Decision making and population decoding with strongly inhibitory neural field models

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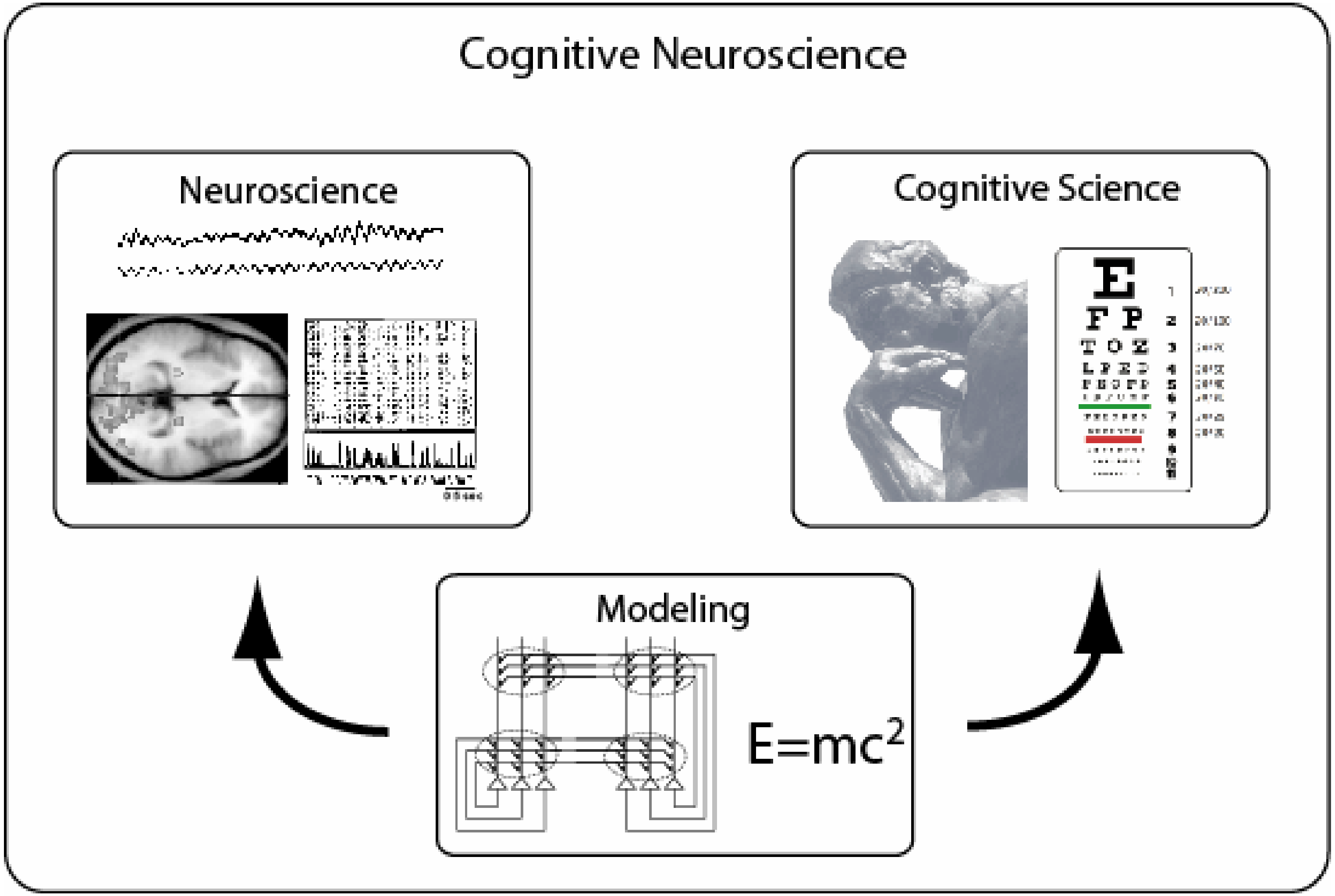
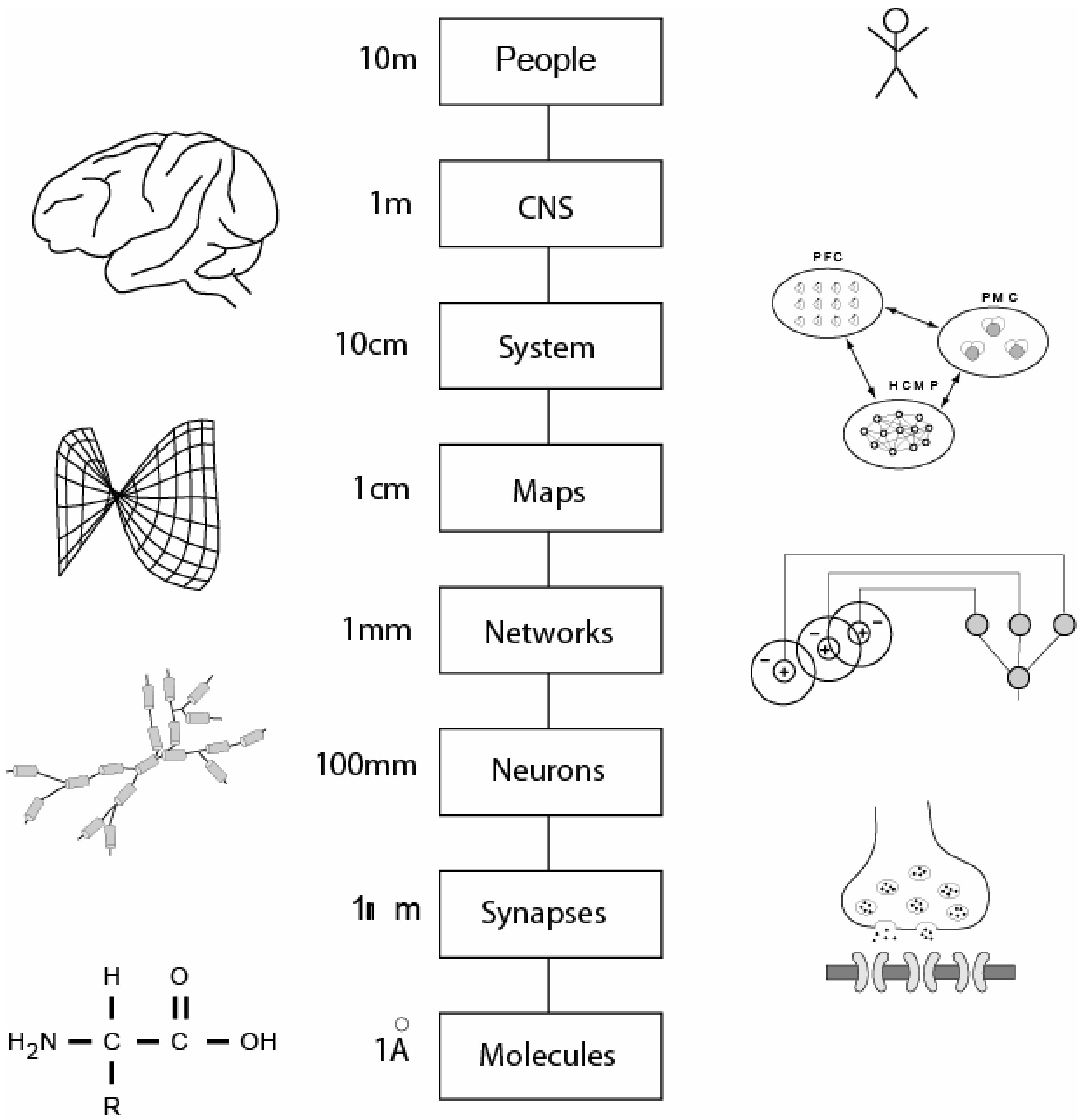
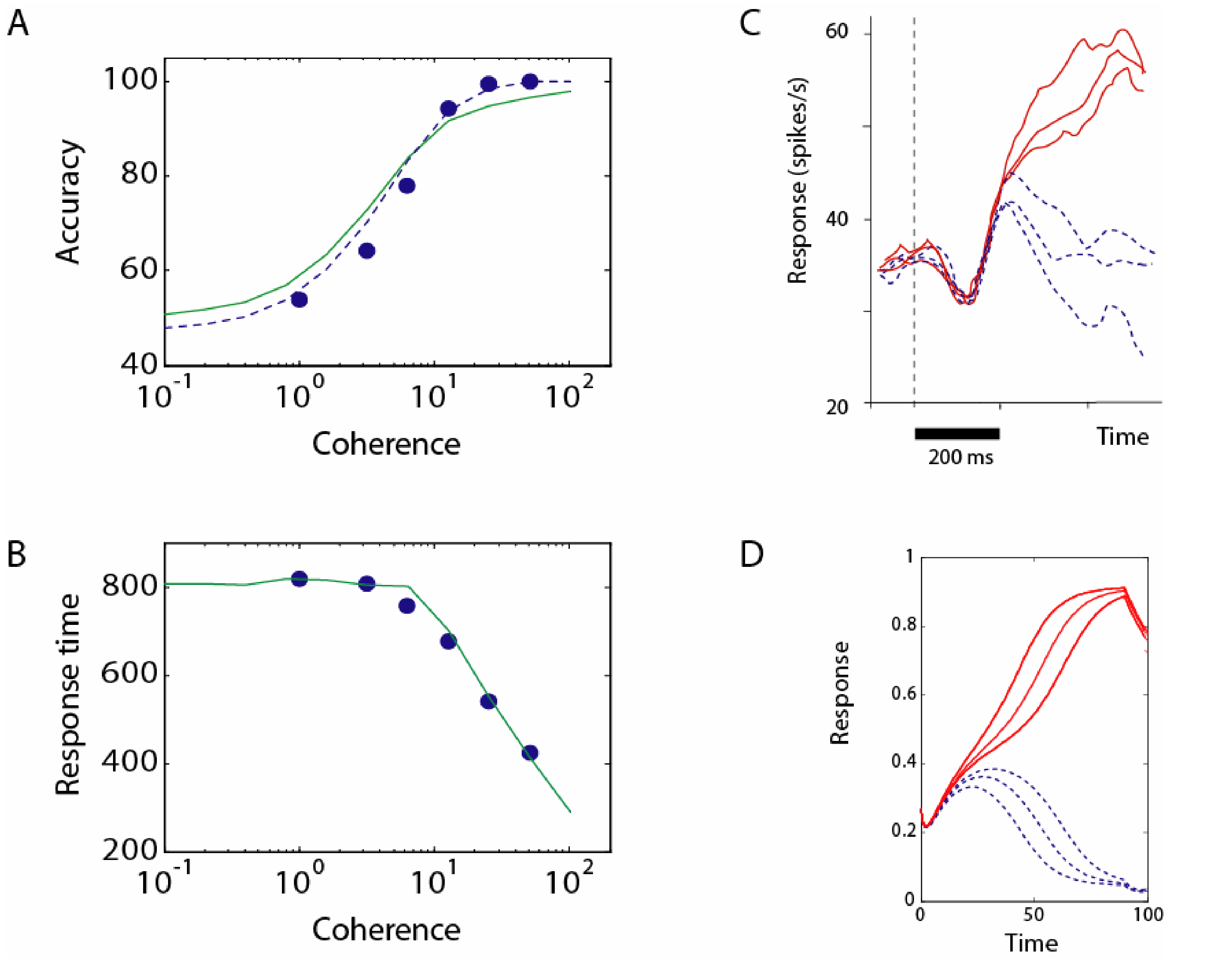
COMPUTATIONAL NEUROSCIENCE GROUP
Studying Minds


Cognitive Neuroscience
Neuroscience
Cognitive Science
Modeling
E=mc²



10m
People
1m
CNS
10cm
System
1cm
Maps
1mm
Networks
100mm
Neurons
Synapses
1Å
Molecules
PFC
PMC
HCMP
H
O
H_2N
C
C
OH
R



Experimental data from Shadlen et al.

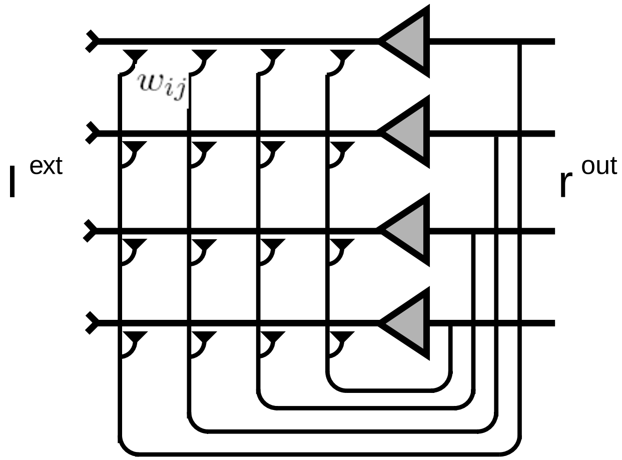
Model		Application
Dynamic Neural Field (DNF) Model	1	Cortical Hypercolumn
Center-Surround Neural Fields (CSNFs)		Working Memory
Continuous Attractor Neural Network (CANN)		Hippocampal Place Fields
Bump or Bubble model	3	Population Decoding
Biased Competition		Attention (saliency maps)
Cooperation and Competition	4	Readiness Dynamics (SC)
Hypercolumn		Biased Competition
		Motion Recognition
		Biological SOMs
		Thalamo-cortical loops
	2	Decision Making

Dynamical field equation (updating network states)

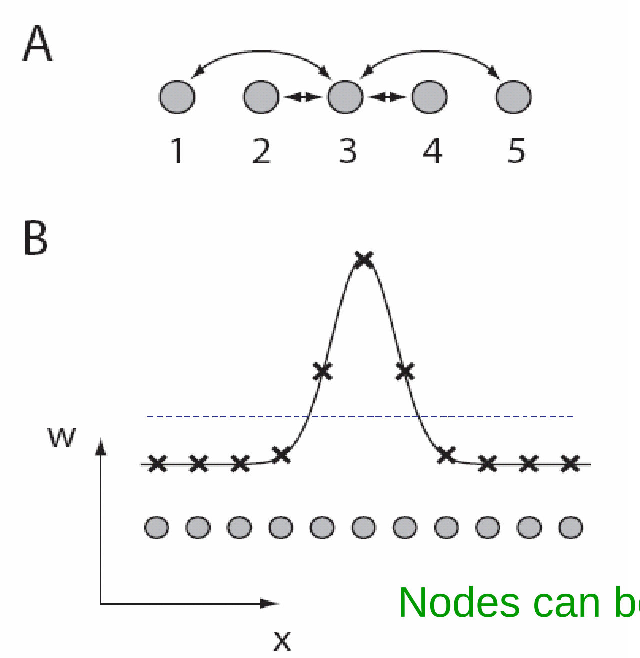
$$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_y w(|x-y|) r(y,t) \mathrm{d}y + I^{\mathrm{ext}}(x,t)$$

Gain function: $r(\mathbf{x},t) \quad = \quad g(u(\mathbf{x},t))$

Weights (Hebbian learning): Typically Mexican hat



$$r_i = g(\sum_j w_{ij} r_j)$$



$$w_{ij} \;\propto\; \sum_\mu r_i^\mu r_j^\mu$$

Nodes can be scrambled!

CANNs can be trained with Hebb

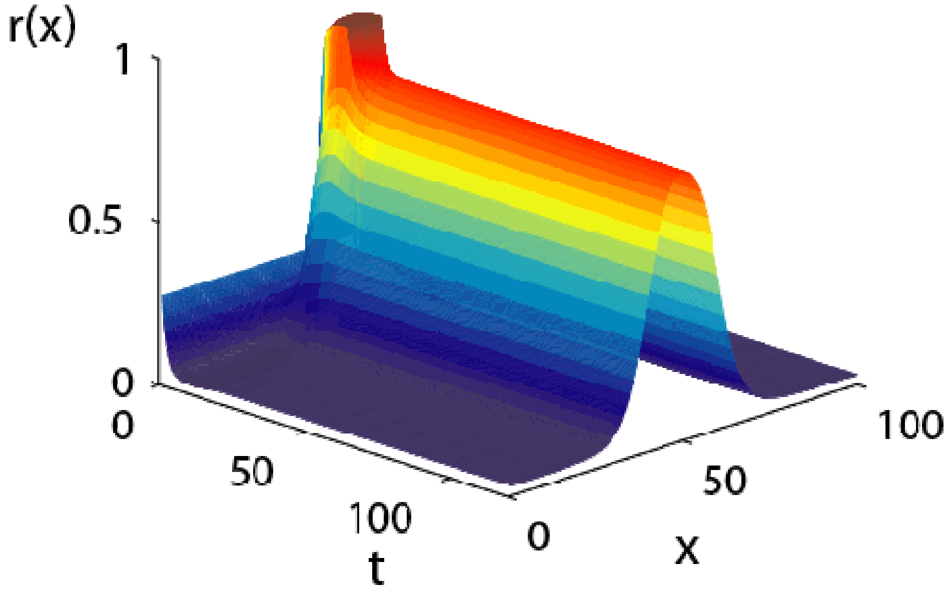
Hebb: $w_{ij} \propto \sum_\mu r_i^\mu r_j^\mu$

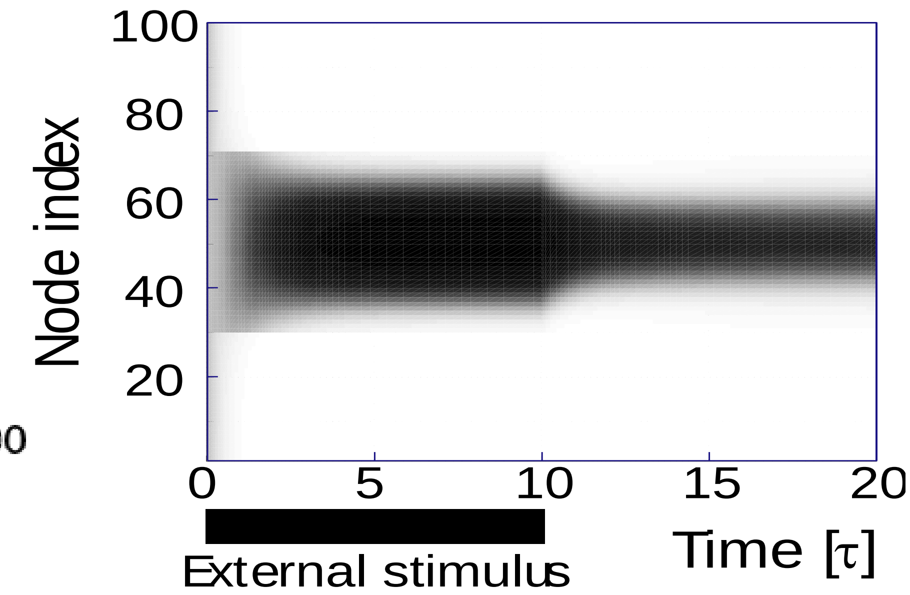
Training pattern: $r(x) = A_\mathrm{r} \mathrm{e}^{-d(x,x_0)^2/2\sigma_\mathrm{r}^2}$

$$\begin{aligned} w(x_1,x_2) &= \int_{-\infty}^{\infty} r(x-x_1) * r(x-x2)\mathrm{d}x \\ &= A_\mathrm{r}\sqrt{\pi}\sigma_\mathrm{r}\mathrm{e}^{-(x_1-x_2)^2/4\sigma_\mathrm{r}^2}. \end{aligned}$$

$$w_{ij} = A_\mathrm{w}\left(\frac{1}{A_\mathrm{r}\sqrt{\pi}\sigma_\mathrm{r}} w_{ij}^{\mathrm{ex}} - C\right)$$

Network can form bubbles of persistent activity (in Oxford English: activity packets)

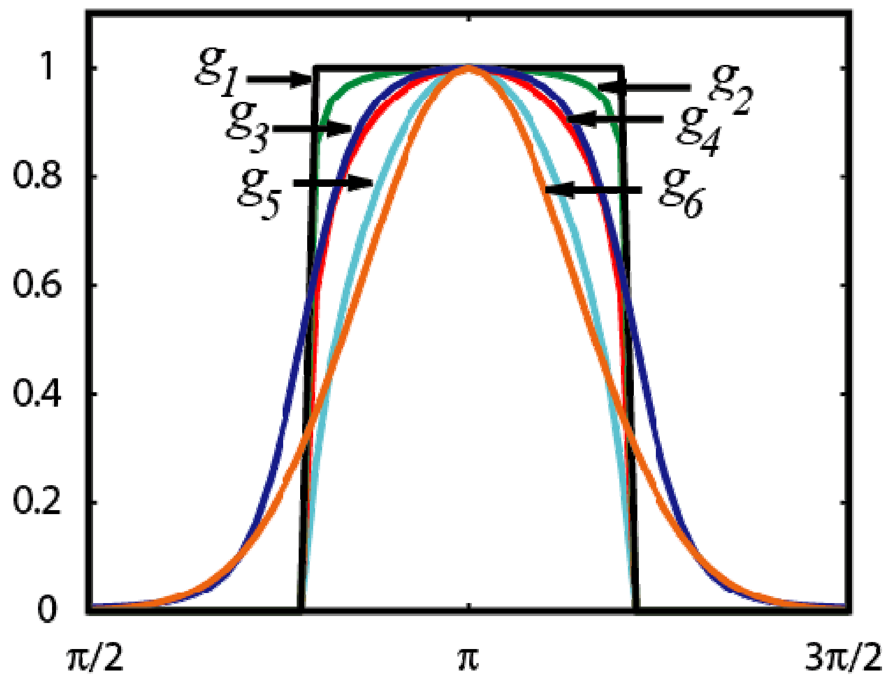




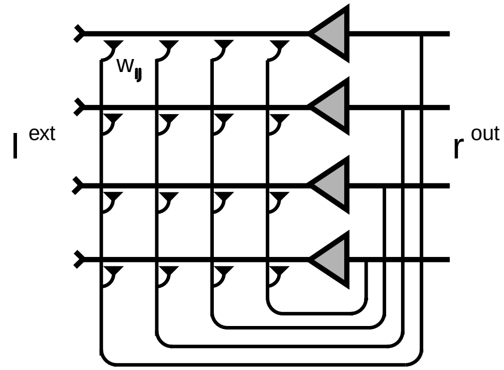
Various gain functions are used

$$
\begin{aligned}
g_1(u) &= \Theta(u) \\
g_2(u) &= \frac{\Theta(u - 1/\tau)}{t^{\mathrm{ref}} - \tau \log(1 - \frac{1}{\tau u})} \\
g_3(u) &= \frac{1}{1 + e^{-0.1u}} \\
g_4(u) &= \Theta(u-1)\log(u) \\
g_5(u) &= \Theta(u)u^2 \\
g_6(u) &= \frac{u^2}{1 + \mu \int u^2 dx}
\end{aligned}
$$

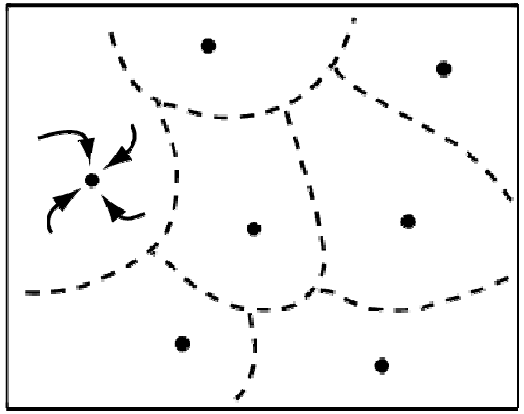
End states



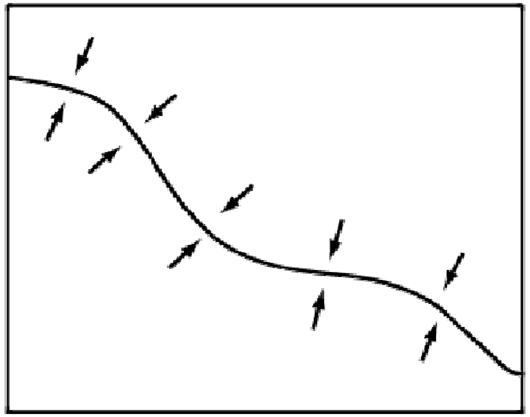
CANNs have a continuum of point attractors



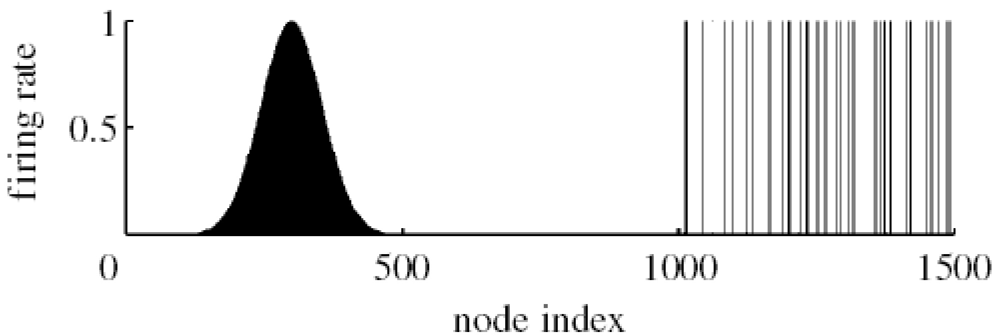
Point attractors and basin of attraction



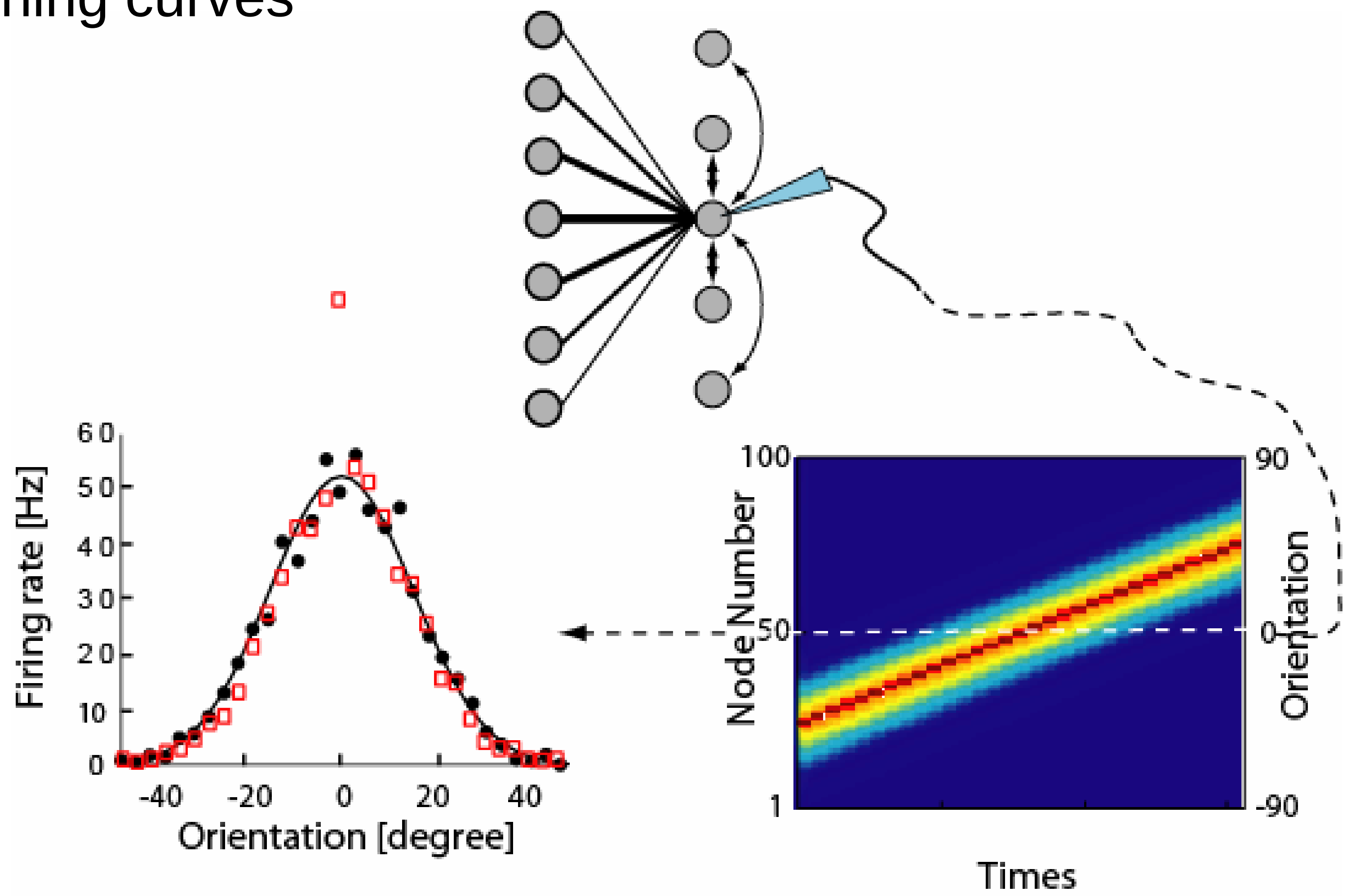
Line of point attractors



Can be mixed:
Rolls, Stringer, Trappenberg
A unified model of spatial and episodic memory
Proceedings B of the Royal Society
269:1087-1093 (2002)

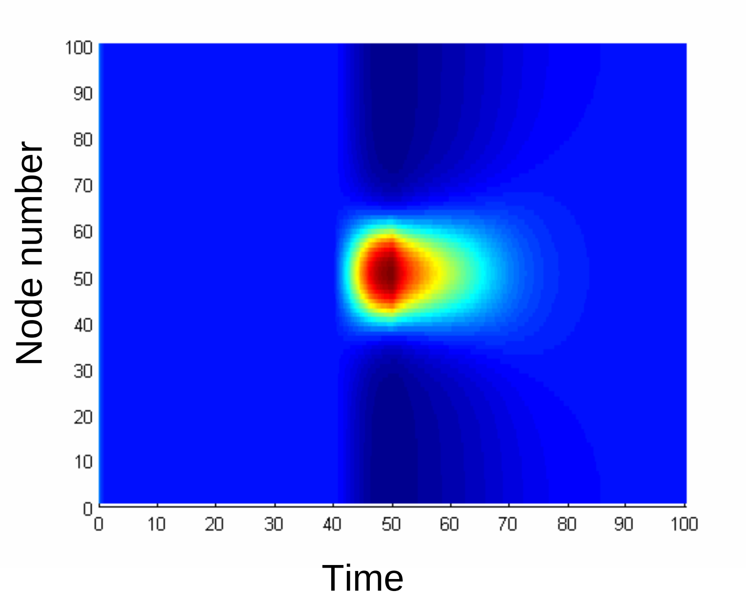


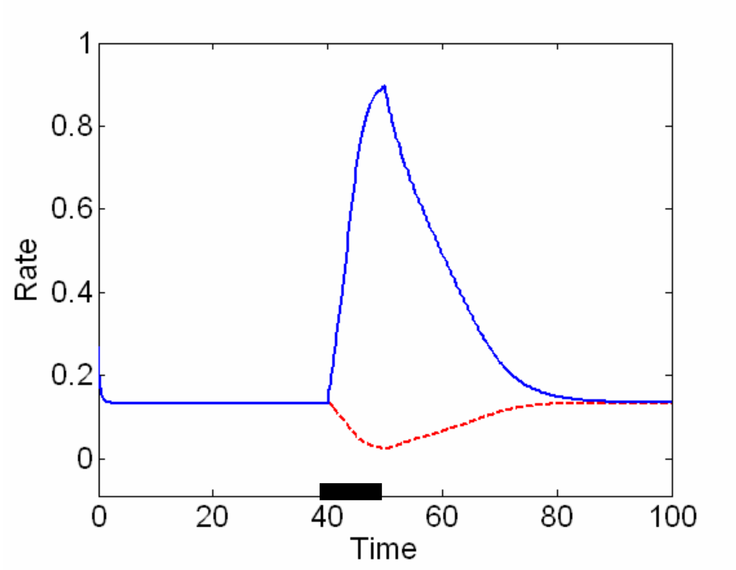
Tuning curves

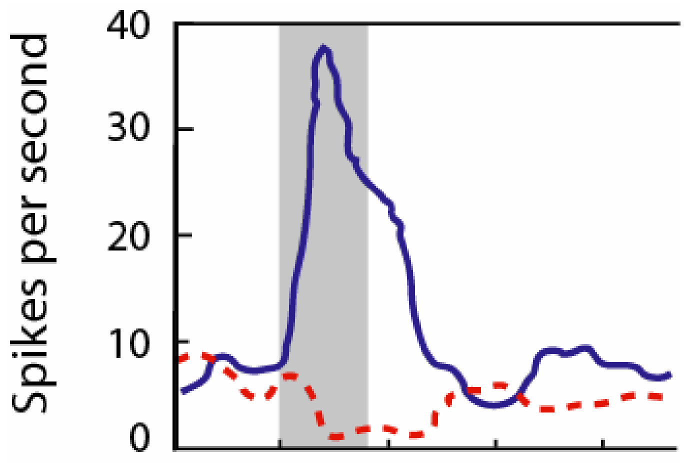


- **Experimental Data from Henry at al. 1974**

Strong inhibition regime (no memory)

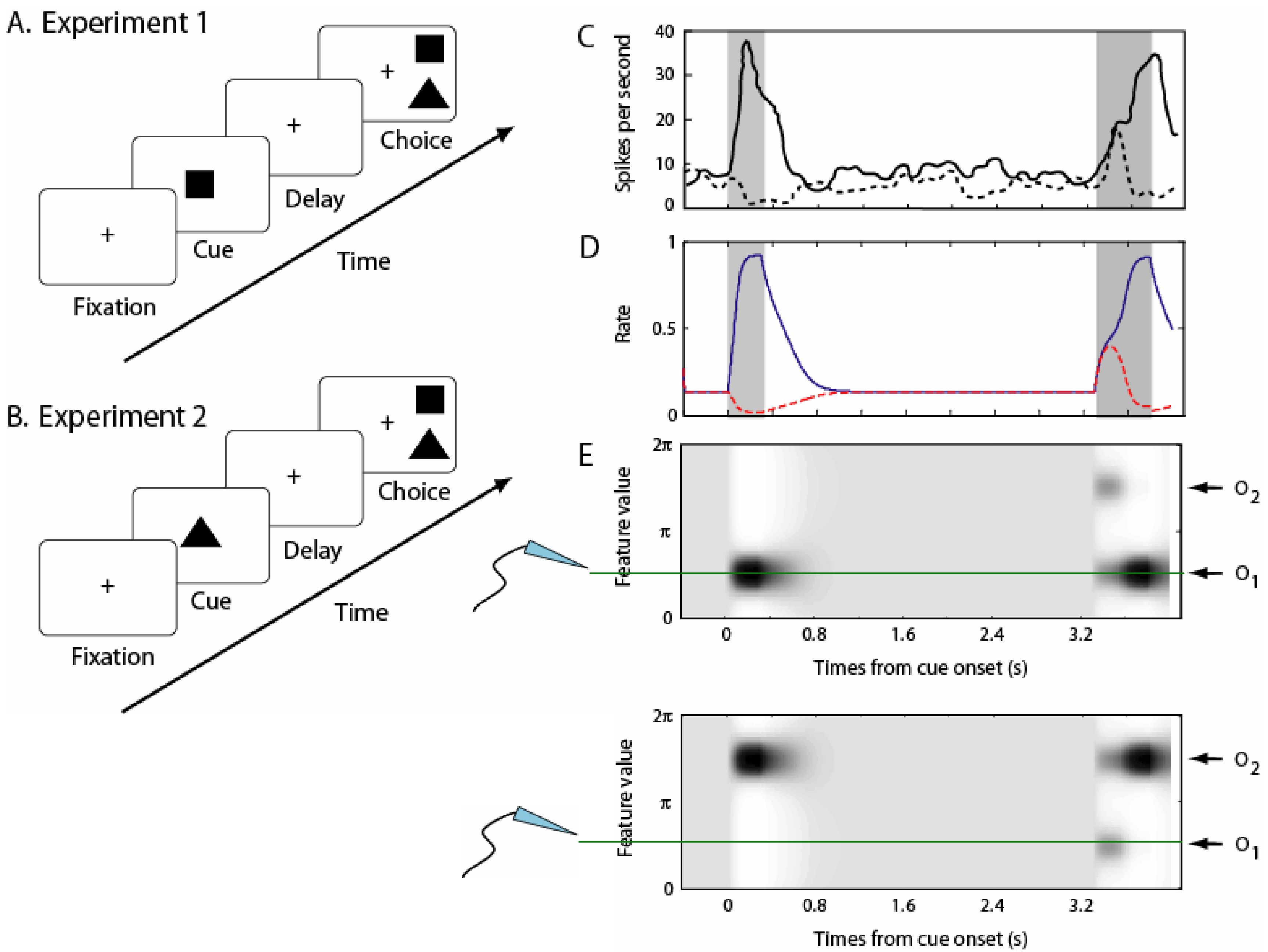


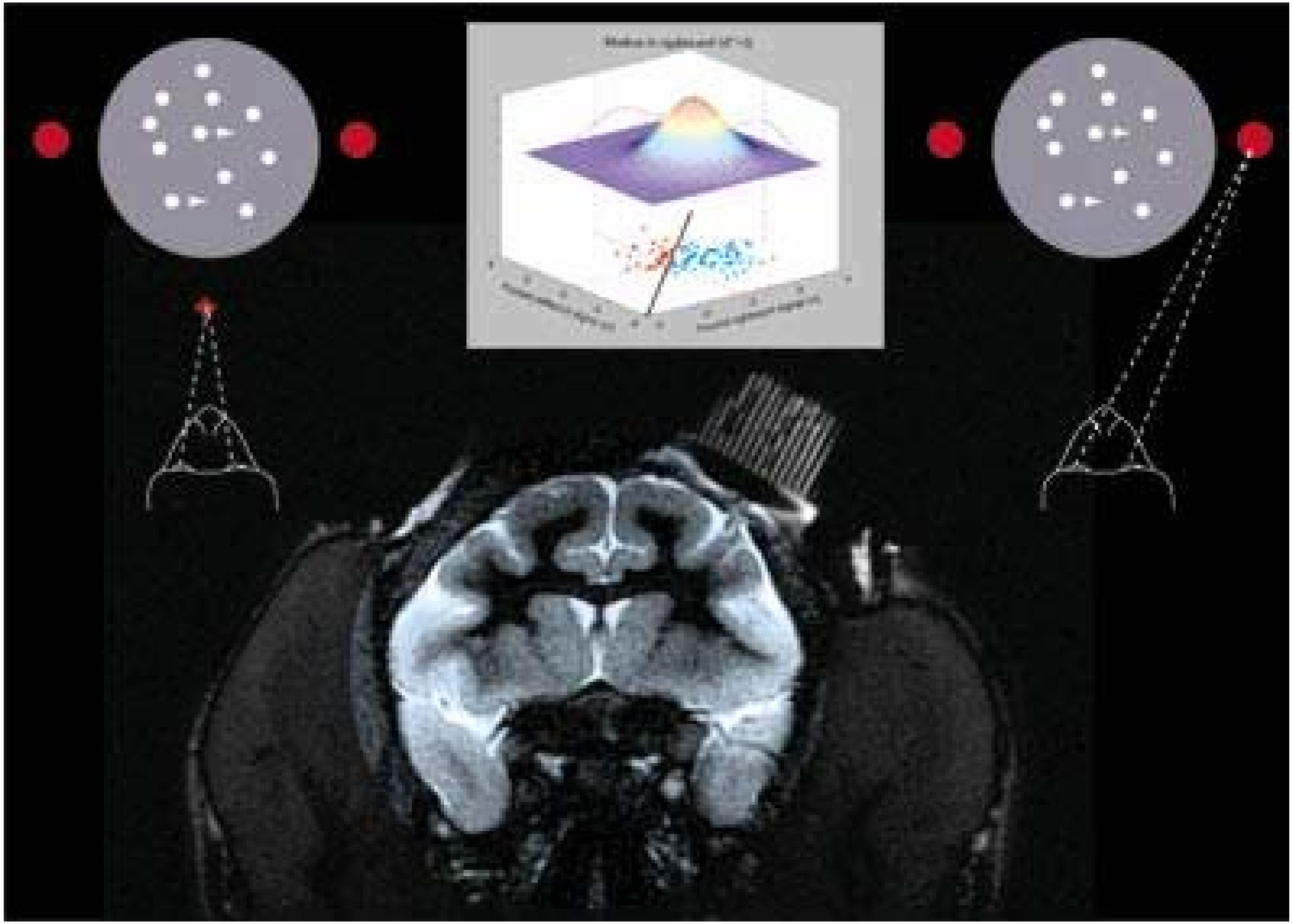




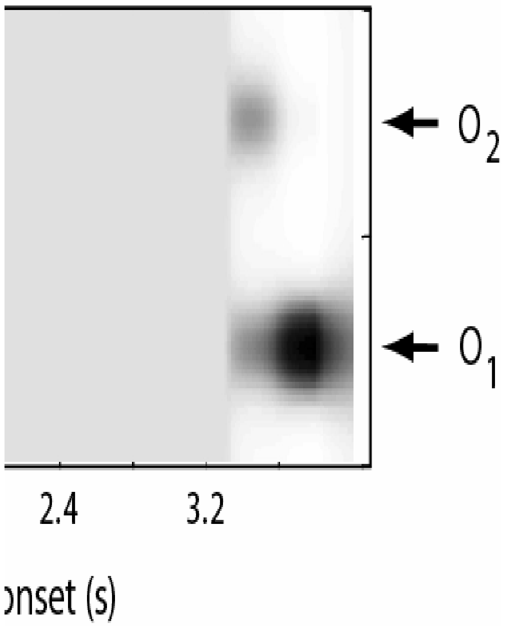
Chelazzi, Miller, Duncan & Desimone, Nature 1993

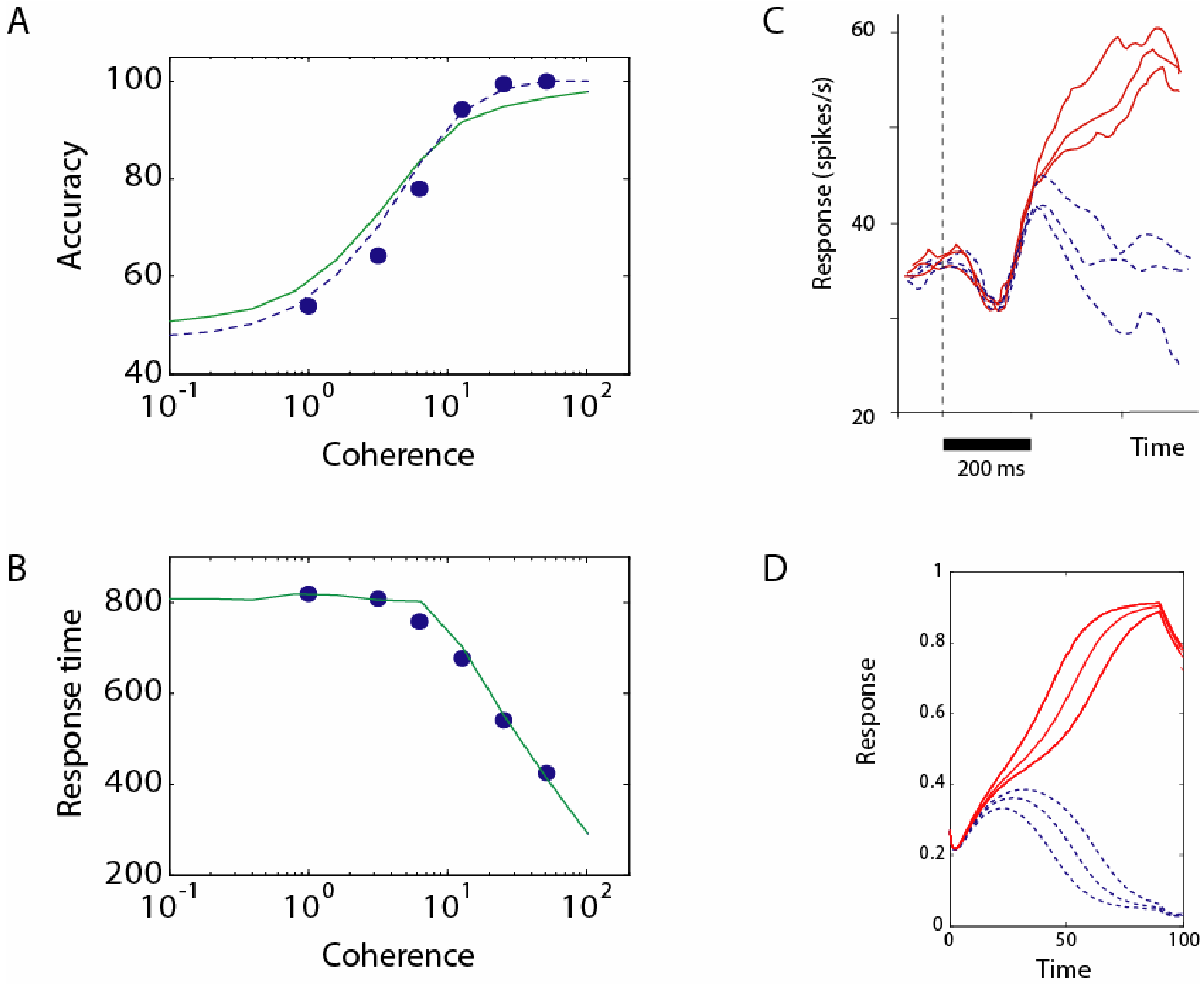
Chelazzi, Miller, Duncan & Desimone, Nature 1993





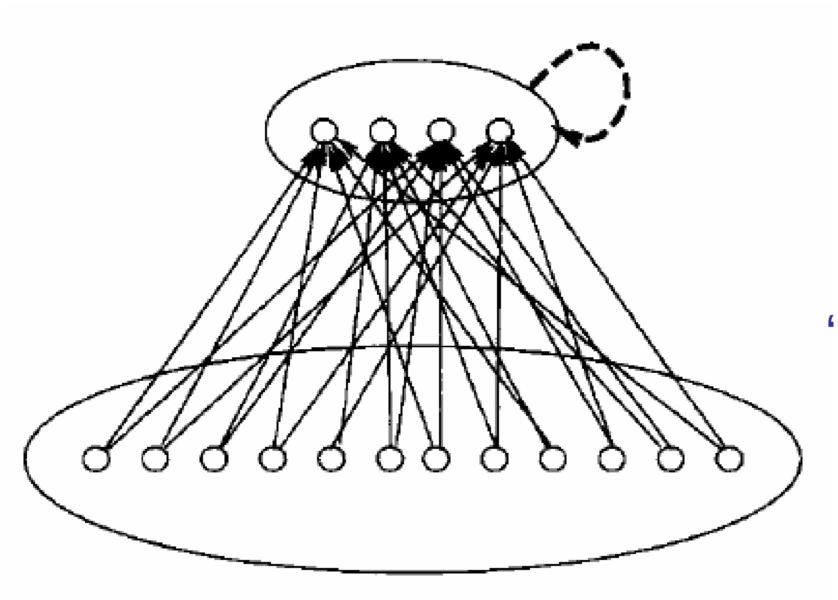
Michael Shadlen et al.





Experimental data from Shadlen et al.

Usher and McClelland (2001)

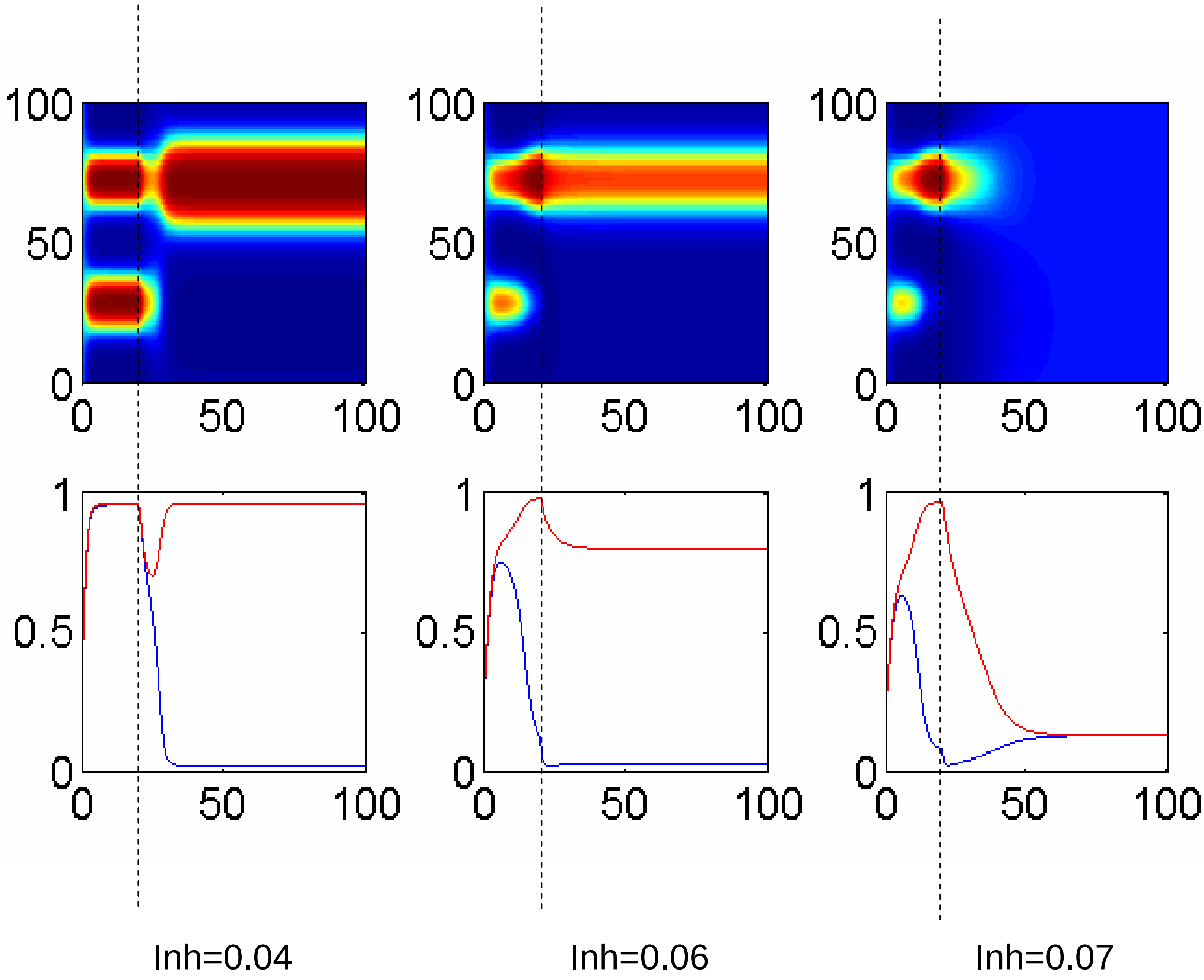


- accumulator models
- diffusion models

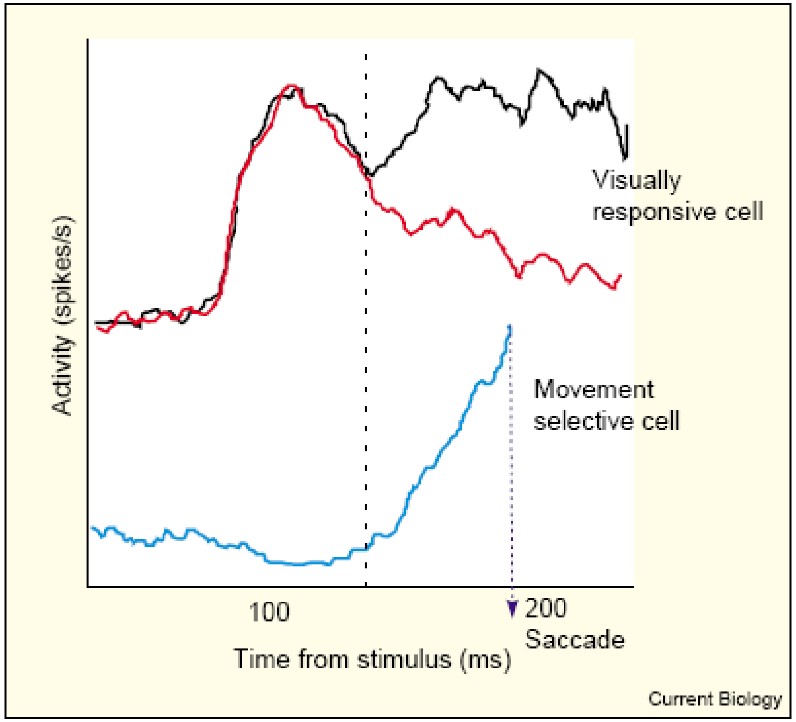
‘leaky, competing accumulator model’

$$dx_i = [\rho_i - kx_i - \beta \Sigma_{i' \neq i} x_{i'}] \frac{dt}{\tau} + \xi_i \sqrt{\frac{dt}{\tau}}$$

$$x_i \rightarrow \max(x_i, 0).$$

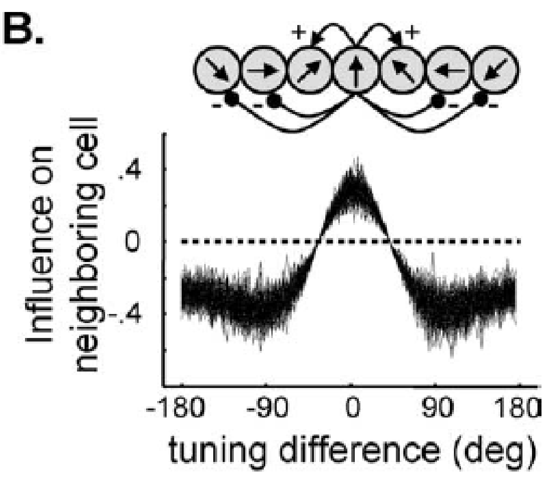

100
50
0
0
50
100
1
0.5
0
Inh=0.04
Inh=0.06
Inh=0.07

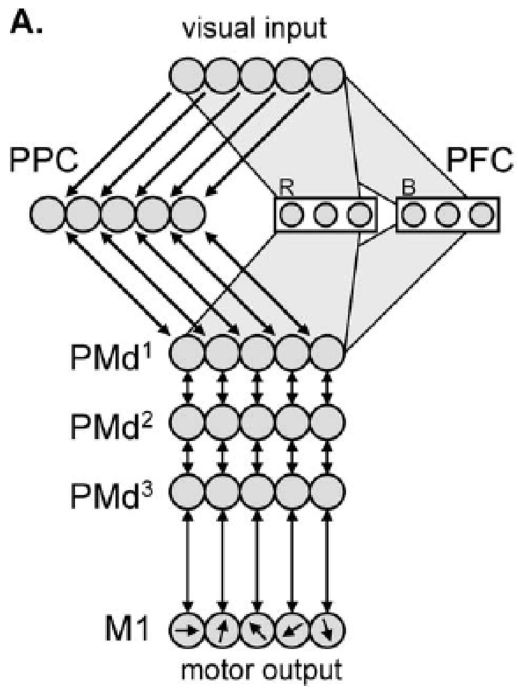
Thompson, Hanes, Bichot and J. D. Schall, 1996
as reviewed by Reddi, 2001

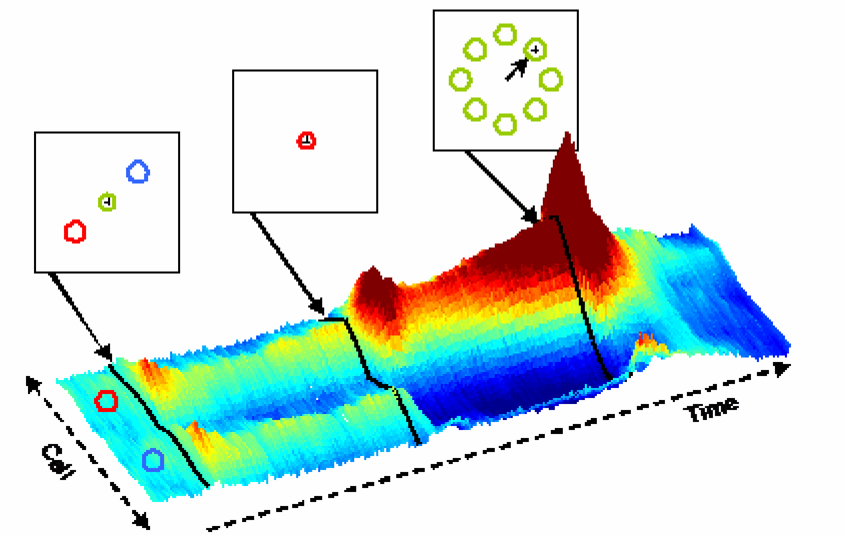


FEF

Paul Cisek
(Montreal)





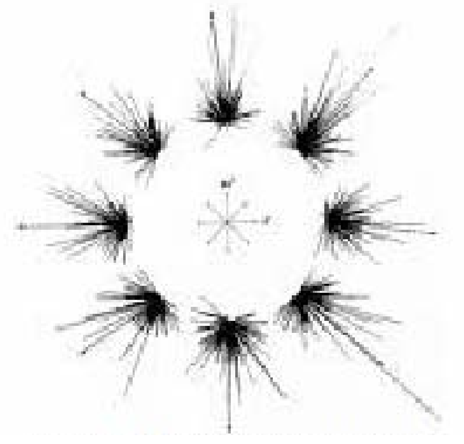


Neural activity in the brain of a monkey performing a decision task: when two cues are presented, two populations of cells become active in parallel; when the decision is made, one population increases activity while the other is suppressed.

Conclusion 1: Decision theory

- DNF theory is a good model for cortical feature representation and the accumulation of evidence
- Describes neural and behavioral data

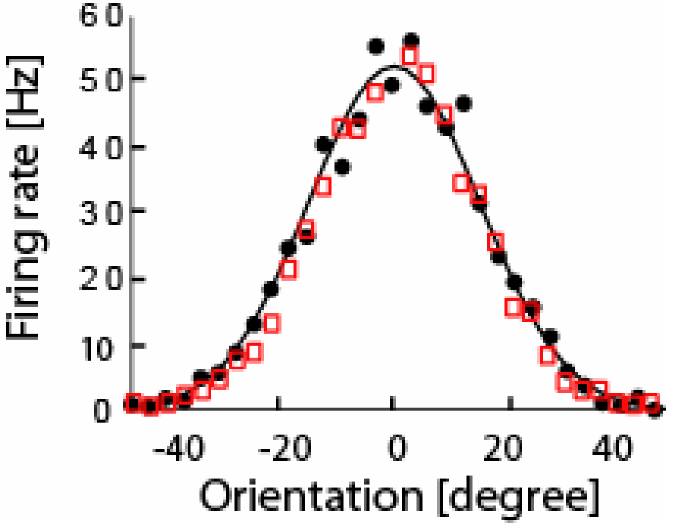
Population decoding



Vector average (a la Georgopoulos)

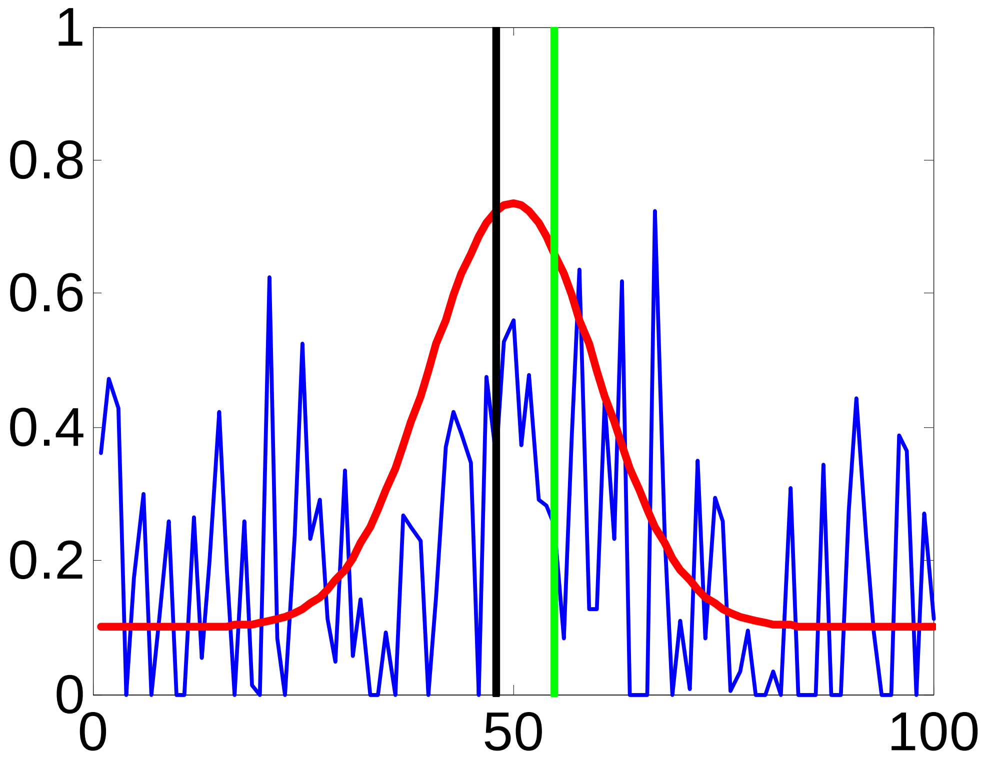
simple WTA very noise sensitive

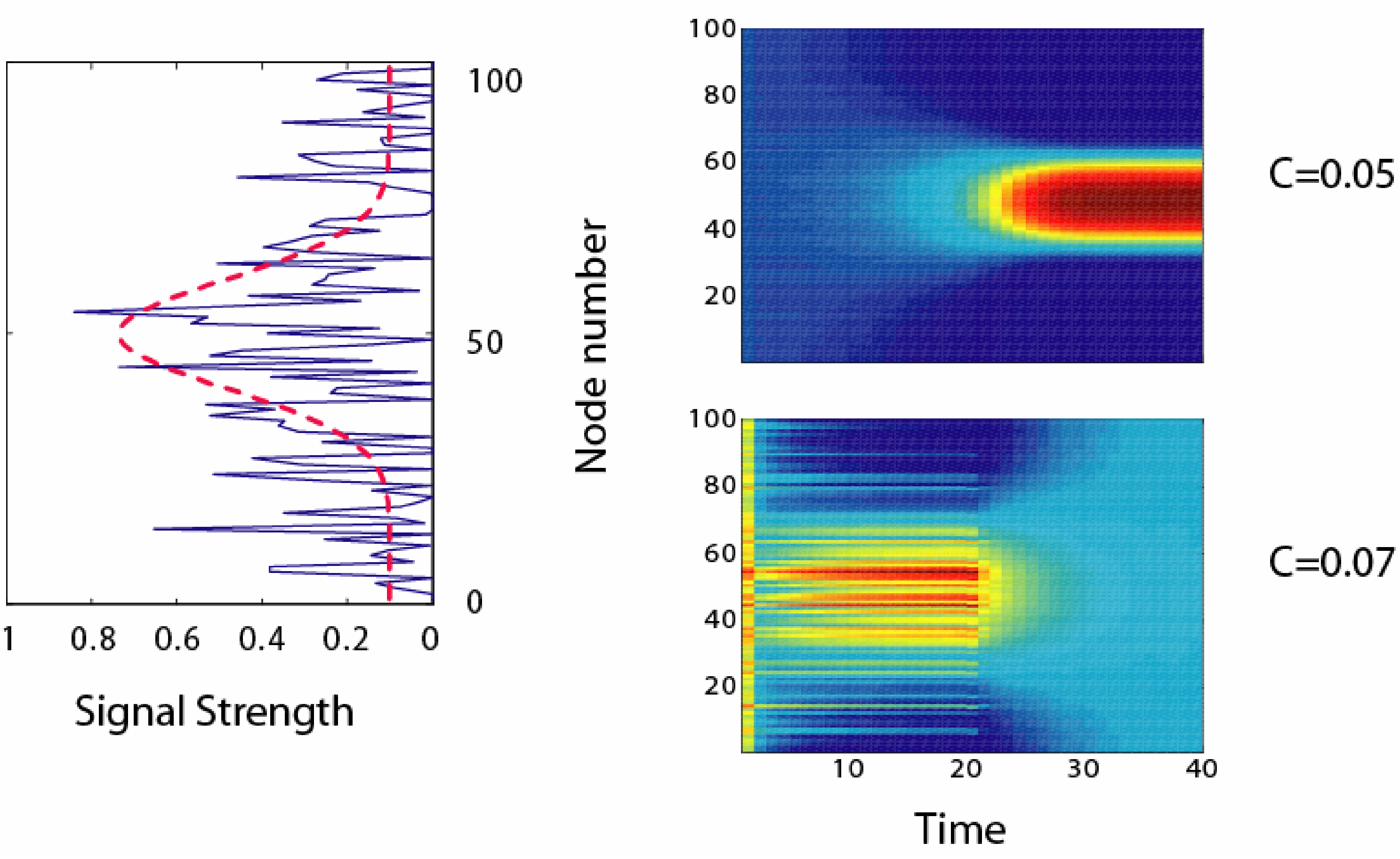
centre of mass

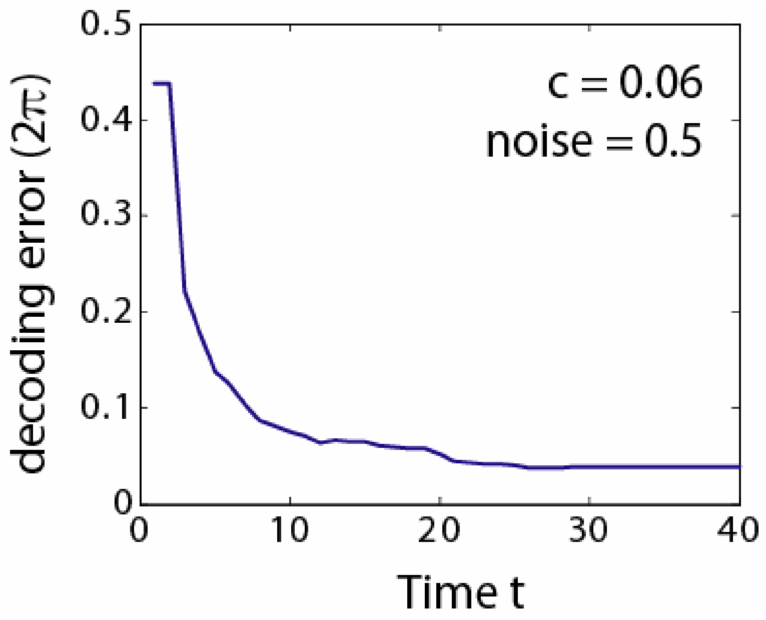


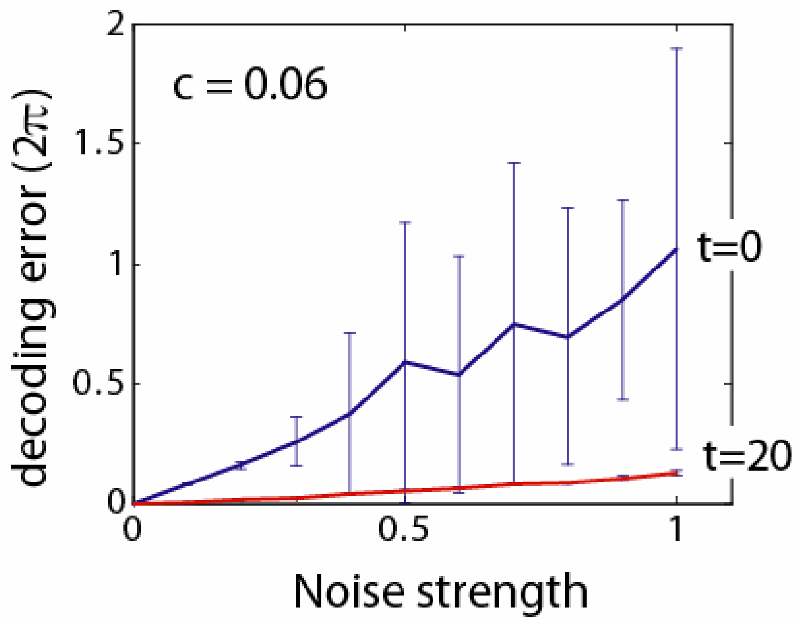
Population decoding

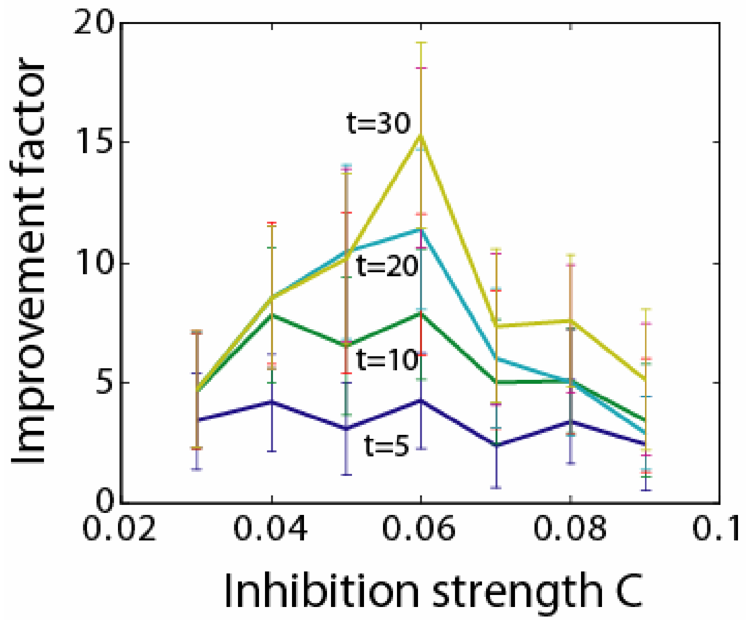
What is the encoded direction?




100
50
0
1
0.8
0.6
0.4
0.2
0
Signal Strength
Node number
100
80
60
40
20
C=0.05
100
80
60
40
20
10
20
30
40
C=0.07
Time


c = 0.06
noise = 0.5
decoding error (2π)
Time t

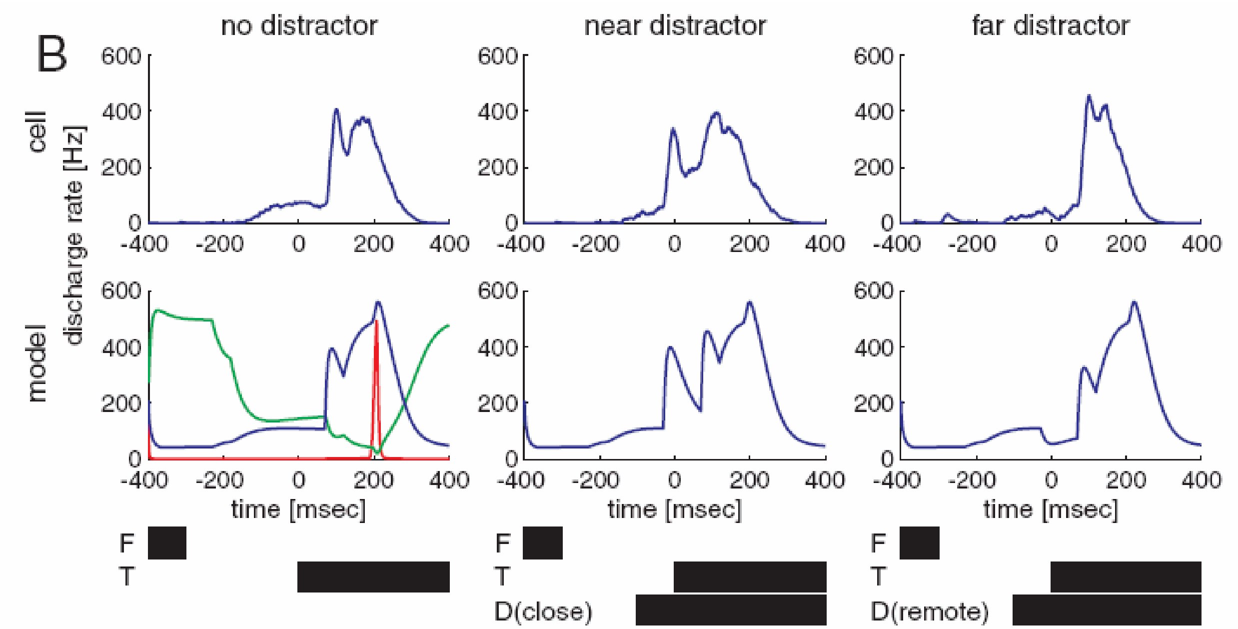

c = 0.06
t=0
t=20
decoding error (2π)
Noise strength

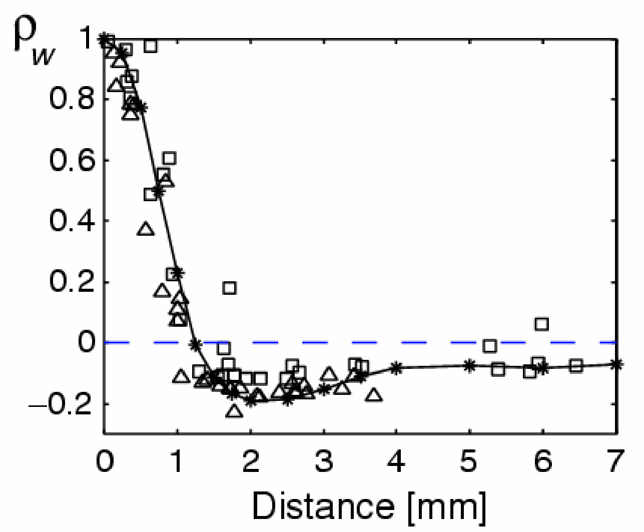

t=30
t=20
t=10
t=5
Improvement factor
Inhibition strength C

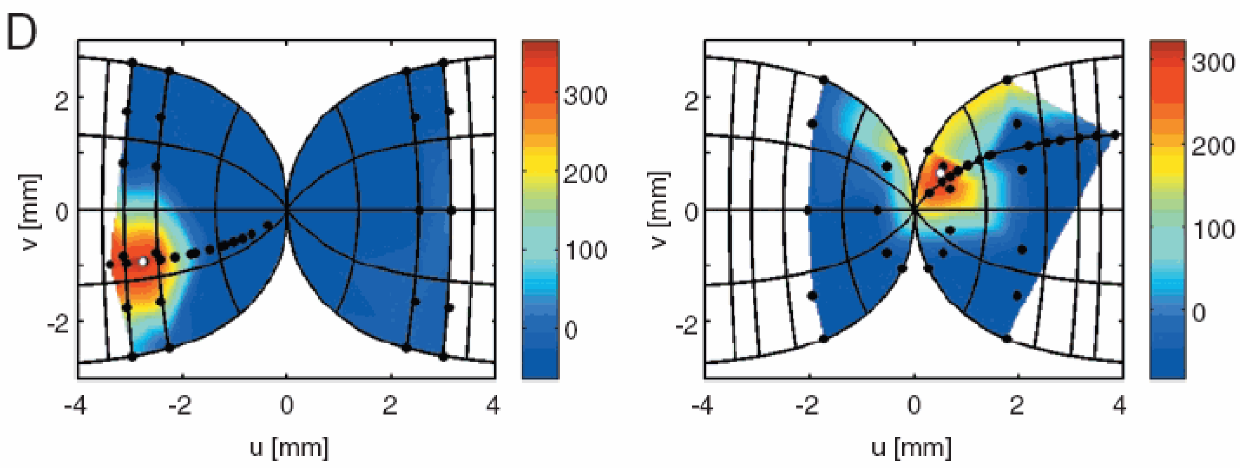
Conclusion 2: Population decoding

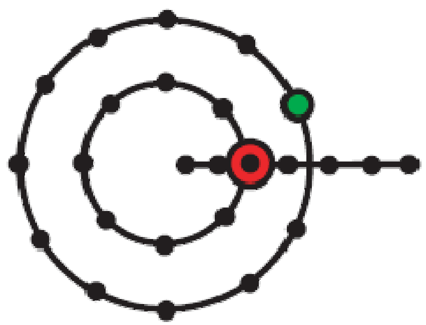
- DNF are a great and biological obvious mechanisms for population decoding
- Optimal inhibition at the transition to sustained activity

Superior Colliculus is a CANN



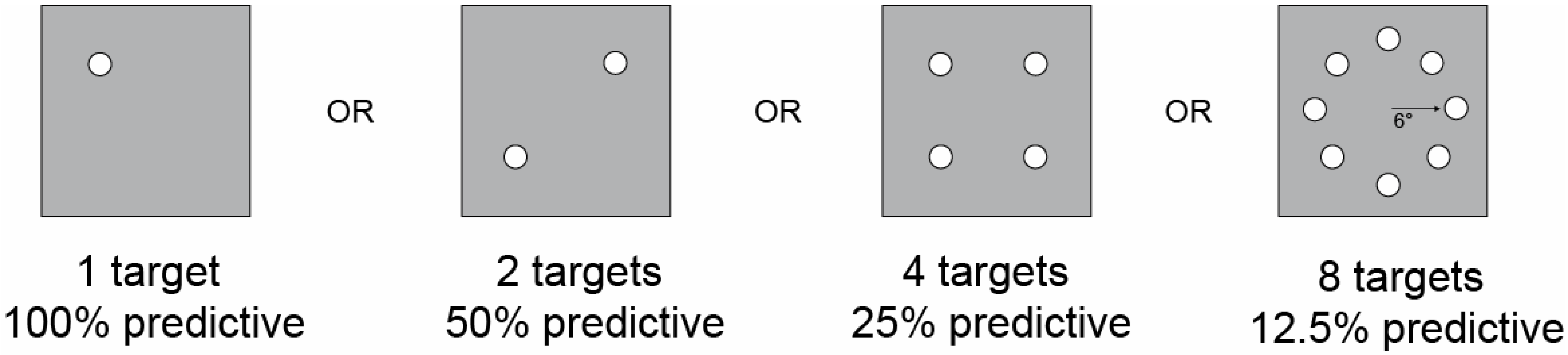


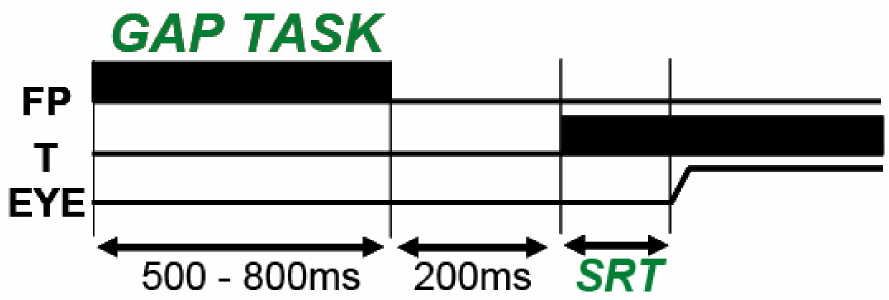




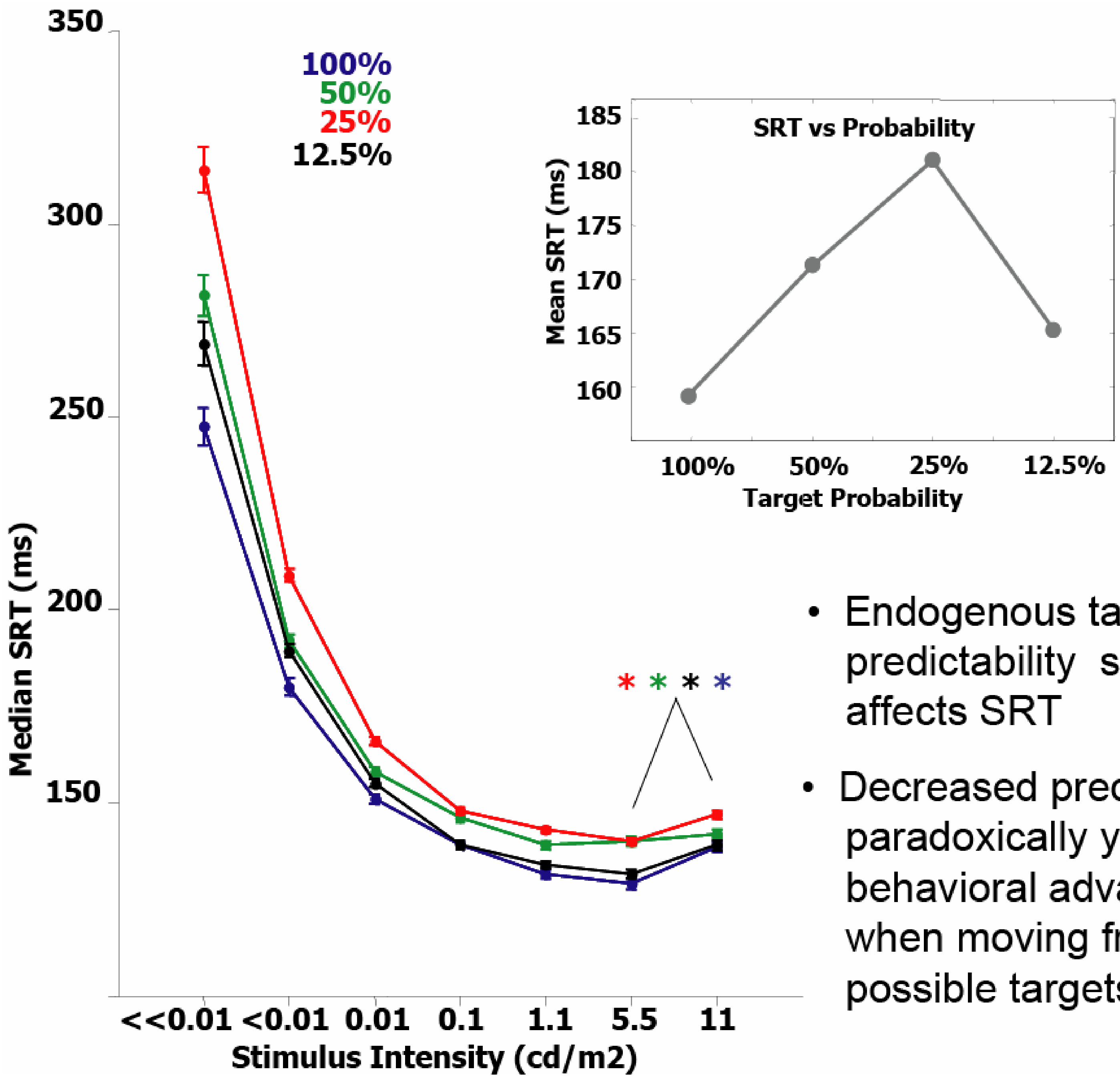
Trappenberg, Dorris, Klein & Munoz,
A model of saccade initiation based on the competitive integration of exogenous and endogenous inputs
J. Cog. Neuro. 13 (2001)

The Interaction of bottom up and top down manipulations on saccade reaction times in monkeys: R. Marino, T. Trappenberg, D. Munoz

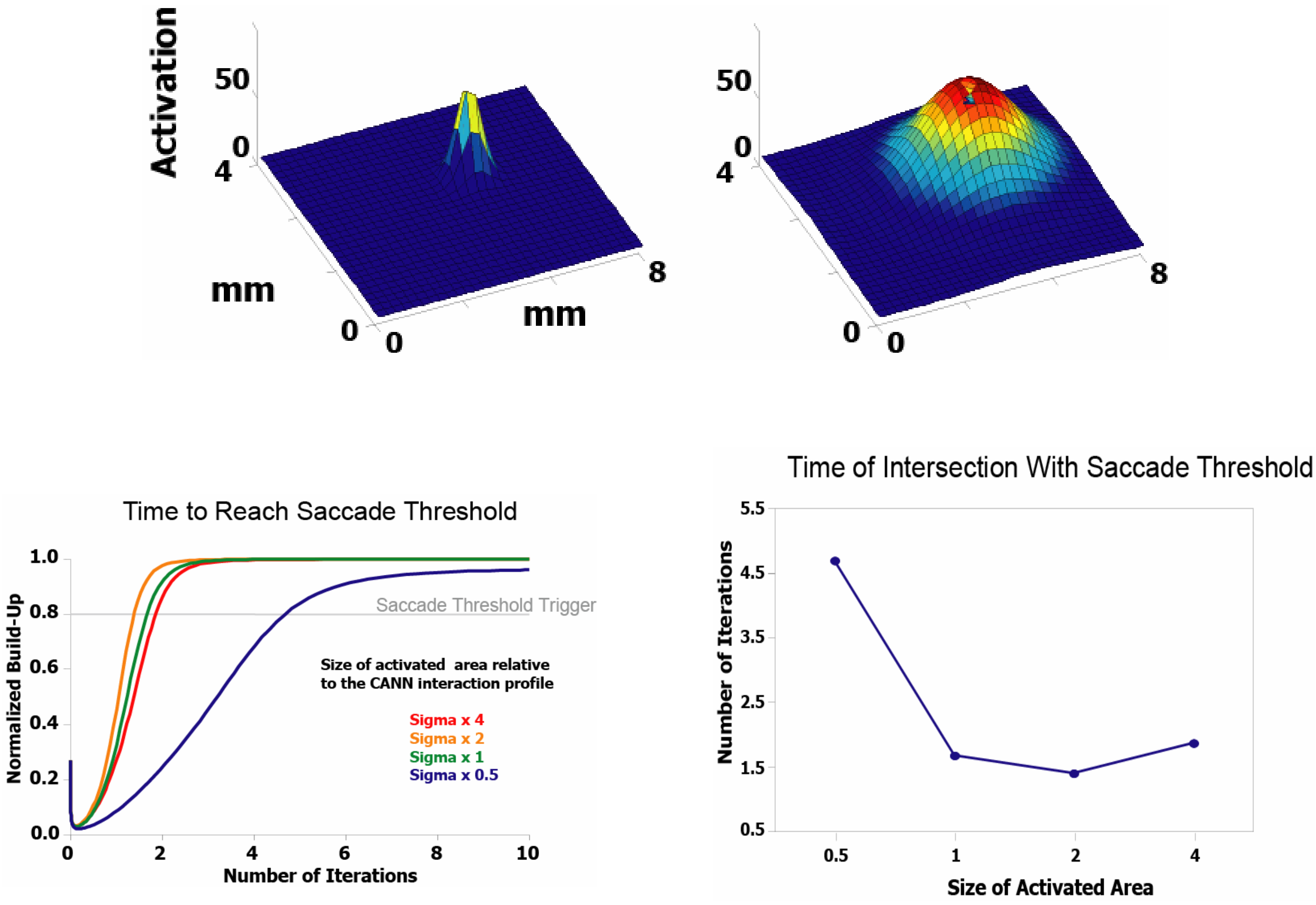


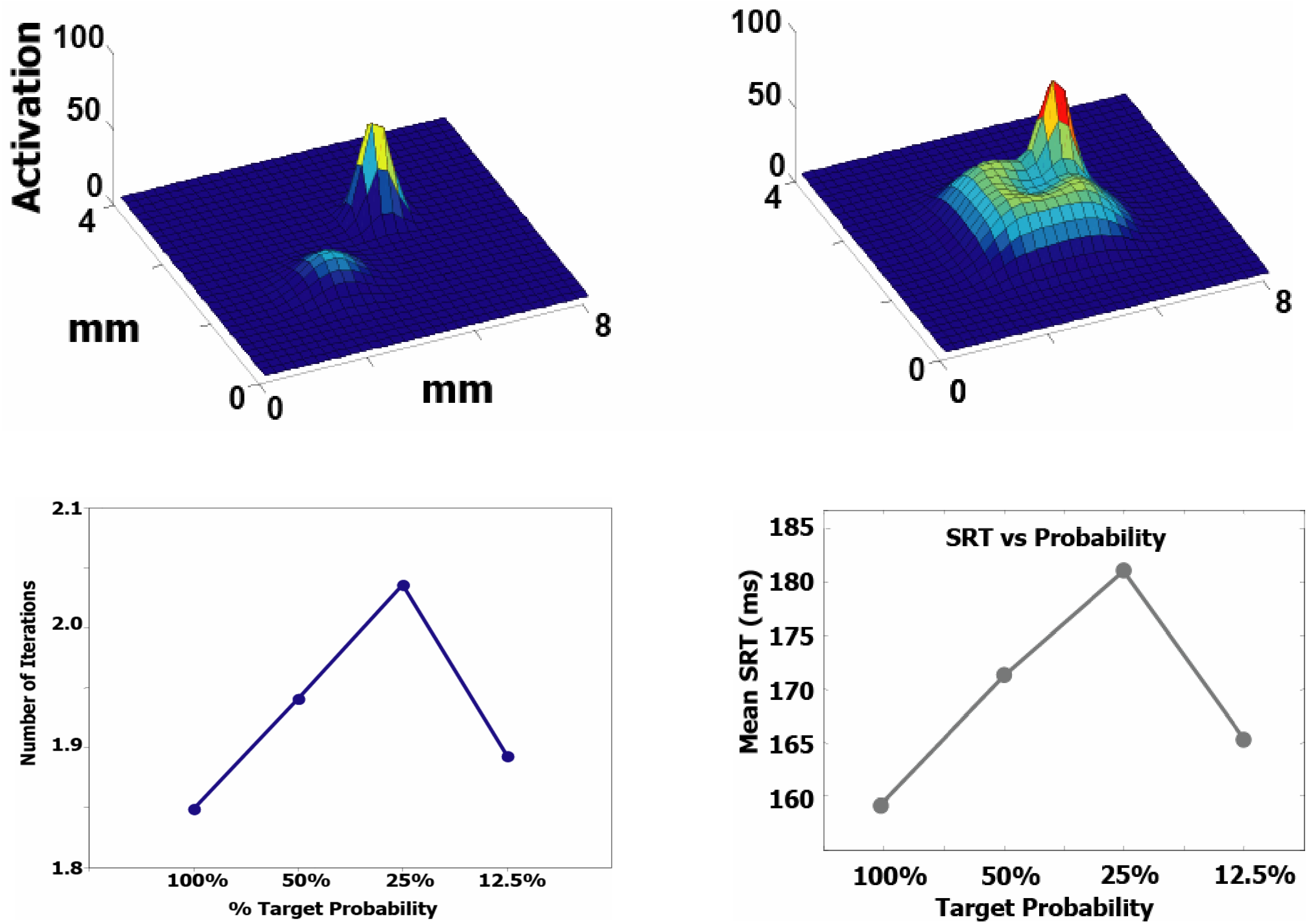


- Monkeys performed visually guided saccades in the Gap task
- Targets with different luminance (bottom up) were presented at one of up to eight equidistant locations (top down)



- Endogenous target predictability significantly affects SRT
- Decreased predictability paradoxically yields a behavioral advantage when moving from 4 to 8 possible targets


Activation
50
0
4
mm
0
0
mm
8
50
0
4
0
0
8
Time to Reach Saccade Threshold
Normalized Build-Up
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8
10
Number of Iterations
Saccade Threshold Trigger
Size of activated area relative
to the CANN interaction profile
Sigma x 4
Sigma x 2
Sigma x 1
Sigma x 0.5
Time of Intersection With Saccade Threshold
Number of Iterations
5.5
4.5
3.5
2.5
1.5
0.5
0.5
1
2
4
Size of Activated Area


Activation
100
50
0
4
mm
0
0
mm
8
100
50
0
4
0
0
8
2.1
2.0
1.9
1.8
Number of Iterations
100%
50%
25%
12.5%
% Target Probability
SRT vs Probability
185
180
175
170
165
160
Mean SRT (ms)
100%
50%
25%
12.5%
Target Probability

Conclusion 3: Superior Colliculus

- DNF explain unexpected non-monotone reaction times based on inhibitory surround
- Prediction of area effect seem to be confirmed with initial cell data