Beyond inspiration:
Five lessons from biology on building intelligent machines

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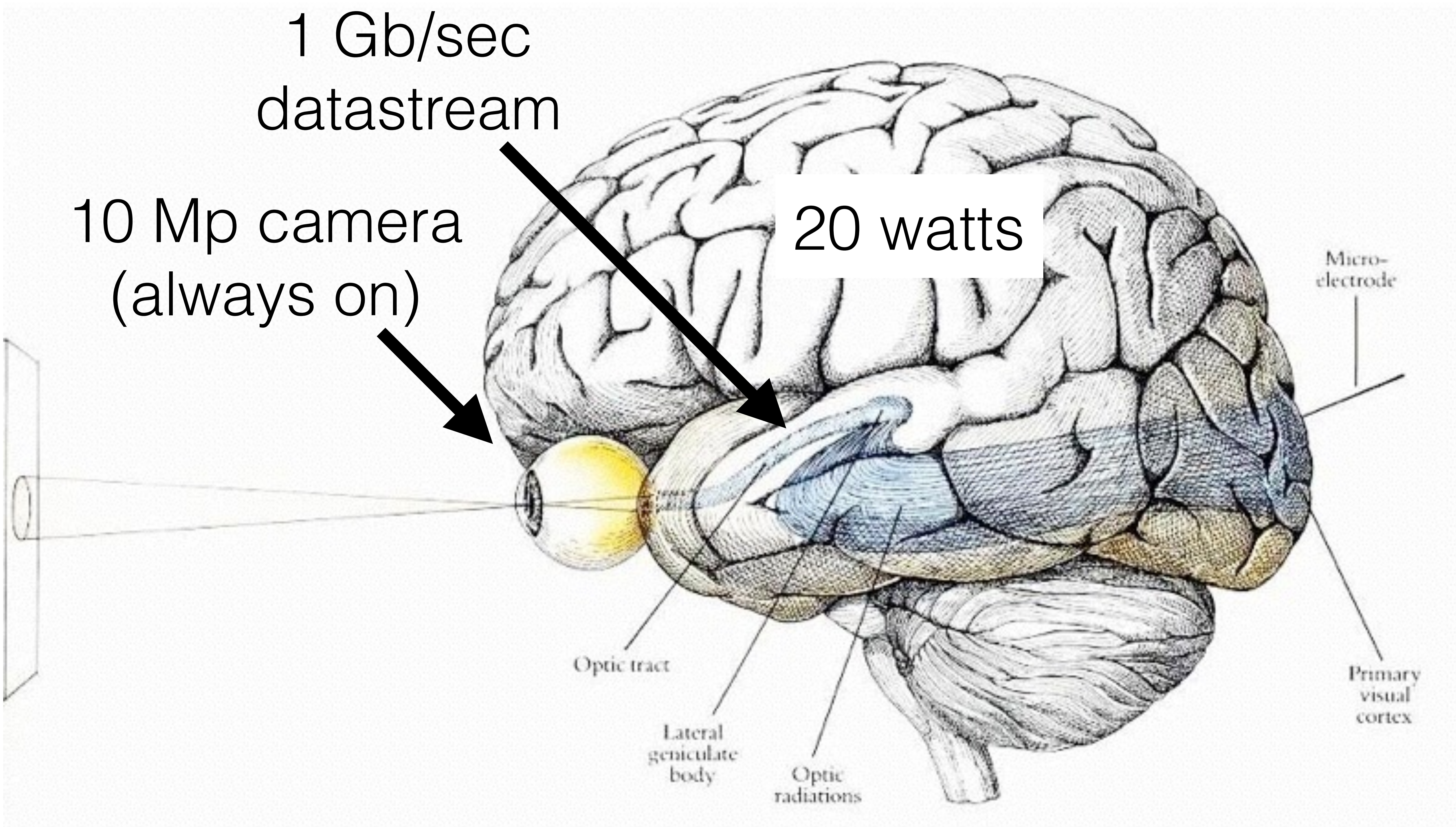
What are the principles governing information processing in this system?



Inspiration is a good start
…but not enough

Real progress will require gaining a more solid understanding of the principles of information processing at work in nervous systems.

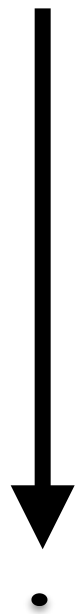
This is both engineering *and* biology.

Five lessons from biology

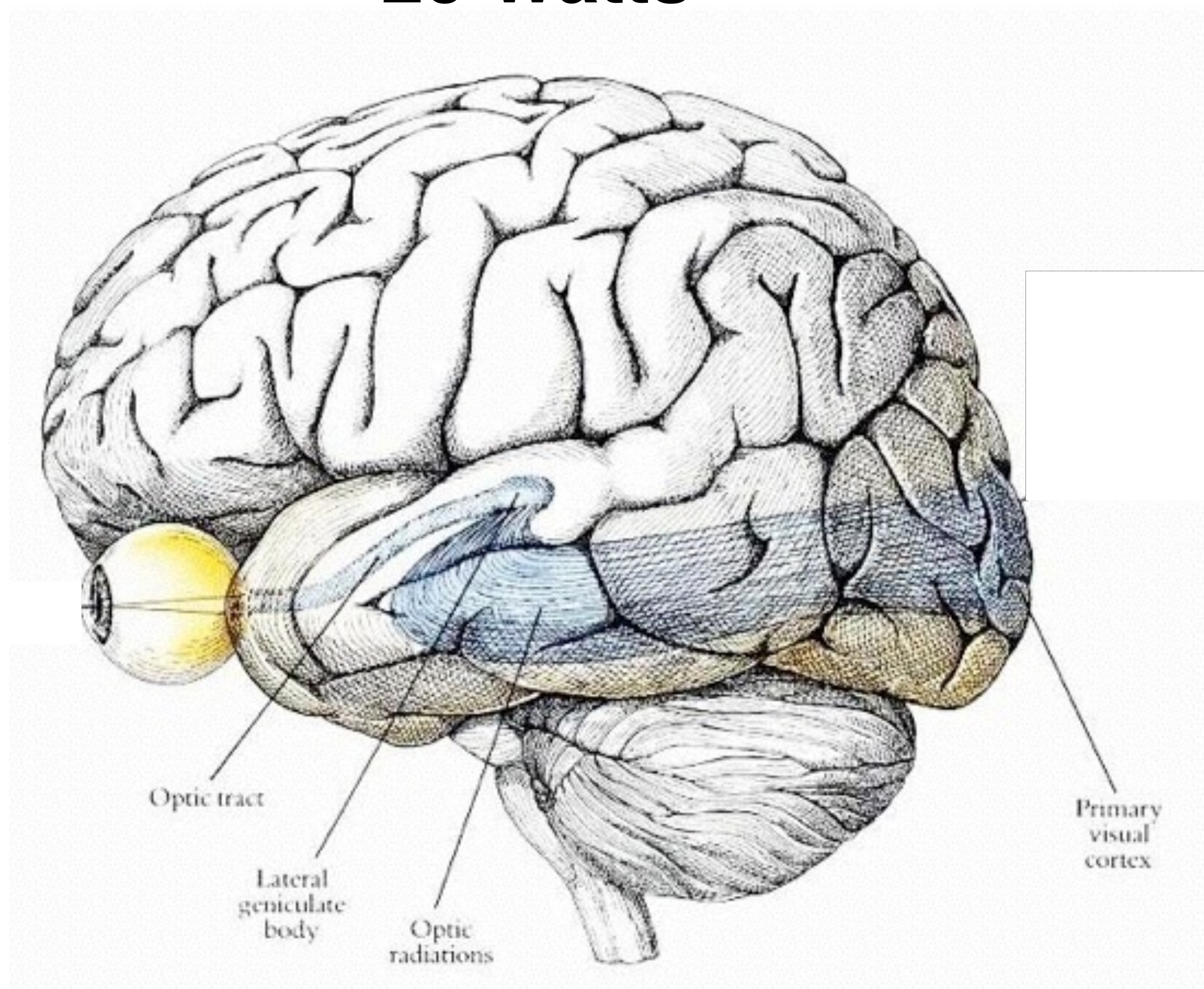
- Tiny brains
- Nonlinear processing in dendritic trees
- Sparse, overcomplete representations
- Feedback
- Active perception

1. Tiny brains

<1 million neurons
< 1 mW

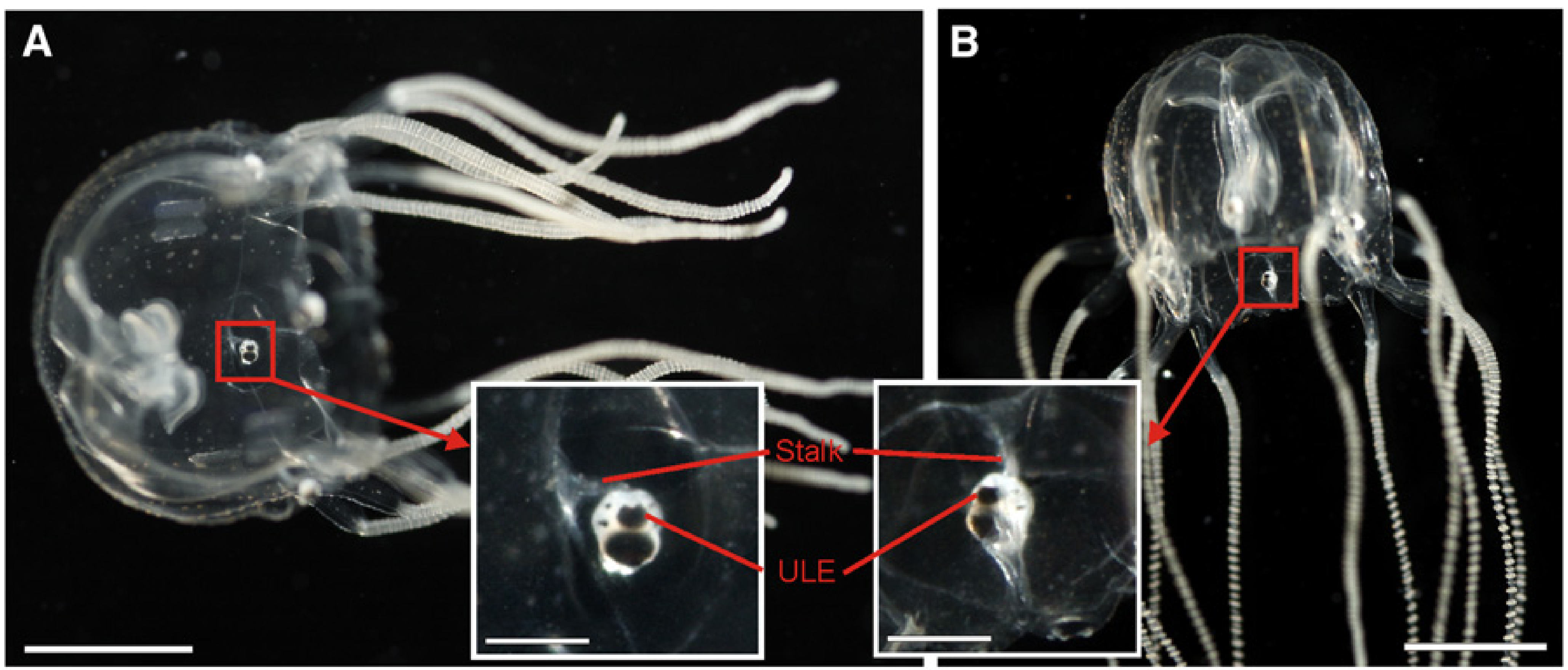


86 billion neurons
20 Watts



jumping spider

sand wasp

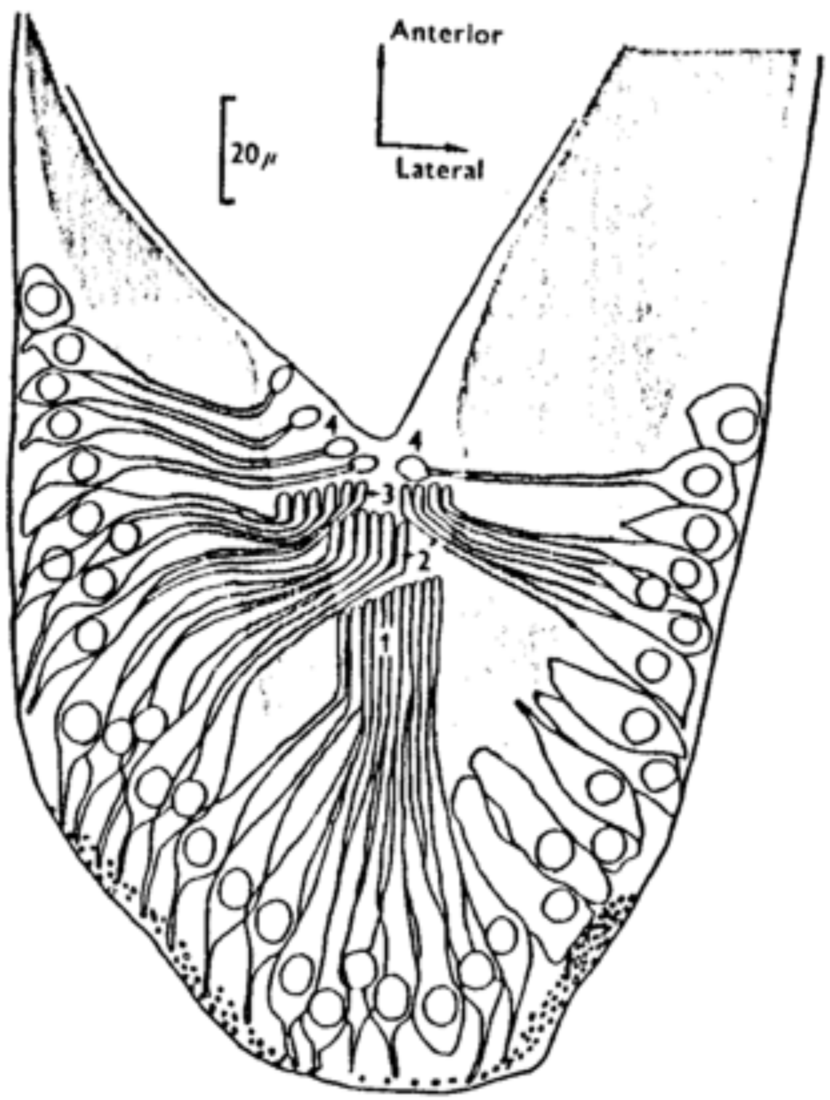


box jellyfish

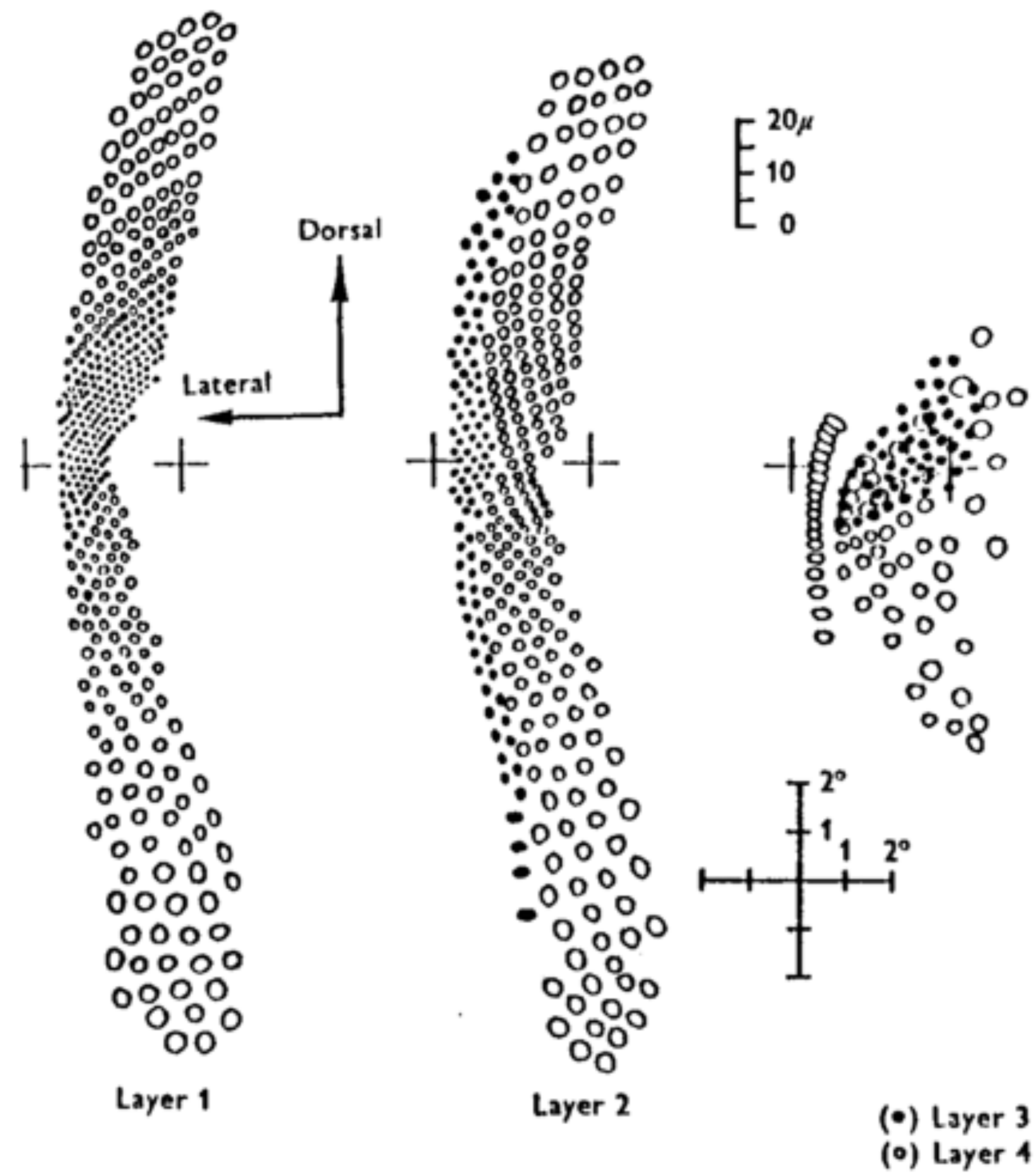
Jumping spider visual system

Jumping spider retina

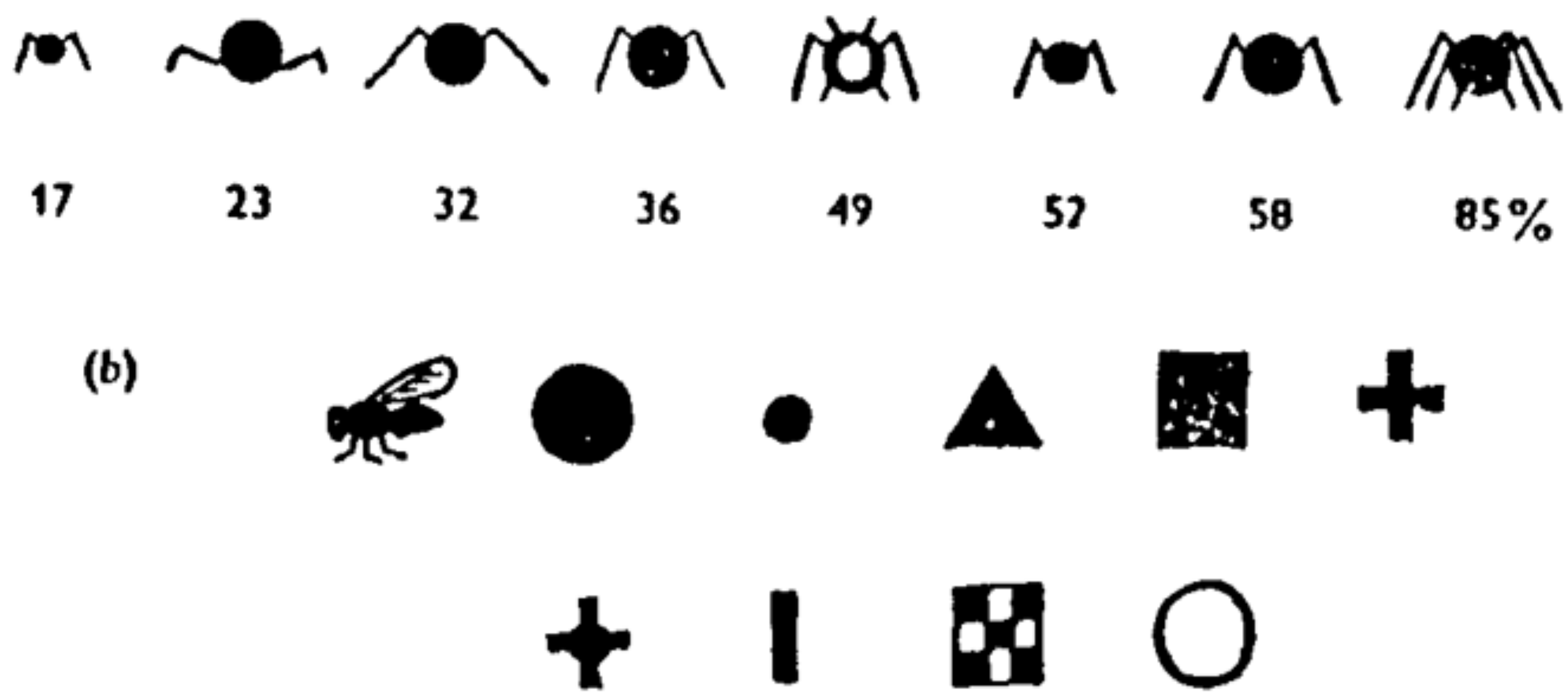
horizontal section



photoreceptor array

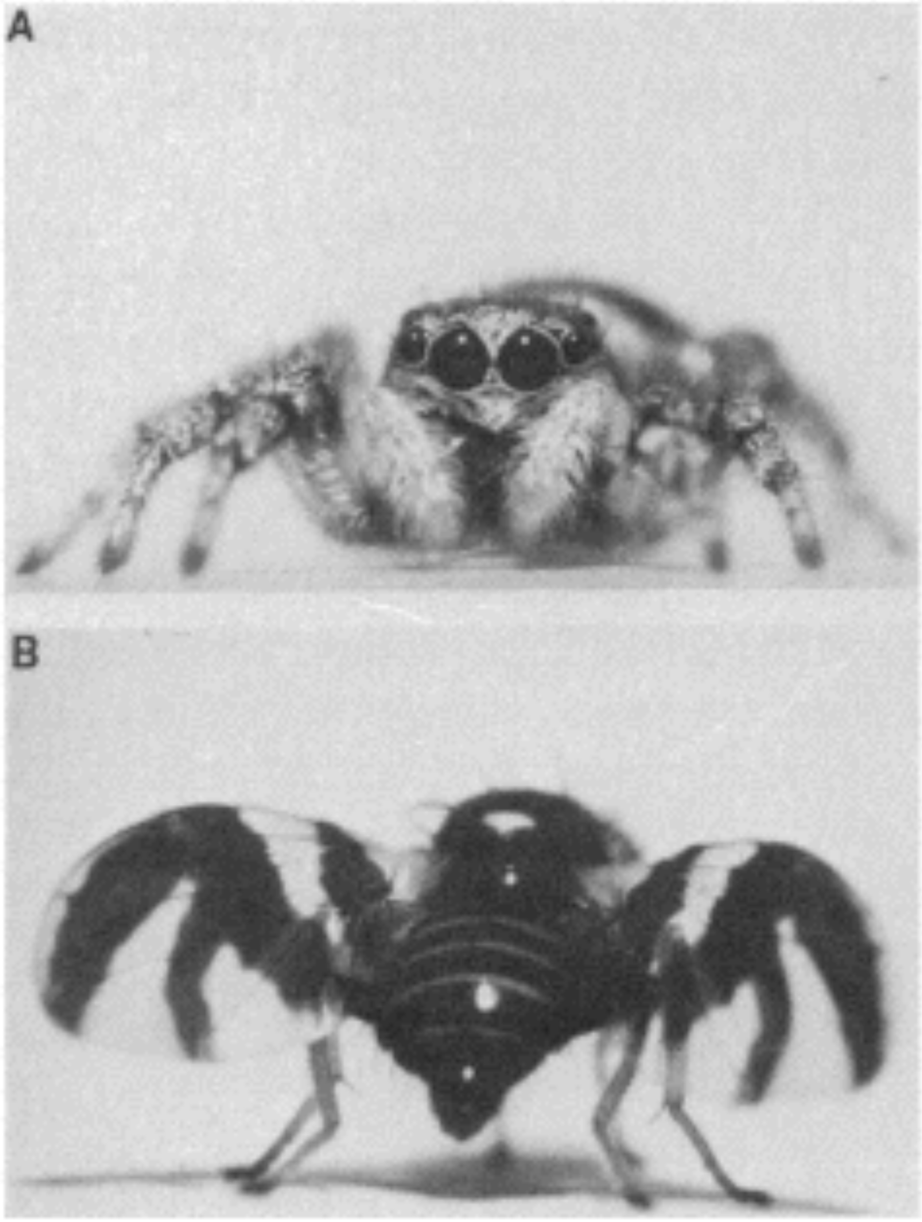


Jumping spiders do object recognition



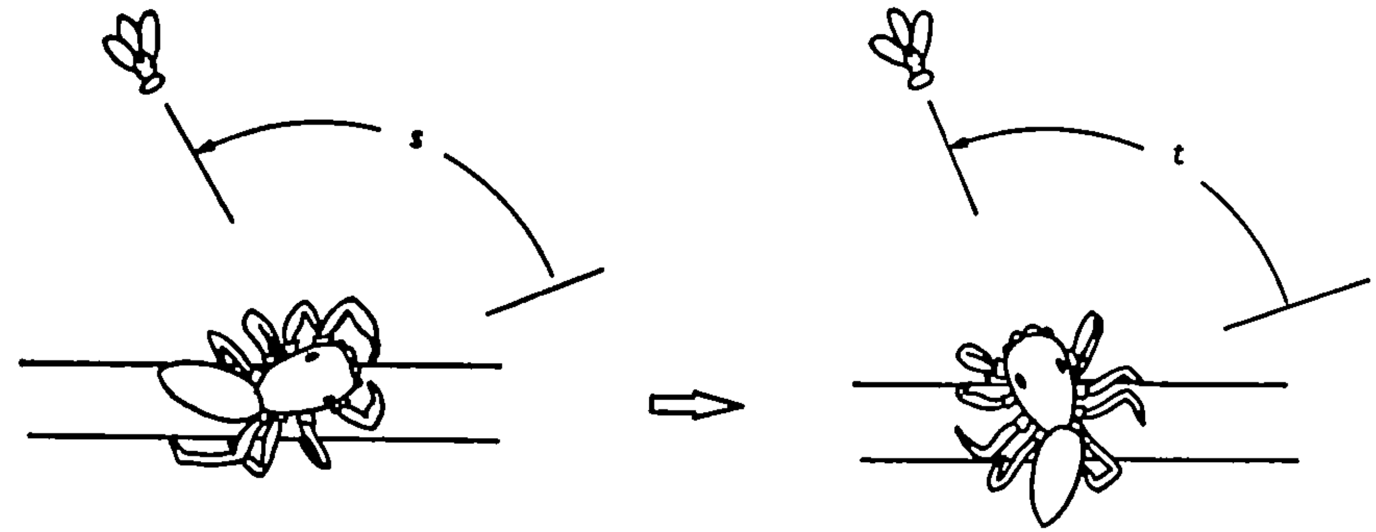
Text-fig. 12. Stimuli found by Drees to evoke courtship (*a*) and prey capture (*b*) in male jumping spiders (*Epiblemum scenicum*). The numbers beneath each figure in (*a*) are the percentage of trials on which courtship was evoked. After Drees (1952).

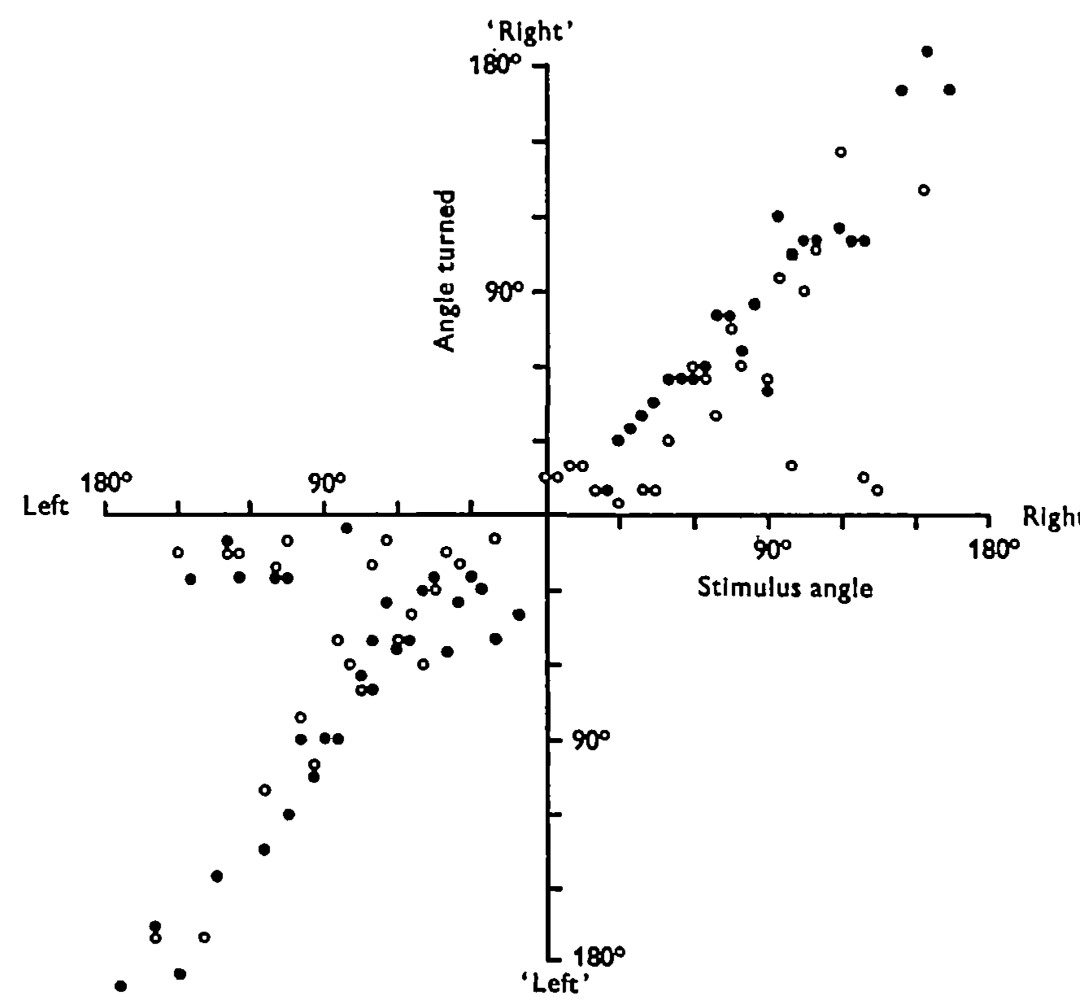
Spider mimicry in flies



Prey capture

- attention
- orienting
- tracking





Navigation

(Tarsitano & Jackson 1997)

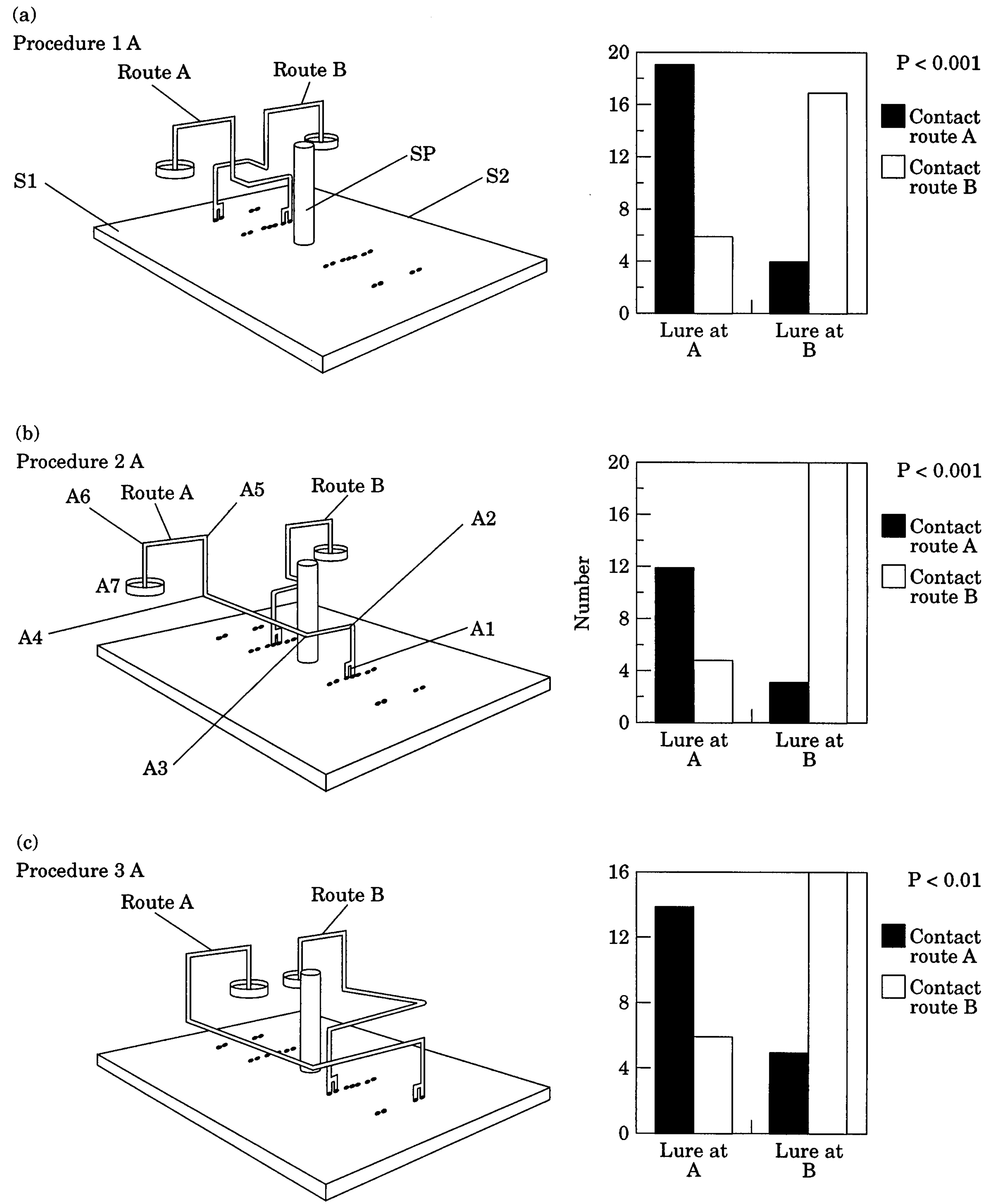


Figure 1 a-c.

One-day old jumping spider
(filmed in the Bower lab, Caltech)

One-day old jumping spider
(filmed in the Bower lab, Caltech)

One-day old jumping spider
(filmed in the Bower lab, Caltech)

One-day old jumping spider
(filmed in the Bower lab, Caltech)

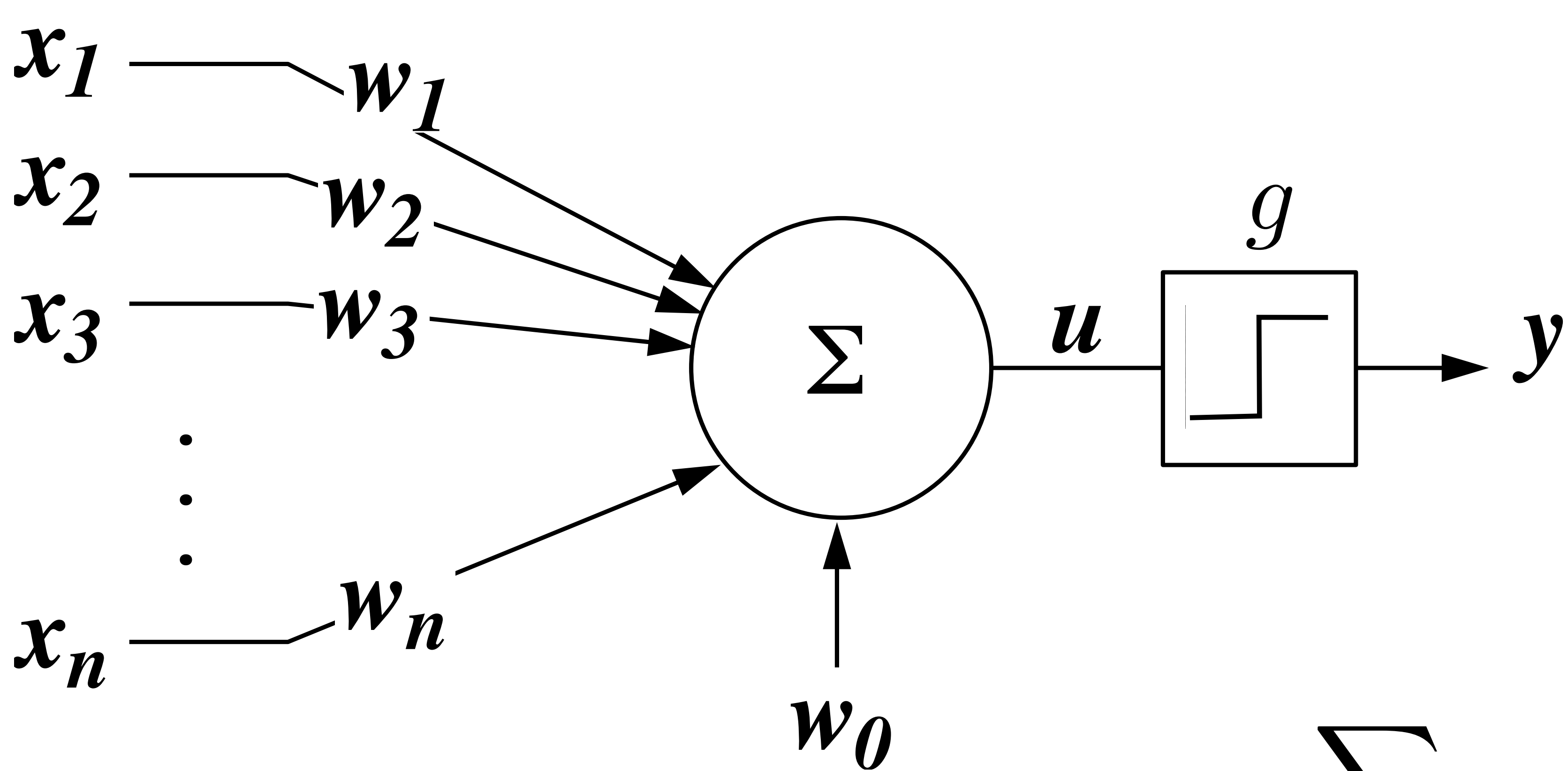
…problem solving behavior, language, expert knowledge and application, and reason, are all pretty simple once the essence of being and reacting are available. That essence is the ability to move around in a dynamic environment, sensing the surroundings to a degree sufficient to achieve the necessary maintenance of life and reproduction. This part of intelligence is where evolution has concentrated its time--it is much harder.

— Rodney Brooks, "Intelligence without representation," *Artificial Intelligence* (1991)

2. Nonlinear processing in dendritic trees

A brief history of neural networks

1960's

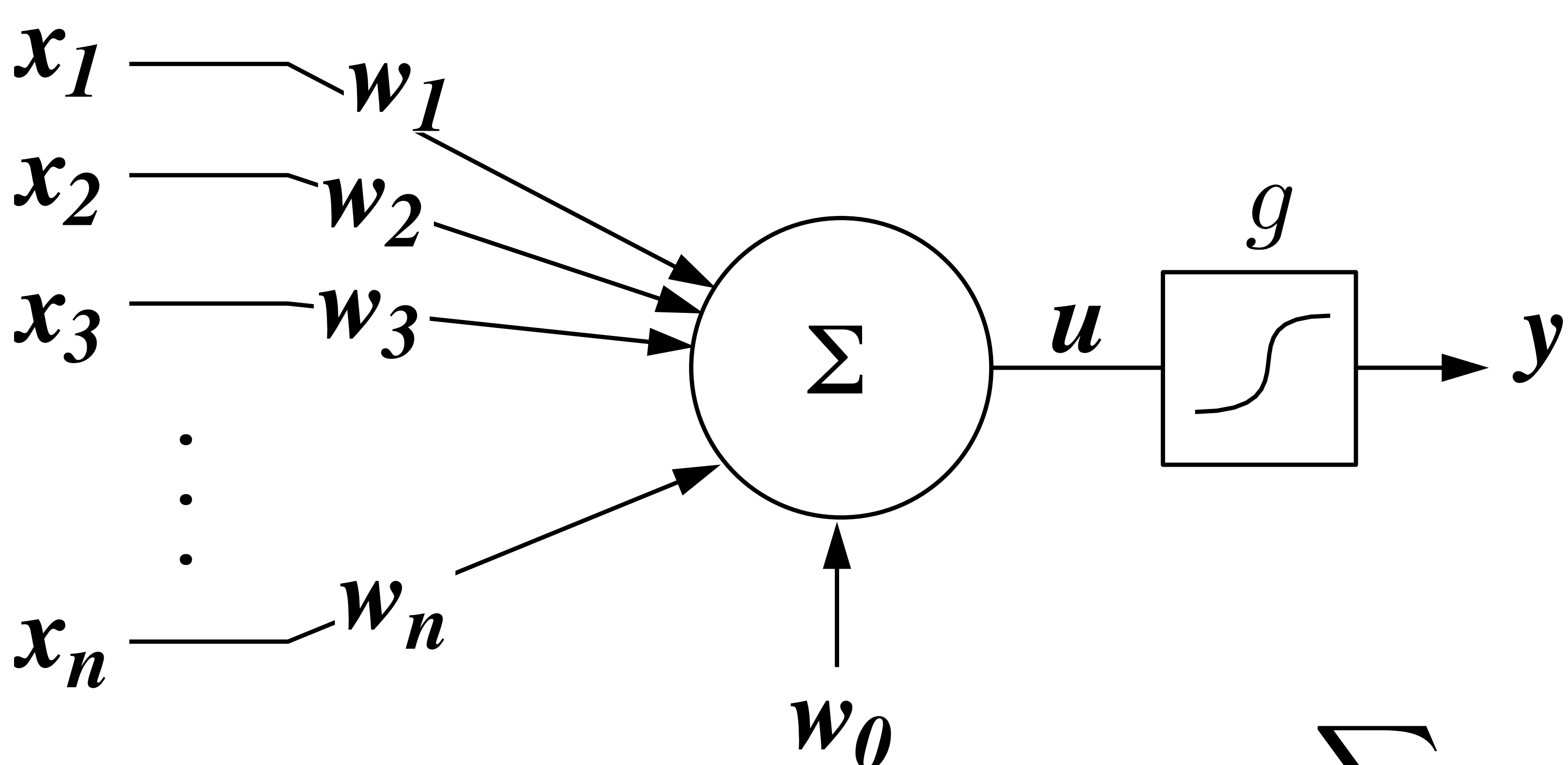


$$u = \sum_i w_i \, x_i$$

$$y = g(u)$$

A brief history of neural networks

1980's



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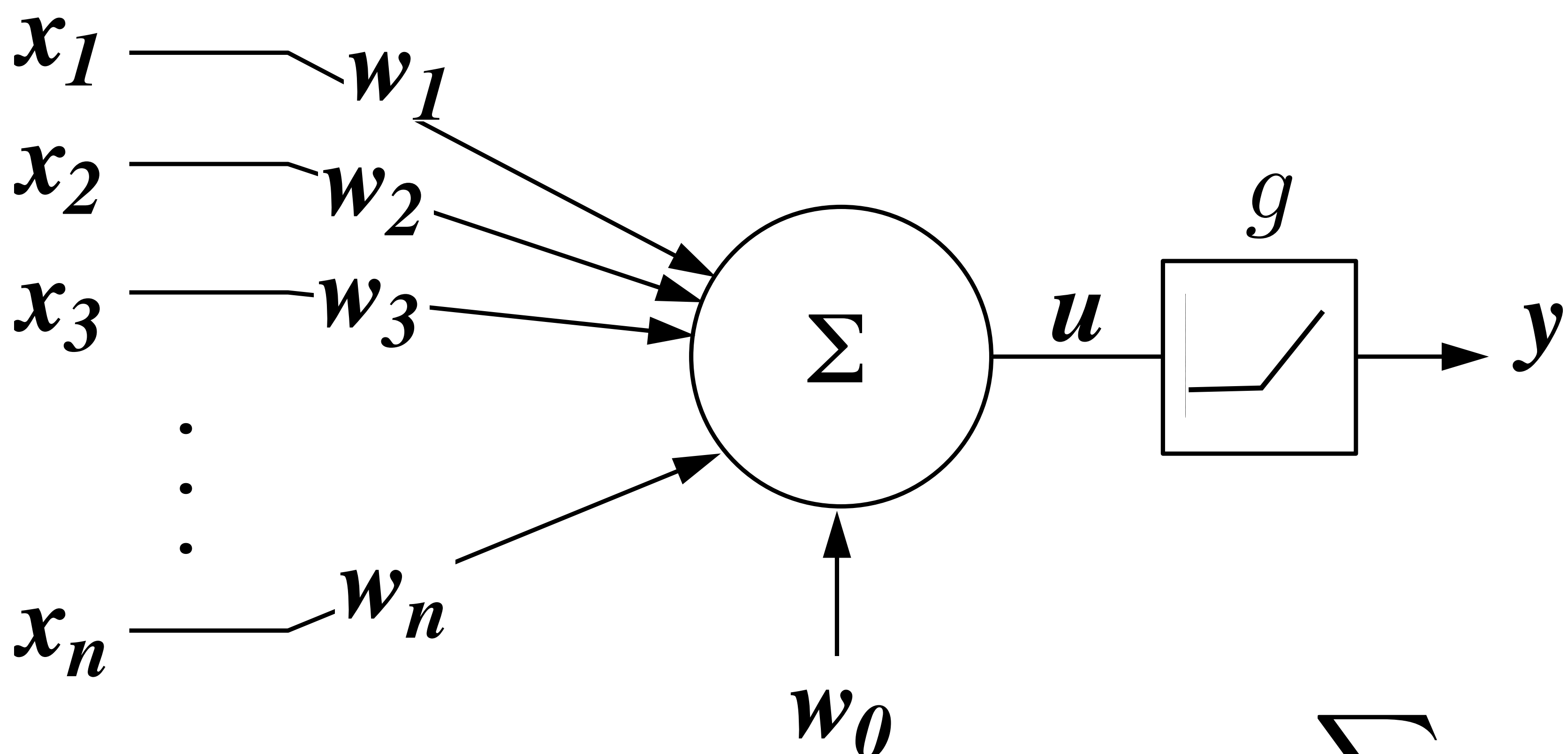
$$y = g(u)$$

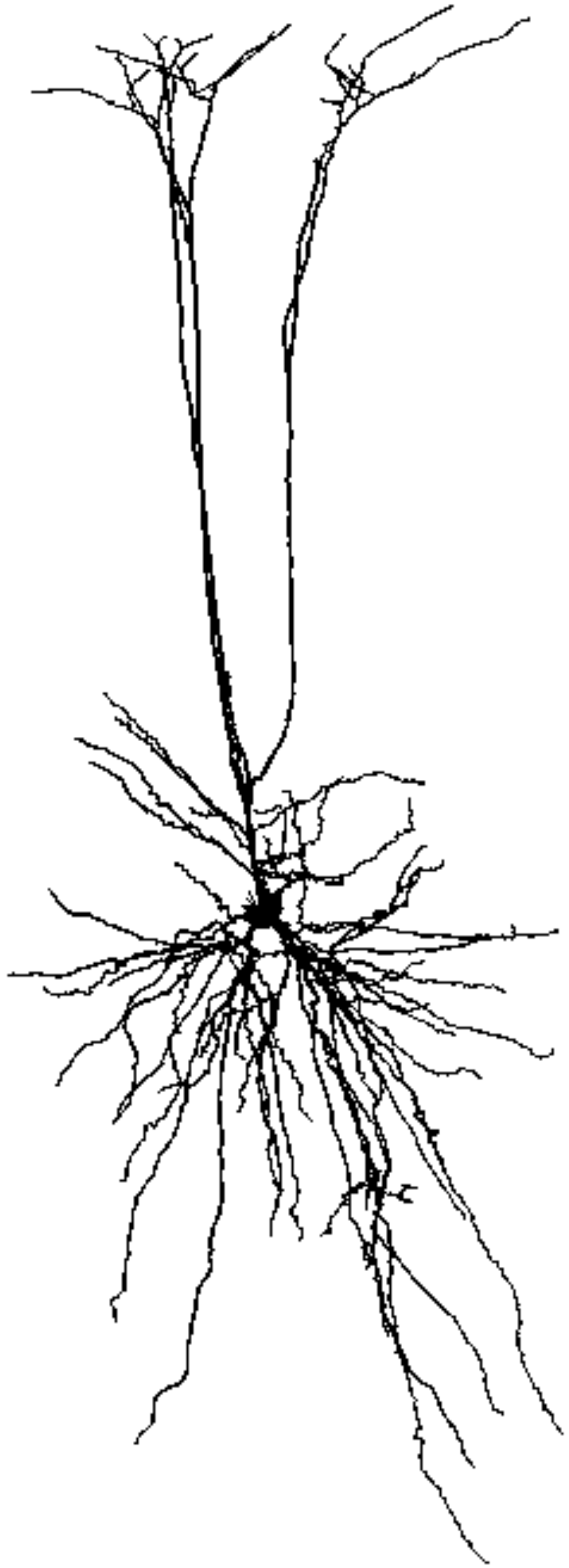
A brief history of neural networks

2000's

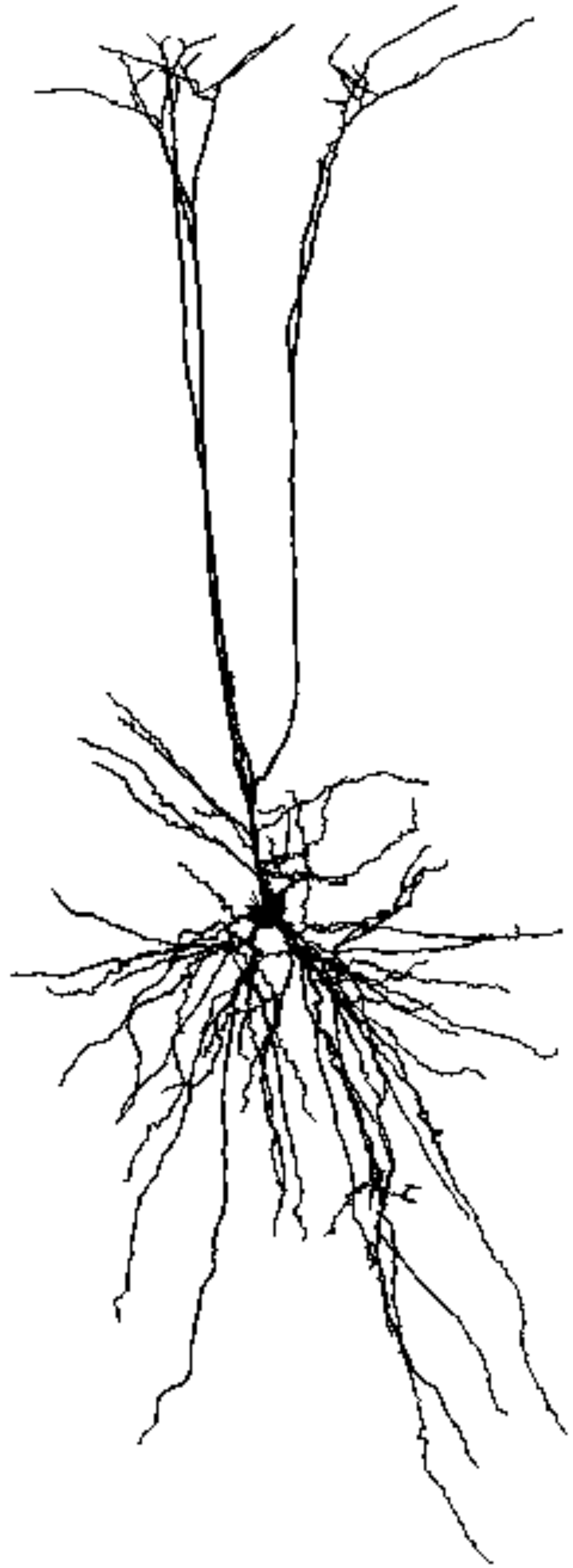


$$u = \sum_i w_i \, x_i$$

$$y = g(u)$$



$$\neq \quad g\Big(\sum_i w_i\, x_i\Big)$$



$$\sim \quad g\Big(\sum_i w_i \, \Pi_{j \in G_i} \, x_j\Big)$$

Bartlett Mel

Mel BW, Koch C. (1990). Sigma-pi learning: on radial basis functions and cortical associative learning. In *Advances in neural information processing systems, vol. 2*, D.S. Touretzky, (Ed.), San Mateo, CA: Morgan Kaufmann, pp. 474-481.

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Hausser M, Mel B. (2003). Dendrites: bug or feature? *Current Opinion in Neurobiology, 13*, 372-83.

Poirazi P, Brannon T, Mel BW. (2003). Arithmetic of Subthreshold Synaptic Summation in a Model CA1 Pyramidal Cell. *Neuron, 37*, 977-987.

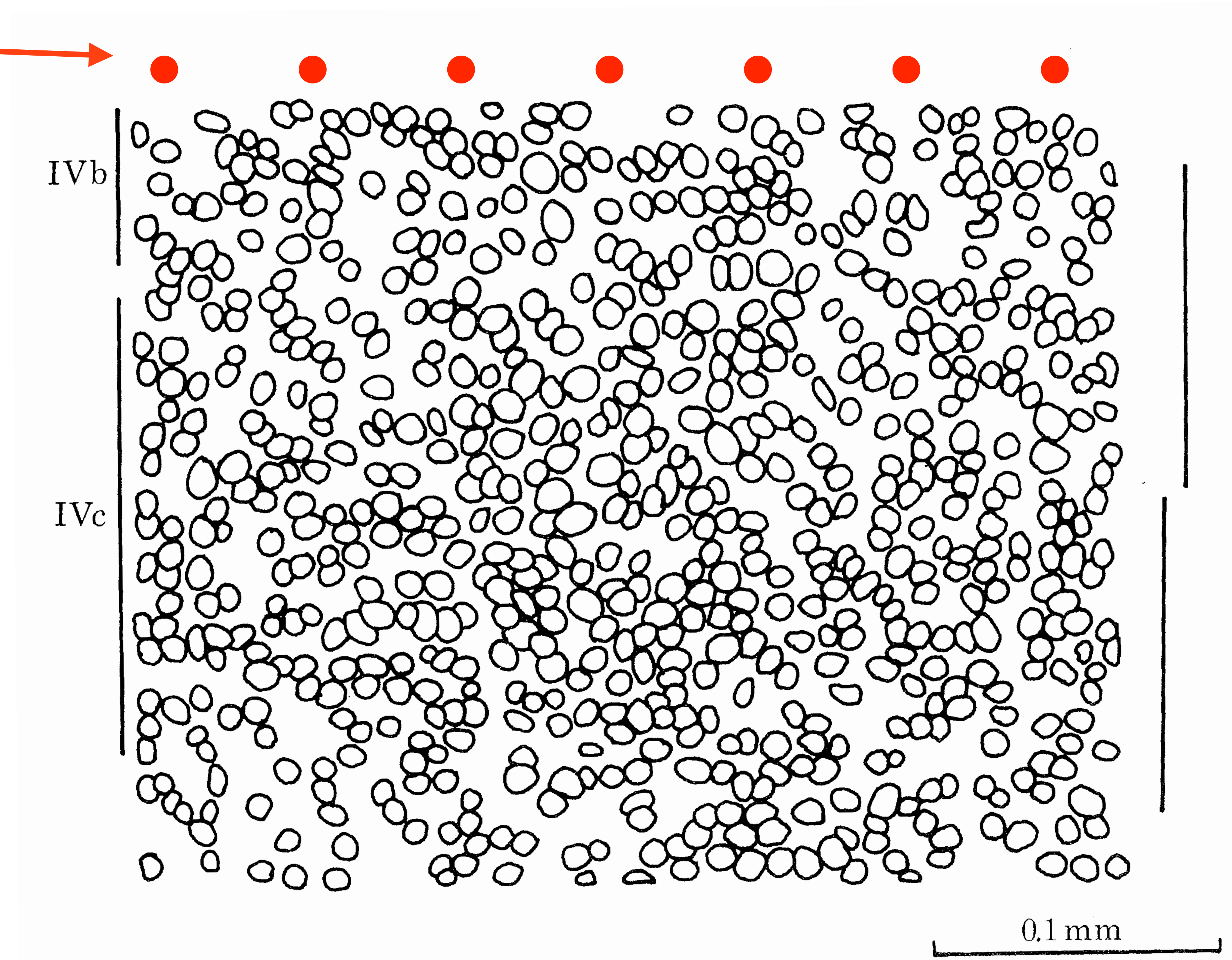
Poirazi P, Brannon T, Mel BW. (2003). Pyramidal Neuron as 2-Layer Neural Network. *Neuron, 37*, 989-999.

3. Sparse, overcomplete representation

V1 is highly overcomplete

LGN afferents

layer 4 cortex

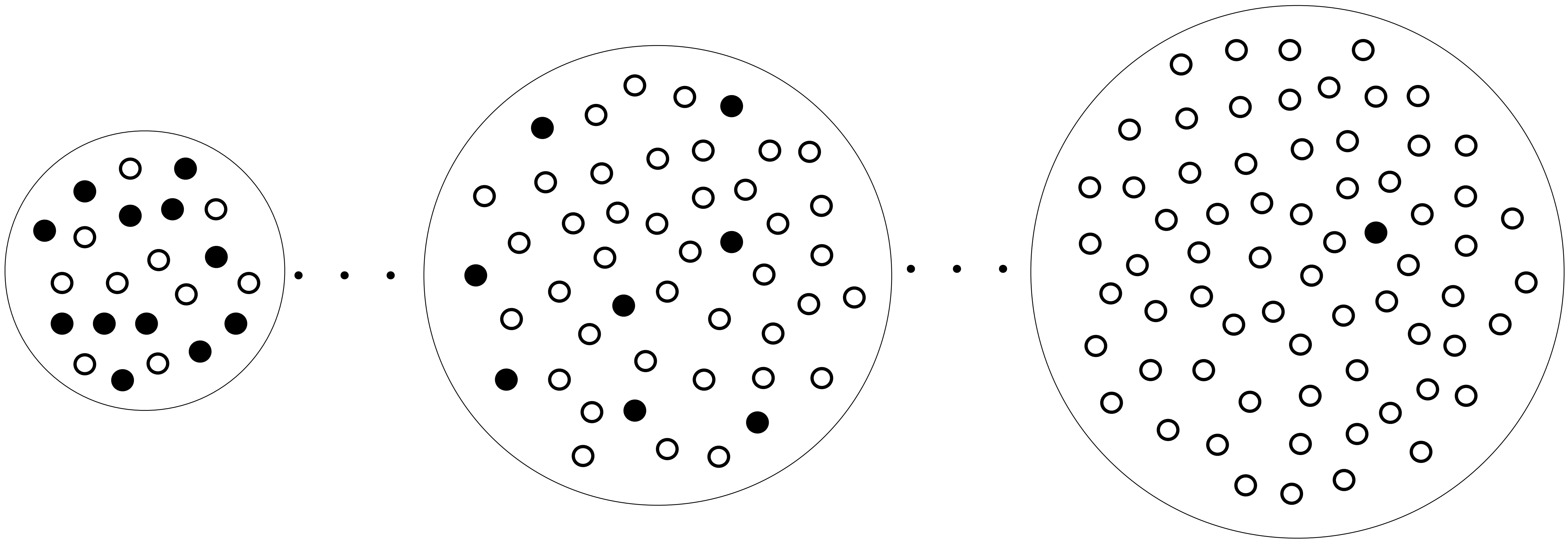


Barlow (1981)

Dense codes
(e.g., ascii)

Sparse, distributed codes

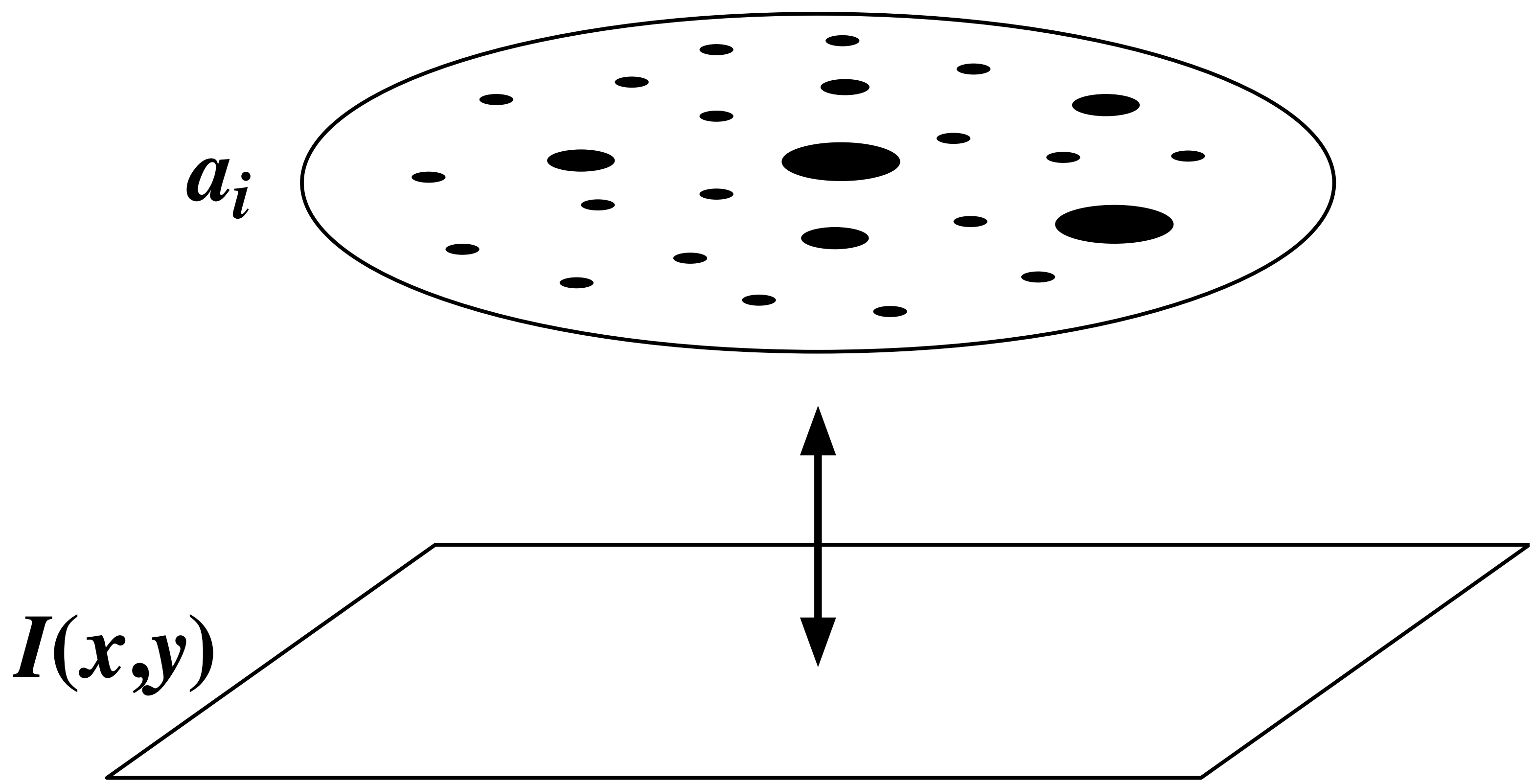
Local codes
(e.g., grandmother cells)



2^N $\binom{N}{K}$ N

(From Foldiak & Young, 1995)

Sparse, distributed representation



$$I(x,y) = \sum_i a_i \, \phi_i(x,y) + \epsilon(x,y)$$

Energy function

$$E = \frac{1}{2}|\mathbf{I} - \Phi\,\mathbf{a}|^2 + \lambda \sum_i C(a_i)$$

preserve information

be sparse

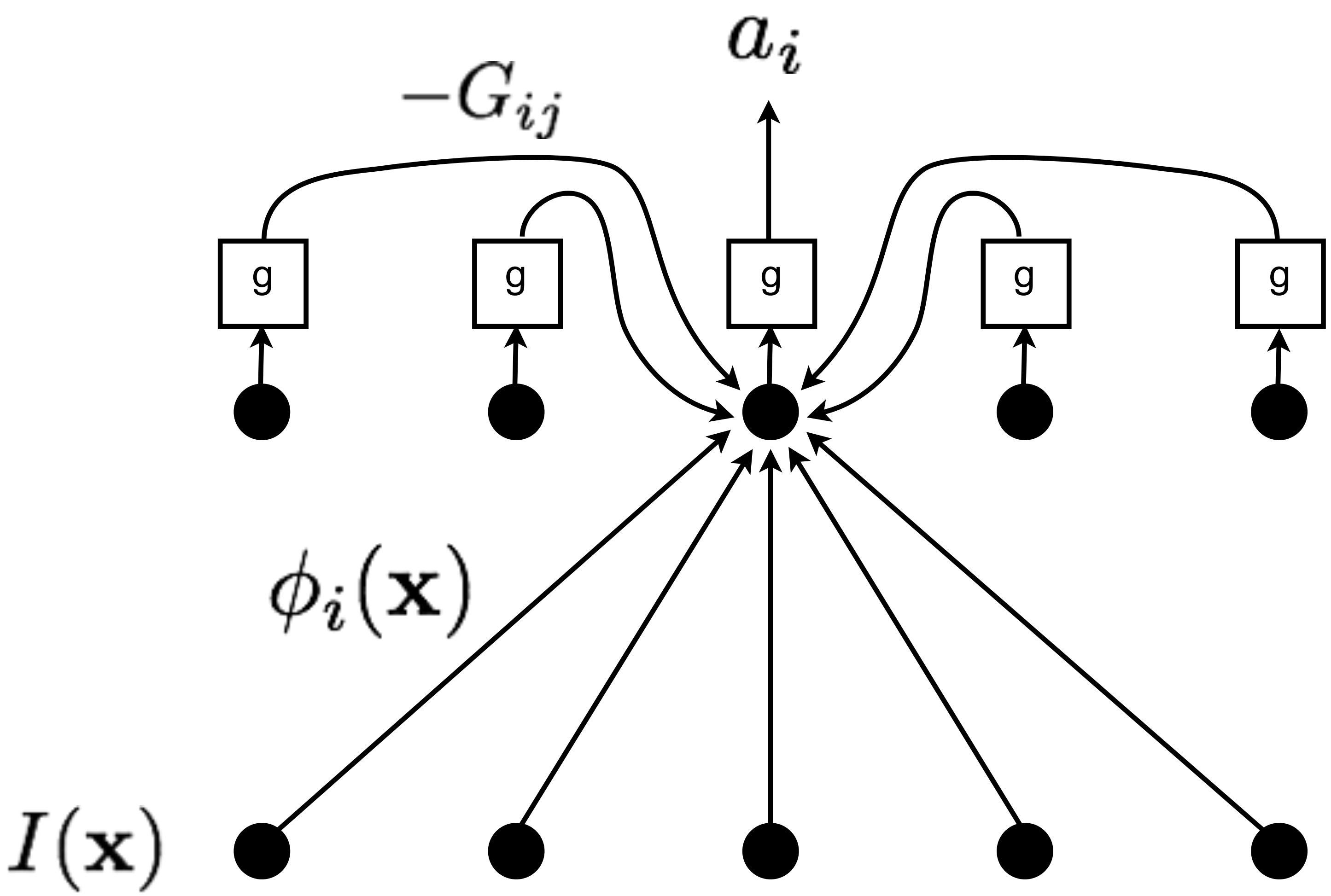
Energy function

$$E = \frac{1}{2}|\mathbf{I} - \Phi\,\mathbf{a}|^2 + \lambda \sum_i C(a_i)$$

-log P(**I** | **a**) P(**a**)

Coefficients a_i may be computed via thresholding and lateral inhibition

('LCA' - Rozell, Johnson, Baraniuk & Olshausen, 2008)

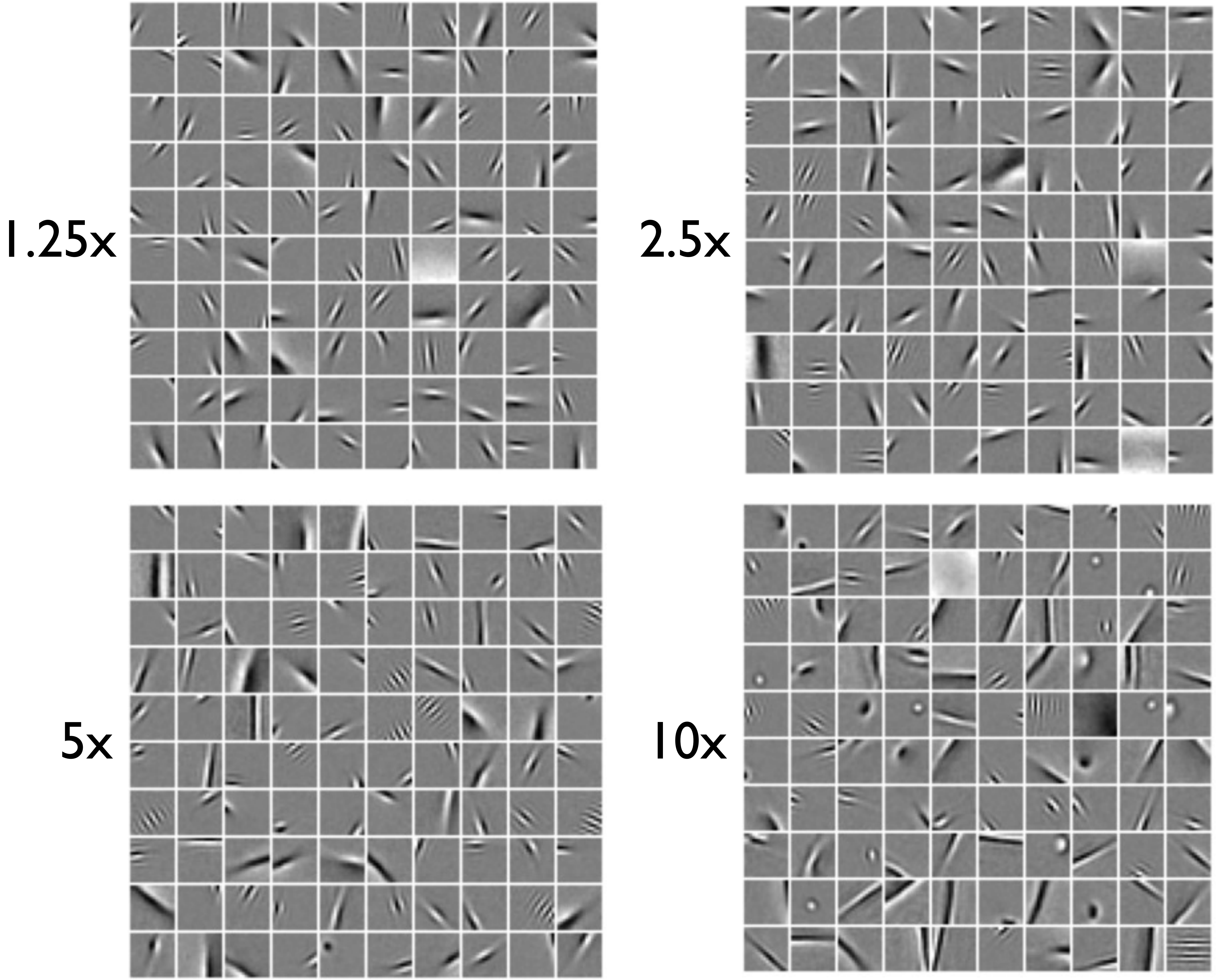


$$\tau \dot{u}_i + u_i = b_i - \sum_{j \neq i} G_{ij} a_j$$

$$a_i = g(u_i)$$

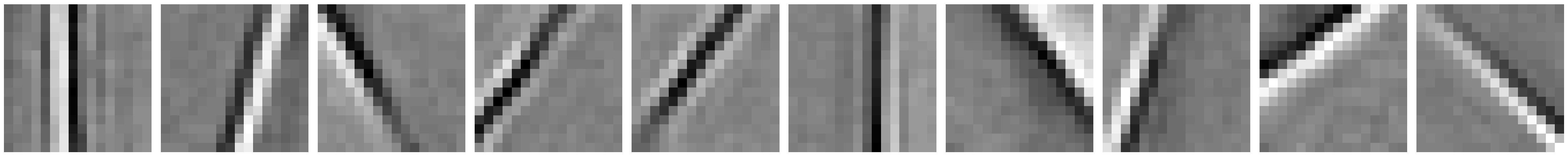
$$b_i = \sum_{\mathbf{x}} \phi_i(\mathbf{x}) I(\mathbf{x})$$

$$G_{ij} = \sum_{\mathbf{x}} \phi_i(\mathbf{x}) \phi_j(\mathbf{x})$$

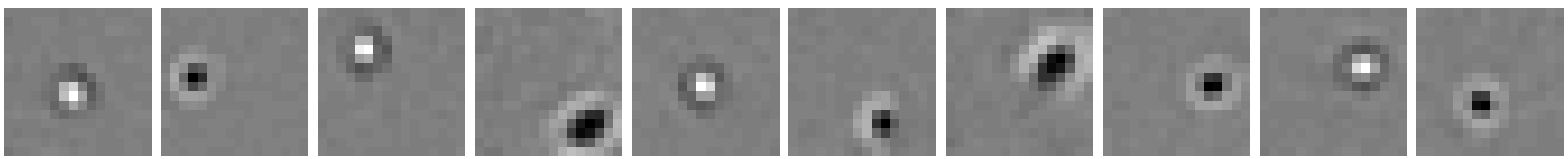

1.25x
2.5x
5x
10x

Examples from 10x dictionary
(Olshausen, 2013)

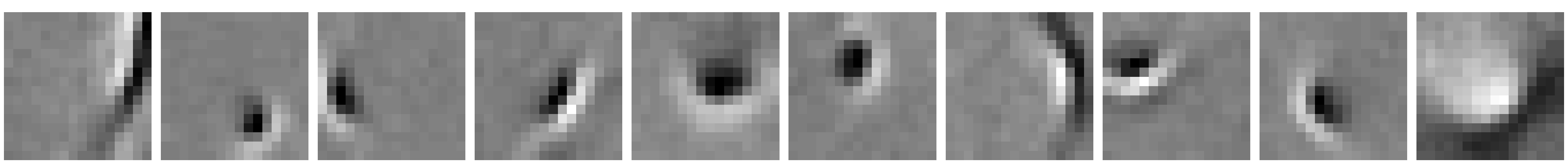
ridgelet



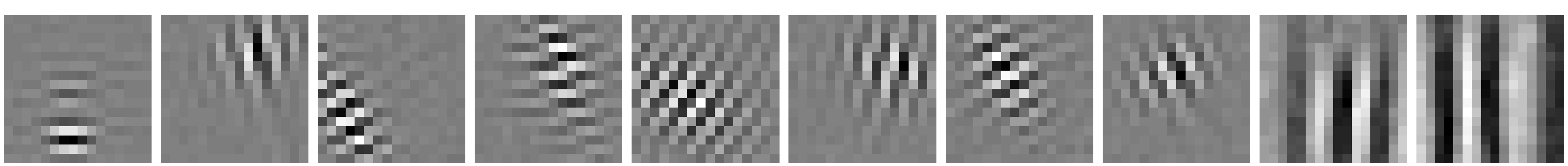
circular



curvature

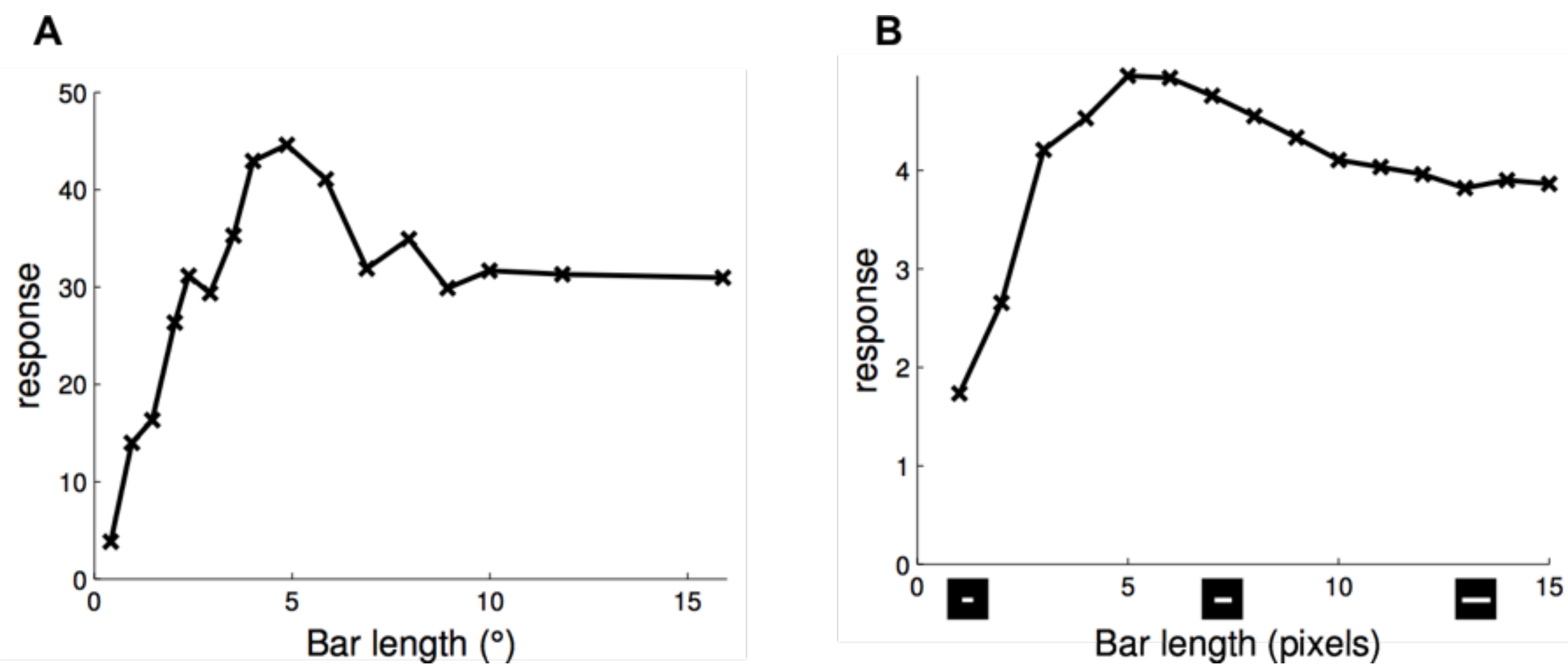


grating



Explaining away can account for non-classical surround effects such as end-stopping

(Lee et al., 2006; Zhu & Rozell, 2013)



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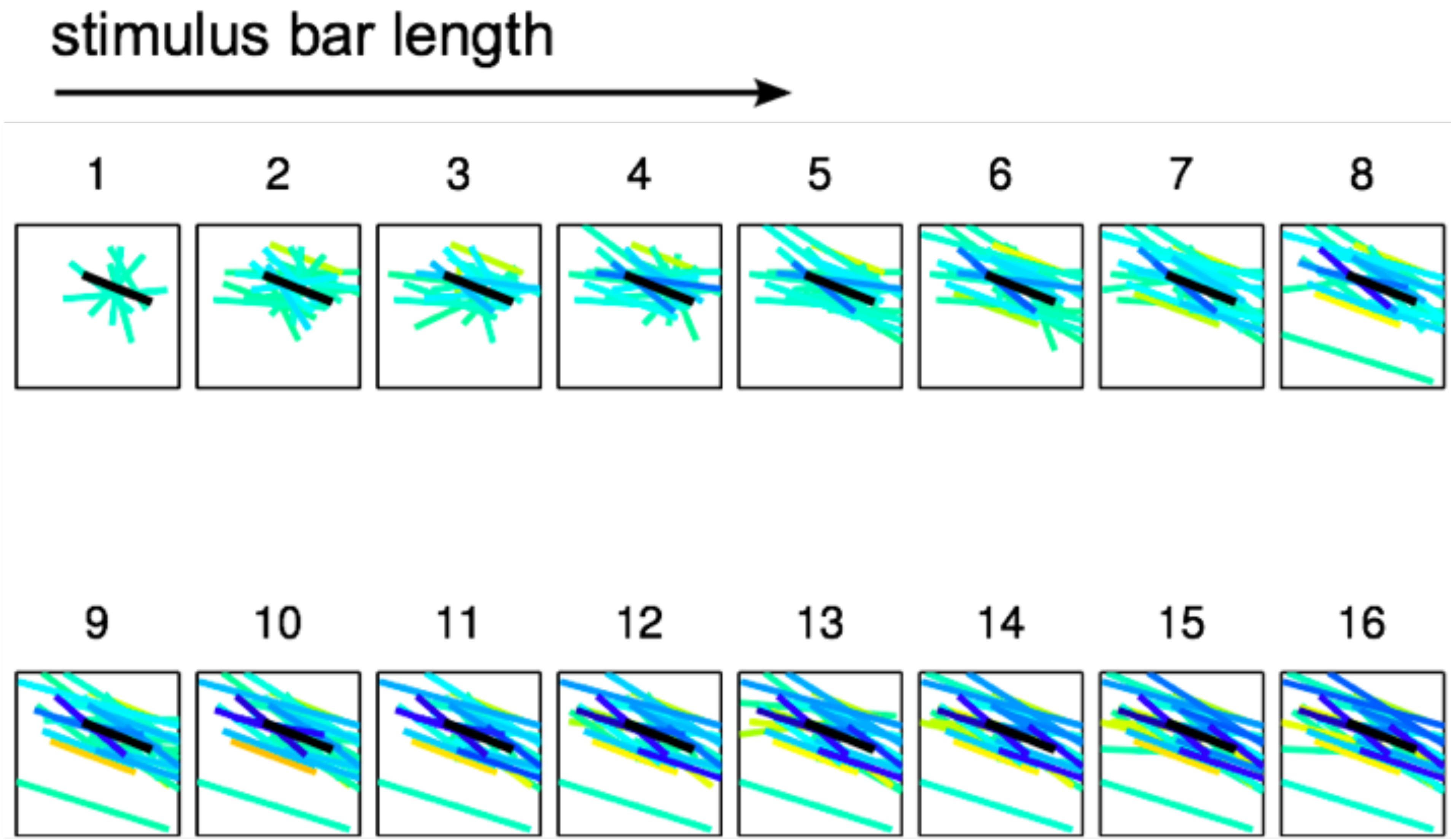
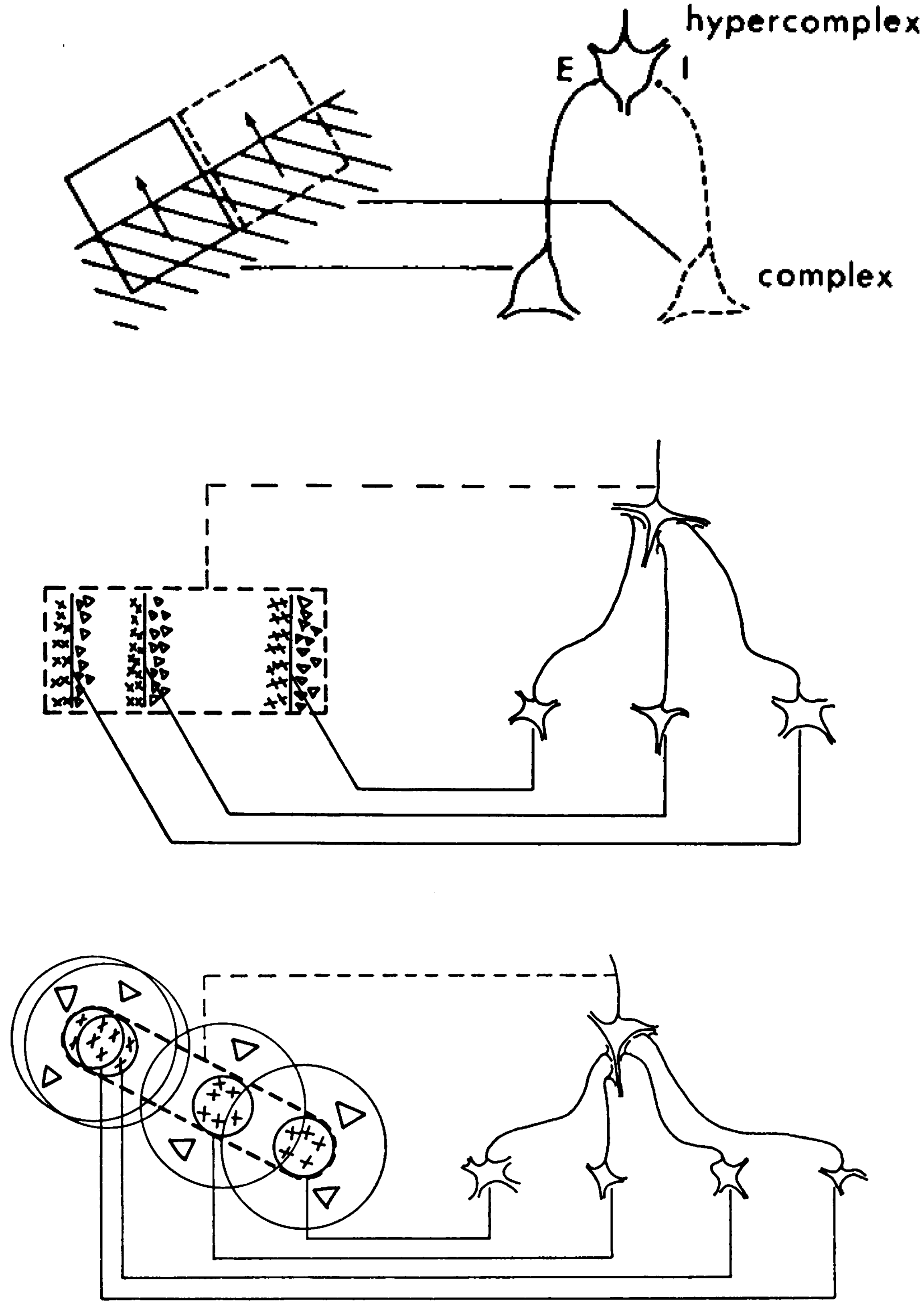


Yellow = excitatory
Blue = inhibitory

4. Feedback

Hubel & Wiesel (1962, 1965)



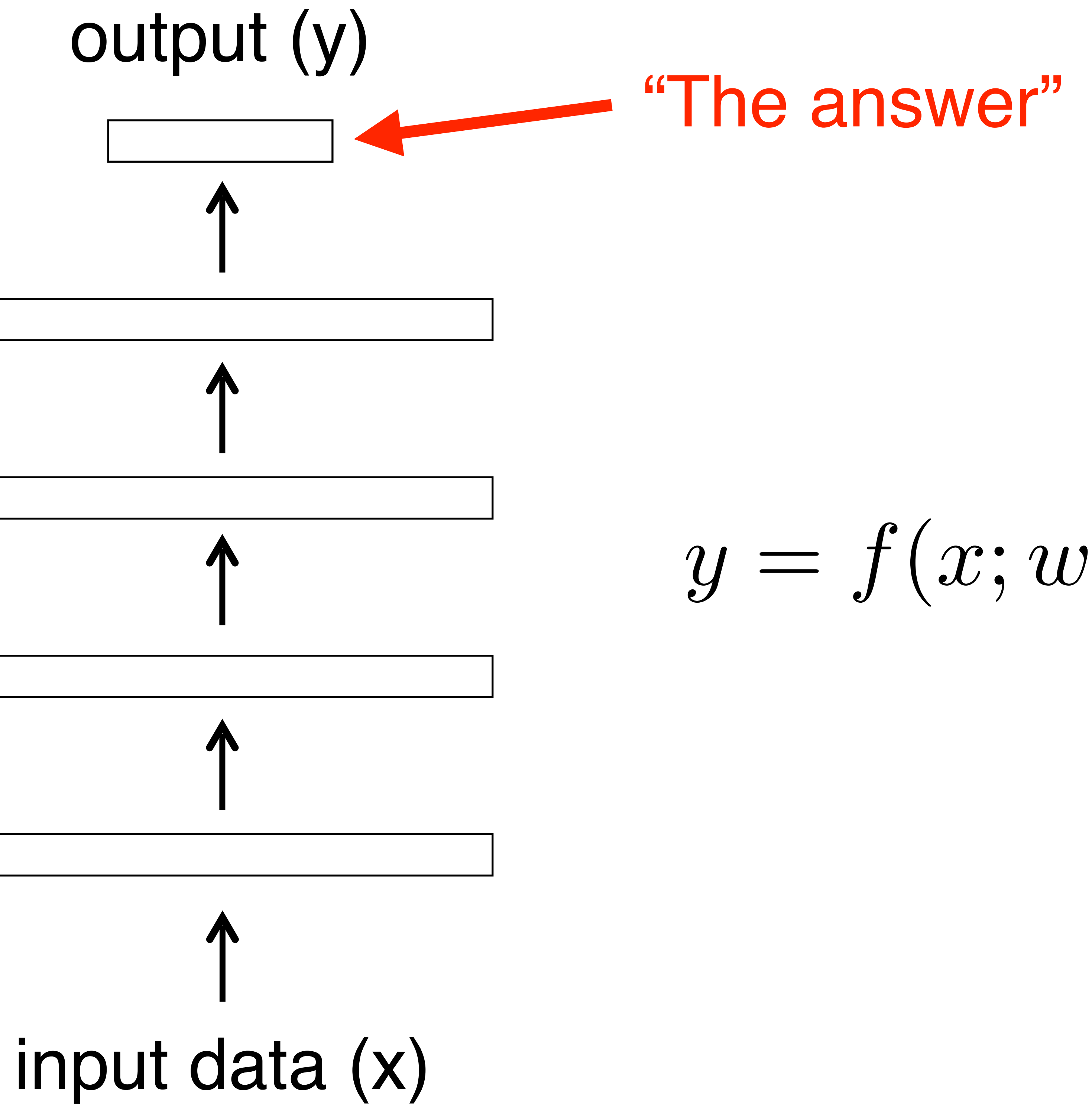
Hypercomplex

↑

Complex

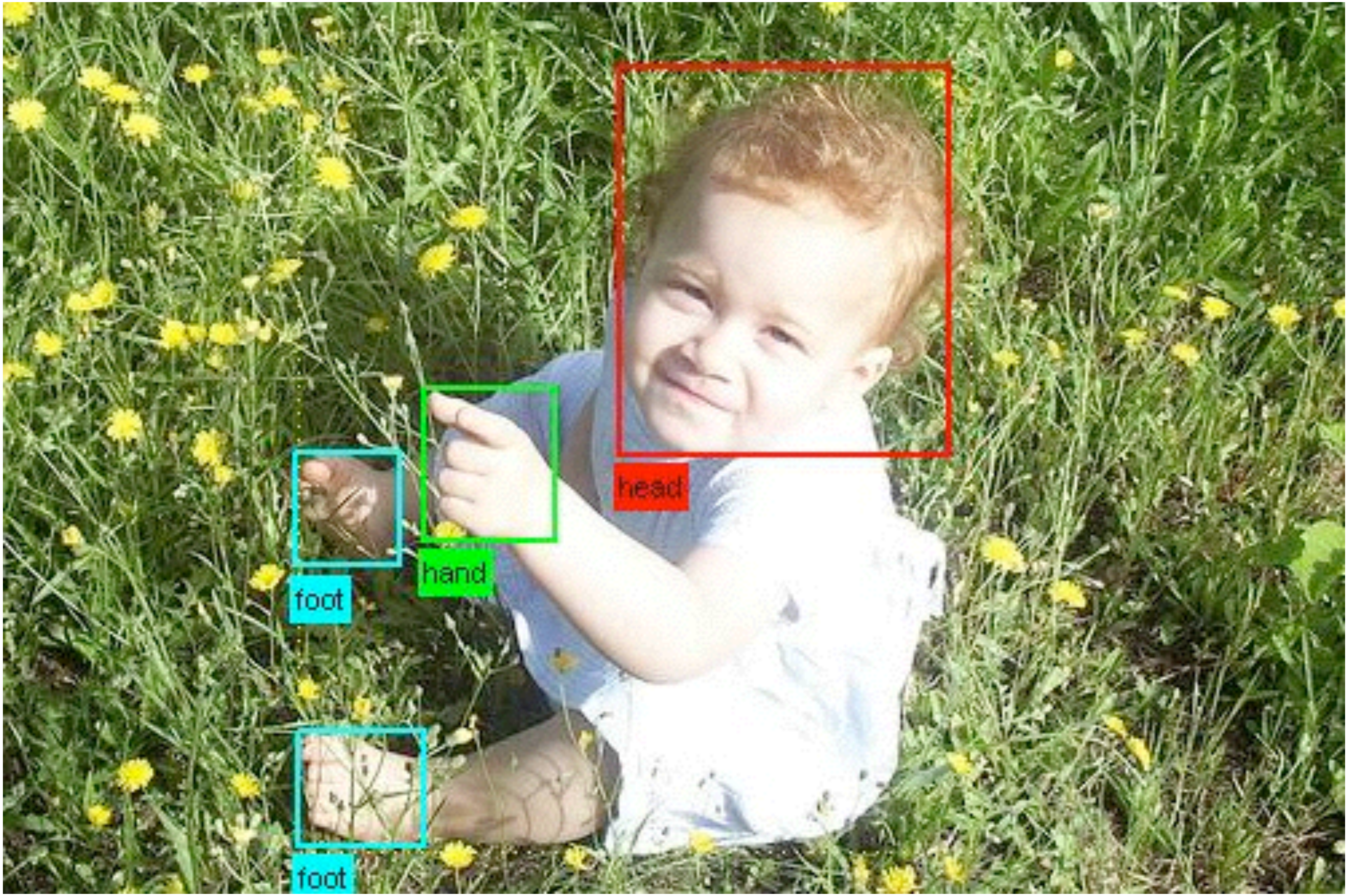
↑

Simple

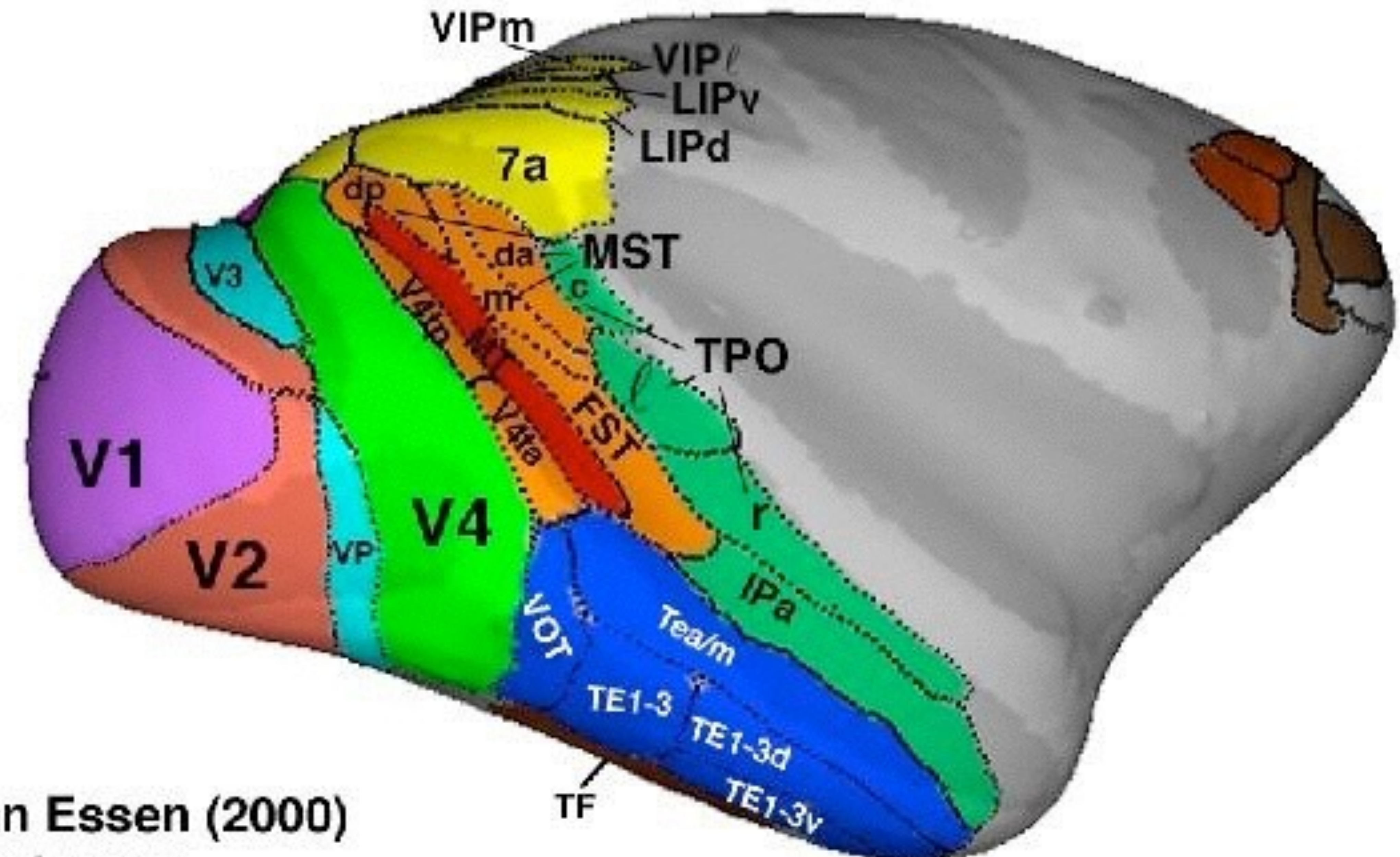


$$y = f(x; w)$$

Is this the goal of vision?

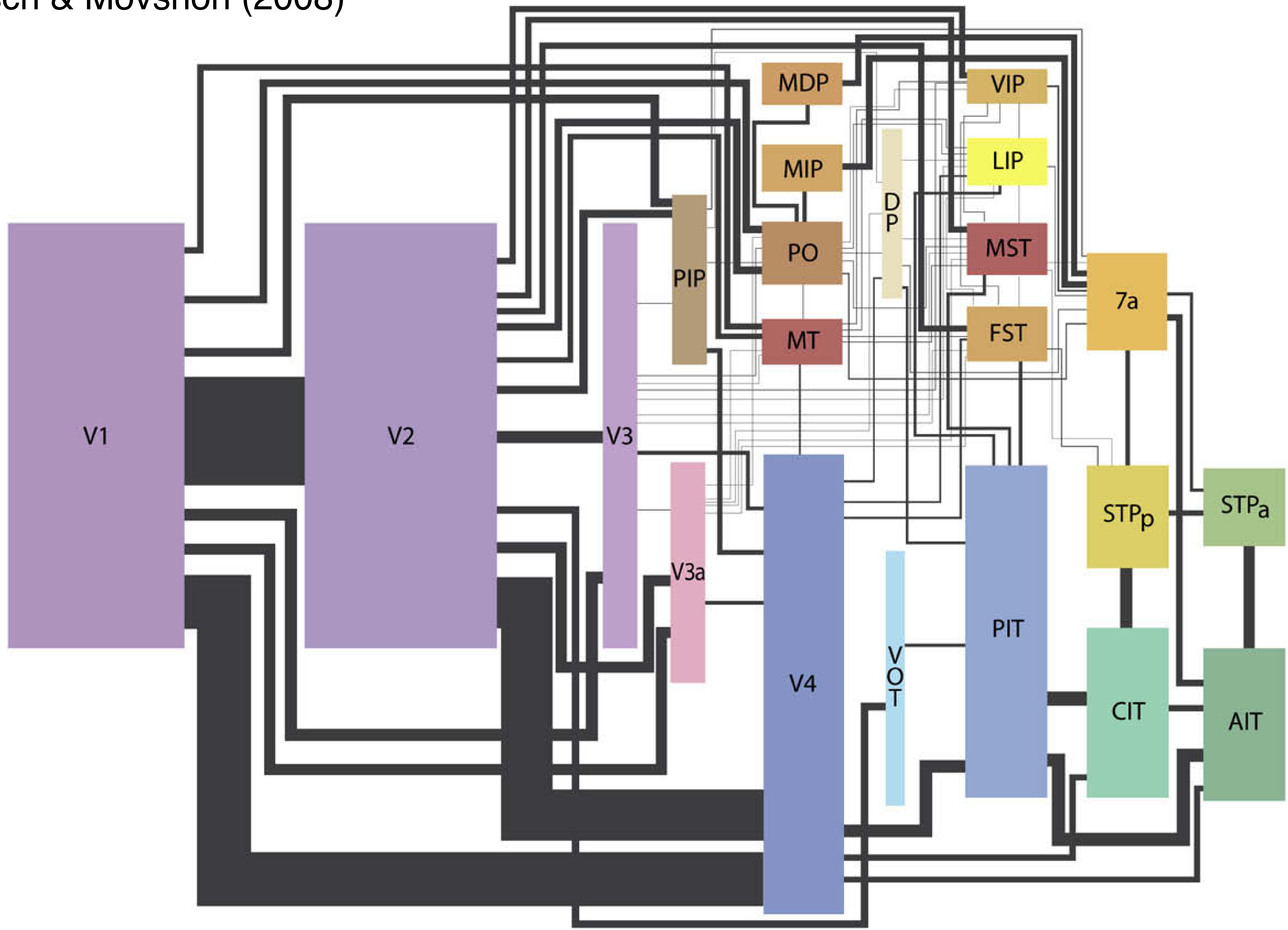


Primate visual cortex

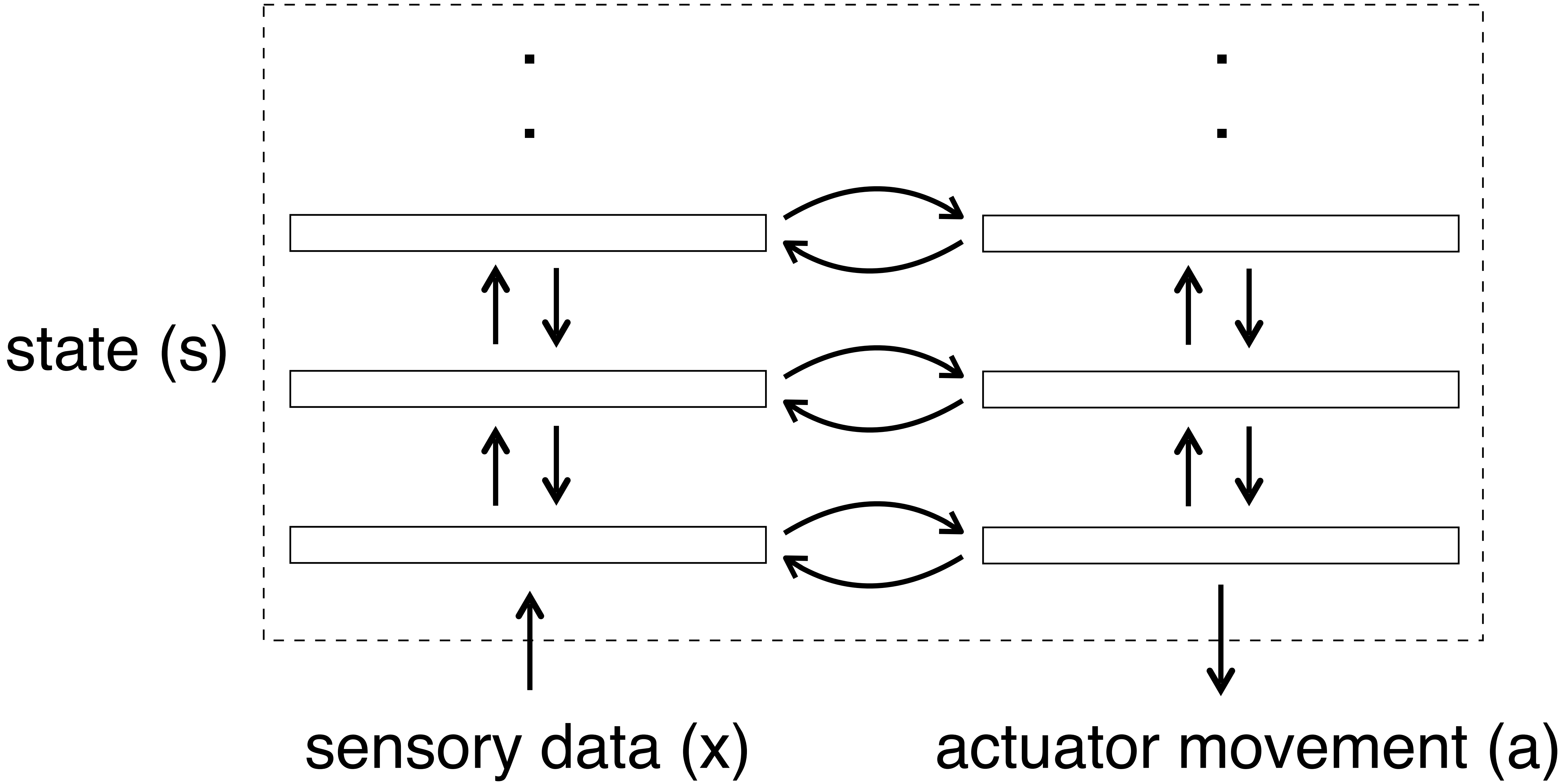


Lewis & Van Essen (2000)
Visual areas

Wallisch & Movshon (2008)

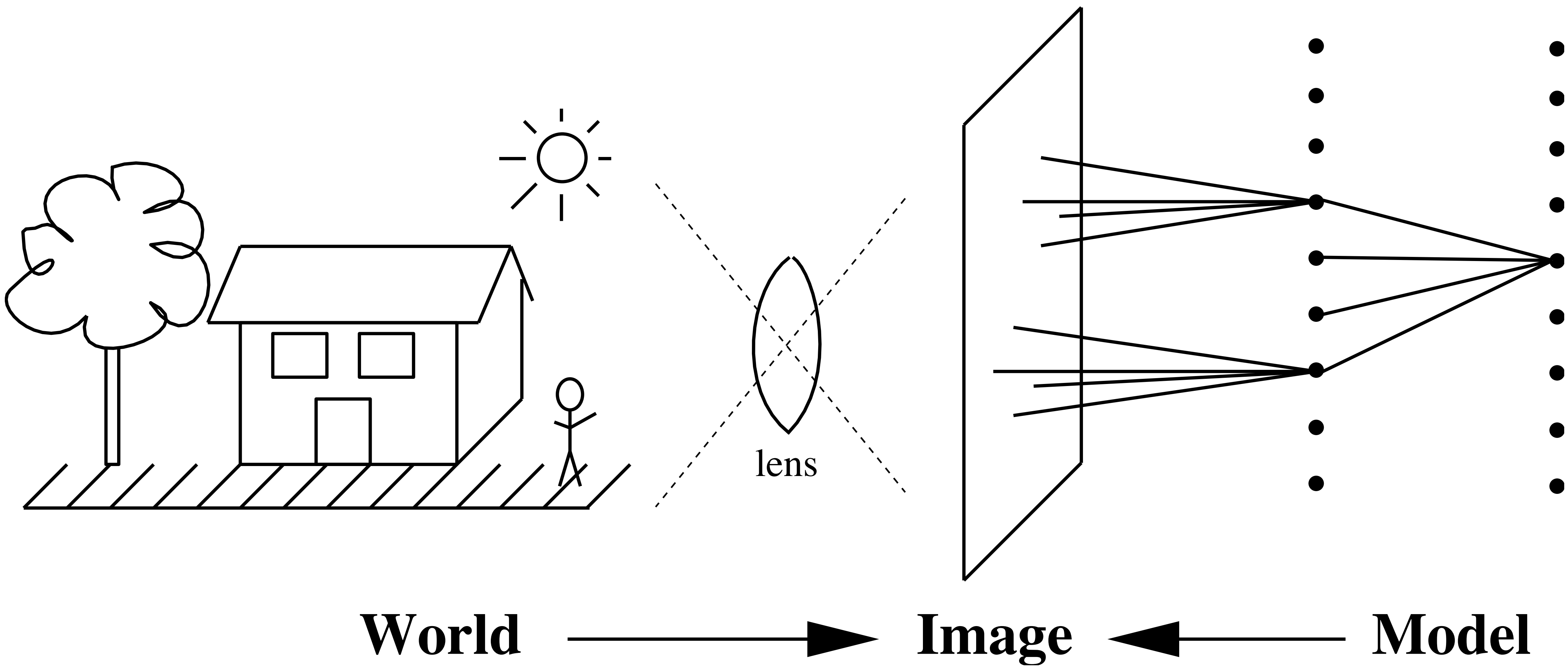


‘Gabor filters’ · · ? · · objects · faces



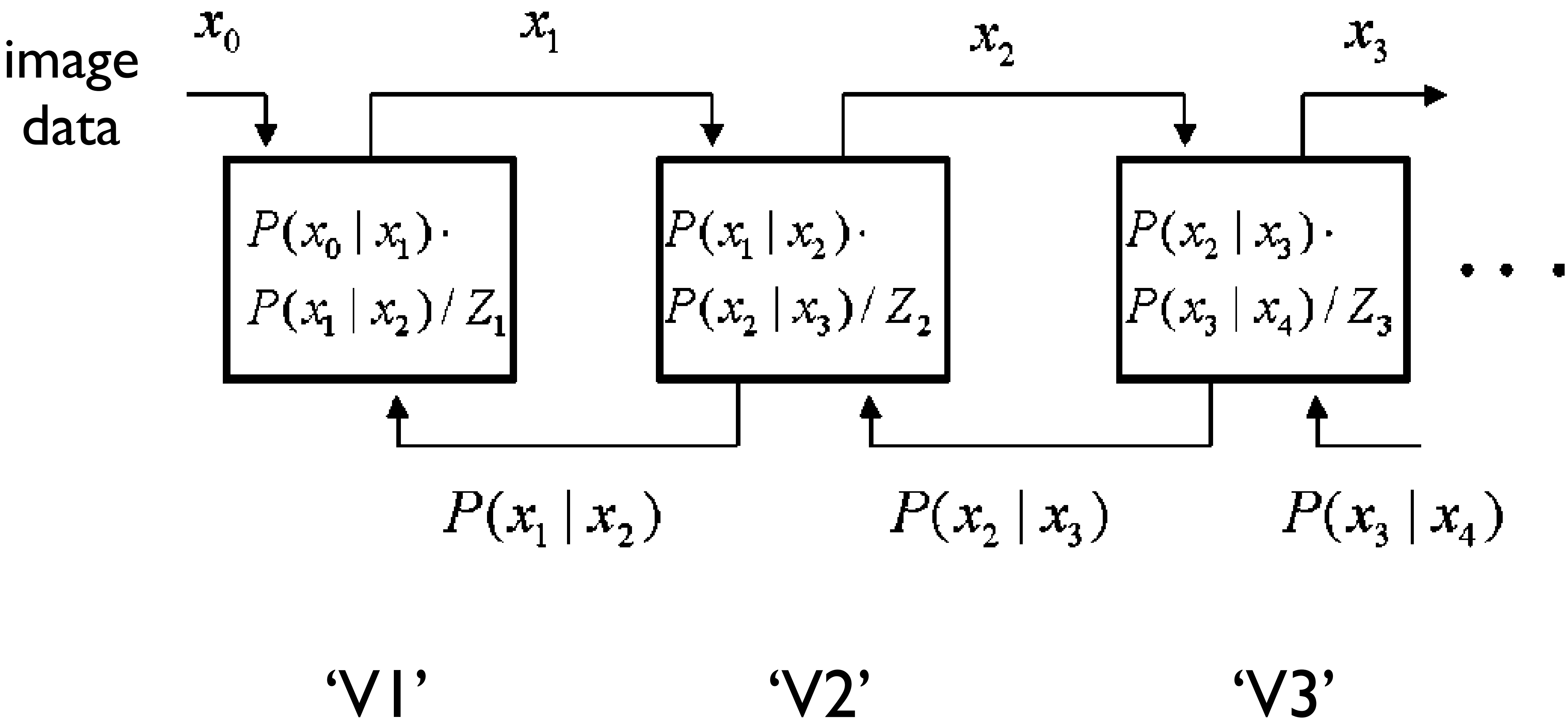
$$
\begin{aligned}
\tau \dot{s} + s &= g(s, x, a; w) \\
a &= f(s)
\end{aligned}
$$

Vision as inference

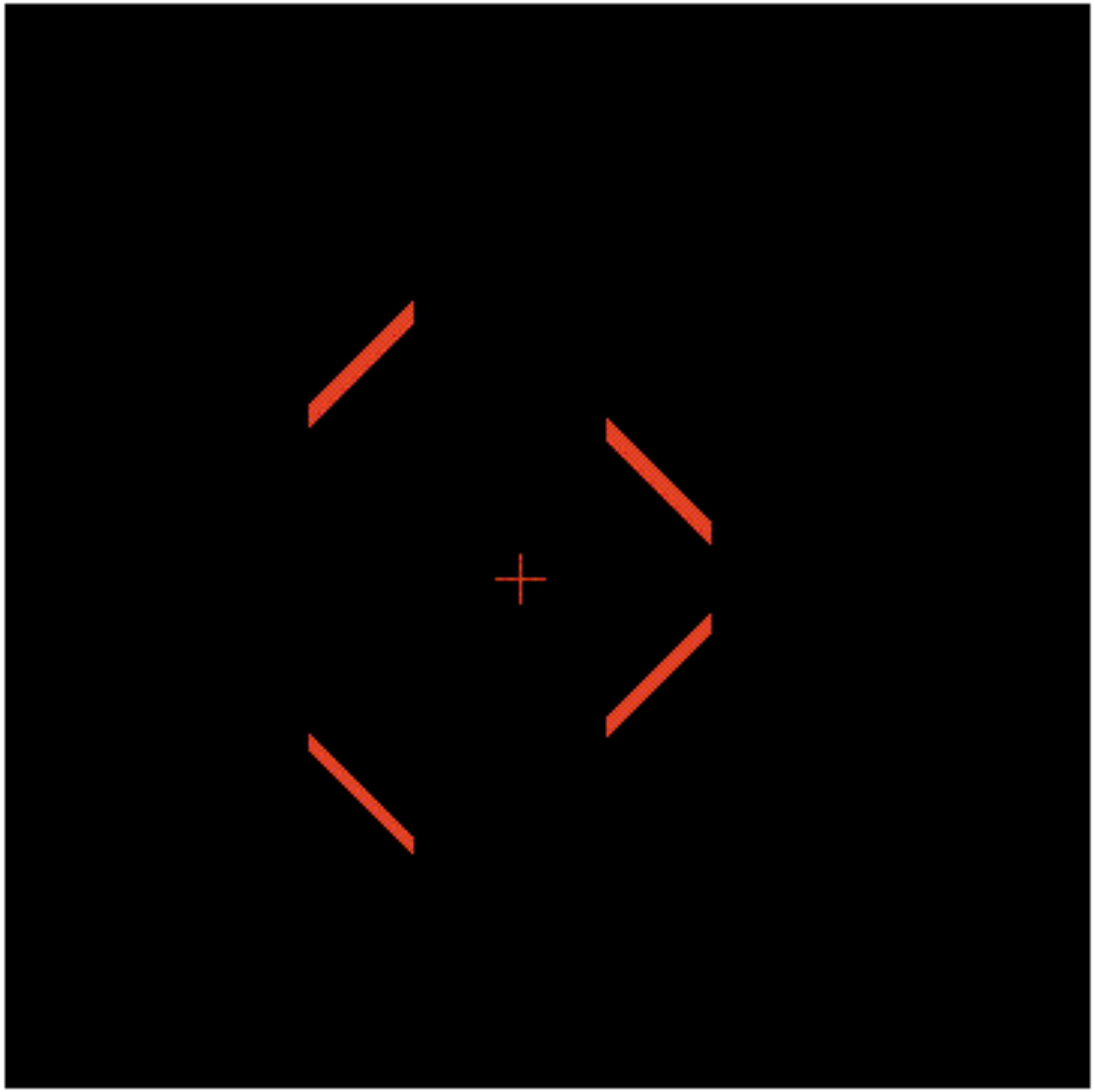


Hierarchical Bayesian inference in visual cortex

(Lee & Mumford, 2003)

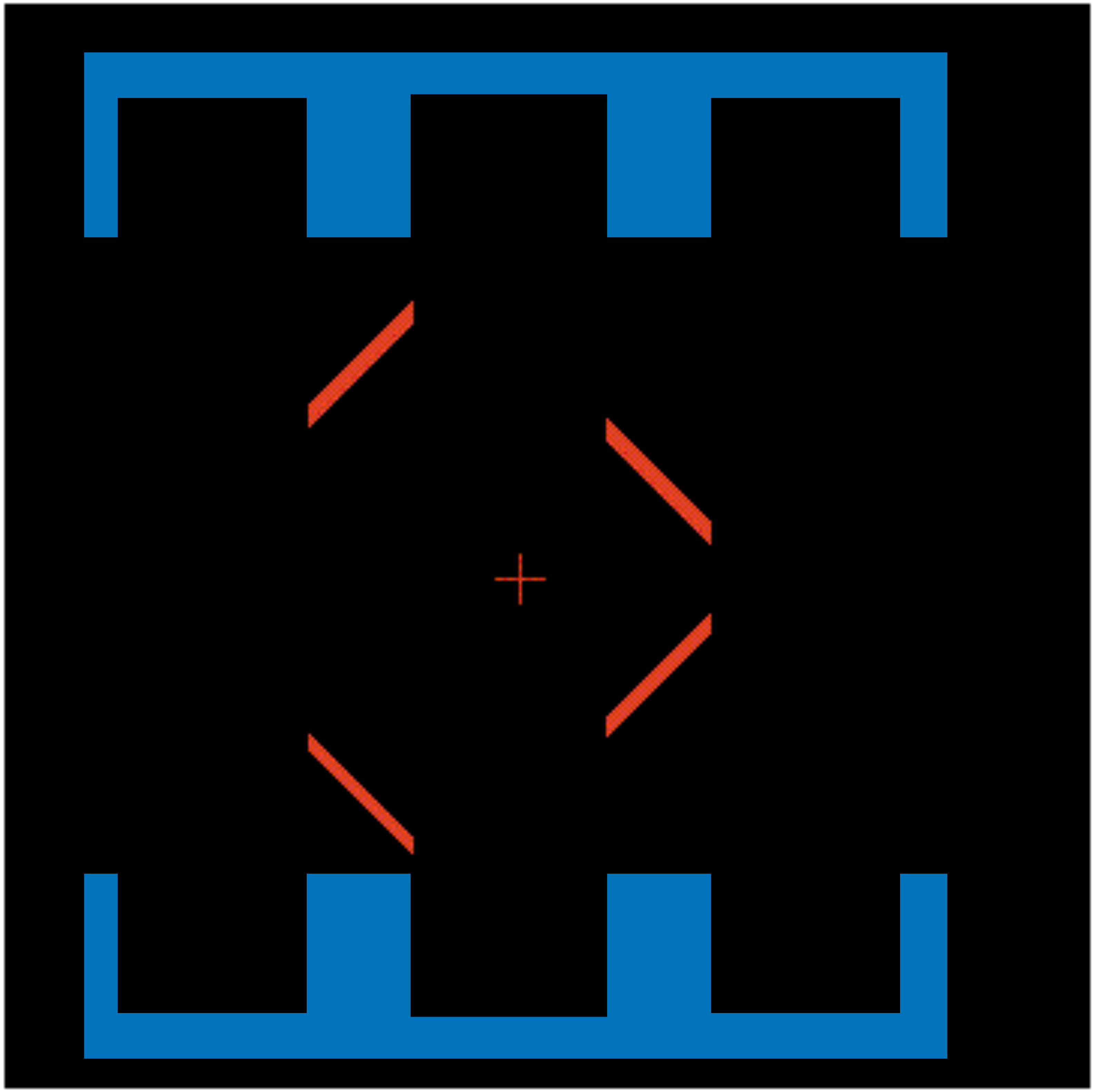


What do you see?



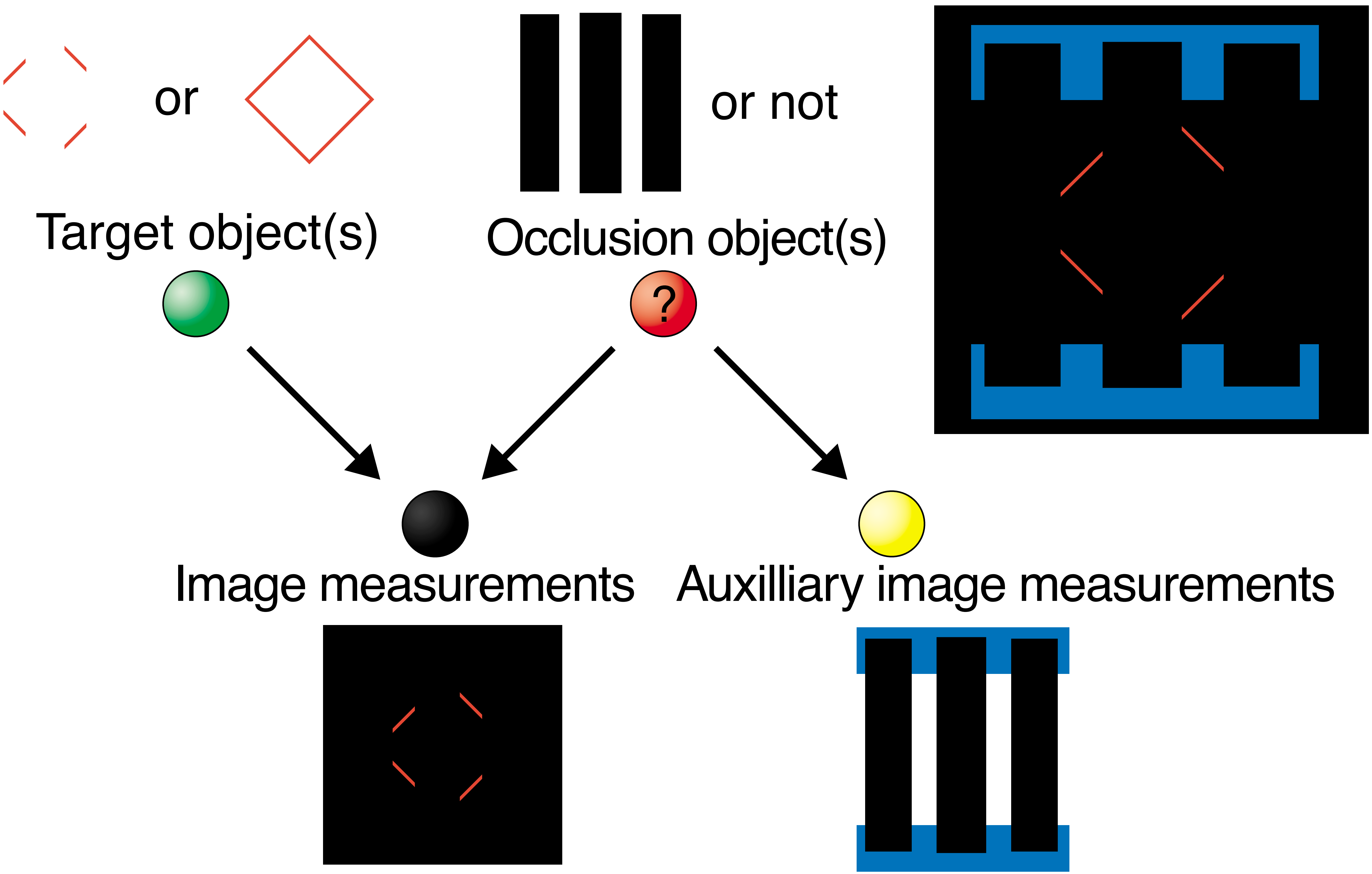
Lorenceau & Shiffrar (1992);
Murray, Kersten, Schrater, Olshausen & Woods (2002)

What do you see?



Lorenceau & Shiffrar (1992);
Murray, Kersten, Schrater, Olshausen & Woods (2002)

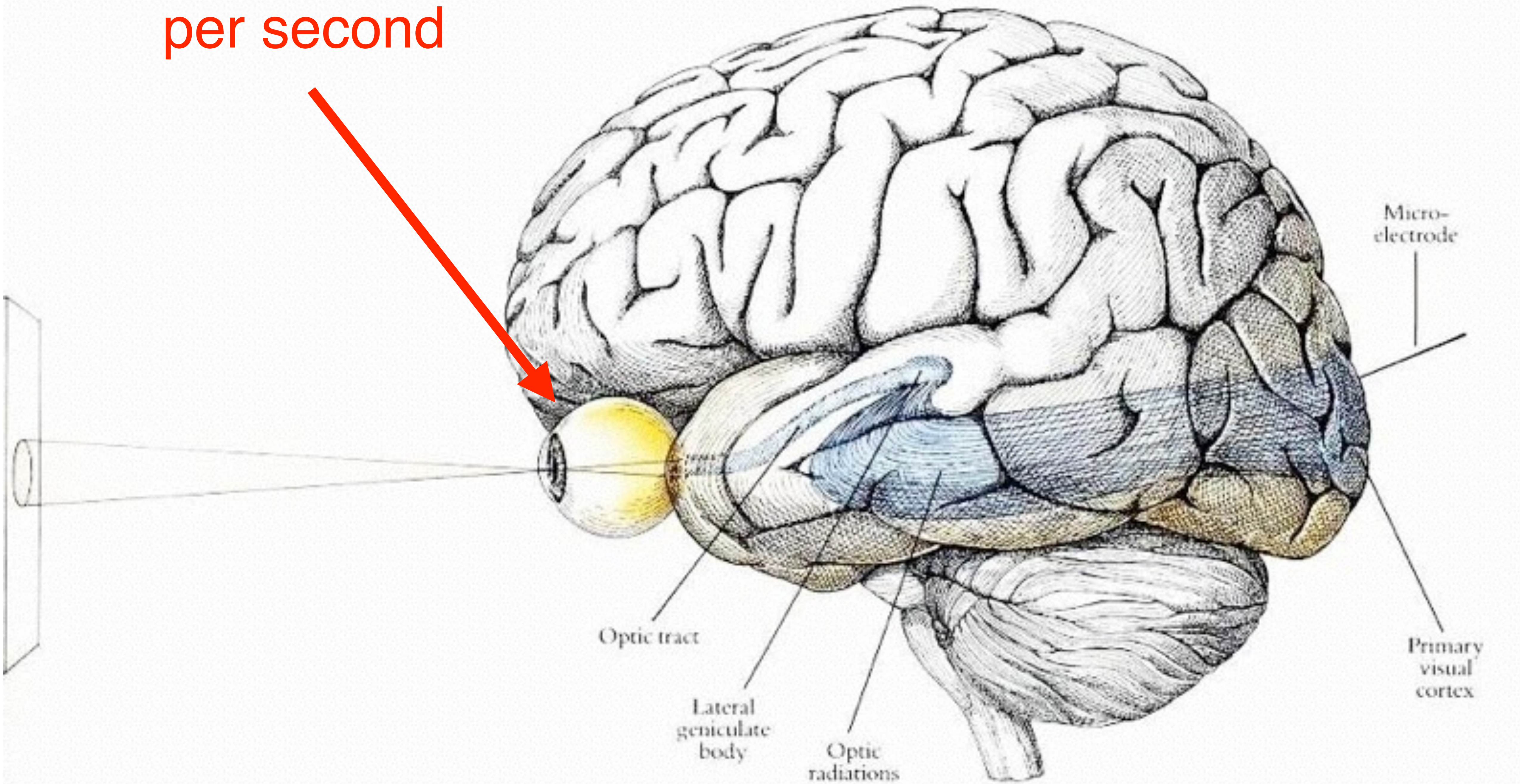
Perceptual "explaining away"



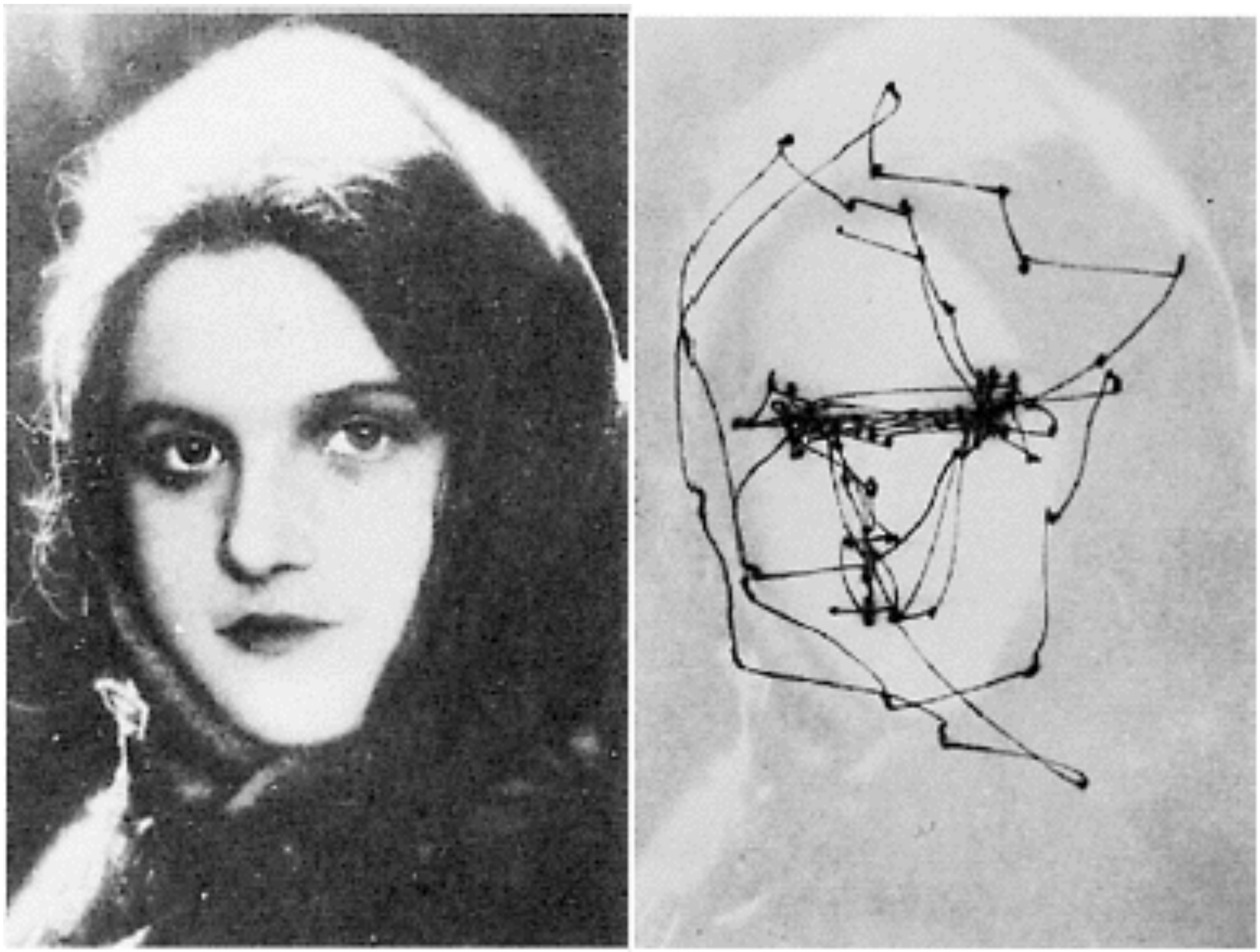
(Kersten & Yuille, 2003)

5. Active perception

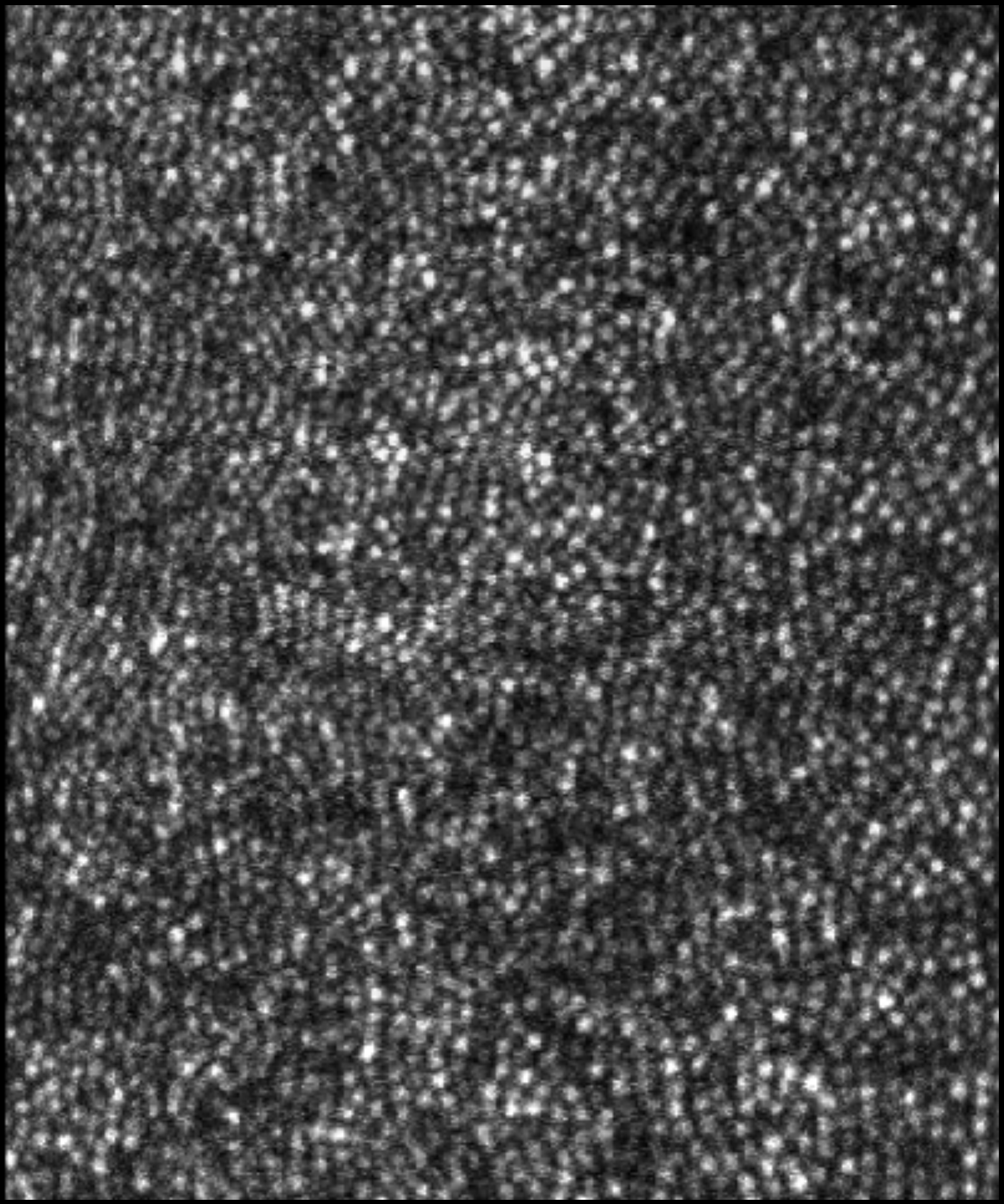
Moves 3-5 times per second



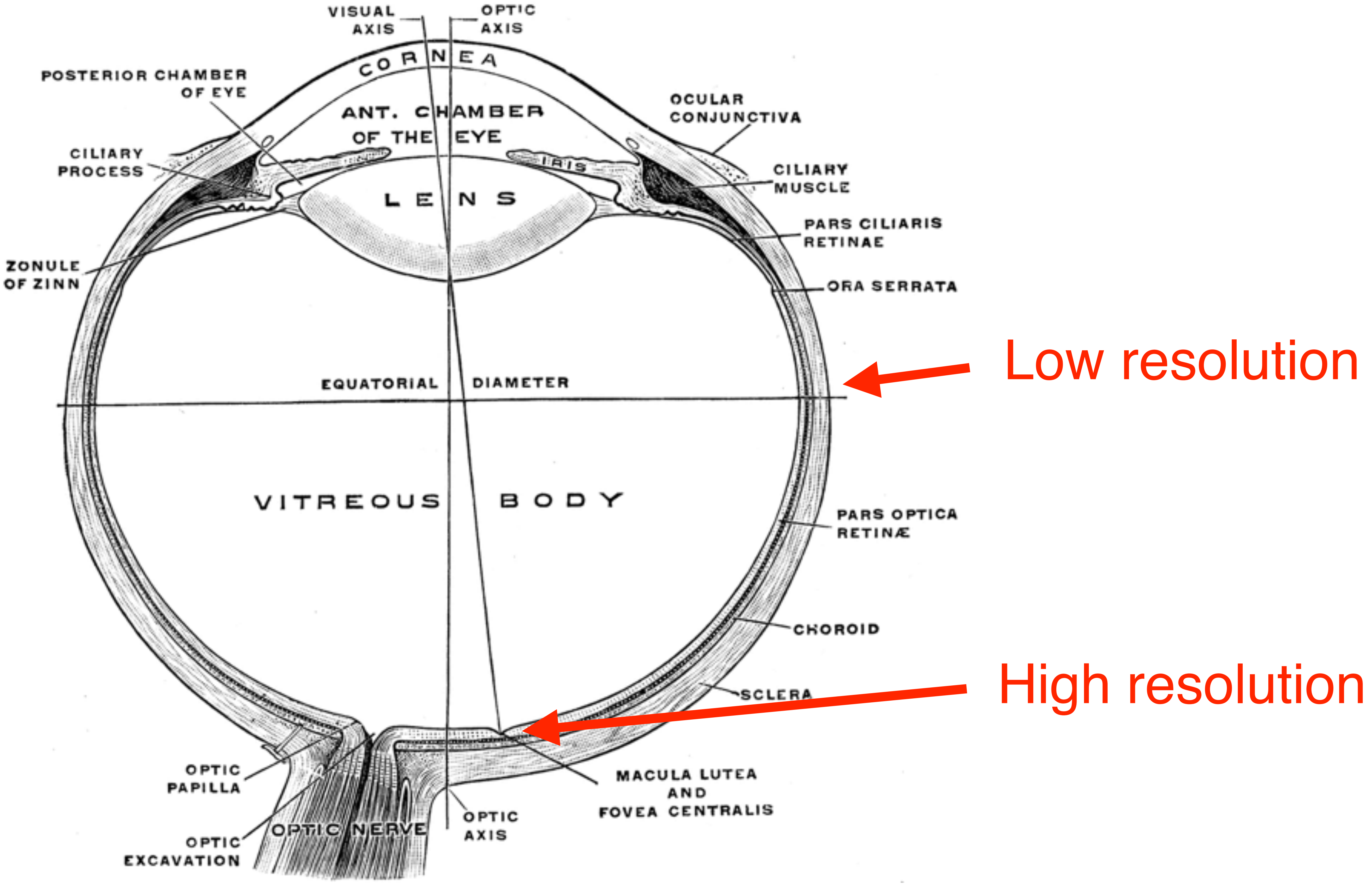
Human eye movements during viewing of an image



Fixational eye movements (drift)

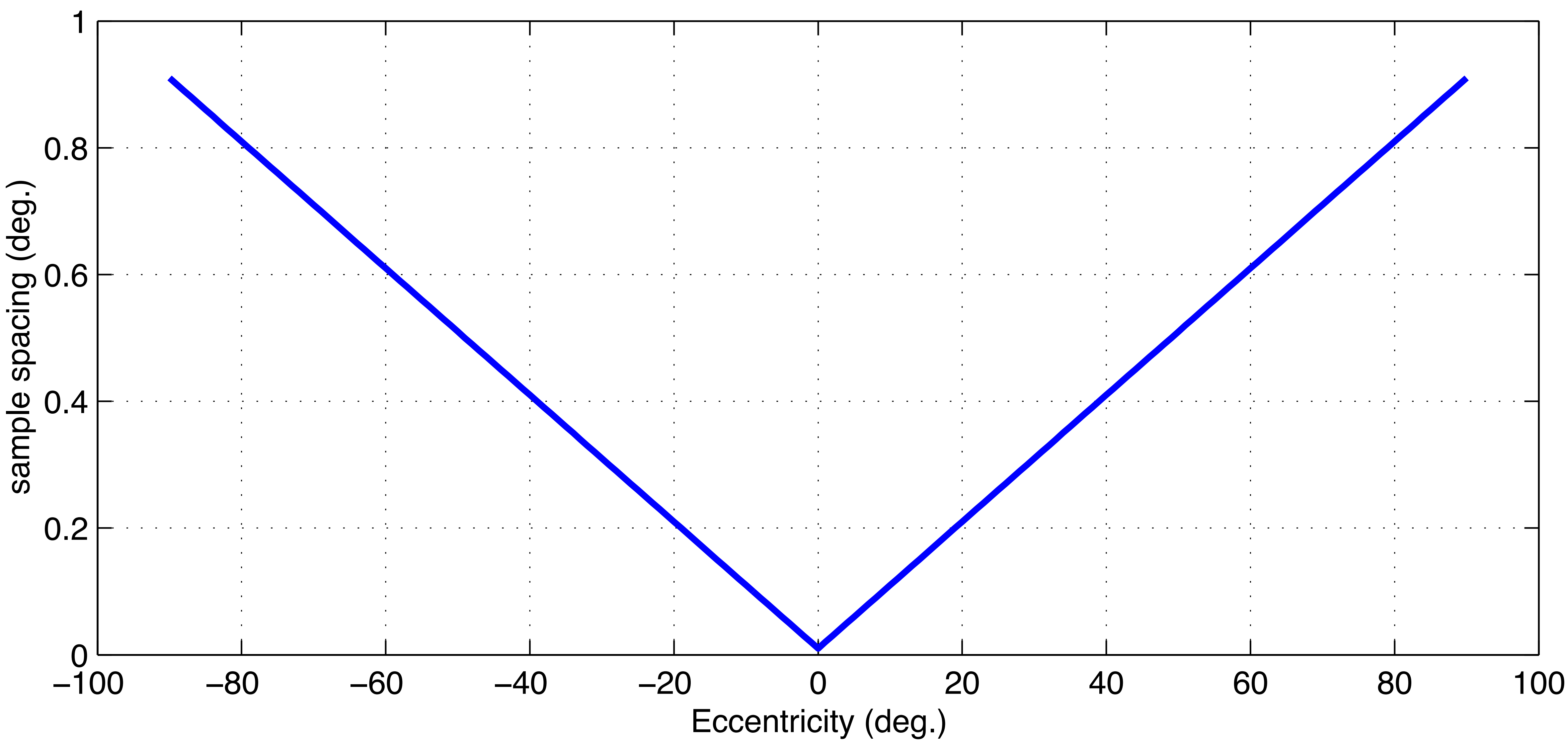


(eye movement data from Austin Roorda, UC Berkeley)

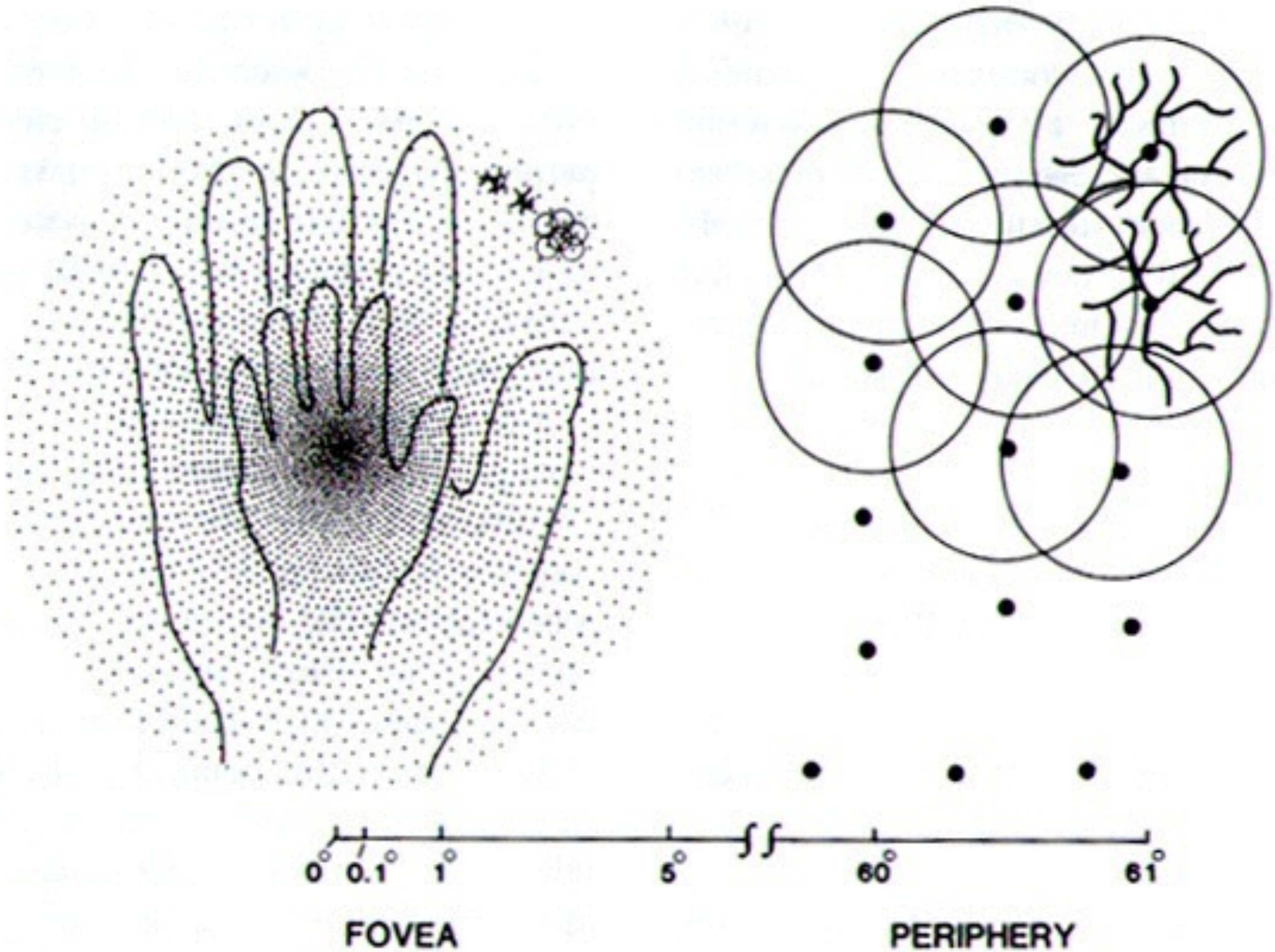

VISUAL AXIS
OPTIC AXIS
CORNEA
POSTERIOR CHAMBER OF EYE
ANT. CHAMBER OF THE EYE
OCULAR CONJUNCTIVA
CILIARY PROCESS
IRIS
CILIARY MUSCLE
LENS
PARS CILIARIS RETINAE
ZONULE OF ZINN
ORA SERRATA
Low resolution
EQUATORIAL DIAMETER
VITREOUS BODY
PARS OPTICA RETINÆ
CHOROID
High resolution
SCLERA
OPTIC PAPILLA
MACULA LUTEA AND FOVEA CENTRALIS
OPTIC NERVE
OPTIC AXIS
OPTIC EXCAVATION

Retinal ganglion cell spacing as a function of eccentricity

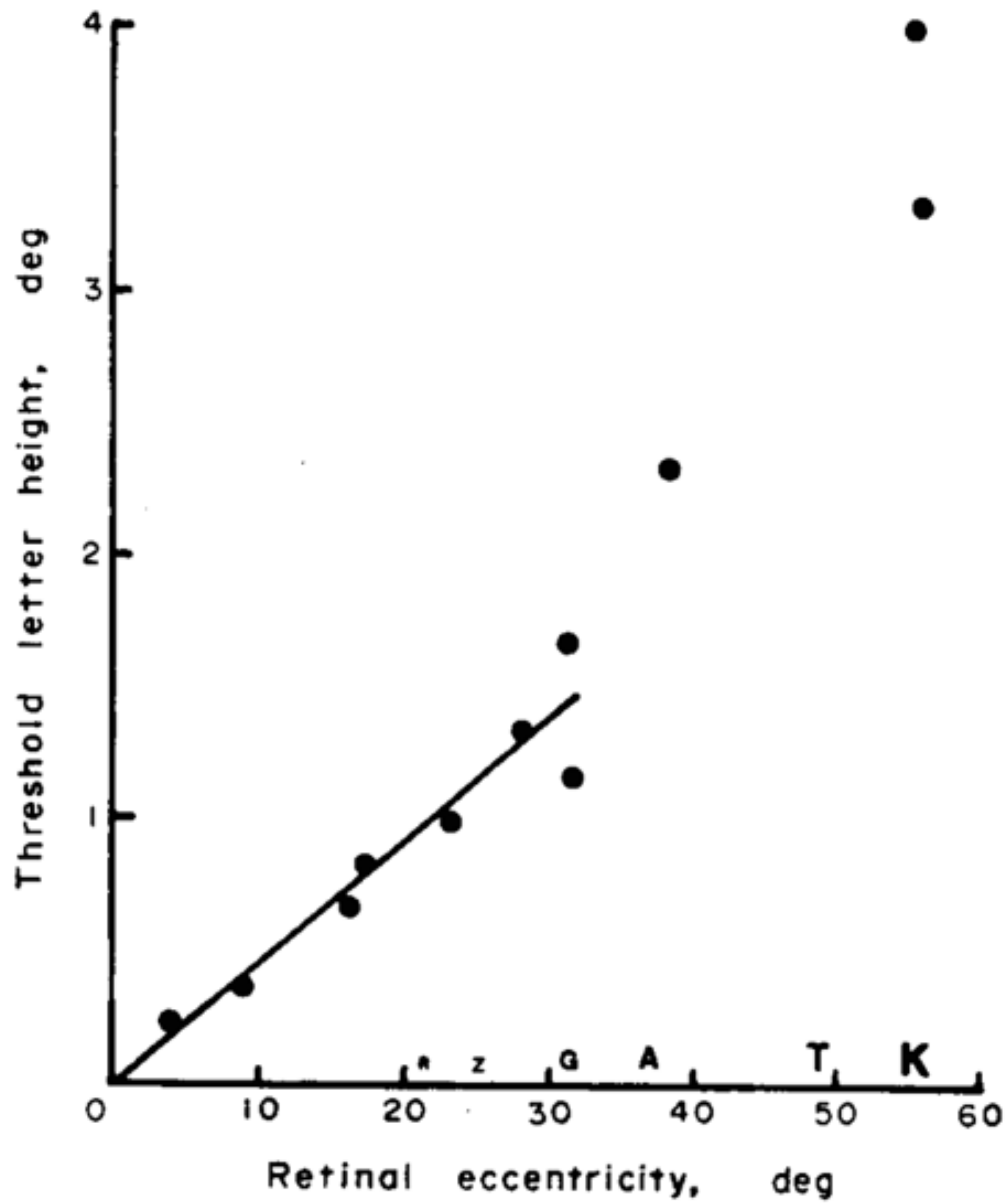
$$\Delta E \approx .01(|E| + 1)$$



Retinal ganglion cell sampling lattice
(shown at one dot for every 20 ganglion cells)

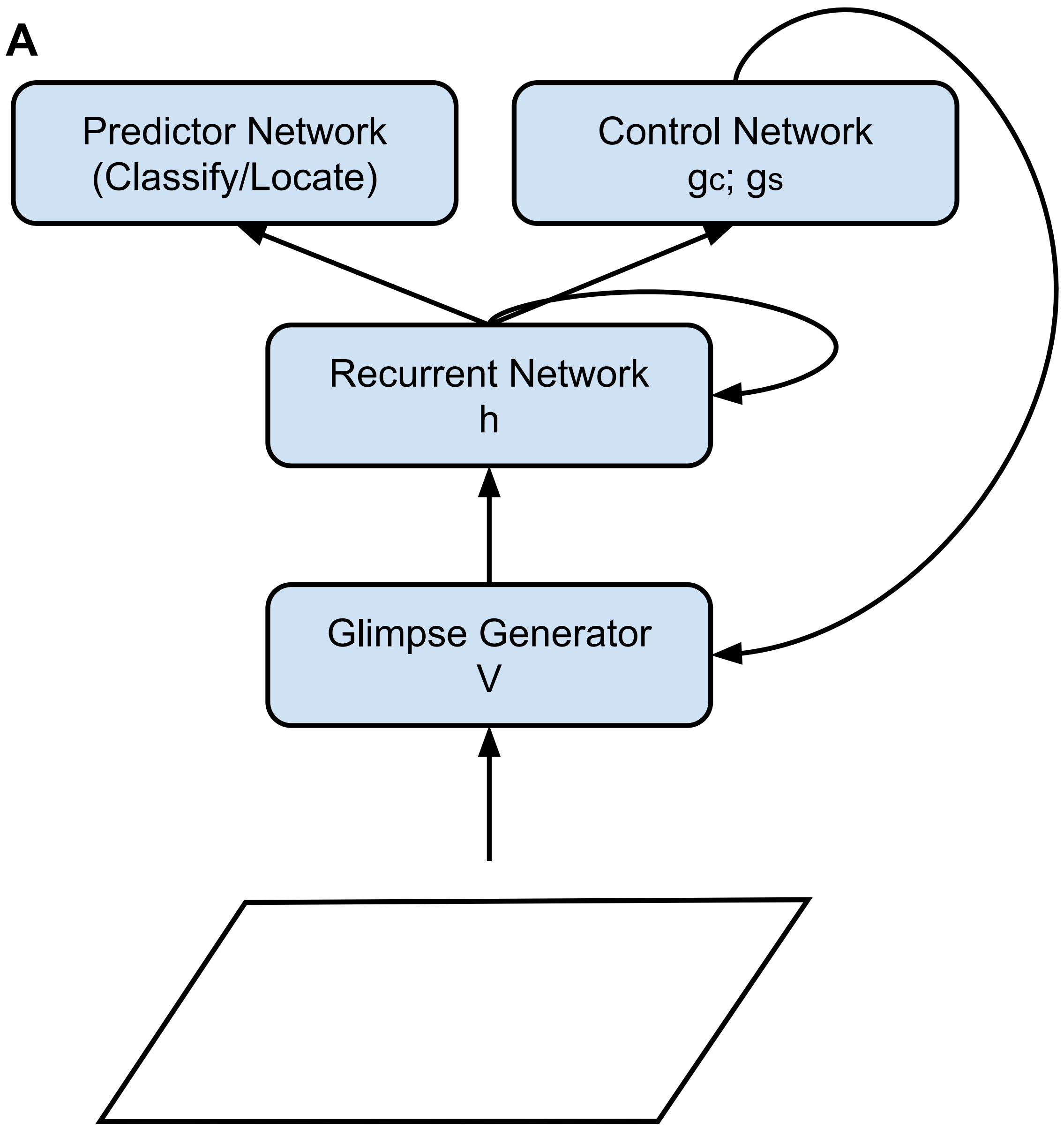


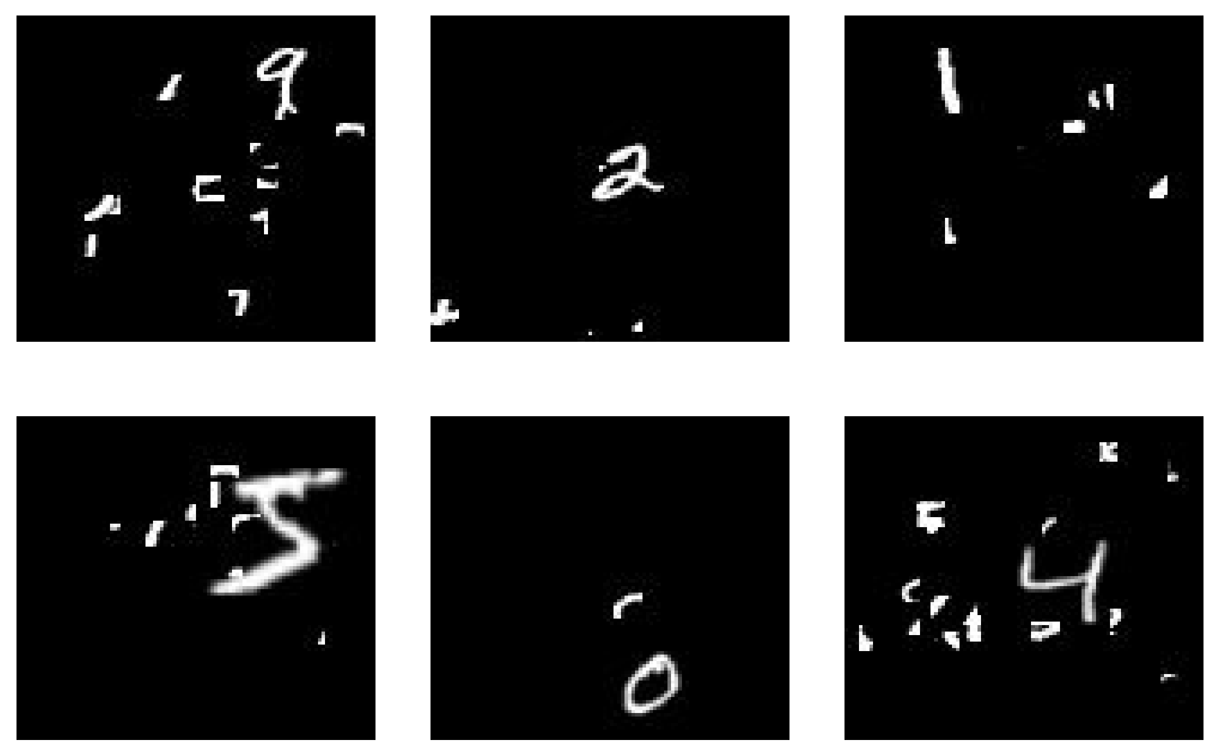
Minimal letter size required for recognition as a function of eccentricity
(Anstis, 1974)



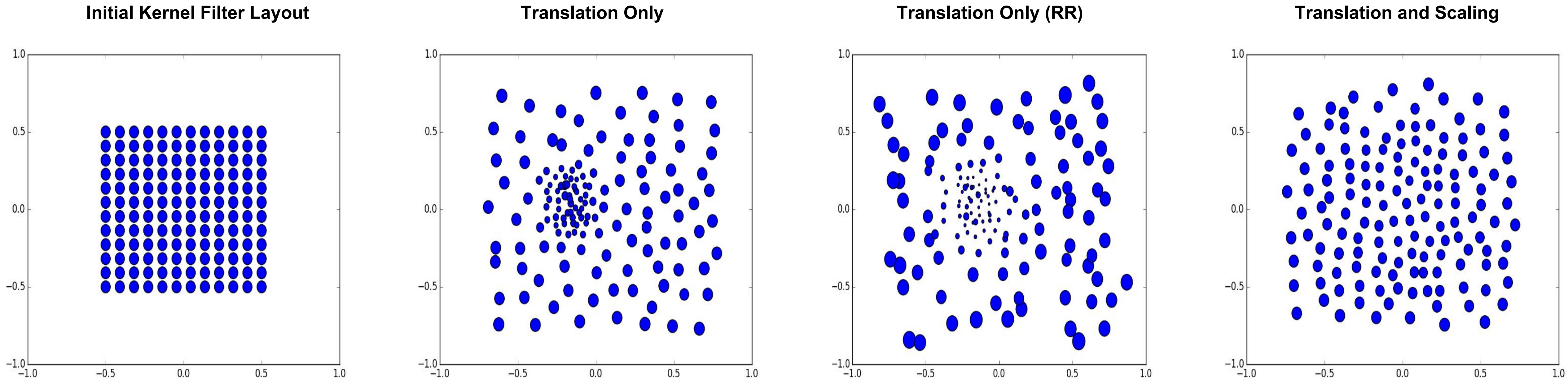
Learning the sampling lattice

(Brian Cheung, Eric Weiss)





Learned glimpse window sampling lattices



Five lessons from biology

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- Nonlinear processing in dendritic trees
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20 years of learning about vision: Questions answered, questions unanswered, and questions not yet asked. In: *20 Years of Computational Neuroscience*. J.M. Bower, Ed. (Symposium of the CNS2010 annual meeting)

Lewicki MS, Olshausen BA, Surlykke A, Moss CF (2014) Scene analysis in the natural environment. *Frontiers in Psychology, 5*, article 199.

Olshausen BA (2014) Perception as an inference problem. In: *The Cognitive Neurosciences V,* M. Gazzaniga, R. Mangun, Eds. MIT Press.

http://redwood.berkeley.edu/bruno