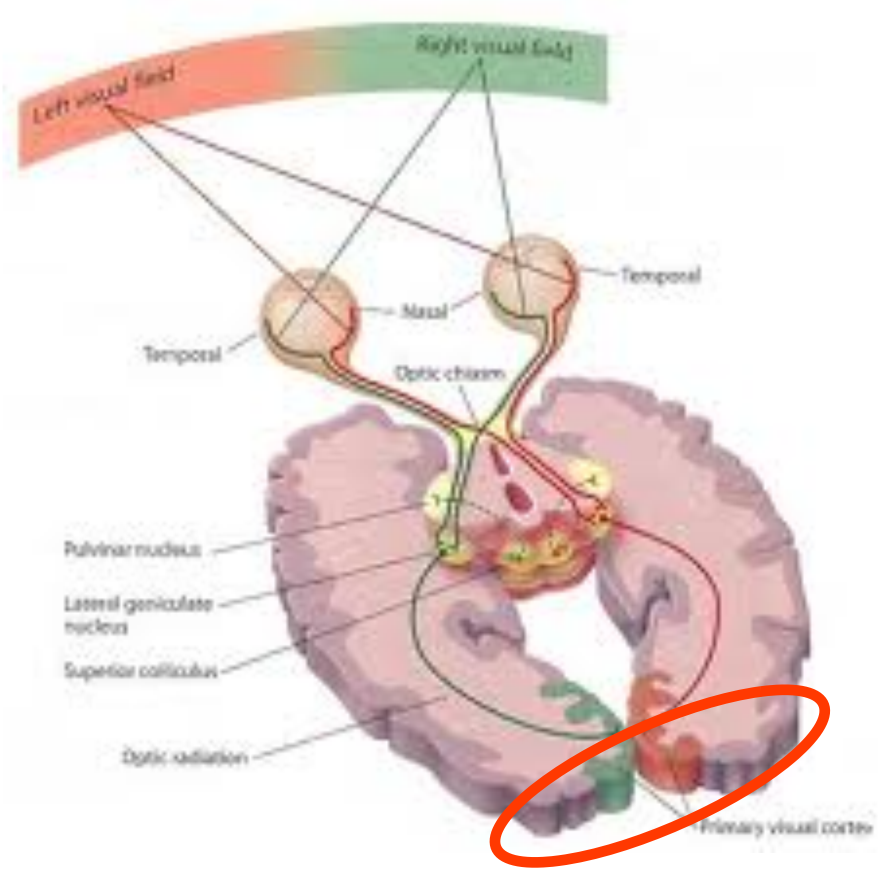
Computational Vision

Learning invariances

- Complex cells
- Learning simple and complex cells

RF organization in V1

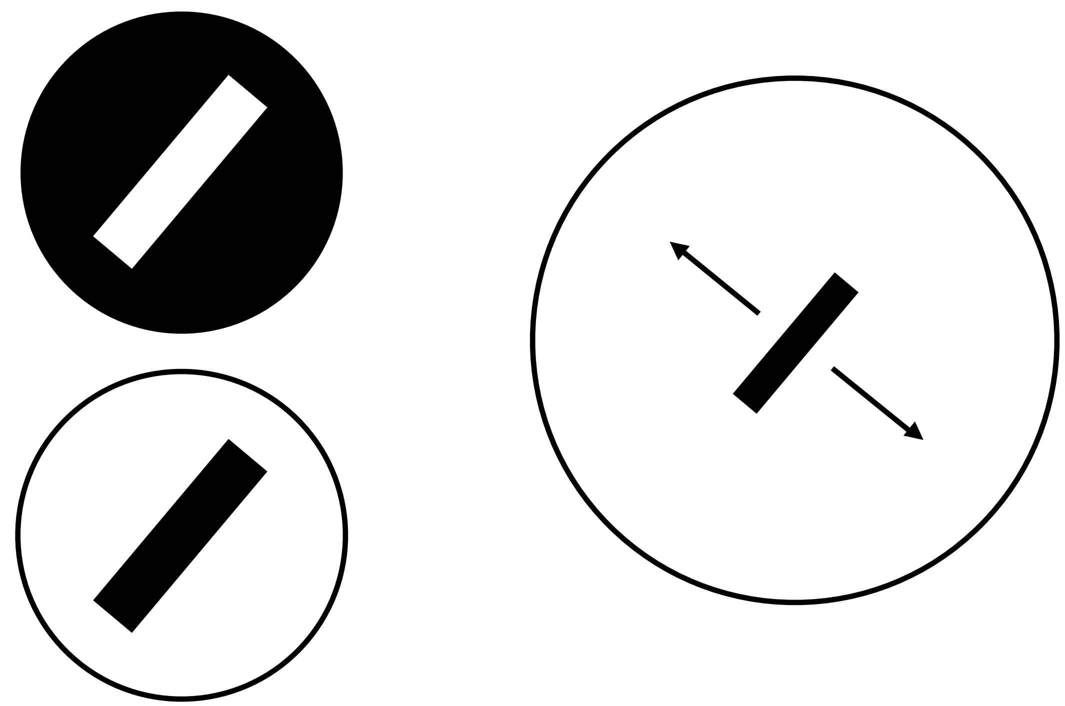
Hubel & Wiesel



Complex cell

simple cells

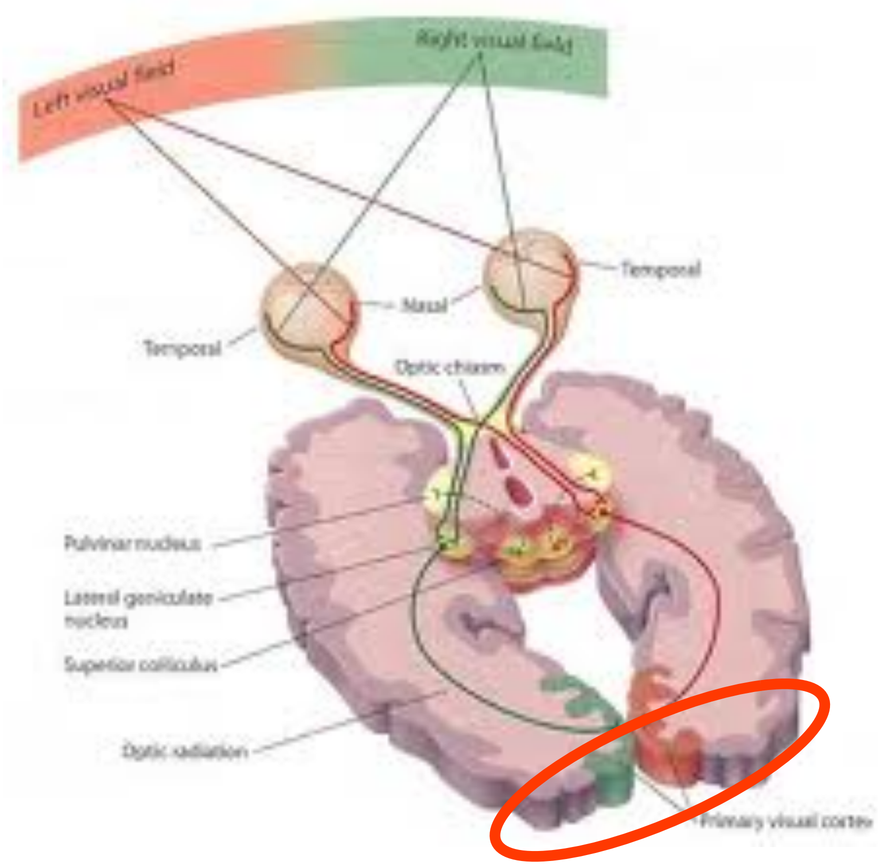
complex cells

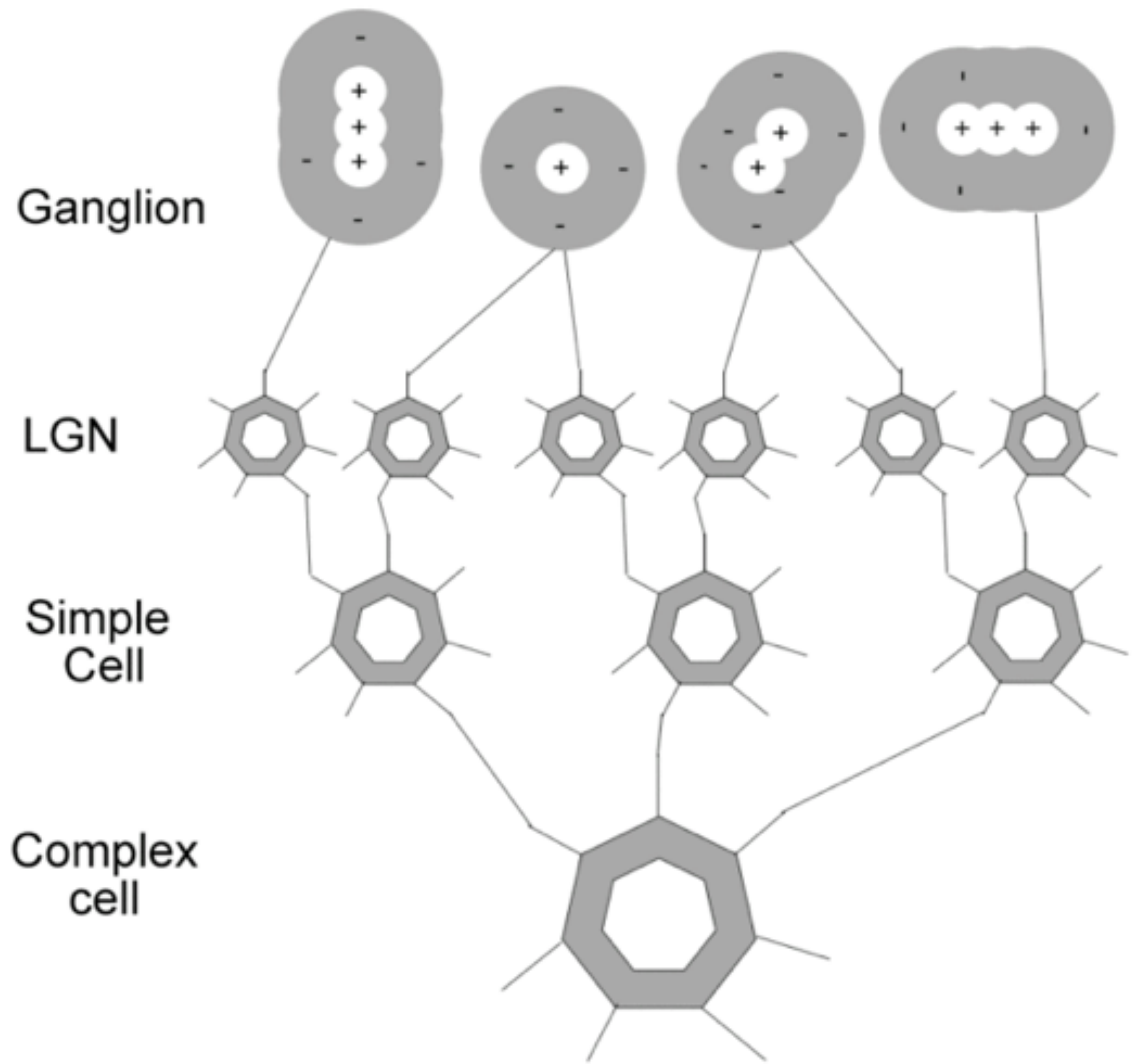


Hubel & Wiesel ’59 ’62 ’68

RF organization in V1

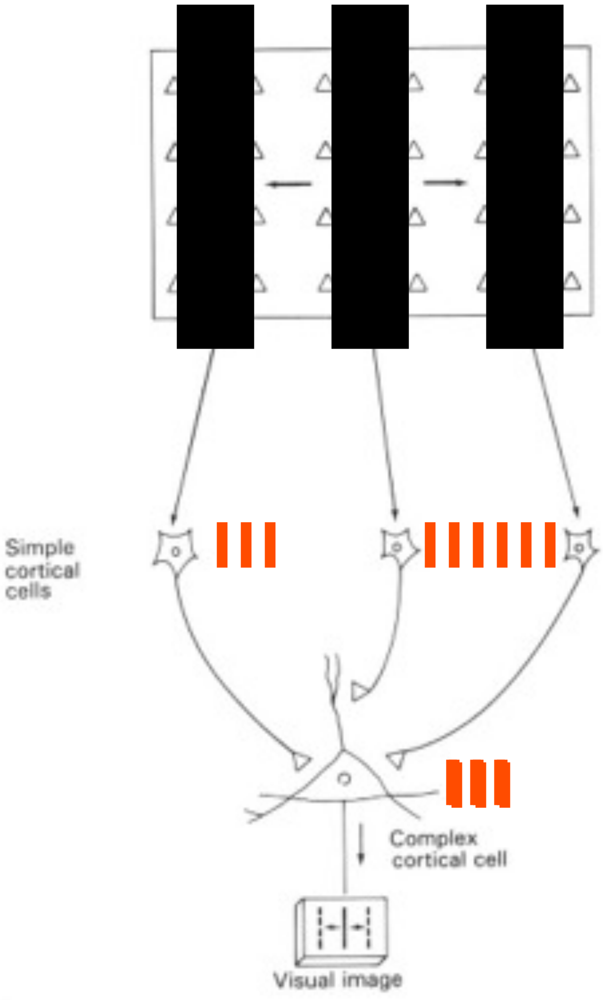
Hubel & Wiesel





Hubel & Wiesel ’59 ’62 ’68

Computational models of complex cells

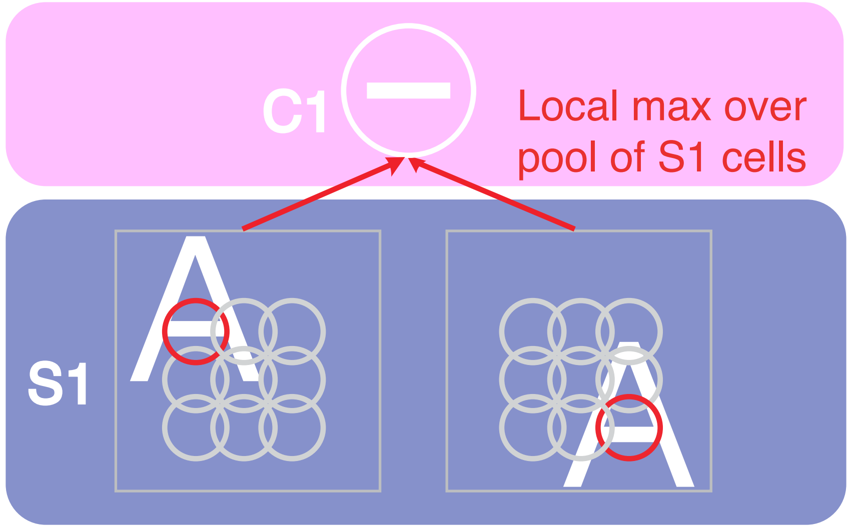


Hubel & Wiesel

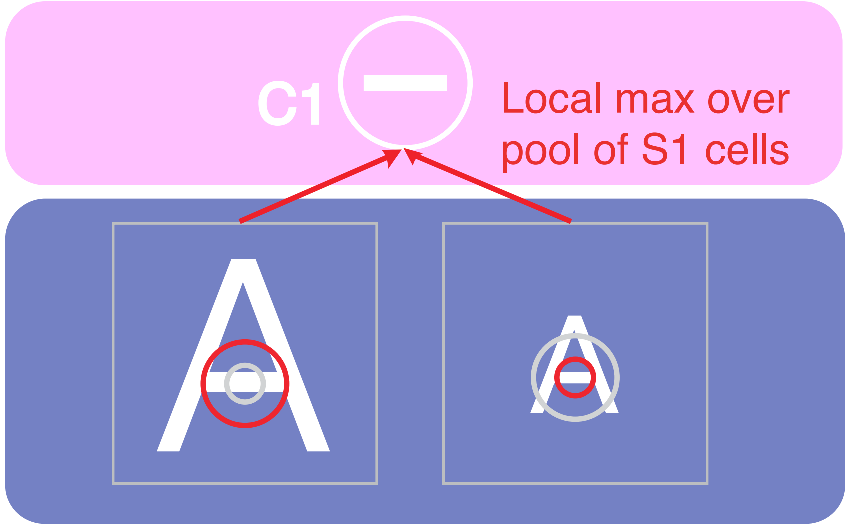
Max pooling

Motivation: Superposition problem and robustness to clutter

Increase in tolerance to position



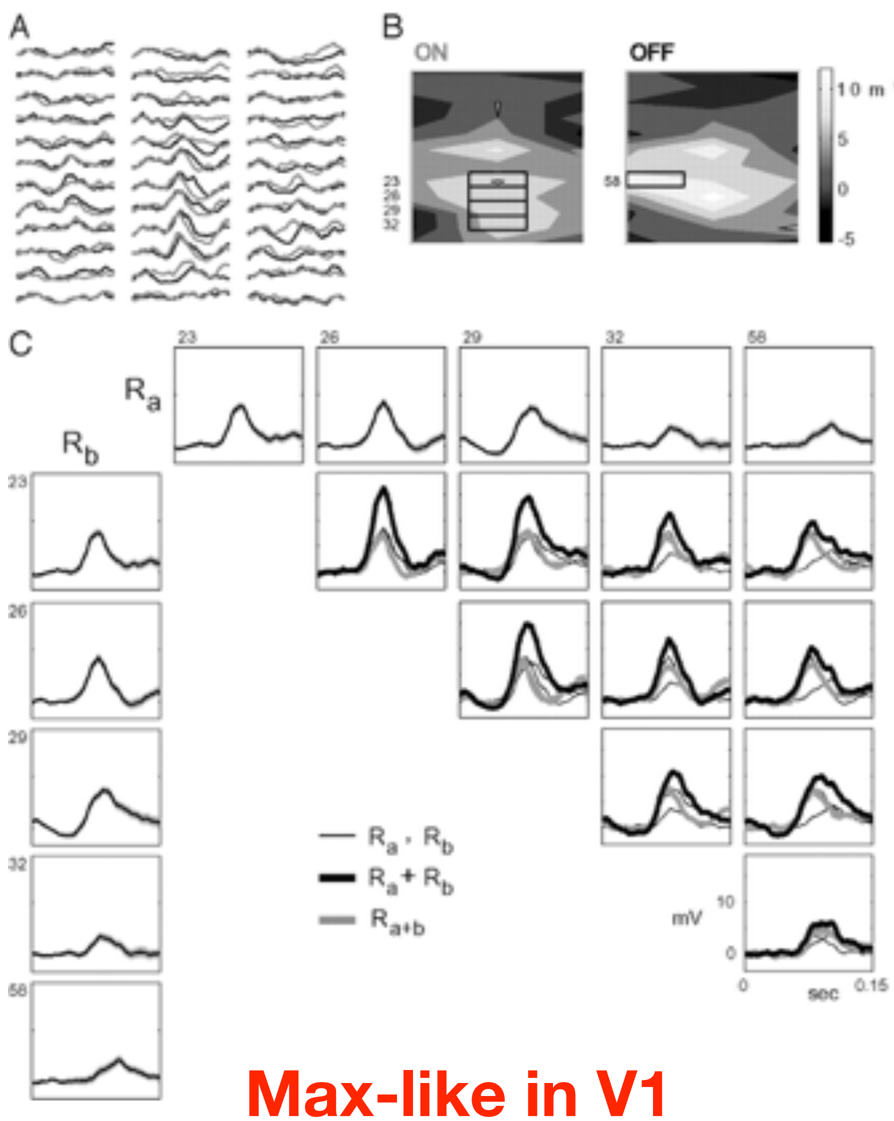
Increase in tolerance to scale



Riesenhuber & Poggio 1999

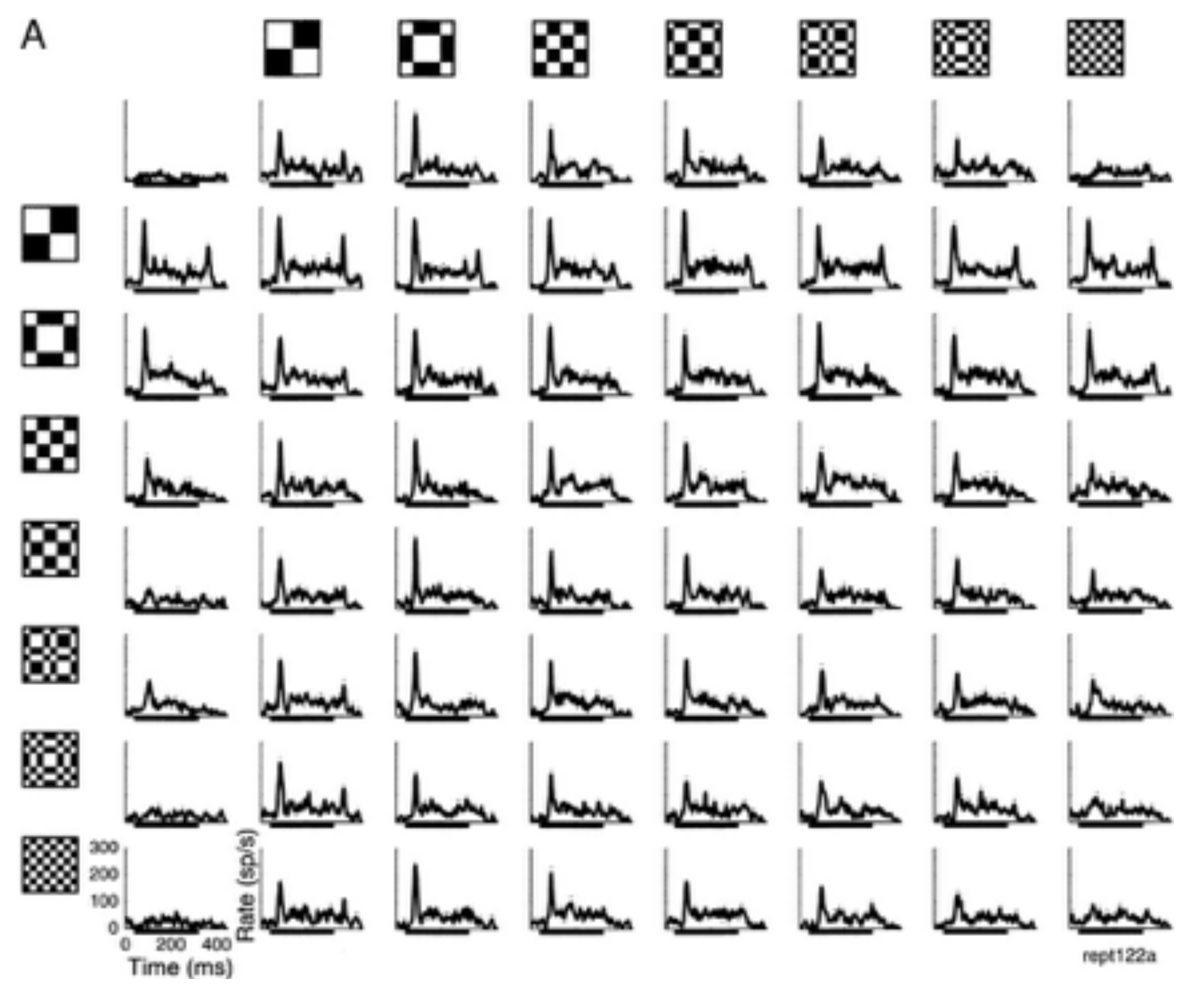
Max-like computation in the visual cortex

Lampl et al ‘04



Max-like in V1

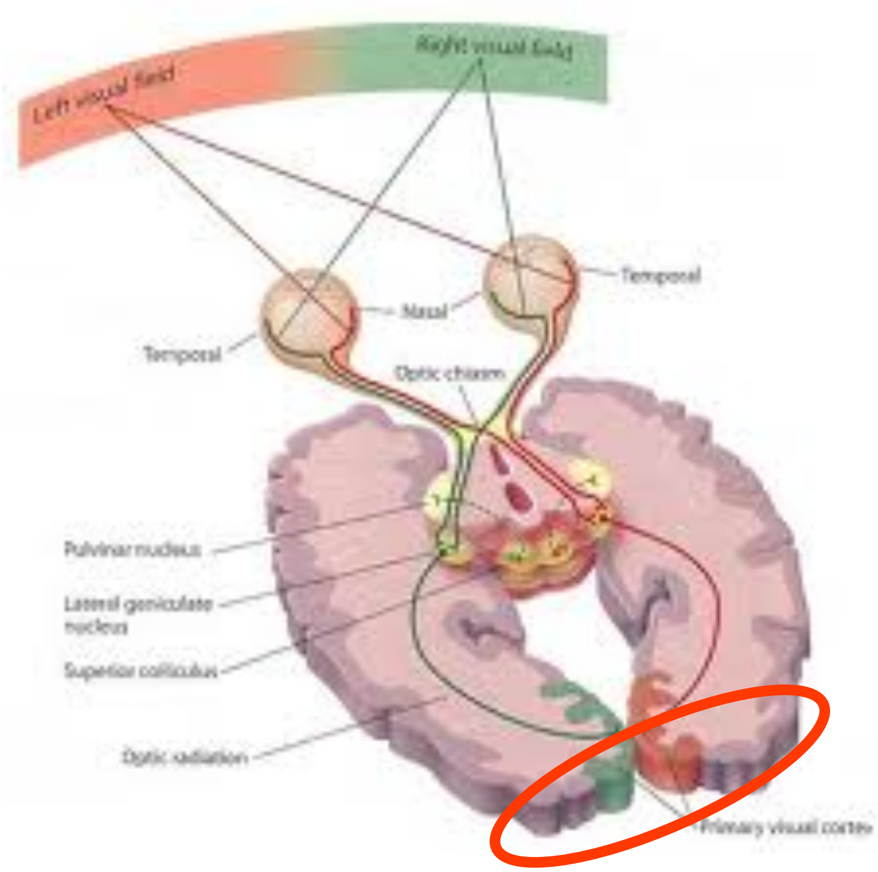
Gawne & Martin ‘02



Max-like in V4

RF organization in V1

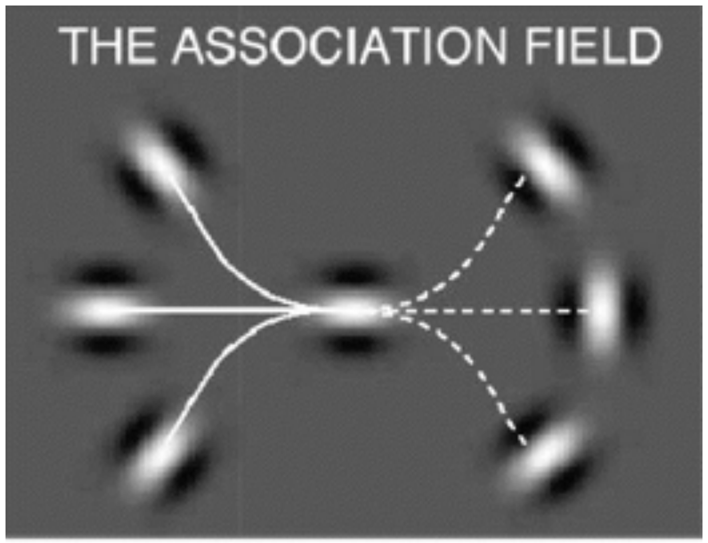
Hubel & Wiesel

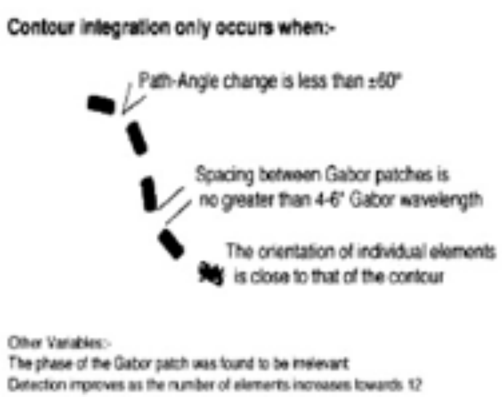


Complex cell

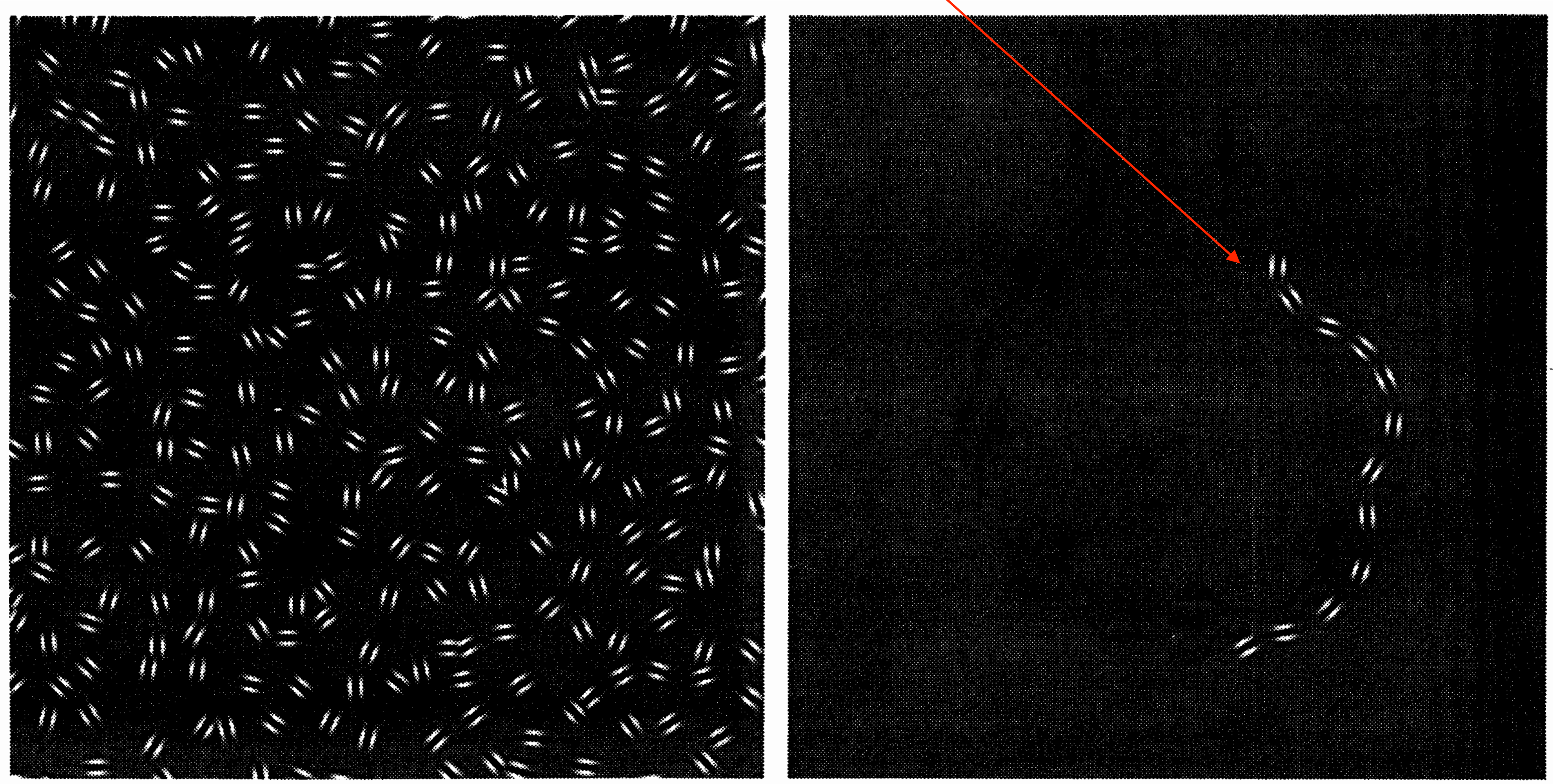
Hubel & Wiesel ’59 ’62 ’68

Computational models of complex cells



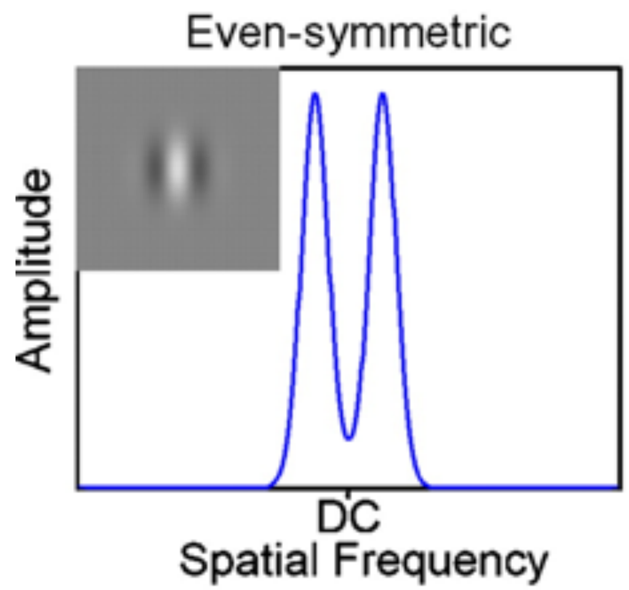


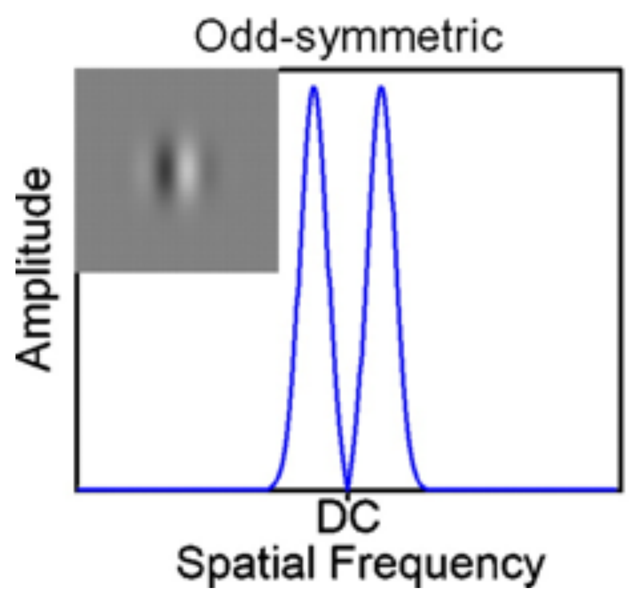
Changing phase has little effect

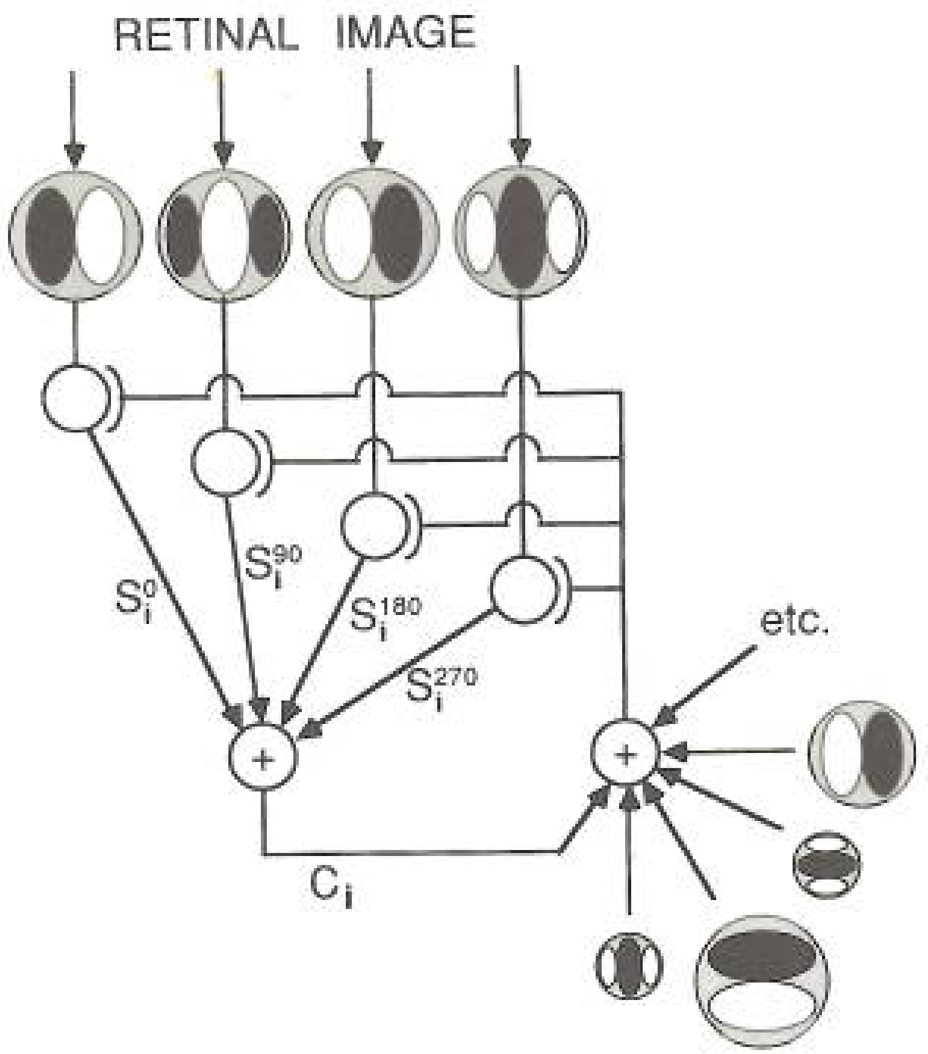


source: Field et al 1993

Energy mechanisms and divisive normalization



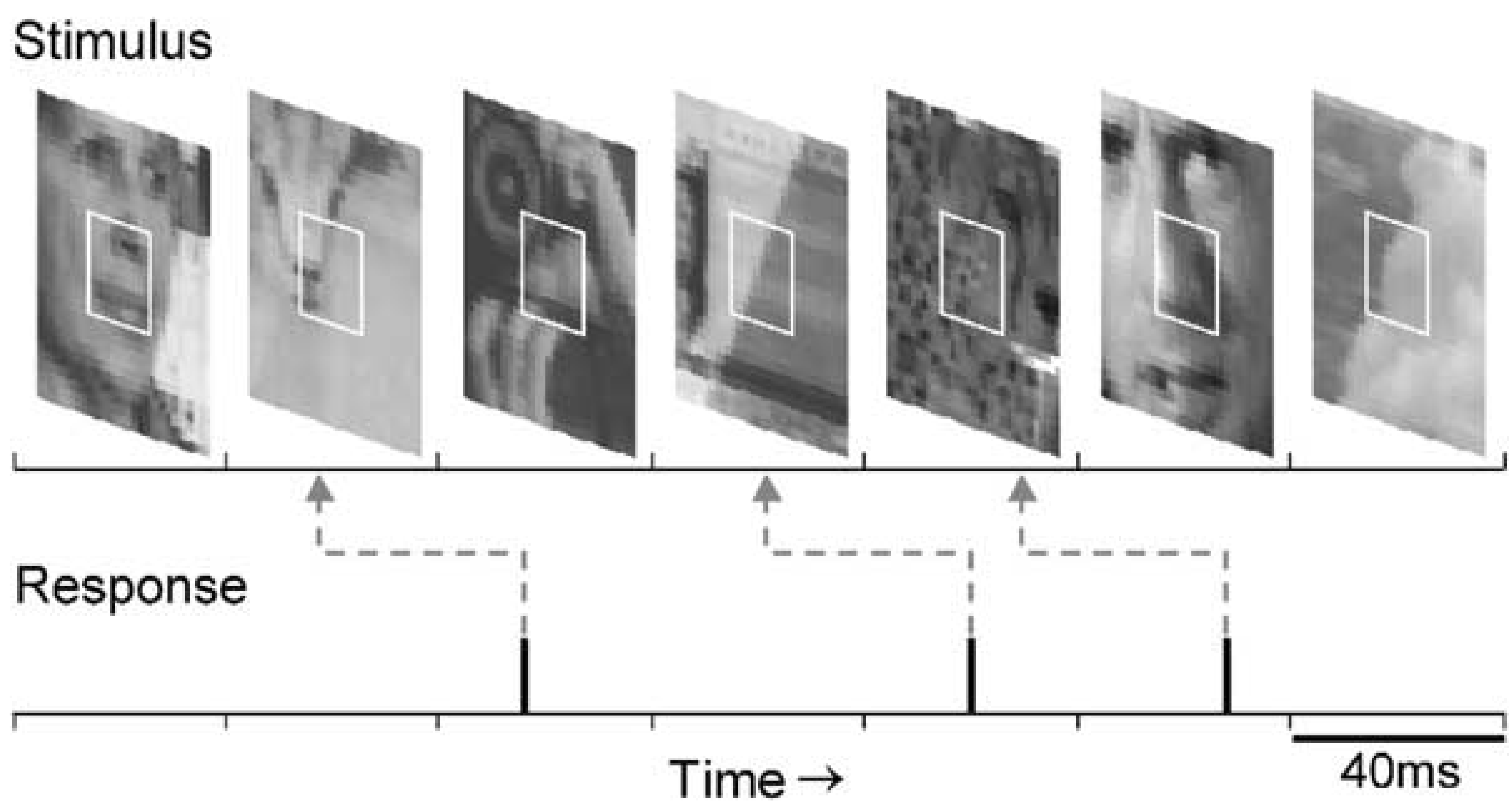




source: Hansen et al 2006

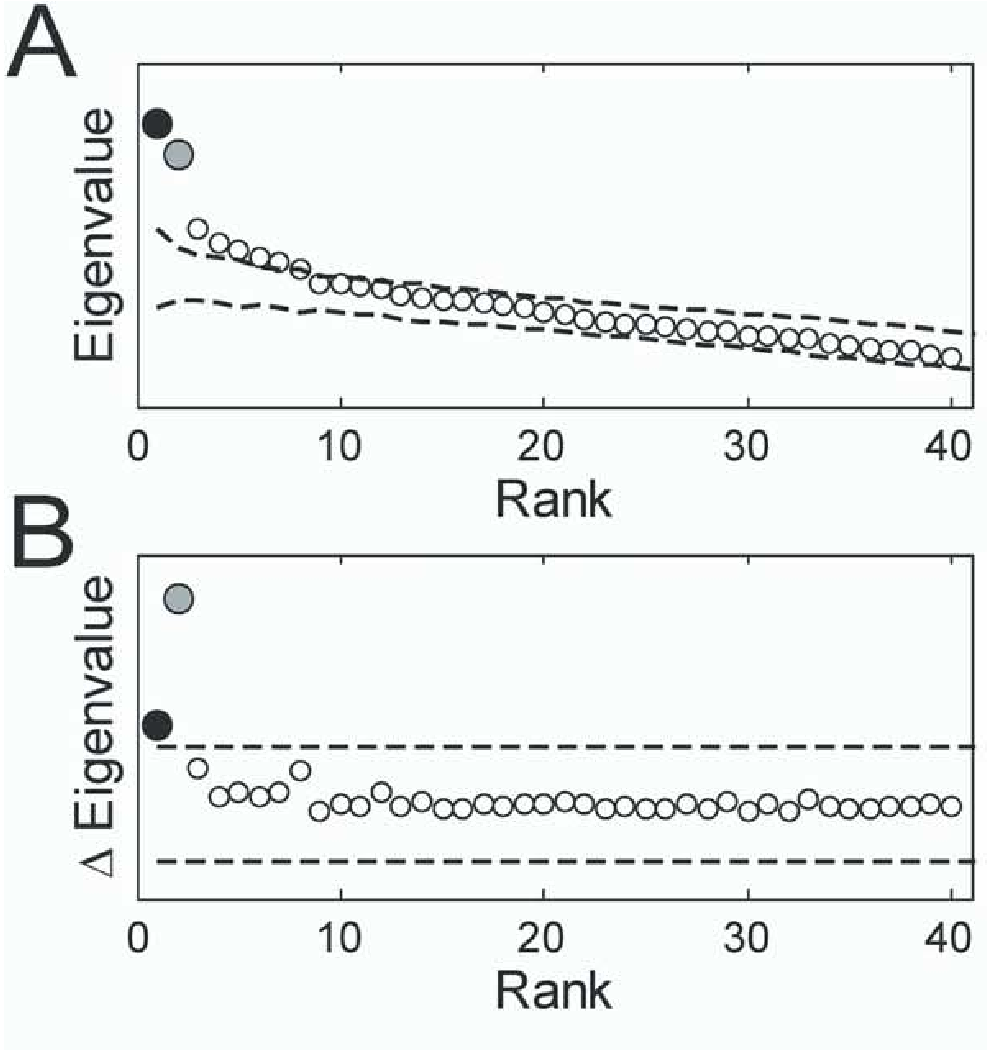
Adelson & Bergen 1985; Heeger 1991

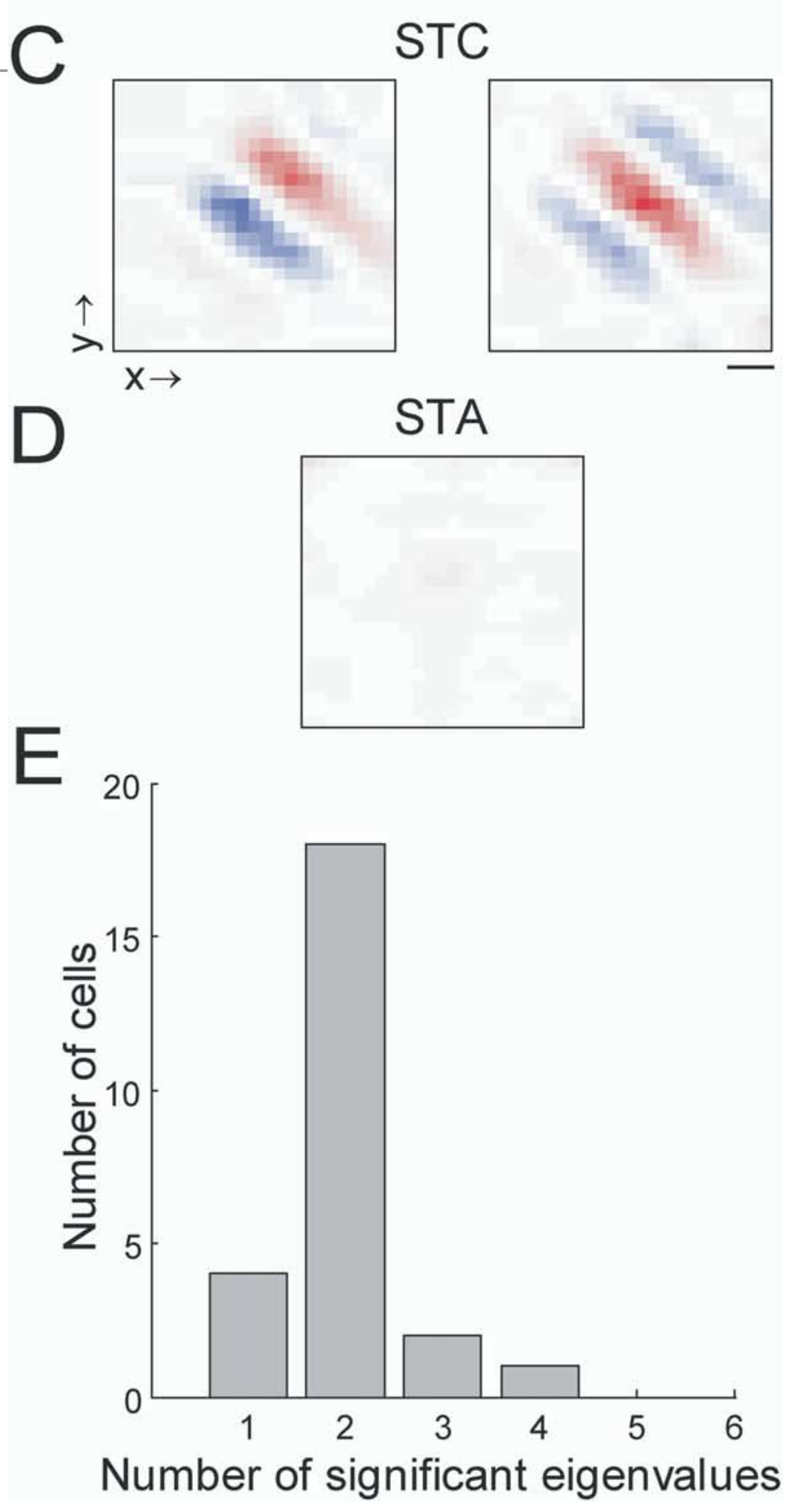
Energy mechanisms and divisive normalization



Touryan et al ’05

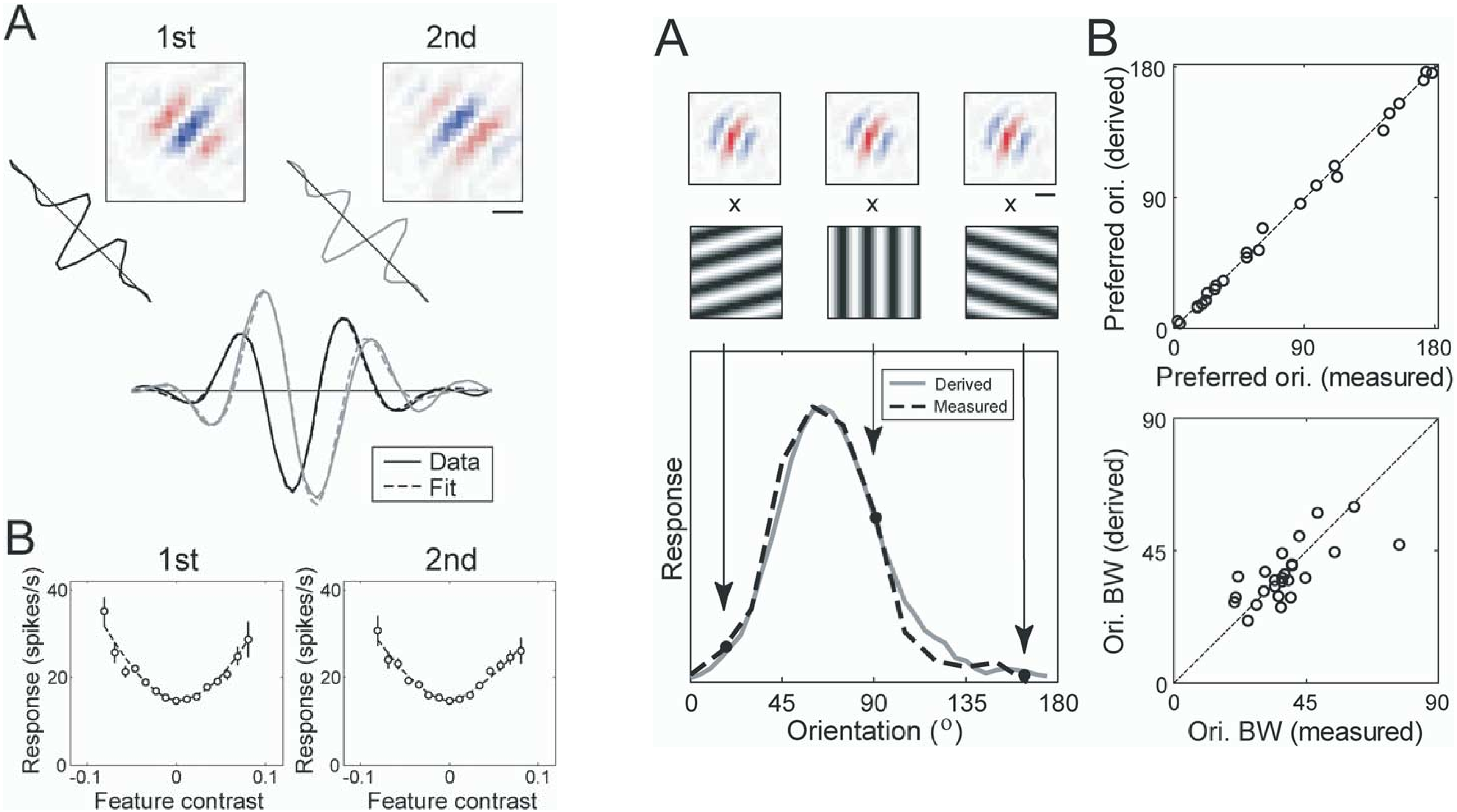
Energy mechanisms and divisive normalization





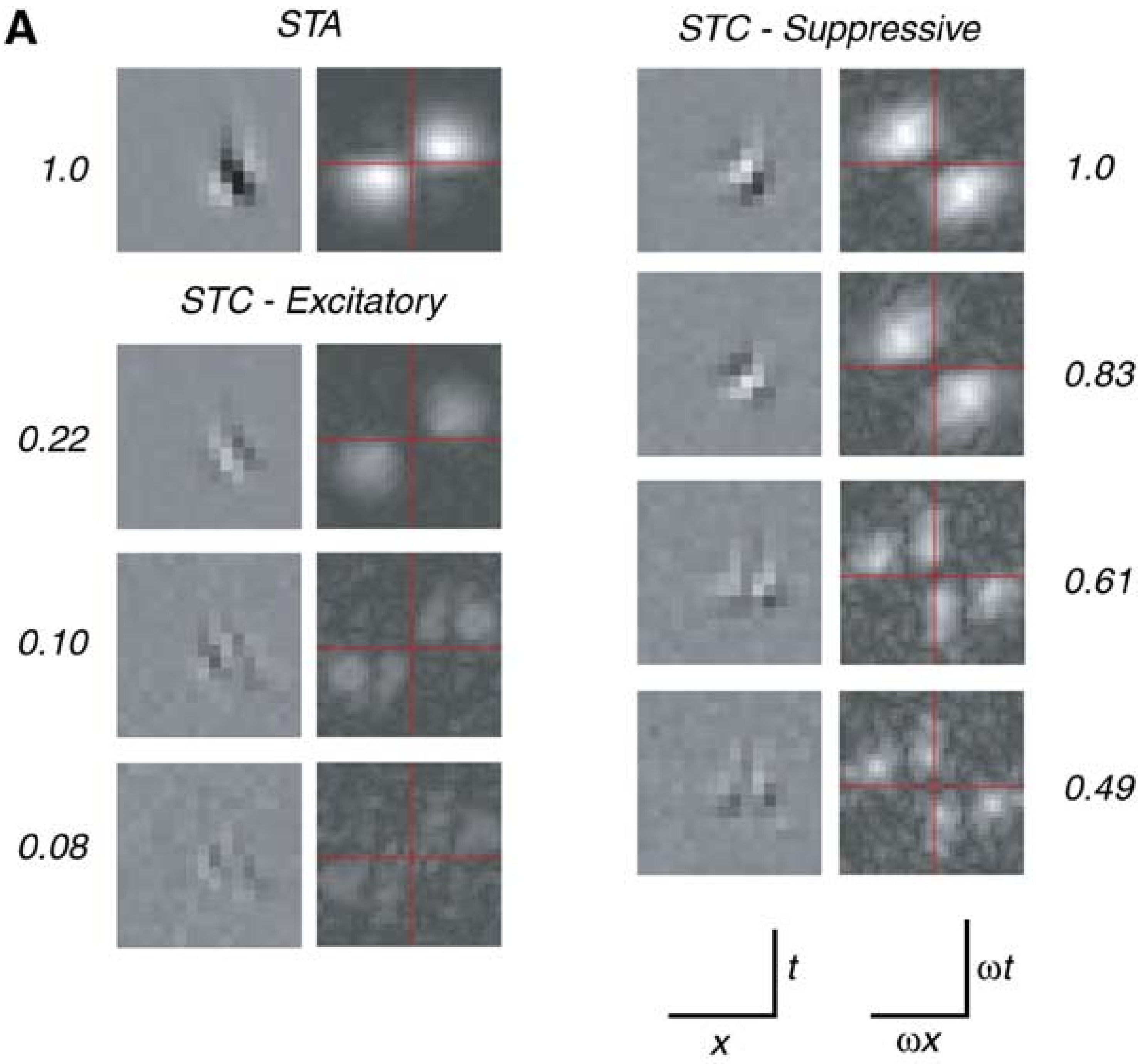
Touryan et al '05

Energy mechanisms and divisive normalization



Touryan et al ’05

Energy mechanisms and divisive normalization



Rust et al '05

9638 • The Journal of Neuroscience, September 5, 2007 • 27(36):9638–9648

Behavioral/Systems/Cognitive

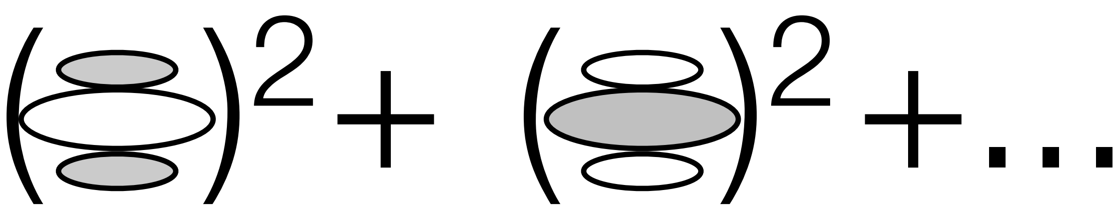
Computational Diversity in Complex Cells of Cat Primary Visual Cortex

Ian M. Finn and David Ferster
Department of Neurobiology and Physiology, Northwestern University, Evanston, Illinois 60208

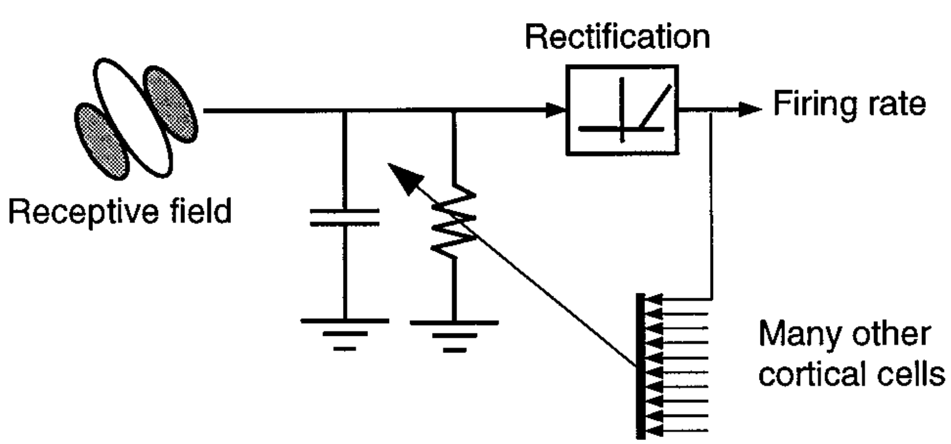
Cortical mechanisms of invariant recognition

C1 complex units

(1) half-rectification and summing over phases *at each location* for tolerance to contrast reversal

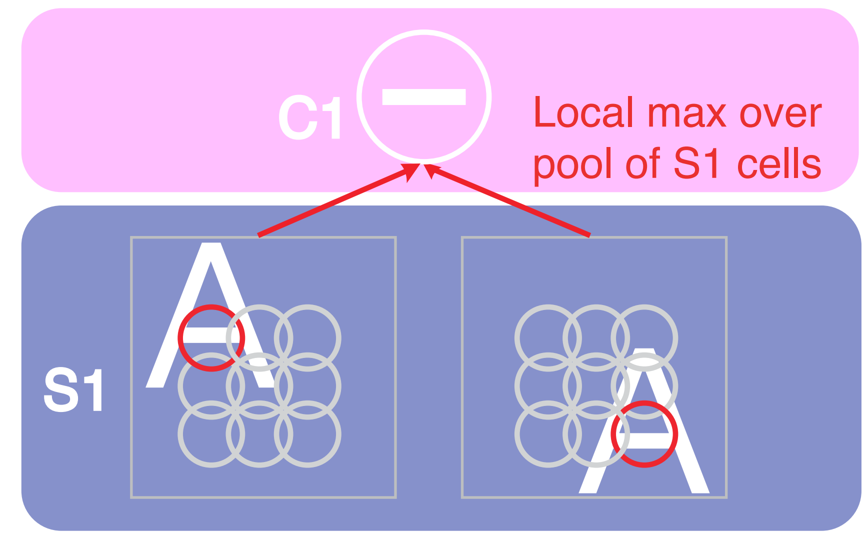


(2) gain control / divisive normalization

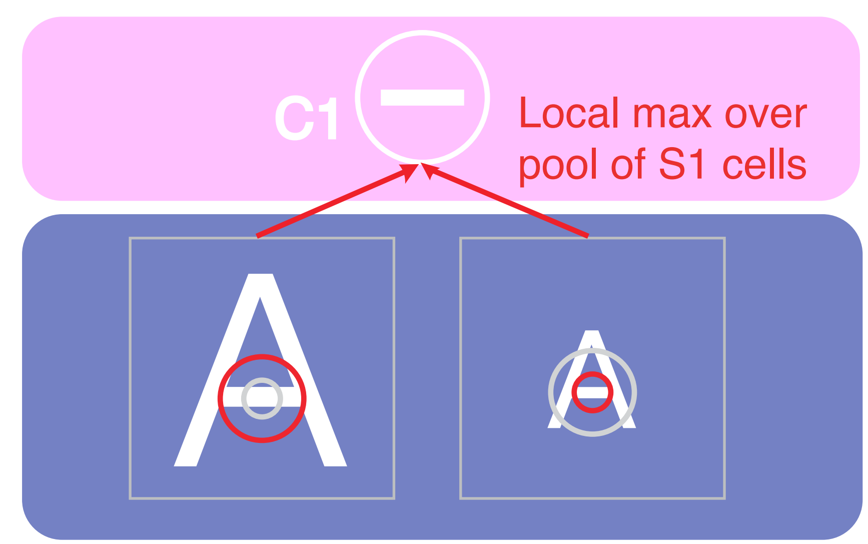


(3) selective max-like pooling over nearby positions and scales for tolerance to 2D transformations

Increase in tolerance to position



Increase in tolerance to scale



Heeger & Carandini ’94; Lampl et al ’01; Touryan et al ’02; Rust et al ’05; Finn & Ferster ’07

Computational Vision

Learning invariances

- Complex cells
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Hebbian learning

- Neurons as coincidence detectors
- 'What fires together, wires together'

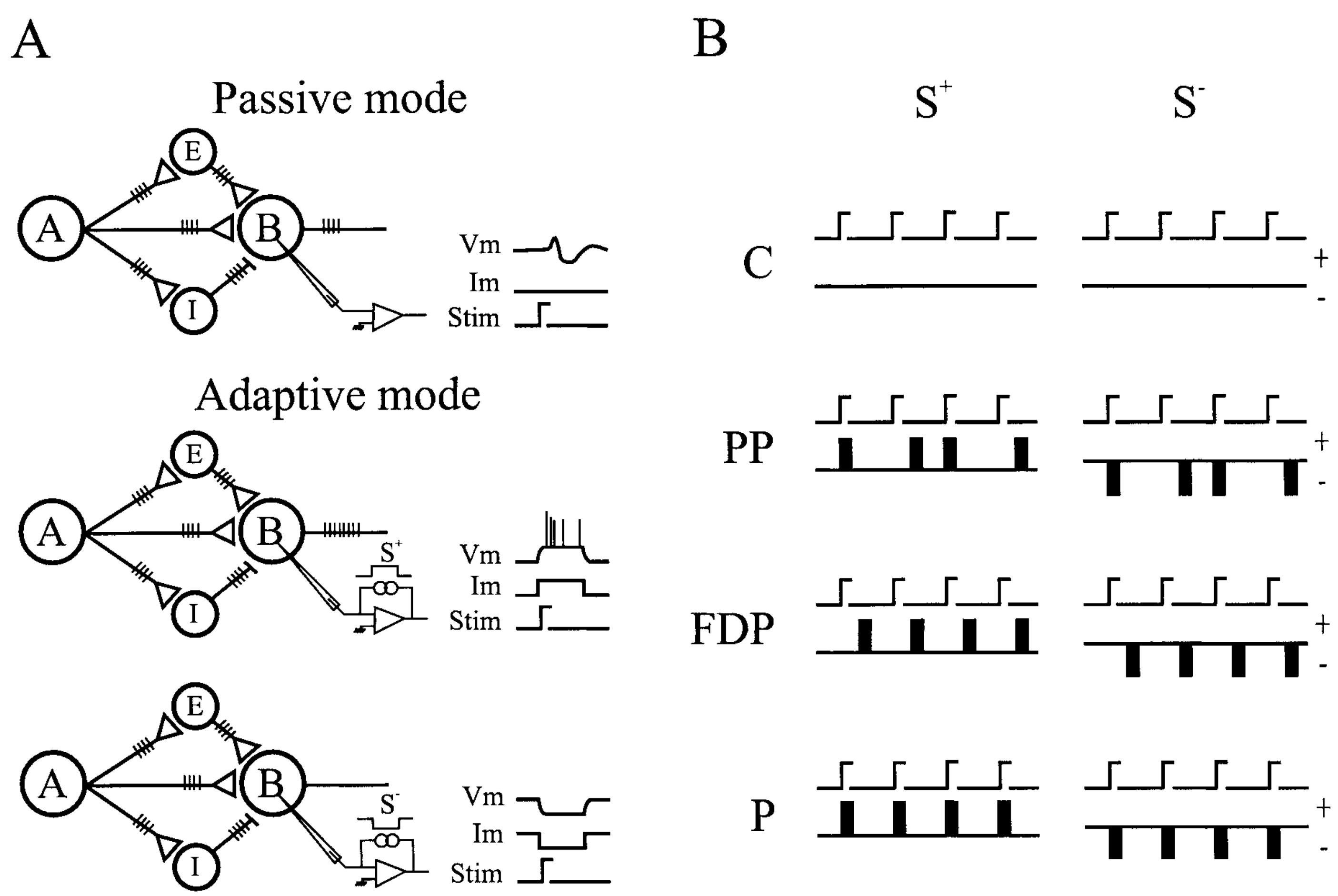
$$\Delta w_i = \eta x_i y$$

$$\Delta w_i = \eta(x_i - w_i)y$$

Fregnac et al. 1988; McLean & Palmer 1998; Fregnac & Shulz 1999

Hebbian learning

- Empirical evidence for 'supervised Hebbian learning' ocular dominance, orientation selectivity and orientation preference, interocular orientation disparity, and the relative dominance of ON and OFF responses



Fregnac & Shulz 1999

Learning transformation sequences

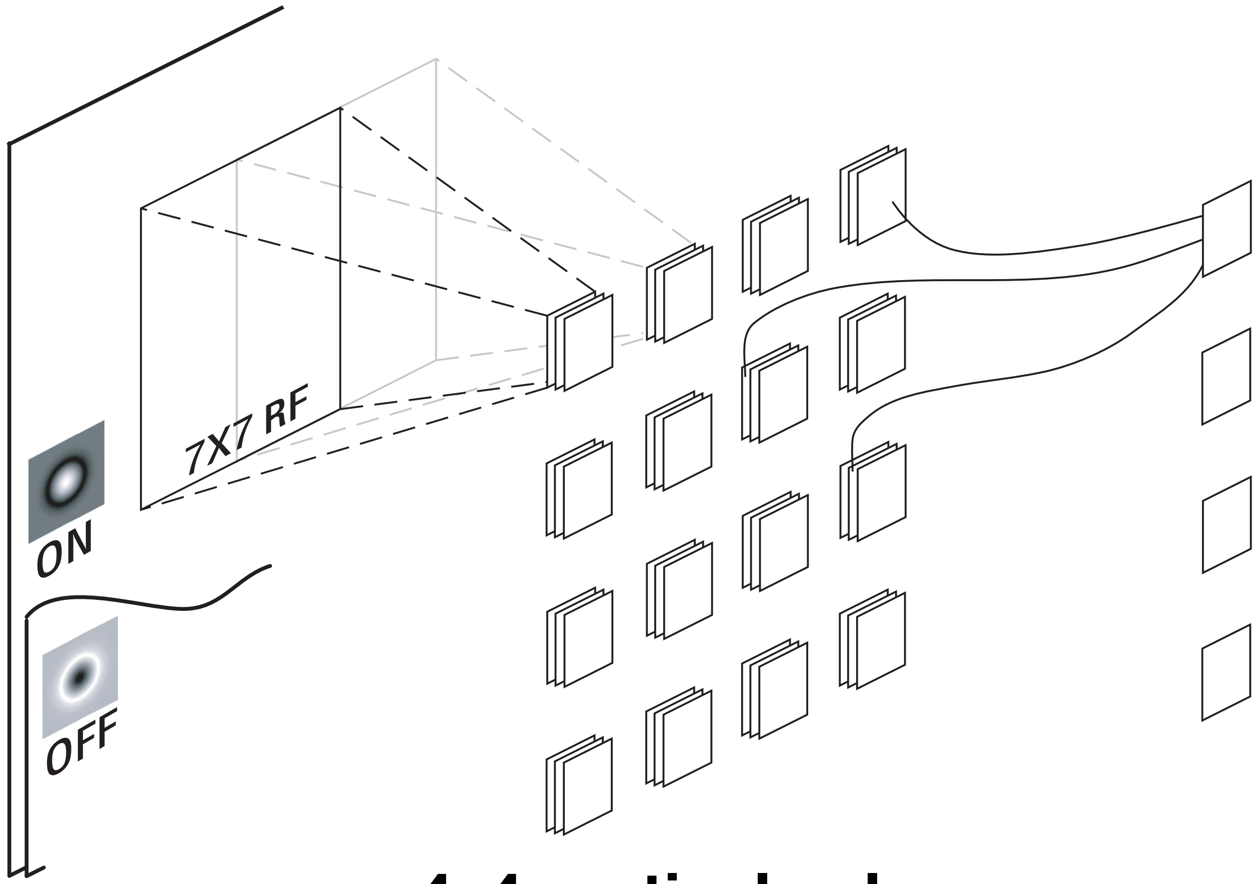
movie courtesy Wolfgang Einhauser

Hypothesis

- Simple cells correspond to learning correlations in space
- Complex cells correspond to learning correlations in time

Masquelier et al 2007 (see also Foldiak 1991)

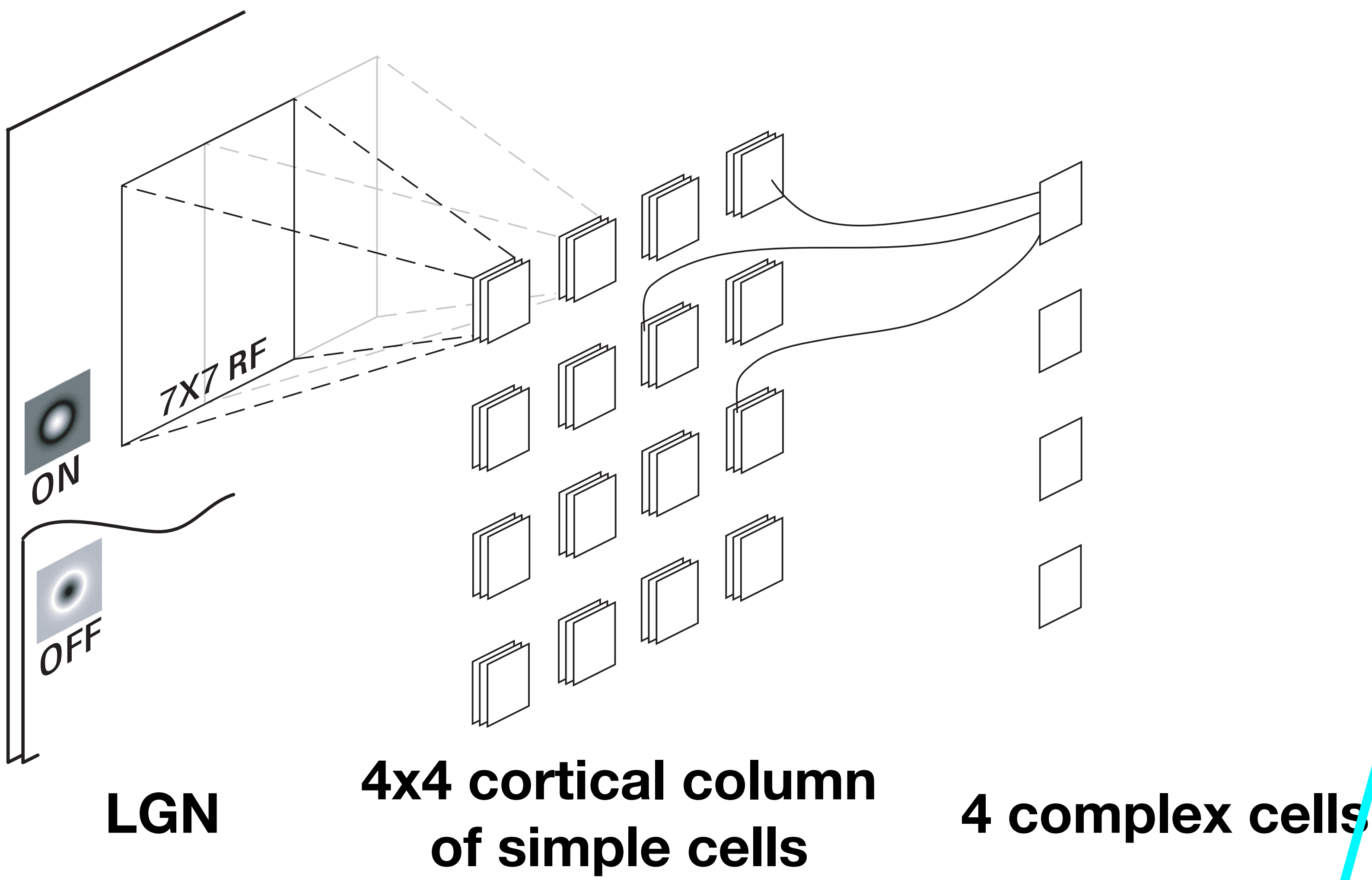
Learning invariances from temporal continuity

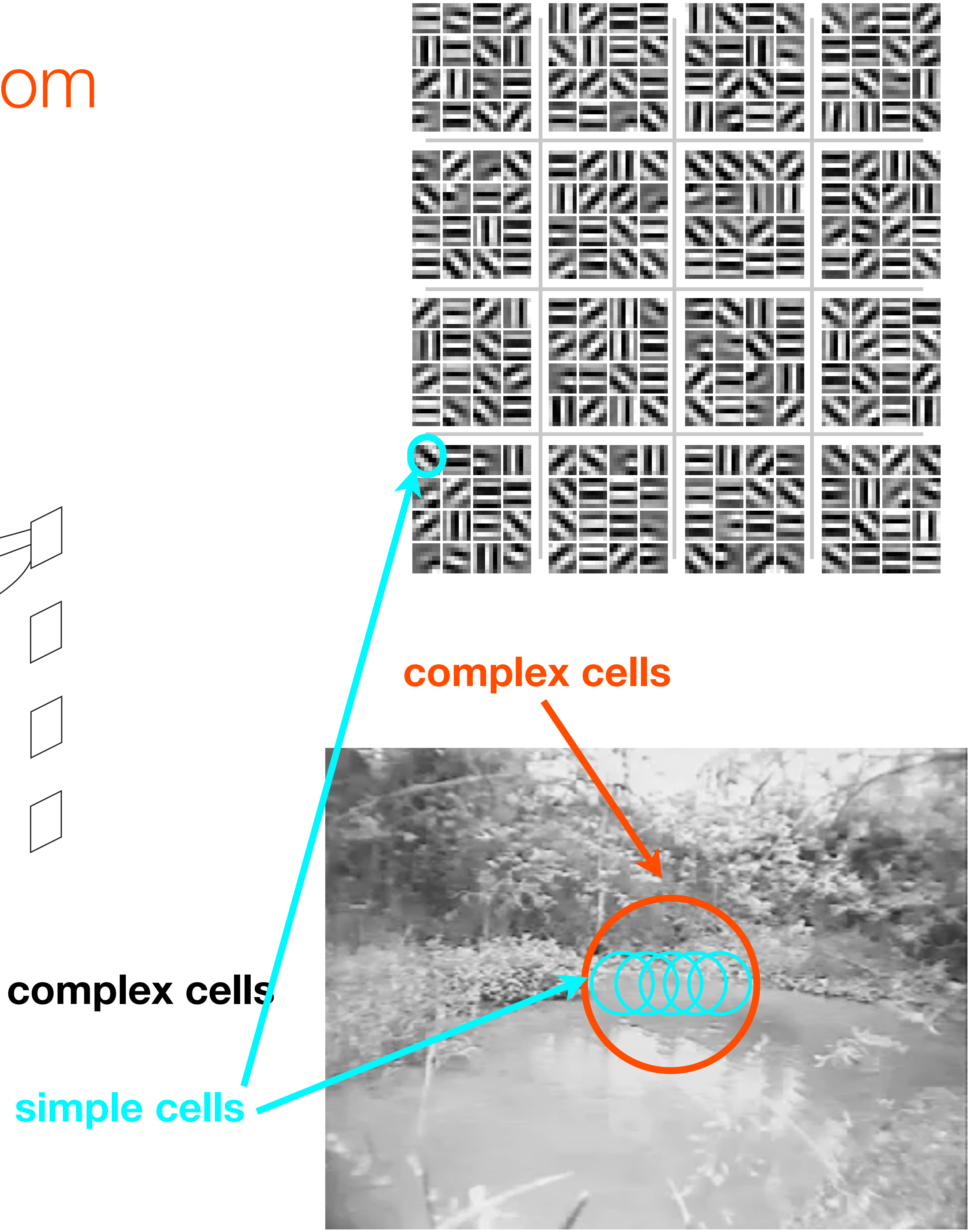


LGN **4x4 cortical column of simple cells** **4 complex cells**

Masquelier et al 2007 (see also Foldiak 1991)

Learning invariances from temporal continuity



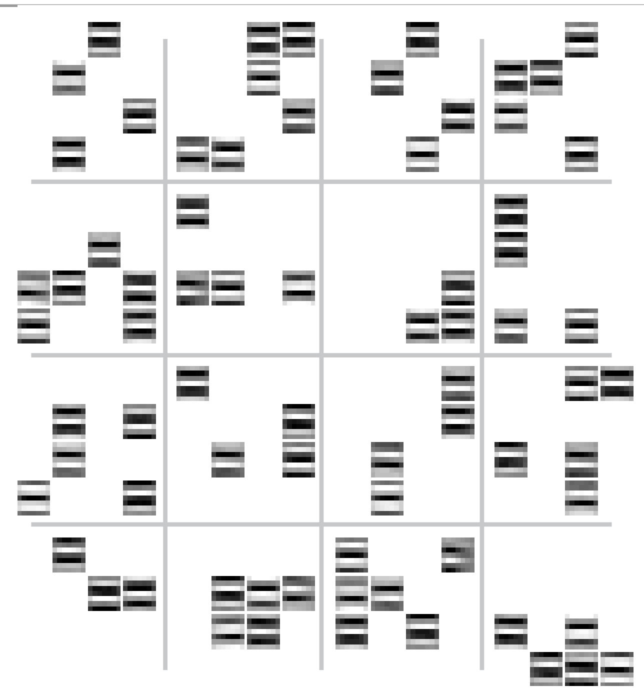


Masquelier et al 2007 (see also Foldiak 1991)

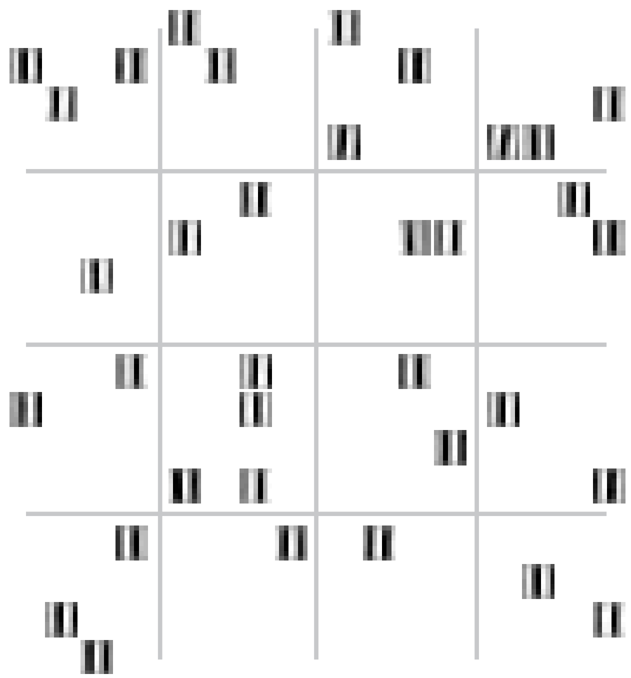
movie courtesy Wolfgang Einhauser

Masquelier et al 2007

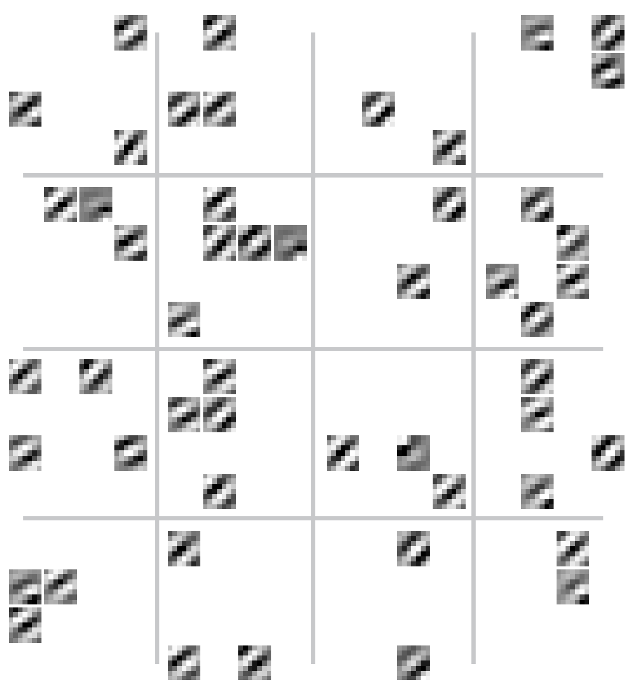
Learning the invariance from temporal continuity



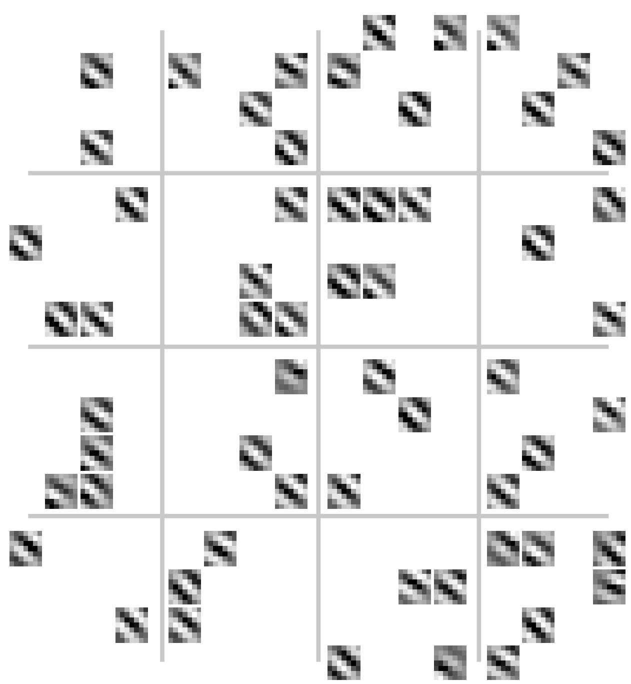
(a) S_1 units (n=73) that remain connected to C_1 unit # 1 after learning



(b) S_1 units (n=35) that remain connected to C_1 unit # 2 after learning



(c) S_1 units (n=59) that remain connected to C_1 unit # 3 after learning



(d) S_1 units (n=38) that remain connected to C_1 unit # 4 after learning

Slow feature analysis

$$\Delta_j := \Delta(y_j) := \langle \dot{y}_j^2 \rangle \quad \textit{is minimal} \tag{1}$$

under the constraints

$$\langle y_j \rangle = 0 \quad \textit{(zero mean)}\,, \tag{2}$$

$$\langle y_j^2 \rangle = 1 \quad \textit{(unit variance)}\,, \tag{3}$$

$$\forall j' < j: \quad \langle y_{j'}\, y_j \rangle = 0 \quad \textit{(decorrelation)}\,, \tag{4}$$

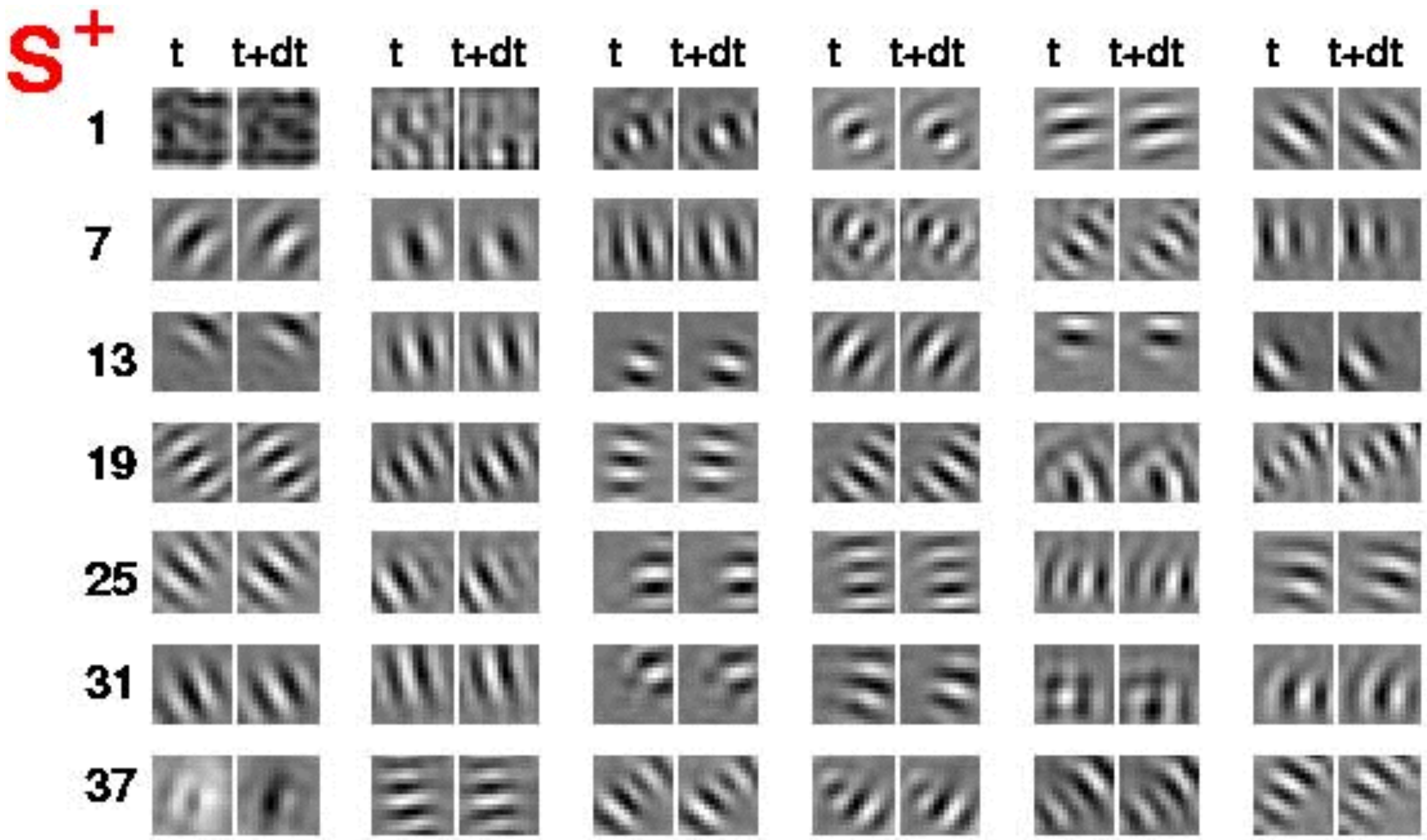
where the angle brackets indicate temporal averaging, i.e. $\langle f \rangle := \frac{1}{t_1 - t_0} \int_{t_0}^{t_1} f(t)\, dt$.

$$y_j(t) = g_j(\mathbf{x}(t)) = \mathbf{w}_j^T \mathbf{h}(\mathbf{x}(t)) = \mathbf{w}_j^T \mathbf{z}(t)$$

$$\Delta(y_j) = \langle \dot{y}_j^2 \rangle = \mathbf{w}_j^T \langle \dot{\mathbf{z}} \dot{\mathbf{z}}^T \rangle \mathbf{w}_j$$

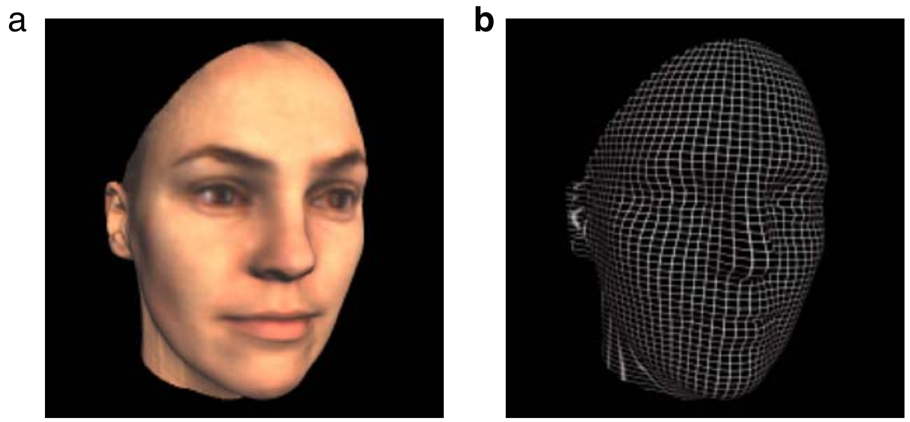
Wiskott & Sejnowski 2002

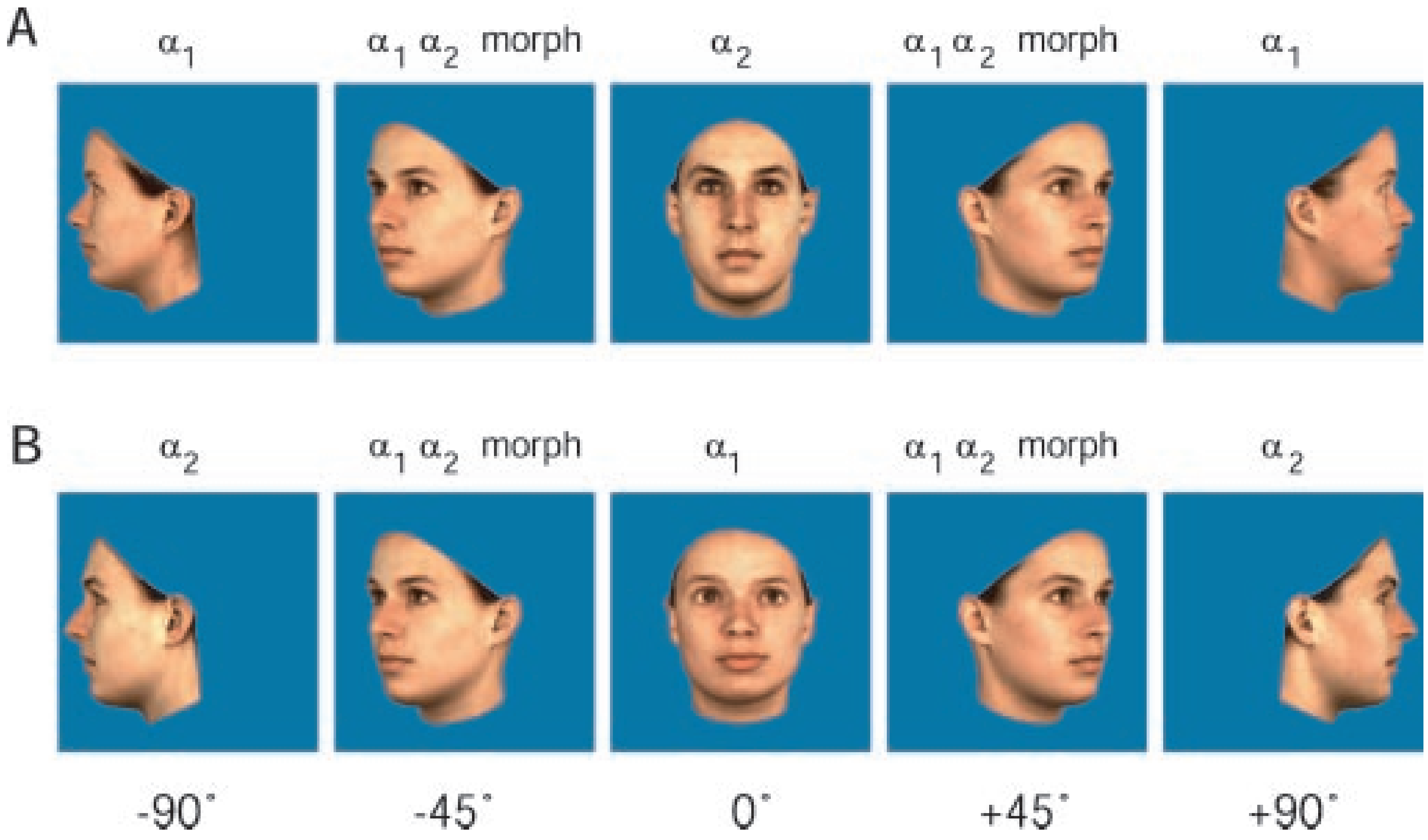
Slow feature analysis



source: scholarpedia

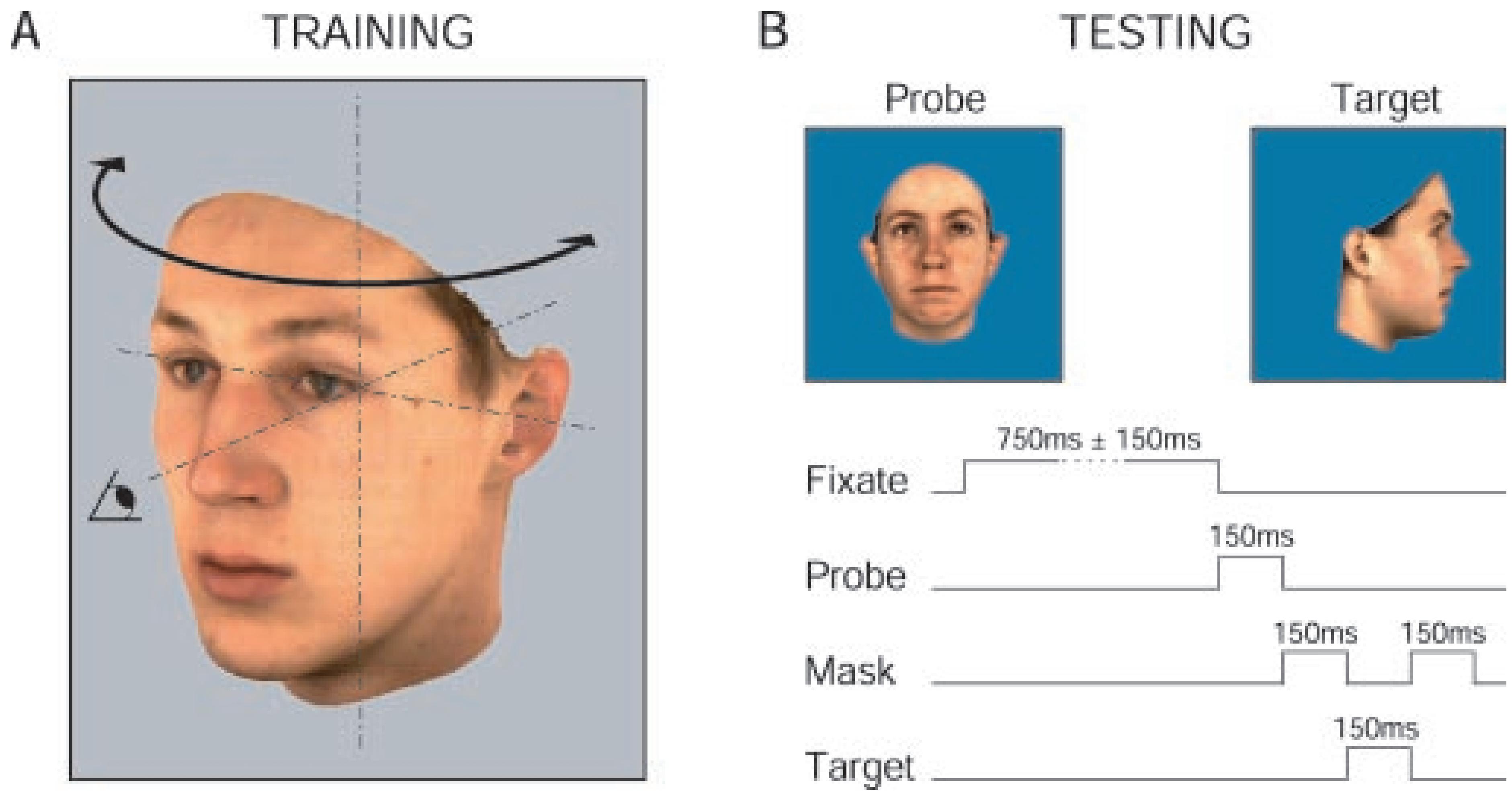
Effects of temporal associations on learning and memory





Wallis & Bulthoff ’01

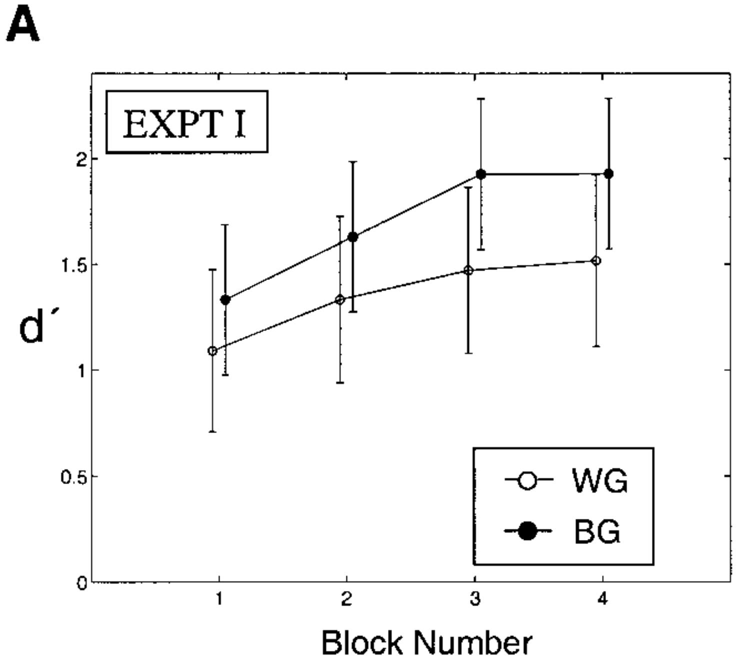
Effects of temporal associations on learning and memory



Wallis & Bulthoff ’01

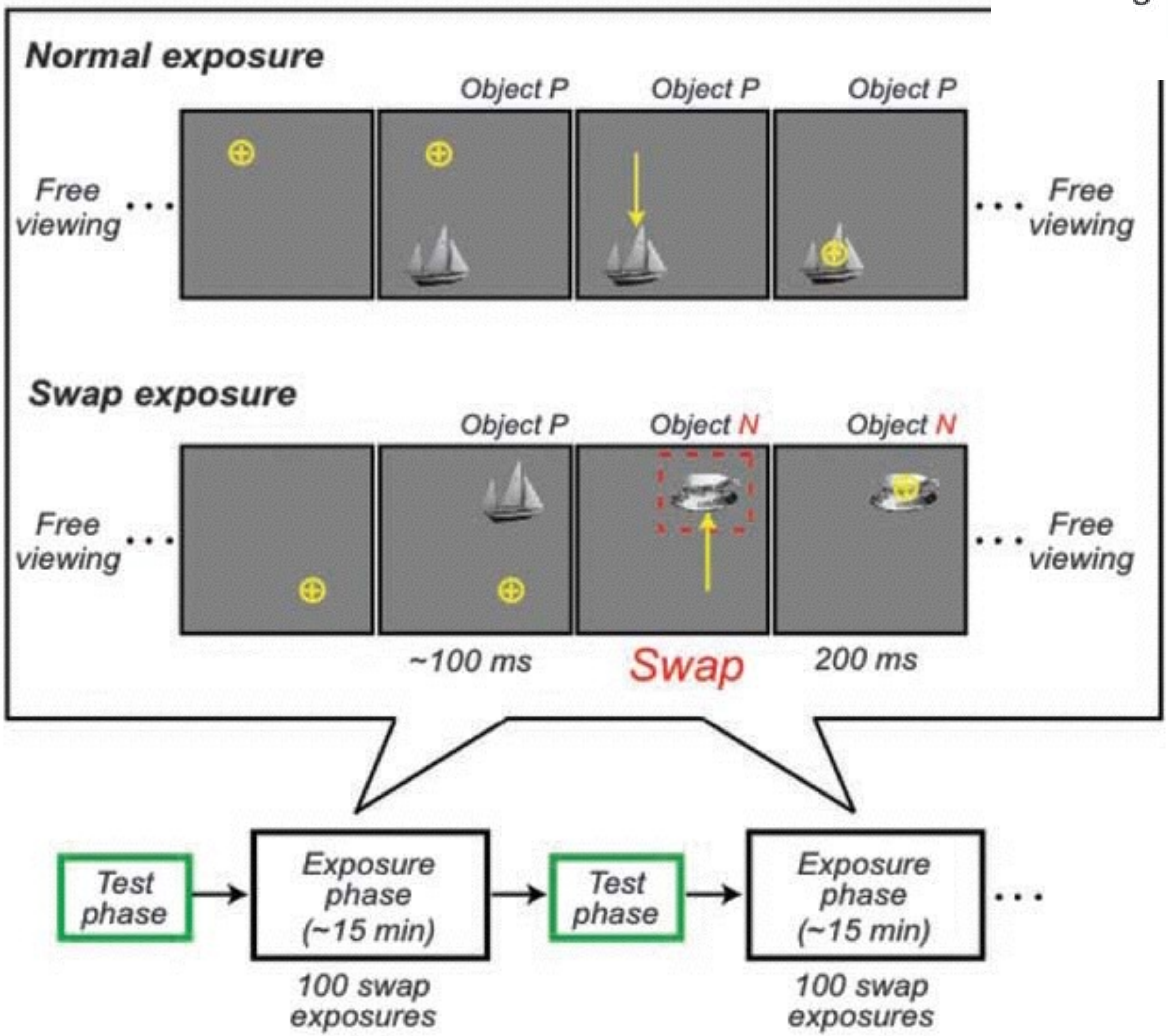
Effects of temporal associations on learning and memory

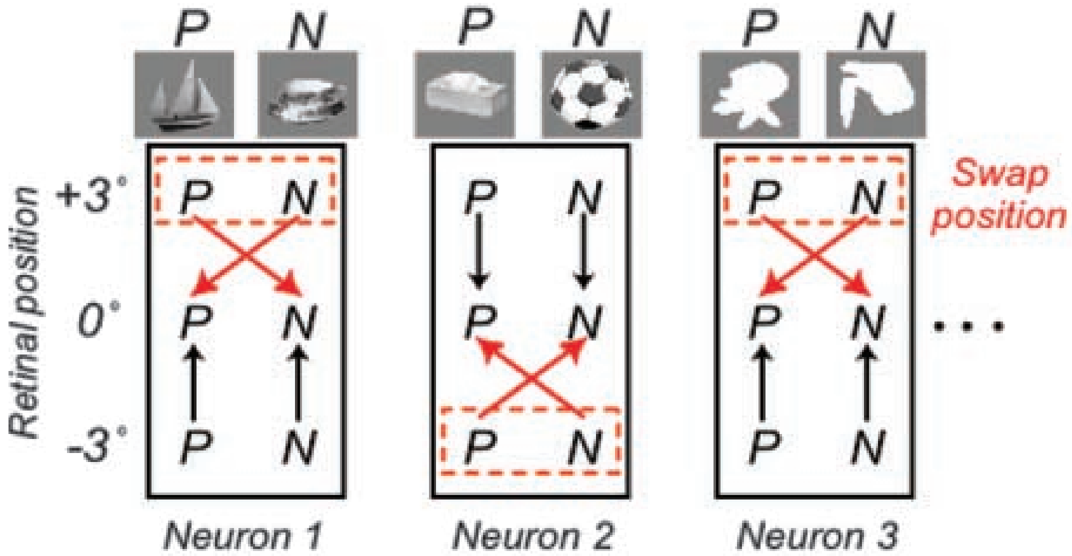
Discrimination worst for prototypes that are part of the same training sequence



Wallis & Bulthoff ’01

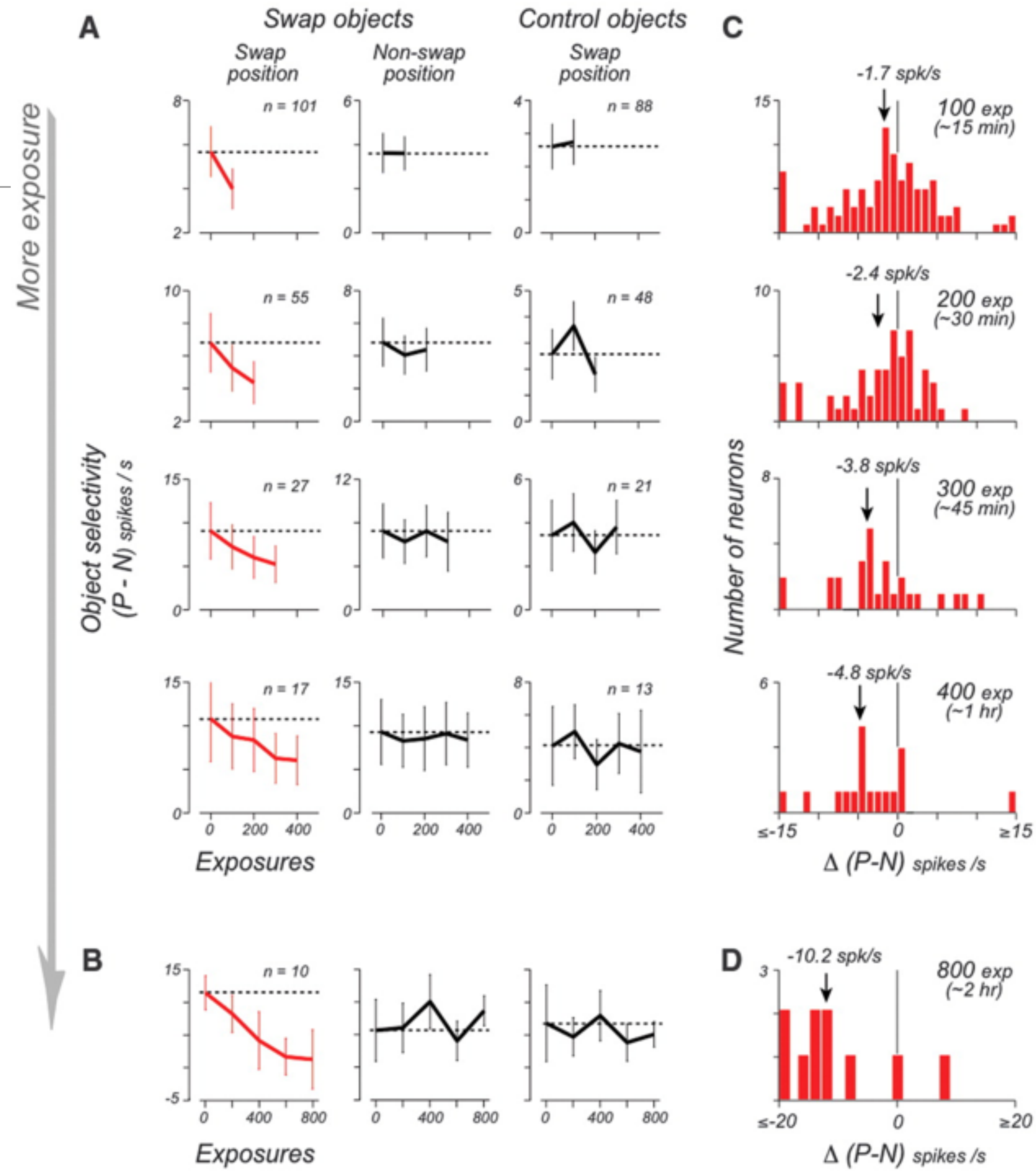
Learning in IT





Li & DiCarlo '08

Learning in IT



Li & DiCarlo '08

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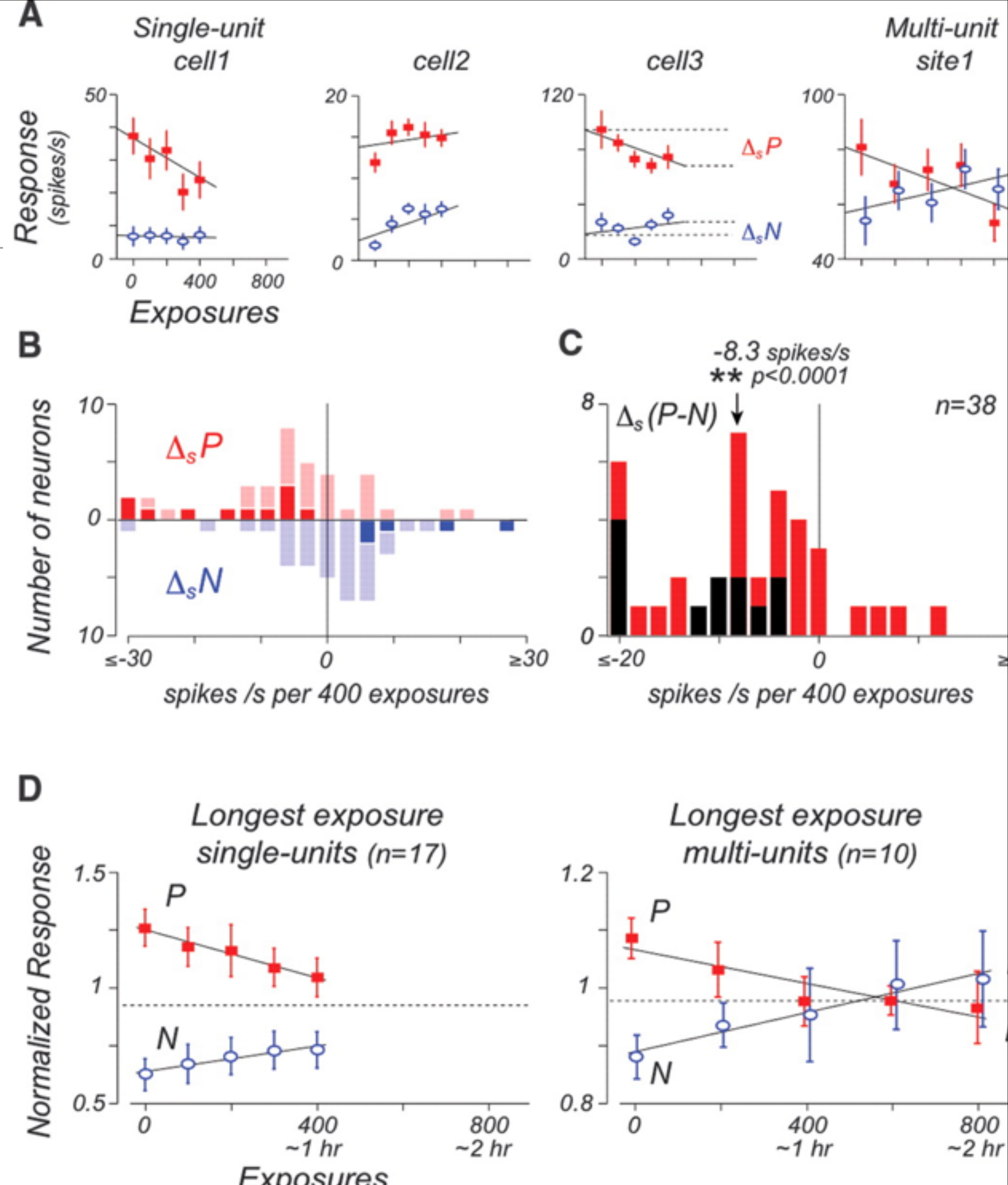
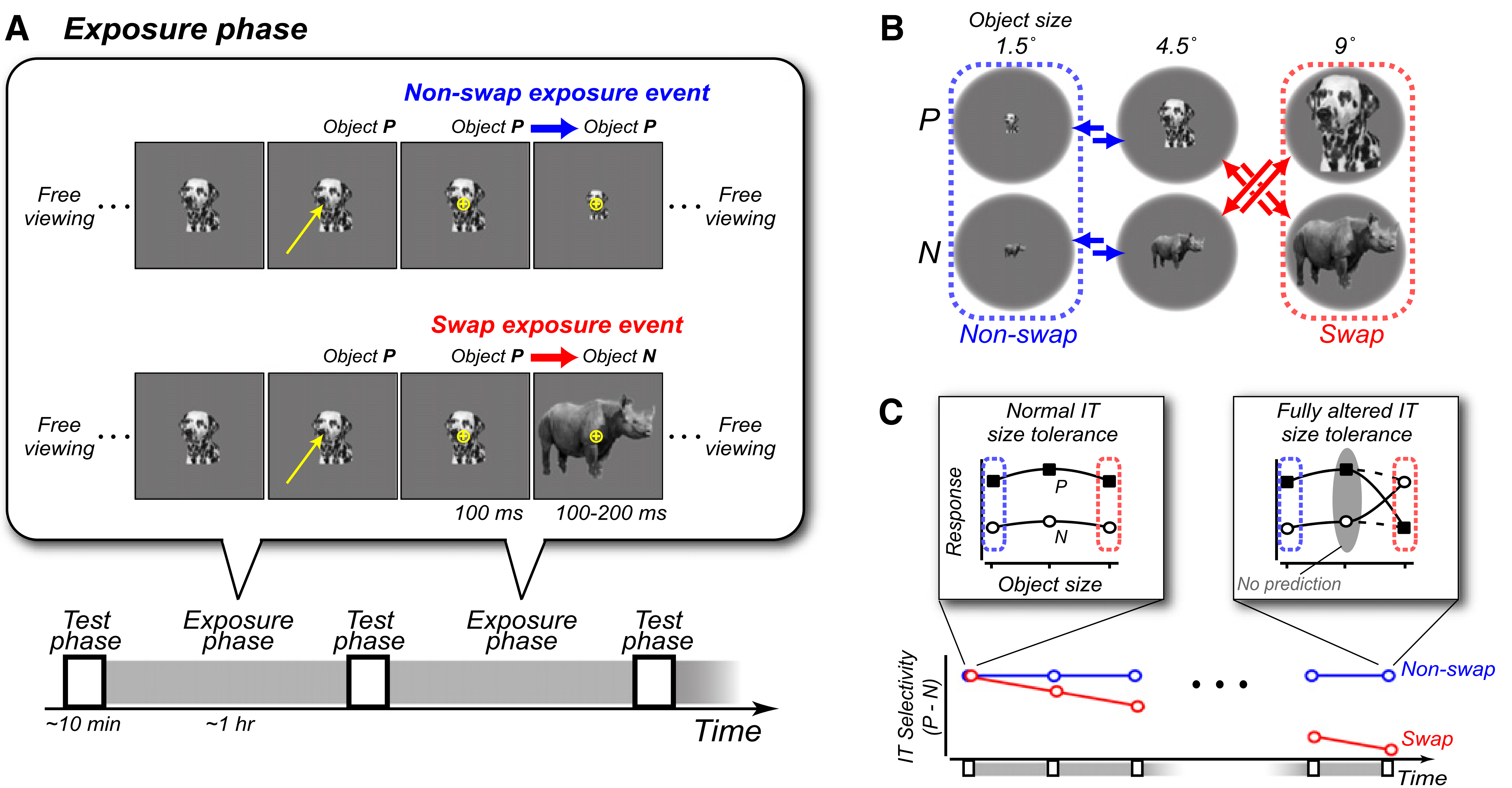


Li & DiCarlo '08

Learning in IT



Li & DiCarlo '10