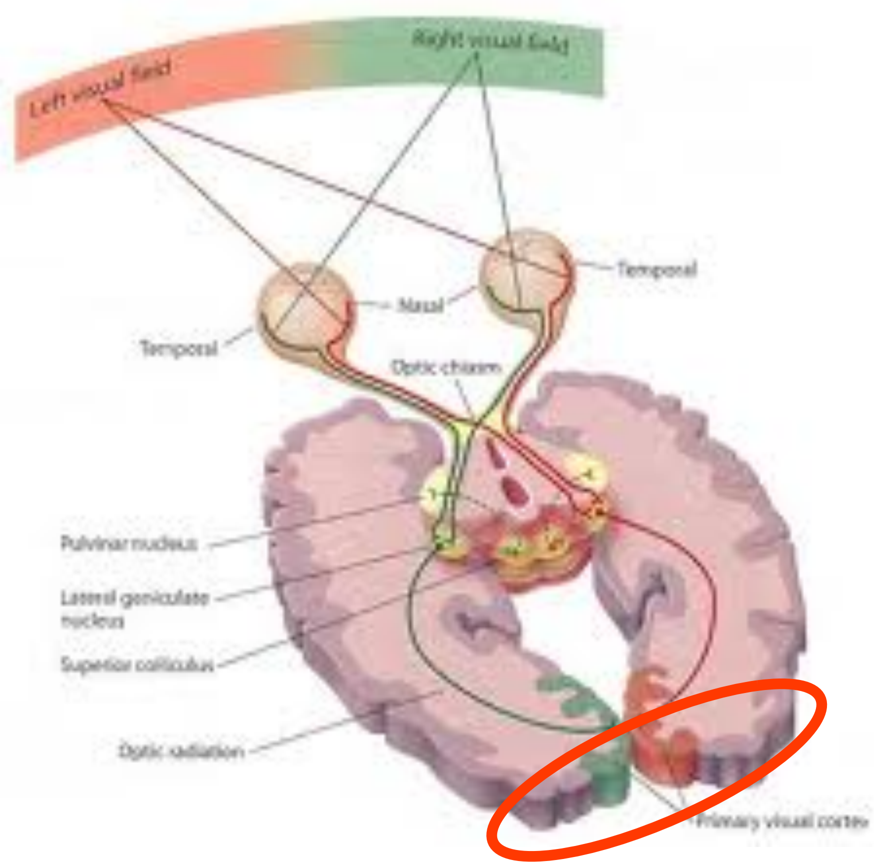
Computational Vision

Beyond the LN

- Gain control / normalization
- Contextual interactions
- Pooling / invariance

RF organization in V1

Hubel & Wiesel

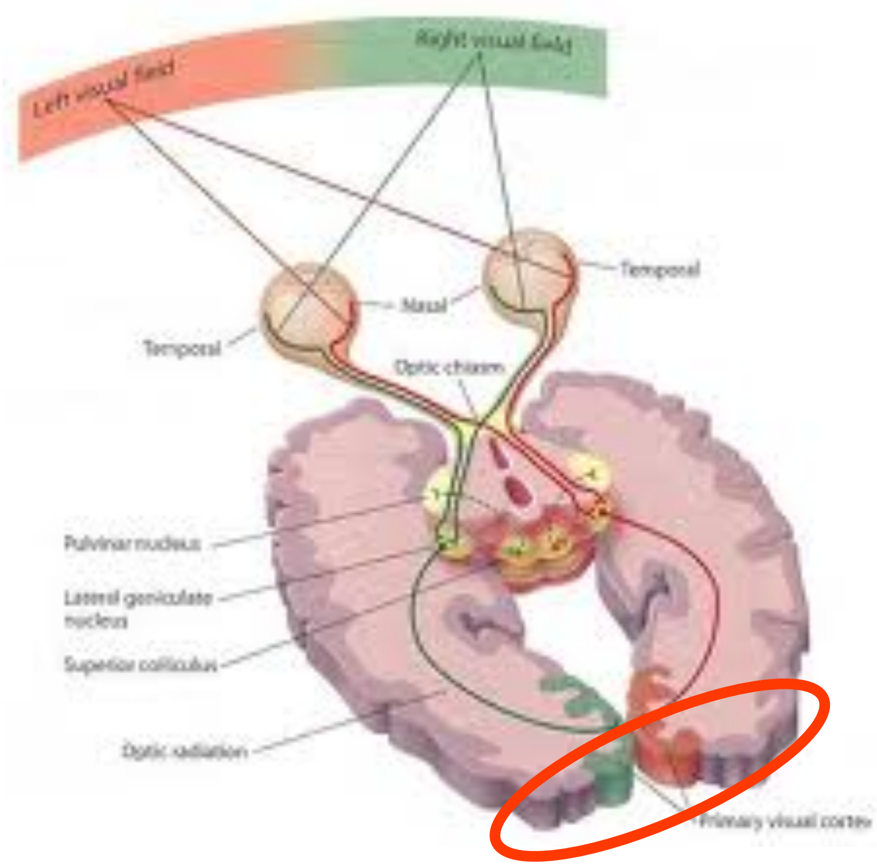


Complex cell

Hubel & Wiesel ’59 ’62 ’68

RF organization in V1

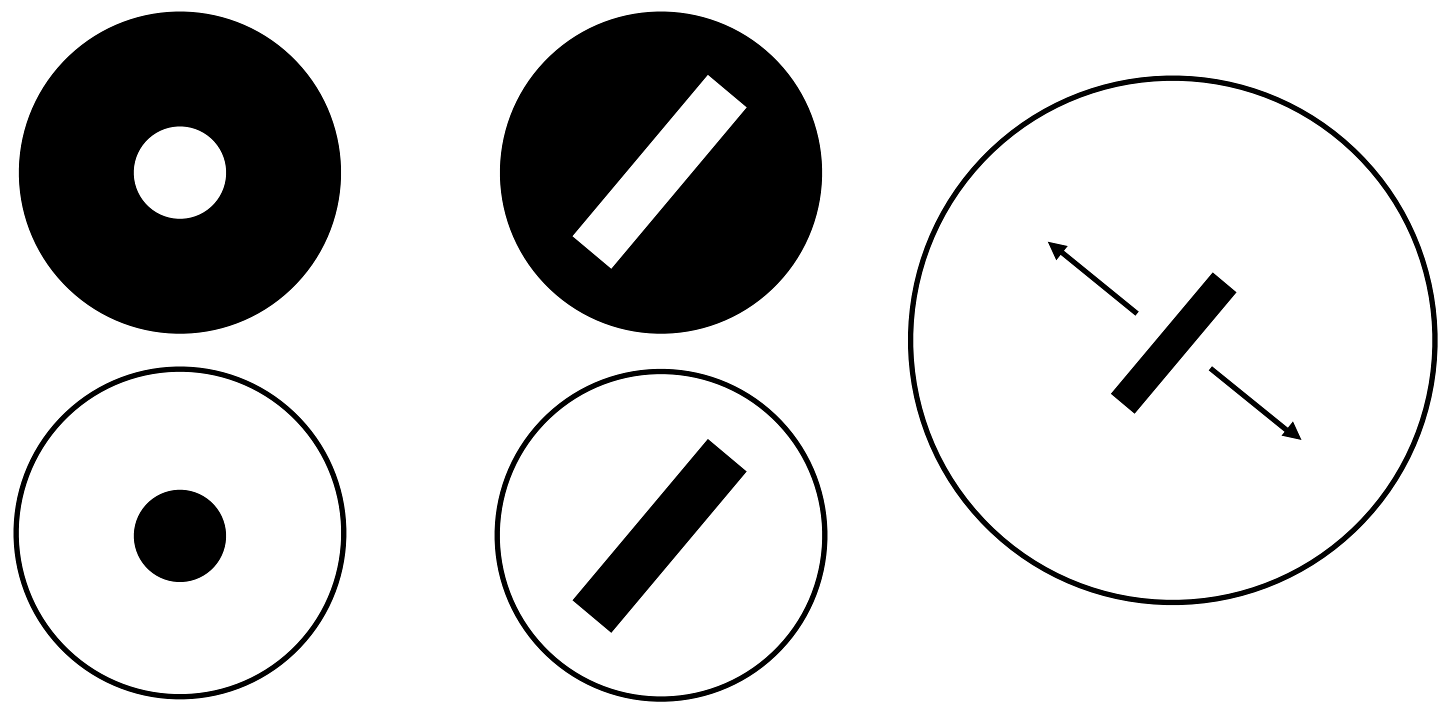
Hubel & Wiesel



ganglion cells

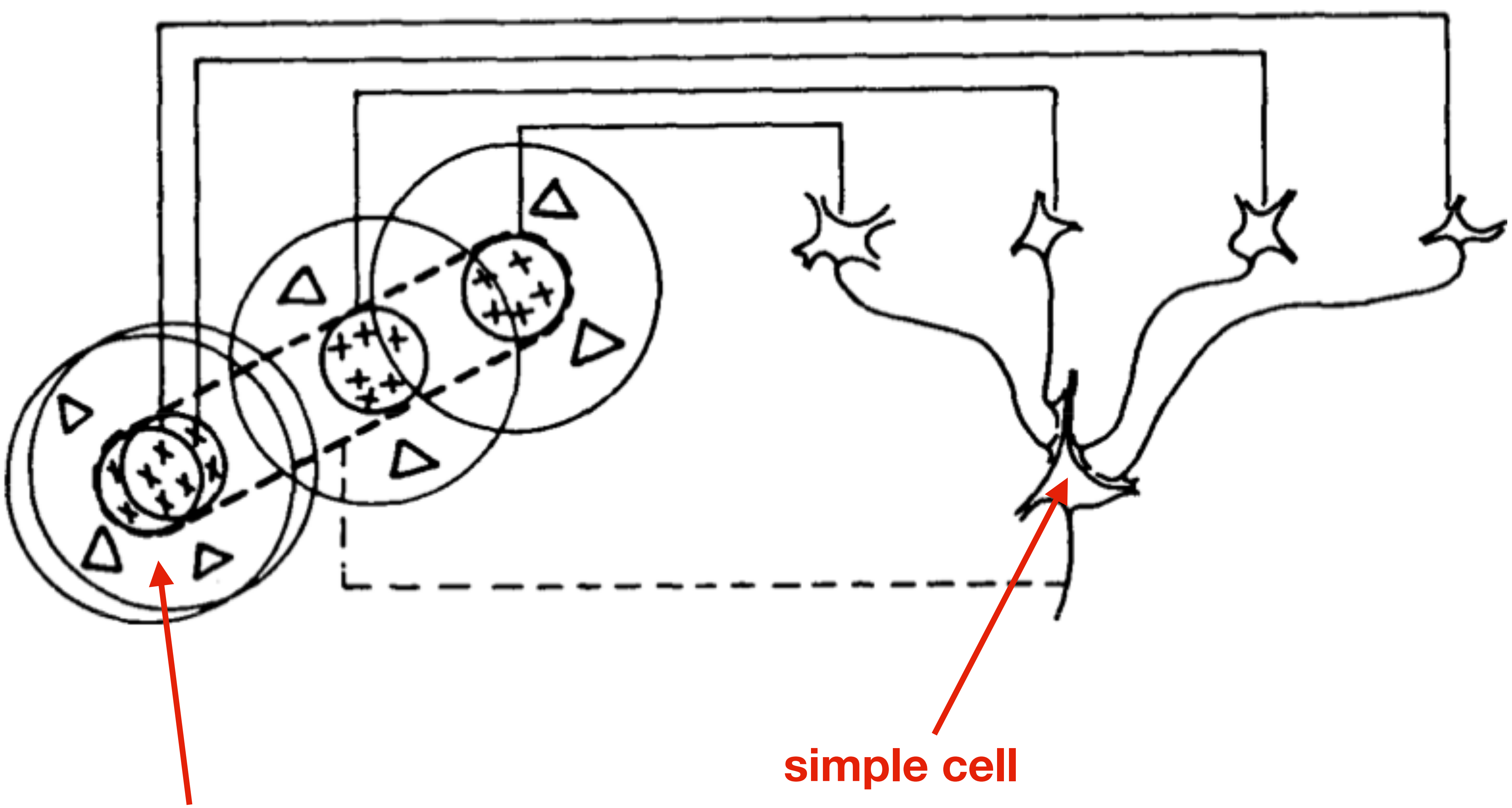
simple cells

complex cells



Hubel & Wiesel ’59 ’62 ’68

Hubel & Wiesel (feedforward) model

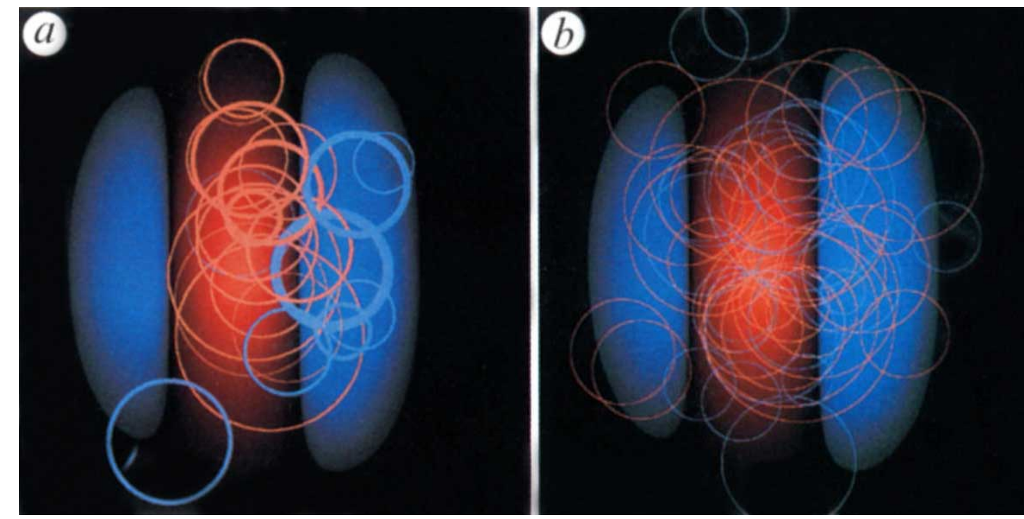


Hubel & Wiesel ’62

Validation of the feedforward model

V1-LGN simultaneous recordings

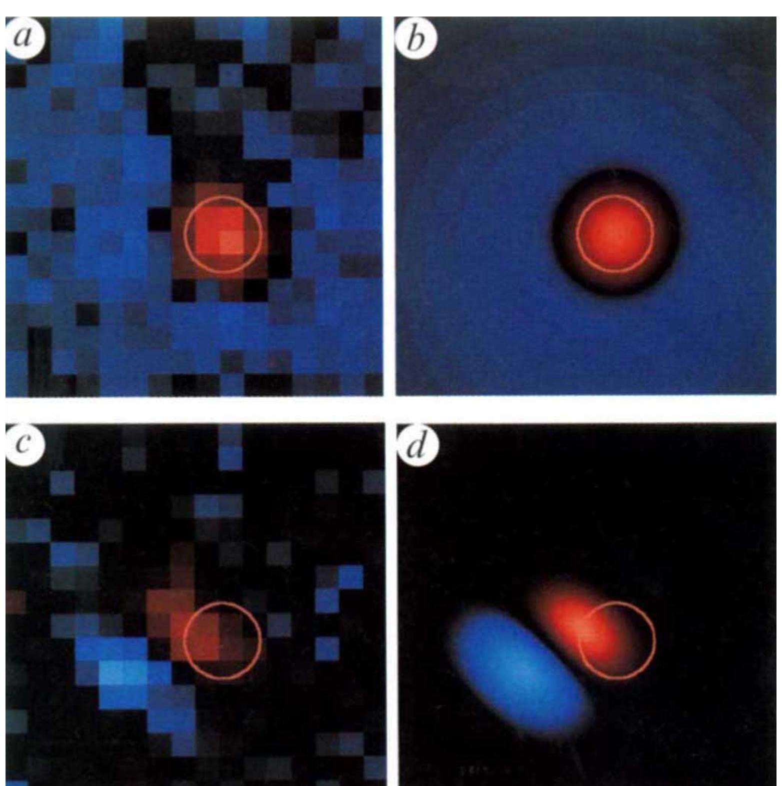
TABLE 1 Connections between overlapping X cells and simple cells	Connected	Total	Percentage	Strength mean/median (%)
Same-sign	17	27	63%	3.5/2.6
(centred)	6	7	86%	2.1/1.6
Border	5	31	19%	2.4/2.0
Opposite-sign	1	16	6%	0.2/0.2
Total	23	74	31%	3.1/2.4

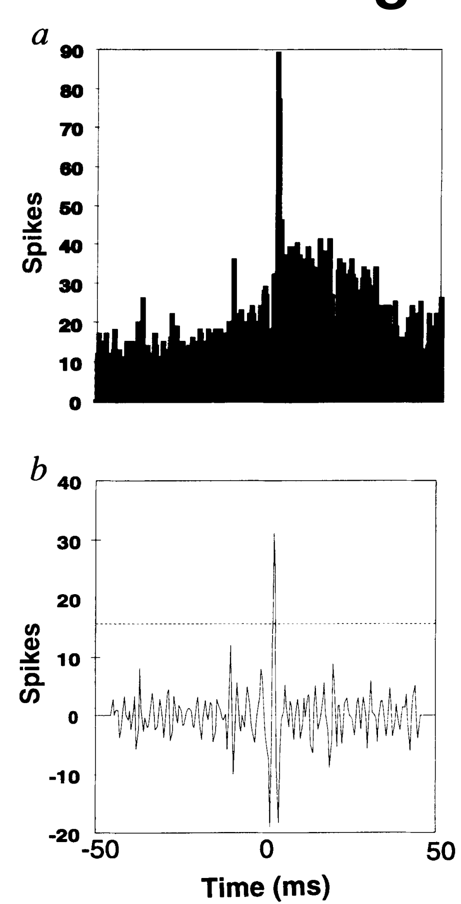


cross-correlogram

LGN cell

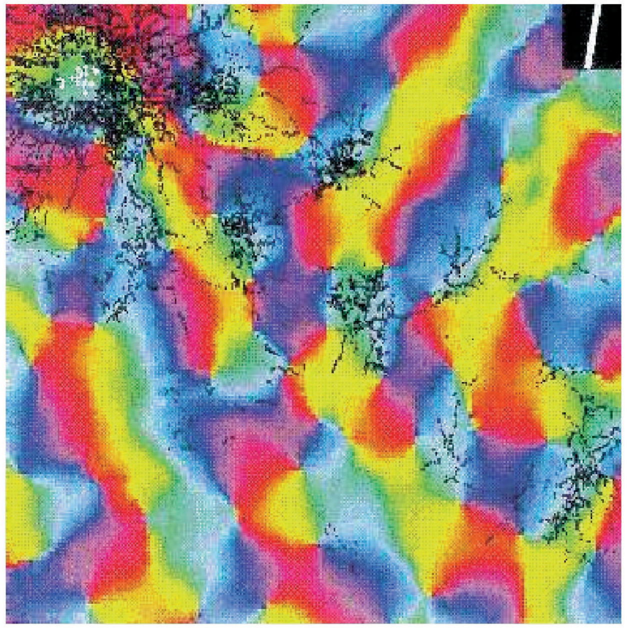
V1 cell

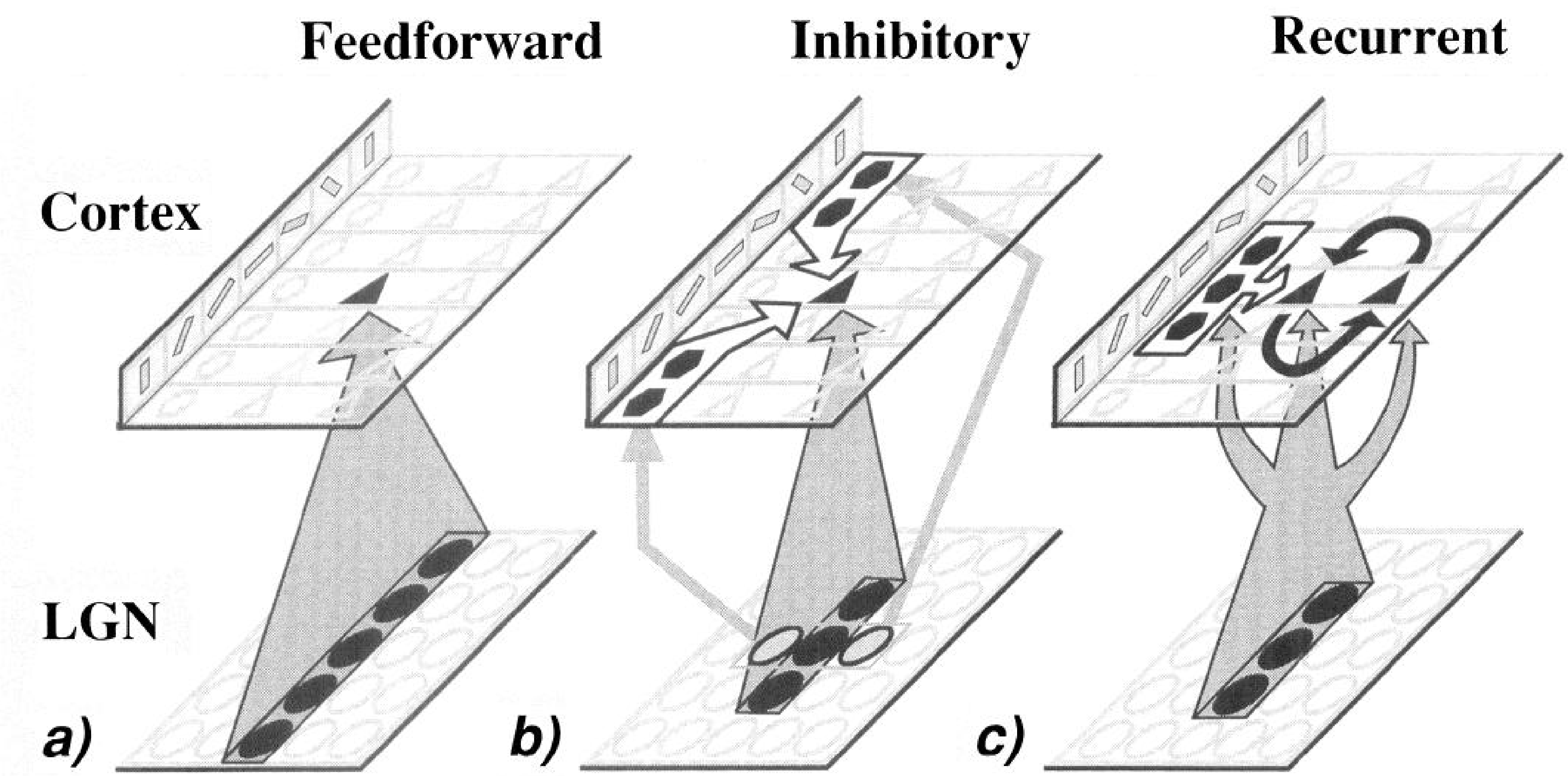




Reid & Alonso 1995

Alternative models

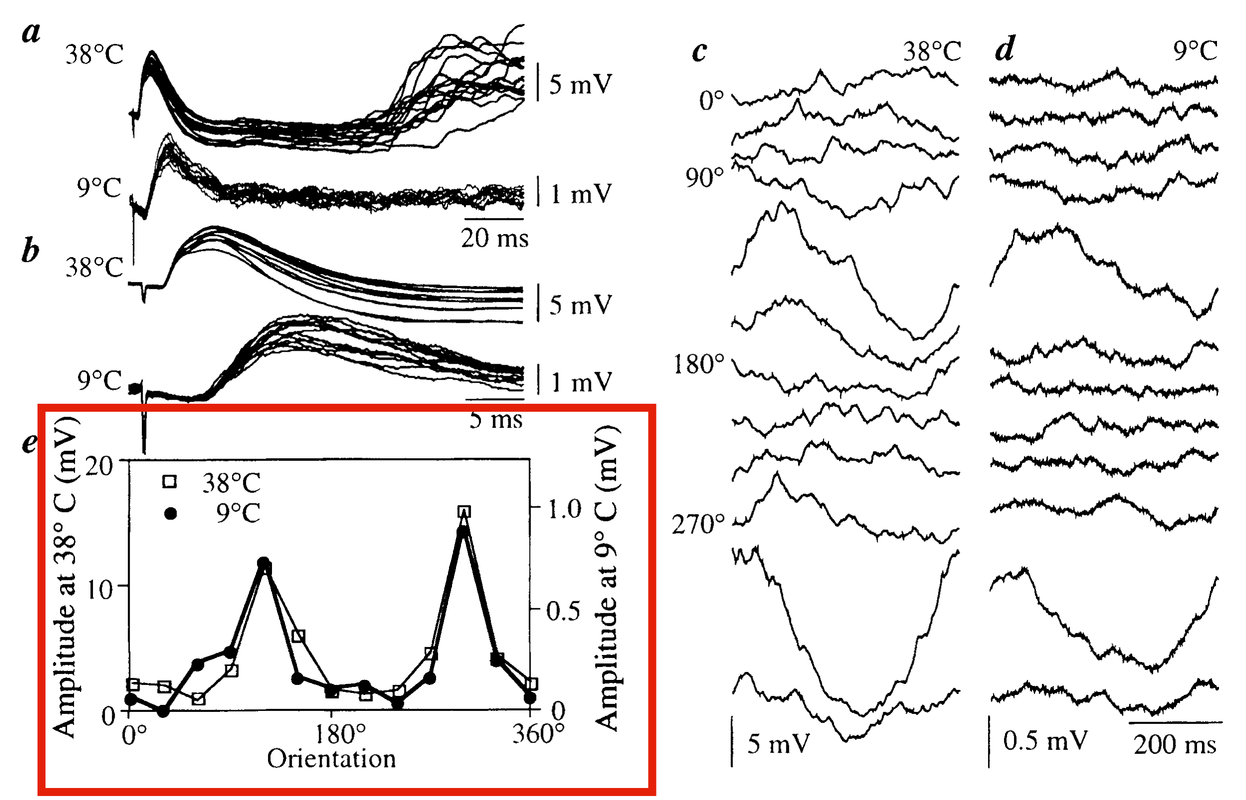




Somers et al 1995

Validation of the feedforward model

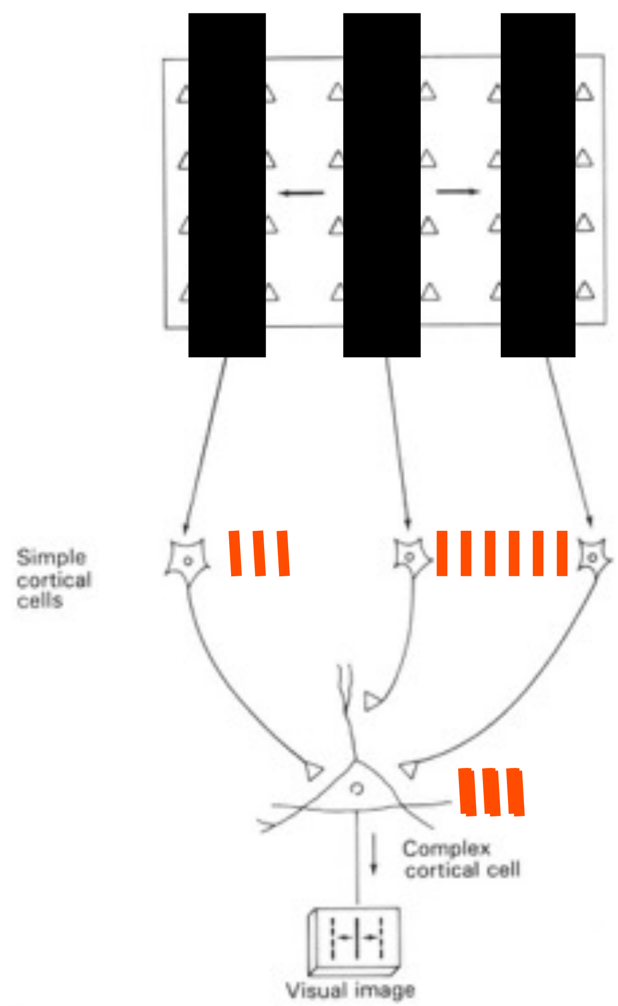
- Silencing/cooling the cortex does not seem to affect orientation tuning
- Suggest that core computation is outside cortex, i.e., in LGN



Ferster et al 1996

How would you go about building a complex cell?

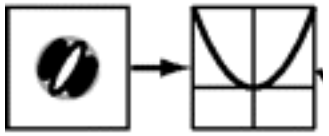
Hubel & Wiesel
(feedforward) model cont'd



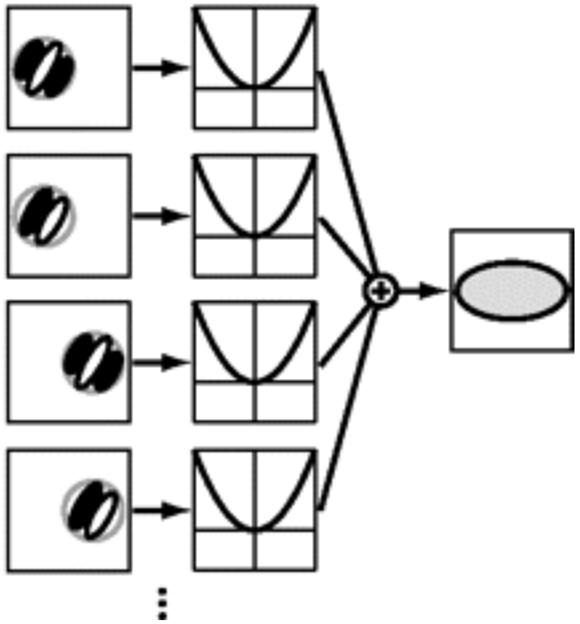
Hubel & Wiesel

Hubel & Wiesel (feedforward) model cont'd

squaring / "energy model"



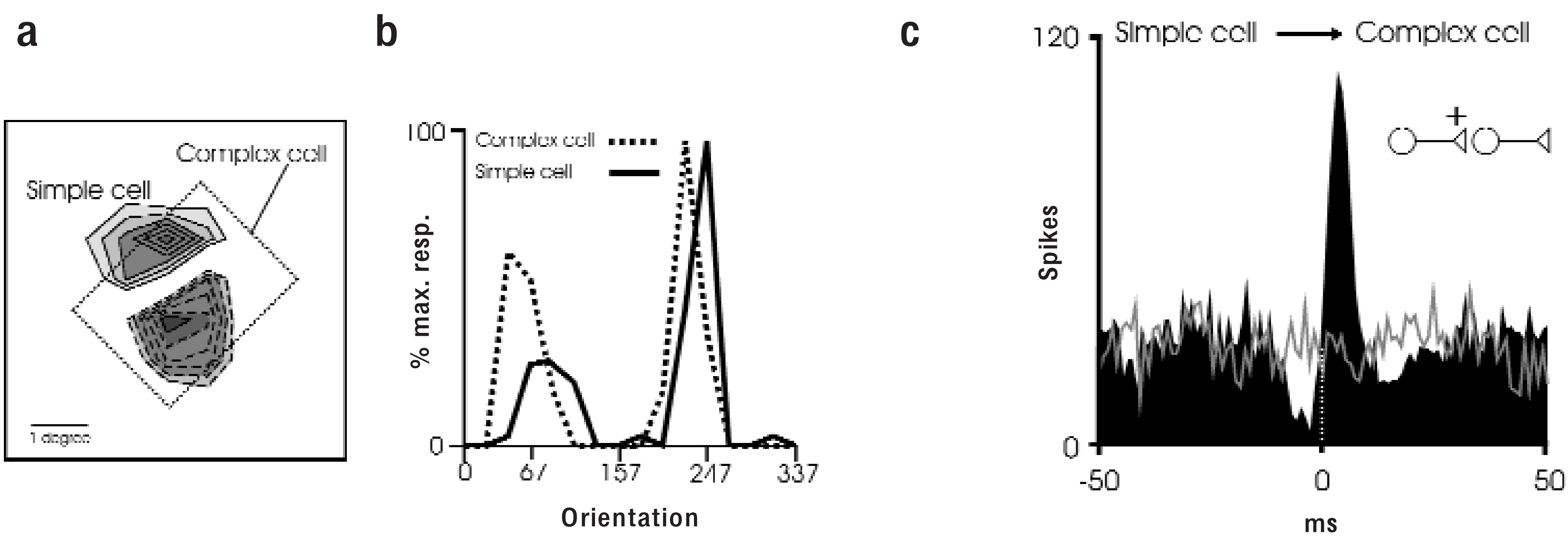
complete model



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

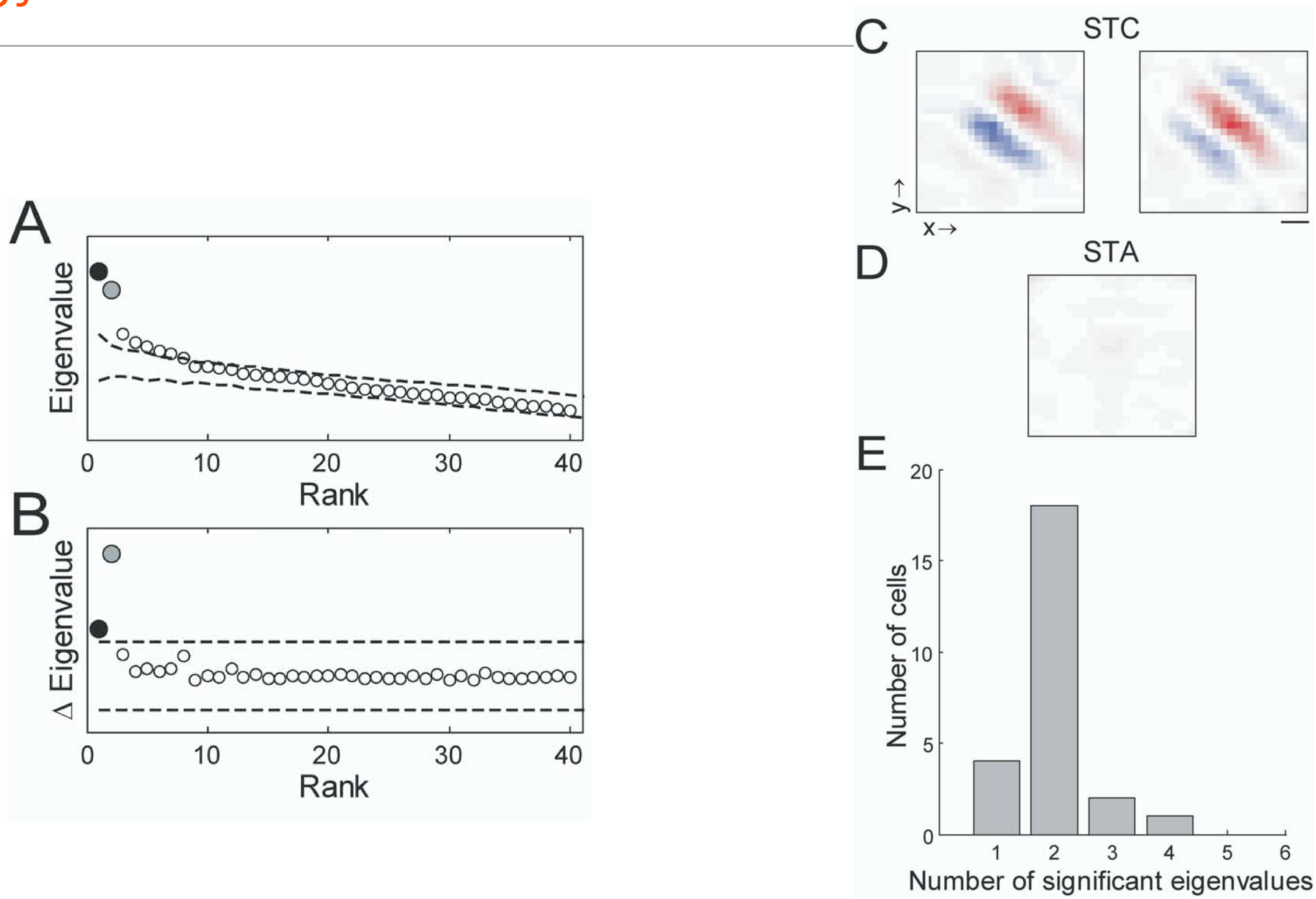
Validation of the feedforward model

simple-complex cells connected pair



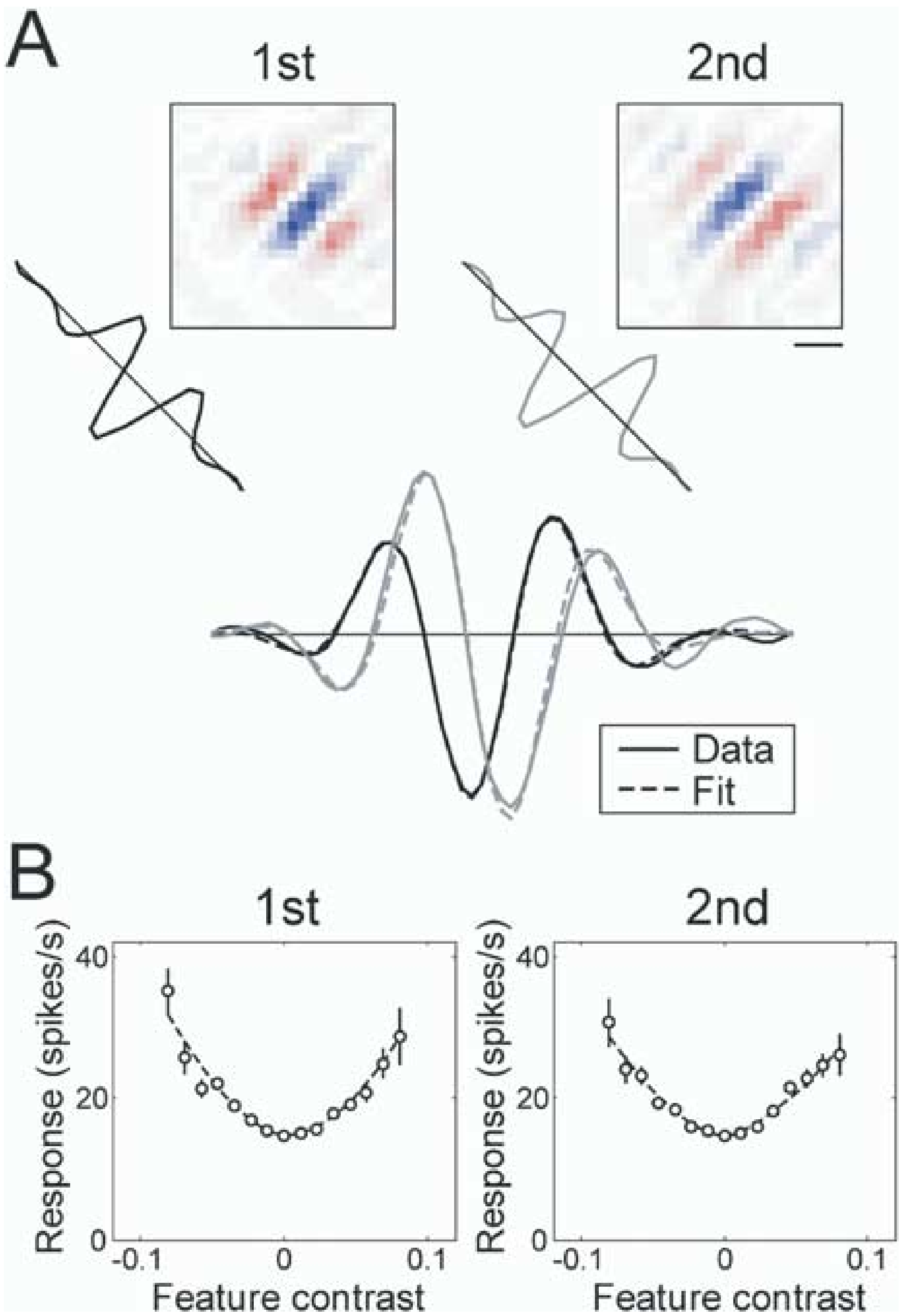
Alonso & Martinez1998

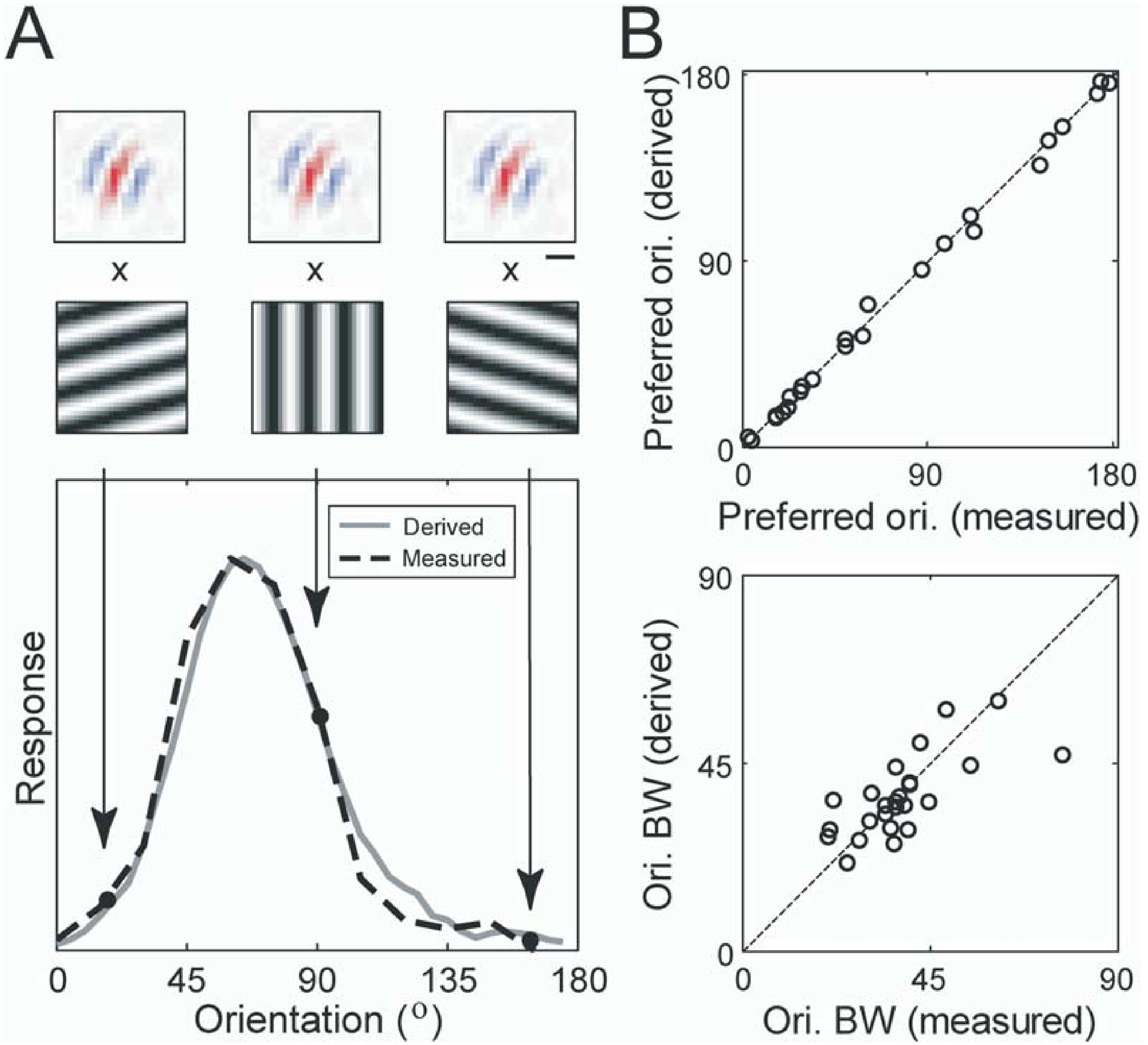
Energy mechanisms and divisive normalization



Touryan et al '05

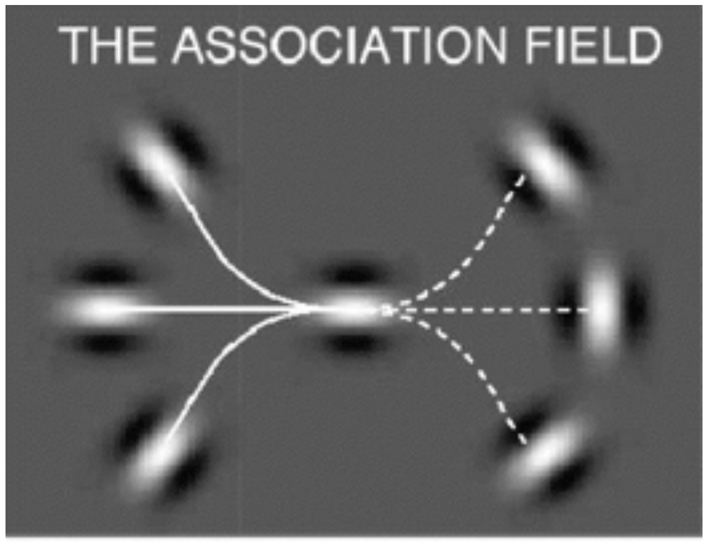
Energy mechanisms and divisive normalization

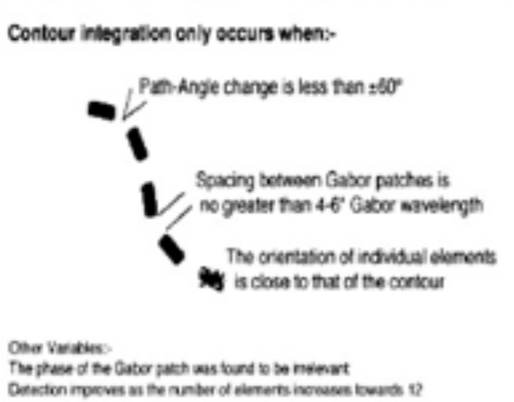




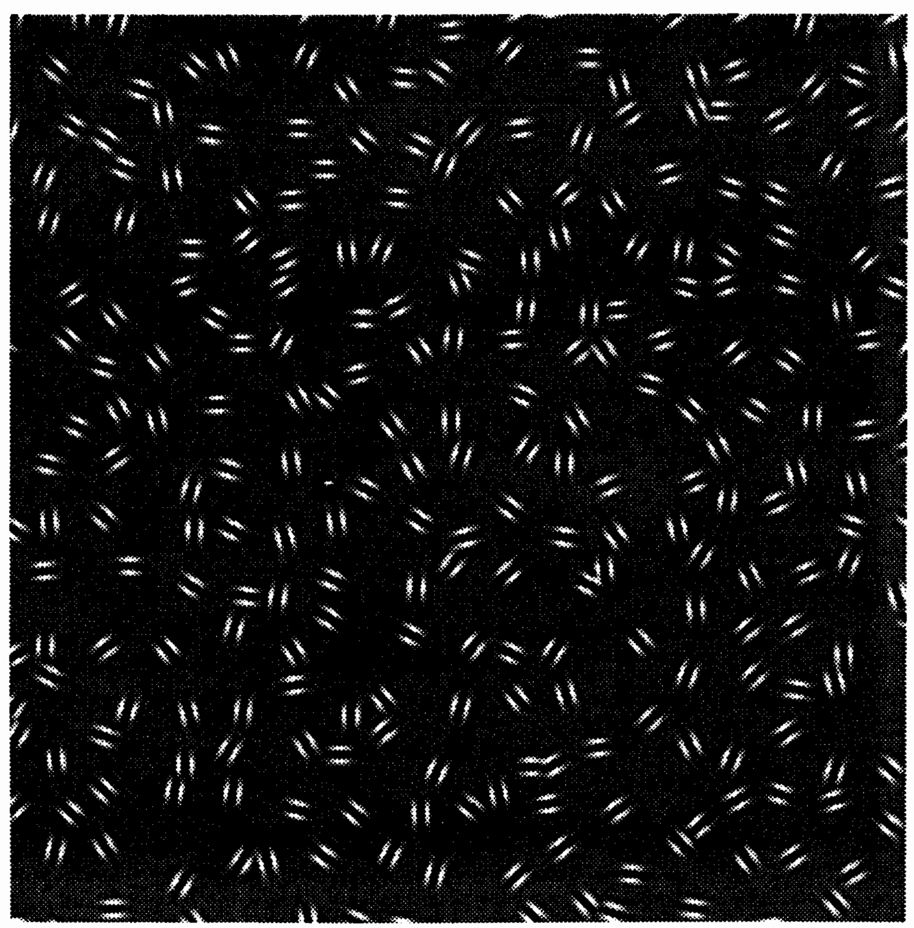
Touryan et al '05

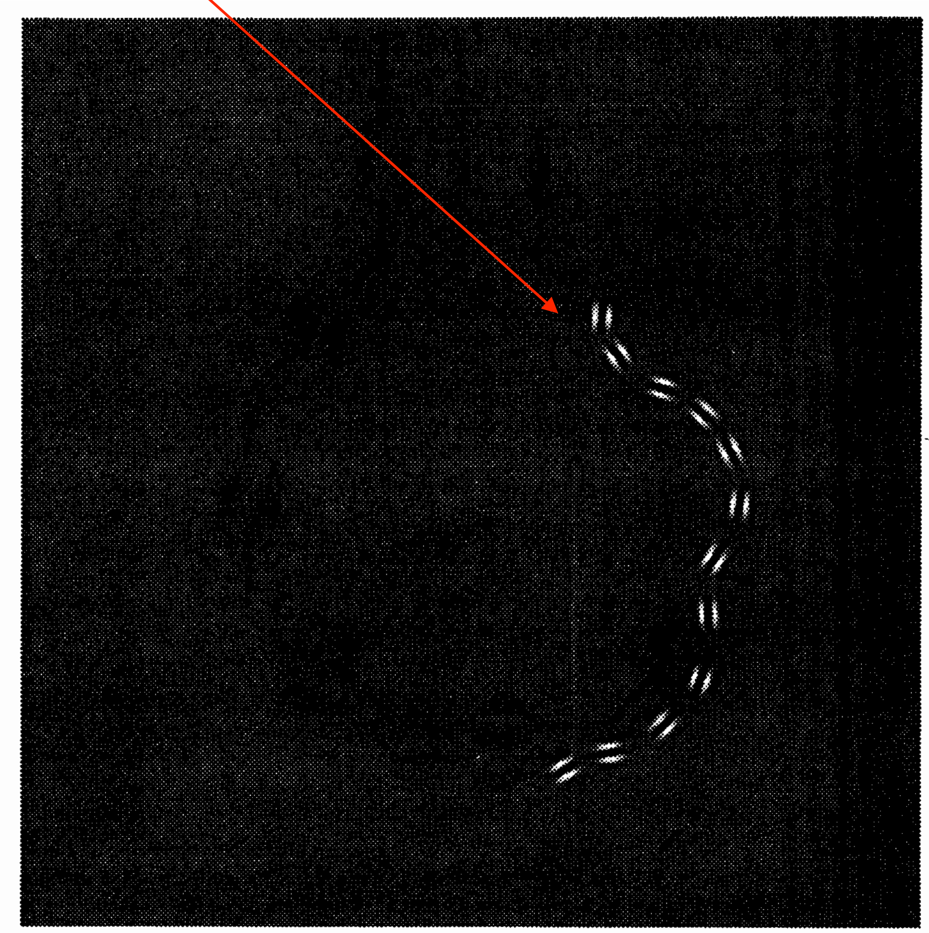
Computational models of complex cells





Changing phase has little effect



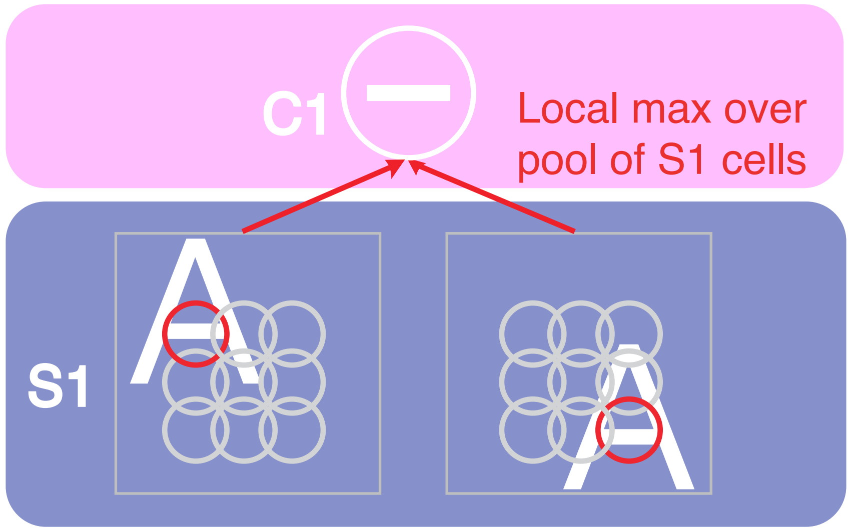


source: Field et al 1993

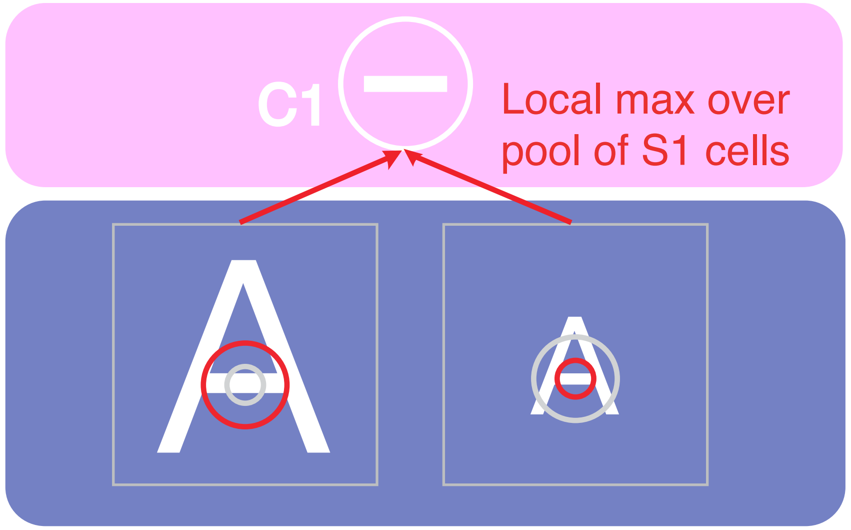
Max pooling

Motivation: Superposition problem and robustness to clutter

Increase in tolerance to position

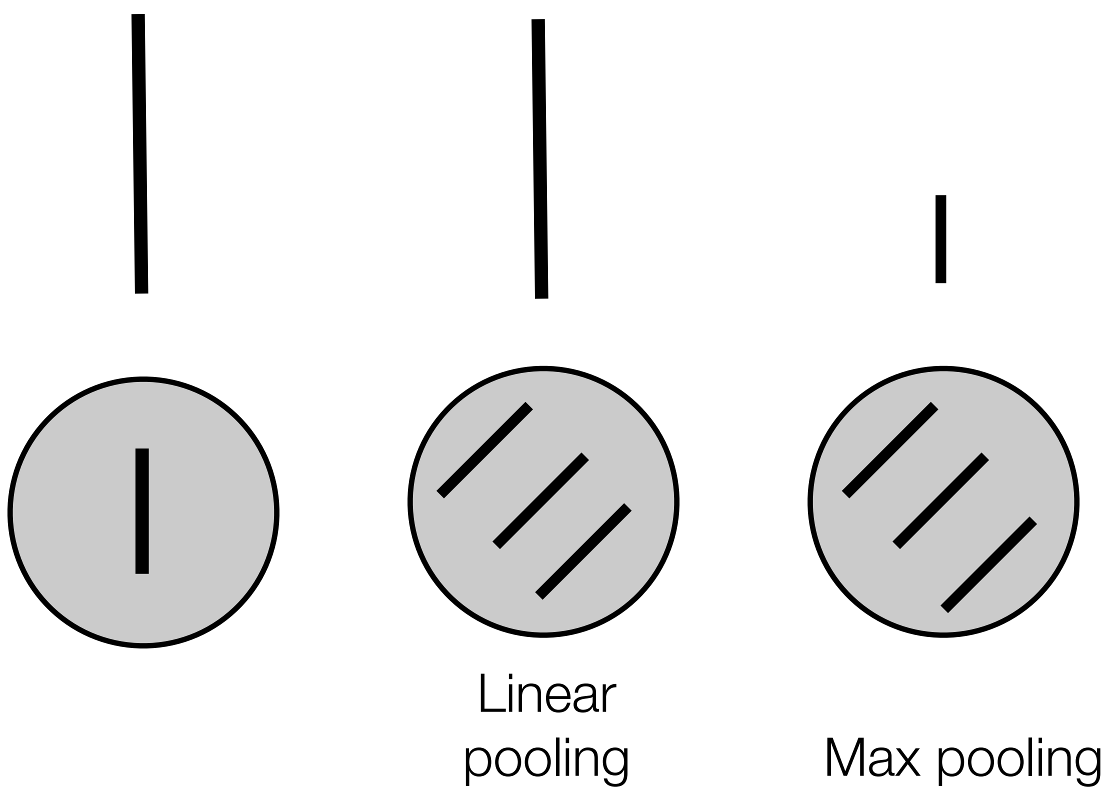


Increase in tolerance to scale



Riesenhuber & Poggio 1999

Superposition problem



Computational diversity

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

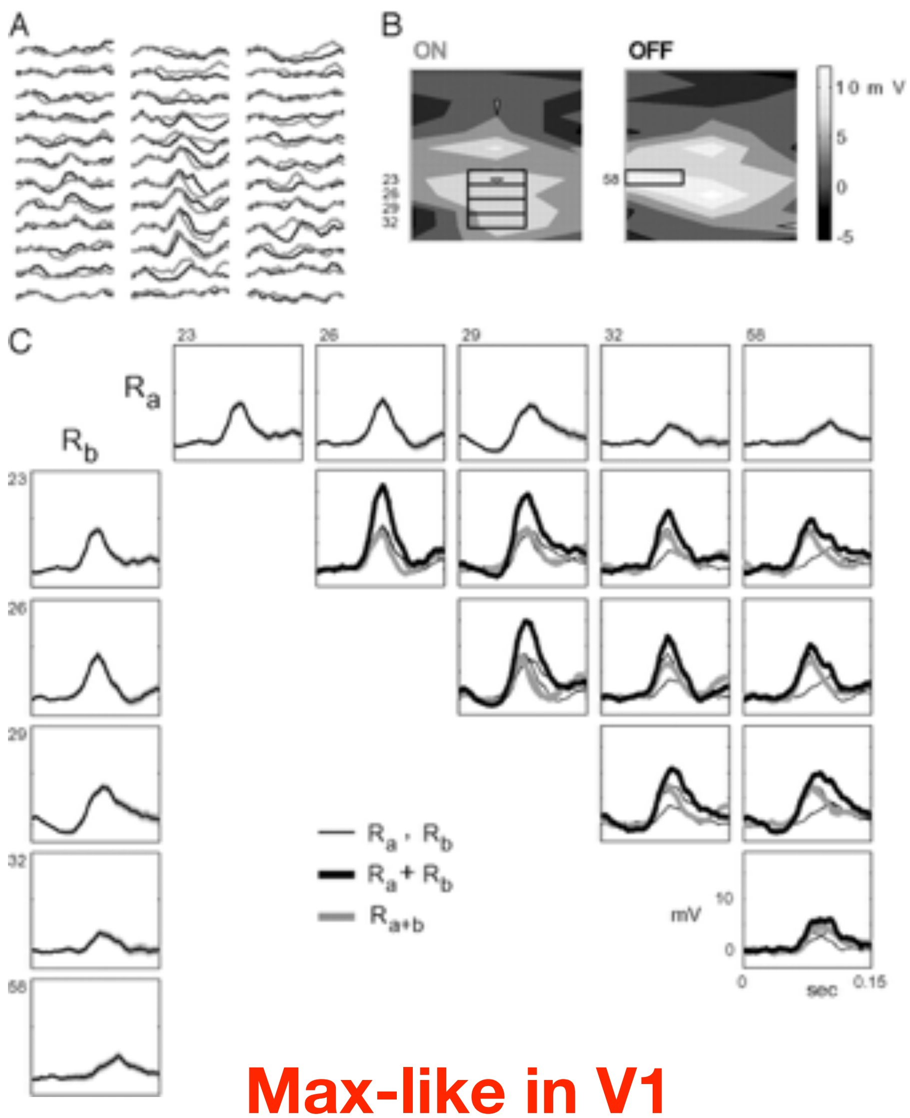
Behavioral/Systems/Cognitive

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

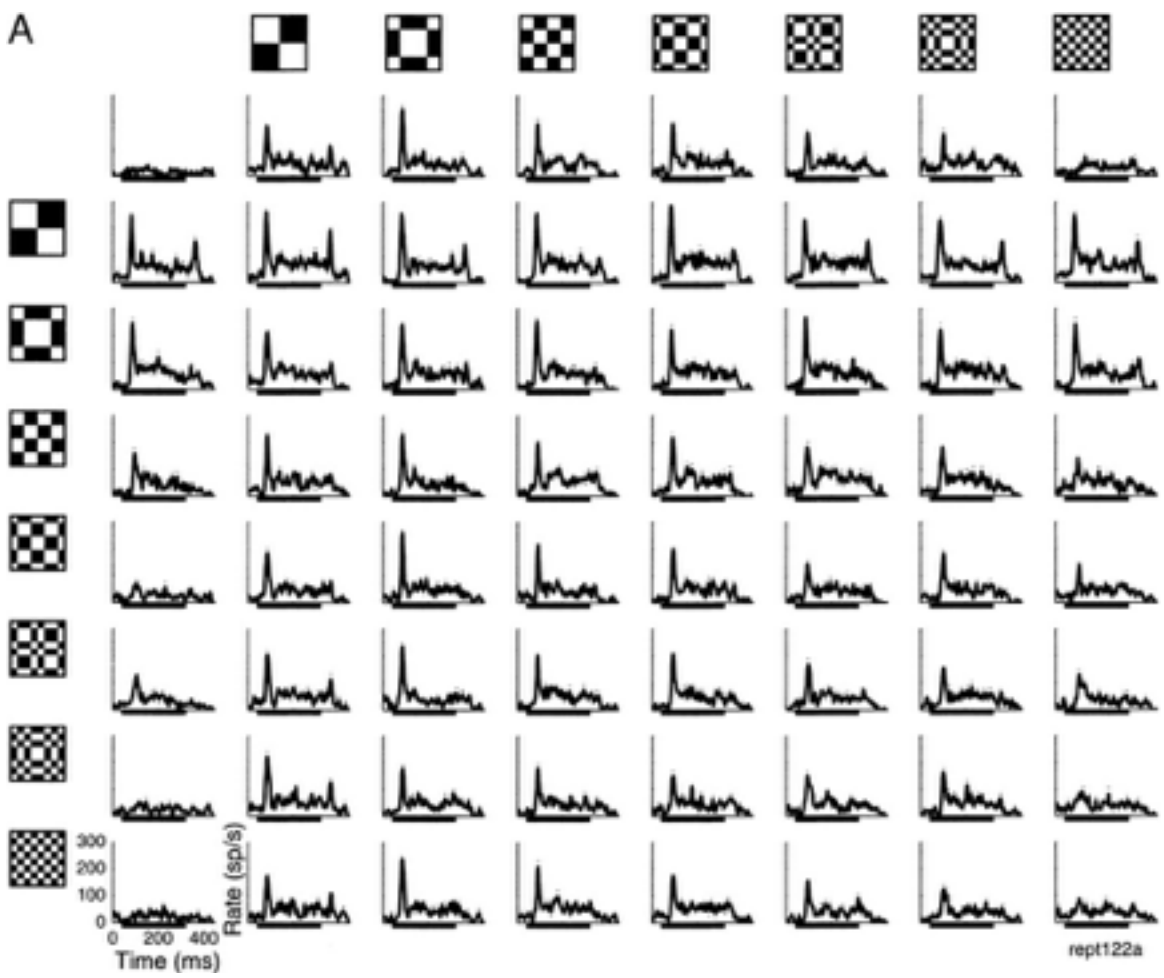
Max-like computation in the visual cortex

Lampl et al ‘04



Max-like in V1

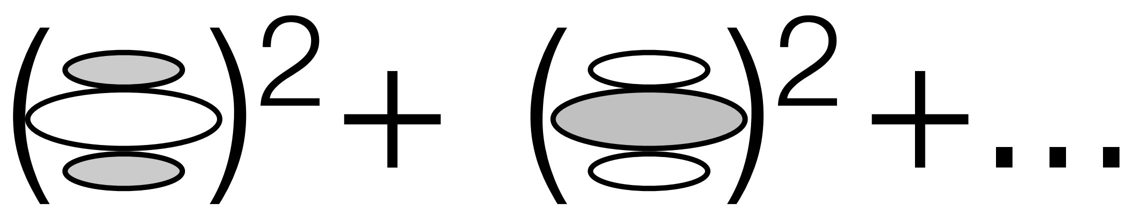
Gawne & Martin ‘02



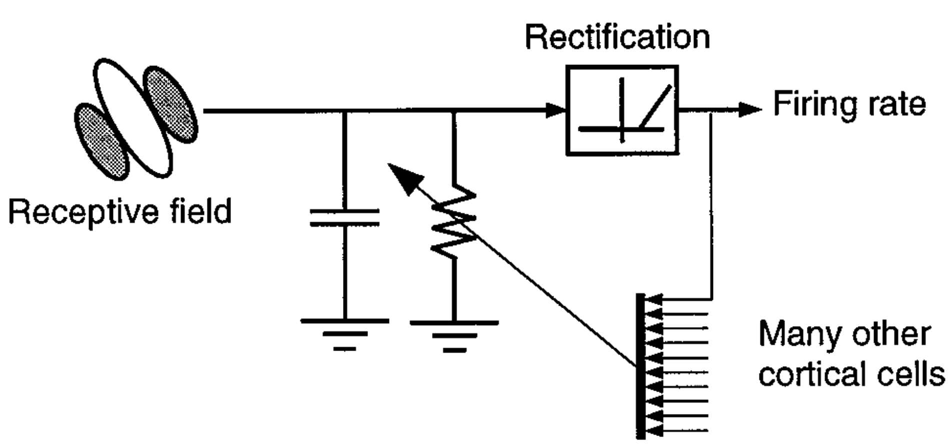
Max-like in V4

Complex cell model

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

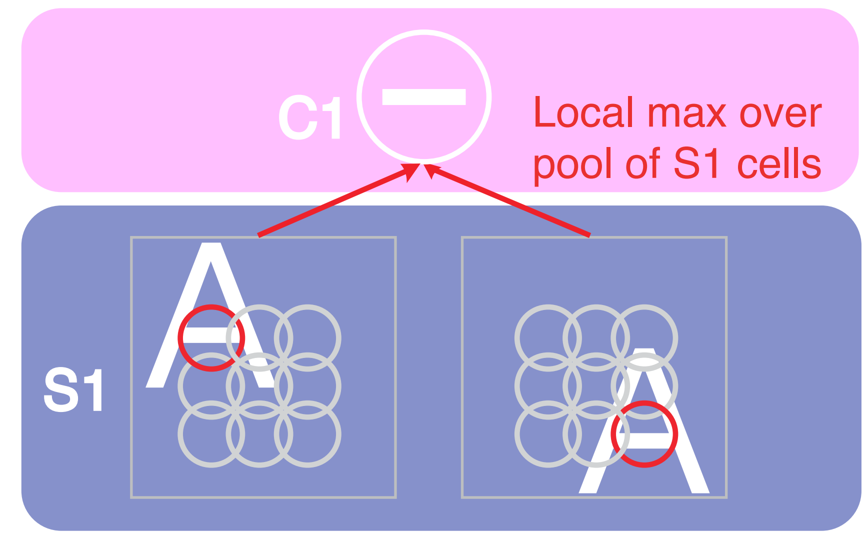


(2) gain control / divisive normalization

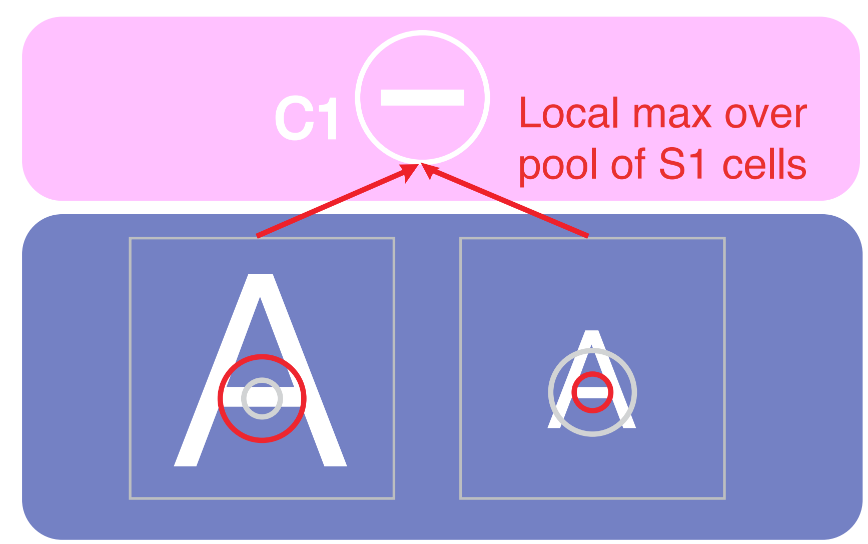


(3) selective max-like pooling over nearby positions and scales for tolerance to 2D transformations

Increase in tolerance to position

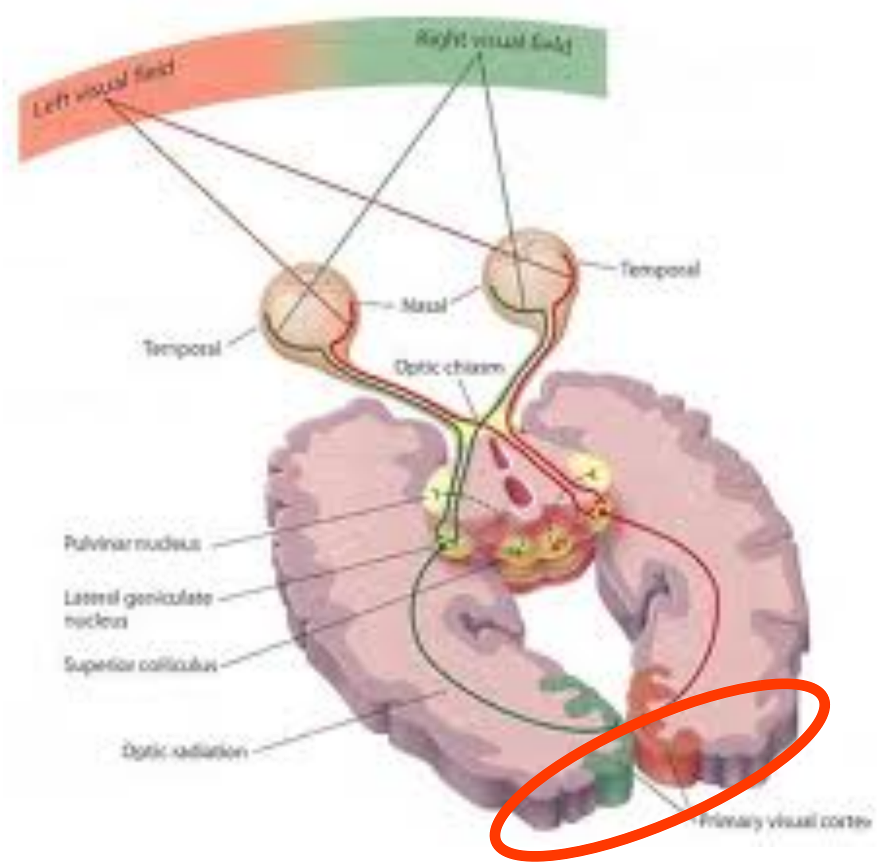


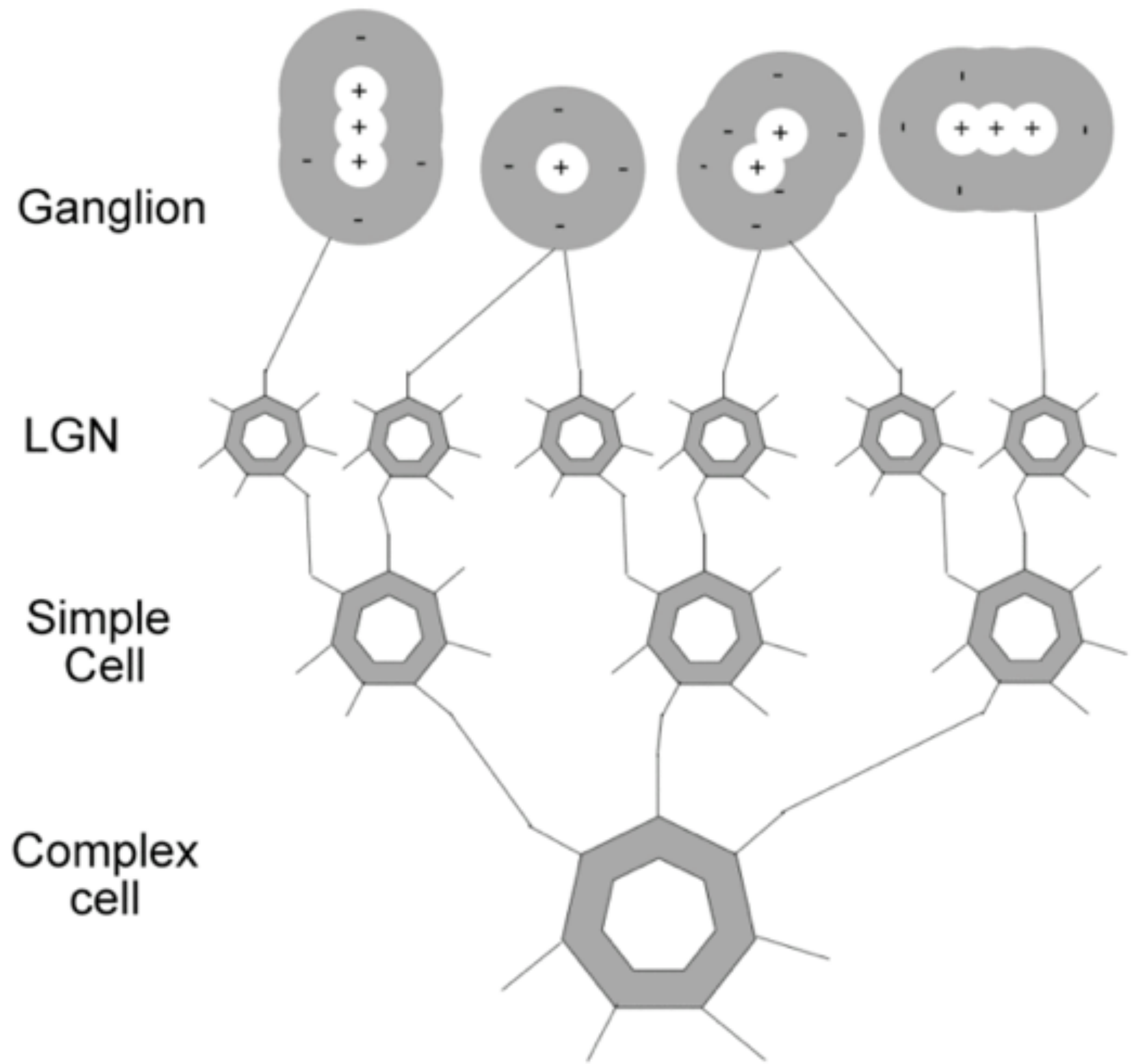
Increase in tolerance to scale



RF organization in V1

Hubel & Wiesel

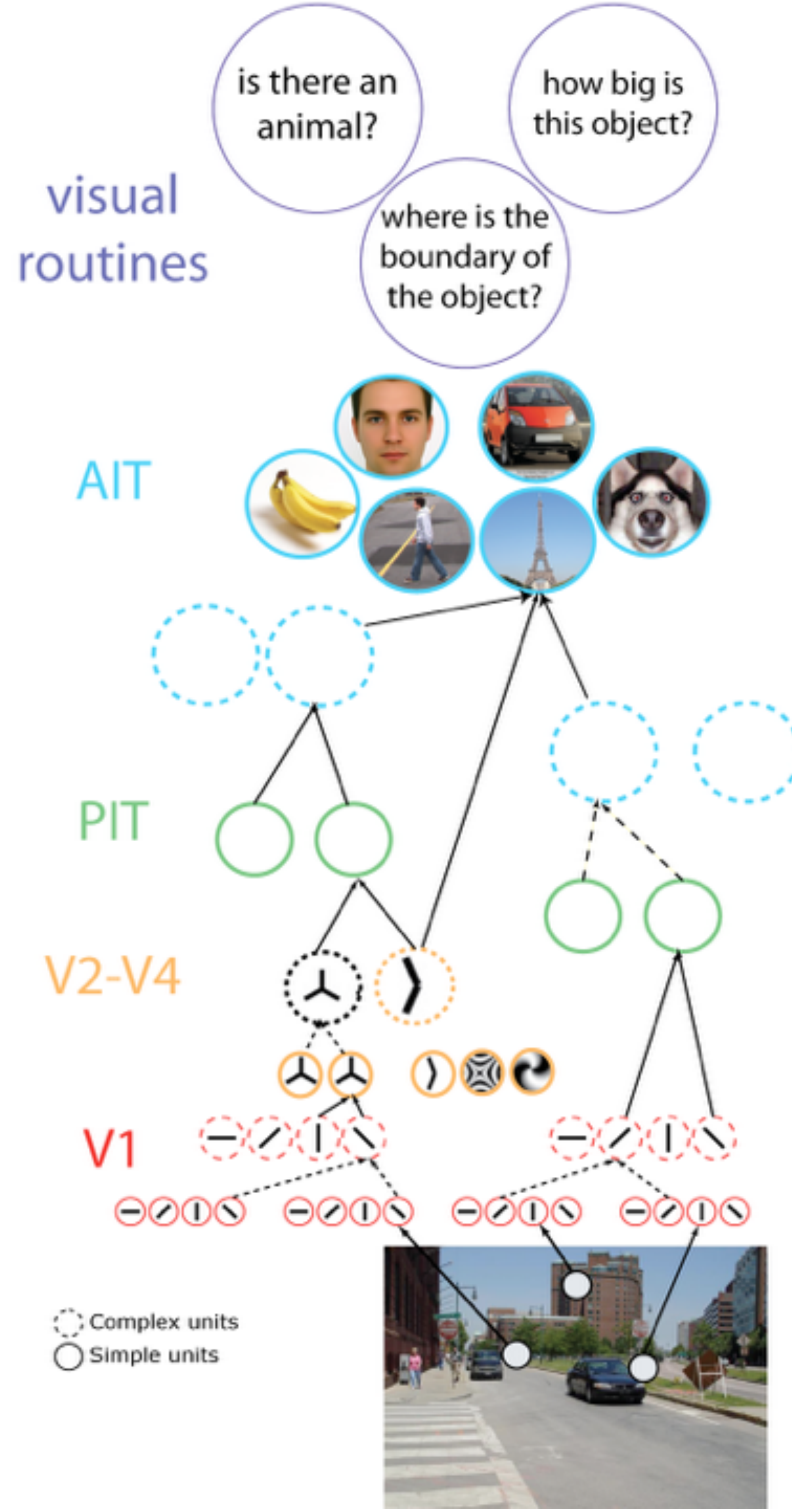




Hubel & Wiesel ’59 ’62 ’68

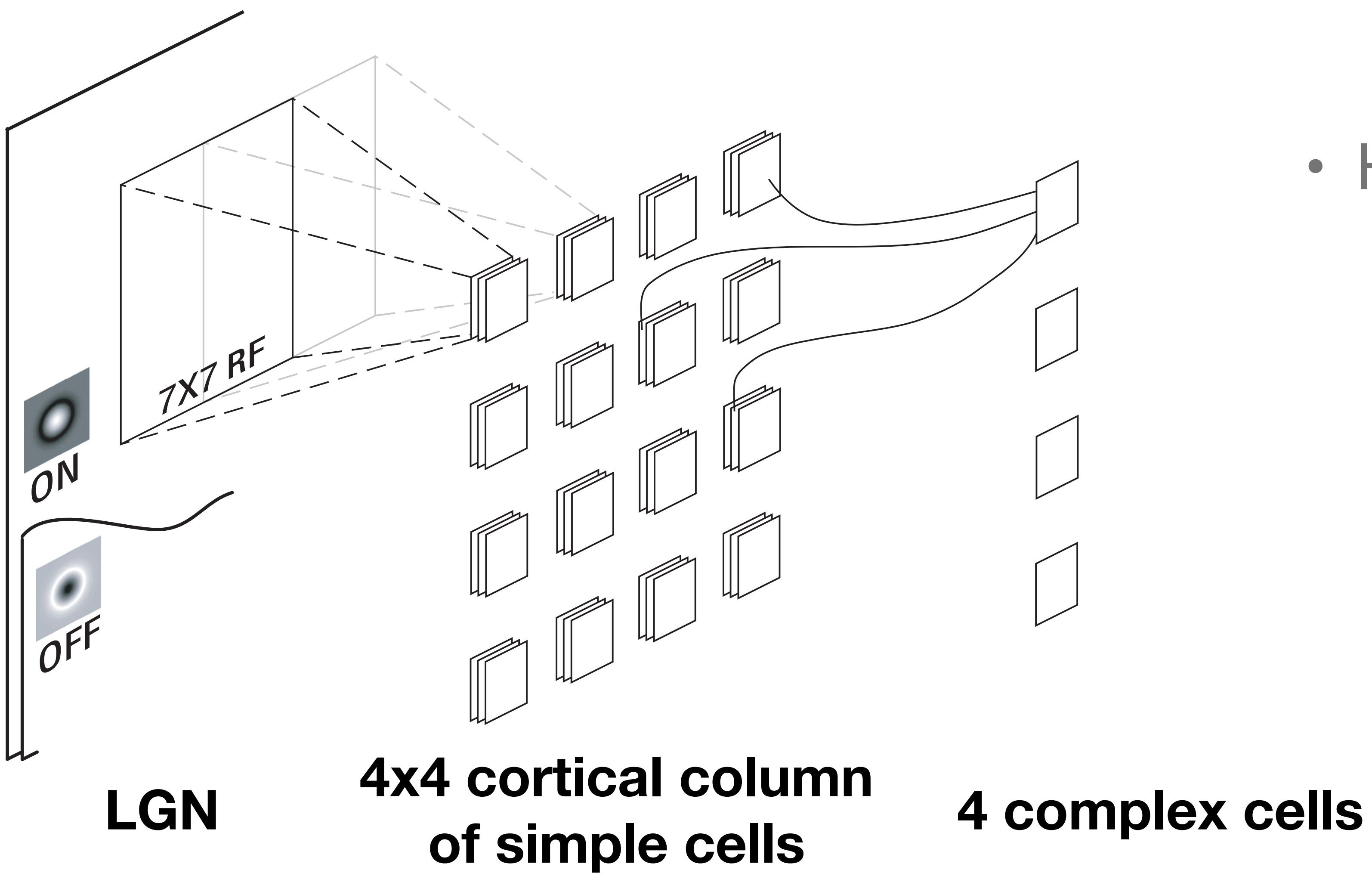
Feedforward hierarchical models

- Earlier models: Hubel & Wiesel ’62, Fukushima ’80, Wallis & Rolls ’97, Mel’ 97)
- HMAX (Riesenhuber & Poggio ’99, Serre Kouh Cadieu Knoblich Kreiman Poggio ’05 ’07; Serre Oliva & Poggio ’07) and many extensions (e.g., Mutch & Lowe ’06; Masquelier & Thorpe ’07)
- High-throughput screening (Pinto et al ’09, Cadieu et al ’14, Yamins et al ’14)



Learning invariances from temporal continuity

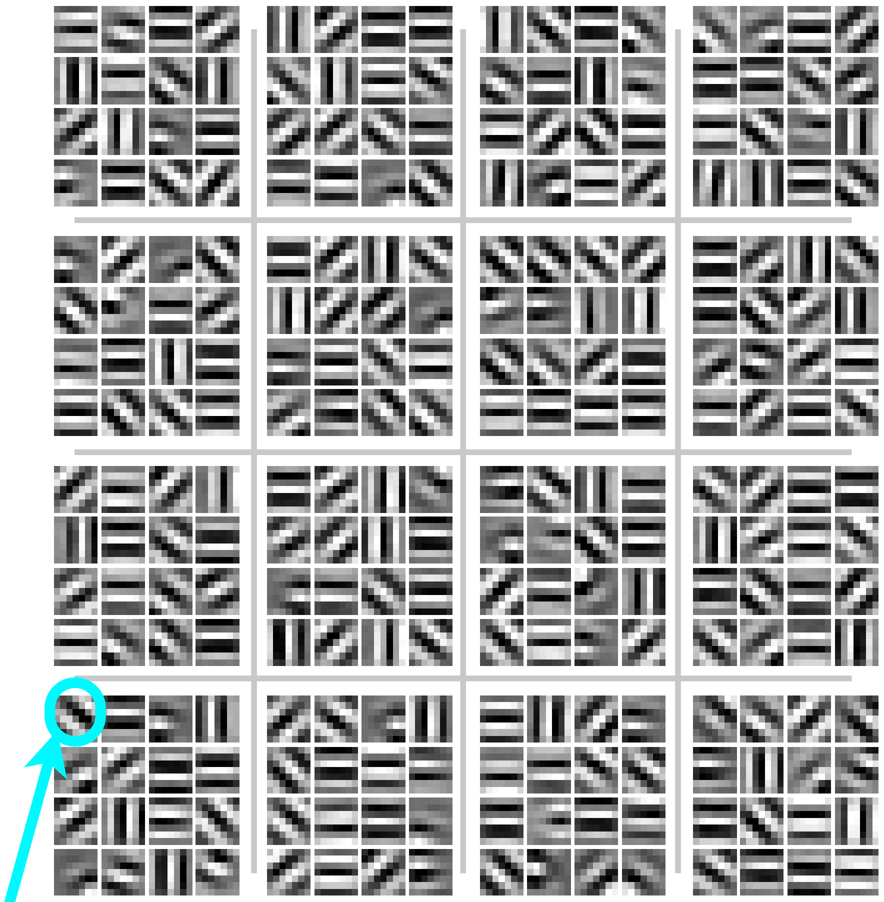
Learning invariances from temporal continuity

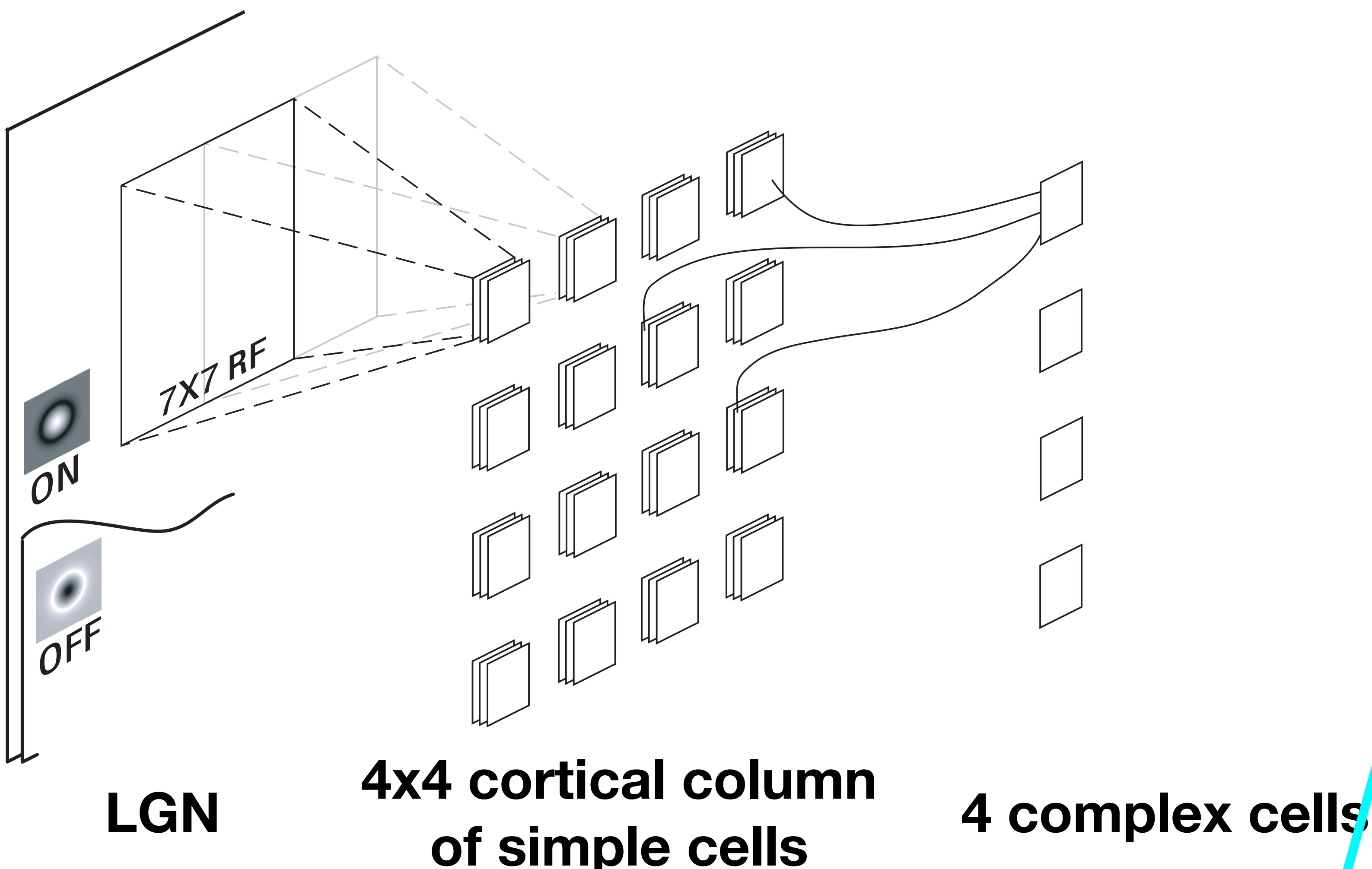


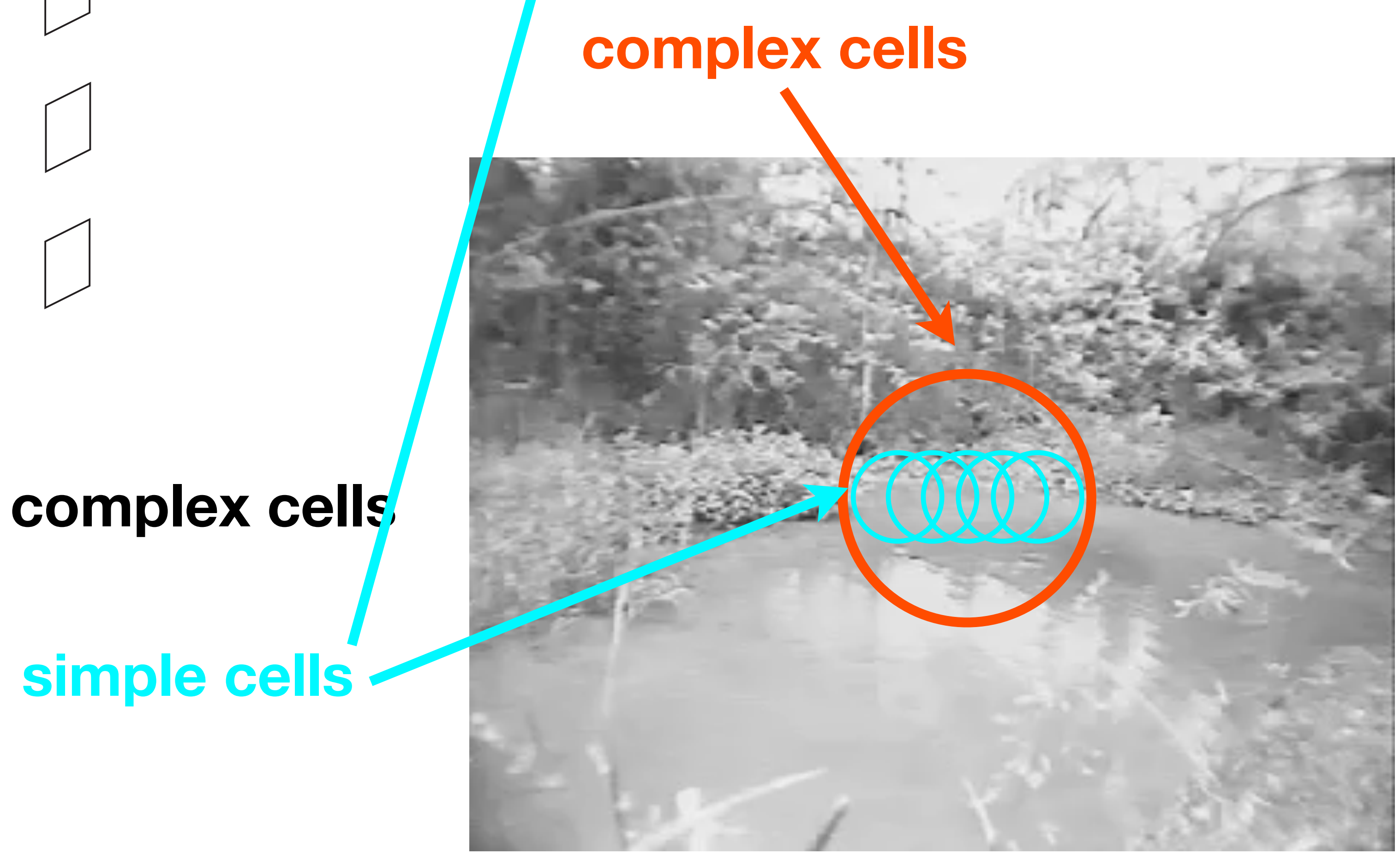
- Hebbian learning:
  - Neurons as coincidence detectors
  - ‘What fires together, wires together’
- Hypothesis:
  - S cells learn corr. in space
  - C cells learn corr. in time

Masquelier et al 2007 (see also Foldiak 1991)

Learning invariances from temporal continuity



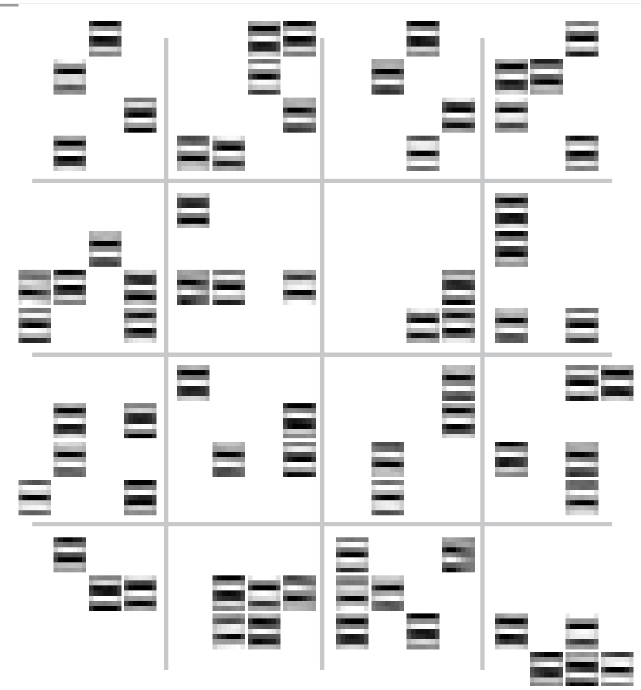




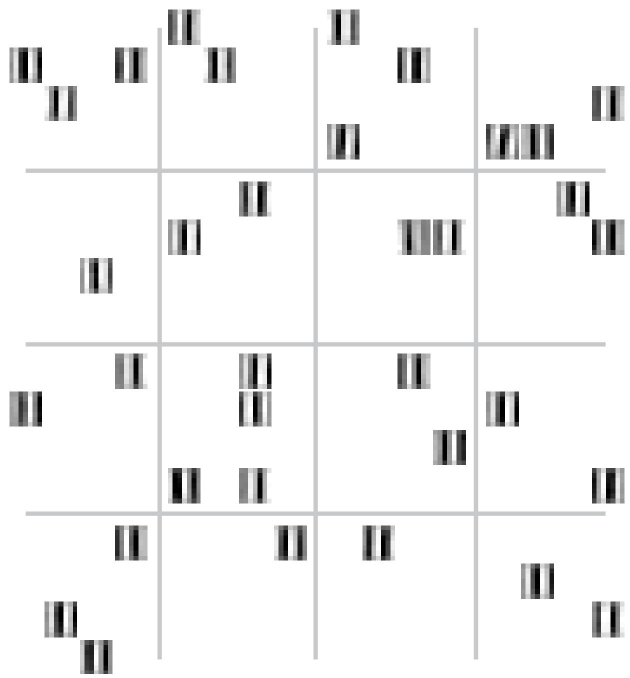
Masquelier et al 2007 (see also Foldiak 1991)

movie courtesy Wolfgang Einhauser

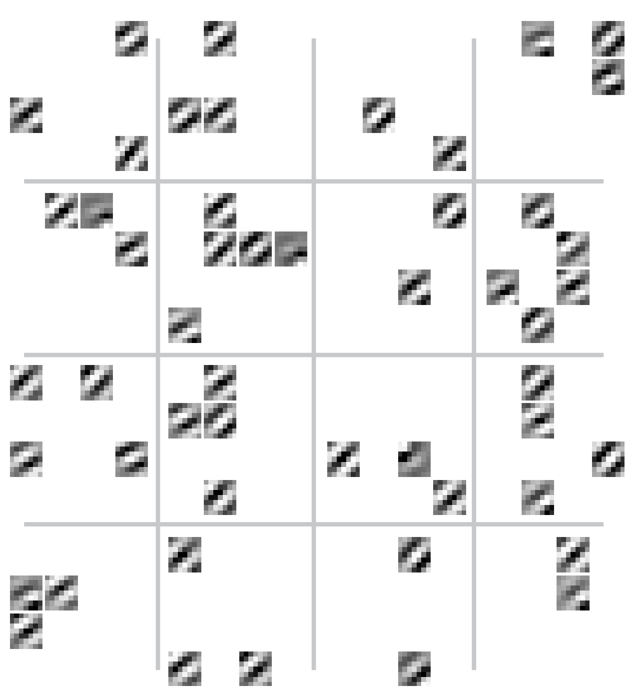
Learning the invariance from temporal continuity



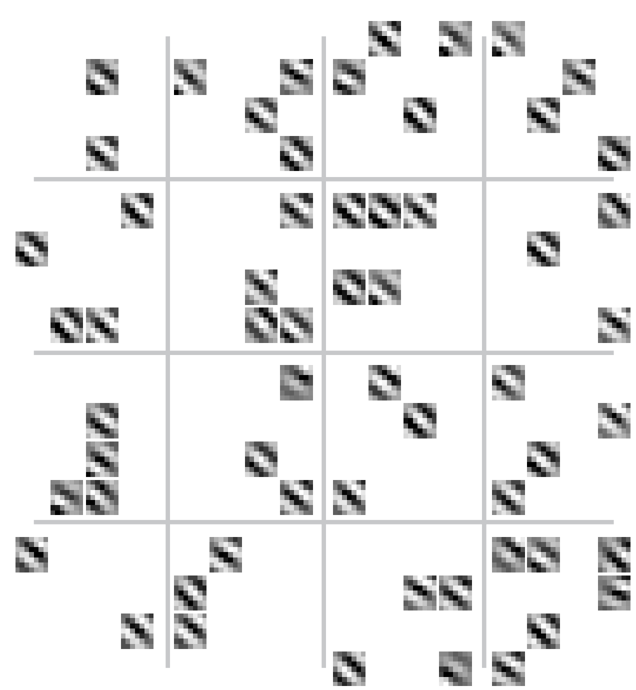
(a) S_1 units (n=73) that remain connected to C_1 unit # 1 after learning



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

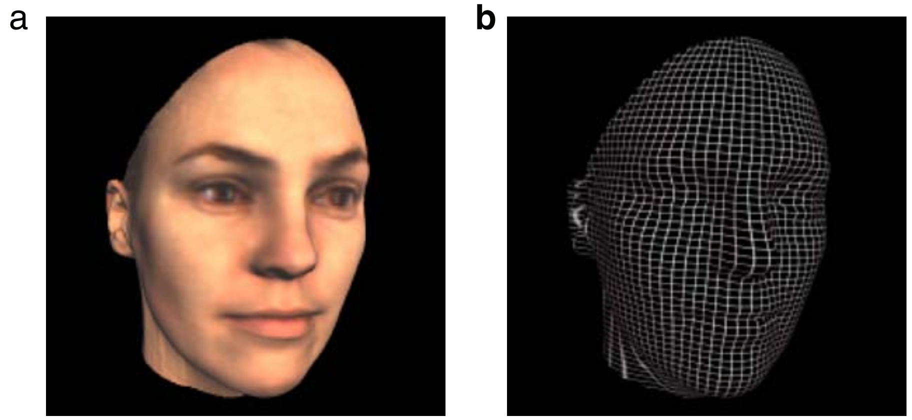


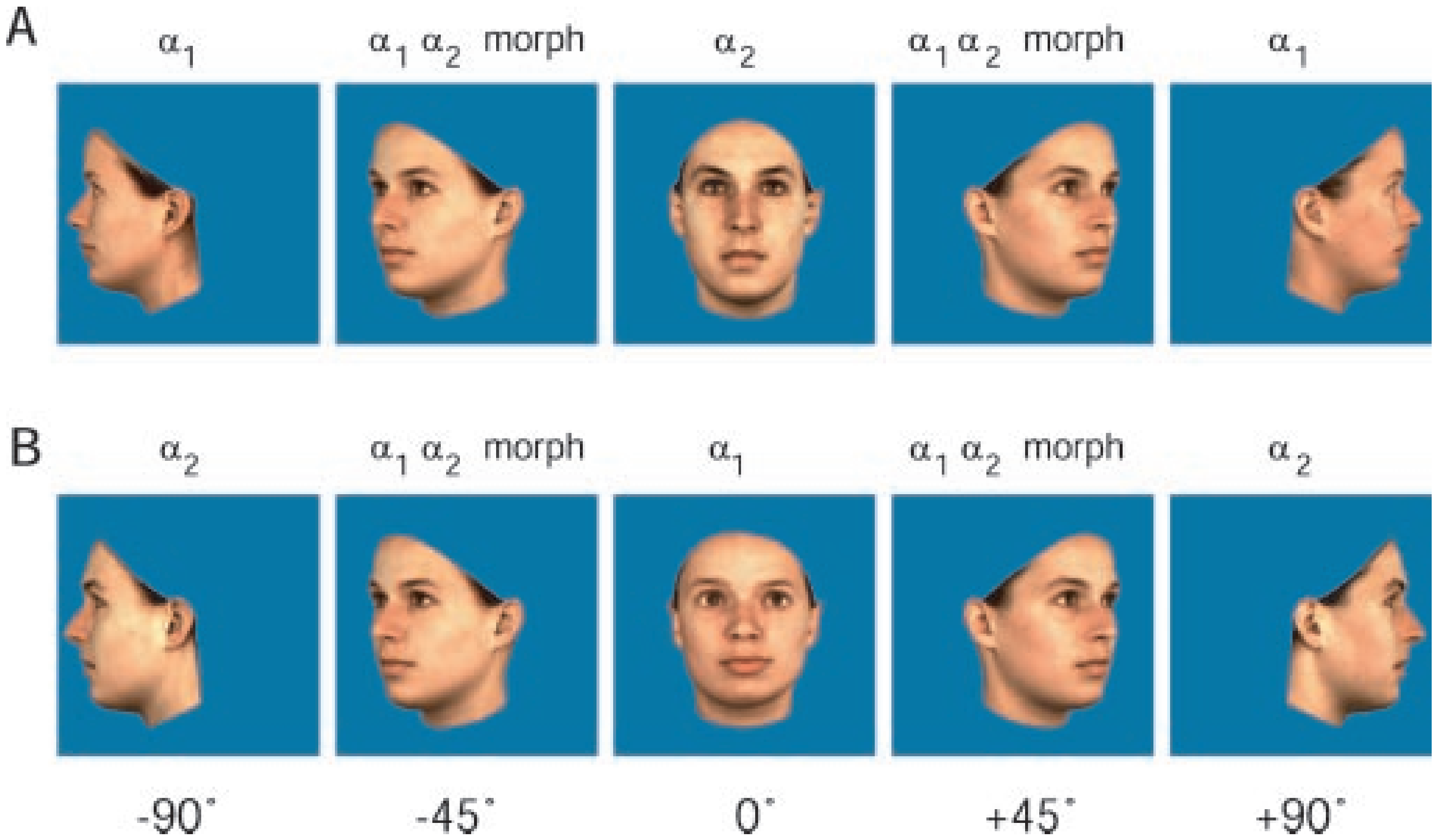
(c) S_1 units (n=59) that remain connected to C_1 unit # 3 after learning



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

Effects of temporal associations on learning and memory

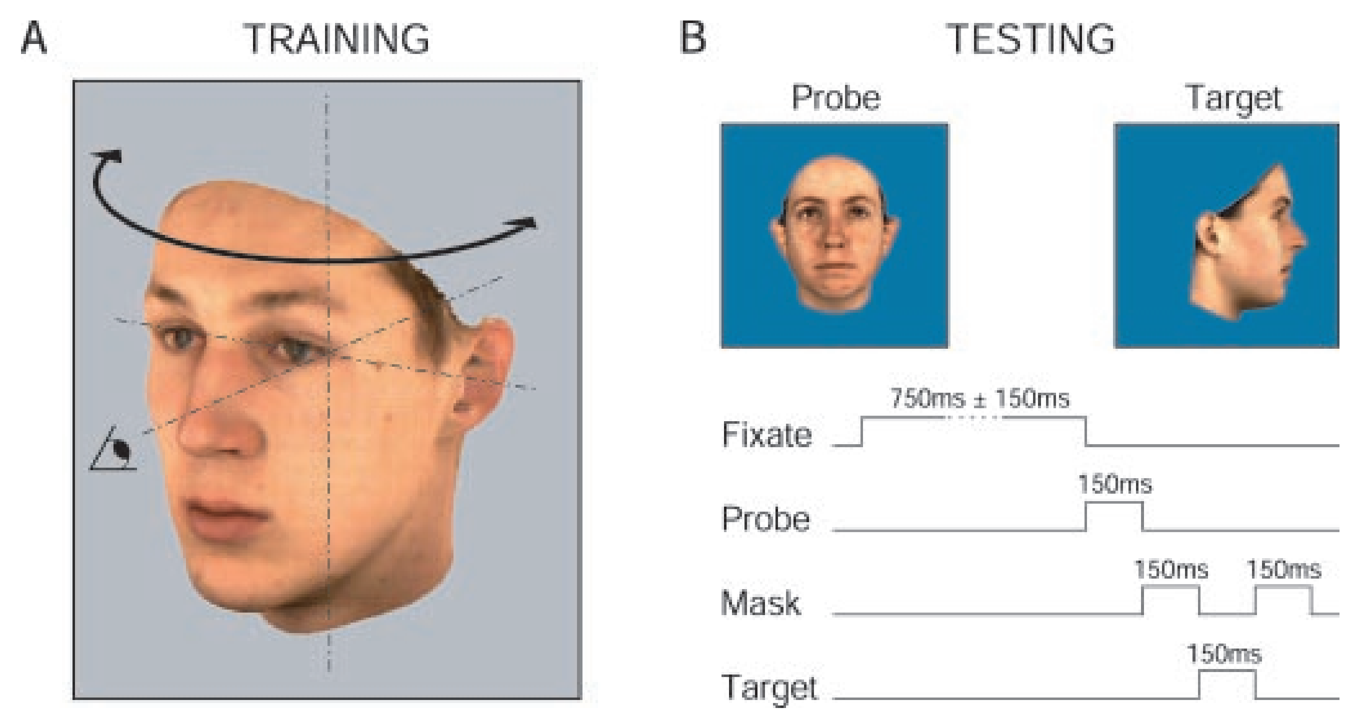




Wallis & Bulthoff '01

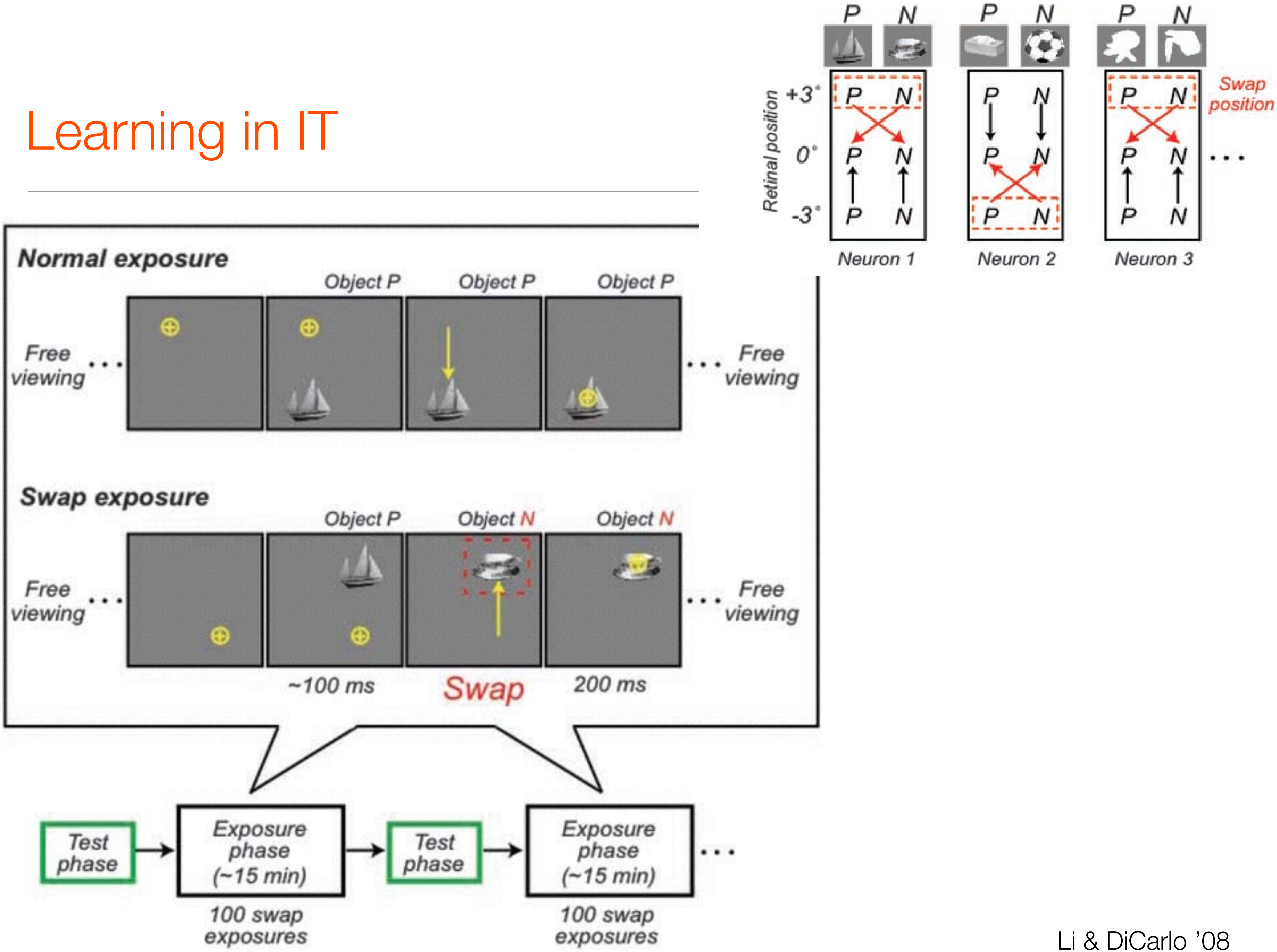
Effects of temporal associations on learning and memory

- Discrimination worst for prototypes that are part of the same training sequence
- ***Control:*** Performance unaffected when faces presented simultaneously rather than in sequence
- ***Control:*** Performance unaffected when faces presented during rd sequence



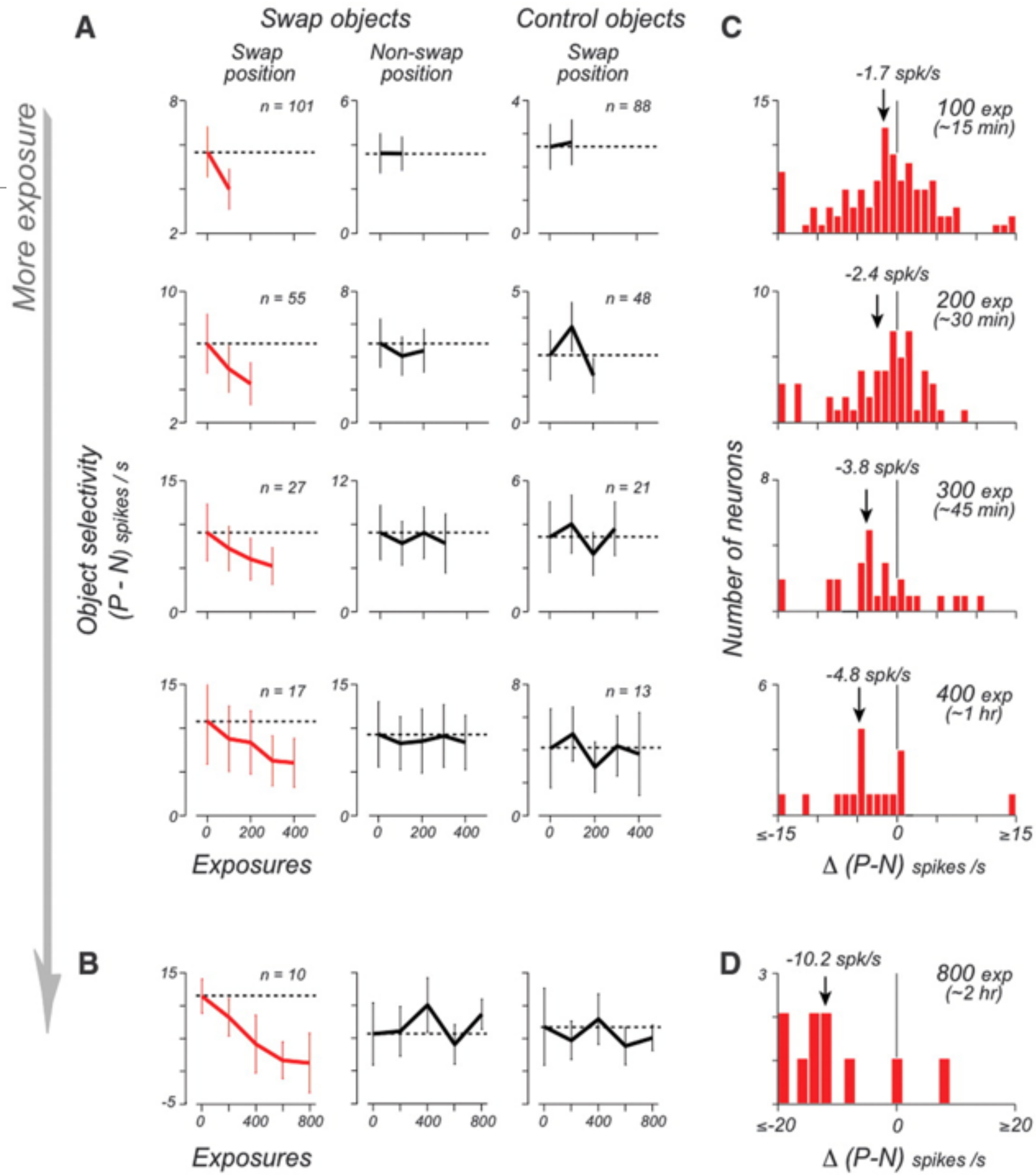
Wallis & Bulthoff '01

Learning in IT



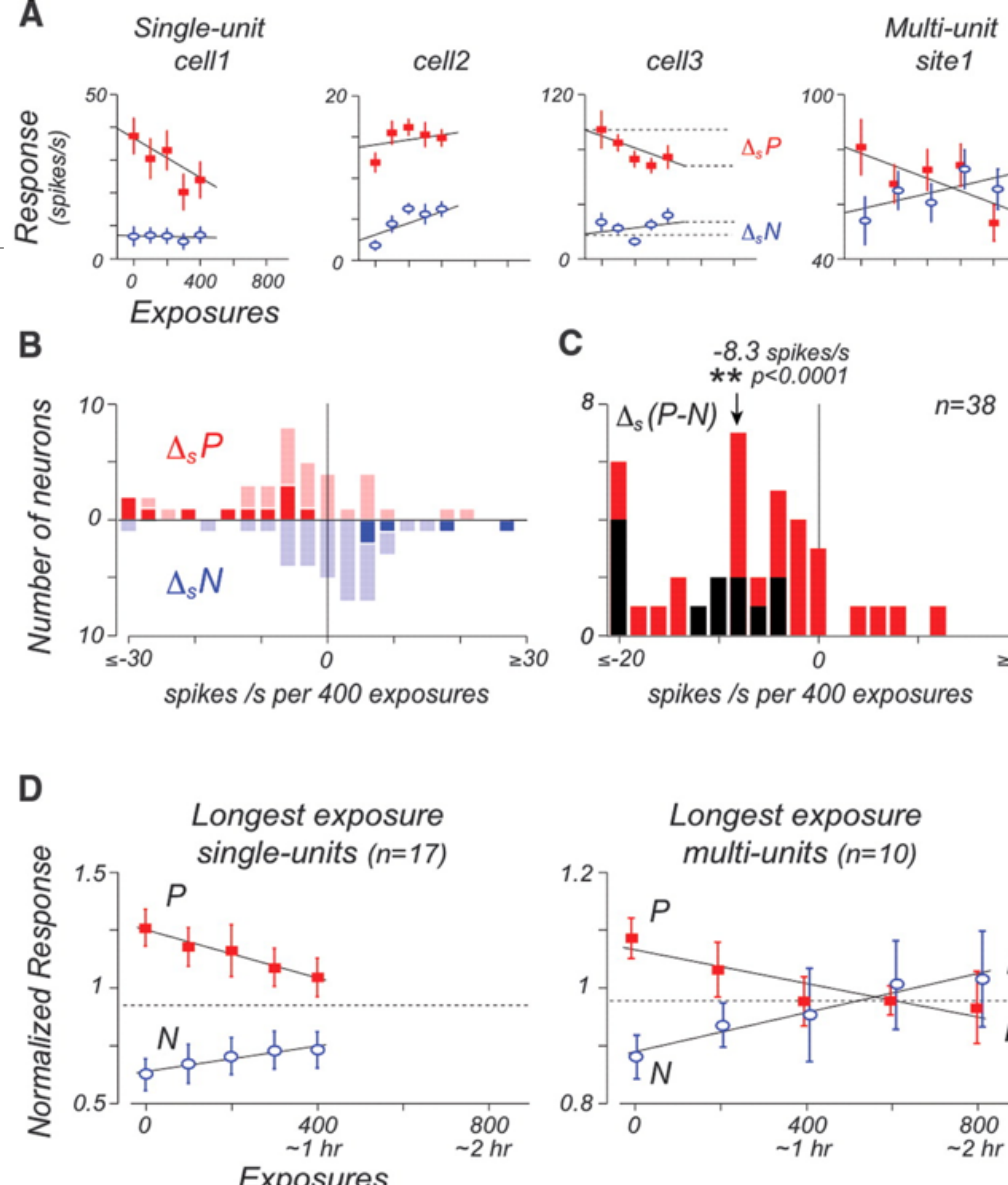
Li & DiCarlo '08

Learning in IT



Li & DiCarlo ’08

Learning in IT



Li & DiCarlo ’08