close to "free choice"
- because task set plays a major role in such tasks, I will discuss these only a little later

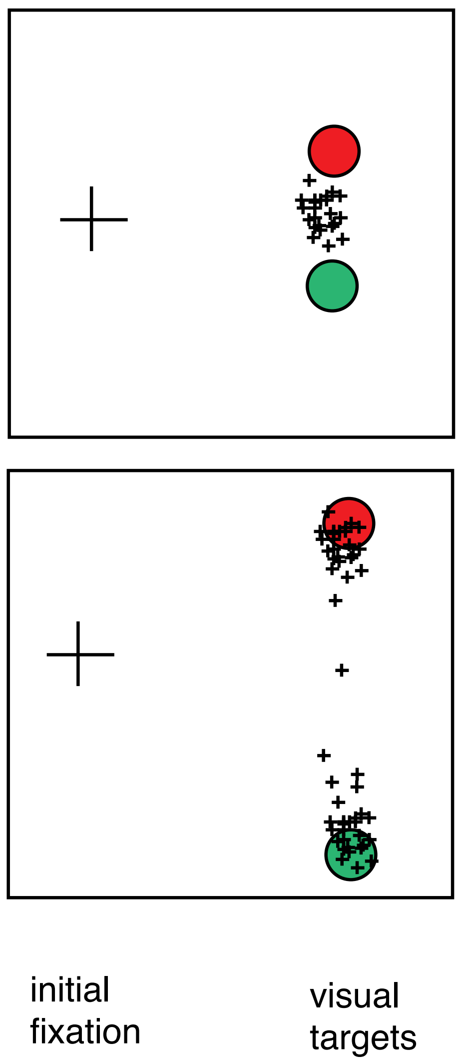
one system of "free choice"

- selecting a new saccadic location

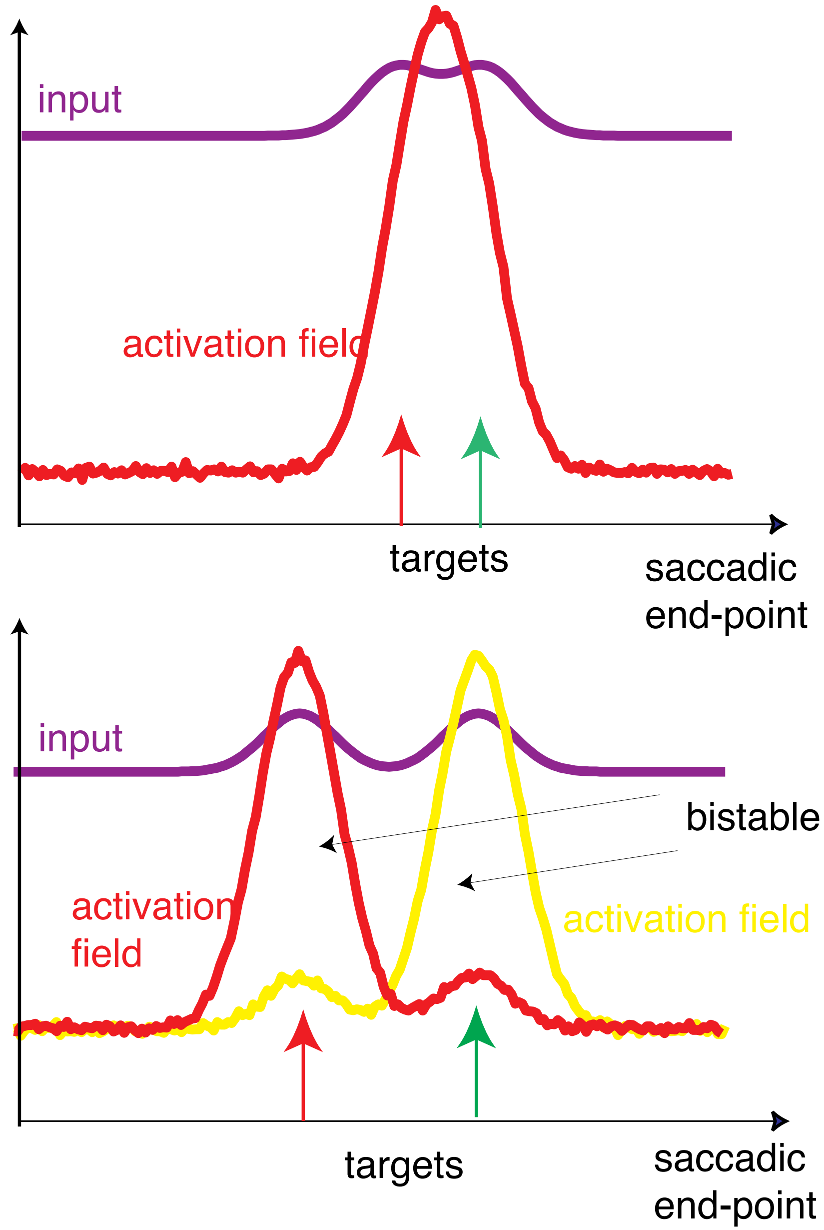


[O'Reagan et al., 2000]

saccade generation



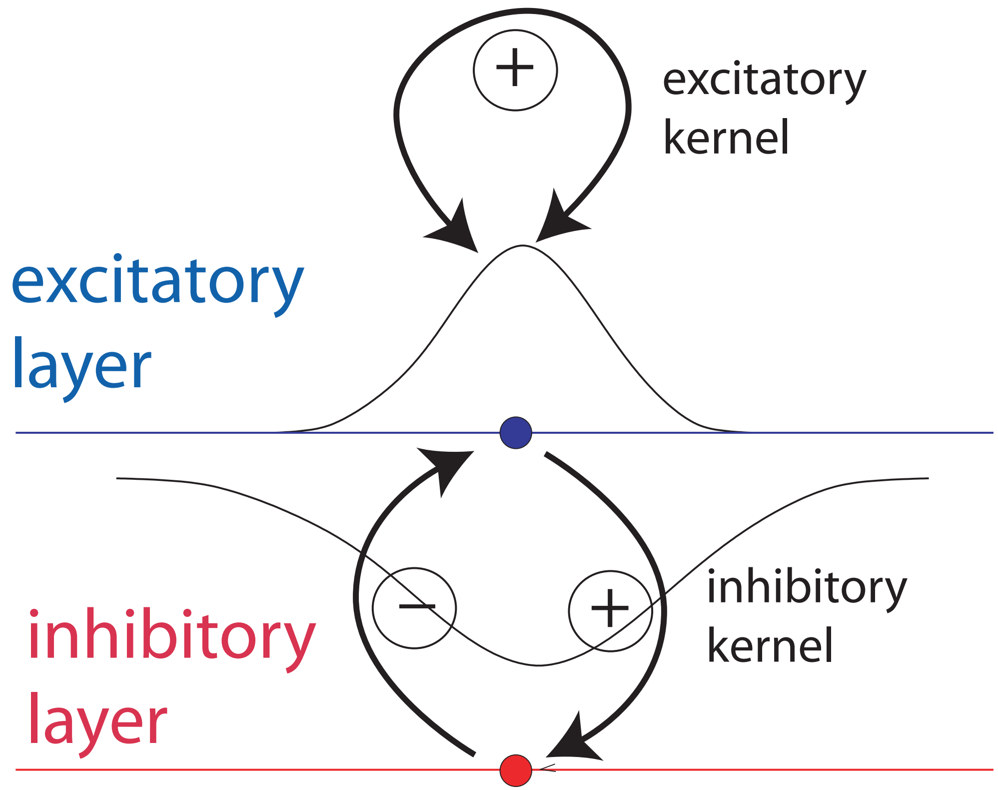
[after: Ottes et al., Vis. Res. 25:825 (85)]



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

2 layer Amari fields

- to comply with Dale's law
- and account for difference in time course of excitation (early) and inhibition (late)



[figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006]

2 layer Amari model

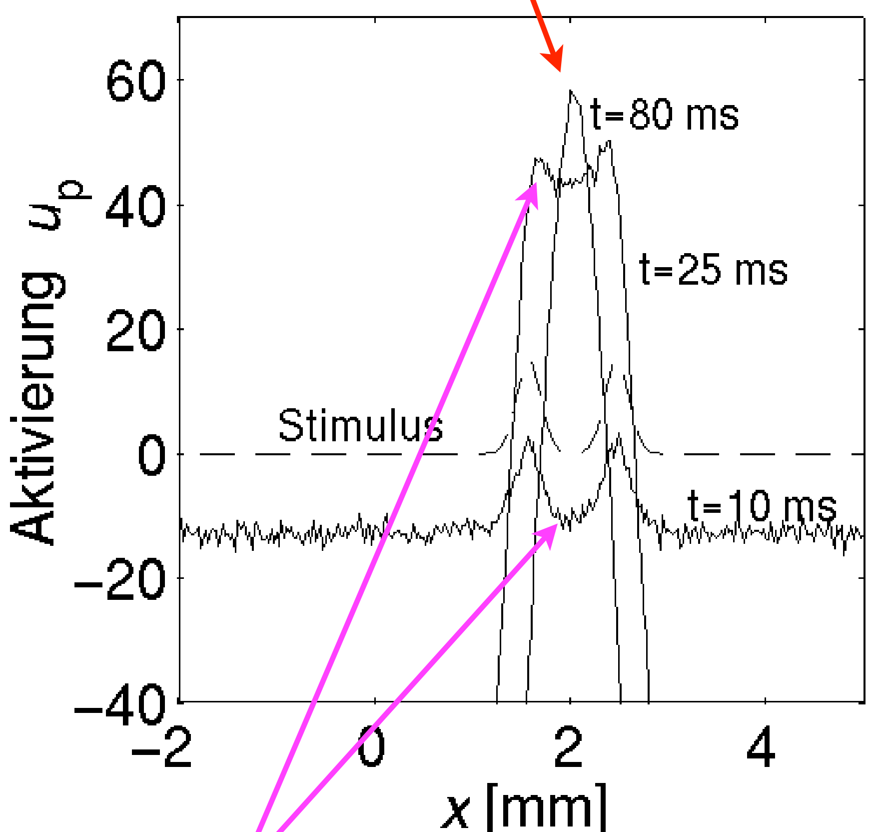
$$
\begin{aligned}
\tau \dot{u}(x,t) &= -u(x,t) + h_u + S(x,t) + \int dx' \; c_{\mathrm{uu}}(x-x') \; \sigma(u(x',t)) \\
&- \int dx' \; c_{\mathrm{uv}}(x-x') \; \sigma(v(x',t)) \\
\tau \dot{v}(x,t) &= -v(x,t) + h_v + \int dx' \; c_{\mathrm{vu}}(x-x') \; \sigma(u(x',t))
\end{aligned}
$$

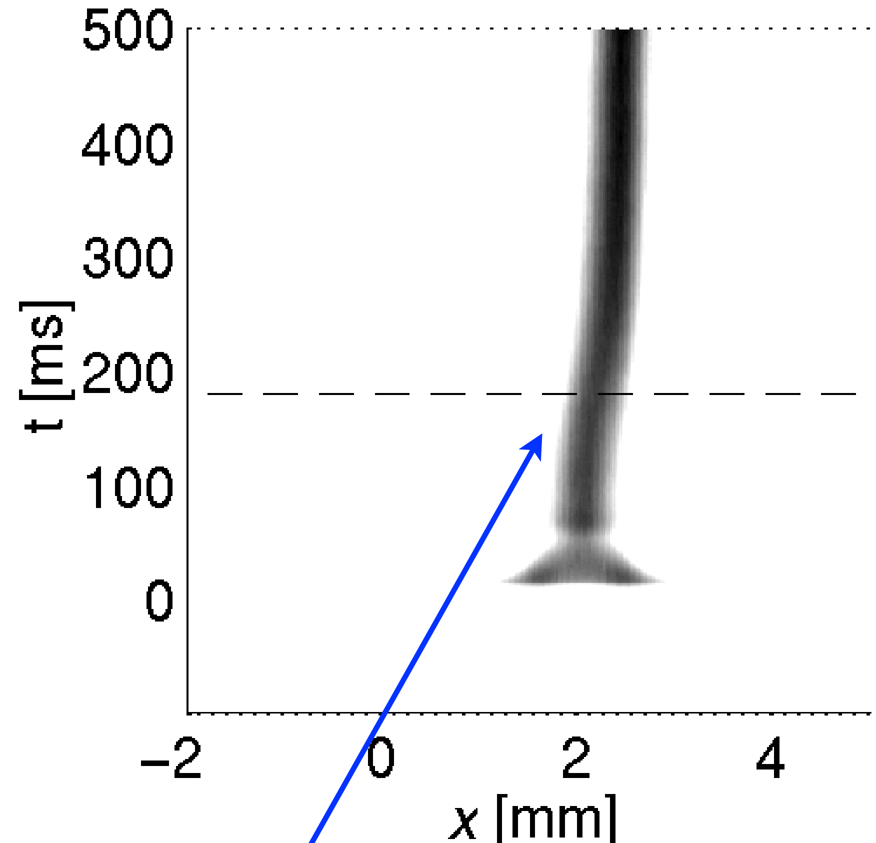
$$
c_{ij}(x-x') = c_{i,j,\mathrm{strength}} \; \exp\left[-\frac{(x-x')^2}{2\sigma_{ij}^2}\right].
$$

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

time course of selection

intermediate: dominated by excitatory interaction



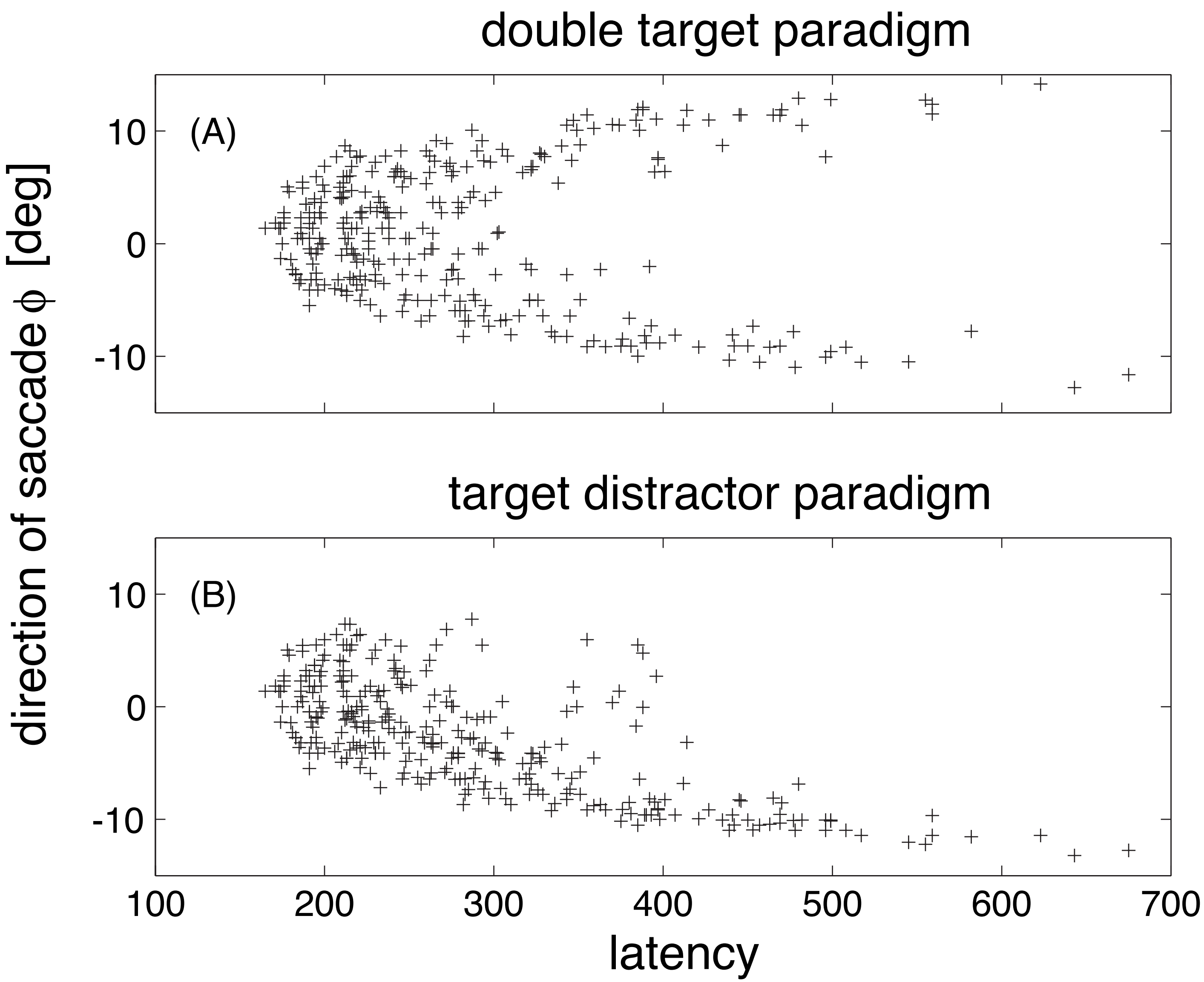


early: input driven

late: inhibitory interaction drives selection

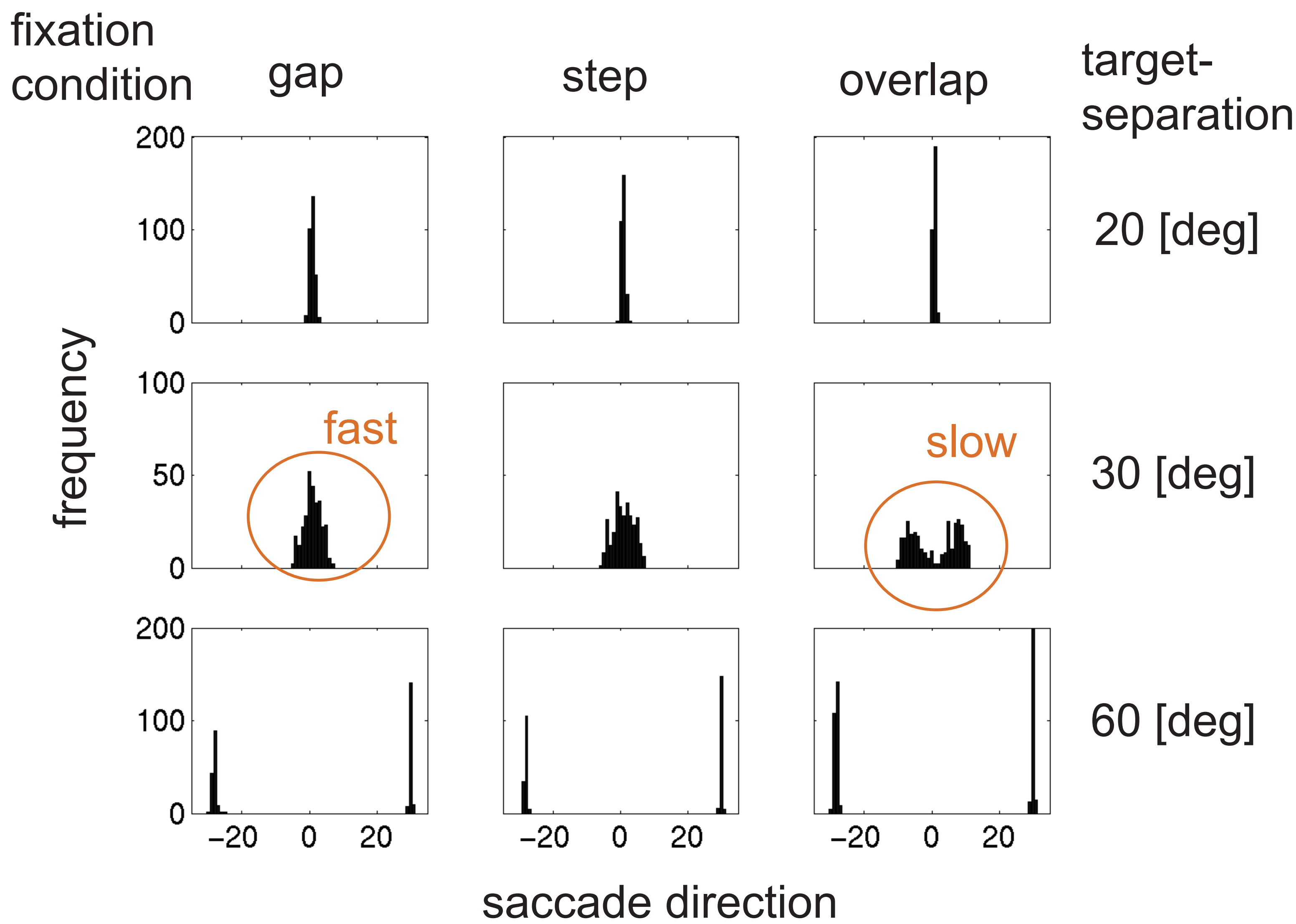
Wilimzig, Schneider, Schöner, Neural Networks, 2006

=> early fusion, late selection



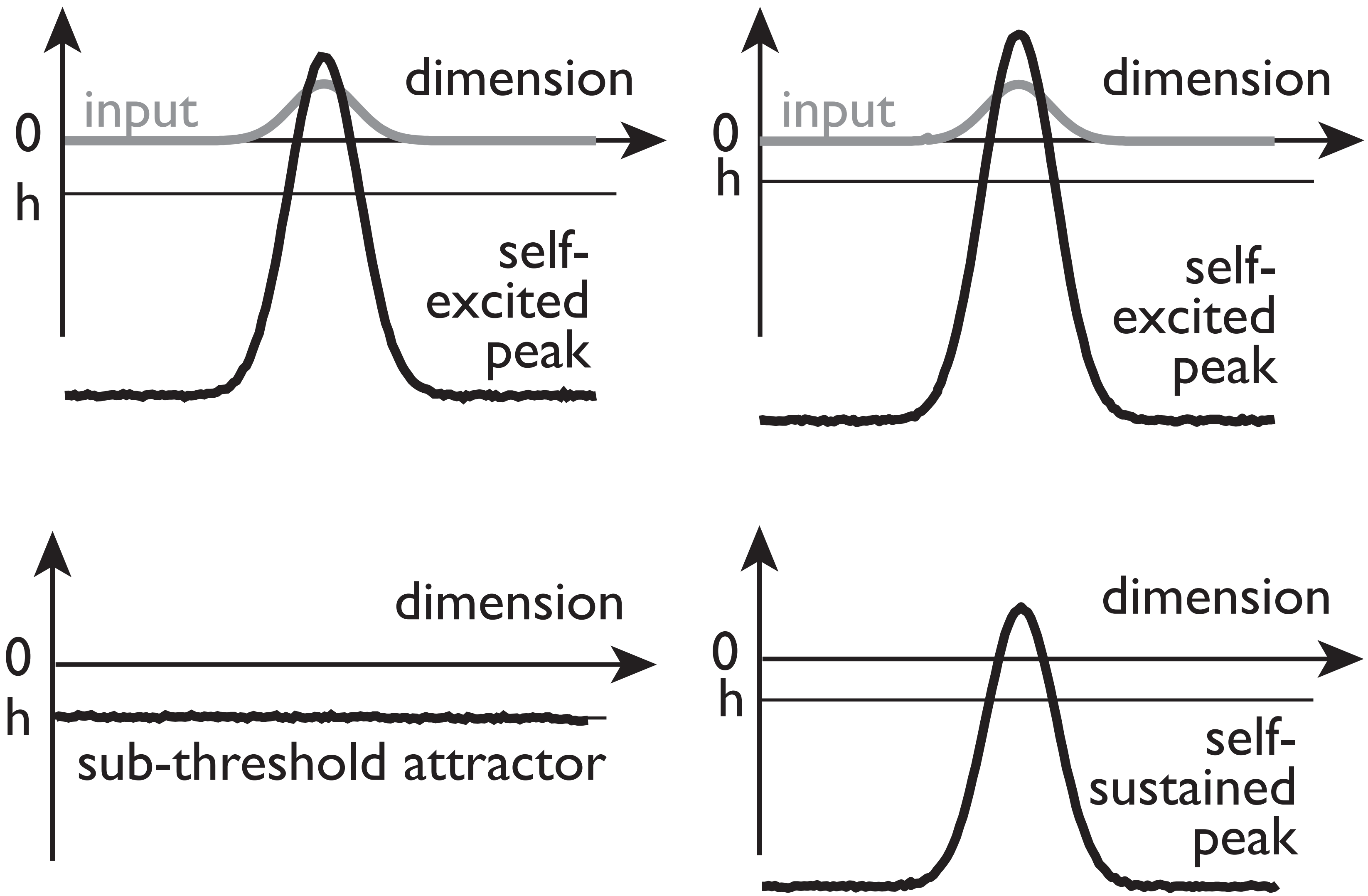
Wilimzig, Schneider, Schöner, Neural Networks, 2006

fixation and selection

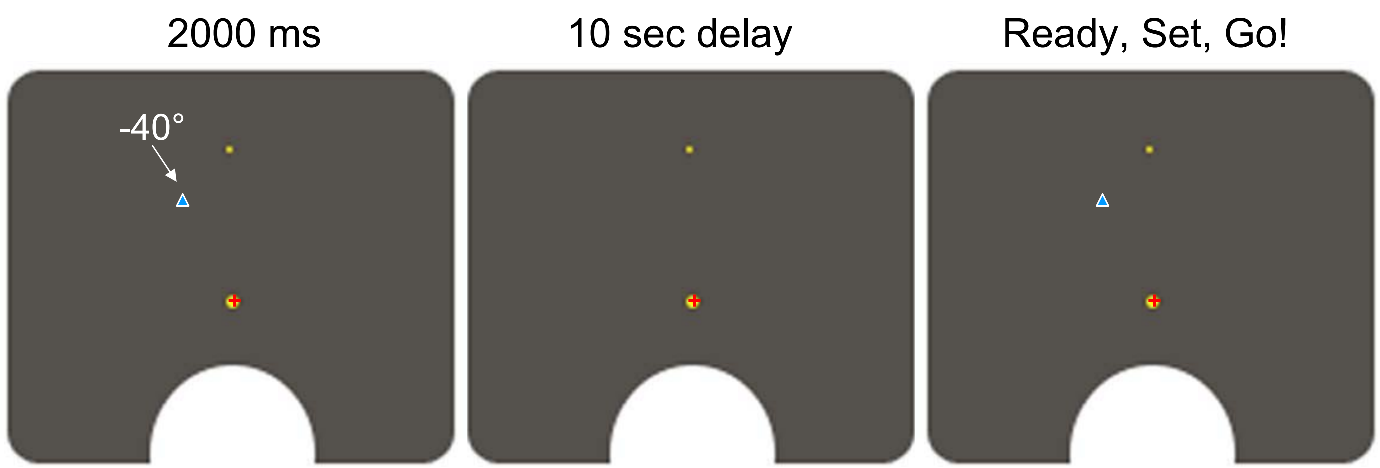


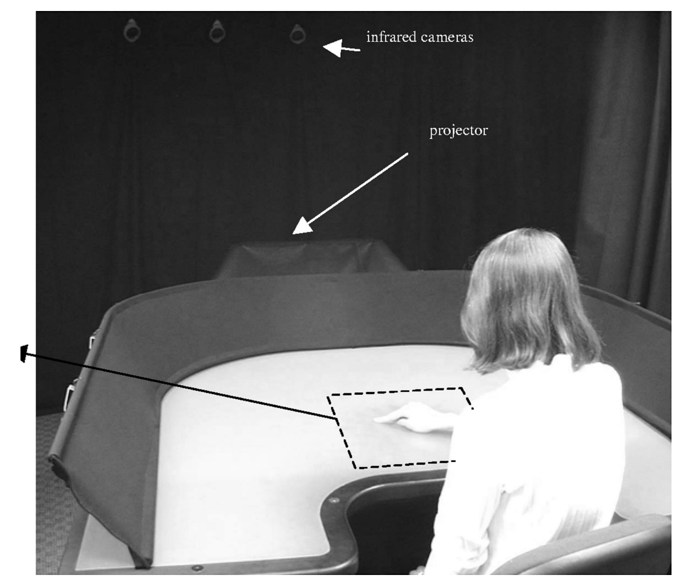
Wilimzig, Schneider, Schöner, Neural Networks, 2006

Memory instability



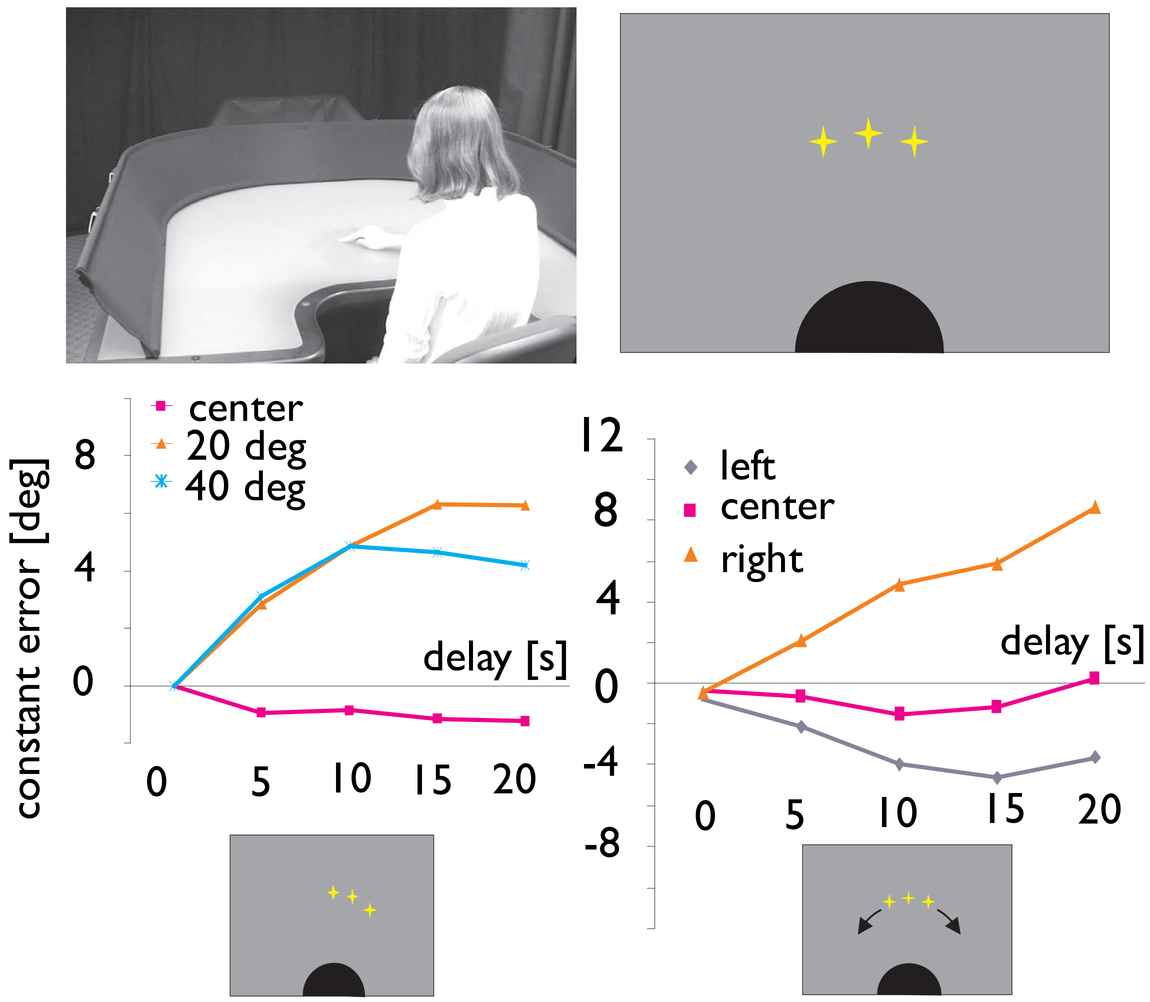
- “space ship” task probing spatial working memory





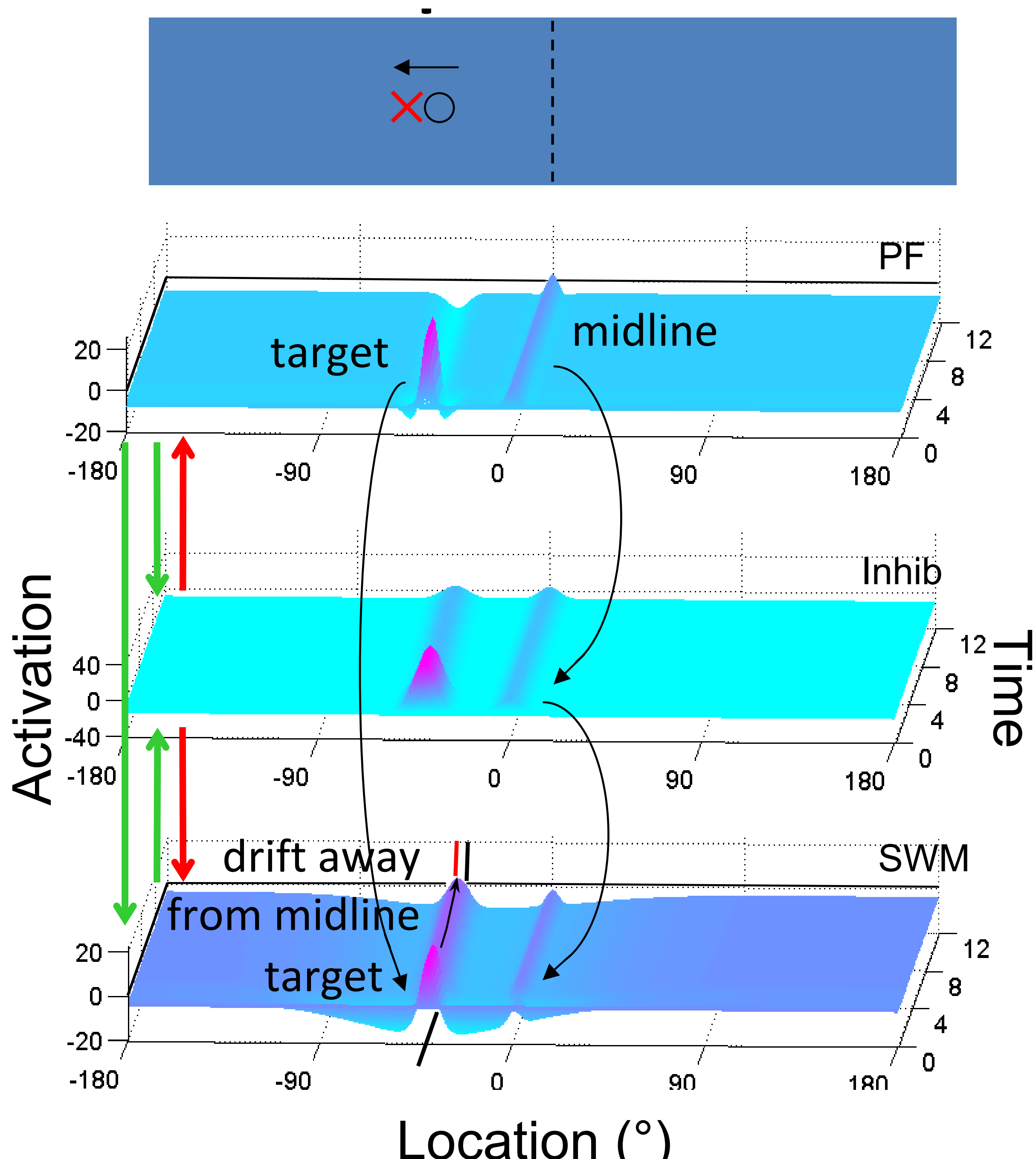
[Schutte, Spencer, JEP:HPP 2009]

repulsion from midline/landmarks



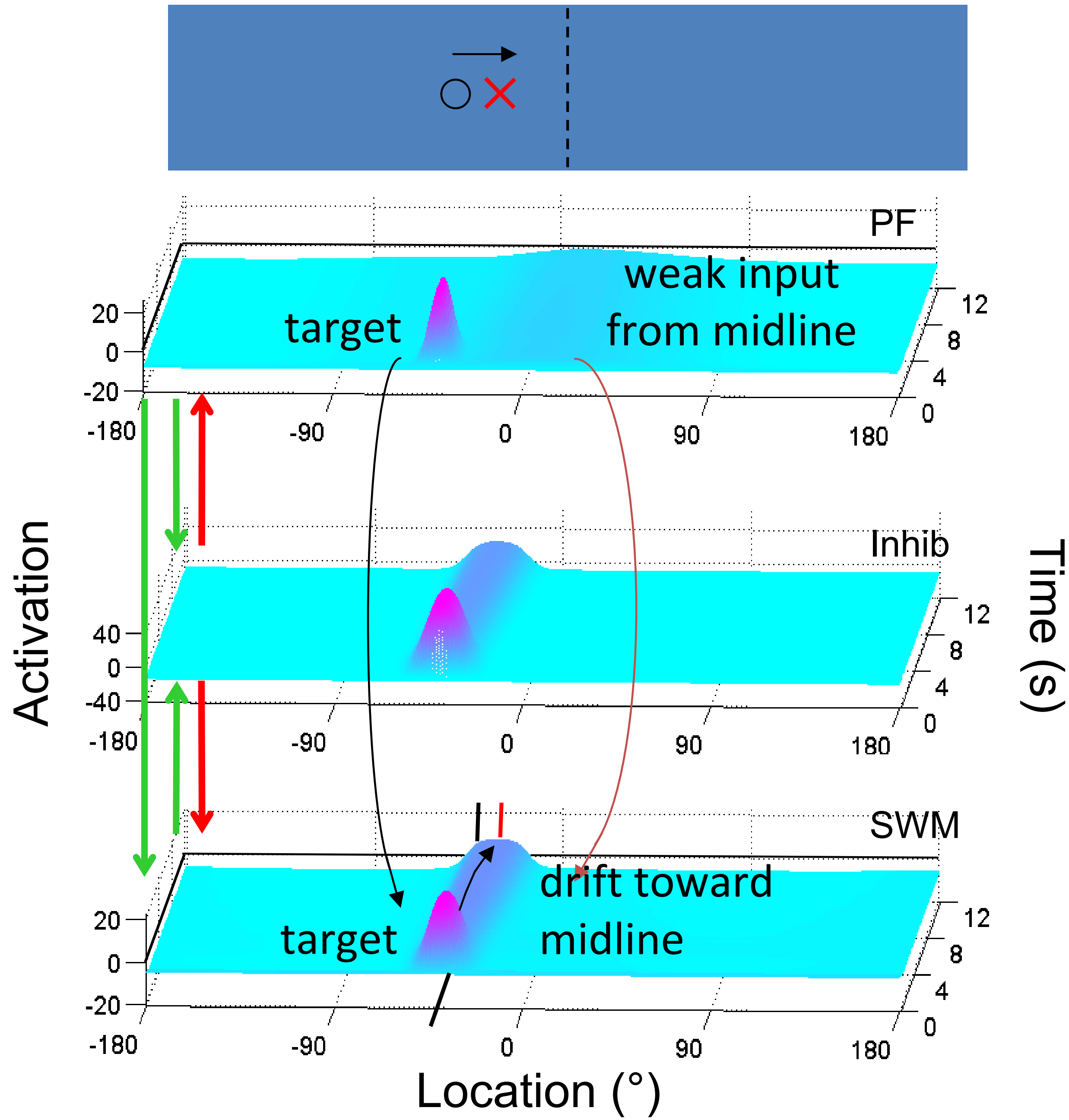
[Schutte, Spencer, JEP:HPP 2009]

- DFT account of repulsion: inhibitory interaction with peak representing landmark

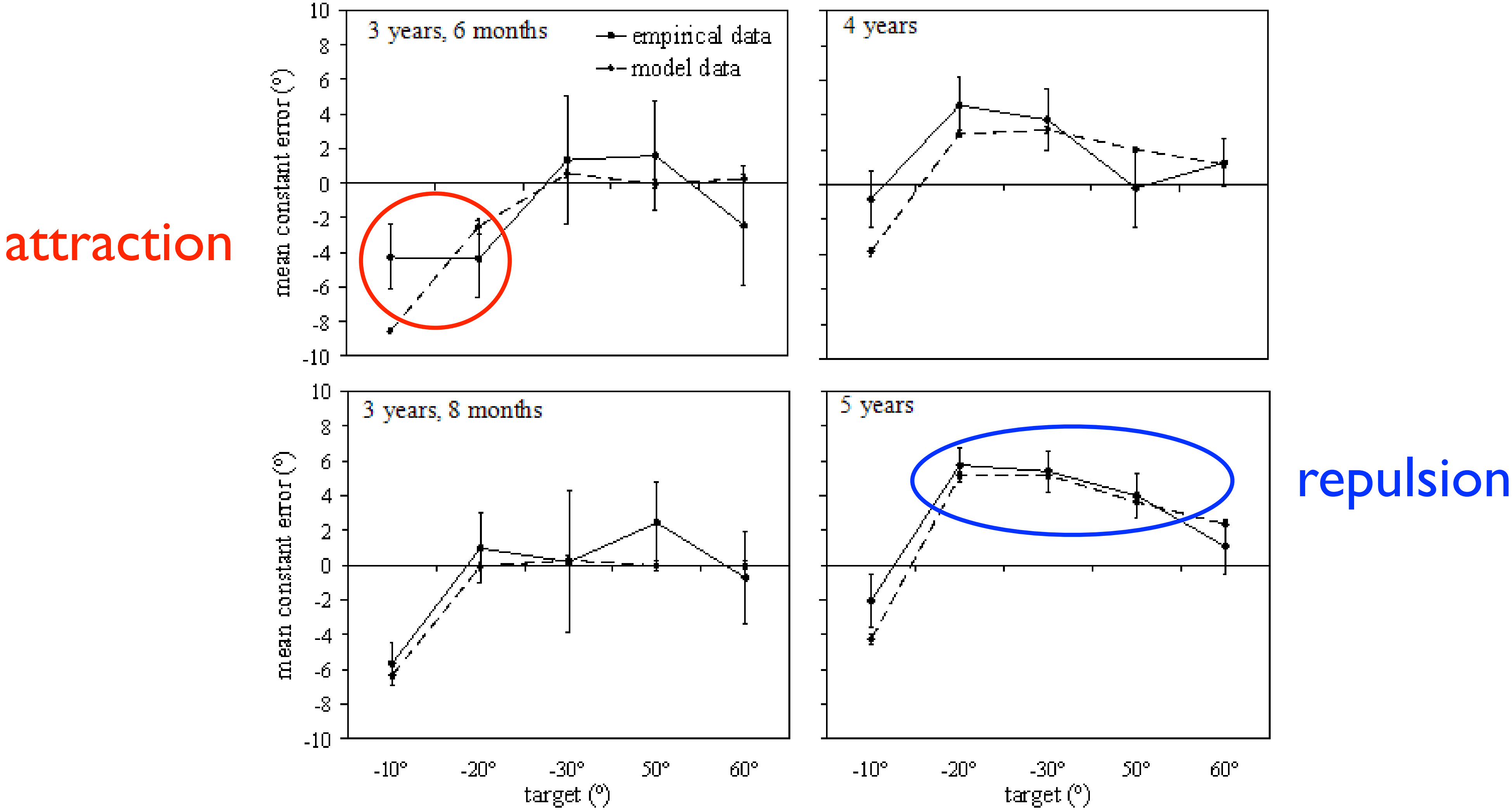


[Simmering, Schutte, Spencer: Brain Research, 2007]

- DFT + spatial precision hypotheses prediction: young infants are attracted rather then repelled

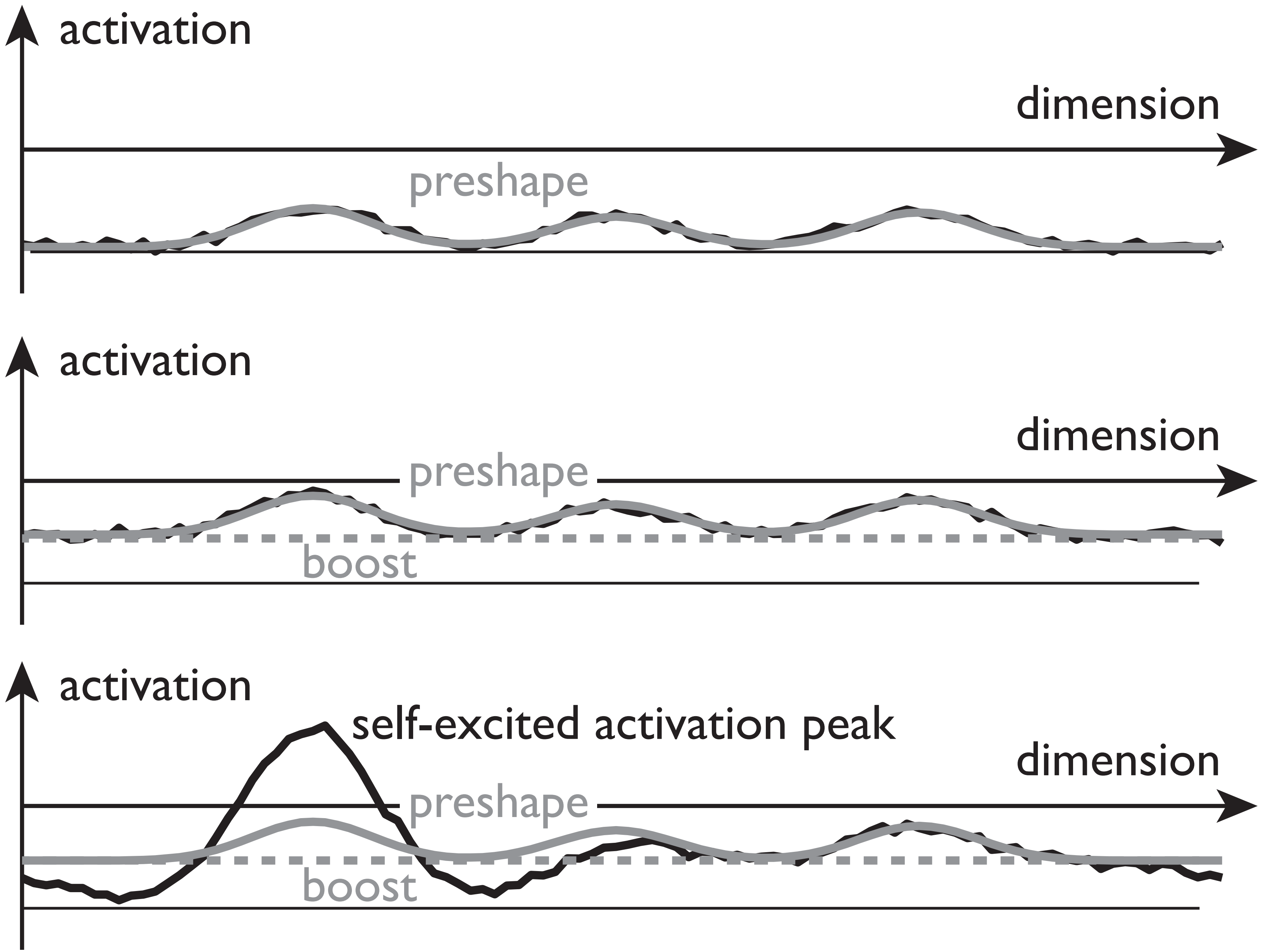


[Simmering, Schutte, Spencer: Brain Research, 2007]



[Schutte, Spencer: JEP:HPP (2009)]

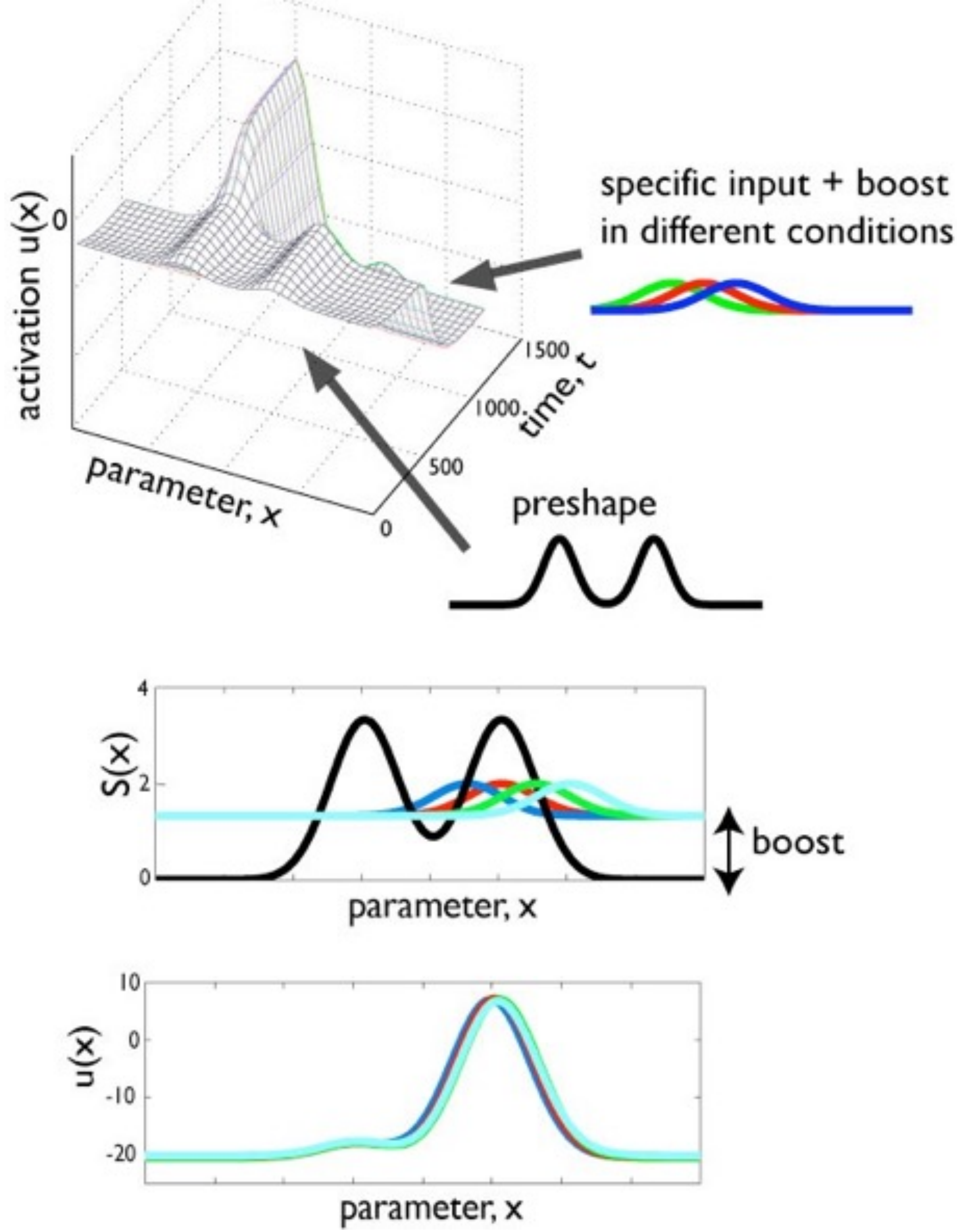
boost-induced detection instability



boost-driven detection instability

- inhomogeneities in the field existing prior to a signal/stimulus that leads to a macroscopic response="preshape"
- the boost-driven detection instability amplifies preshape into macroscopic selection decisions

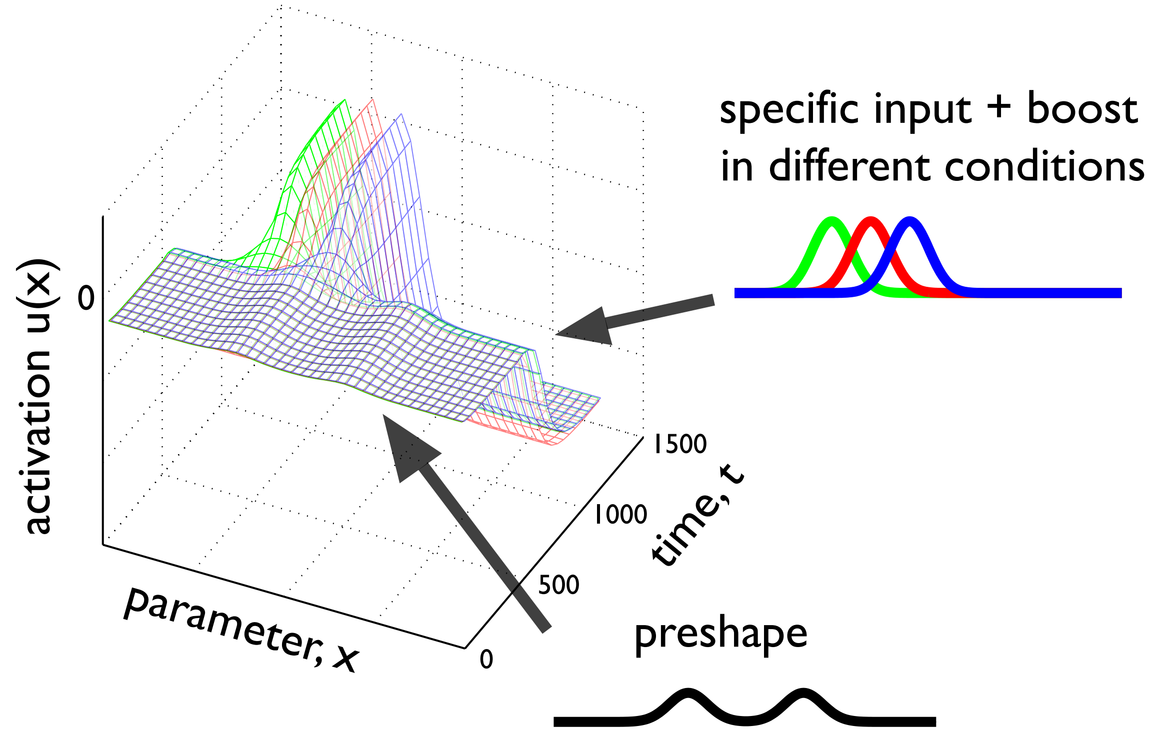
this supports categorical behavior



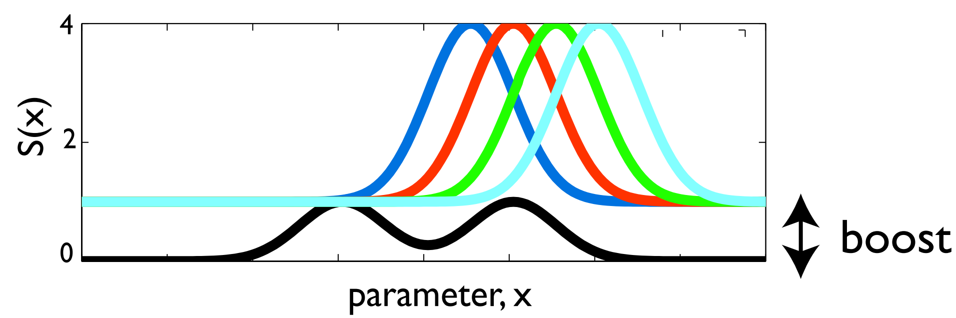
- when preshape dominates

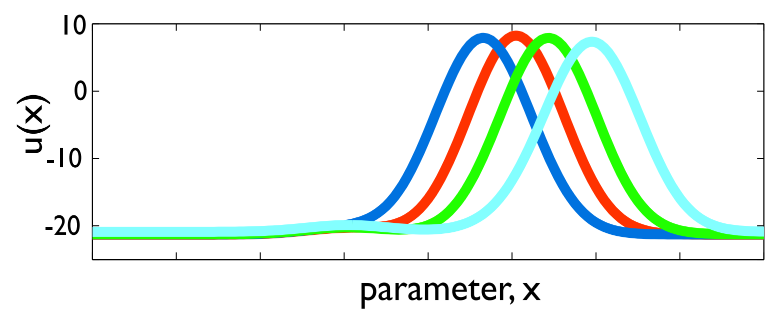
[Wilimzig, Schöner, 2006]

weak preshape in selection



- specific (imperative) input dominates and drives detection instability





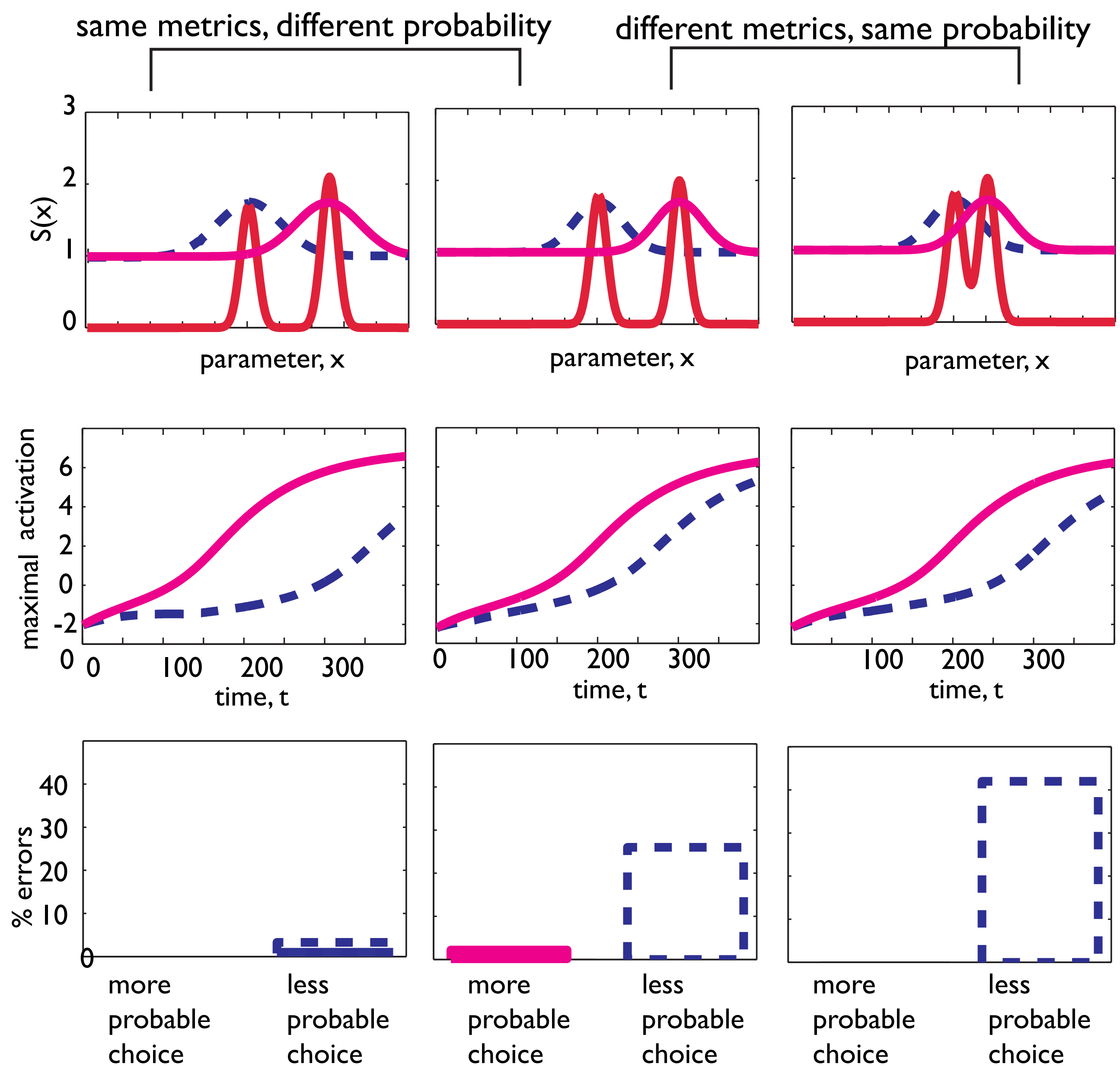
[Wilimzig, Schöner, 2006]

distance effect

- common in categorical tasks
  - e.g., decide which of two sticks is longer... RT is larger when sticks are more similar in length

interaction metrics-probability

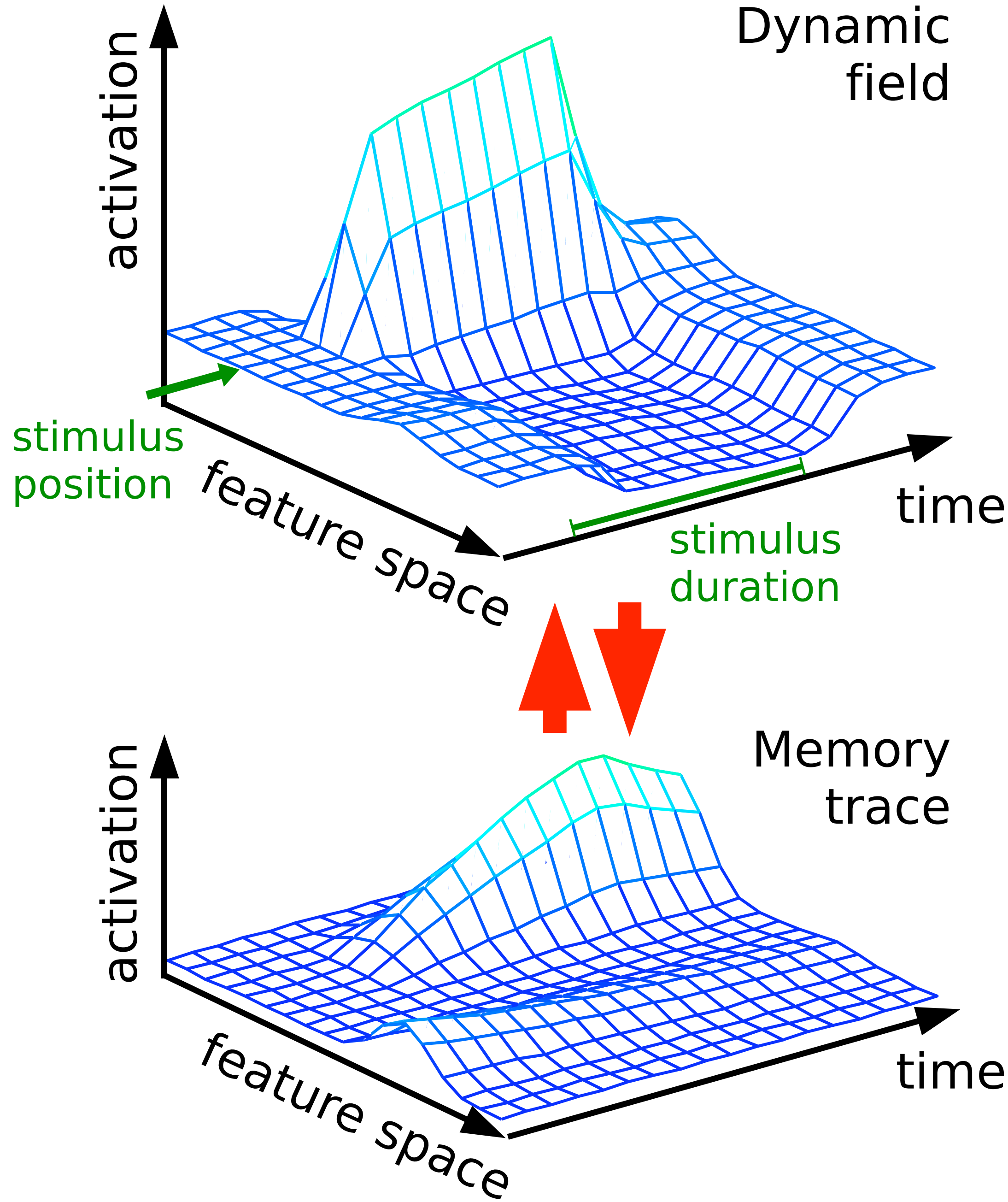
- opposite to that predicted for input-driven detection instabilities:
- metrically close choices show larger effect of probability



Wilimzig, Schöner, 2006

simplest form of learning: the memory trace

- William James: habit formation as the simplest form of learning
  - (habituation: same for inhibition)

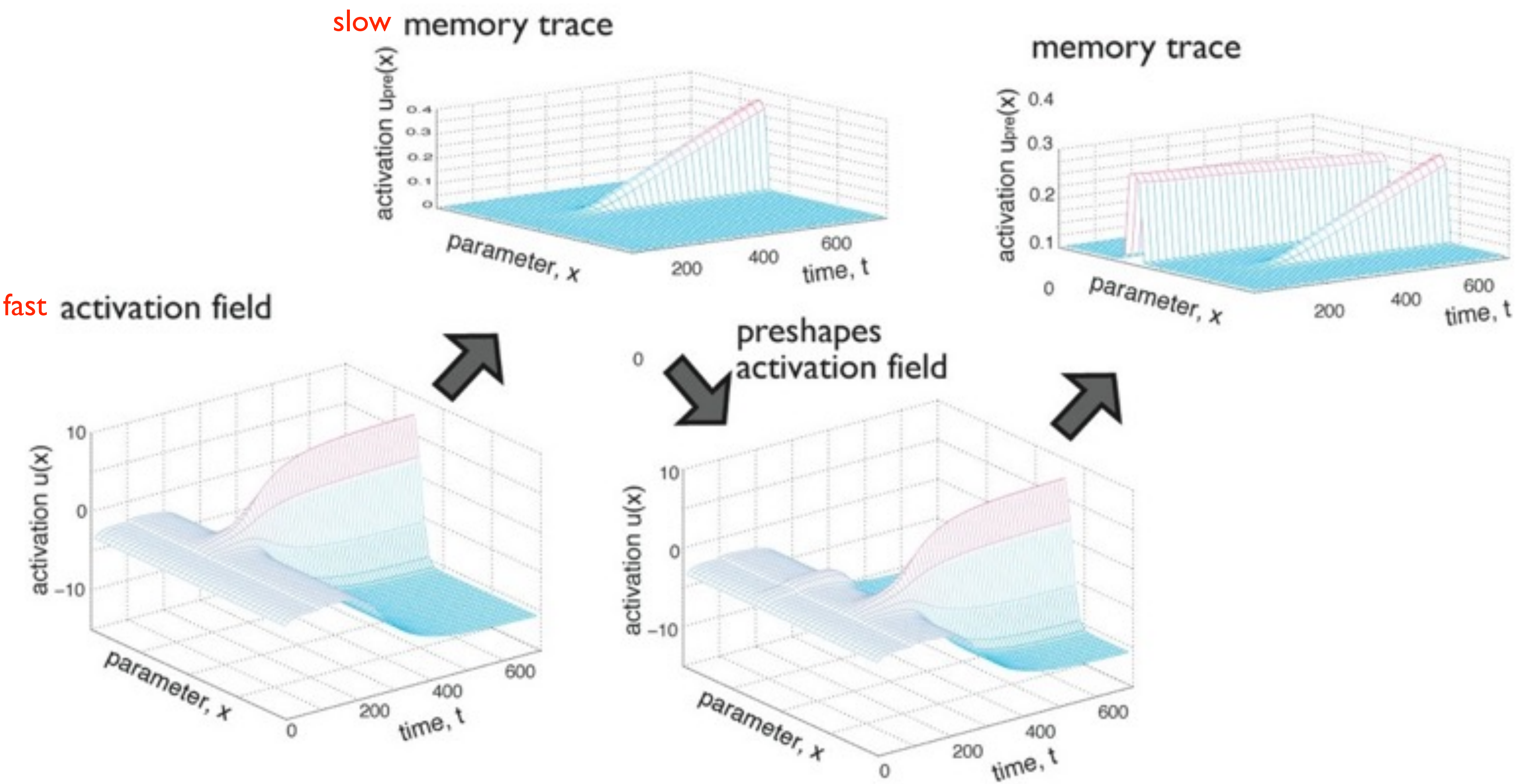


mathematics of the memory trace

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

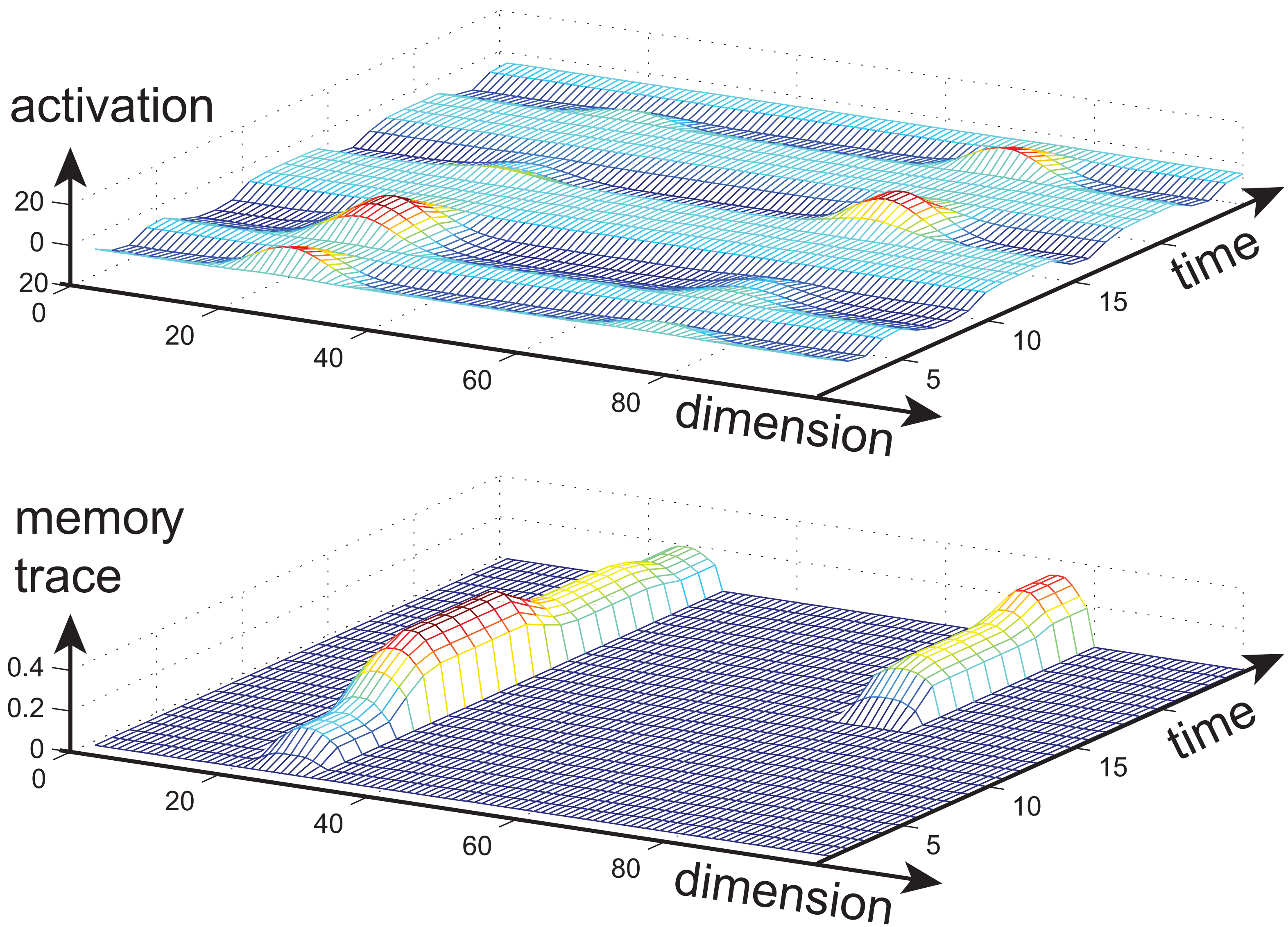
$$\tau_{\text{mem}} \; \dot{u}_{\text{mem}}(x,t) = -u_{\text{mem}}(x,t) + \int dx' \; w_{\text{mem}}(x-x')\sigma(u(x',t))$$

- memory trace only evolves while activation is excited
- potentially different growth and decay rates

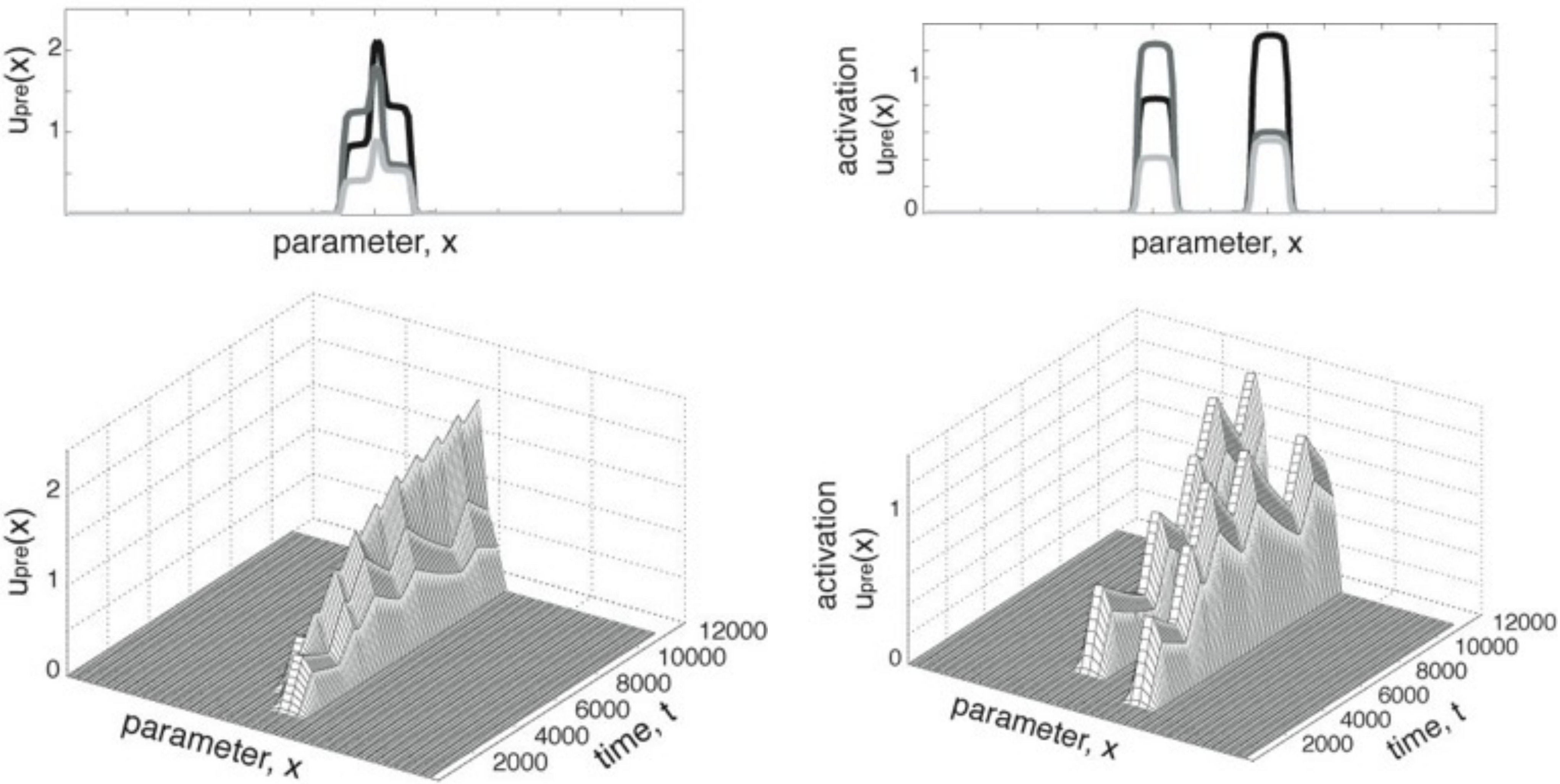


Wilimzig, Schöner 2006

memory trace reflects history of decisions formation



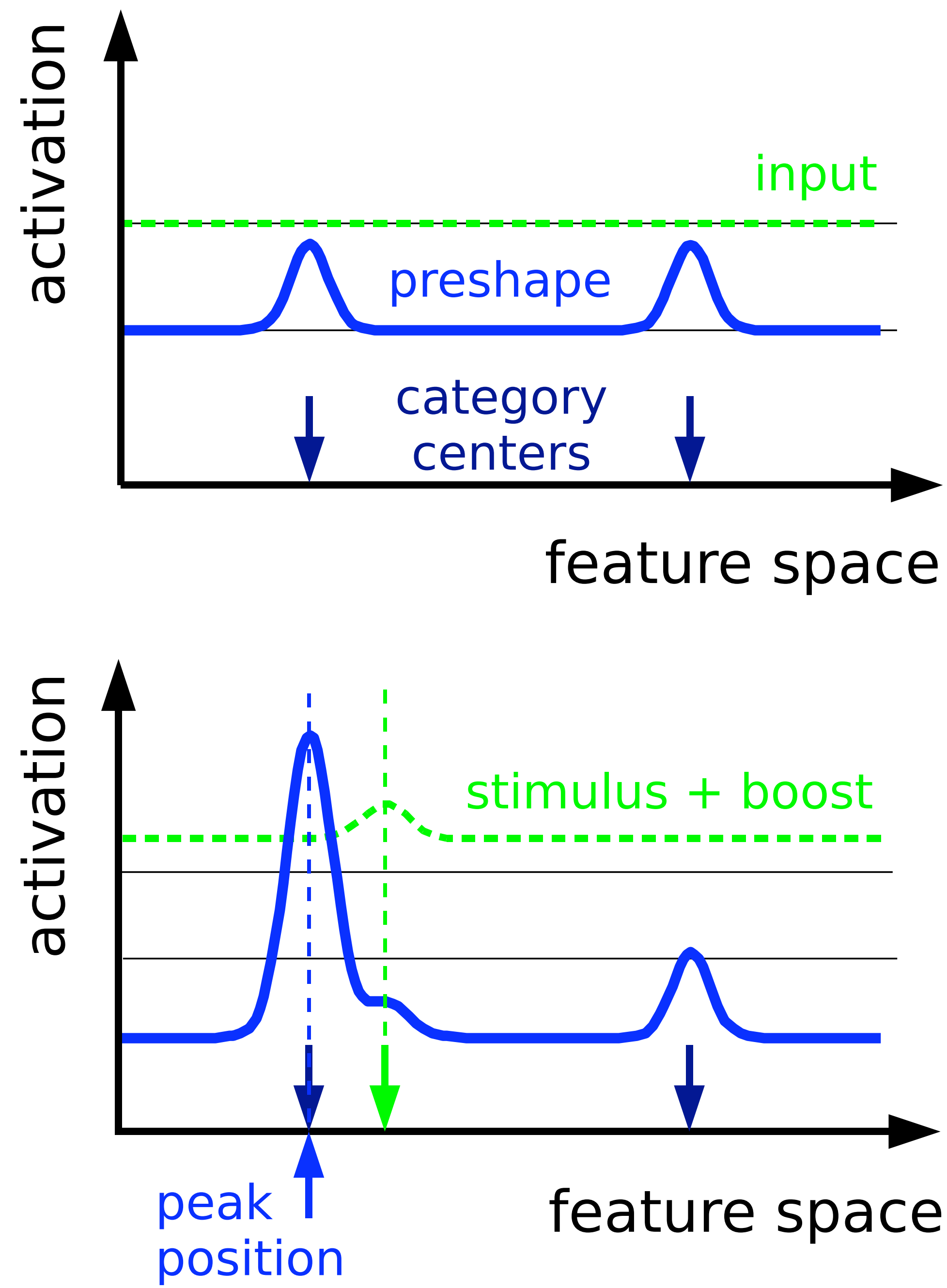
categories may emerge ...



Wilimzig, Schöner 2006

categories may emerge ...

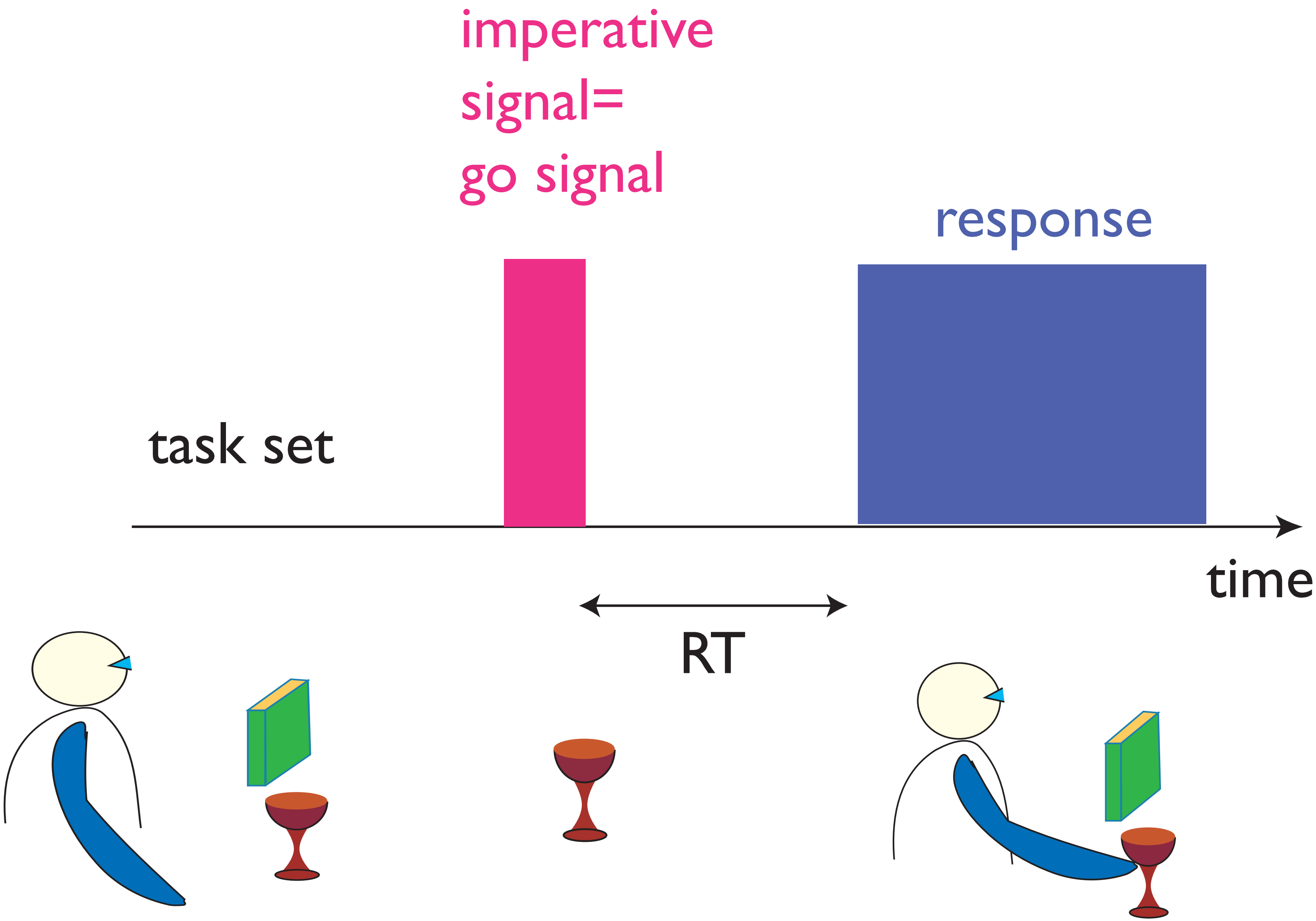
- based on categorical memory trace and boost-driven detection instability
- => field responds categorically



studying selection decisions in the laboratory

- using an imperative signal...

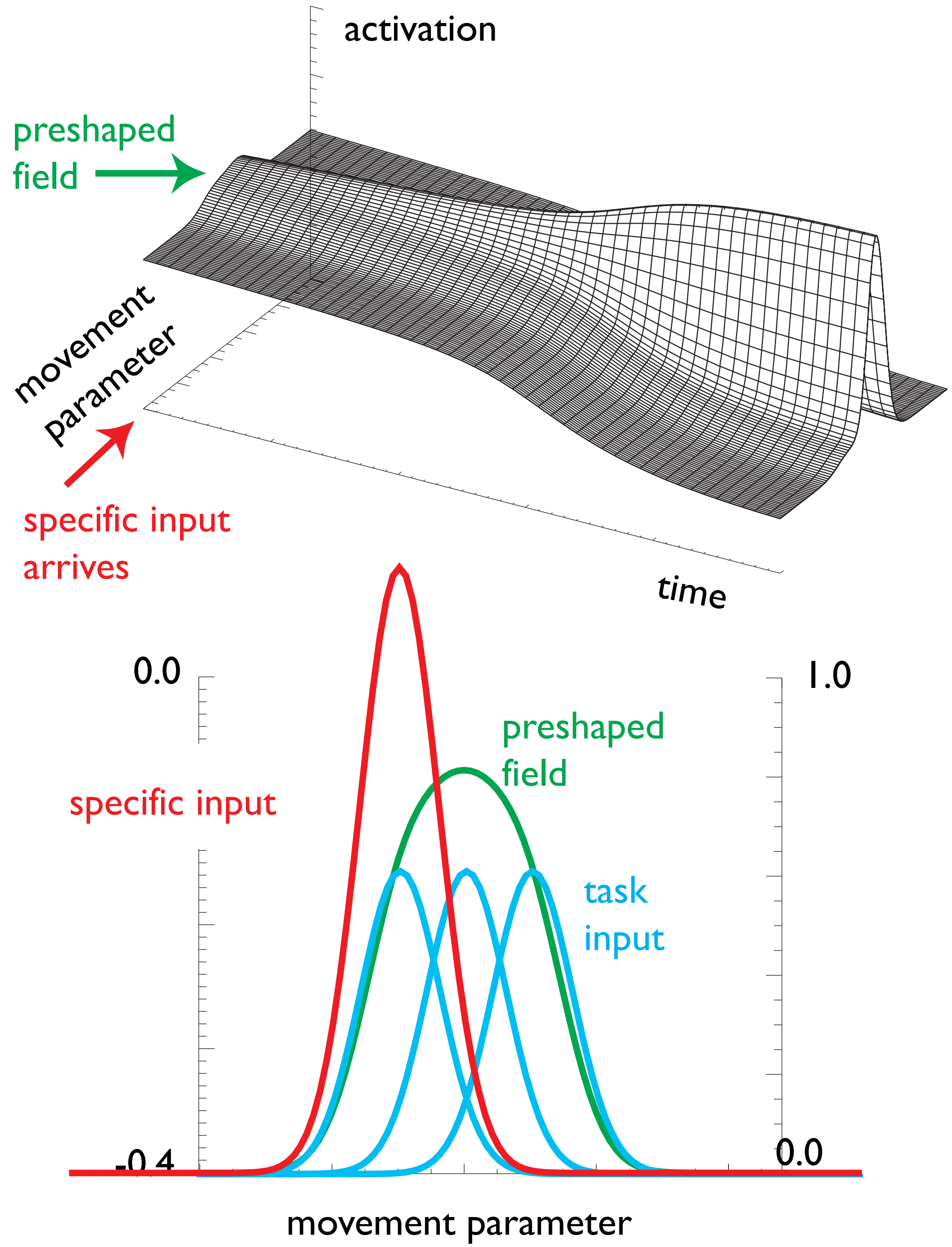
reaction time (RT) paradigm



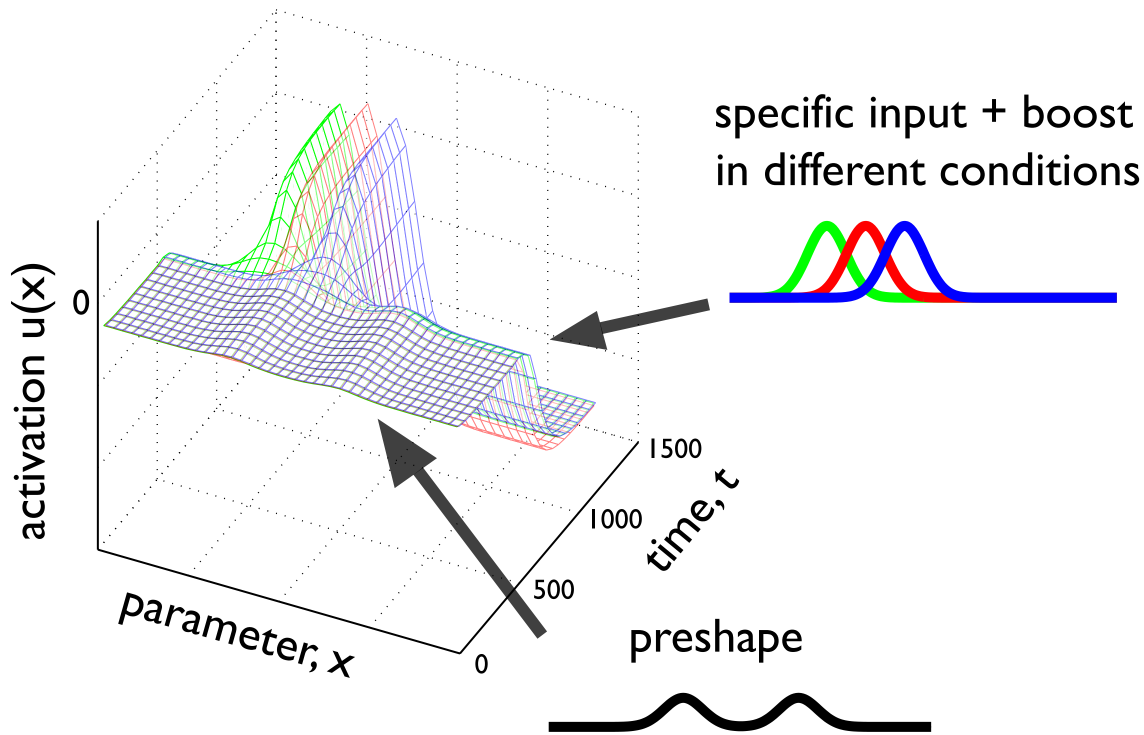
task set

- that is the critical factor in most studies of selection!
  - for example, the classical Hick law, that the number of choices affects RT, is based on the task set specifying a number of choices
- (although the form in which the imperative signal is given is varied as well...)
- how do neuronal representations reflect the task set?

notion of preshape



weak preshape in selection



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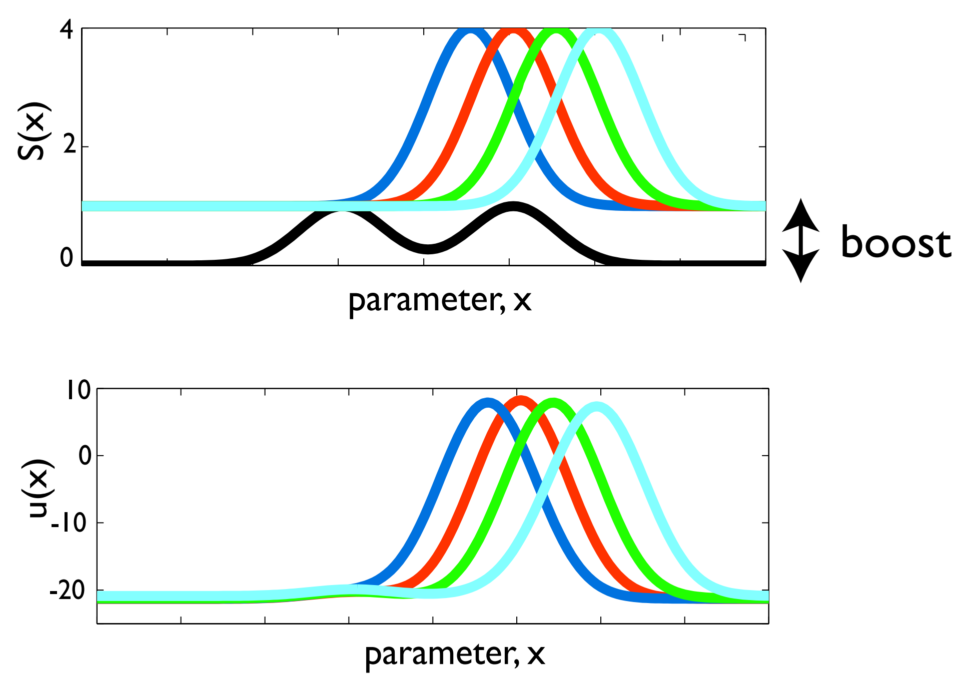
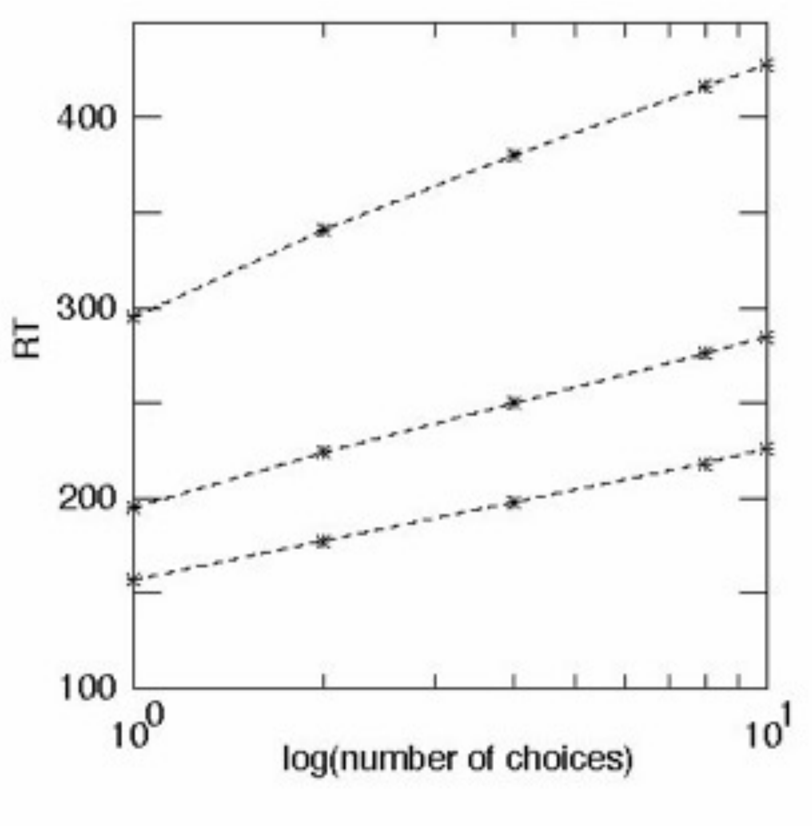
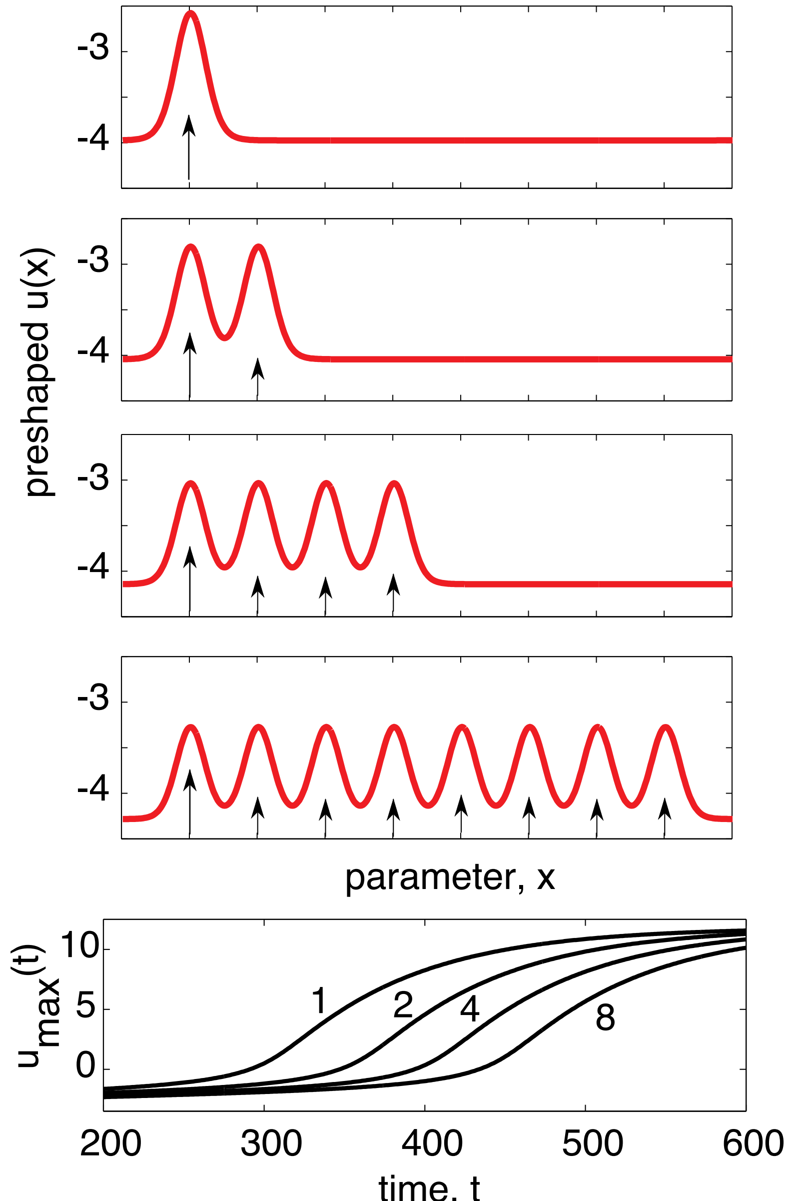


[Wilimzig, Schöner, 2006]

using preshape to account for classical RT data

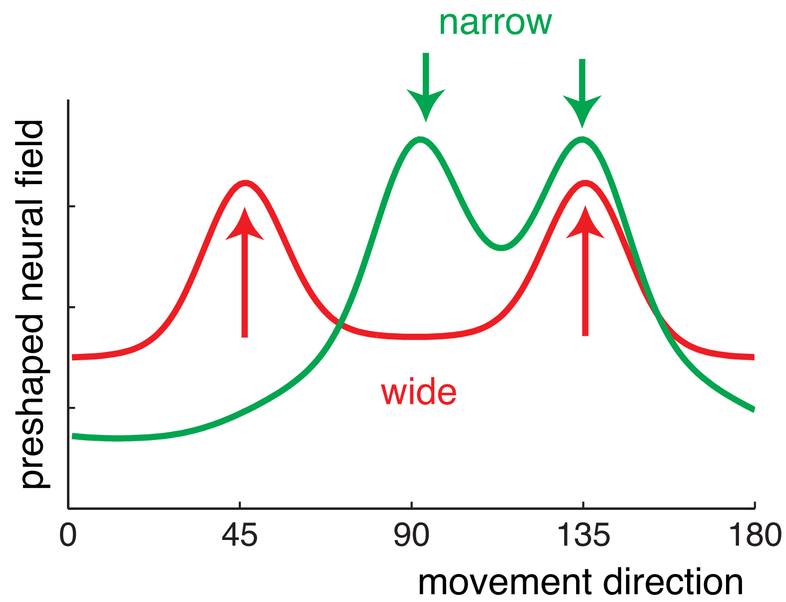
- Hick's law: RT increases with the number of choices



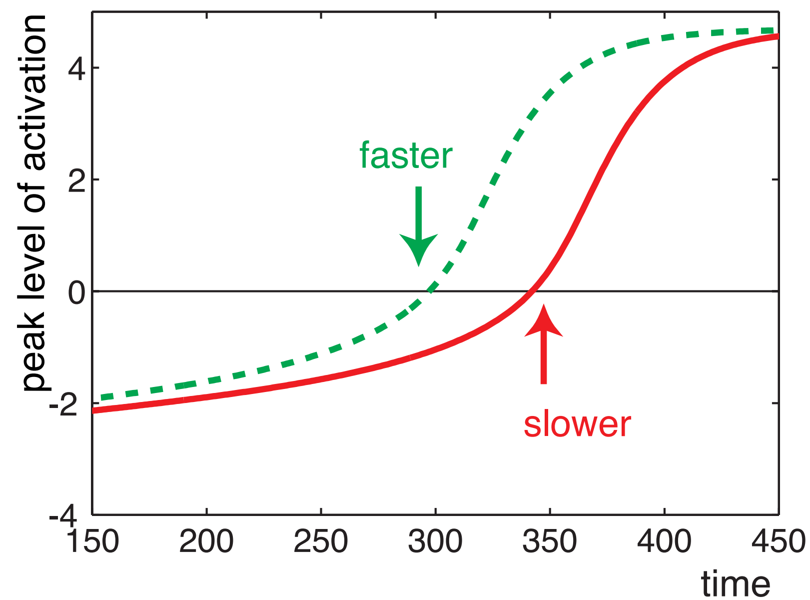


[Erlhagen, Schöner, Psych Rev 2002]

metric effect



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



[from Schöner, Kopecz, Erlhagen, 1997]