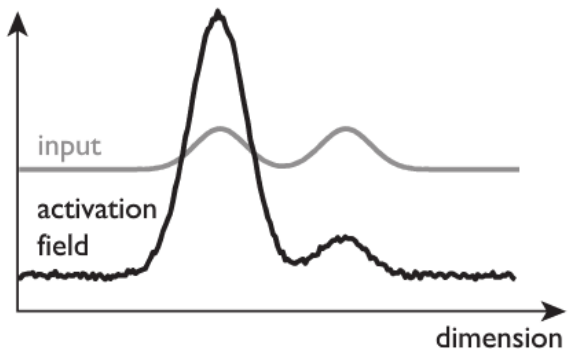
This has already been shown!

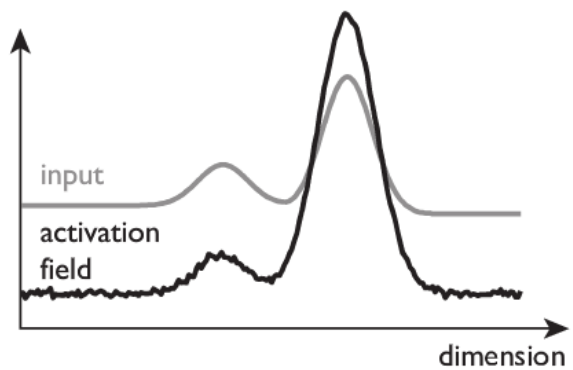
Learning in Dynamic Field Theory: The Memory Trace

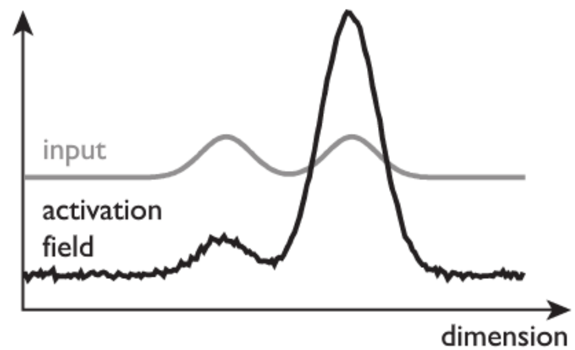
Jan Tekülve

23.11.2017

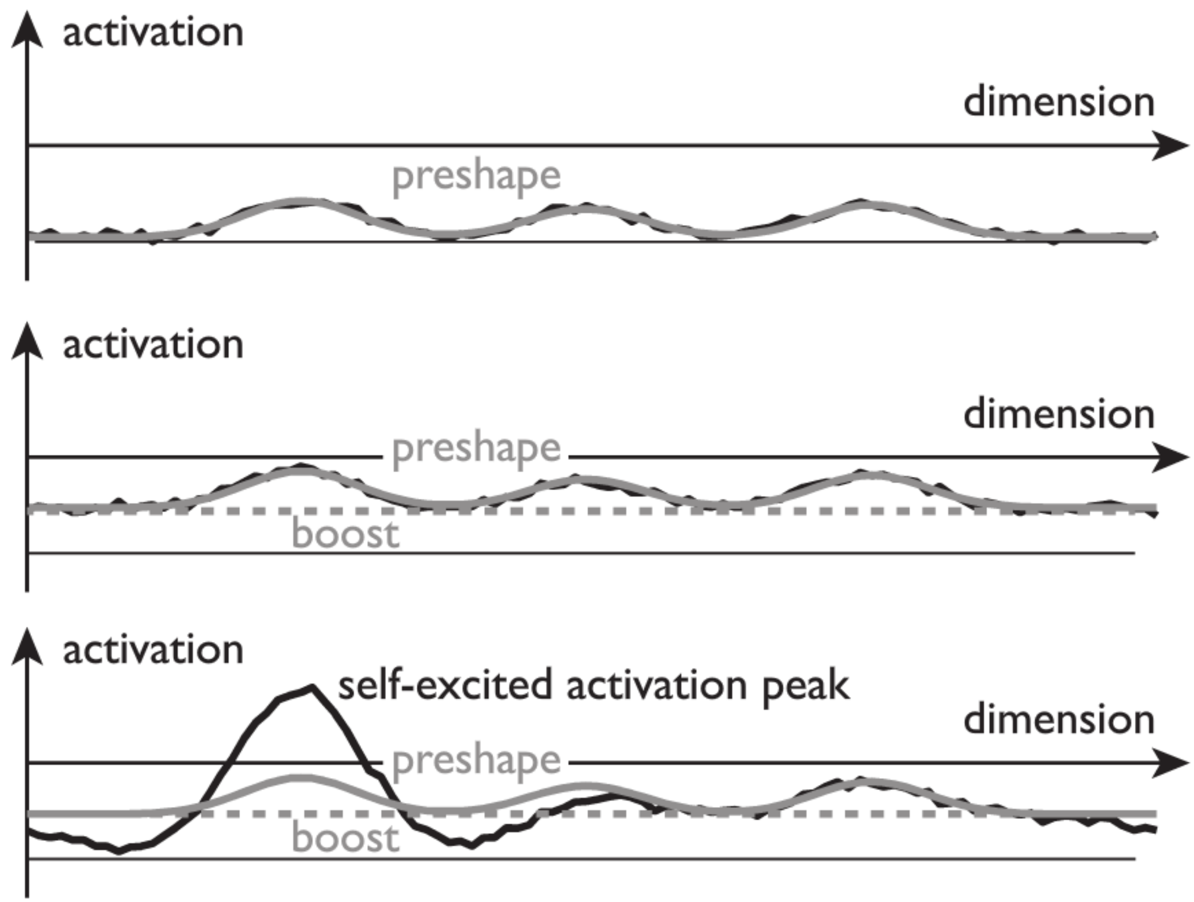
Recap: Selection Instability



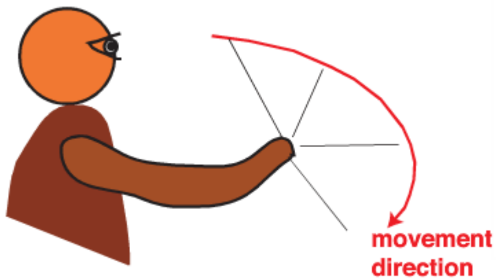


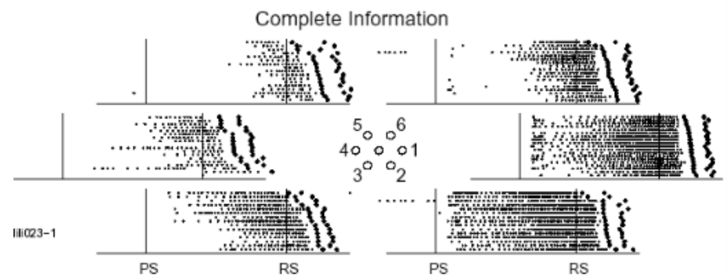


Recap: Preshape

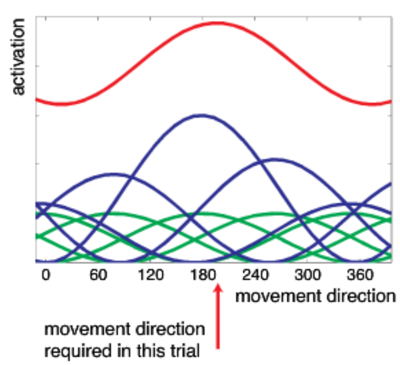


Neural Evidence For Preshape

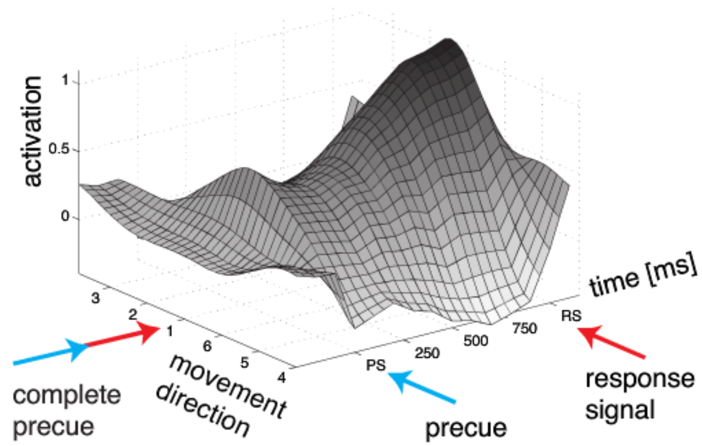




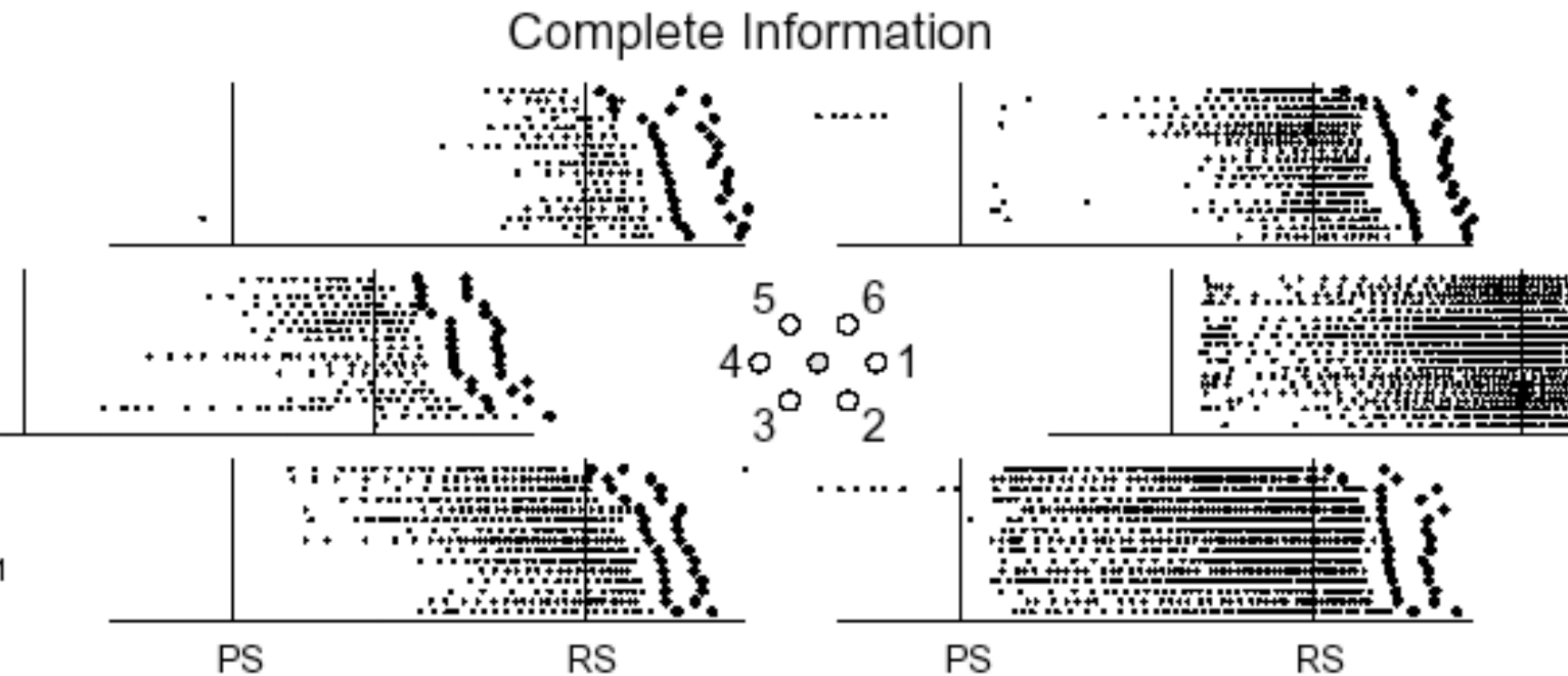
Distribution of population activation =
$\sum_{\text{neurons}}$ tuning curve * current firing rate



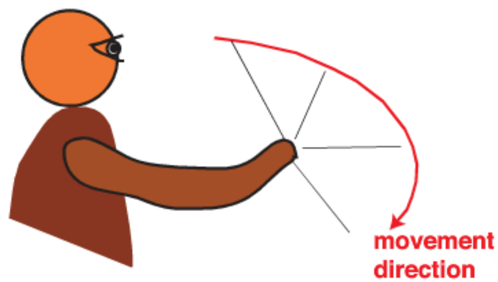
[after Bastian, Riehle, Schöner, submitted]

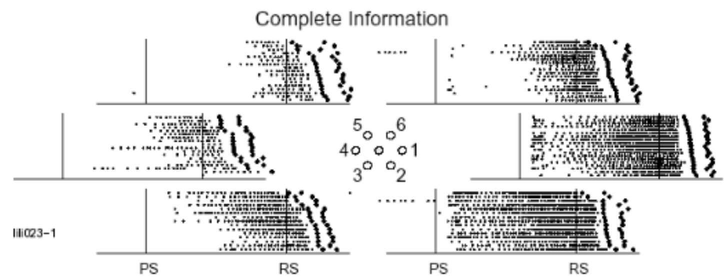


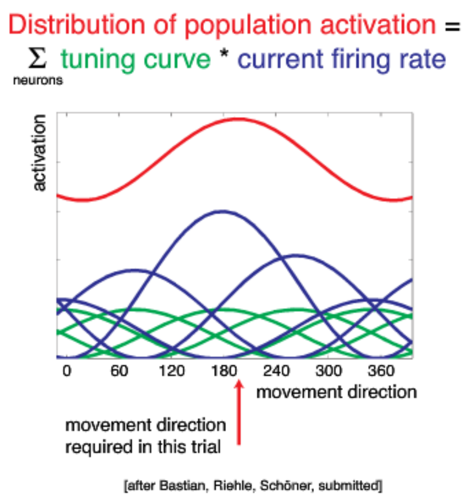
[Bastian, Riehle, Schöner: Europ J Neurosci 18: 2047 (2003)]

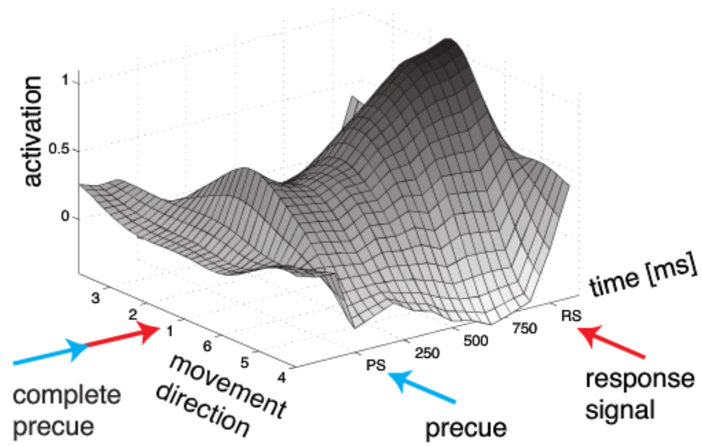

Complete Information
5
6
4
1
3
2
PS
RS
PS
RS

Neural Evidence For Preshape

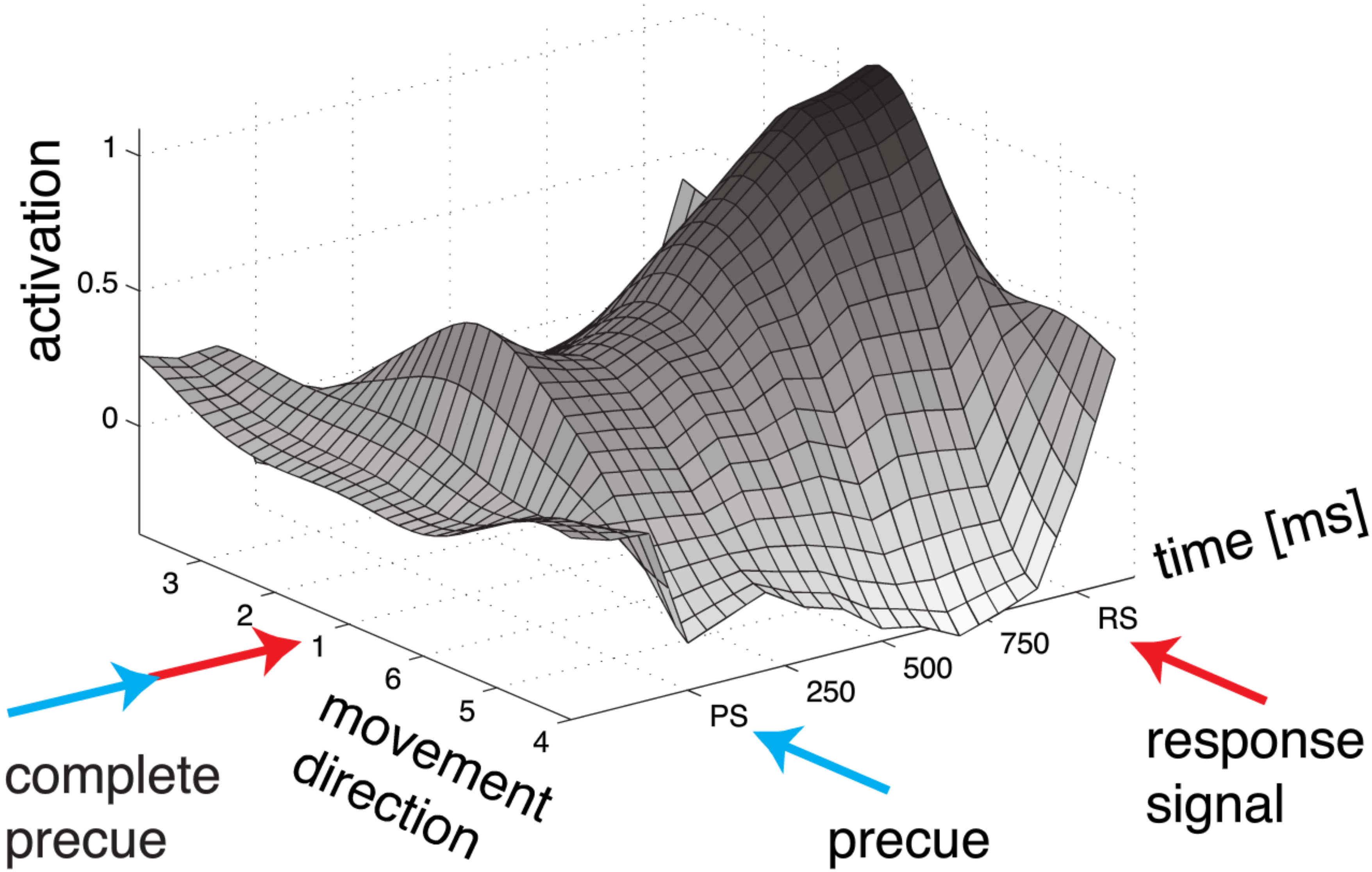








[Bastian, Riehle, Schöner: Europ J Neurosci 18: 2047 (2003)]

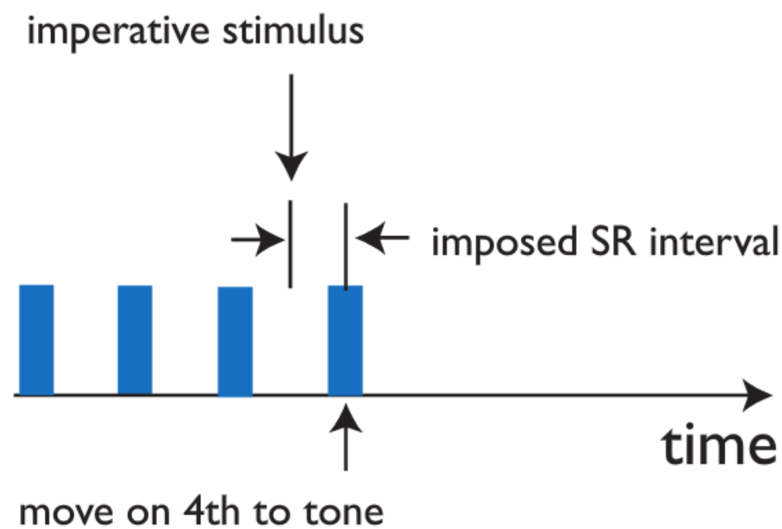


ian, Riehle, Schöner: Europ J Neurosci 18: 2047 (2003)]

Behavioral Evidence For Preshape

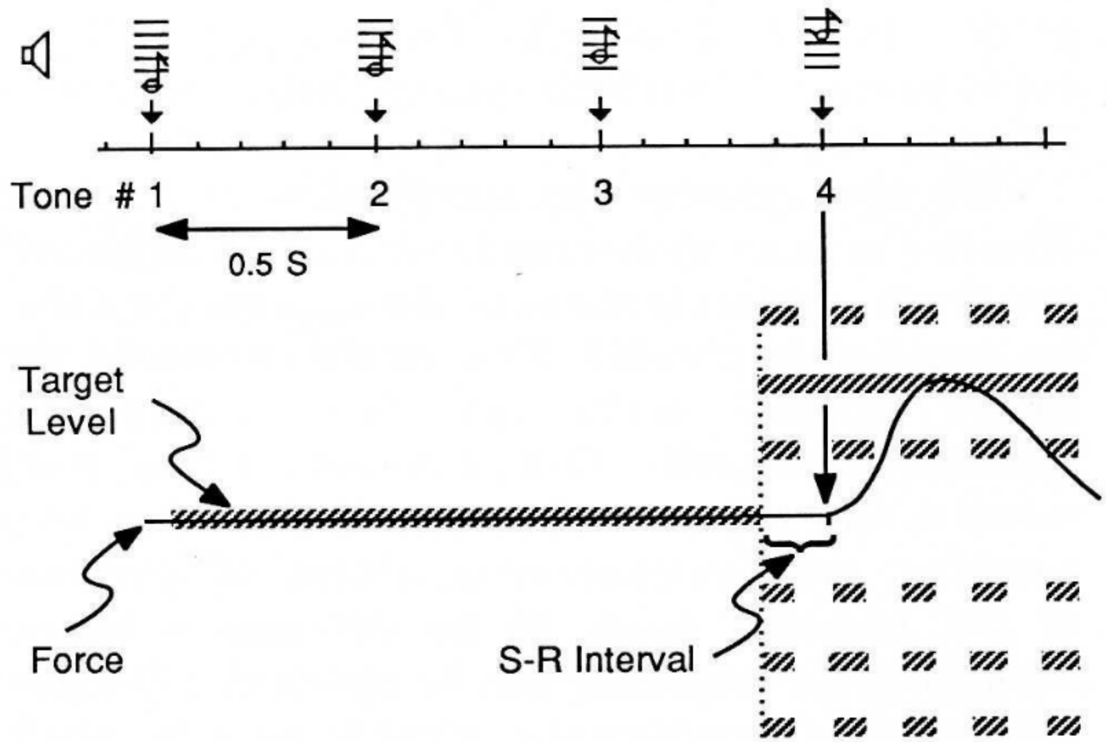
- movement preparation is **graded** and **continuous** in time

timed movement initiation paradigm



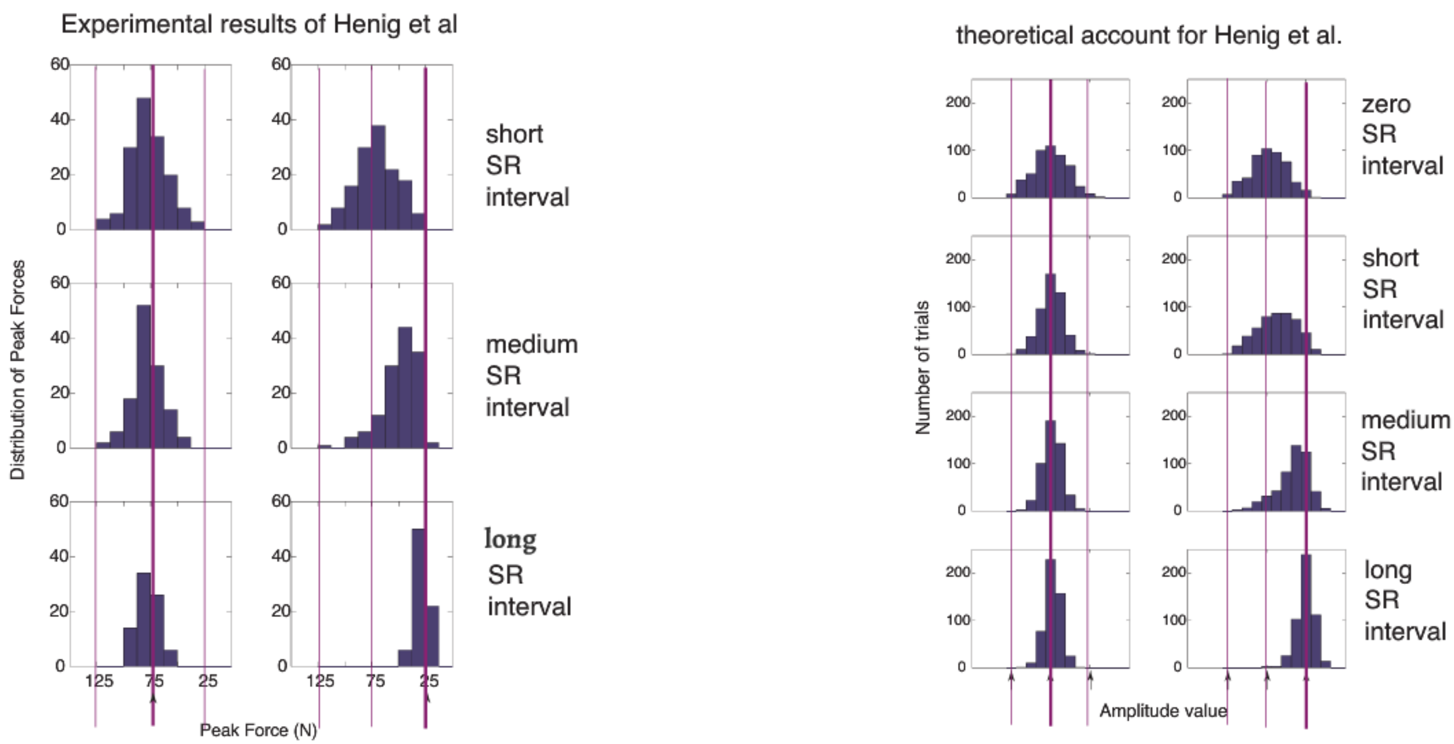
[Ghez and colleagues, 1988 to 1990's]

Experimental Setup



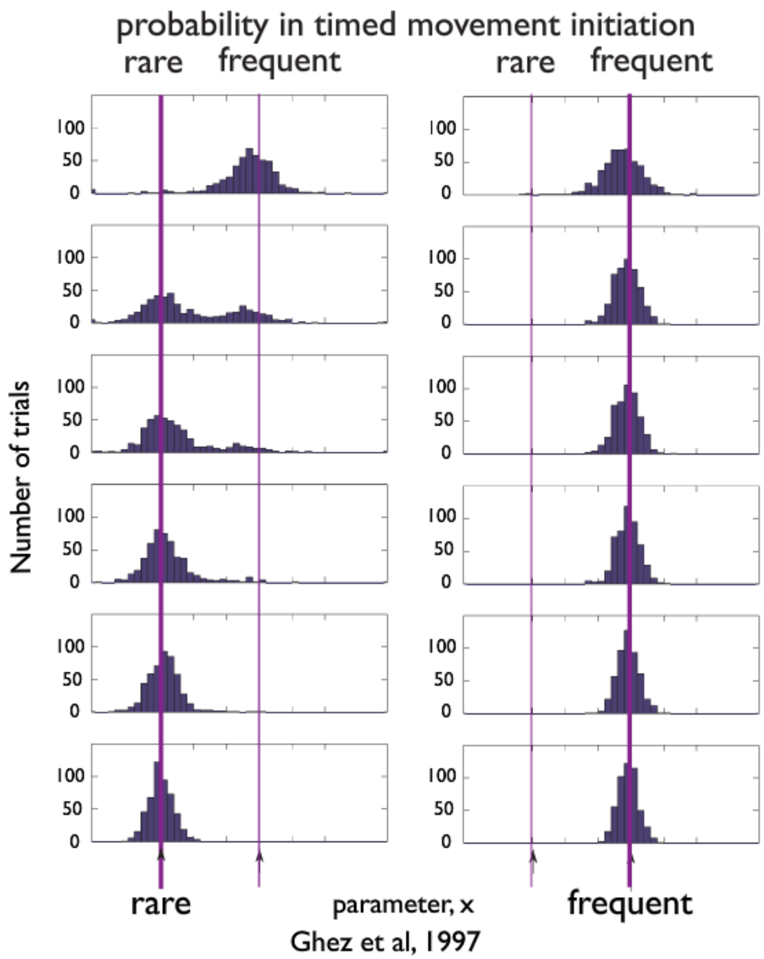
[Favilla et al. 1989]

Preshape Dynamics Fit Experimental Data



[Schöner,Erlhagen 2002]

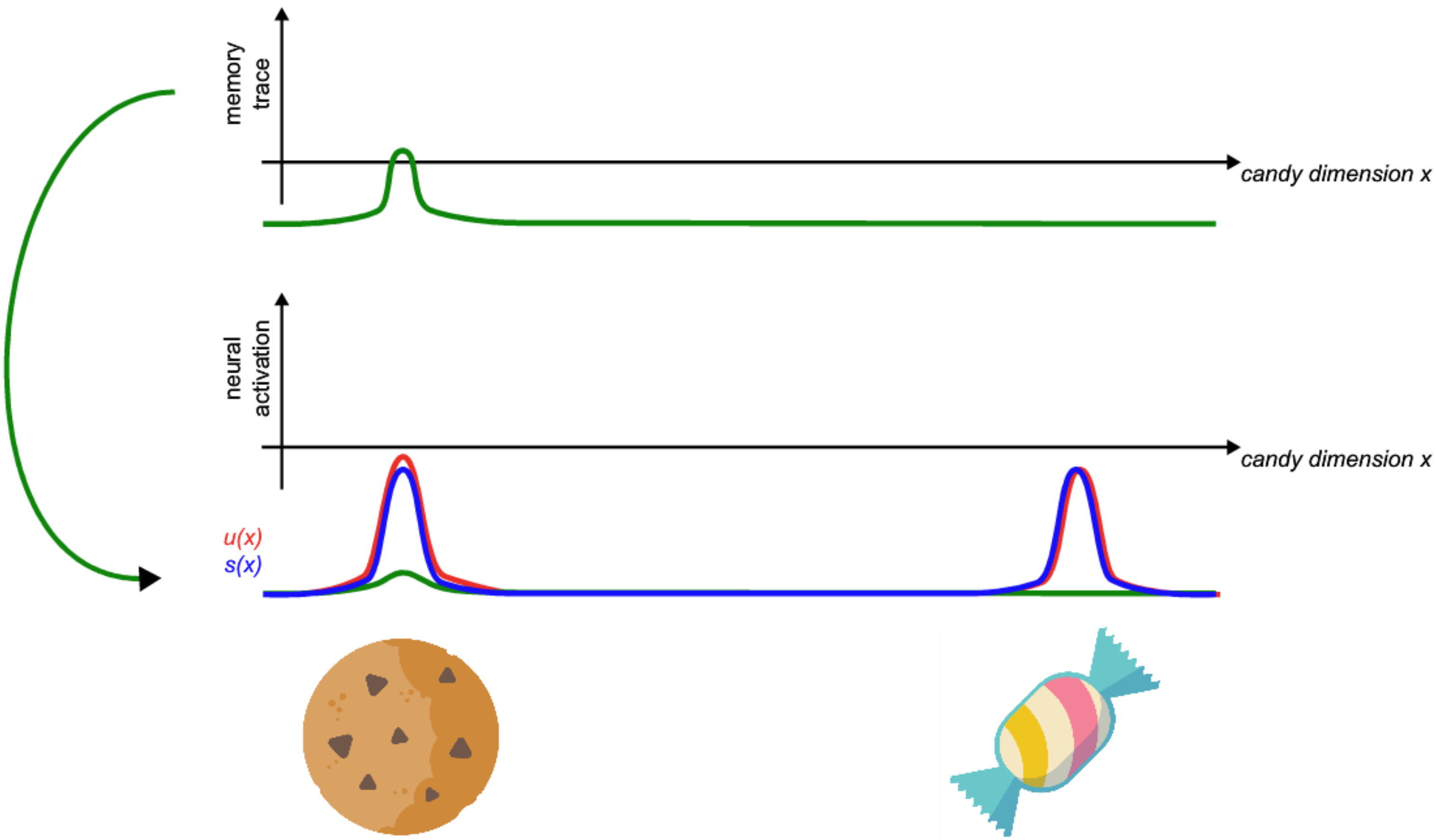
Target Probabilites are encoded as Preshapes



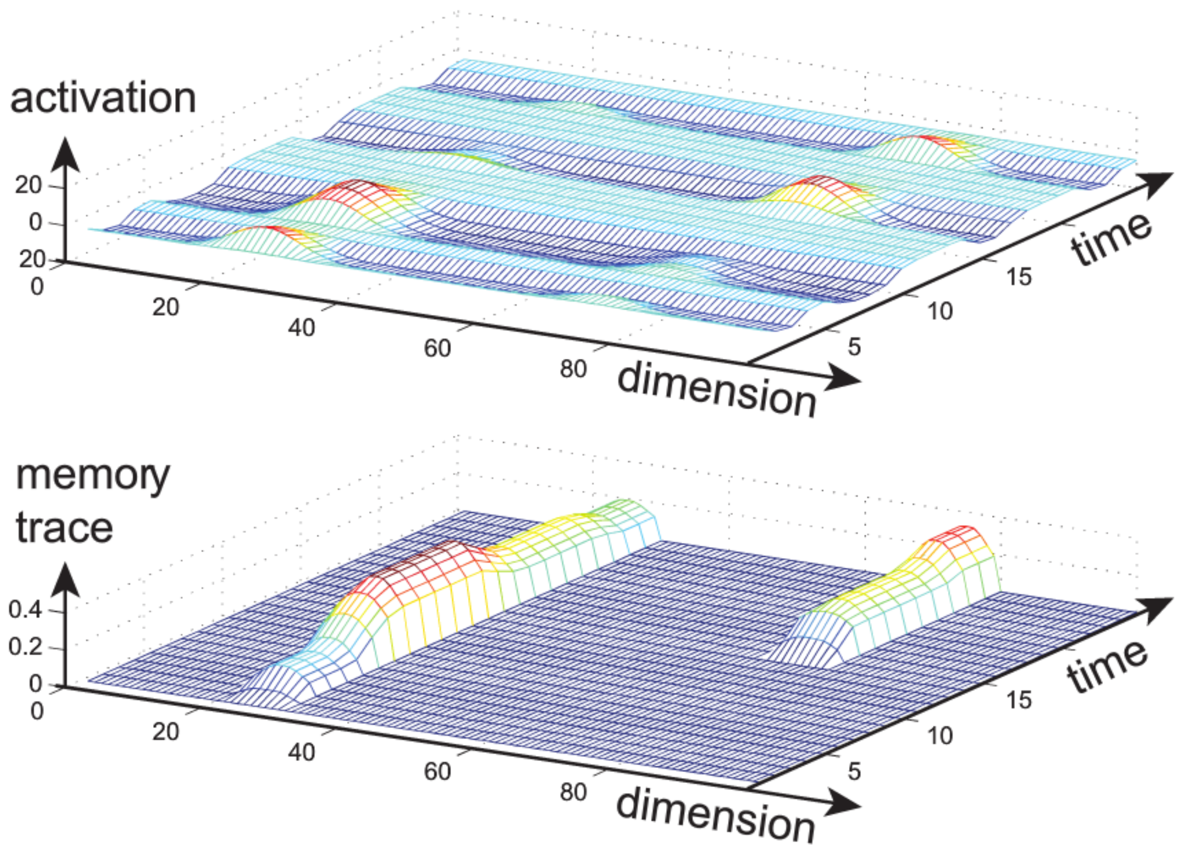
short SR interval: observe preshape

long SR interval: observe stimulus-defined movement plan

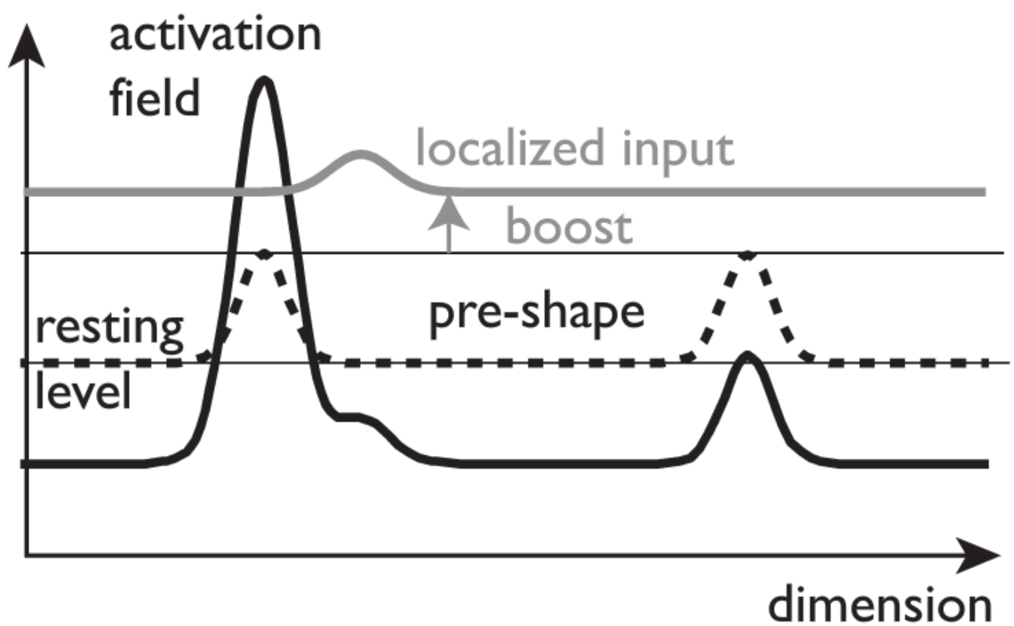
Inspiration: Habit Formation



Memory Trace Buildup



Recap: Categorical Response



- Memory traces enable category learning

Dynamics on Different Timescales

$$\tau_{\text{mem}} \gg \tau$$

Trace Dynamics

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

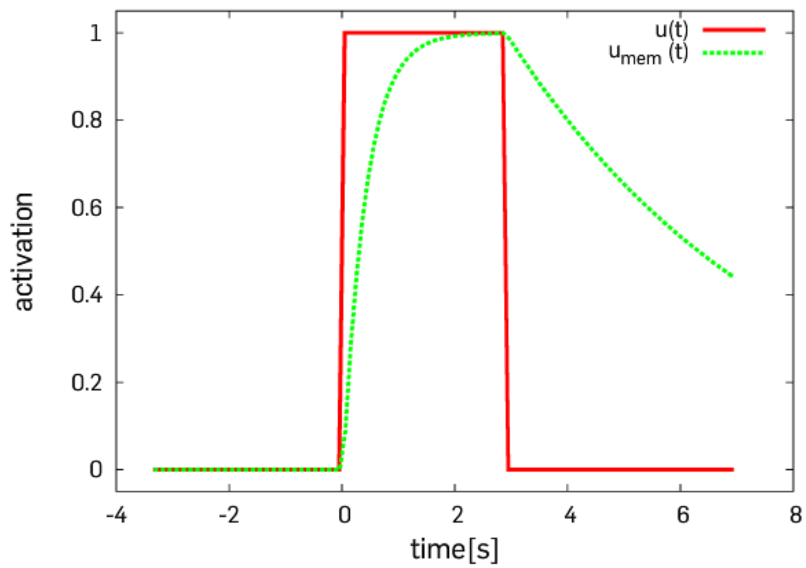
Field Dynamics

$$\begin{aligned}\tau \dot{u}(x,t) = {} & -u(x,t) \\ & + h + s(x,t) + c_{\text{mem}} u_{\text{mem}}(x,t) \\ & + \int k(x-x')\, g\big(u(x',t)\big)\, dx'\end{aligned}$$

Memory Trace Variations

$$\tau_{\text{mem}}\dot{u}_{\text{mem}}(x,t) = \lambda_{\text{build}}\Big(-u_{\text{mem}} + g(u(x,t))\Big)g(u(x,t)) - \lambda_{\text{decay}}u_{\text{mem}}\Big(1 - g(u(x,t))\Big)$$

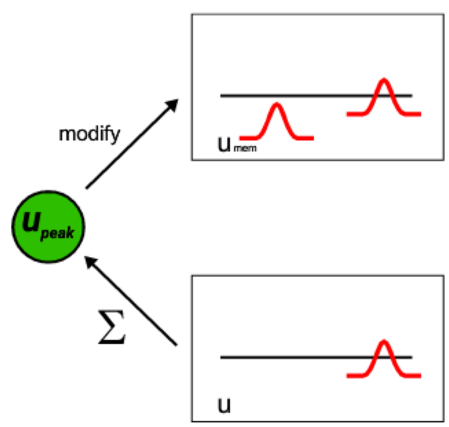
- different timescales for build up and decay



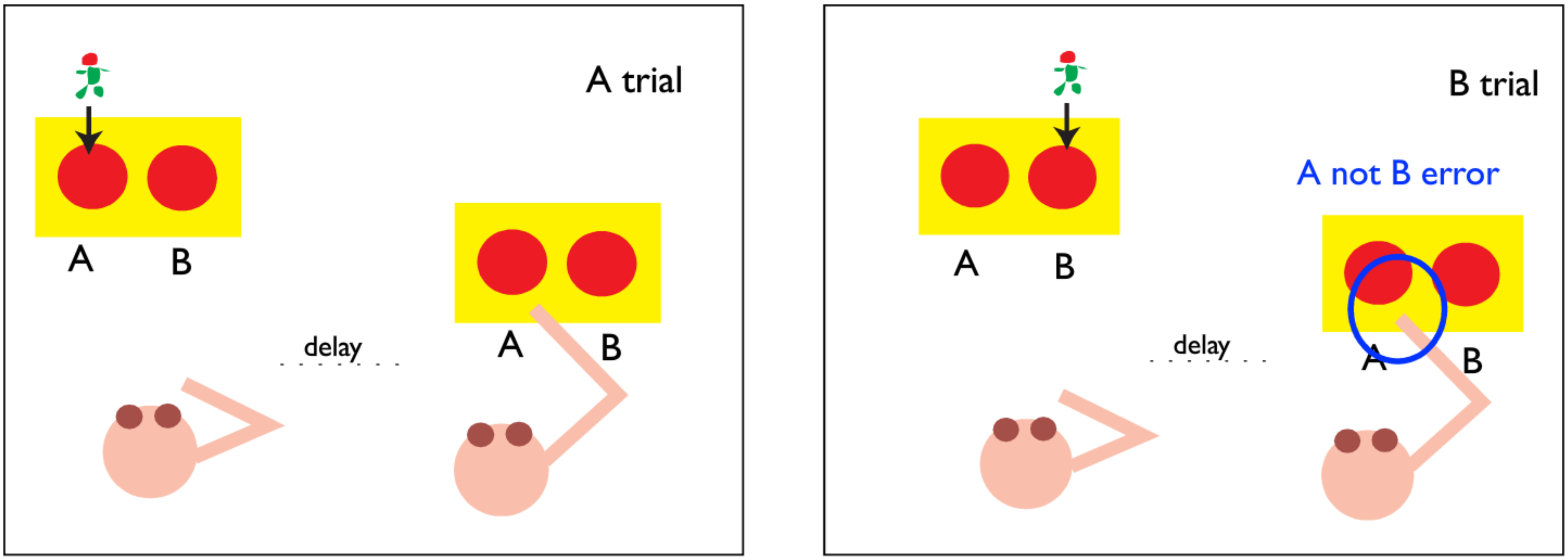
Memory Trace Variations

$$\tau_{\text{mem}}\dot{u}_{\text{mem}}(x,t) = \Bigg[\lambda_{\text{build}}\Big(-u_{\text{mem}} + g(u(x,t))\Big)g(u(x,t))$$
$$- \lambda_{\text{decay}}\, u_{\text{mem}}\Big(1 - g(u(x,t))\Big)\Bigg] g(u_{\text{peak}}(t))$$

- no change in the absence of input

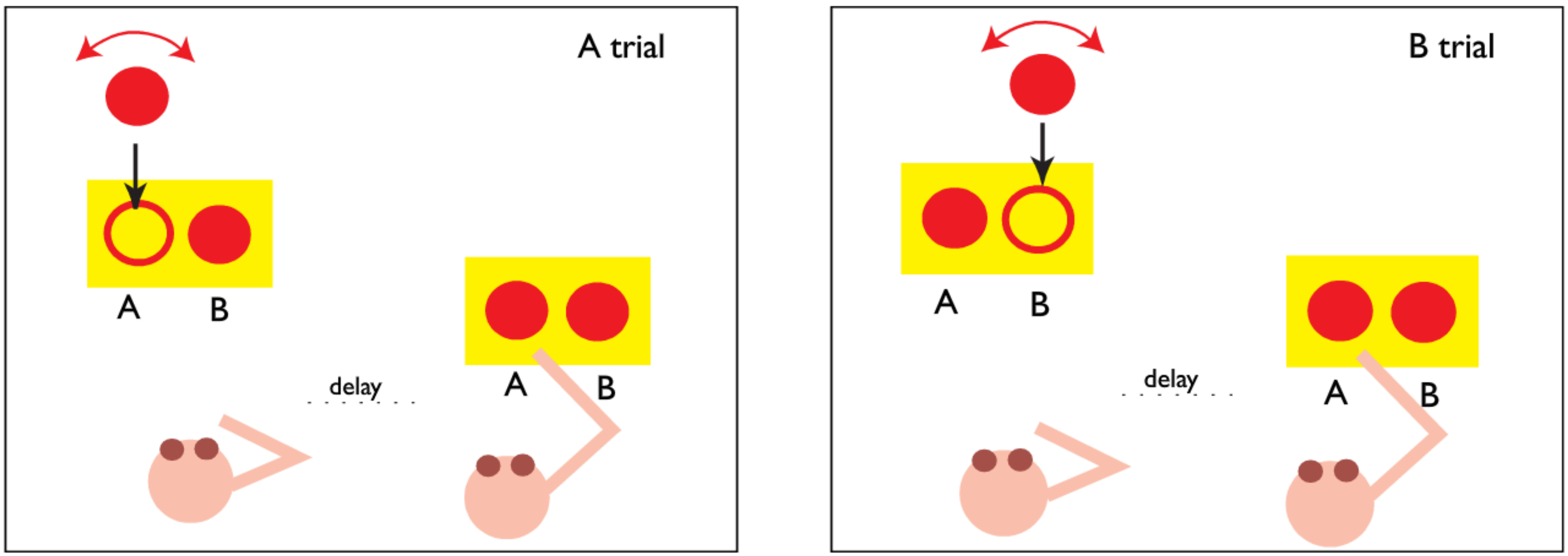


Behavioral Evidence: Piaget's A not B Paradigm



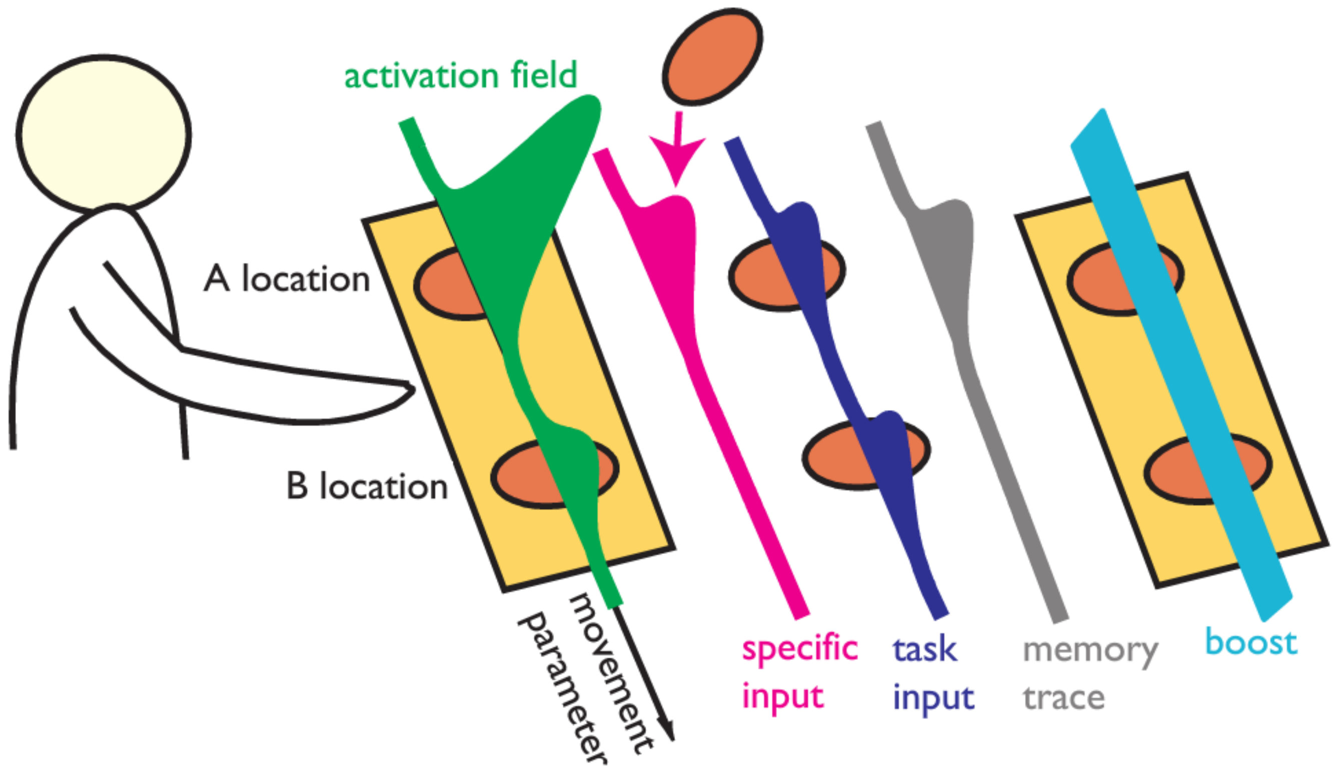
Out of sight - out of mind

Toyless Variant of A not B



[Smith,Thelen et al.: Psychological Review (1999)]

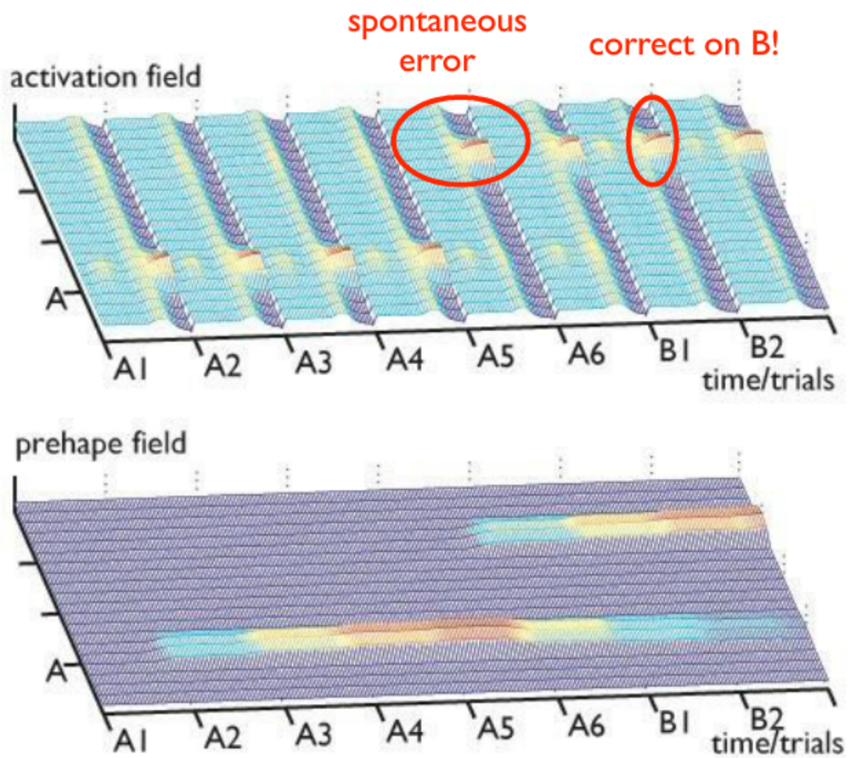
DFT Model for A not B



MODEL LIVE DEMO

DFT of infant perseverative reaching

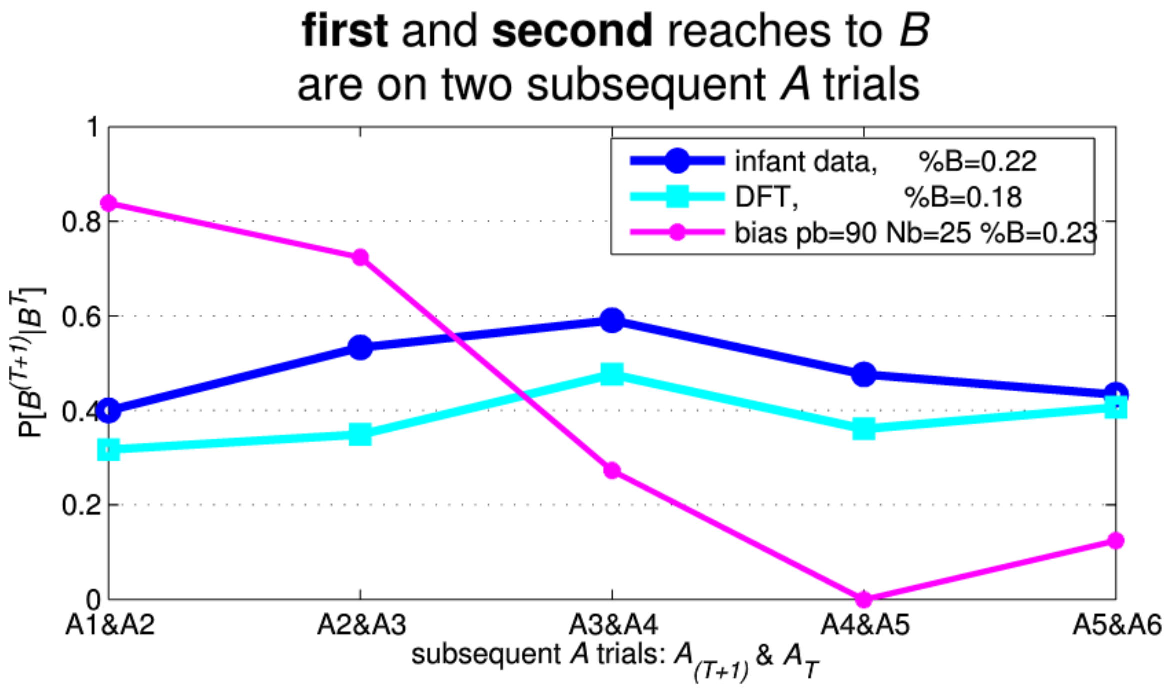
- that is because reaches to B on A trials leave memory trace at B



[Dinveva, Schöner, Dev. Science 2007]

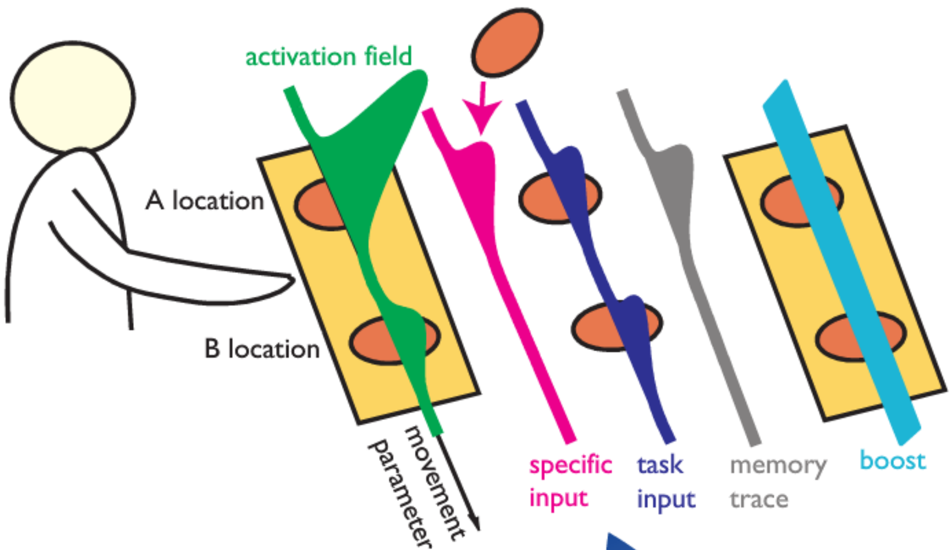
Comparison with Infant Data

- spontaneous errors promote spontaneous errors



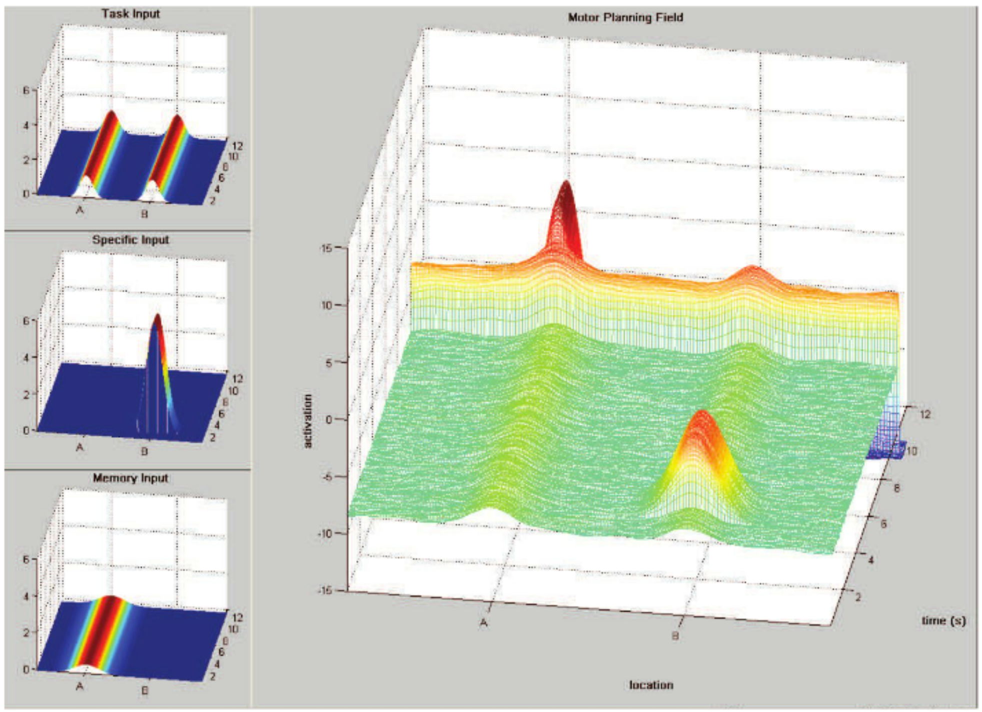
[Dineva,Schöner,Dev. Science 2007]

Why do older infants not make the A not B Error?

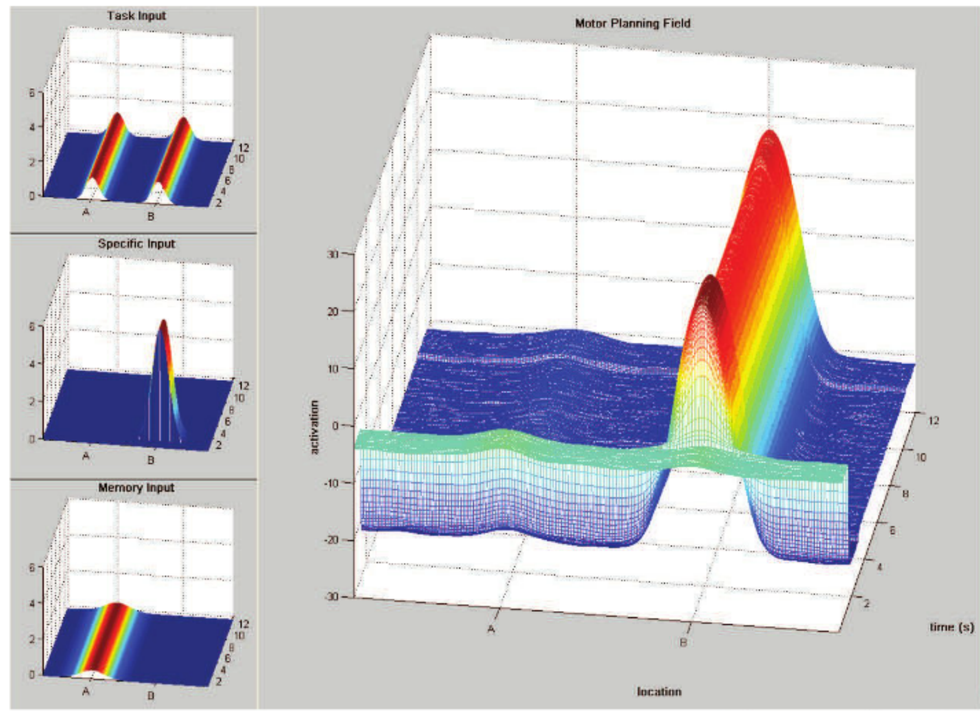


- specific input information is sustained due to the memory instability

Why do older infants not make the A not B Error?

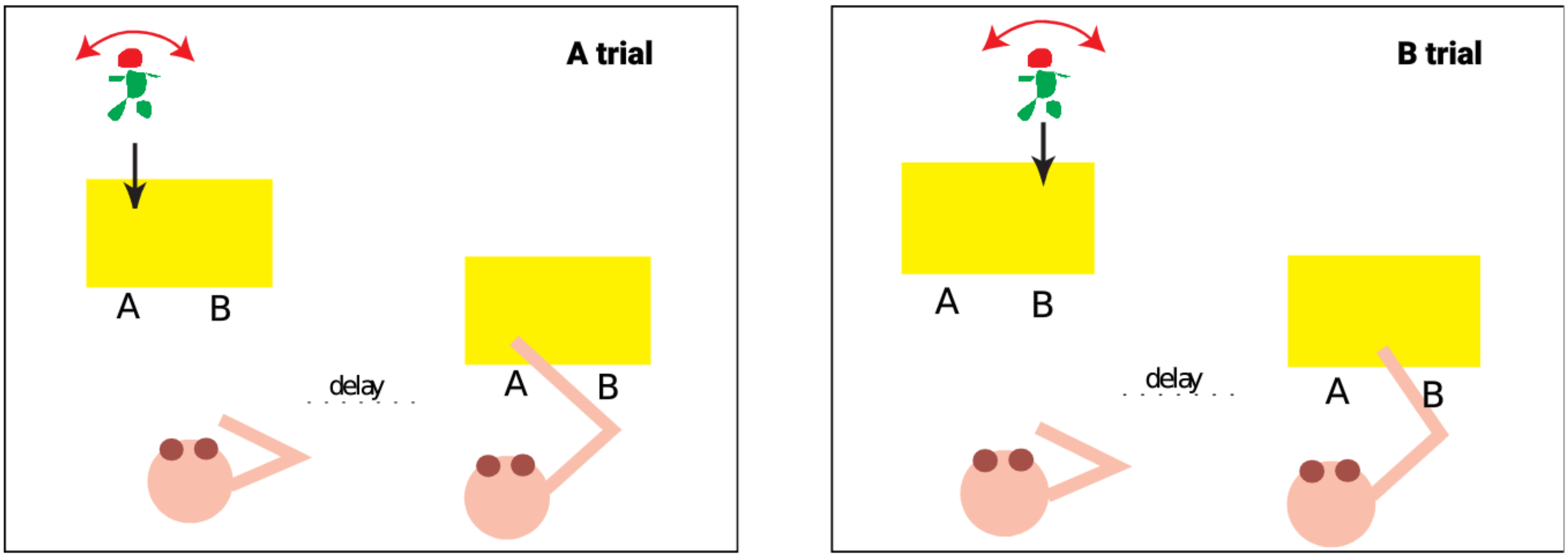


young infant

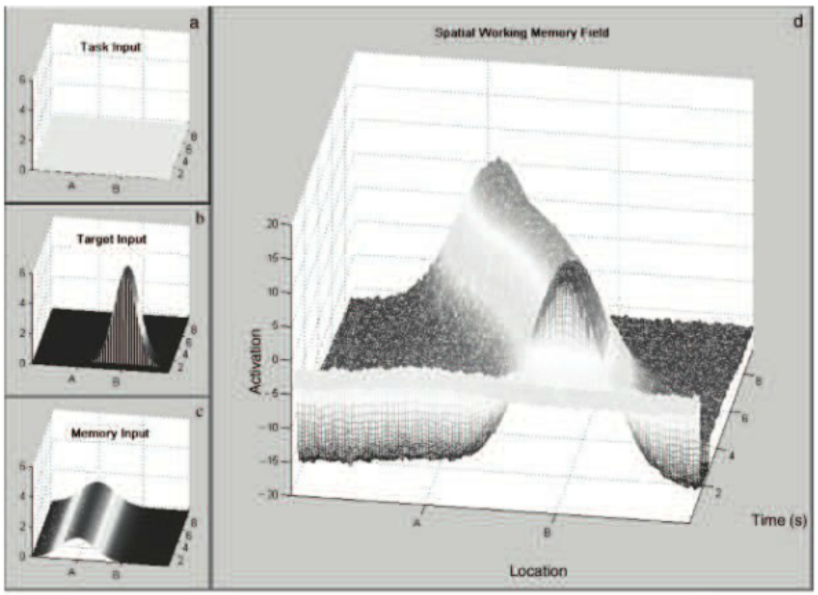


older infant

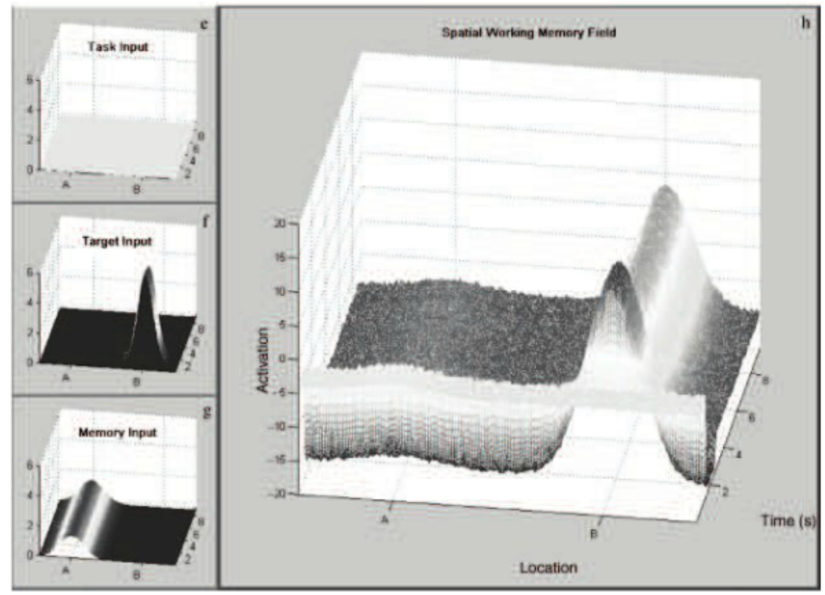
A not B Sandbox Variation



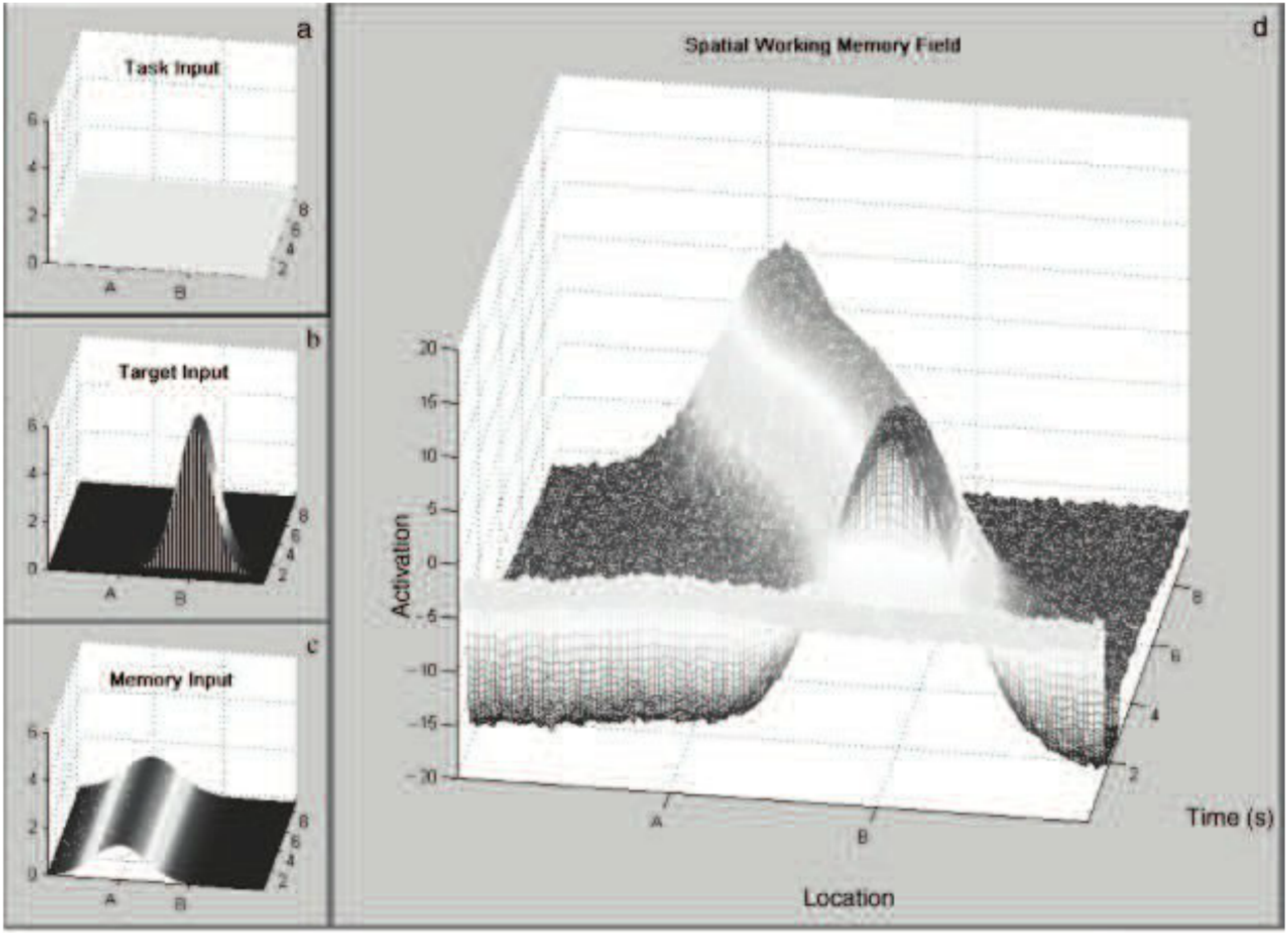
A not B Sandbox Variation



Smaller Location Distance

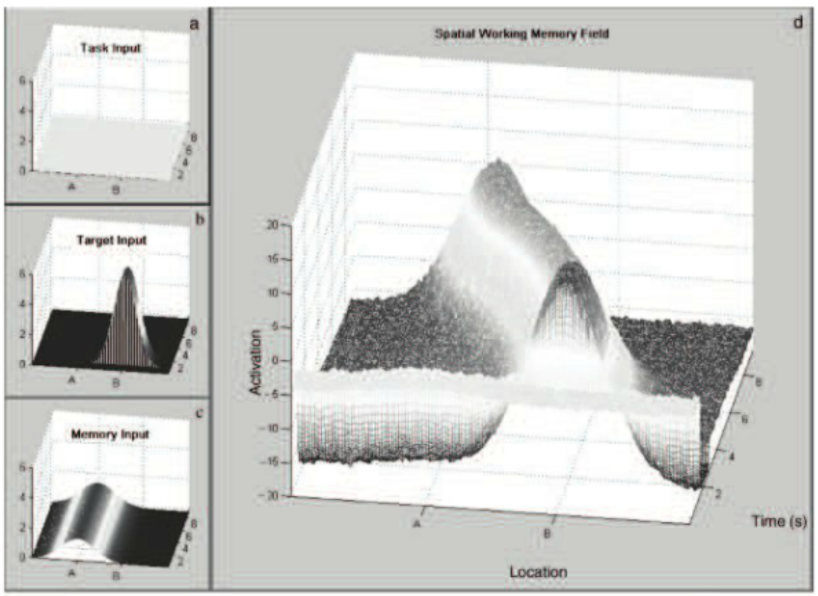


Greater Location Distance

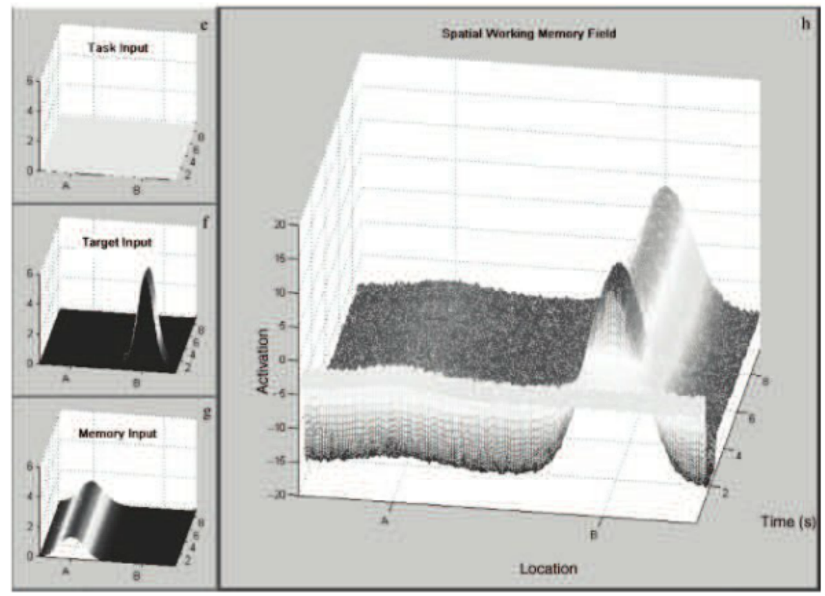


Smaller Location Distance

A not B Sandbox Variation



Smaller Location Distance



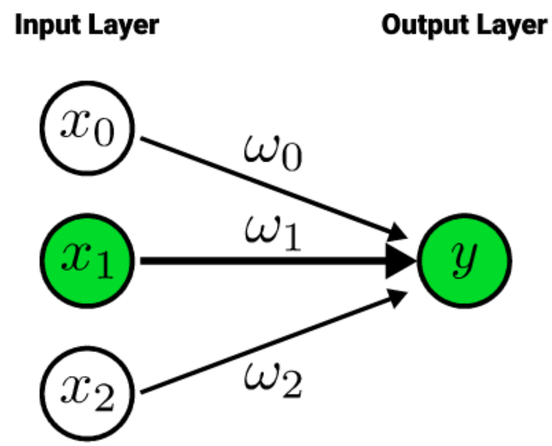
Greater Location Distance

Excursion: Hebbian Learning

Donald Hebb

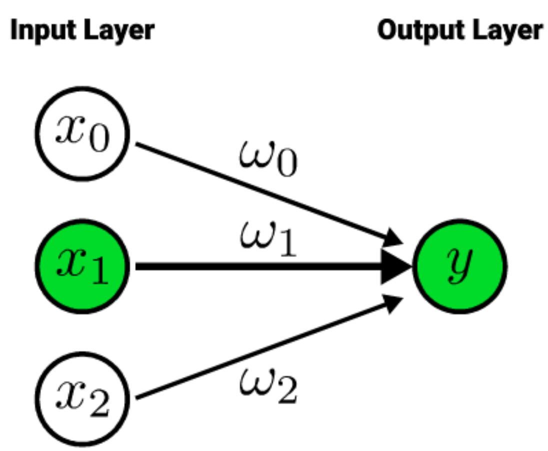
$$\Delta\omega_i = \eta x_i y$$

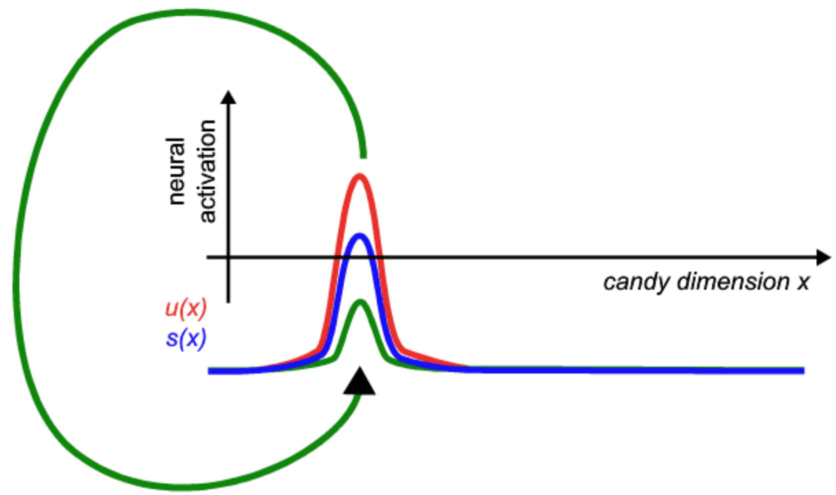
"neurons that fire together wire together"



Comparing Hebbian Learning and the Memory Trace

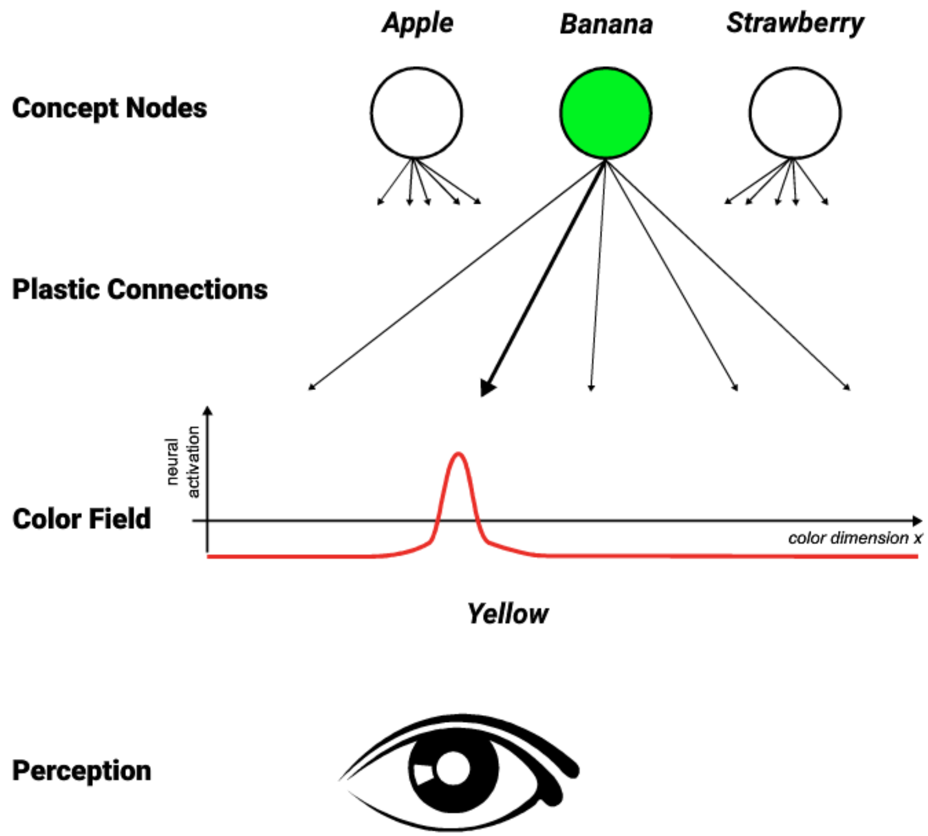
- local learning rule
- previously active states are strengthened





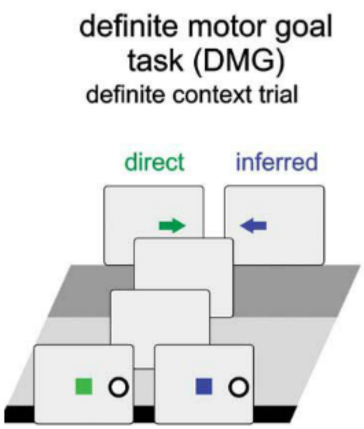
- correlations are learned
- learned states may be amplified

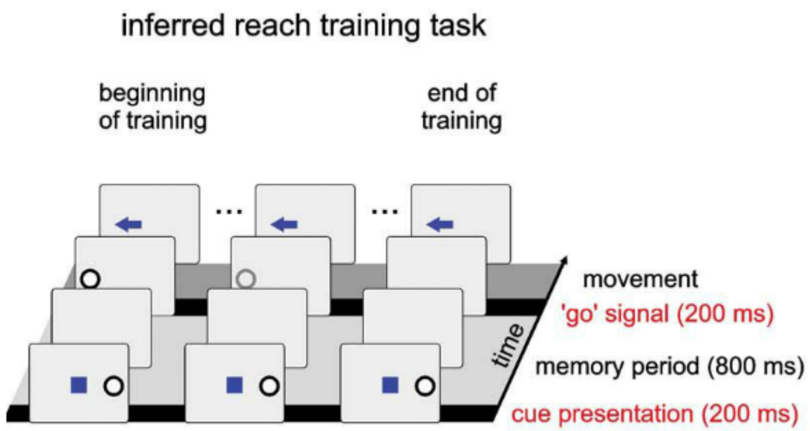
Hebbian Learning in DFT



Reward Based Hebbian Learning

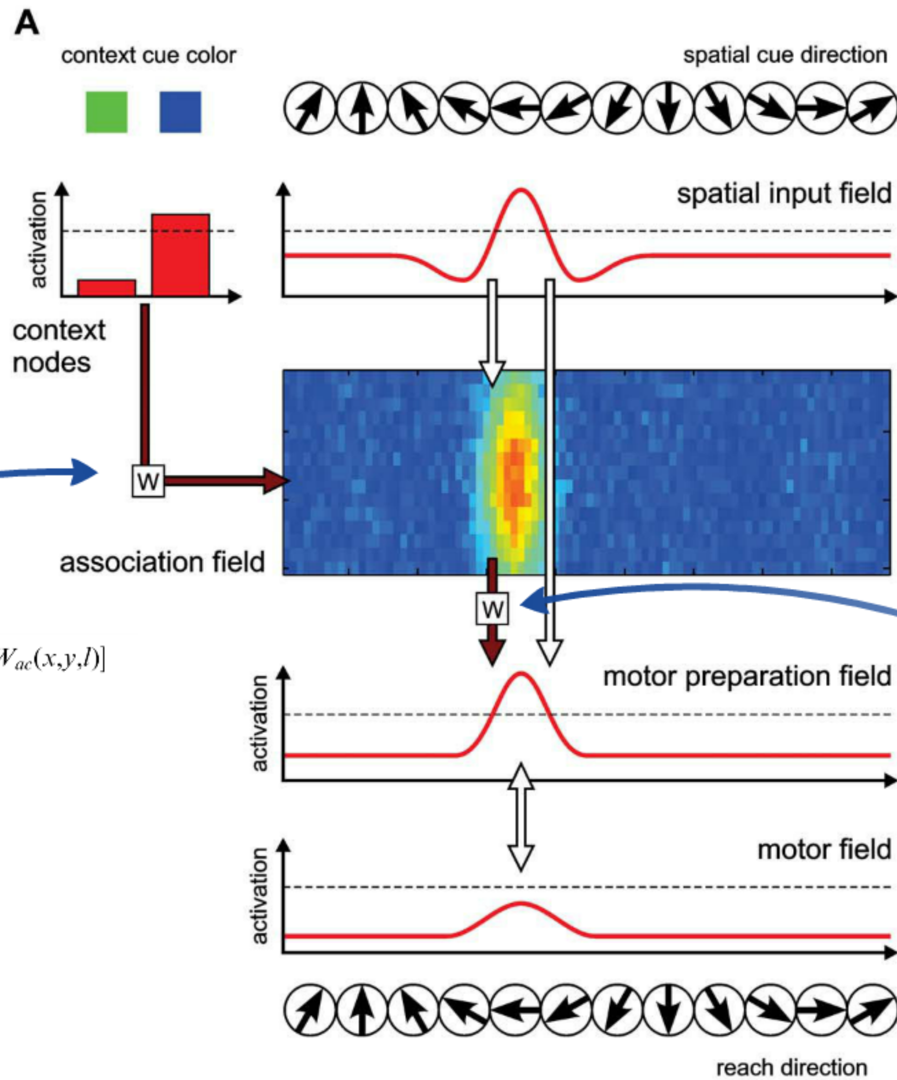
Example: Spatial Decision Task





[Klaes,Schneegans,Schöner,Gail2012]

Architecture



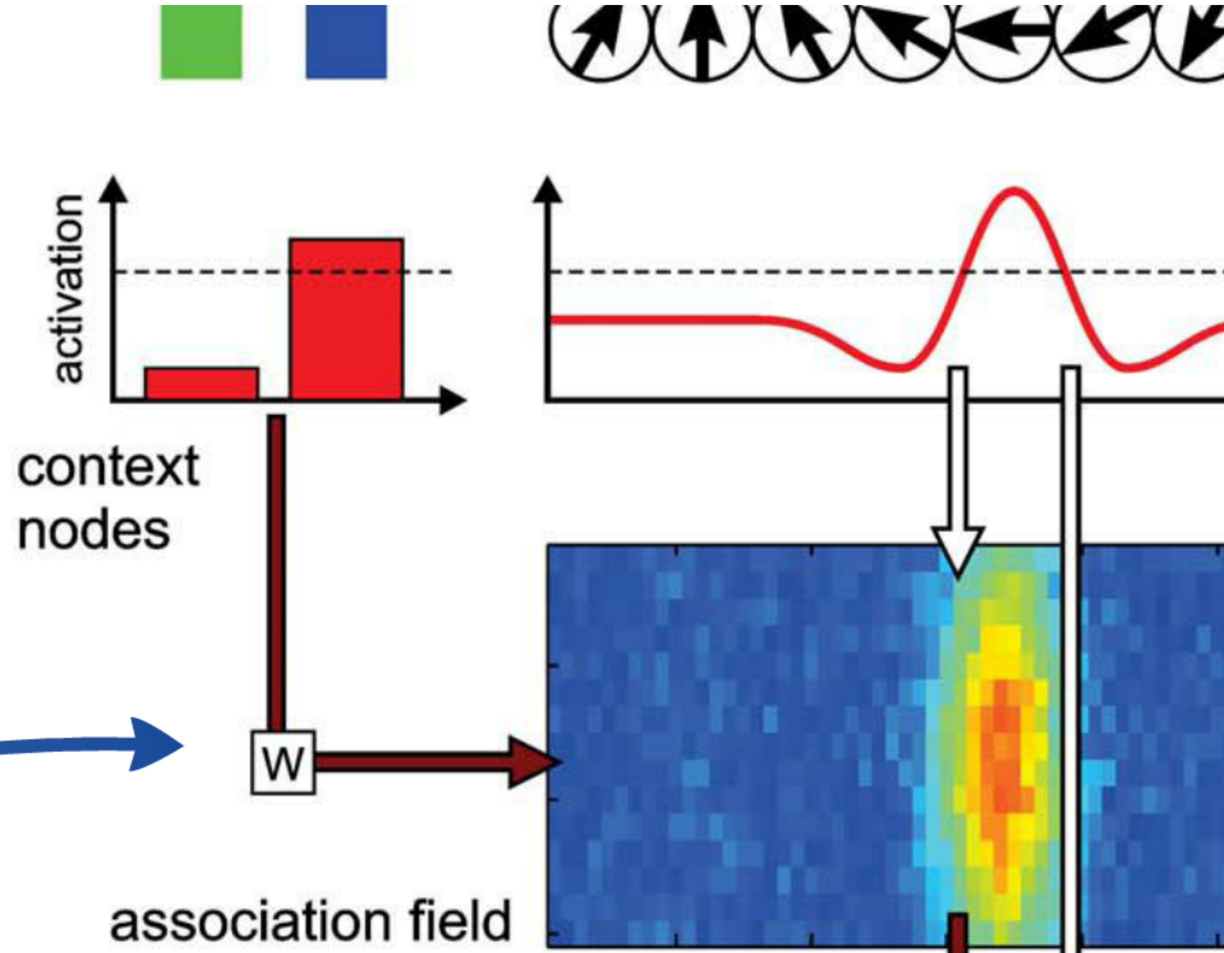
$$\Delta W_{ac}(x,y,l) = \eta(r)\cdot f(u_a(x,y))\cdot[g_c(l) - W_{ac}(x,y,l)]$$

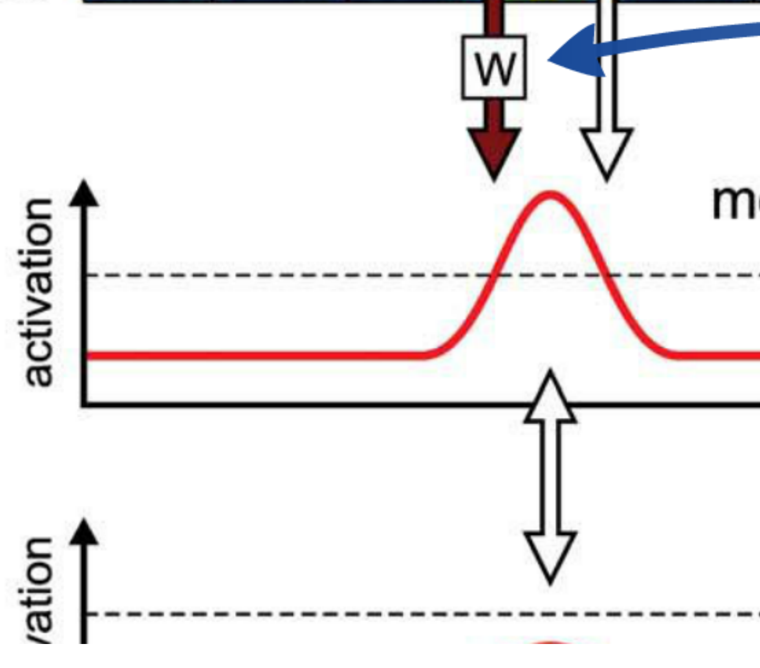
$$g_c(l) = \begin{cases} f(u_c(l)) & \text{for } r>0 \\ N_c\cdot(1-f(u_c(l))) & \text{for } r<0 \end{cases}$$

$$\Delta W_{pa}(z,x,y) = \eta(r)\cdot[g_p(z) - W_{pa}(z,x,y)]\cdot f(u_a(x,y))$$

$$g_p(z) = \begin{cases} f(u_p(z)) & \text{for } r>0 \\ N_p\cdot(1-f(u_p(z))) & \text{for } r<0 \end{cases}$$

[Klaes,Schneegans,Schöner,Gail2012]





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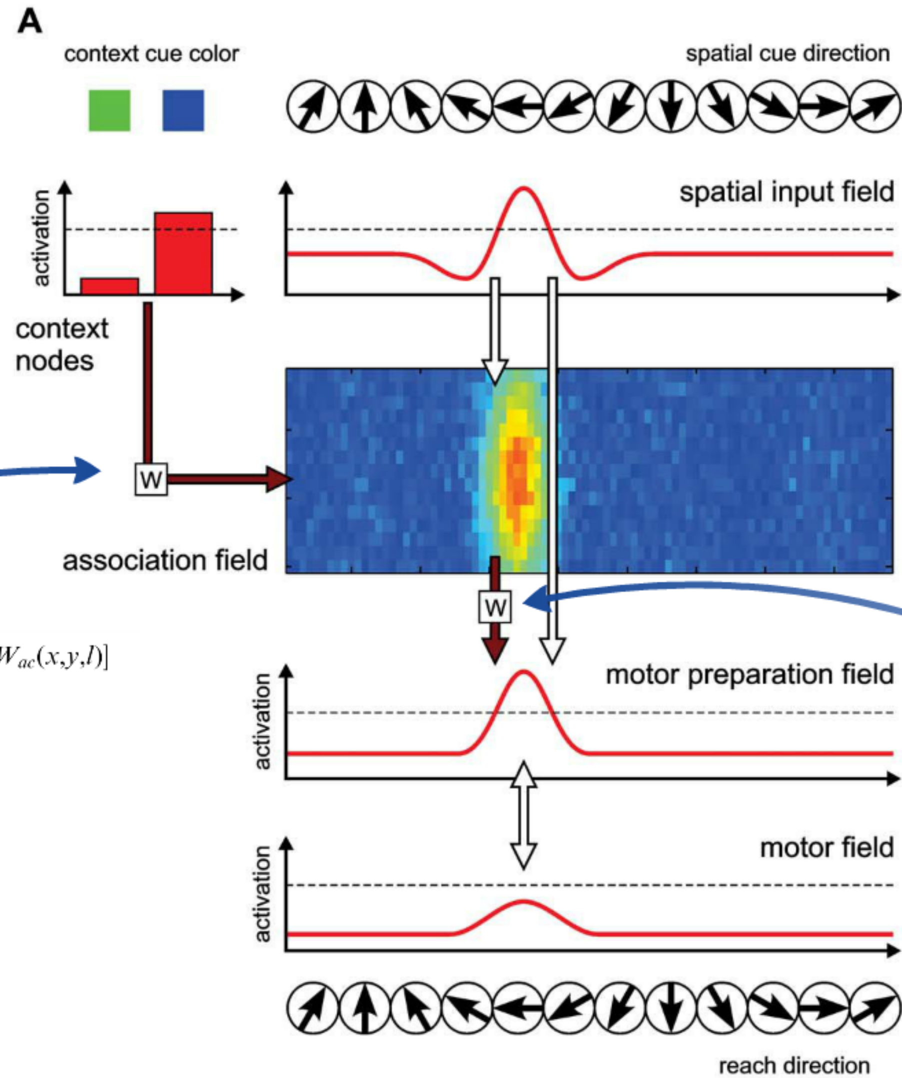
Architecture



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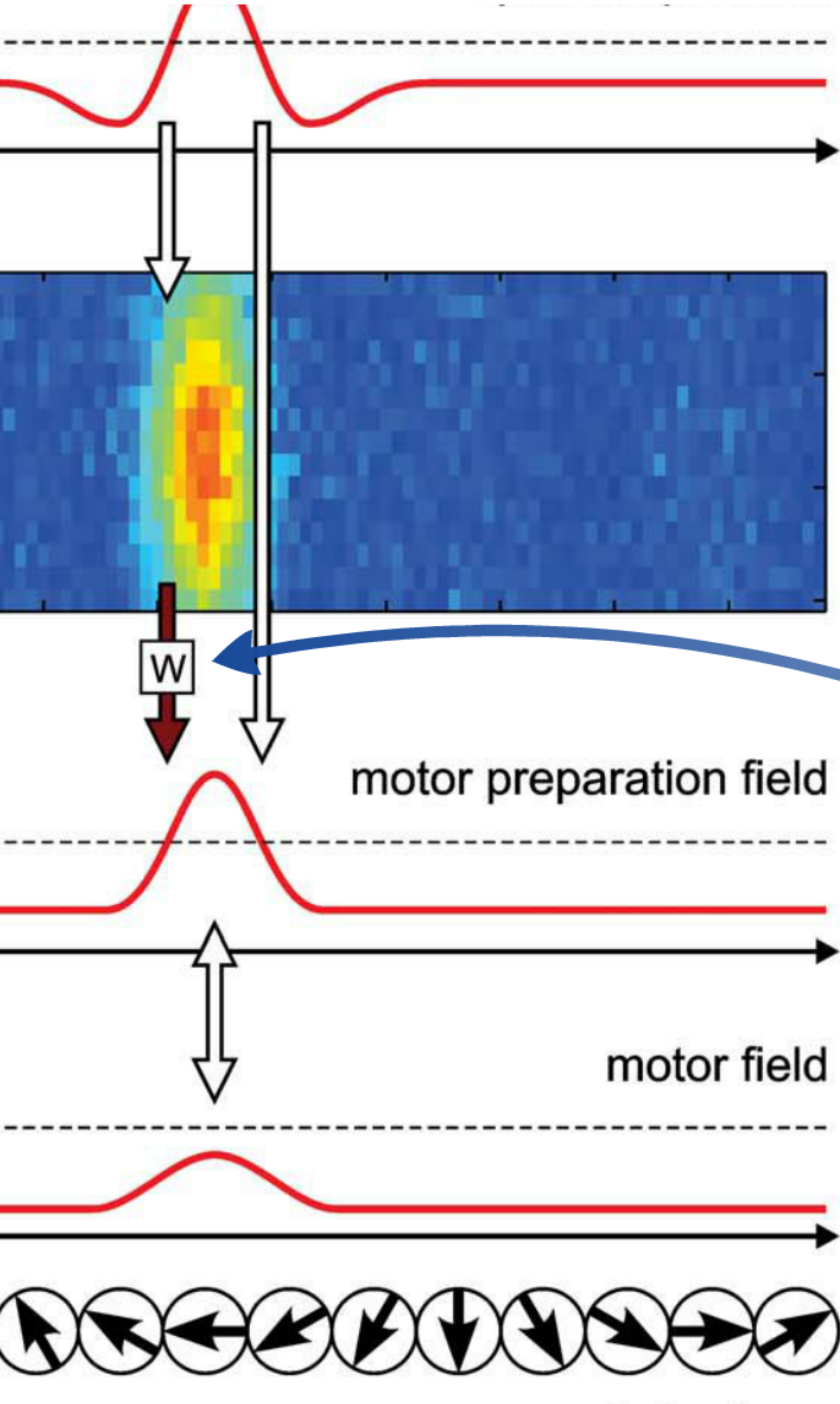
[Klaes,Schneegans,Schöner,Gail2012]



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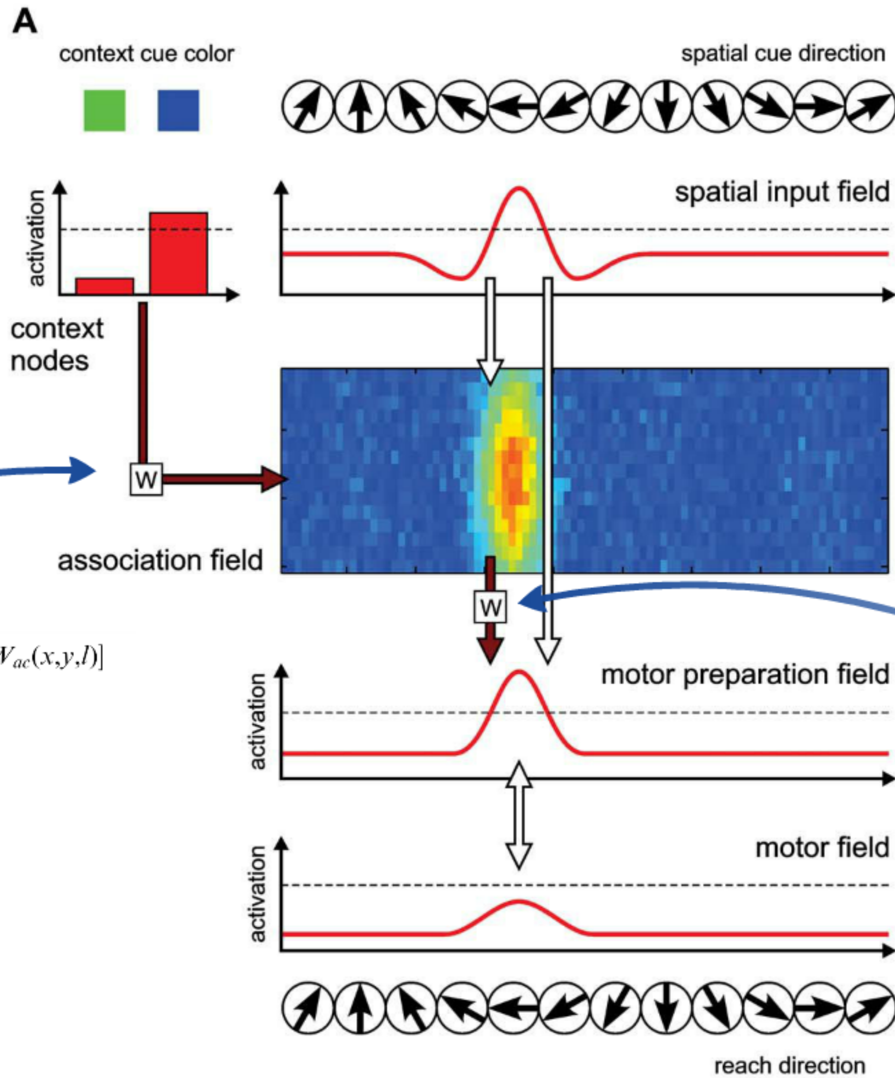
Architecture



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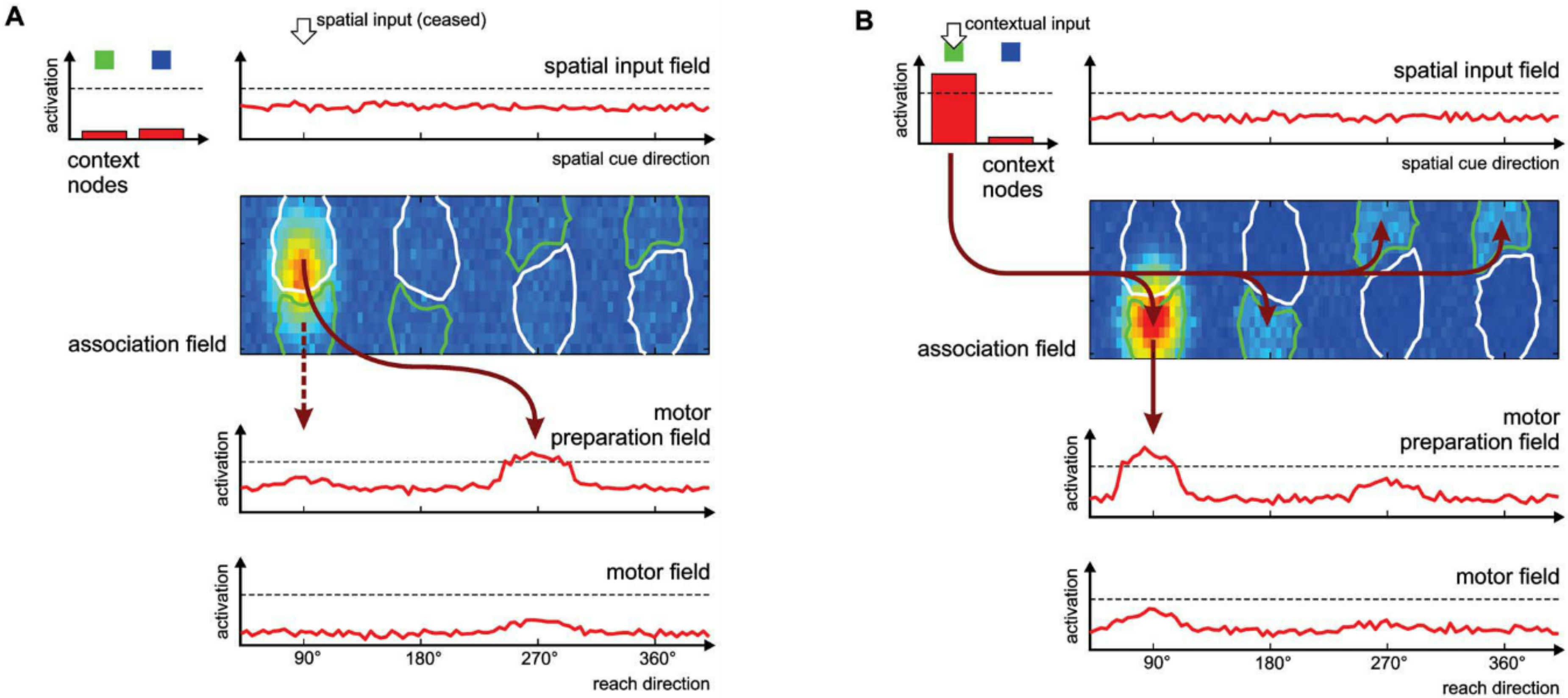
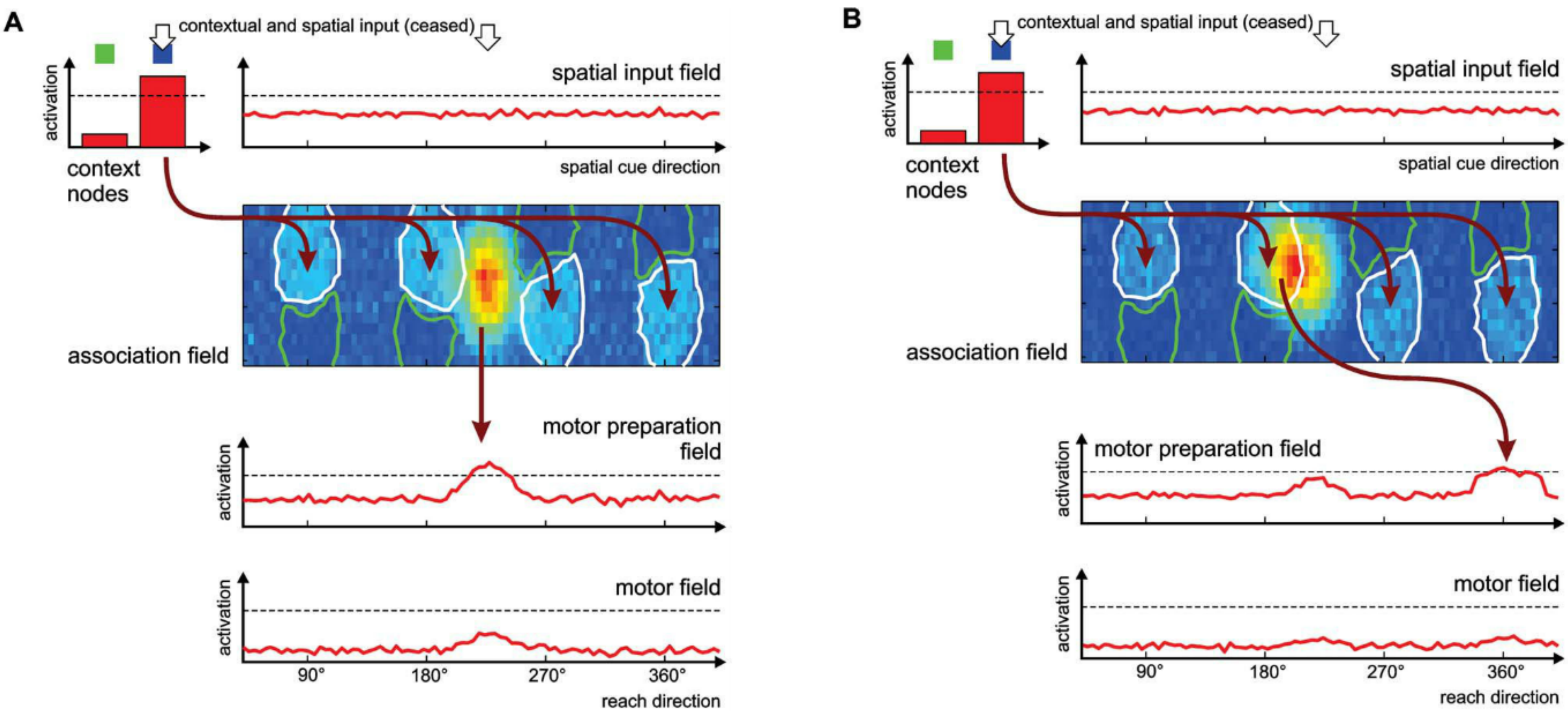
[Klaes,Schneegans,Schöner,Gail2012]

Training Results



[Klaes,Schneegans,Schöner,Gail2012]

Association but no Generalization



[Klaes,Schneegans,Schöner,Gail2012]

Conclusion: Memory Trace

- long term memory
- local learning rule
- preshape built from experience

- (optional) "one-shot"-learning
- (optional) capacity limit
- (optional) indirect interference