Bayesian approaches to Neural dynamics and coding

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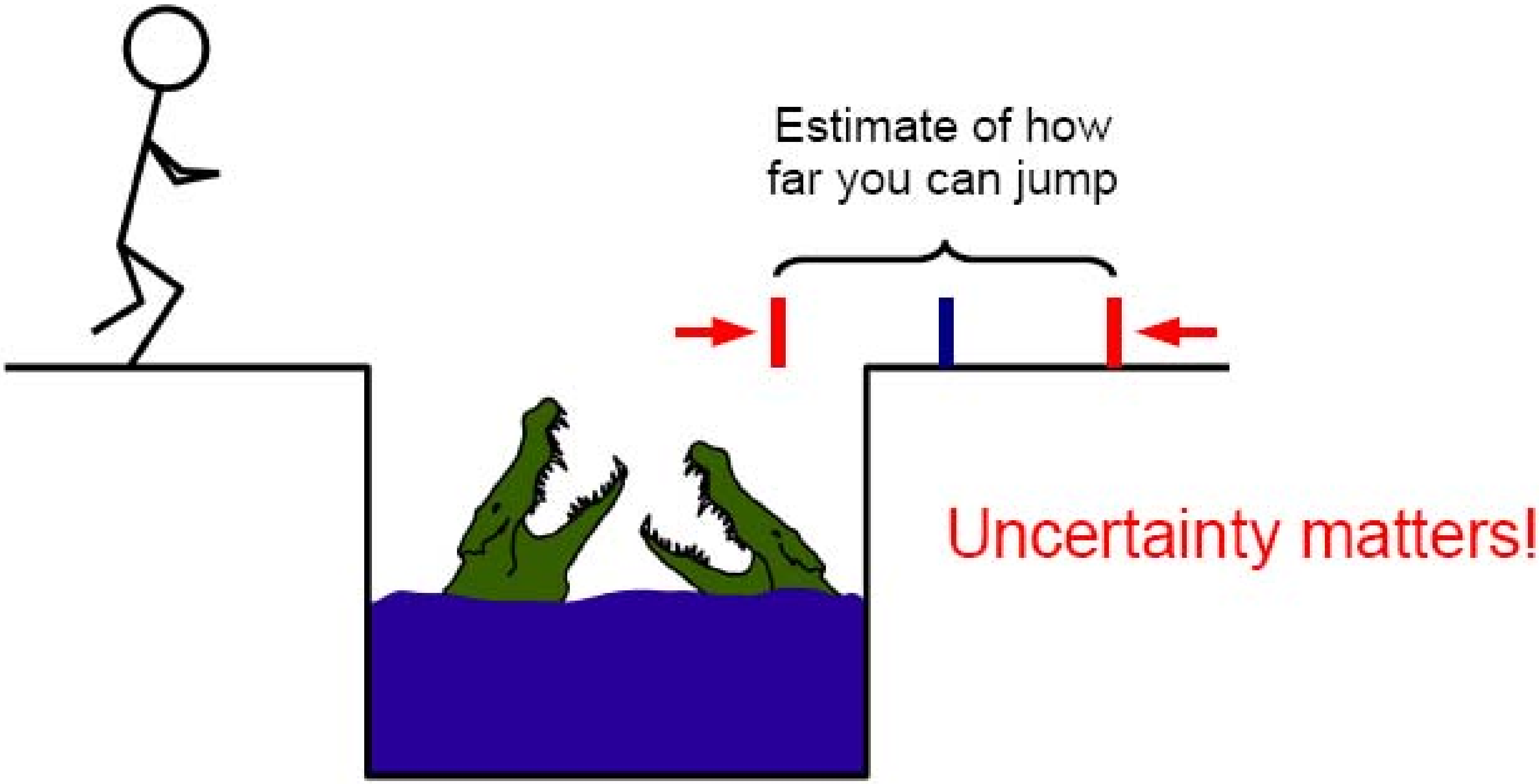
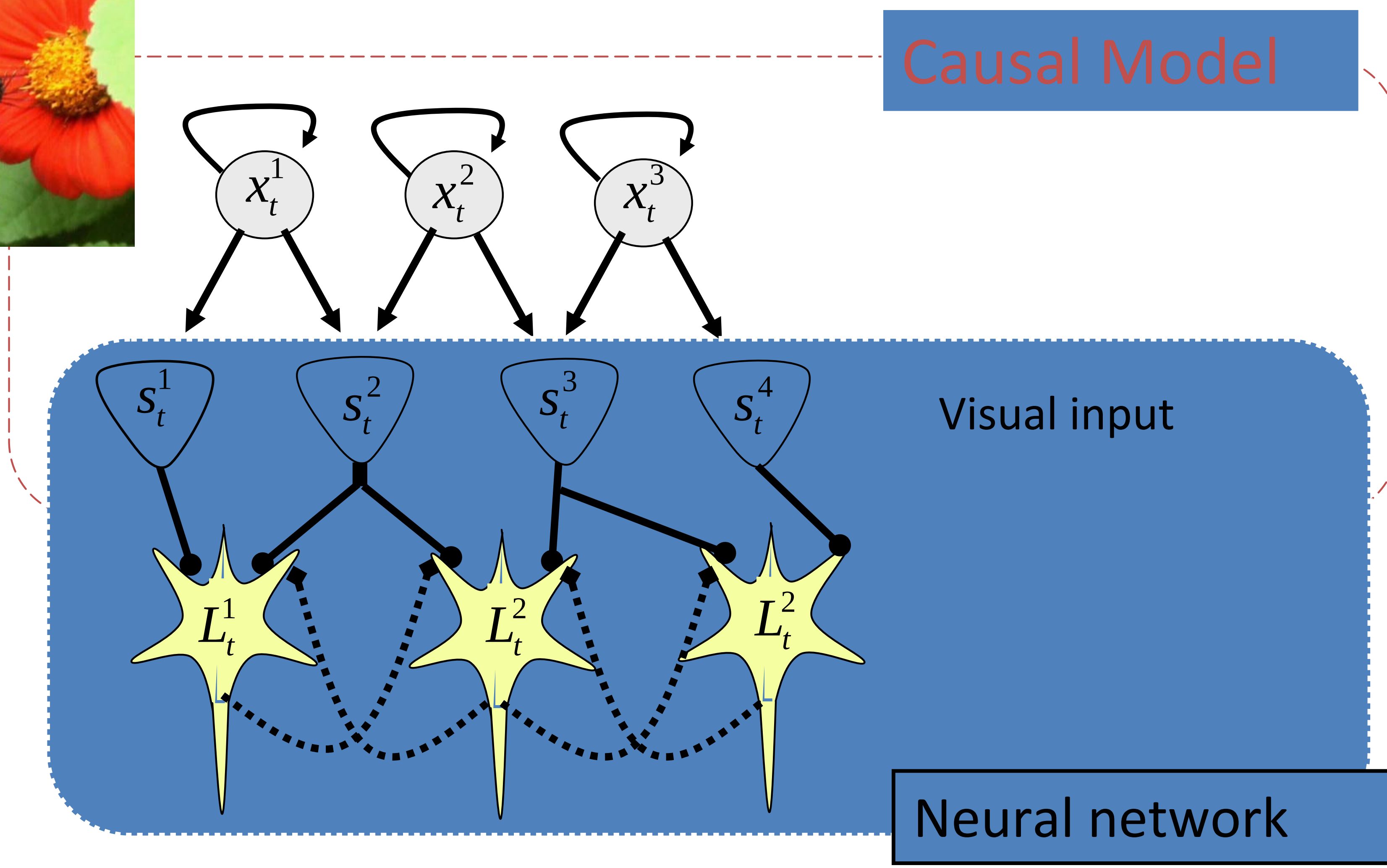
GNT

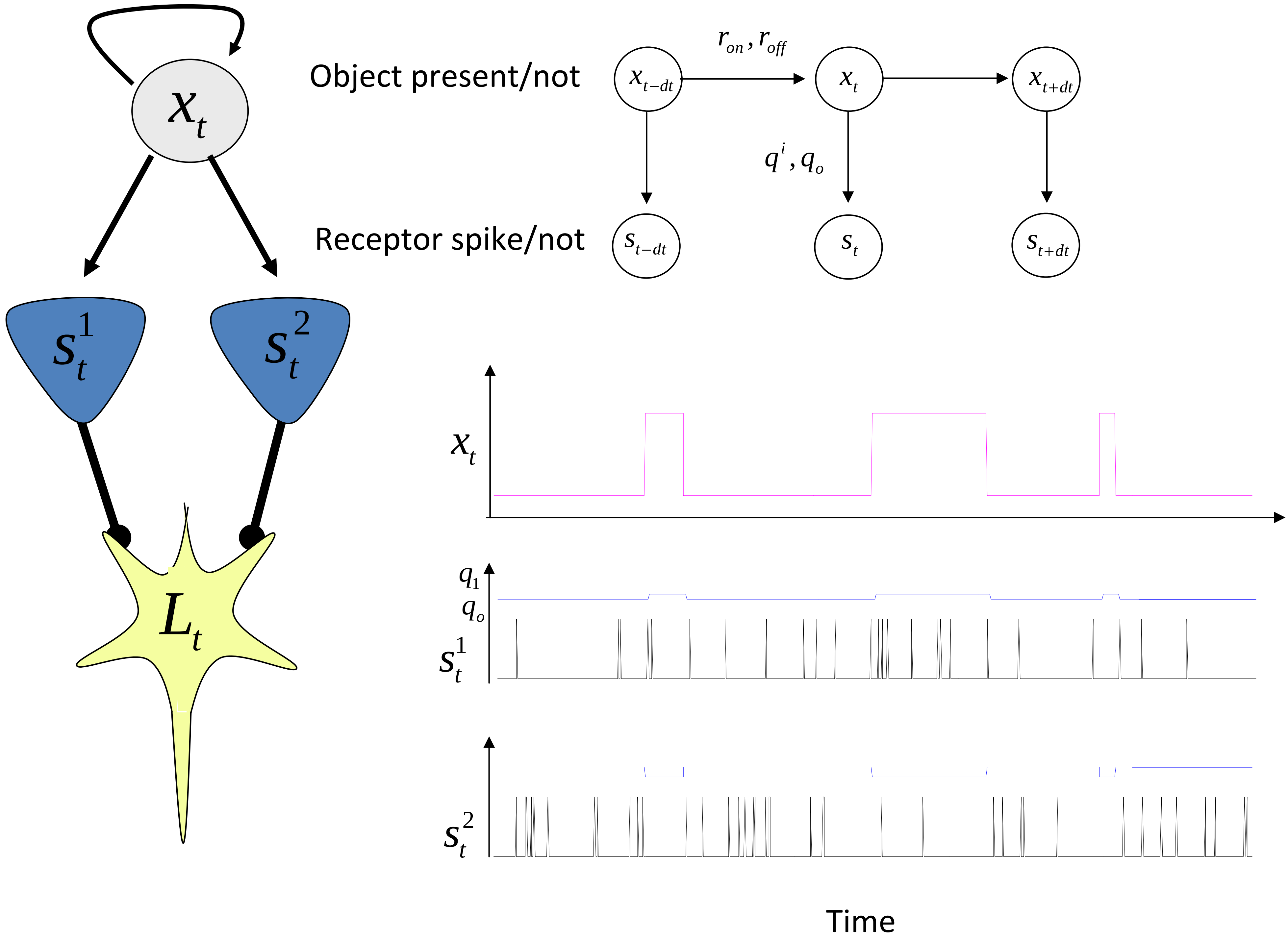
Uncertainty

- All of our decision are subject to uncertainty

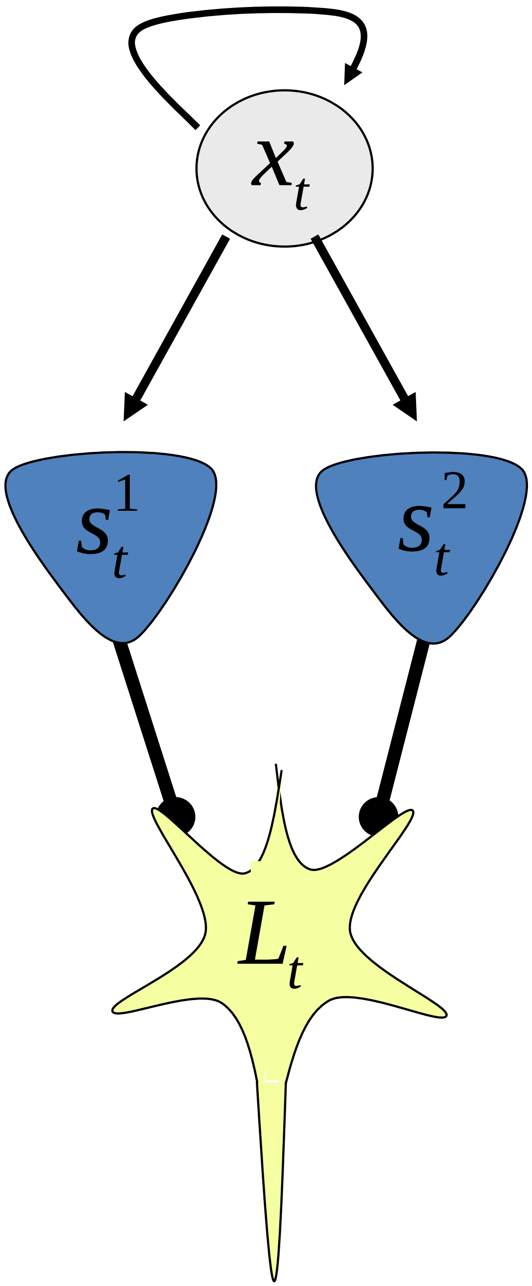


Analysing sensory scenes





x_t
s_t^1
s_t^2
L_t
Object present/not
Receptor spike/not
r_{on}, r_{off}
q^i, q_o
x_{t-dt}
x_t
x_{t+dt}
s_{t-dt}
s_t
s_{t+dt}
x_t
q_1
q_o
s_t^1
s_t^2
Time



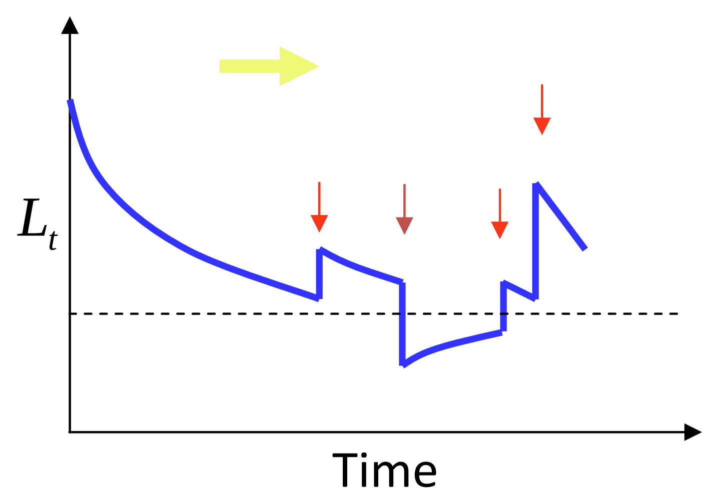
$$L_t = \log\left(\frac{p\left(x_t^1 = 1 \mid \mathbf{s}\right)}{p\left(x_t^1 = 0 \mid \mathbf{s}\right)}\right)$$

$$w_i = \log\left(\frac{q_o + q_i}{q_o}\right)$$

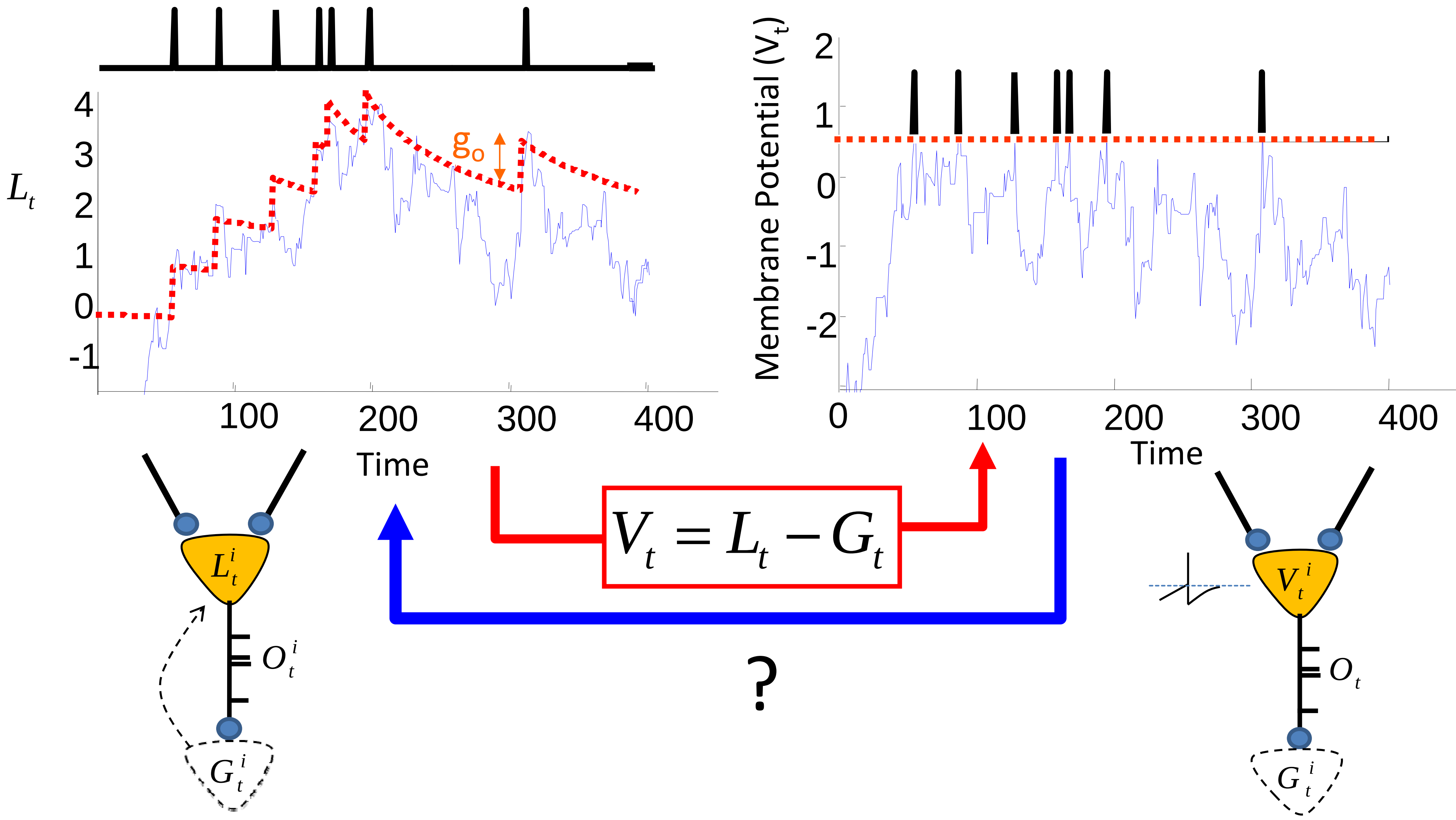
$$\frac{\partial L}{\partial t} = r_{on}\left(1 + e^{-L}\right) - r_{off}\left(1 + e^{L}\right) + \sum_i w_i s_t^i - \theta$$

Leak

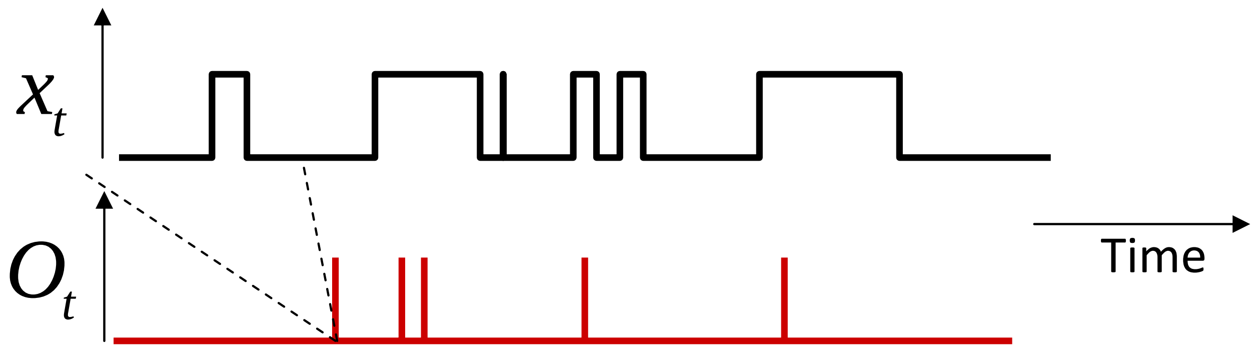
Synaptic input



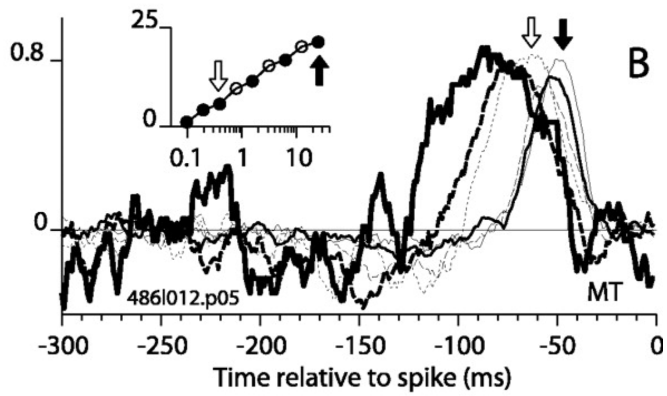
Analogy with a leaky integrate and fire neuron



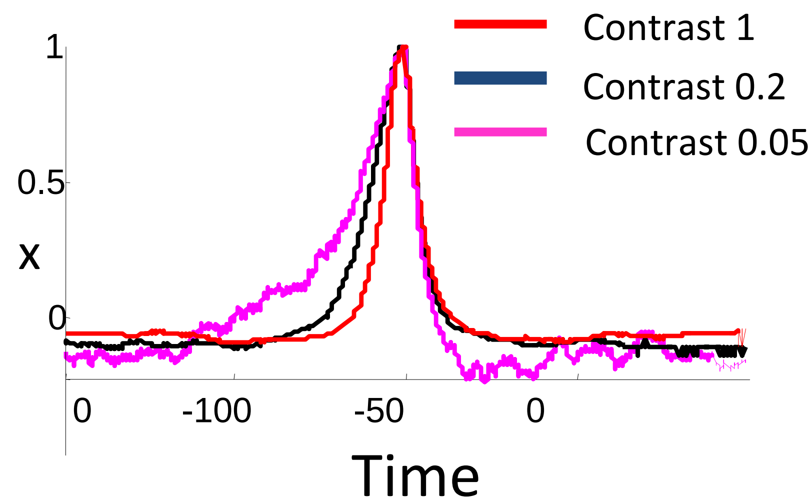
Time constant of integration depends on contrast.



Bair and Movshon 2004



Model



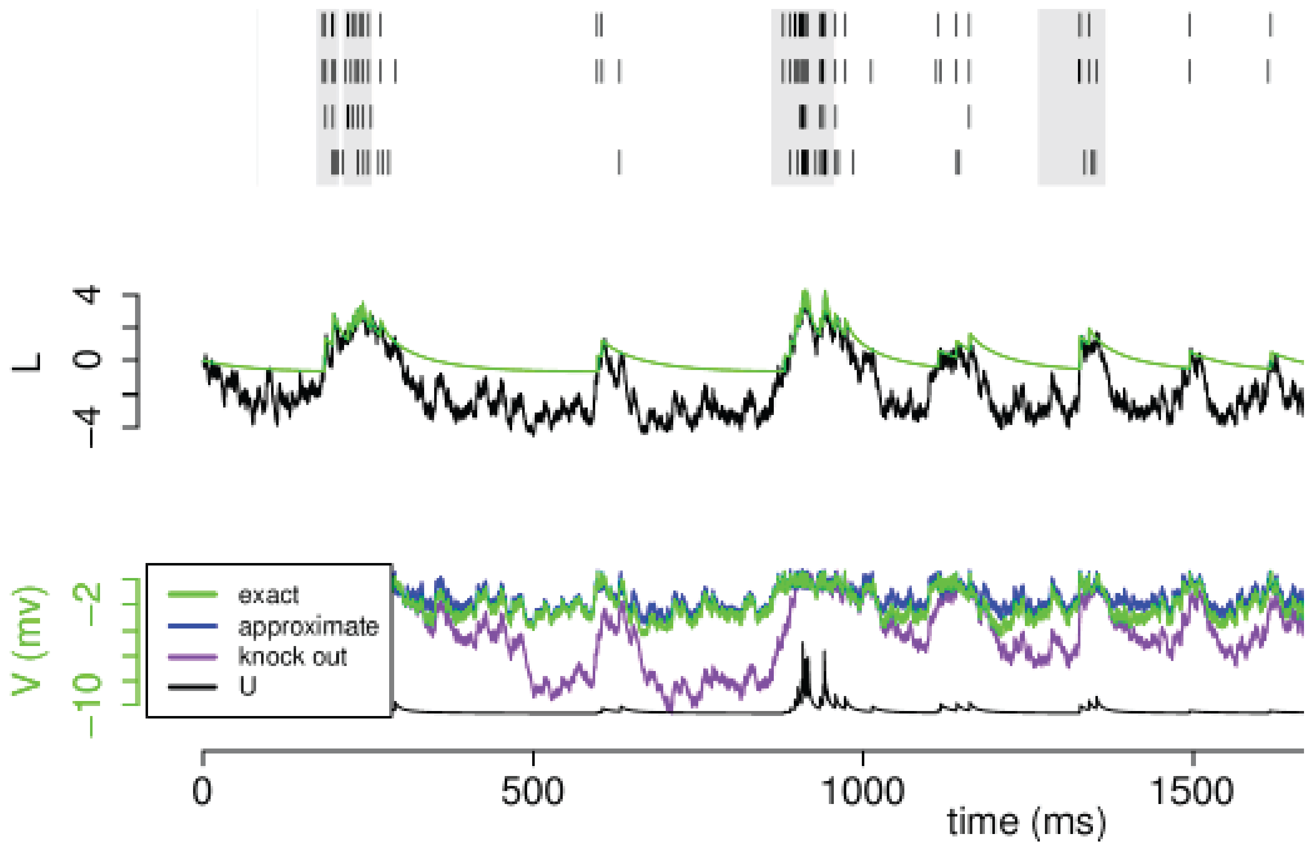
Comparison with Linear Integrate and Fire

Bayesian

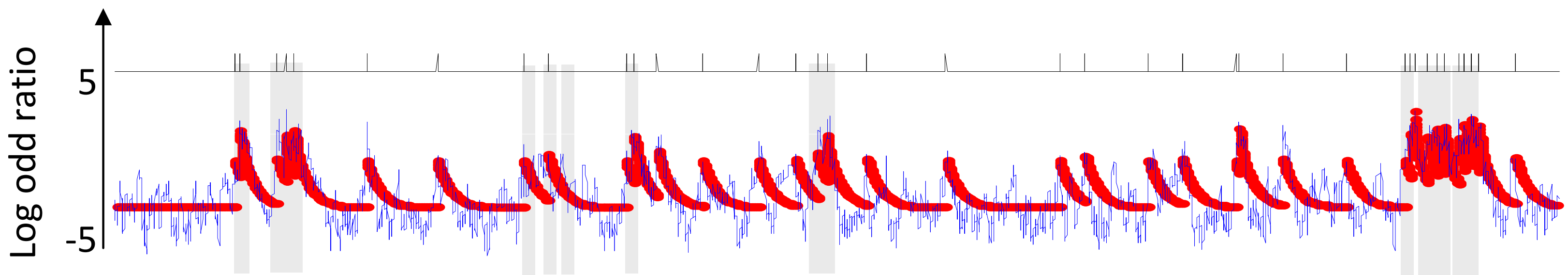
$$V_t = L_t - G_t$$

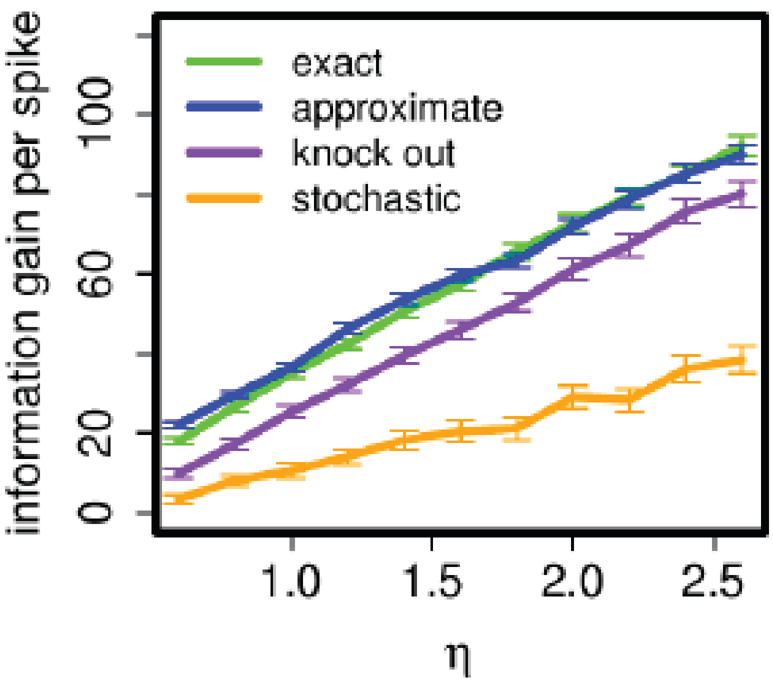
Linear Integrate and fire

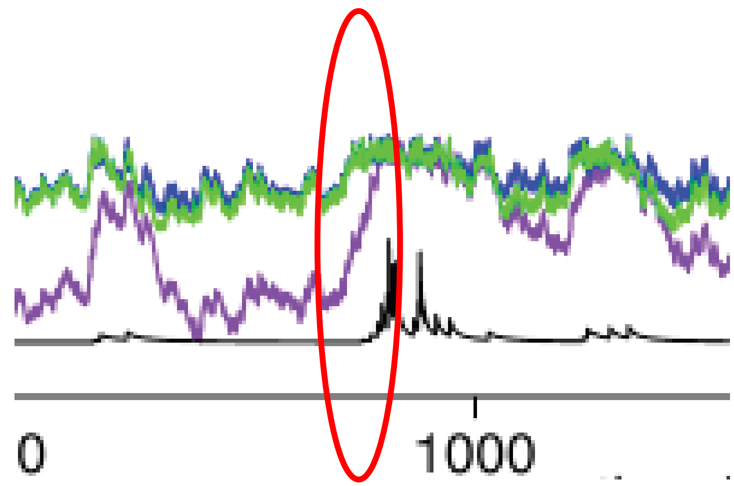
$$\tau \dot{V} = -V + \sum_i w_i s_t^i$$



Information transmission about the stimulus







Towards a biophysical basis of spike-based inference

Object almost certainly absent

Uncertain

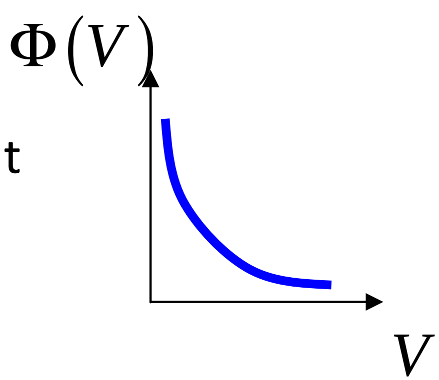
Object almost certainly present

$$\tau \dot{V} = \Phi(V) - V - r_{off} u V + \sum_i w_i s_t^i$$

Adaptive currents

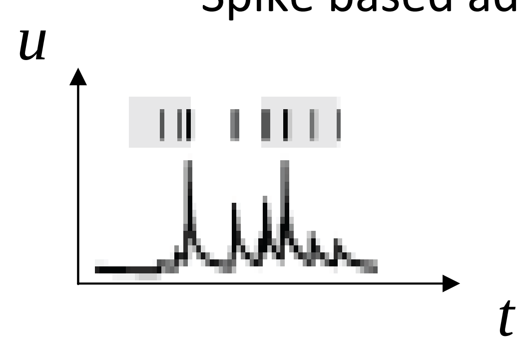
$$\Phi(V) = e^{-V} - 1$$

I_h current



$$\dot{u} = (r_{off} - r_{on}) u - r_{off} u^2 + u O_t$$

Spike based adaptation



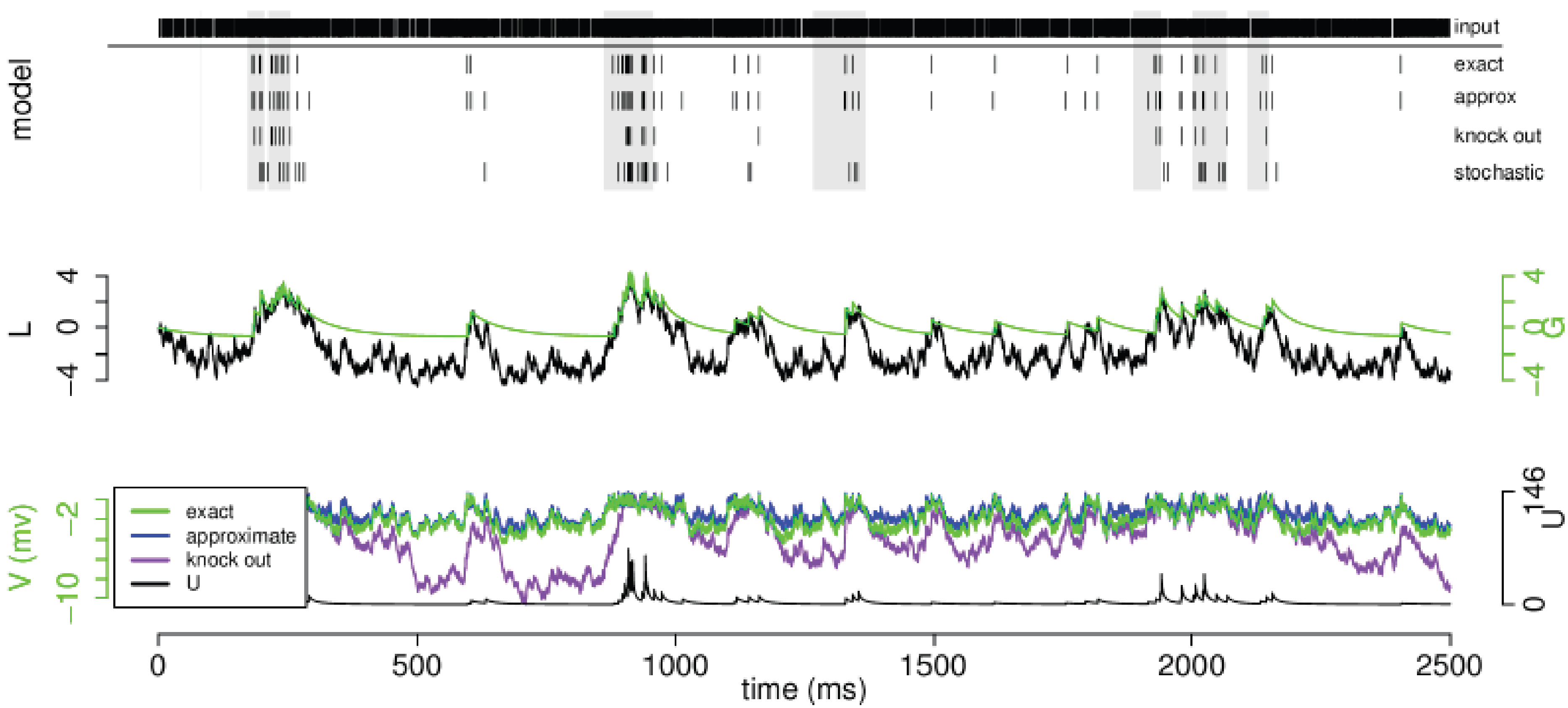
Approx Bayesian (I_h+spike based adapt) :

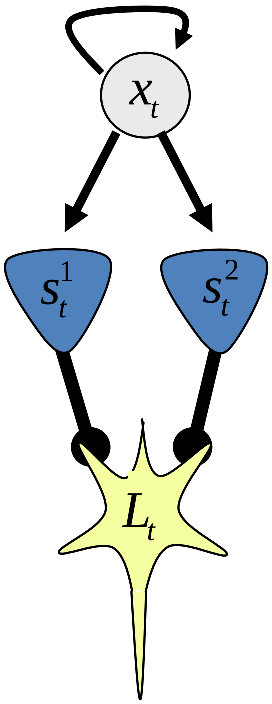
$$\tau\dot{V} = \Phi(V) - V - r_{off}uV + \sum_i w_i s_t^i$$

$$\dot{u} = (r_{off} - r_{on})u - r_{off}u^2 + uO_t$$

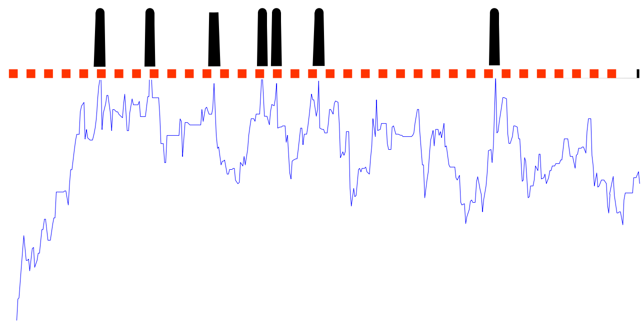
Knock-out (IF)

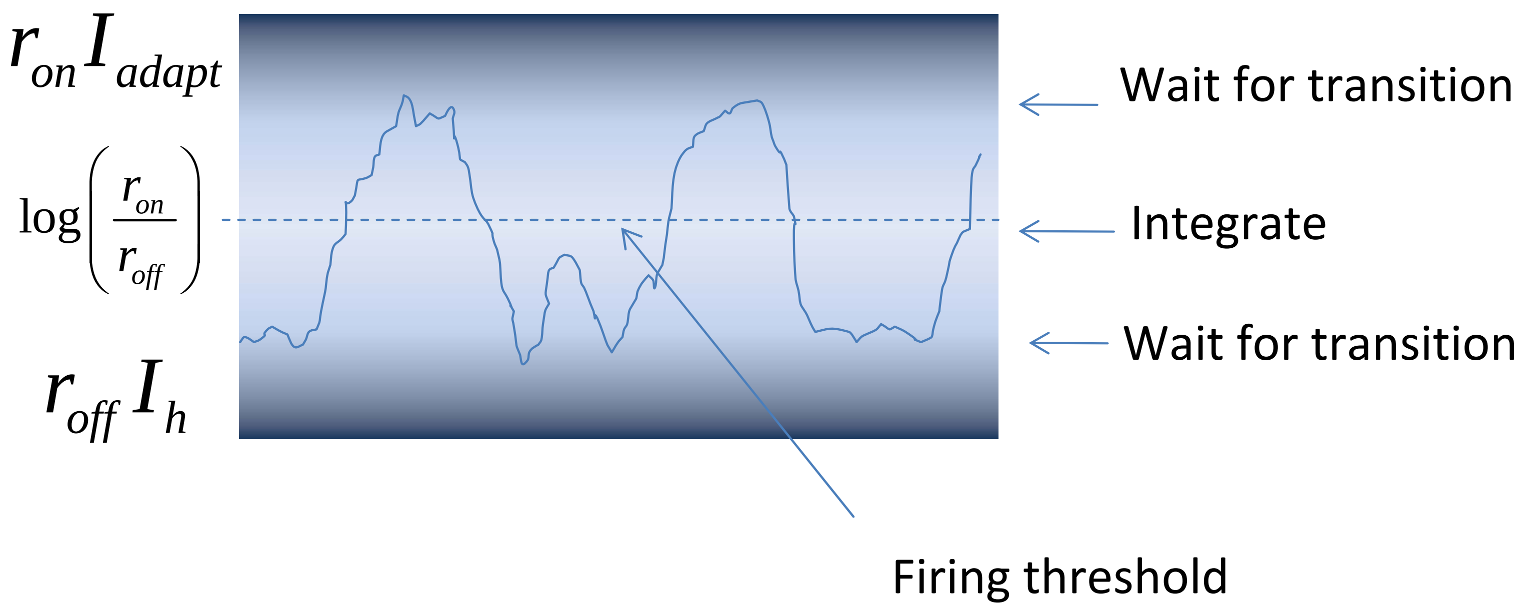
$$\tau\dot{V} = -V + \sum_i w_i s_t^i$$





Inference in single spiking neurons

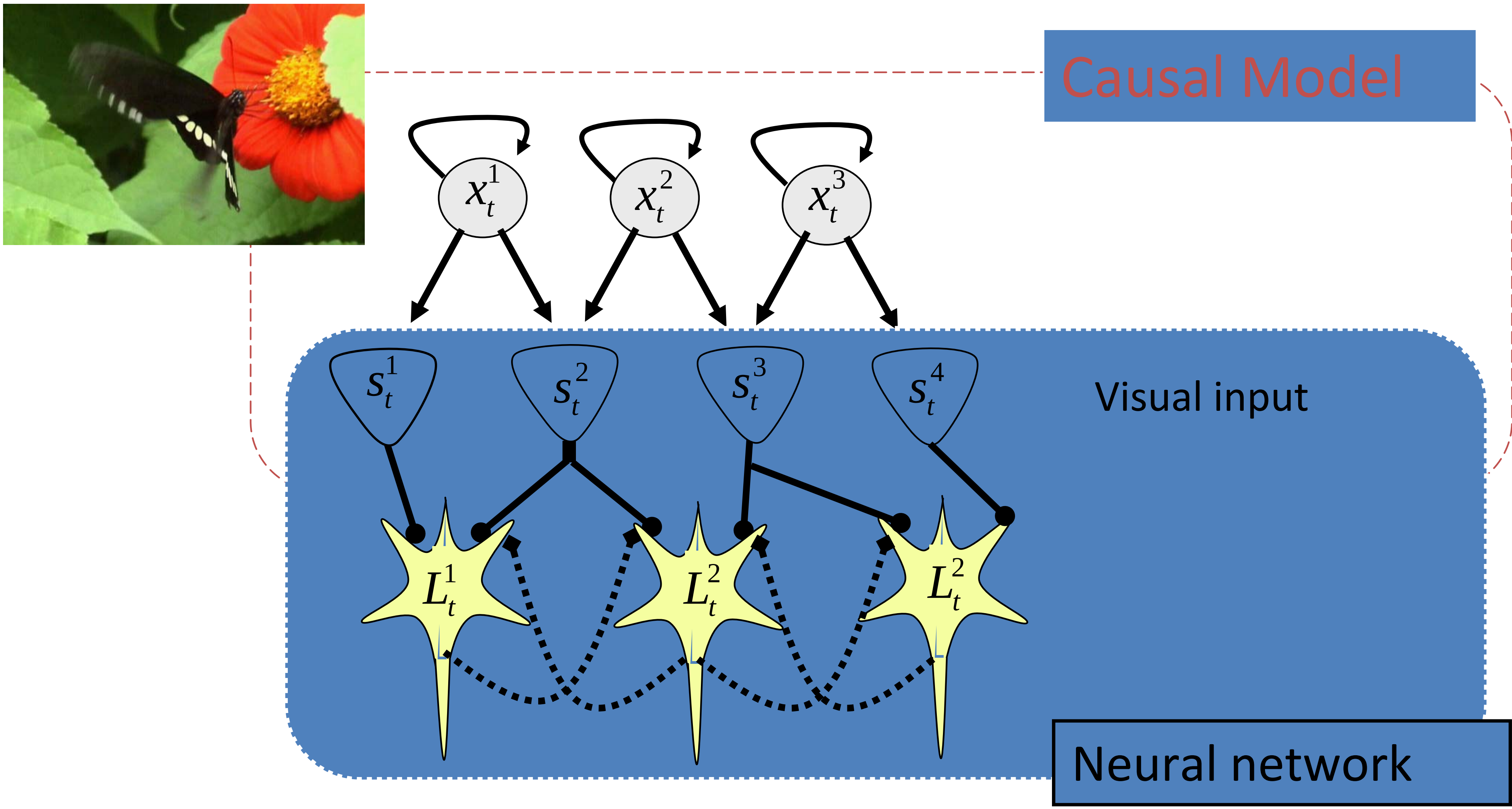




Conclusion 1: Bayesian spiking neuron

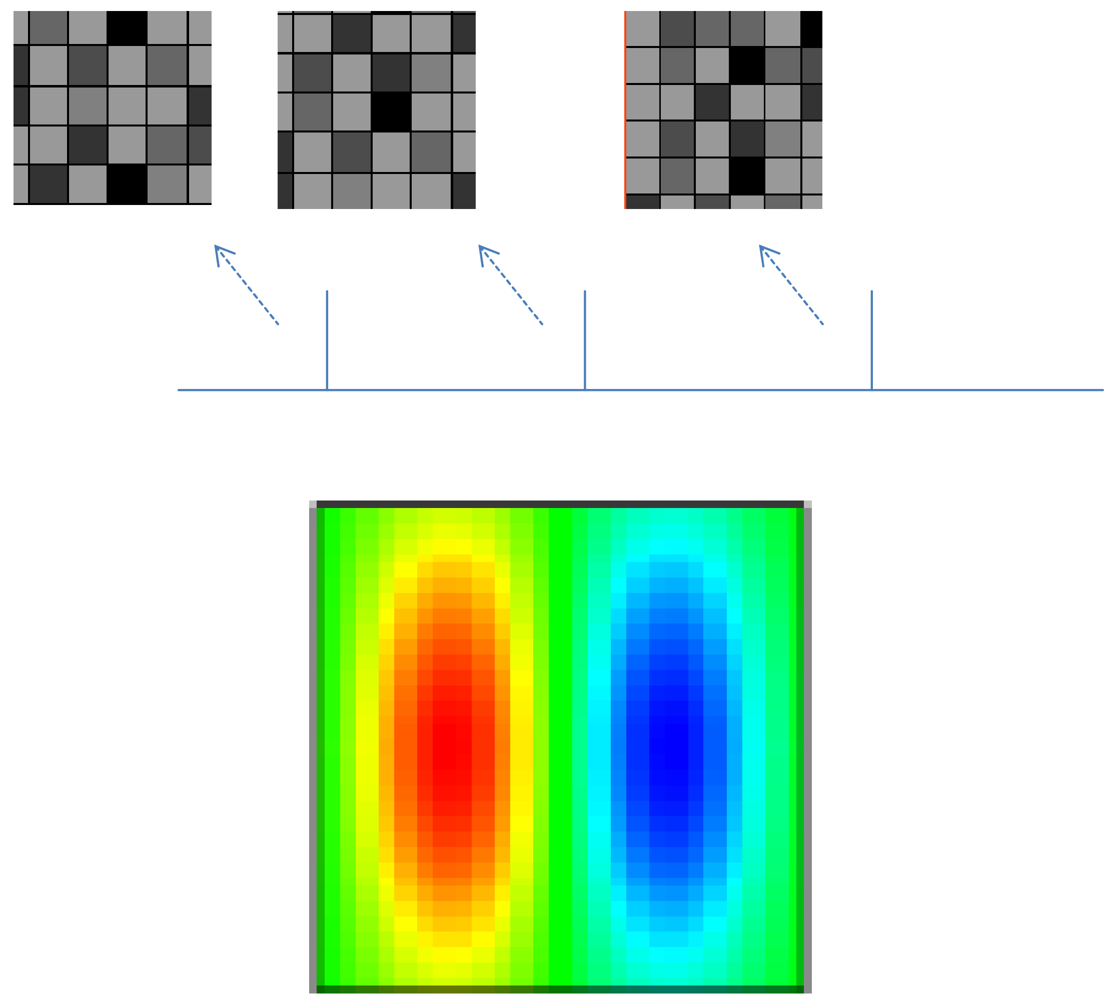
- Integrate and fire neurons can be interpreted as Bayesian integrators.
- Biophysical parameters have functional interpretations.
- Spikes represent increases in probability.
- Optimal neural dynamics can be learnt in an unsupervised was (on-line Expectation maximization).

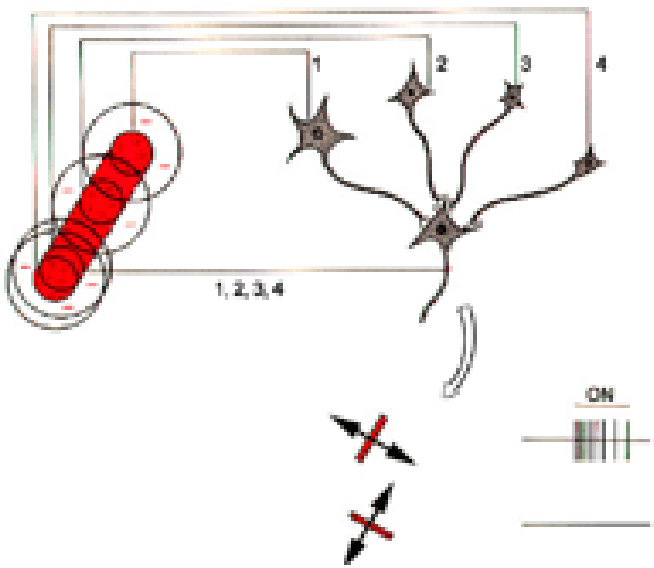
Analysing sensory scenes



Receptive fields

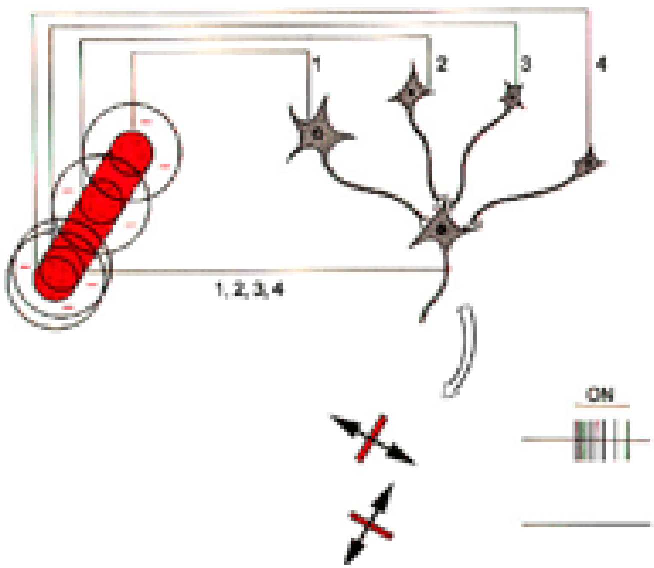
RF for V1 simple cell:





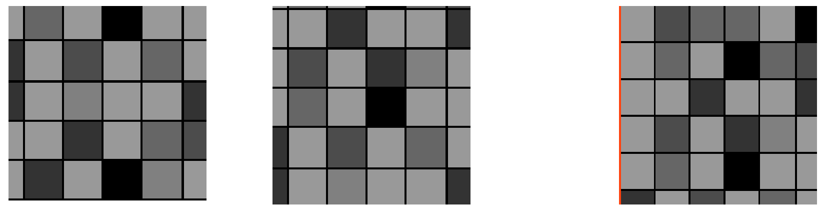
Hubel and Wiesel, 1962

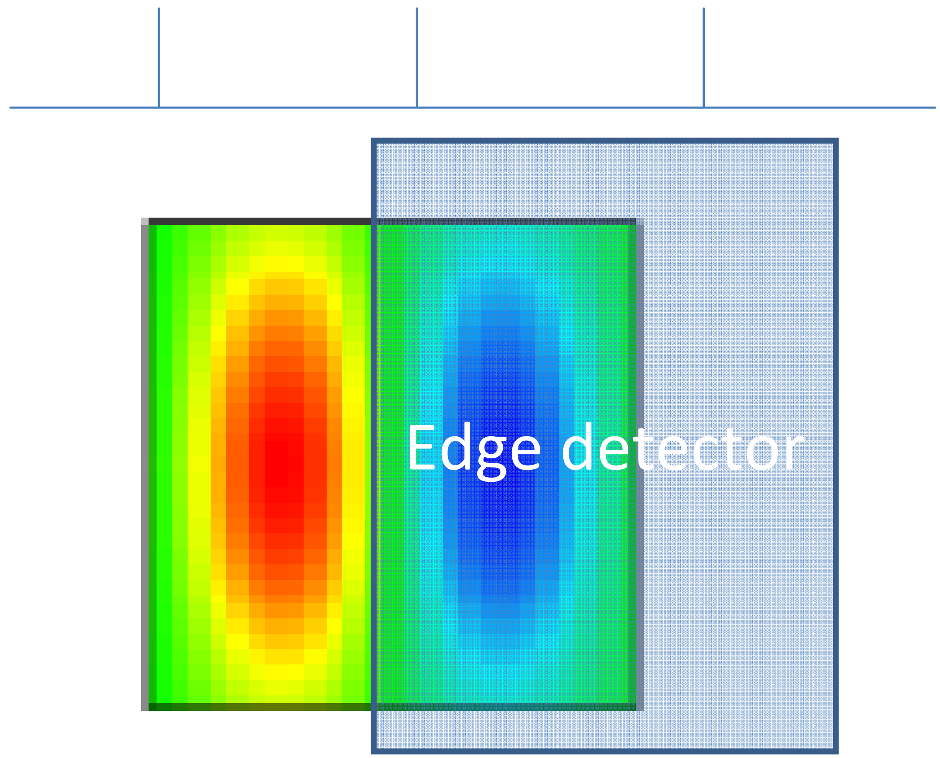
Receptive fields



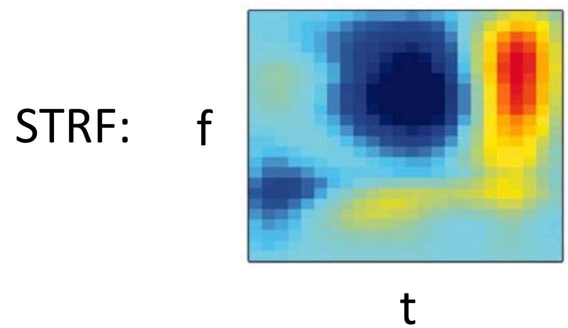
Hubel and Wiesel, 1962

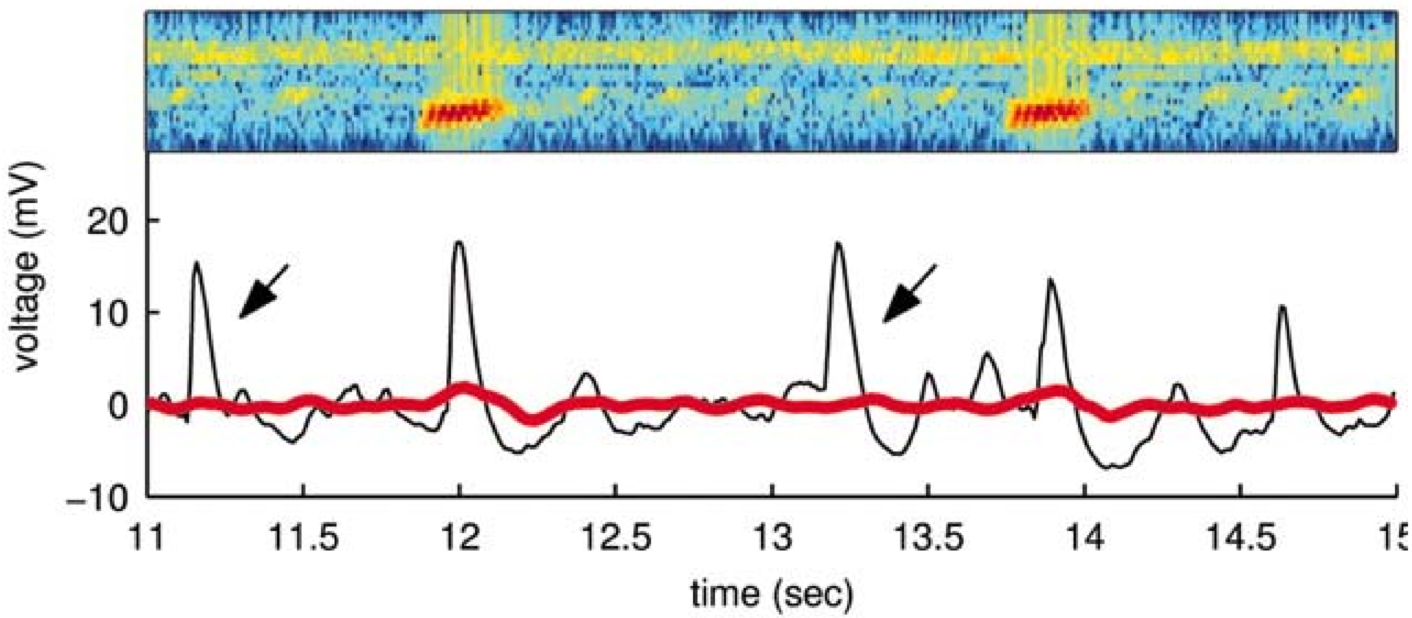
RF for V1 simple cell:





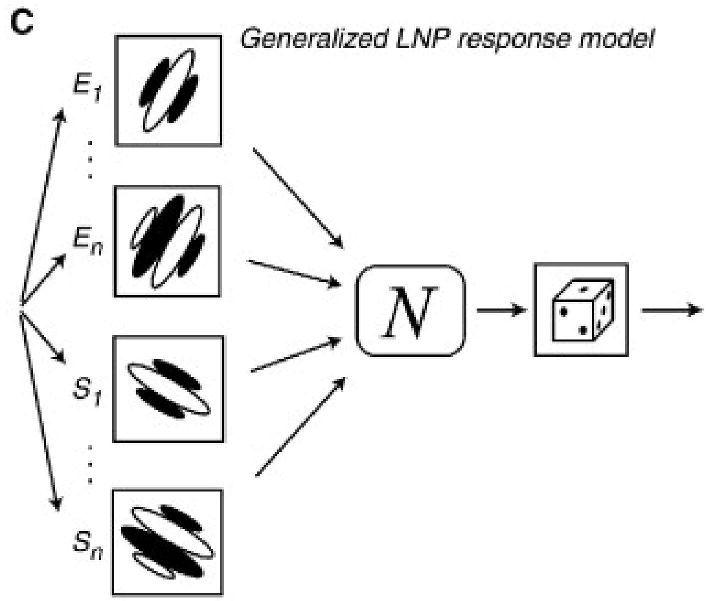
Responses to natural scene are poorly predicted by the RF.





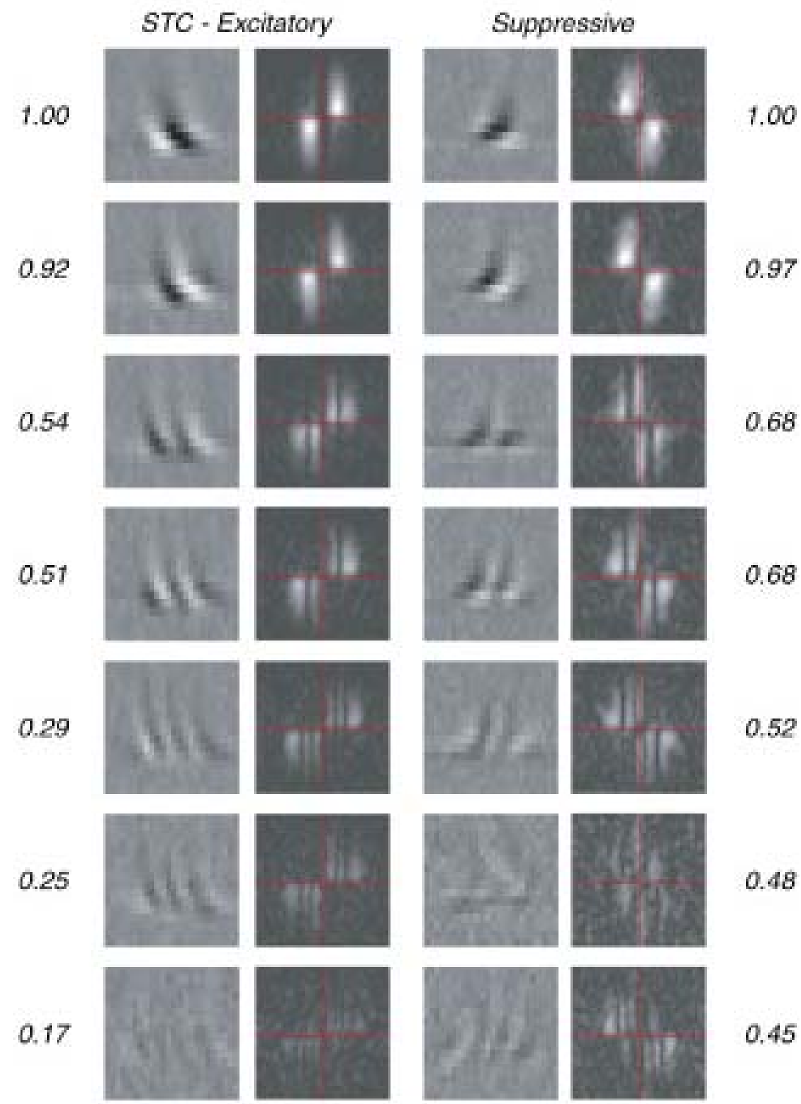
Machens CK, Wehr MS, Zador AM. J Neurosci. 2004

Multiple excitatory and suppressive components

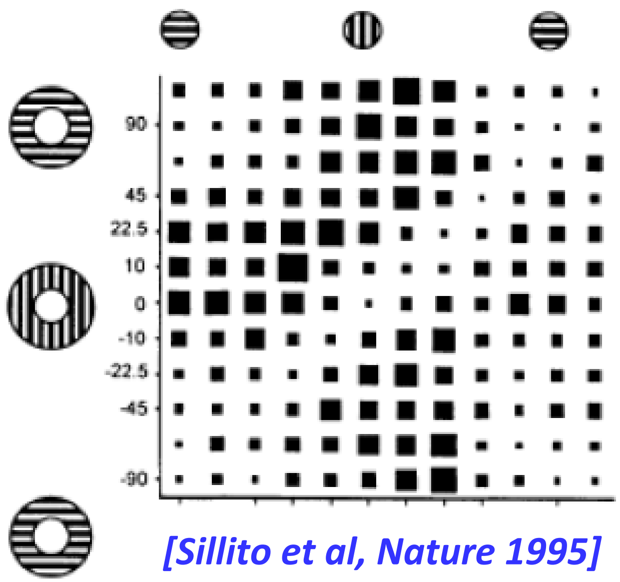


Schwartz et al 2006

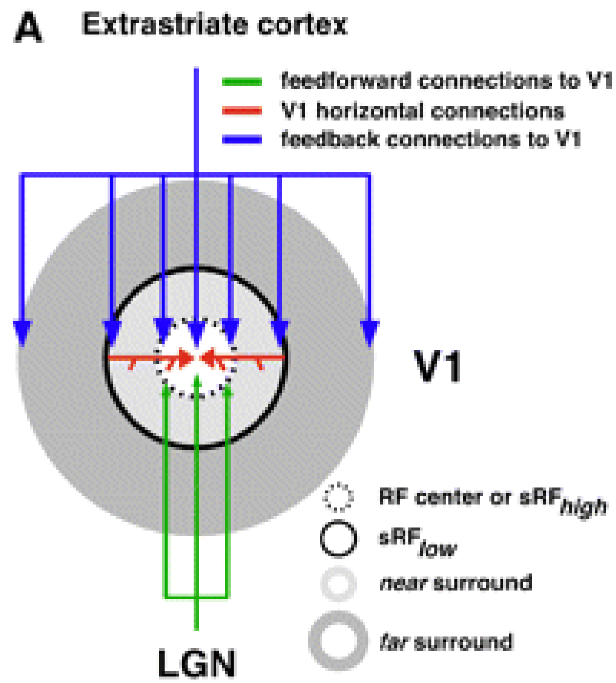
Divisive



Receptive fields depend on surround stimuli

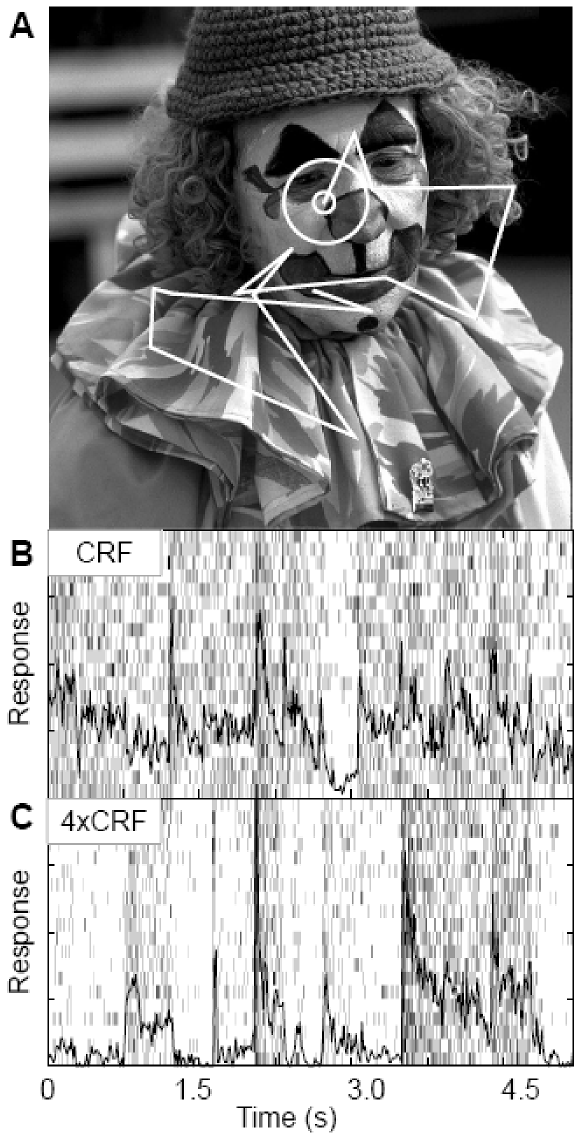


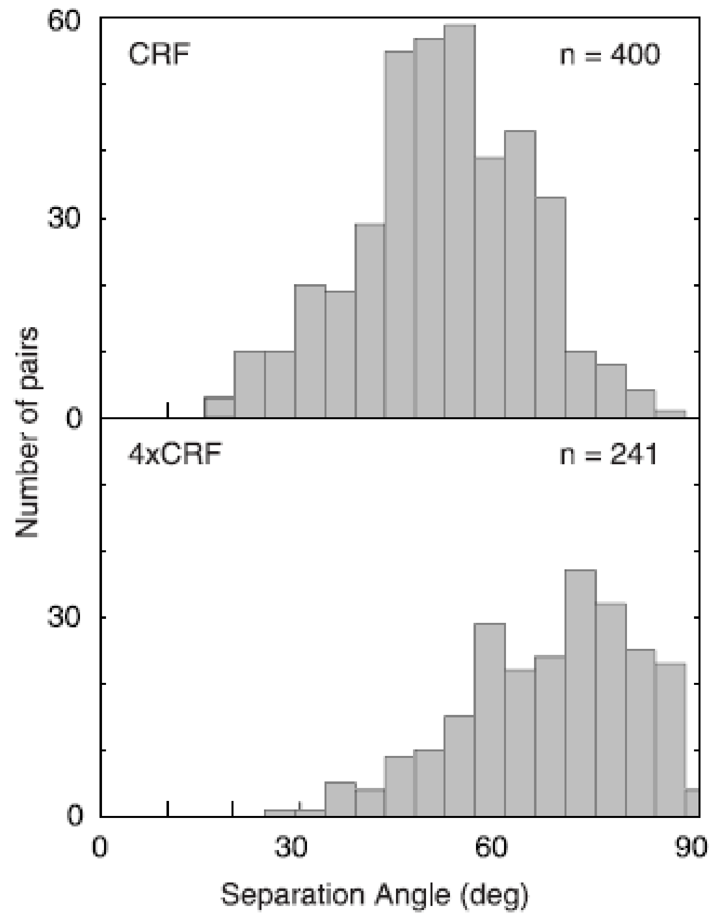
[Sillito et al, Nature 1995]



Angelucci et al 2001

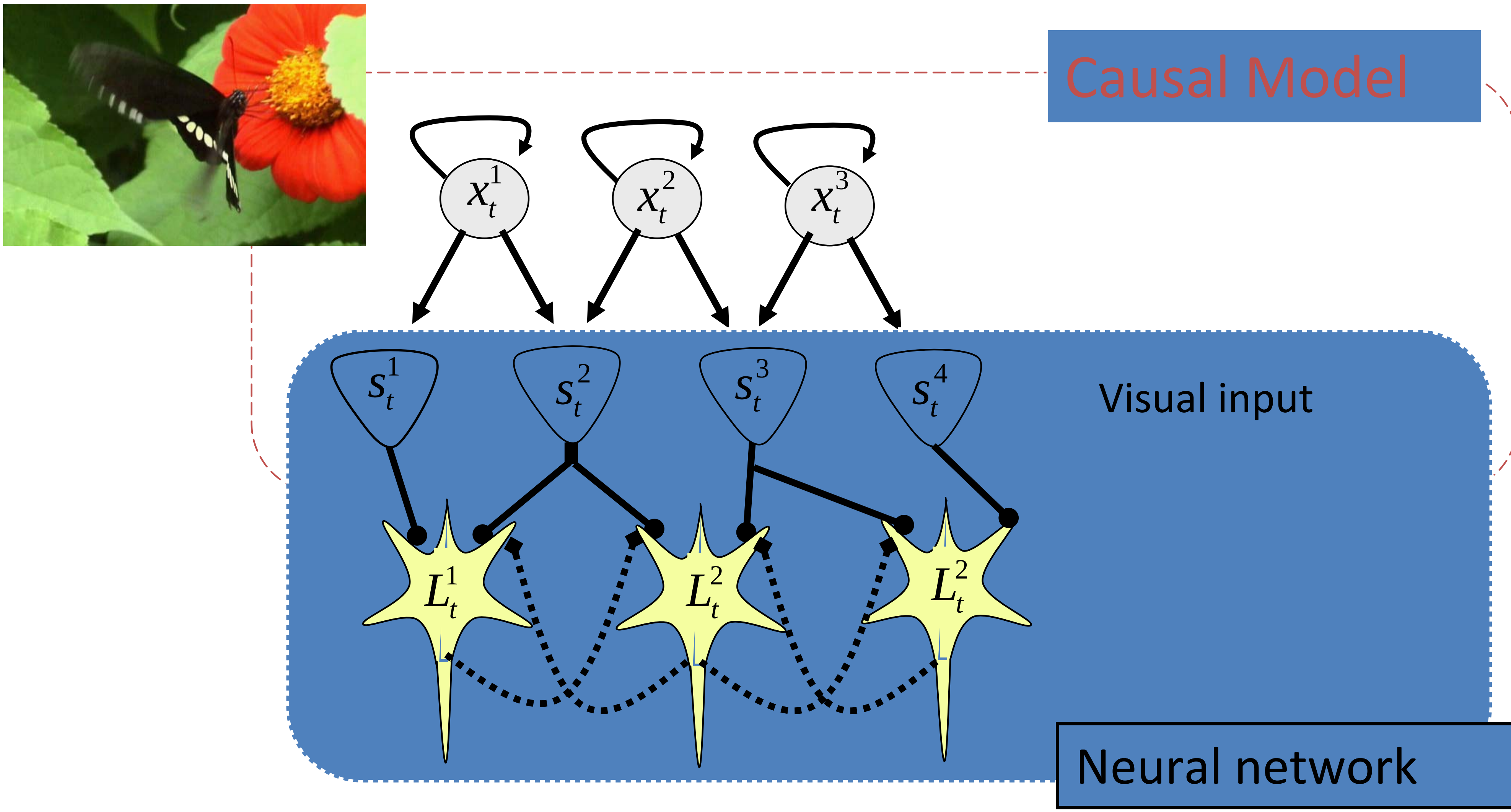
Sparsening and decorrelation by the contextual surround





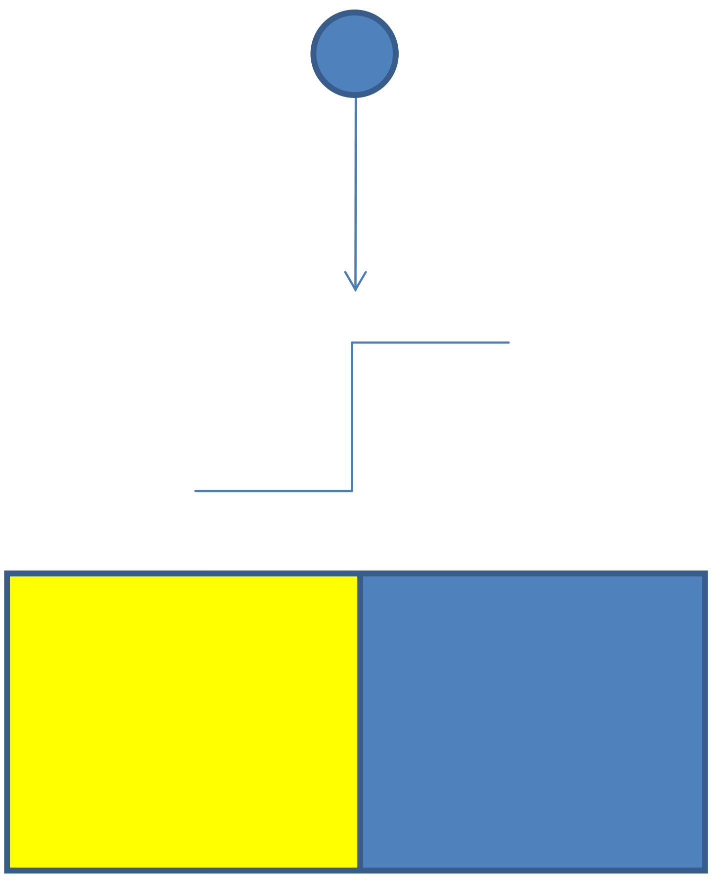
Vinje and Gallant, Science 2000

Analysing sensory scenes

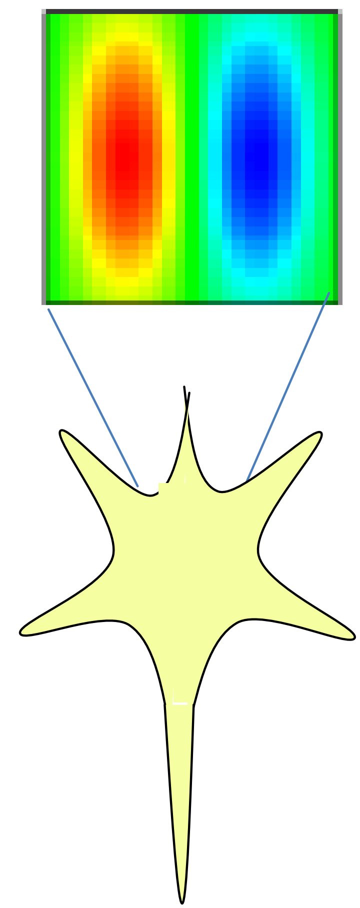


Receptive and Predictive fields

« edge predictor »

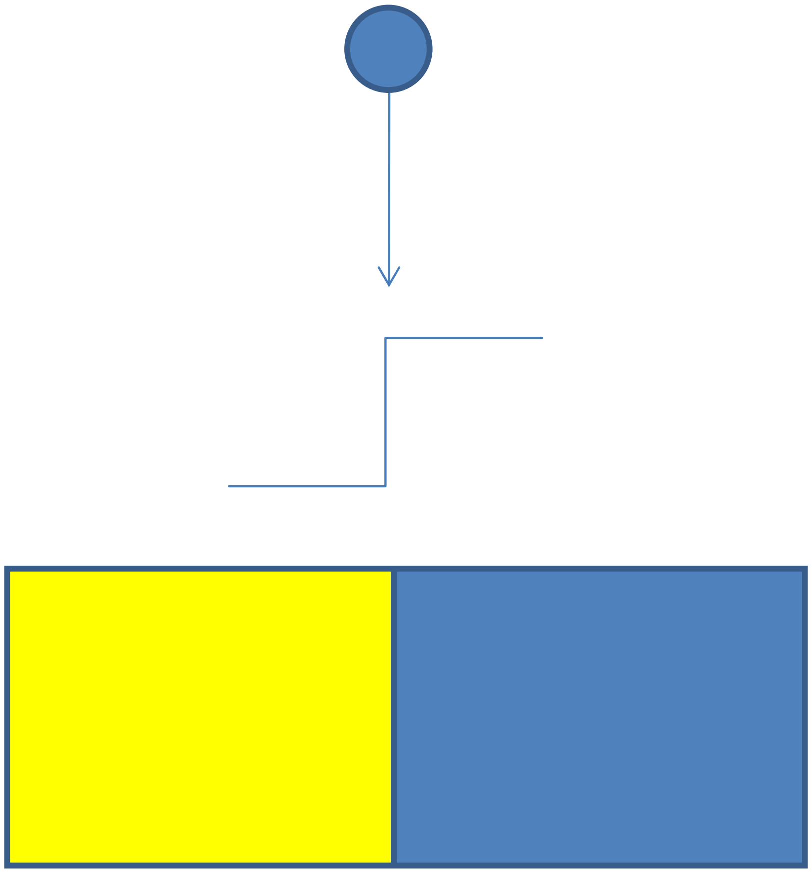


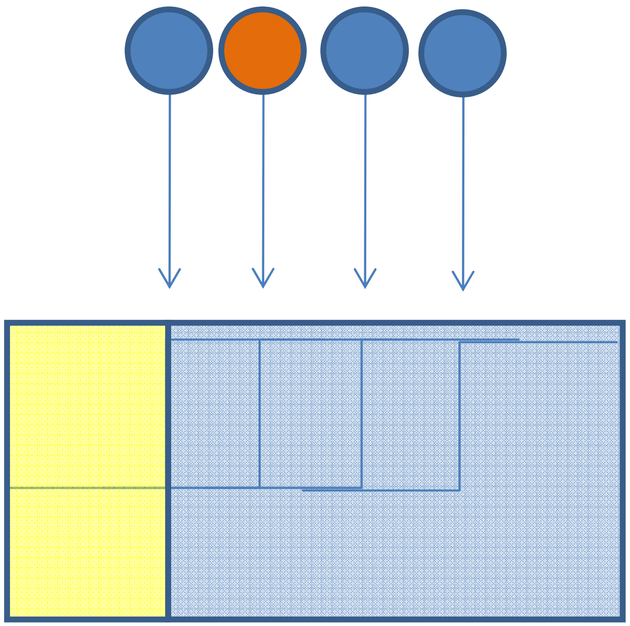
« edge detector »



Predictive fields

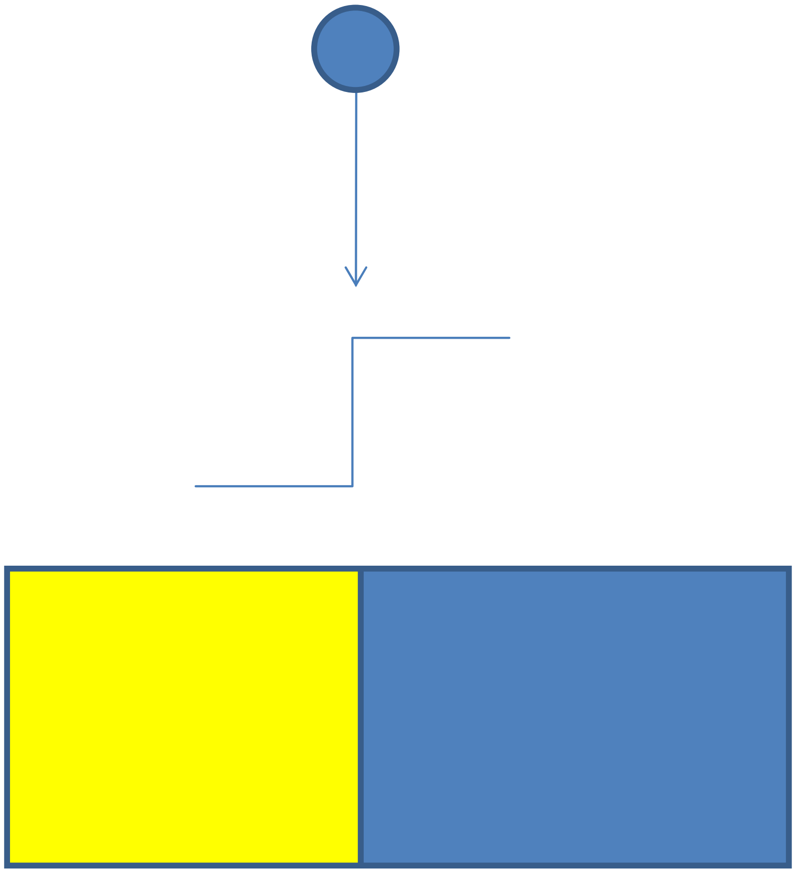
« edge predictor »

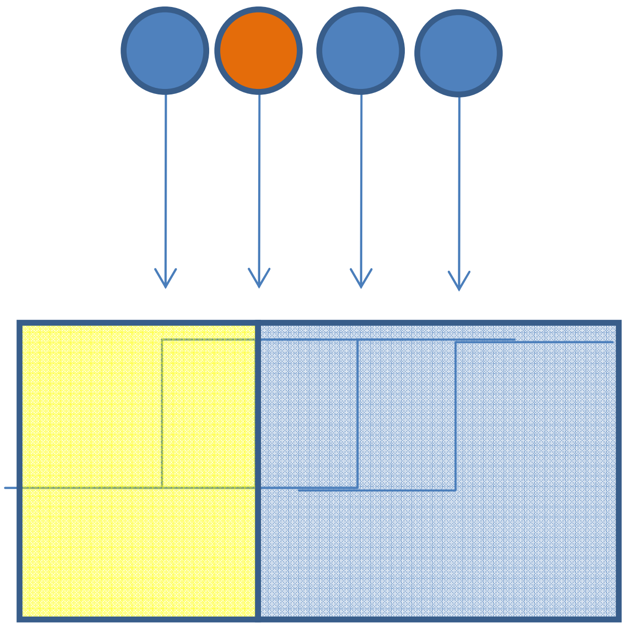




Predictive fields

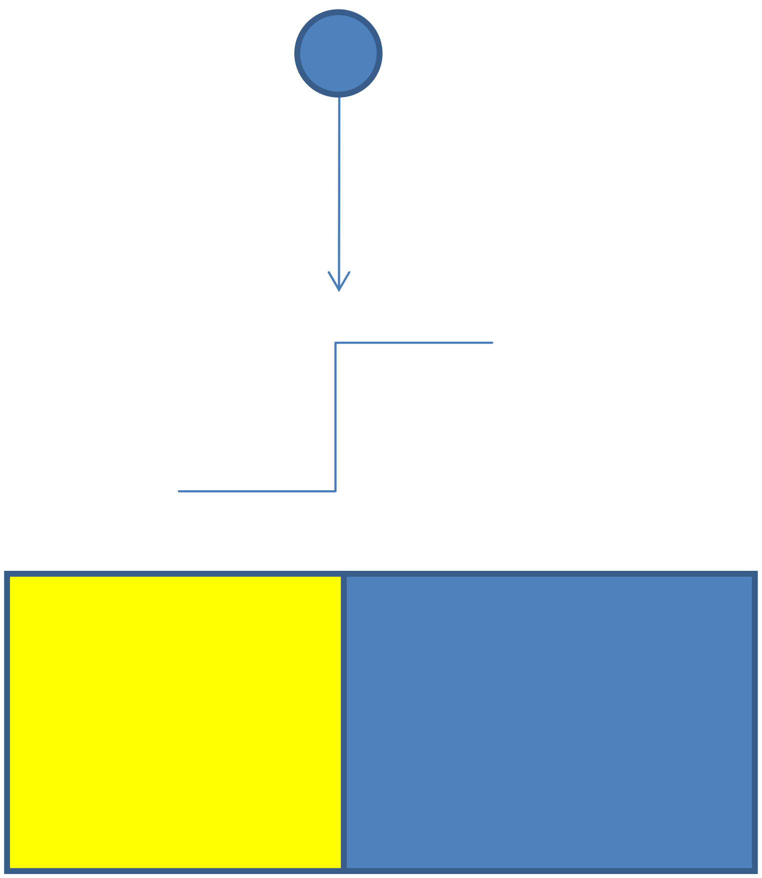
« edge predictor »

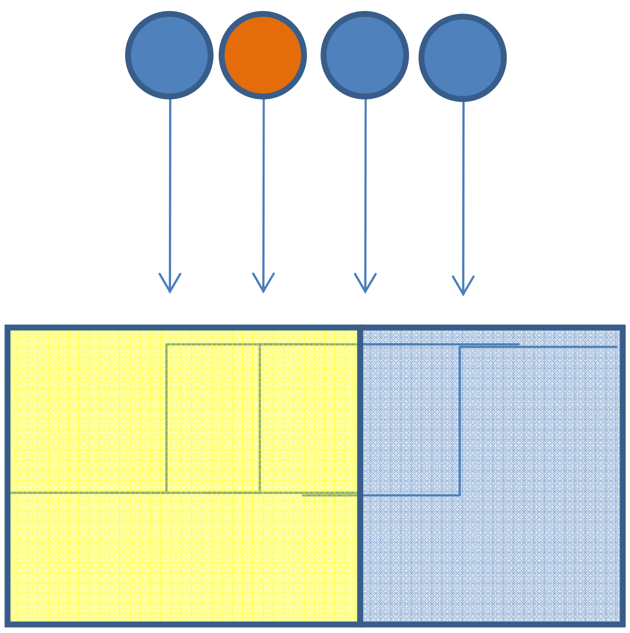




Predictive fields

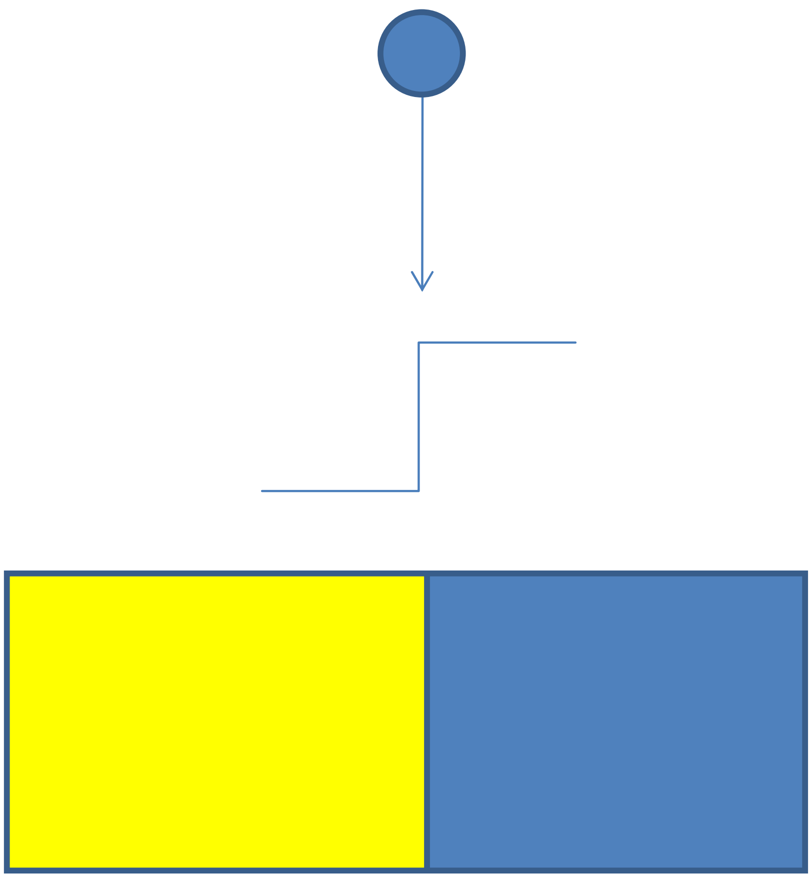
« edge predictor »

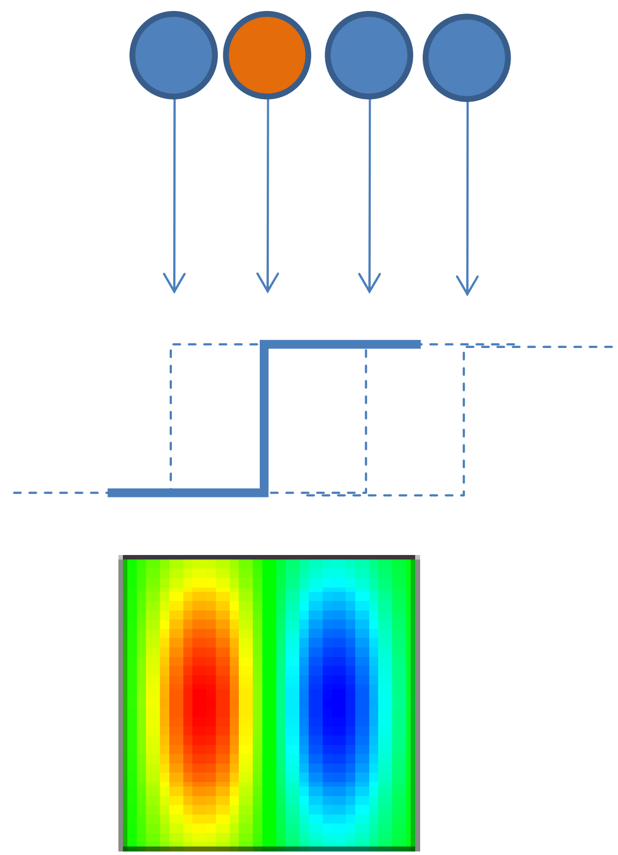




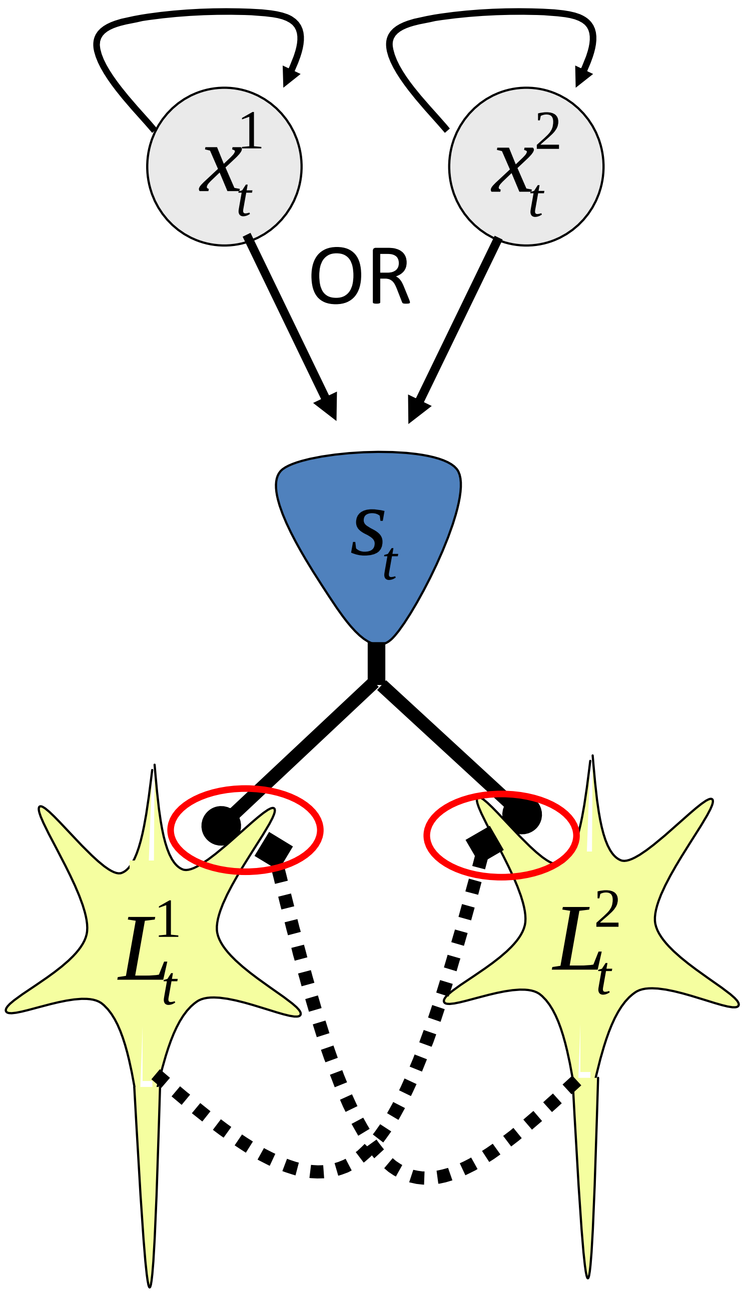
Predictive fields

« edge predictor »

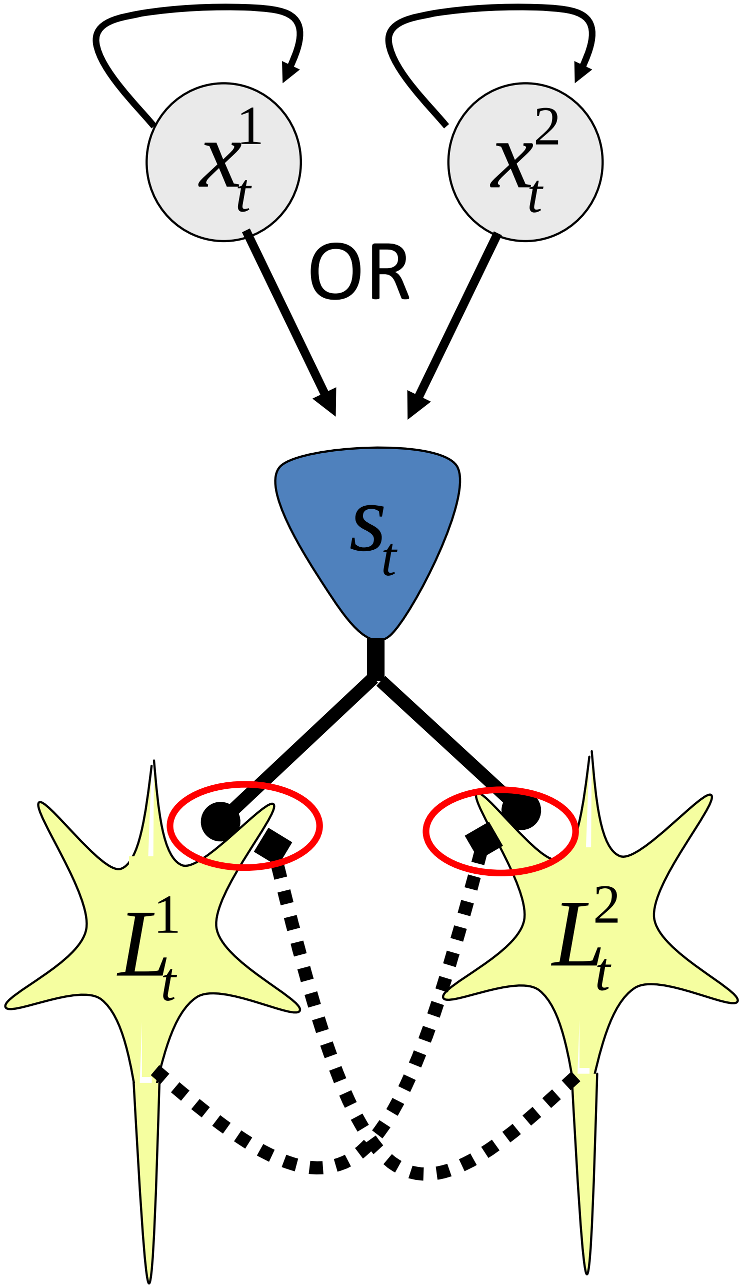


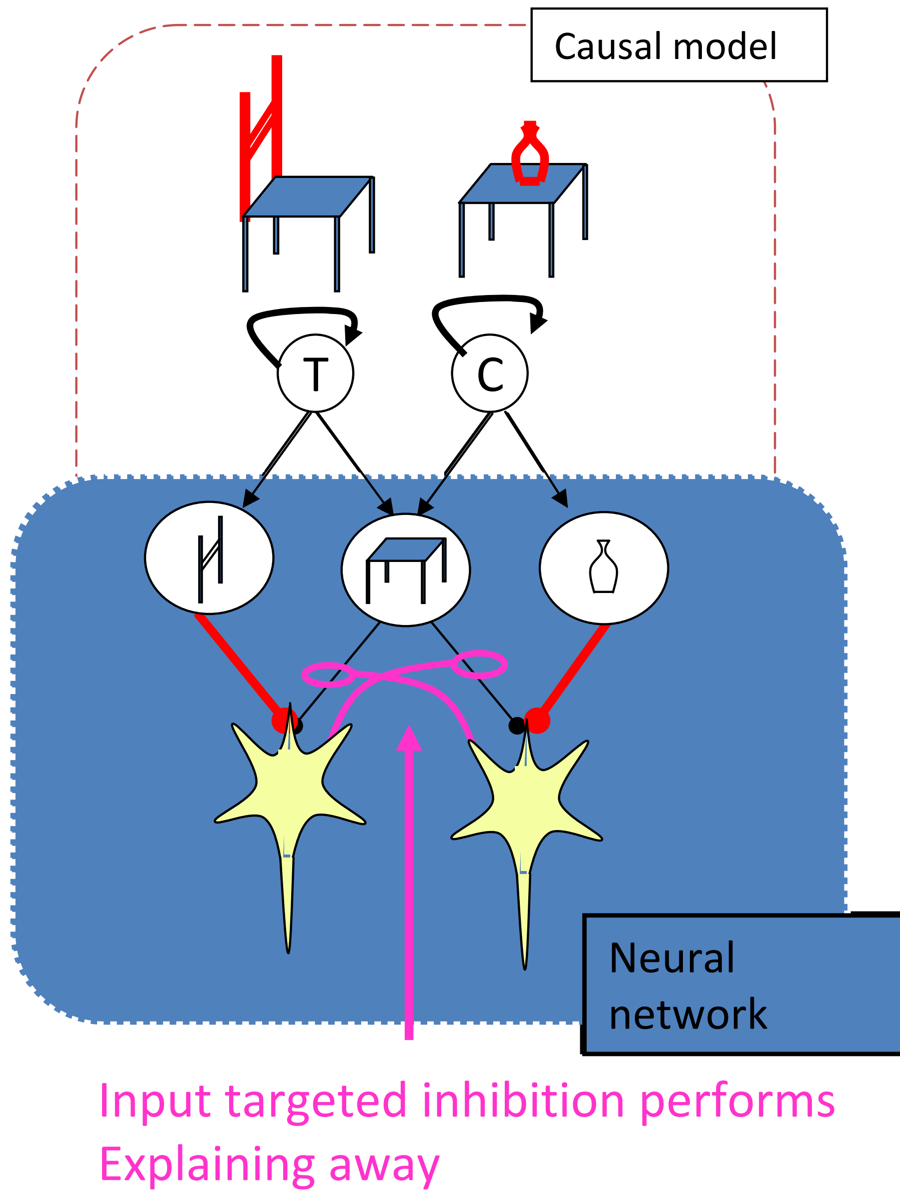


Causal inference to solve ambiguities

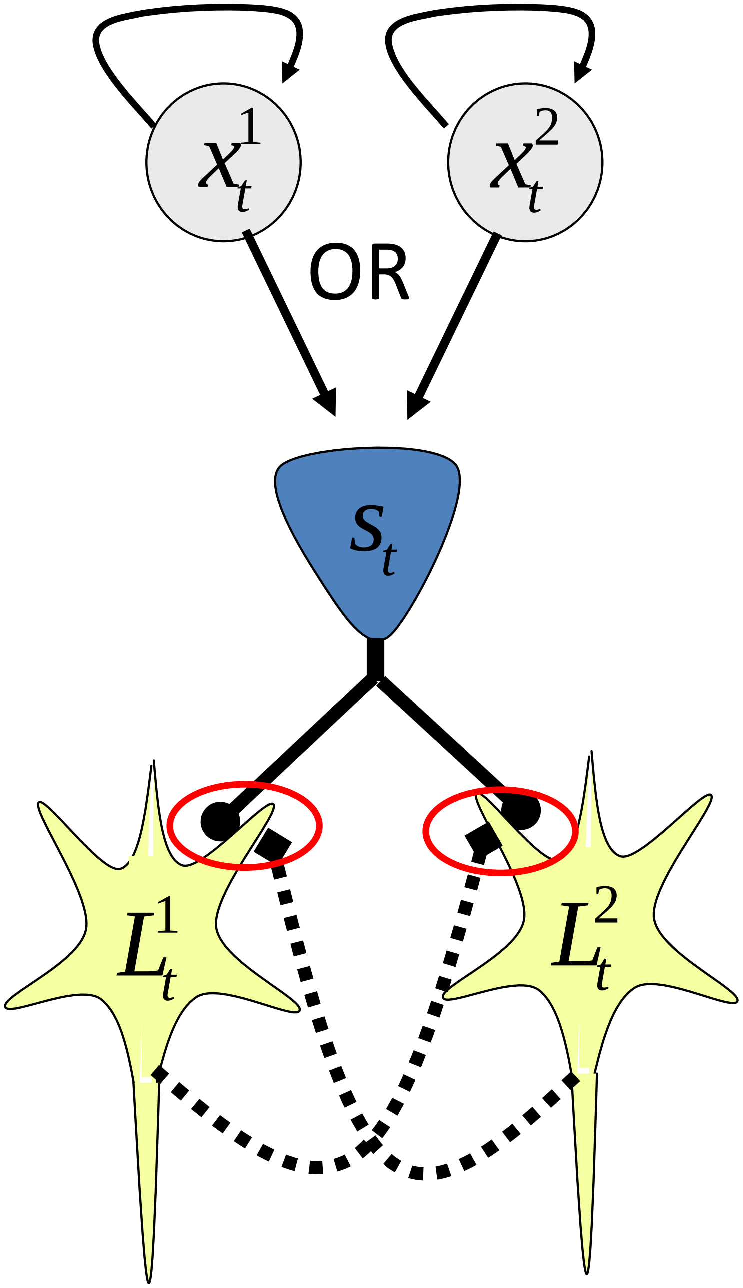


Input targeted divisive inhibition





Input targeted divisive inhibition

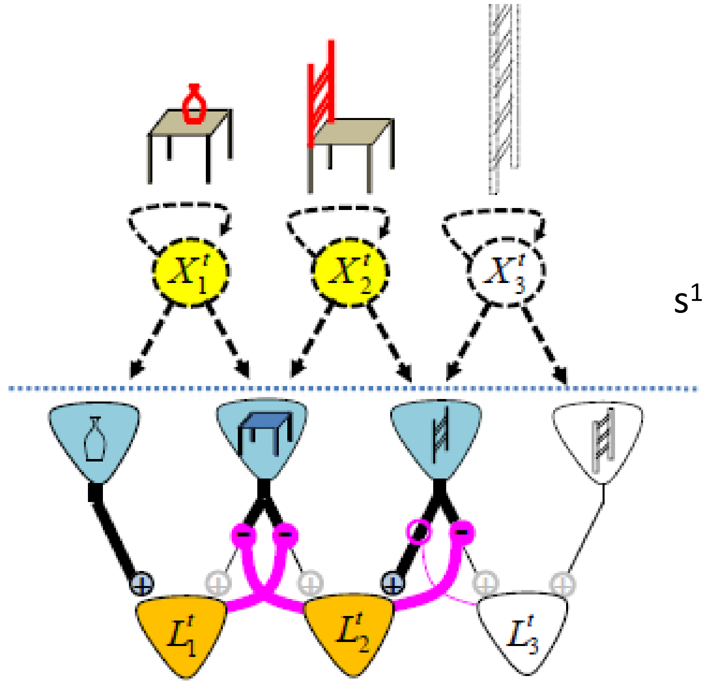


$$\frac{\partial L_j}{\partial t} = \varphi'\left(L_j\right) + \sum_i w_{ij}^t s_t^i$$

$$w_1^t = \log\left(\frac{q_o + q_1 + p\left(x_t^2 = 1 \mid \mathbf{s}\right) q_2}{q_o + p\left(x_t^2 = 1 \mid \mathbf{s}\right) q_2}\right)$$

Prediction by the context

Input targeted divisive inhibition (ITI)

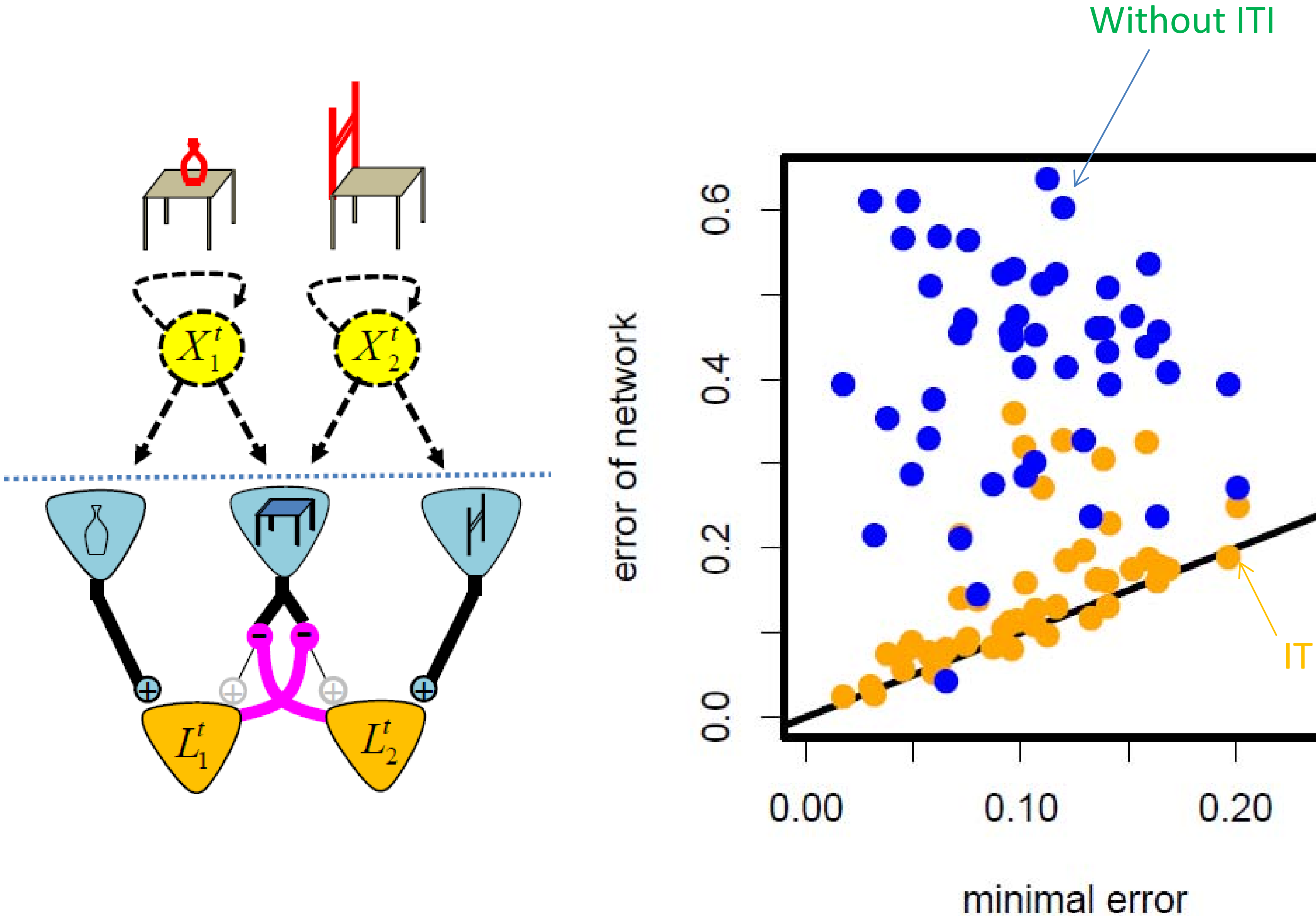


$$\frac{\partial L_j}{\partial t} = \varphi'(L_j) + \sum_i \frac{w_{ij}}{1 + \sum_{k \neq j} w_{ik} p_k(t)} s_t^i - \theta$$

Contextual prediction

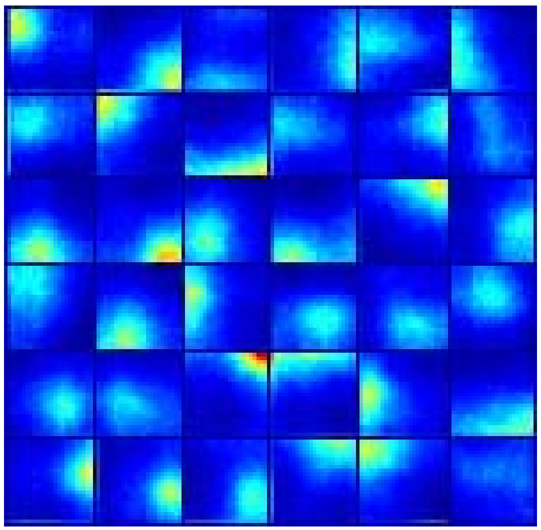
$$p_k(t) = \frac{e^{L_k}}{1 + e^{L_k}}$$

Importance of ITI for object detection



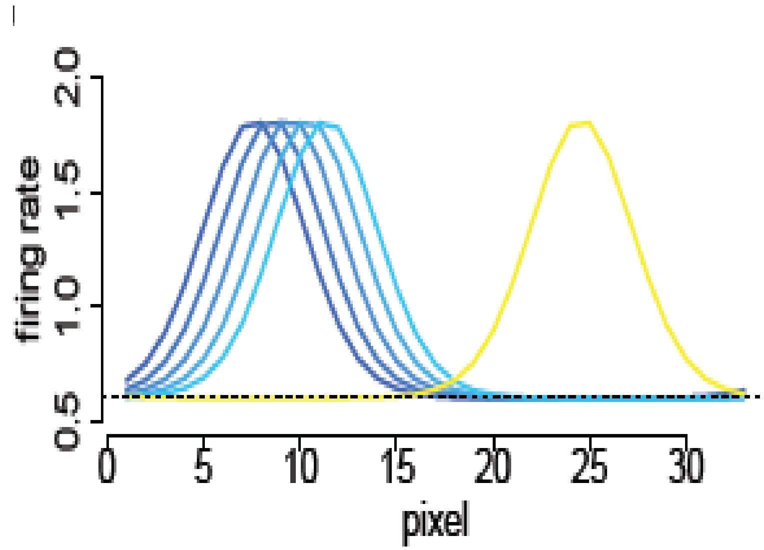
Implication for sensory receptive fields

Causal fields leant from natural movies

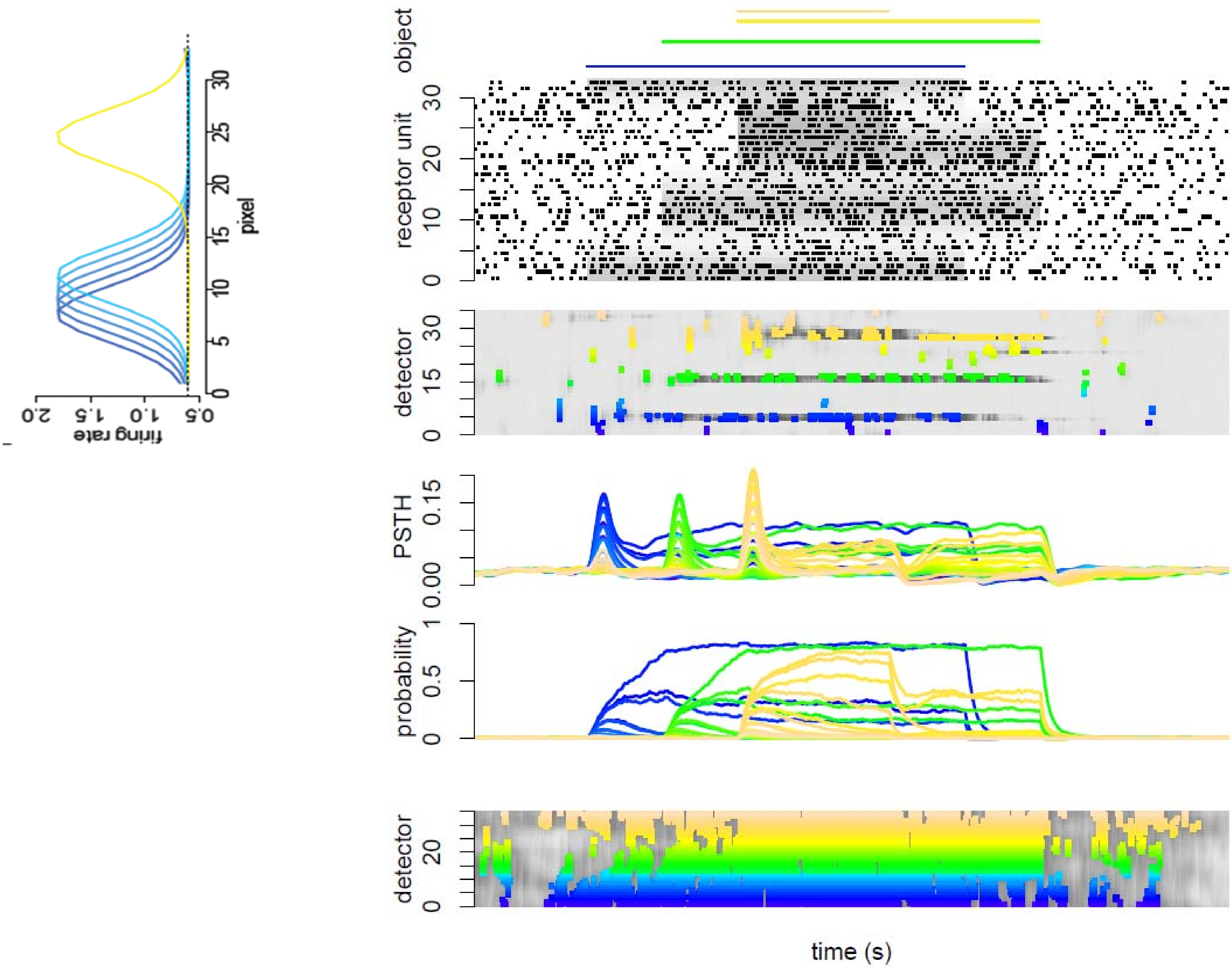


"Blobs"

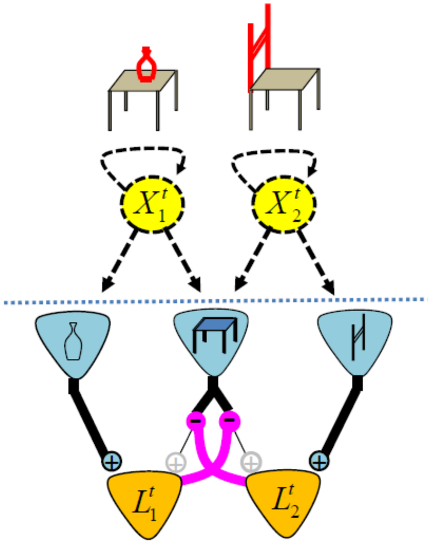
Model causal fields

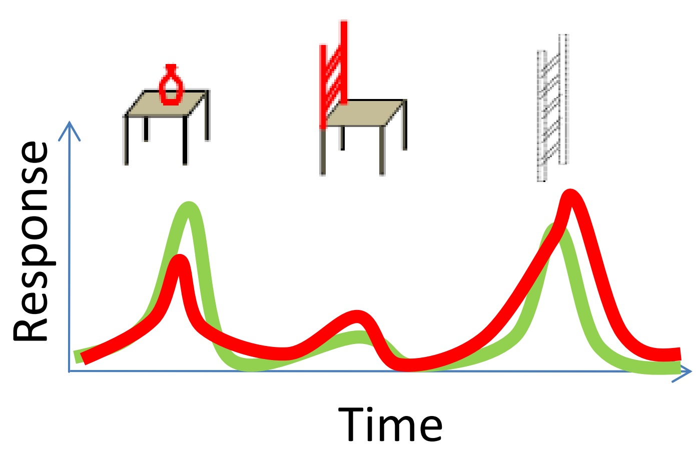


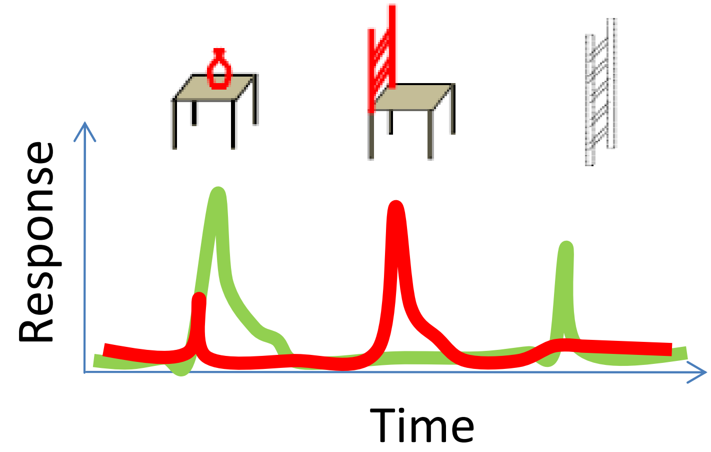
Response to natural scenes

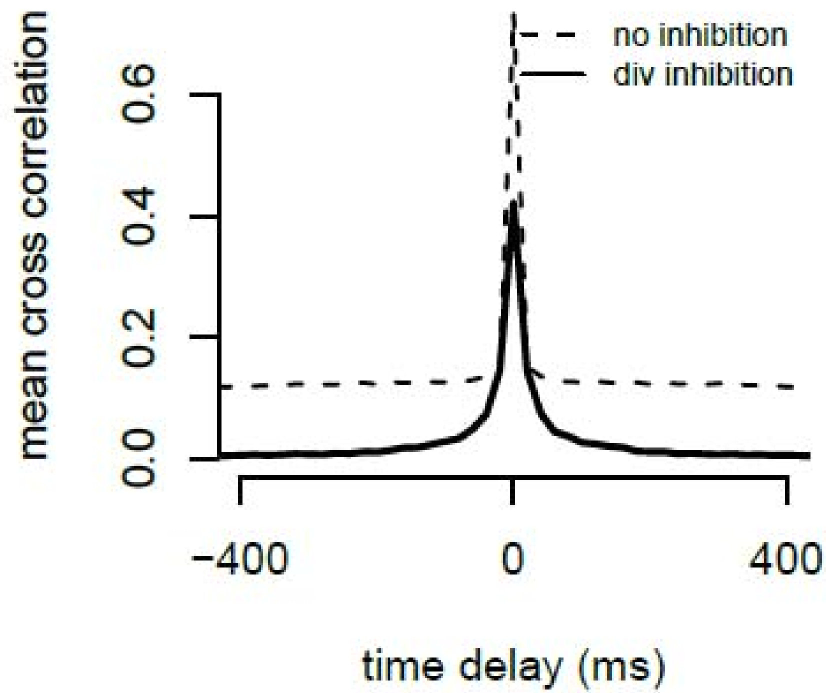


Decorrelation of natural scenes

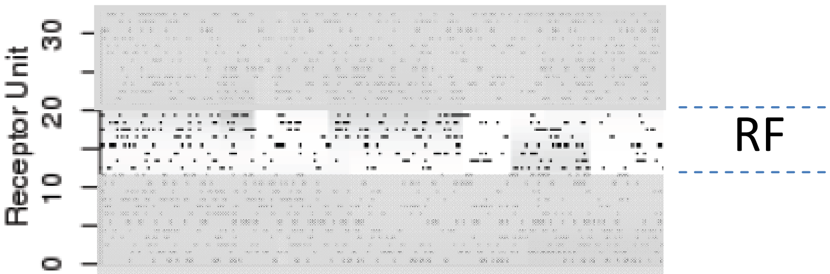


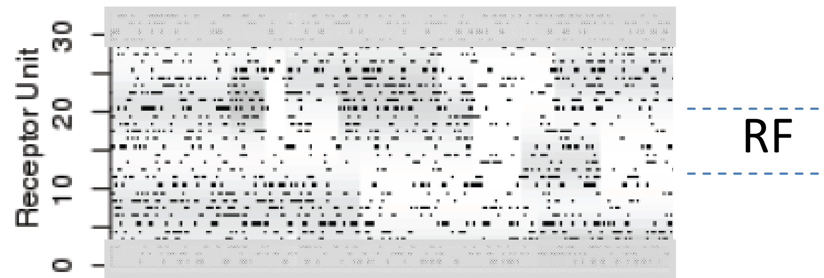


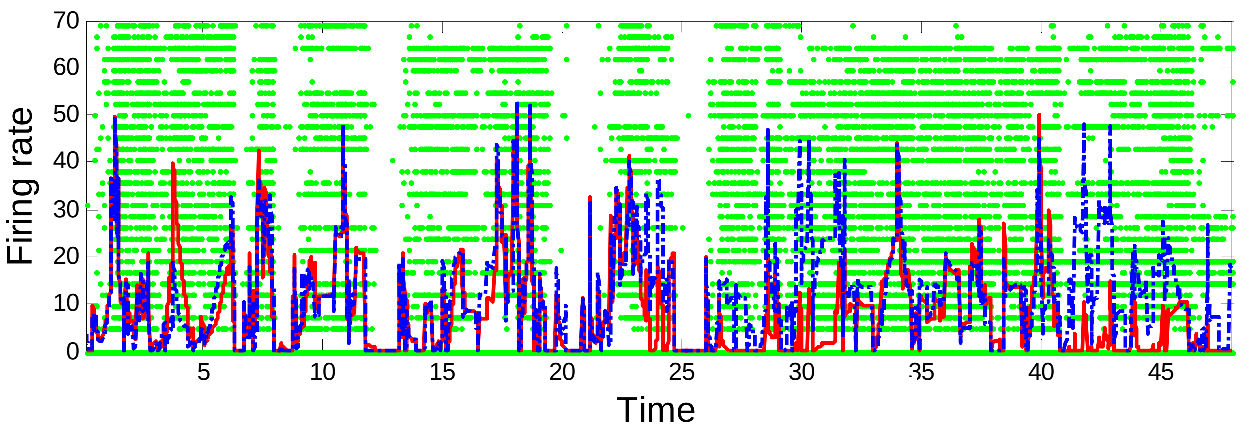


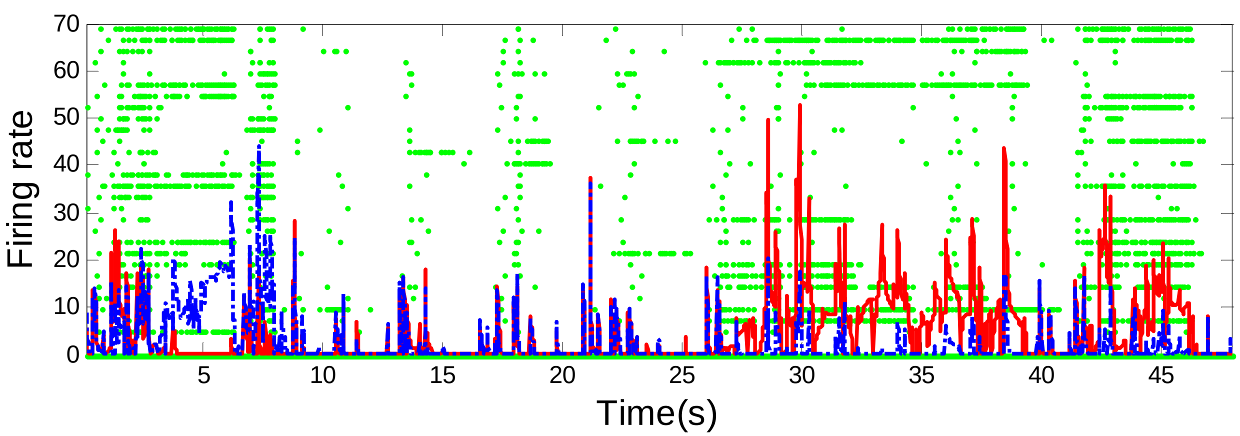


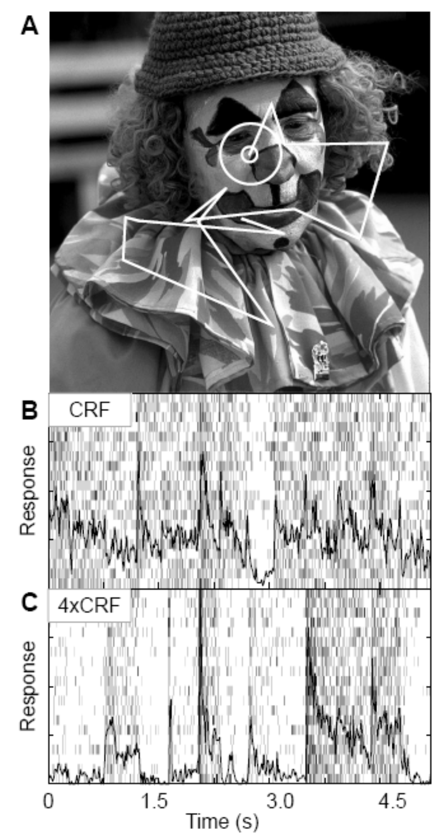
Selectivity relies on context from the entire scene







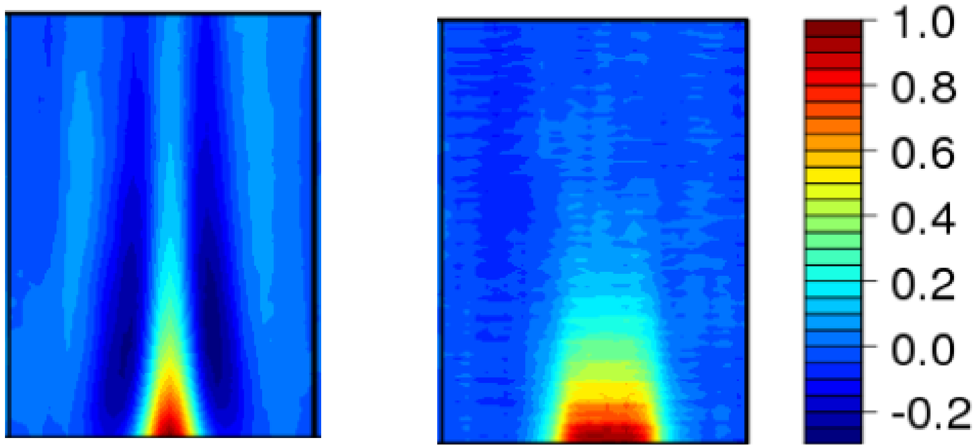


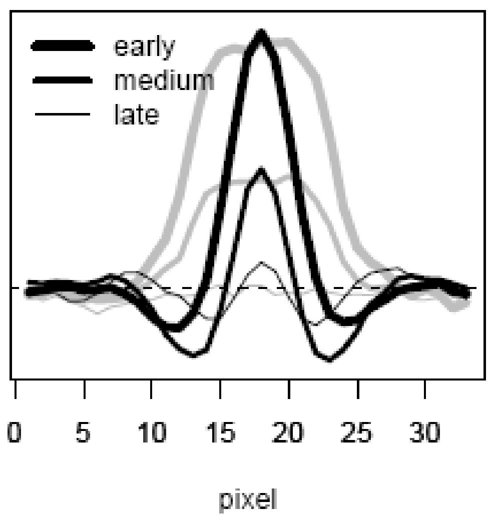


Coarse-to-fine changes in RF over time

With divisive inhibition

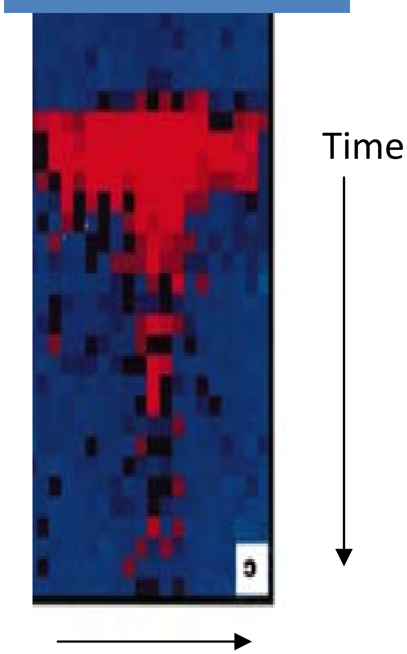
Without divisive inhibition



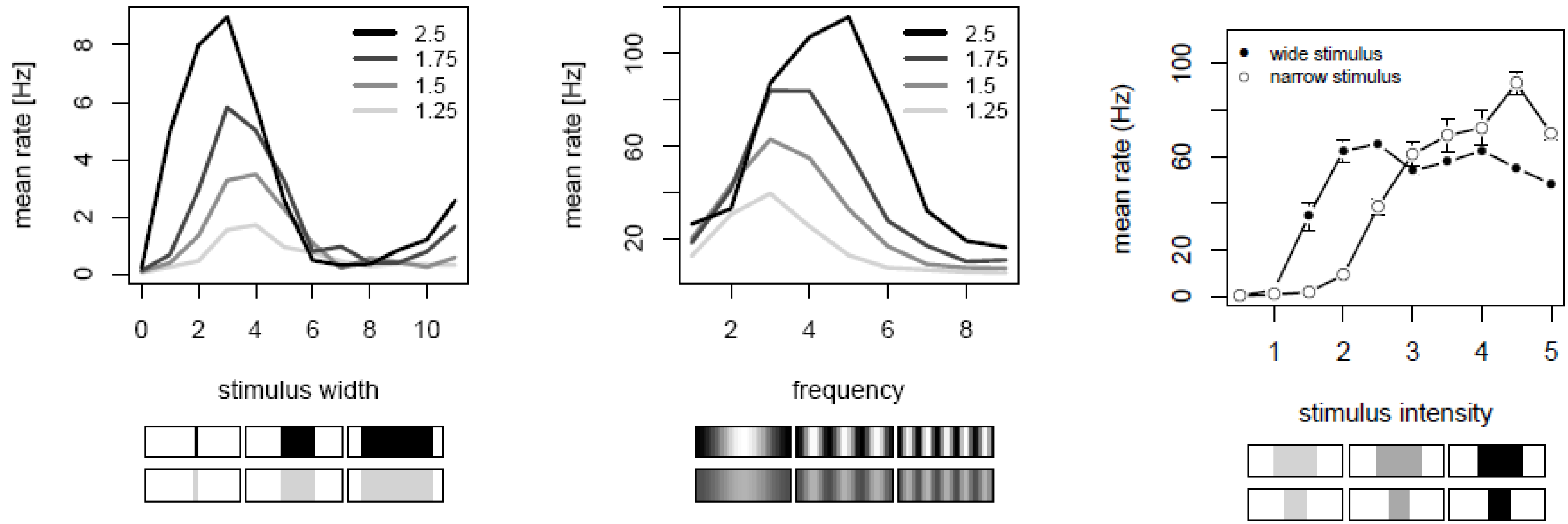


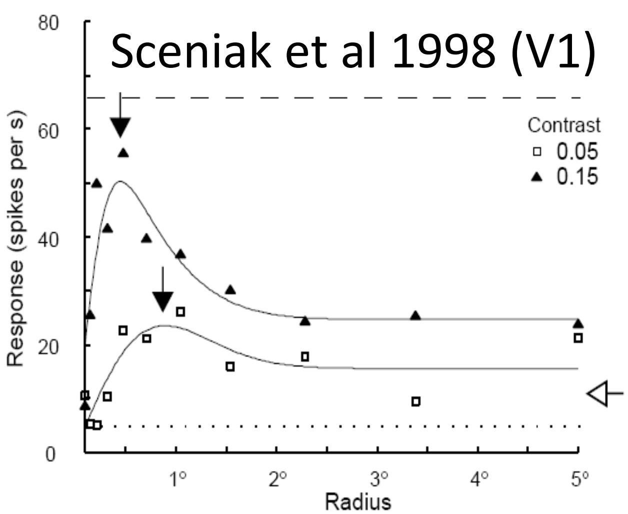
Ringach and Malone, 2006

Woergoetter et al 1998

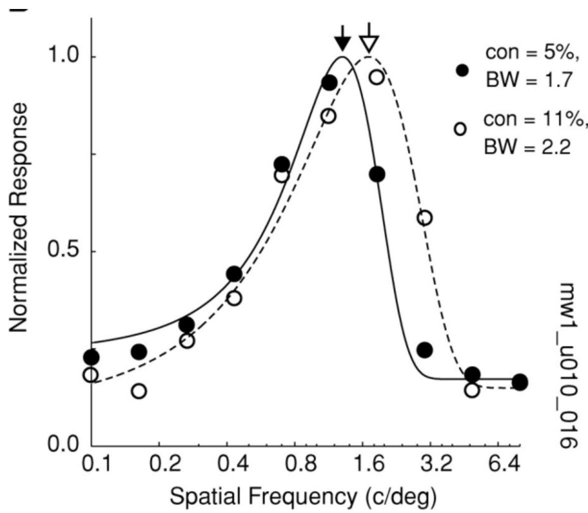


Coarse to fine changes as a function of input reliability

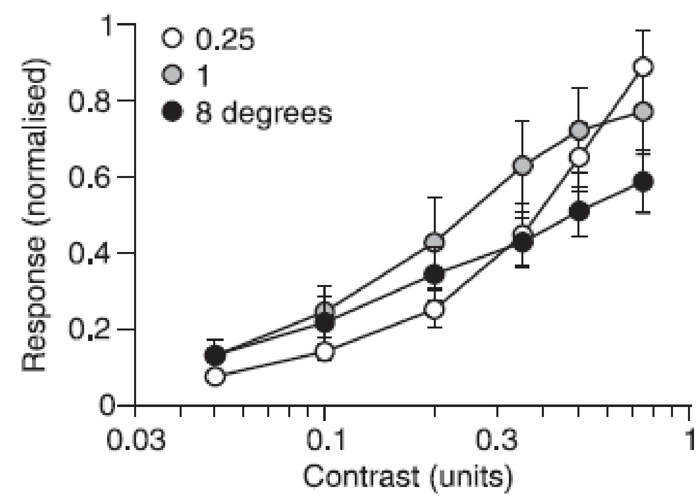




Sceniak et al 2001 (V1)

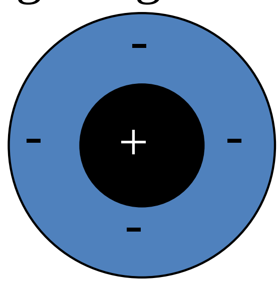


Salomon et al 2006 (M-type RGC)



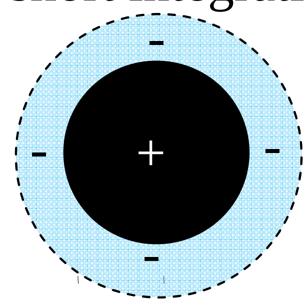
Coarse to fine changes as a function of input reliability

High contrast,
long integration



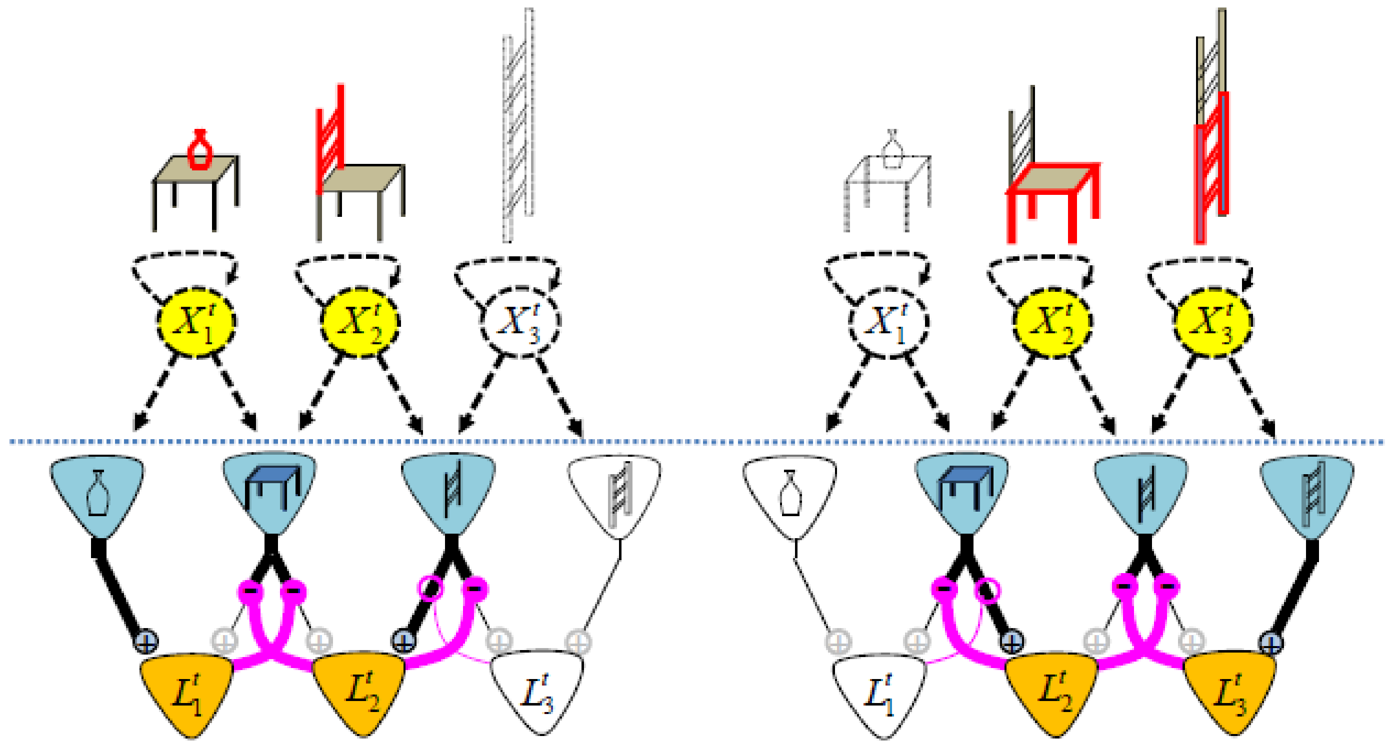
Discrimination

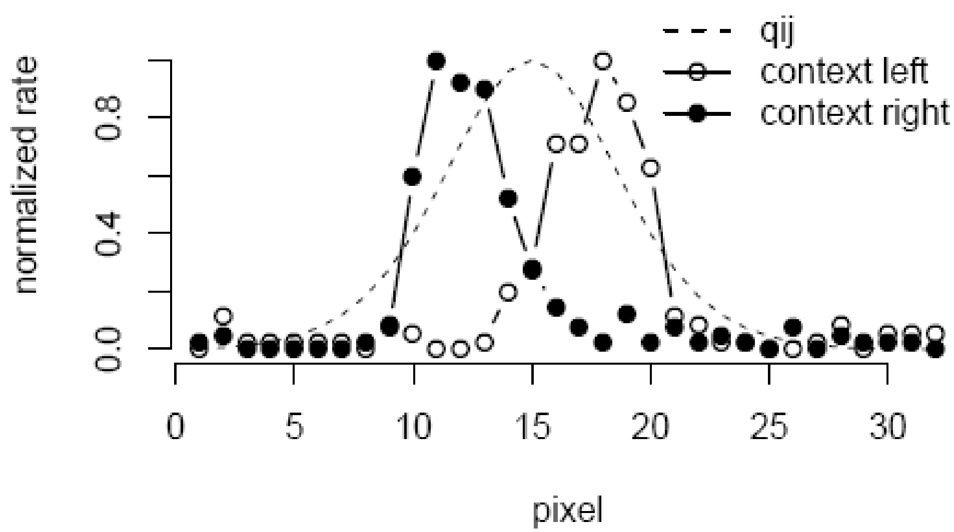
low contrast,
short integration



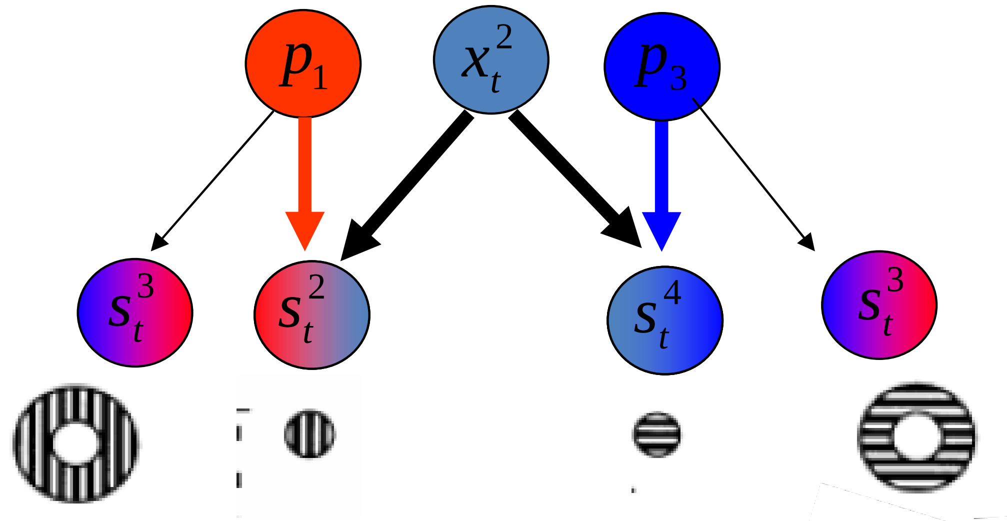
Detection

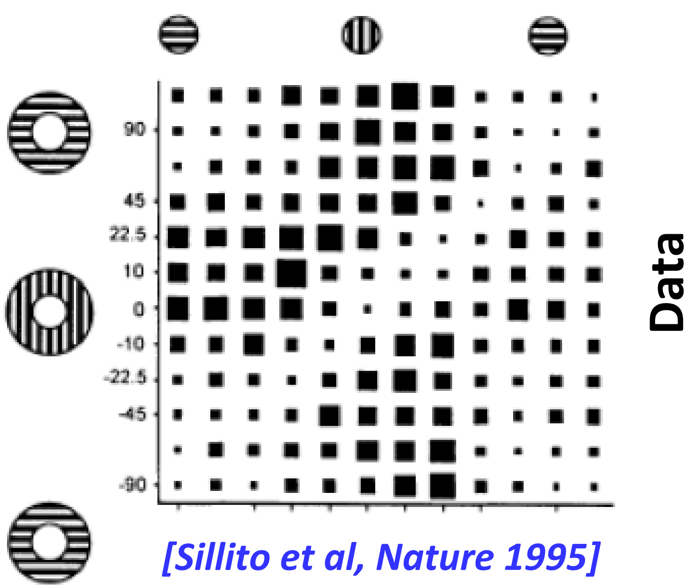
The surround reshapes the receptive field



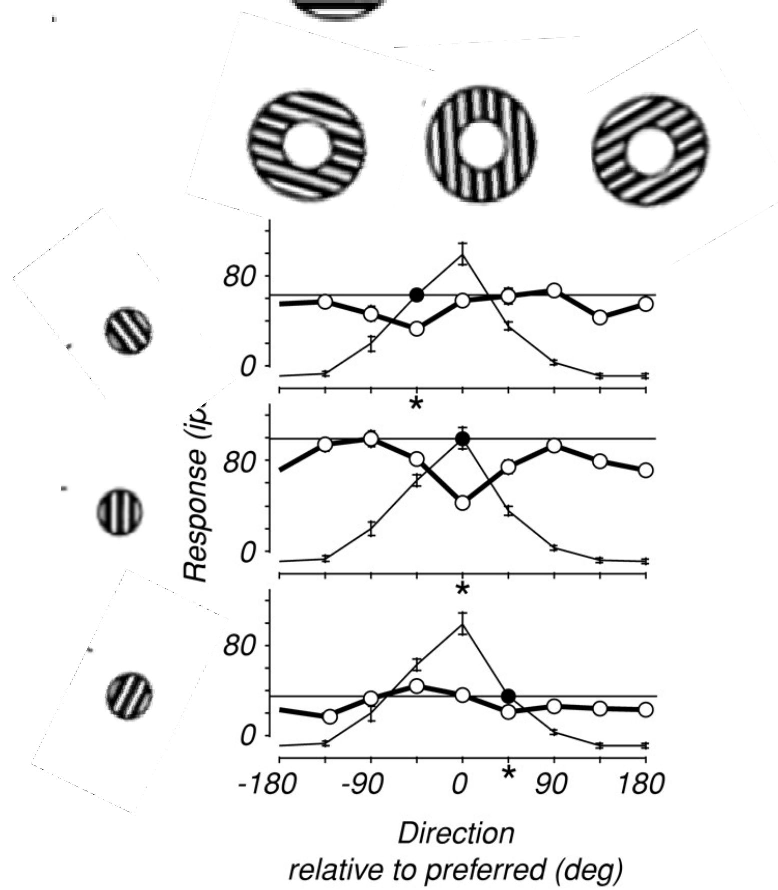


Effect of spatial surround: Saliency

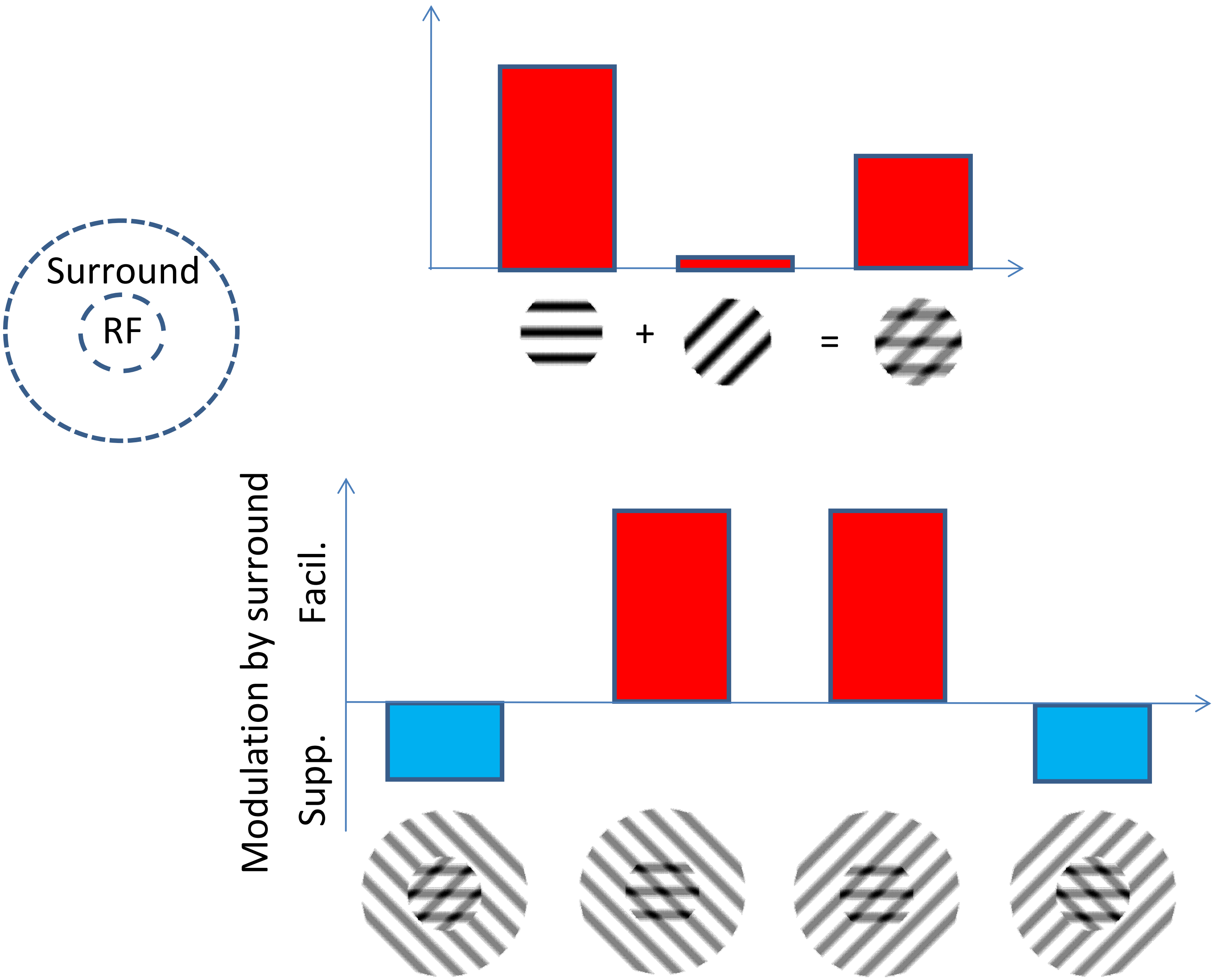




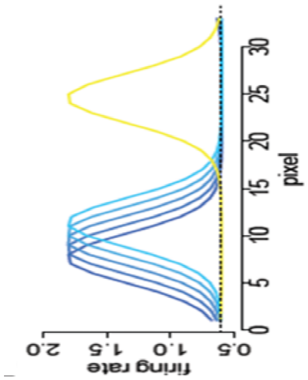
[Sillito et al, Nature 1995]

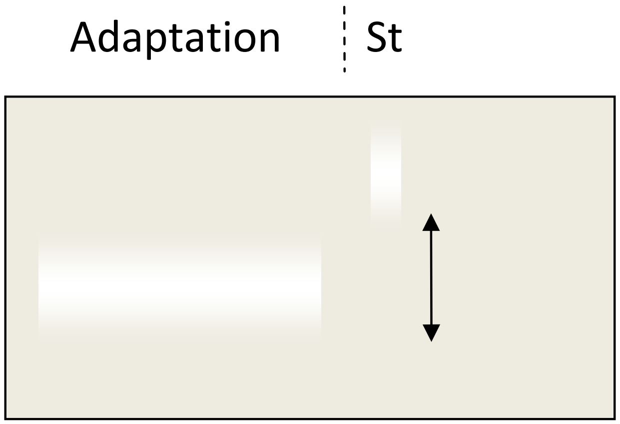


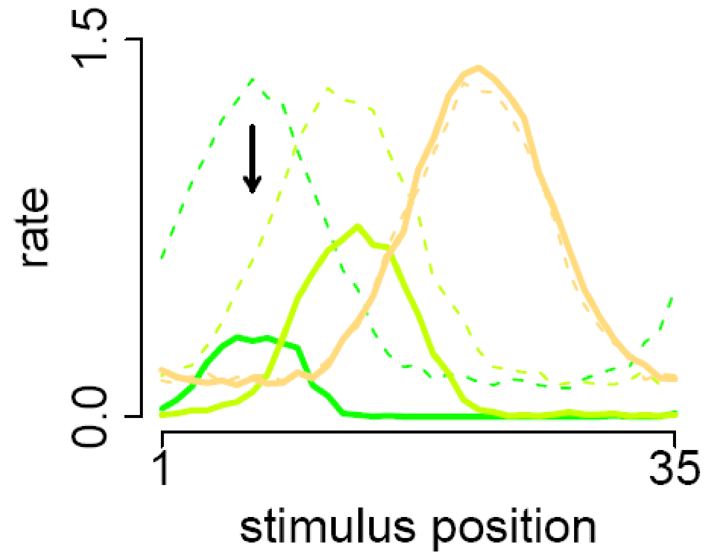
Non-separable center and surround

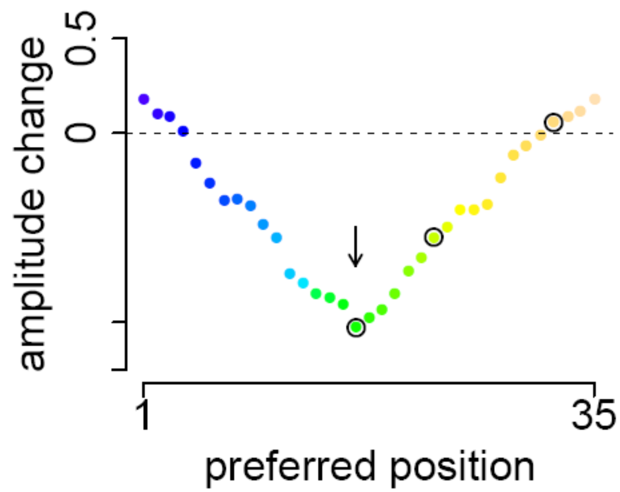


Effect of temporal surround: Adaptation

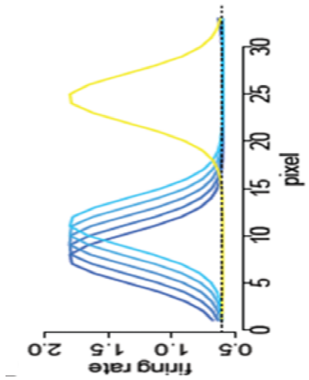


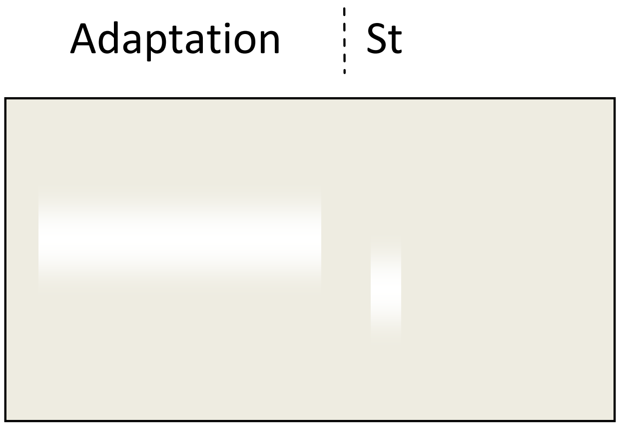


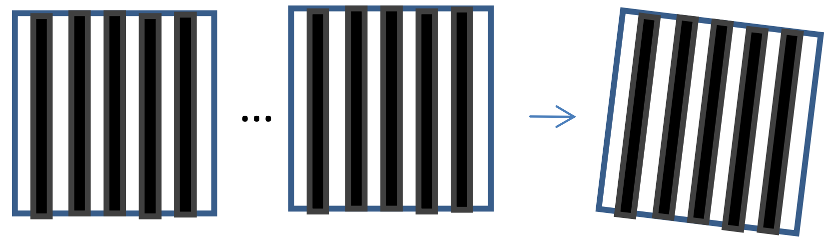




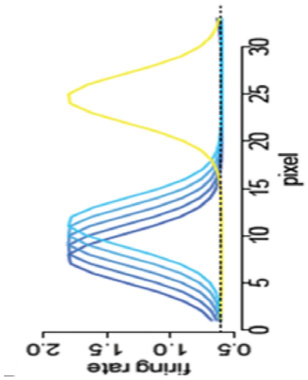
Effect of temporal surround: Perceptual bias away from adapted position

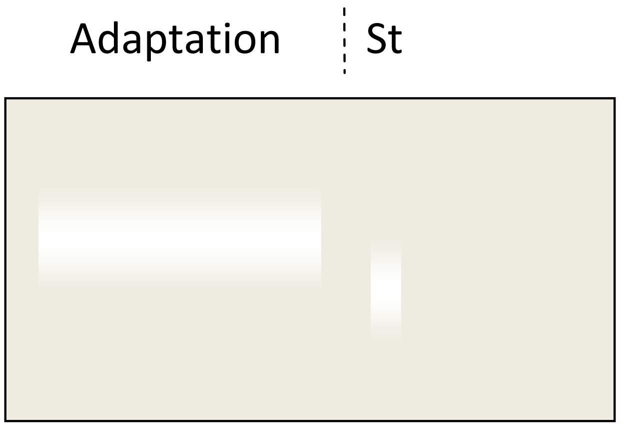


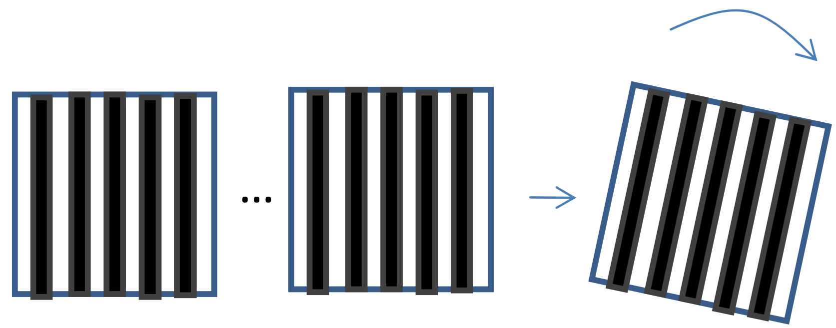


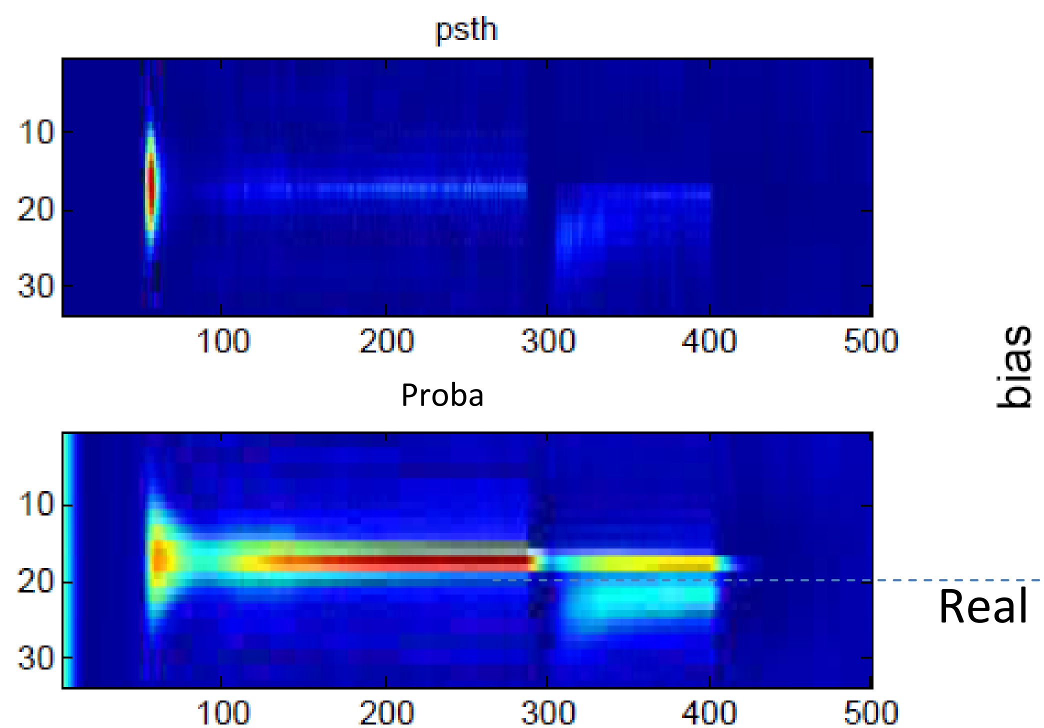


Effect of temporal surround: Perceptual bias away from adapted position

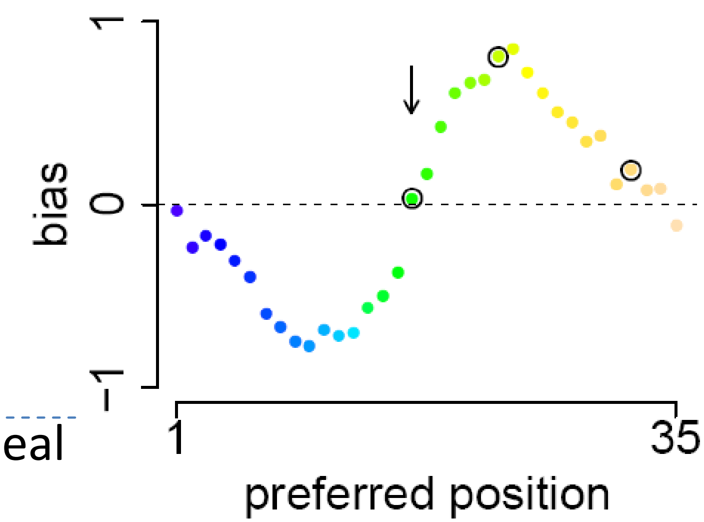




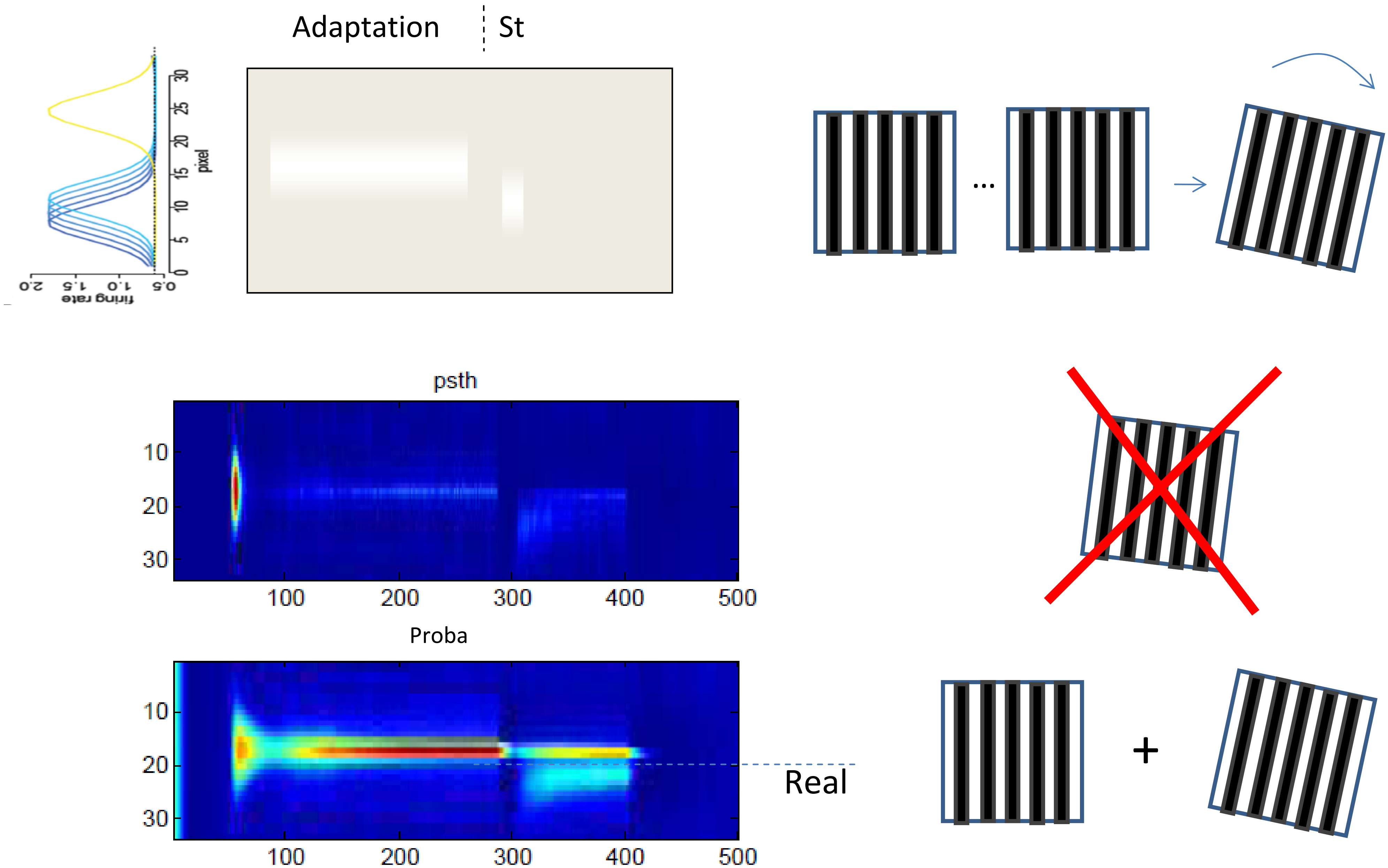




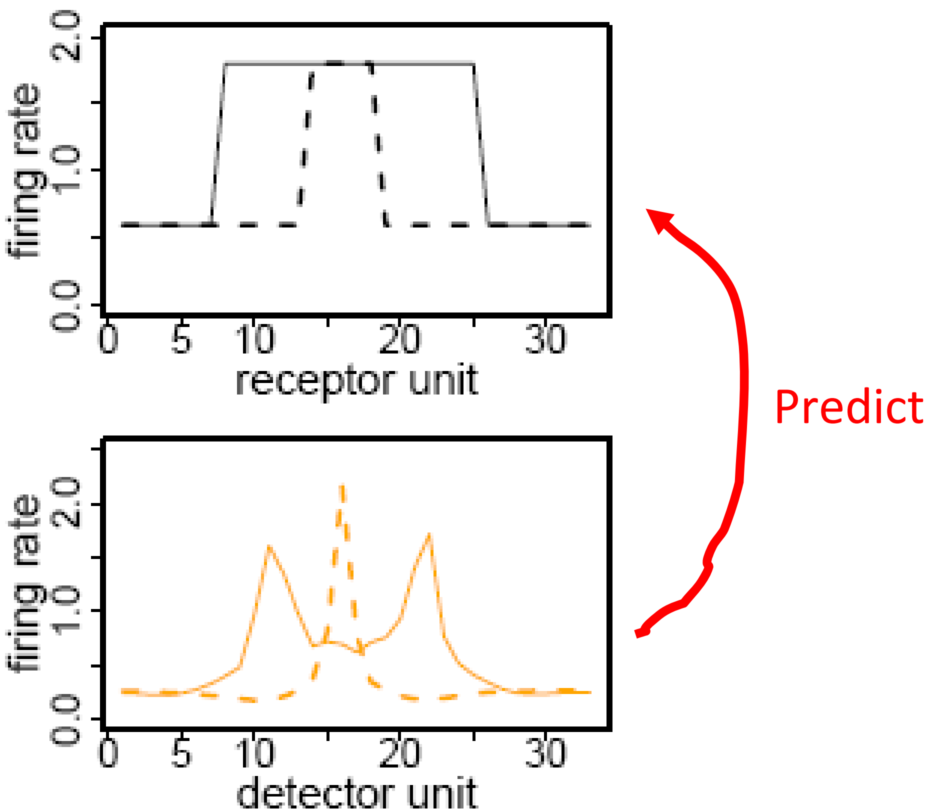
Repulsion in perceived position

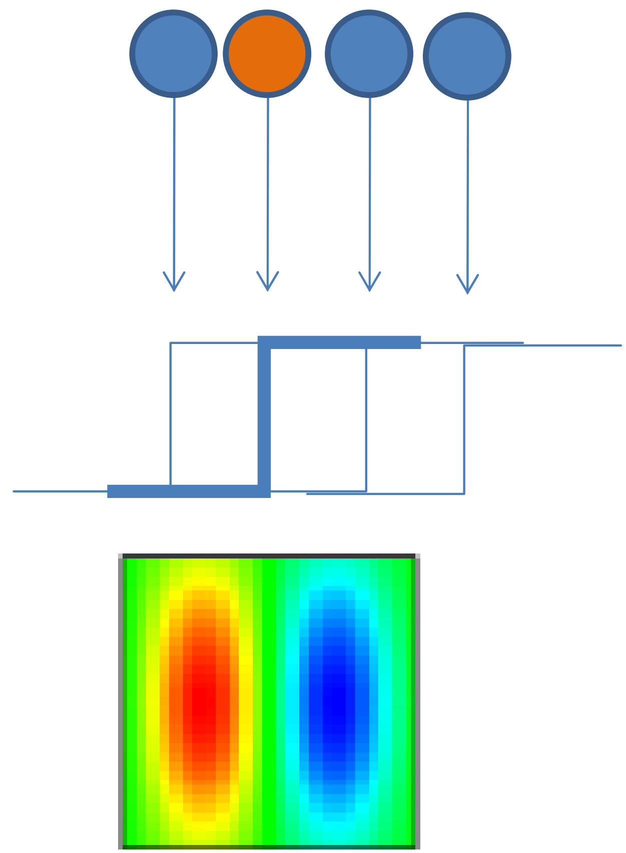


Effect of temporal surround: Perceptual bias away from adapted position



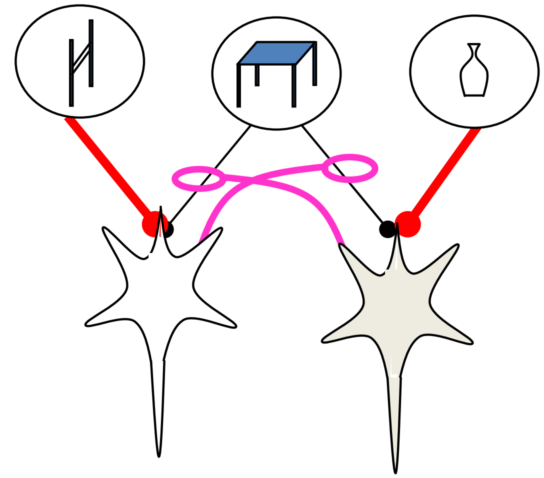
Sensory neurons do not represent local contrast or salience or novelty



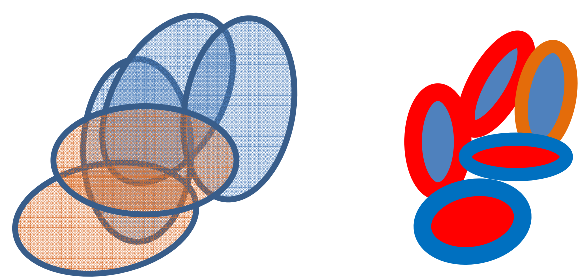


Predictive fields are invariant

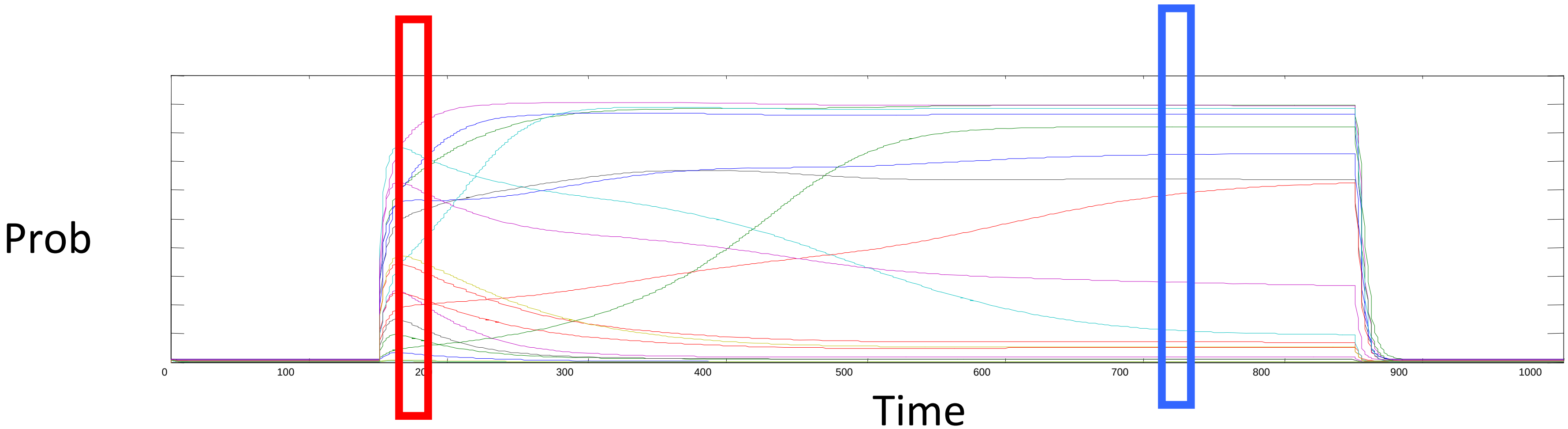
Désirée Palmen / *Zebra* / C-print / 2002 / 30 x 59 inches

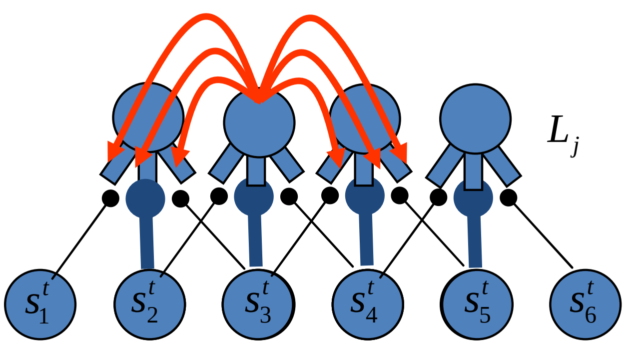


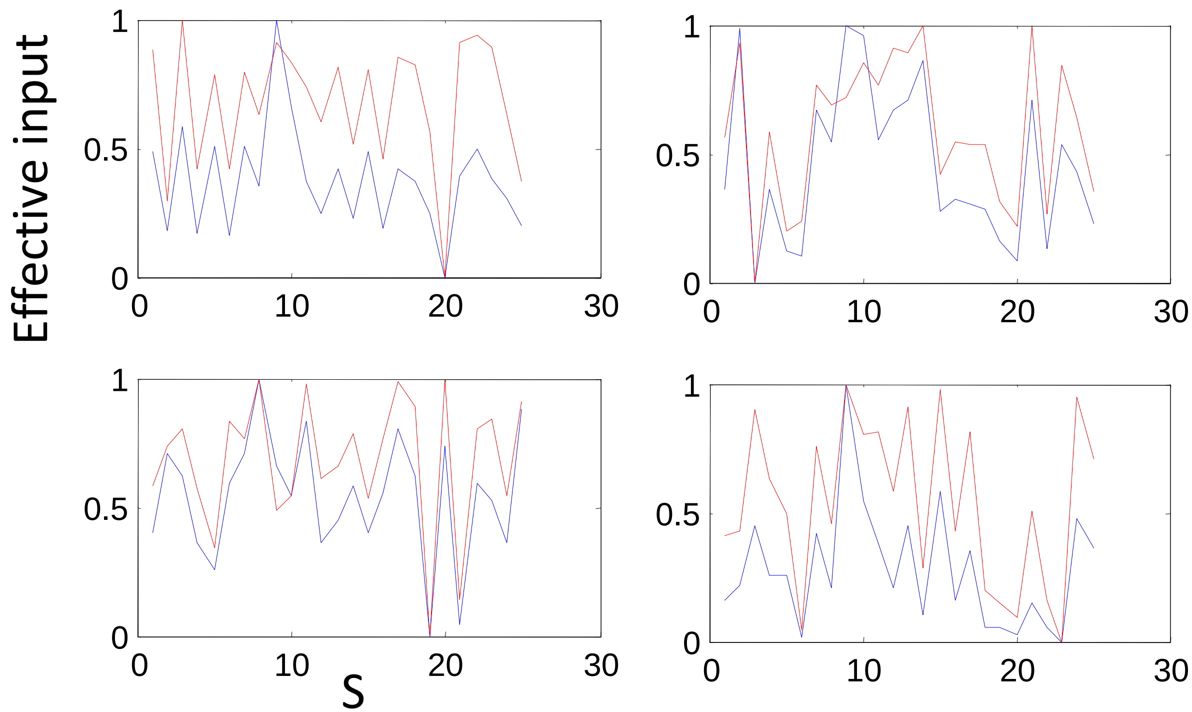
Receptive fields are defined by the context



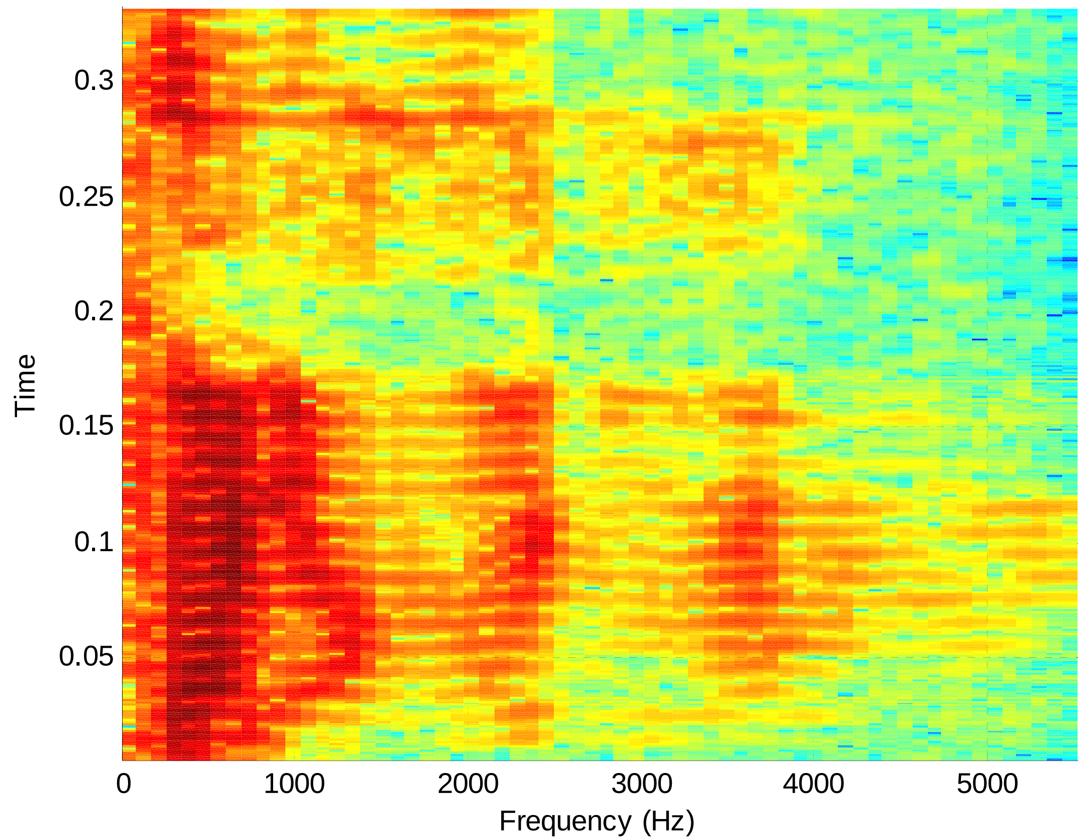
Dynamic reshaping of receptive fields





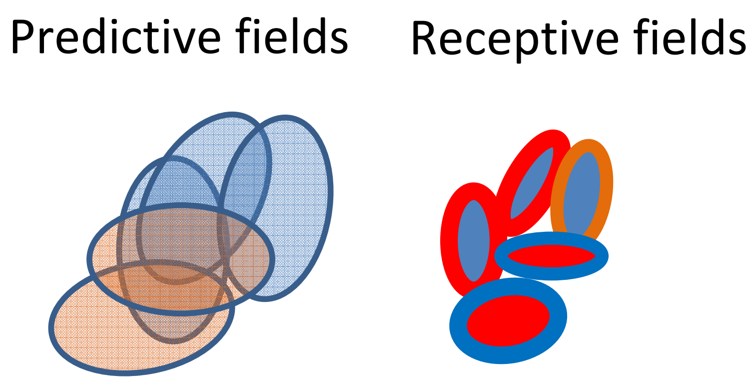


With high degrees of overlap, receptive fields are meaningless



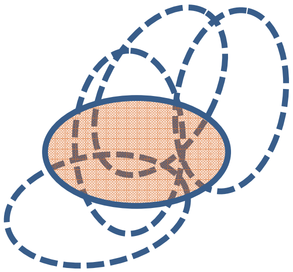
« Welcome »

How can we measure predictive fields?

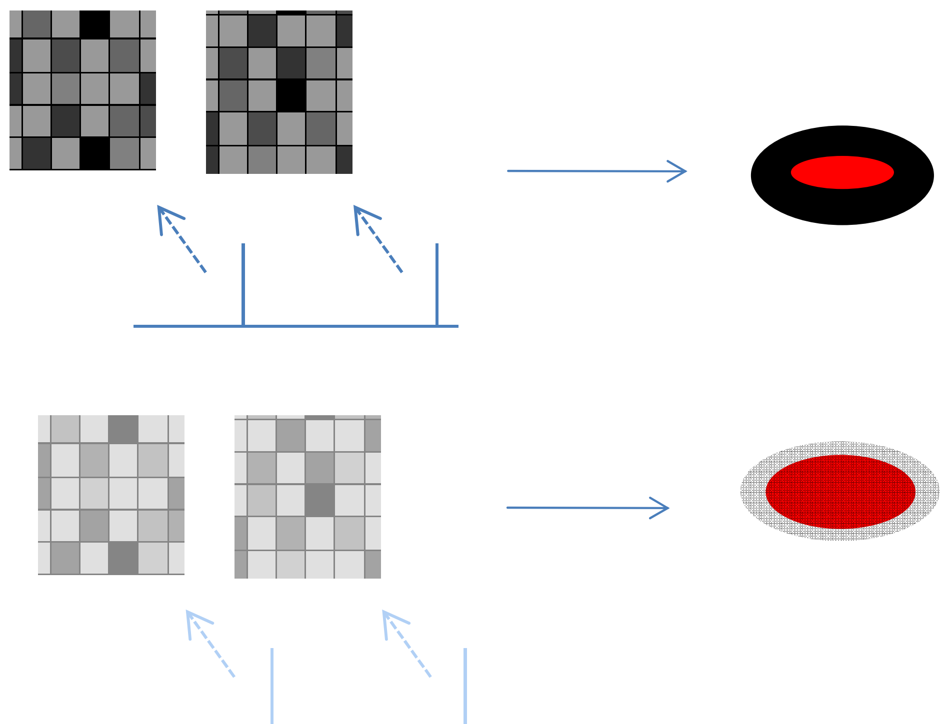


- Low Contrast, subthreshold, short stimuli rather than optimal, high contrast stimuli.
- Measuring subthreshold currents (Patch clamp)
- Selectivity of sustained responses.
- Fit multi-electrode recordings.

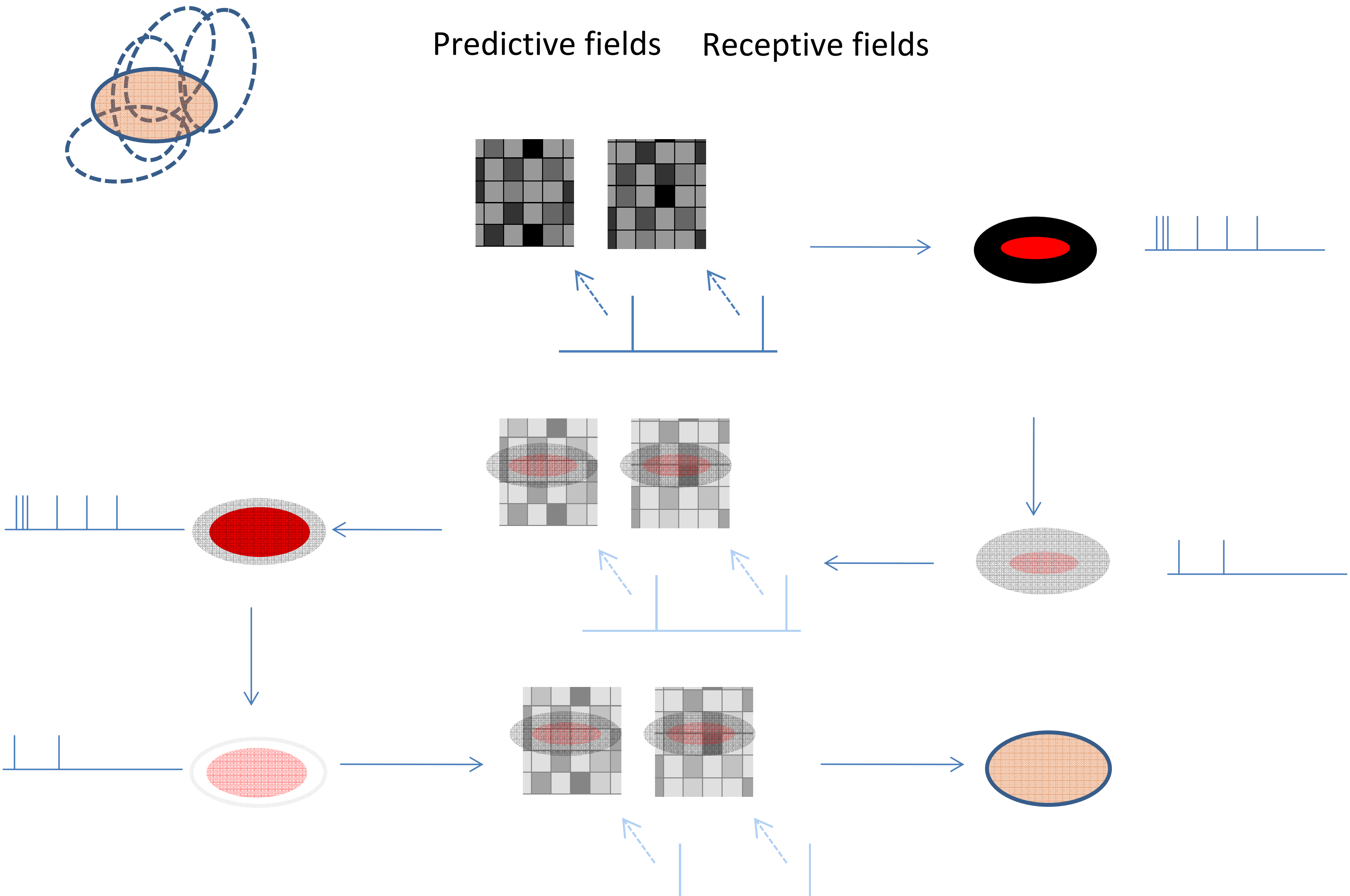
Using low contrast stimuli



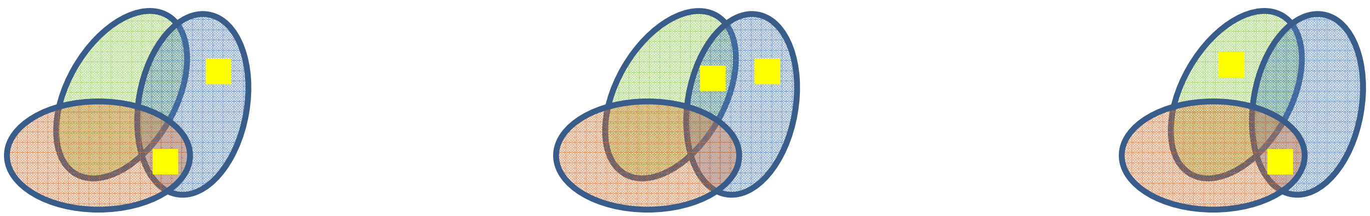
Predictive fields Receptive fields



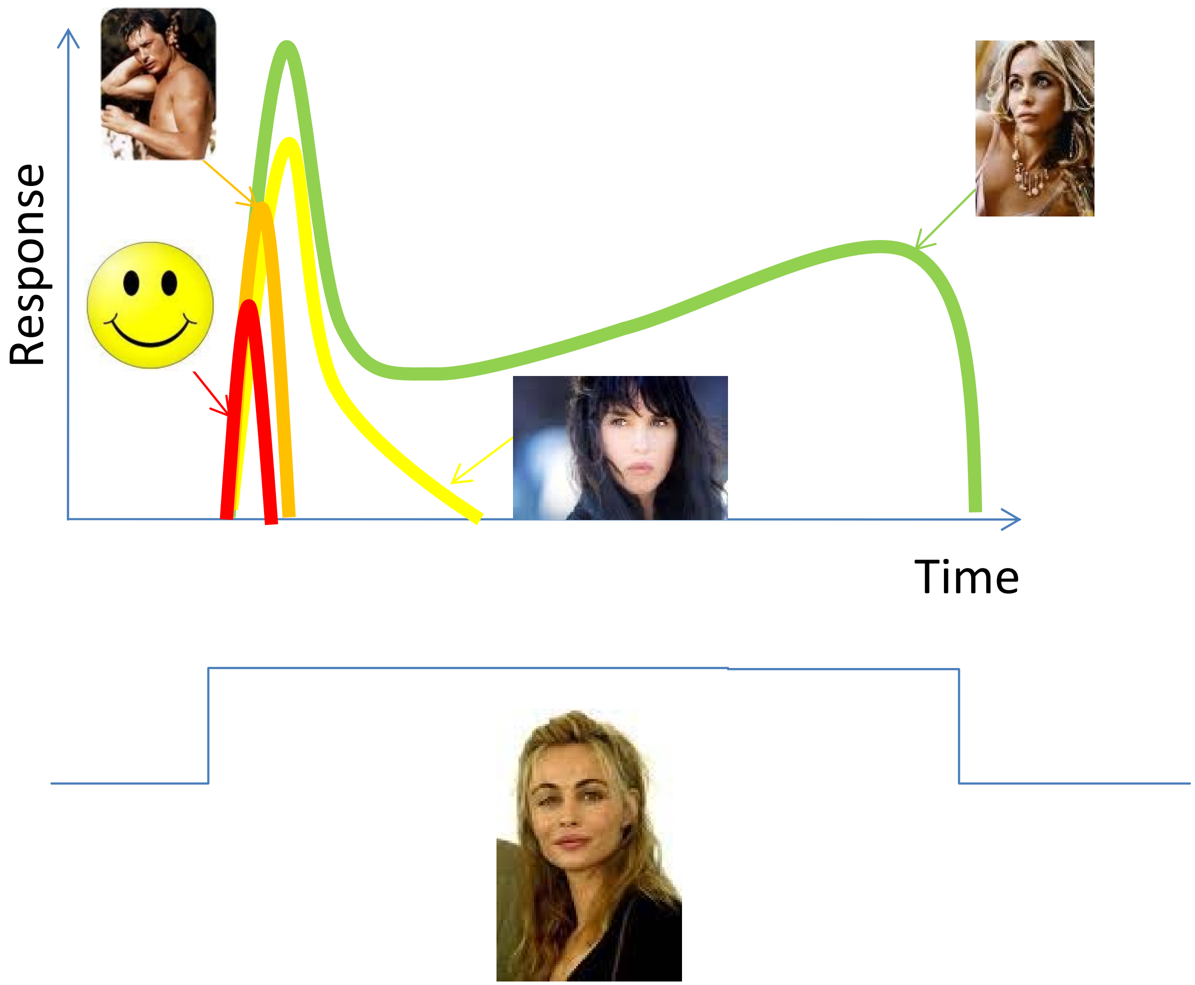
Recursive method for measuring predictive fields



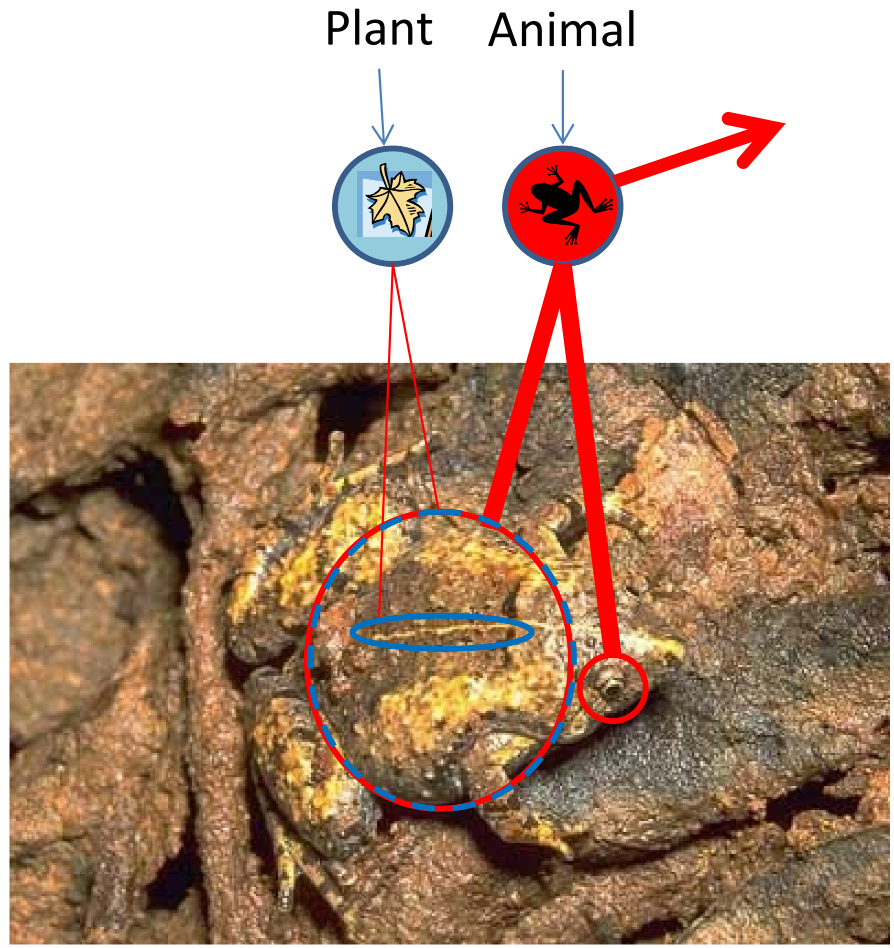
Multi-electrode recordings

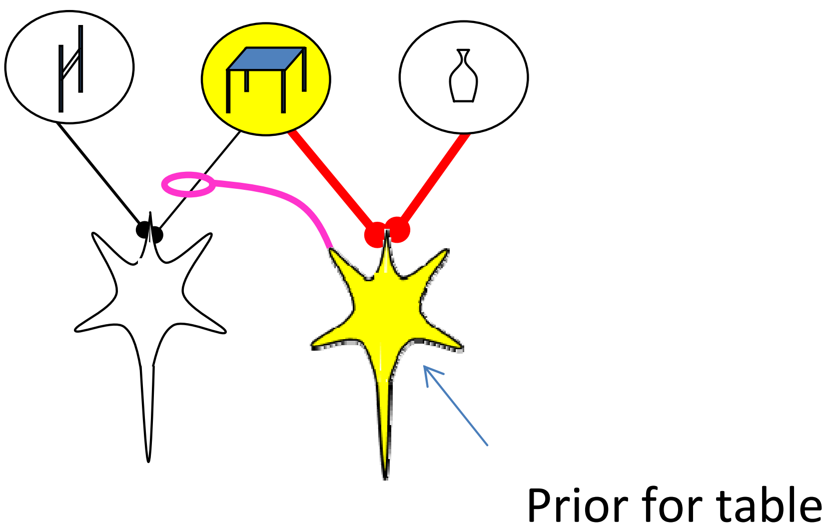


Sustained responses as signature of true selectivity



Expectations redirect sensory flows





Conclusion 2: Normative approach to neurophysiology

- Neural networks are mirror images of underlying causal world models.
- Contextual effects on RFs are signature of perceptual inference.
- Competition (lateral inhibition) is input selective and divisive.
- Perceptual inference is a collective, dynamical process in sensory networks.
- Selectivity of visual cells should be characterized by weak, near threshold stimuli (faint, low contrast, short, noisy) rather than optimal stimuli.
- Future directions: feedback, learning, neural basis of psychiatric disorders.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