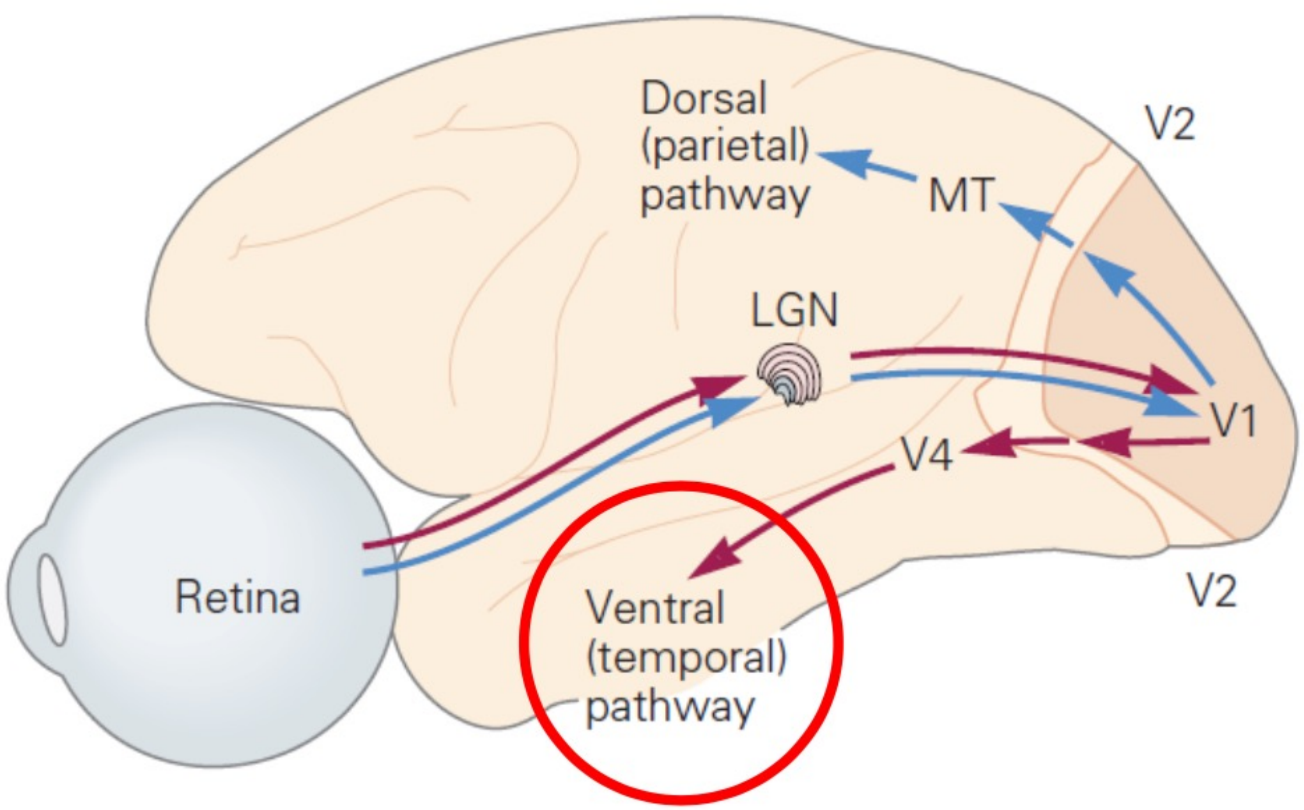
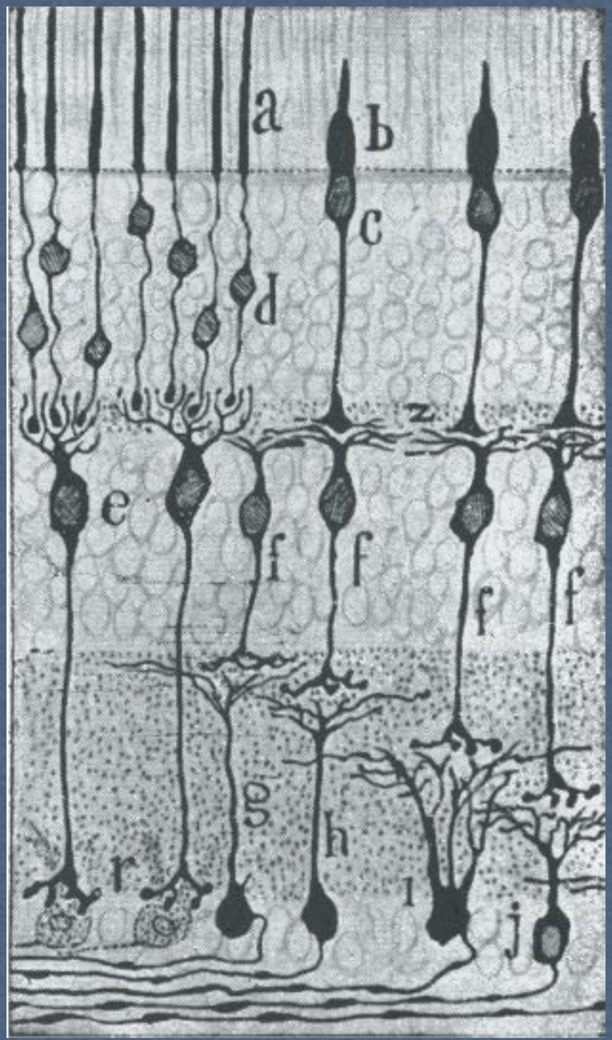
Sensory coding

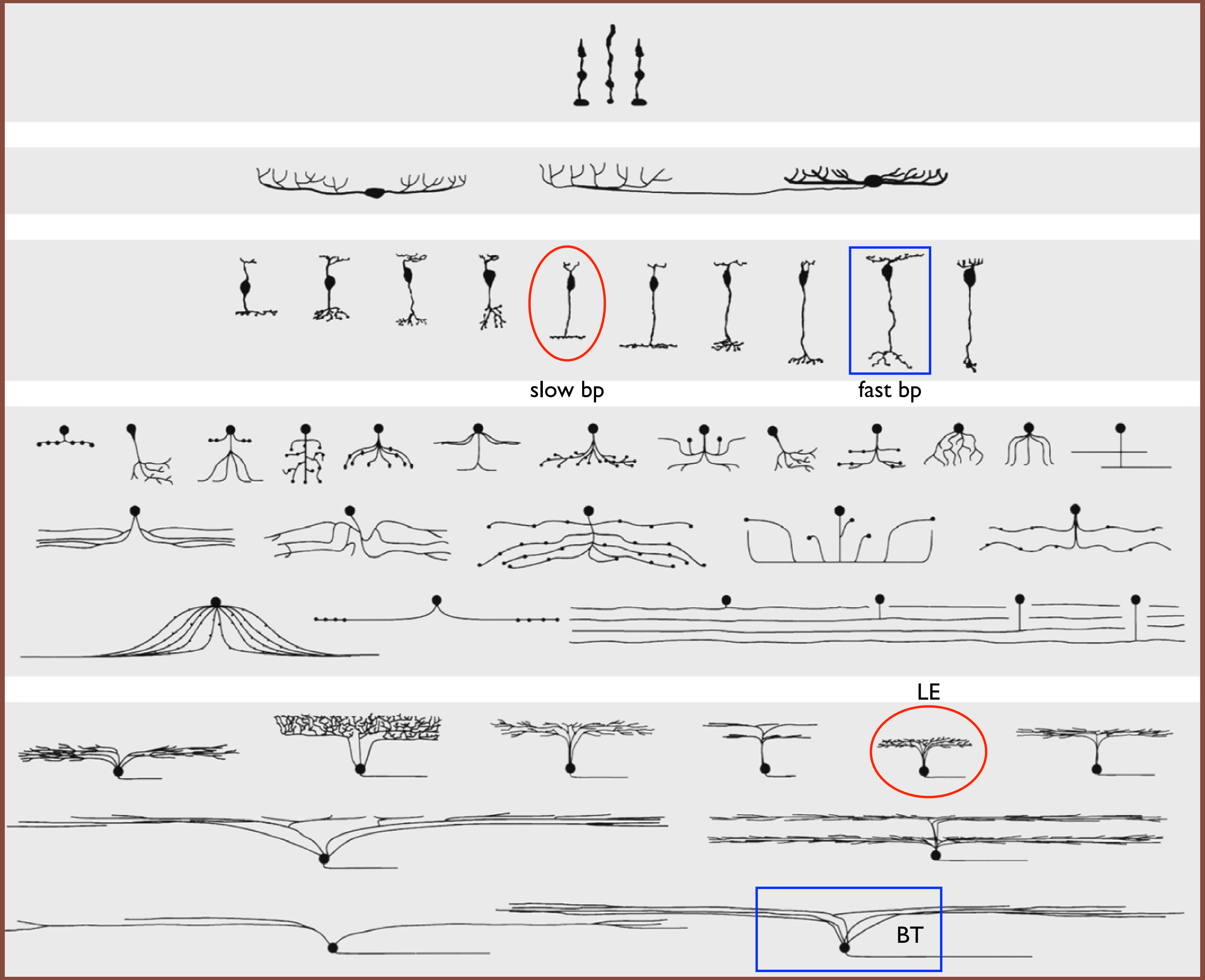
Ventral visual pathway



It really is mind-bogglingly diverse!



Ramón y Cajal 1917

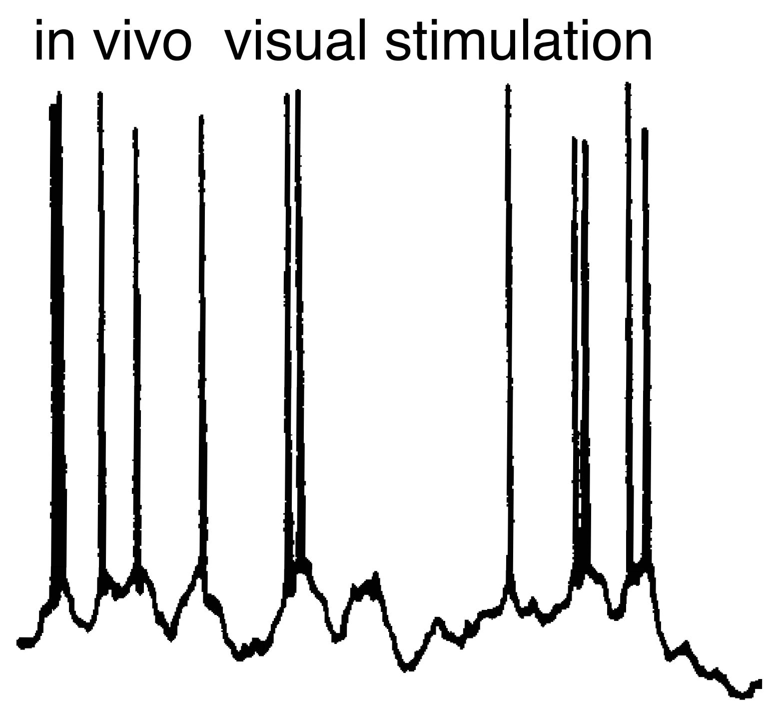


3 cones → 2 horizontal cells → 10 bipolars → 30 interneurons → 15 ganglion cells

Masland 2001

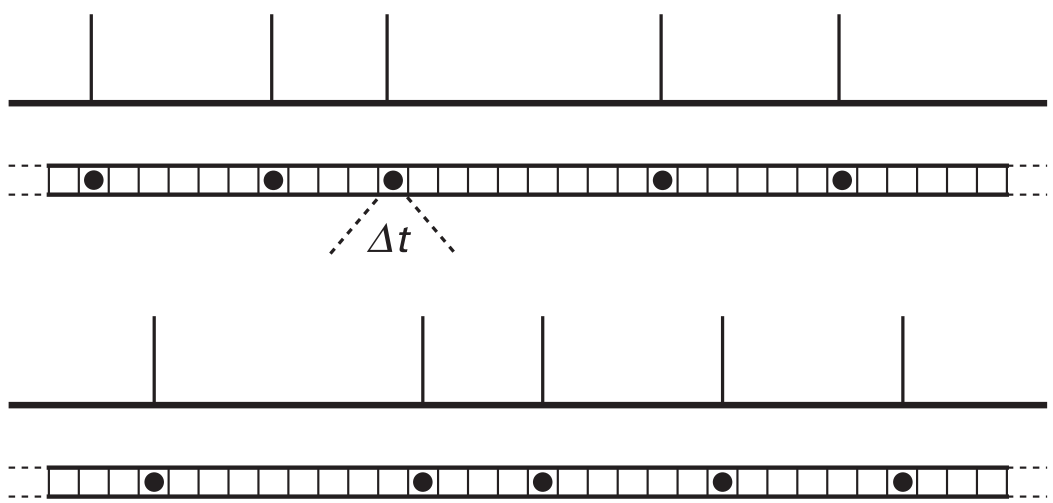
slow bp → LE　　fast bp → BT

Spike trains convey information



$$\rho(t) = \sum_i \delta(t - t_i)$$

Information is entropy

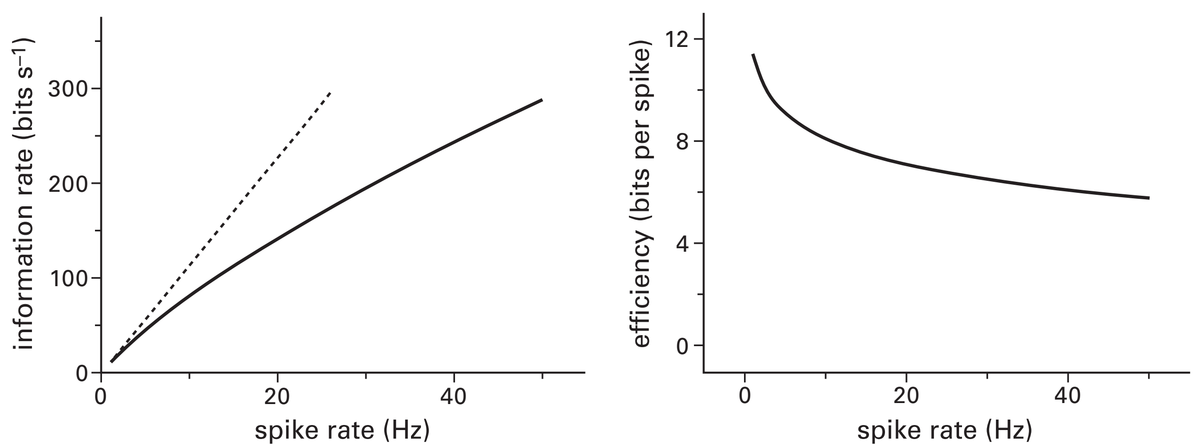


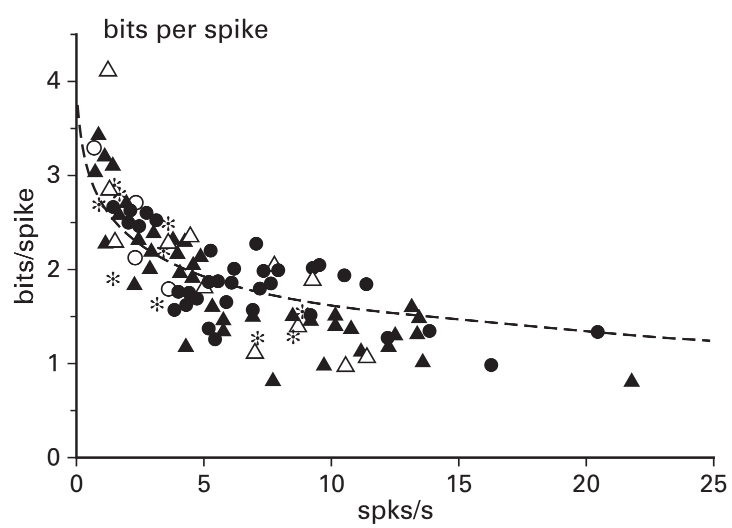
$$T = \frac{1 \text{ sec}}{\Delta t}$$

$$M = \frac{T!}{R!(T-R)!}$$

$$I = \log M$$

Does every spike count?





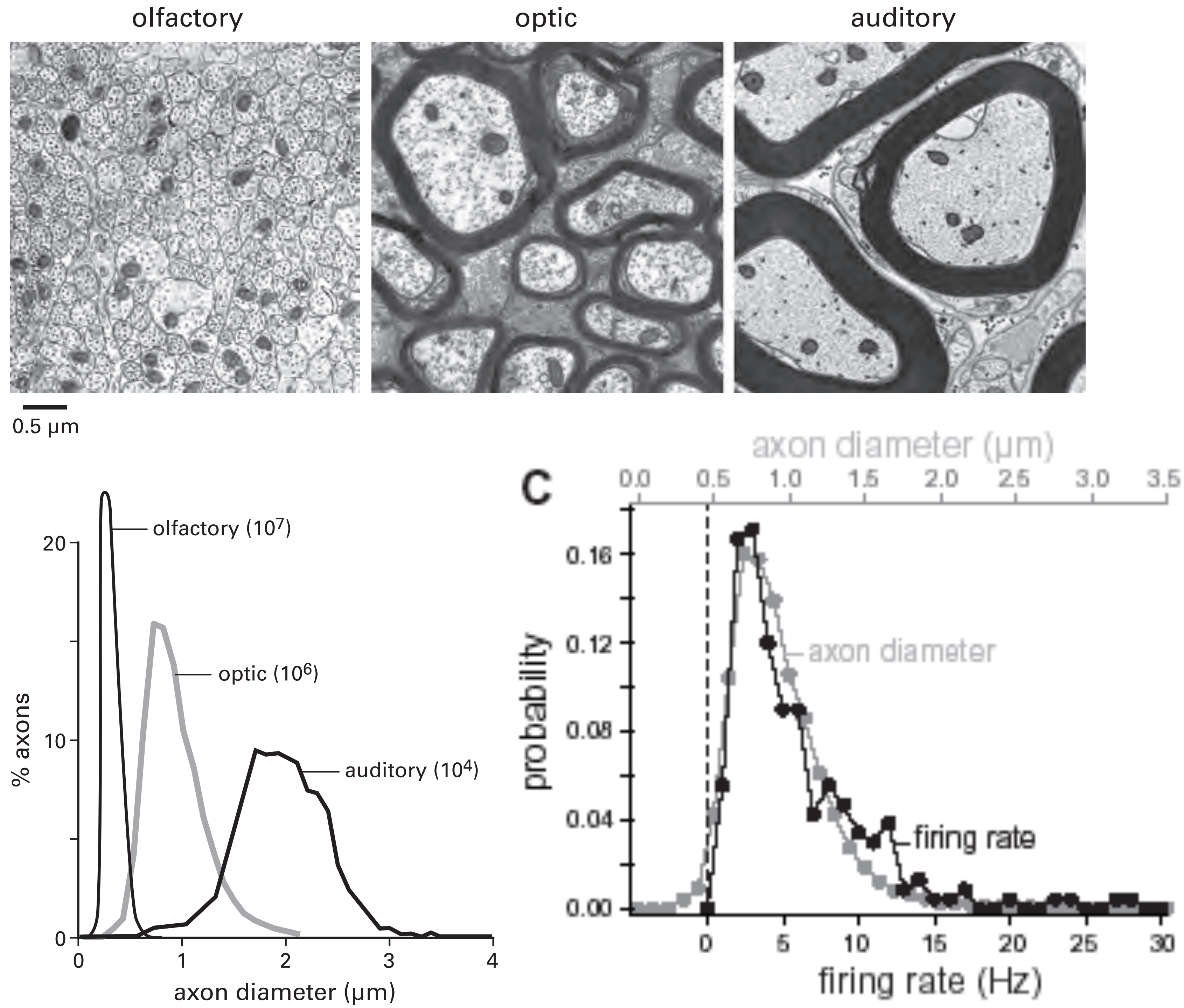
$$T = \frac{1\ \text{sec}}{\Delta t}$$

$$M = \frac{T!}{R!(T-R)!}$$

$$I = \log M$$

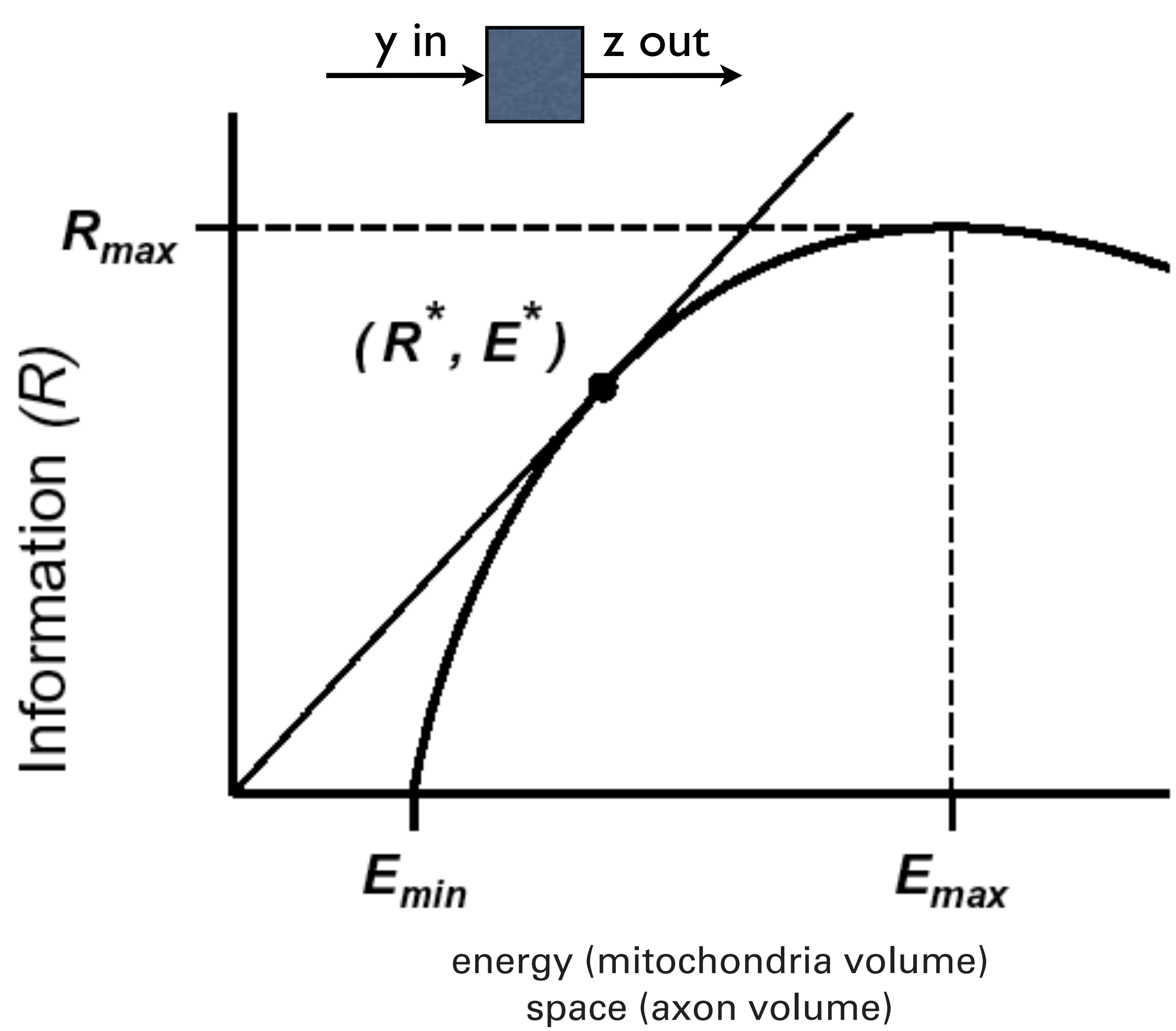
$\dfrac{H}{R}$ bits per spike

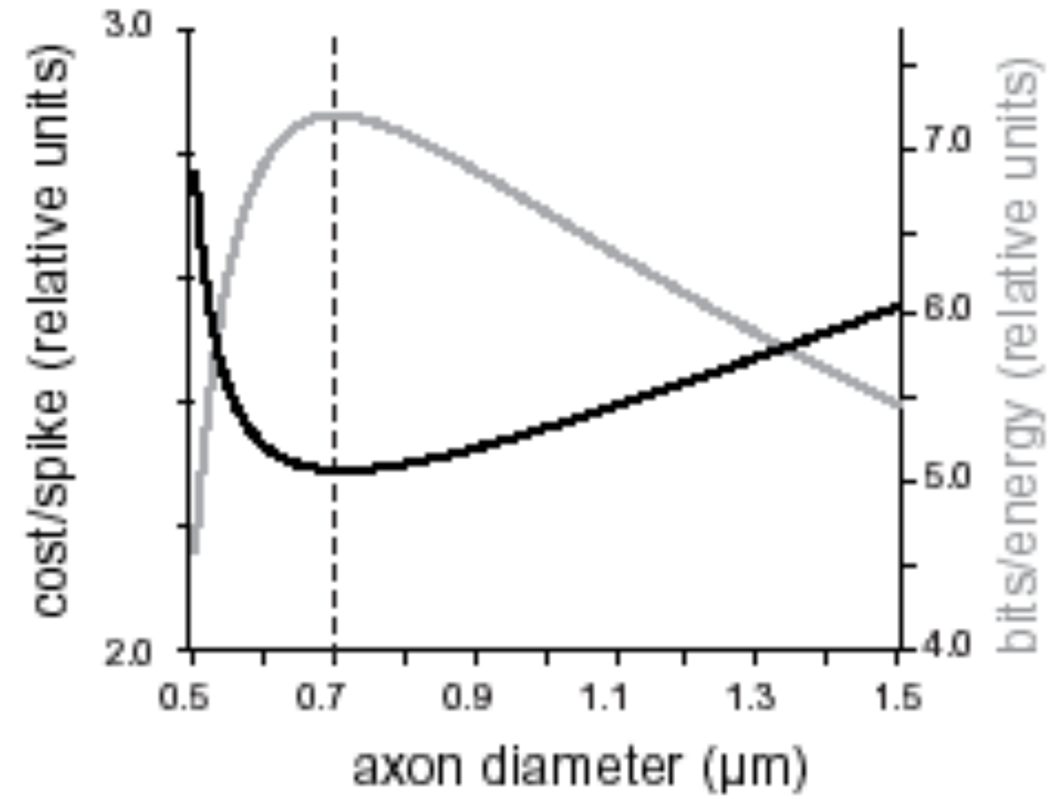
Information transmission is costly



Perge, J. A., Niven, J. E., Mugnaini, E., Balasubramanian, V., & Sterling, P. (2012). *Journal of Neuroscience*, *32*, 626–638.

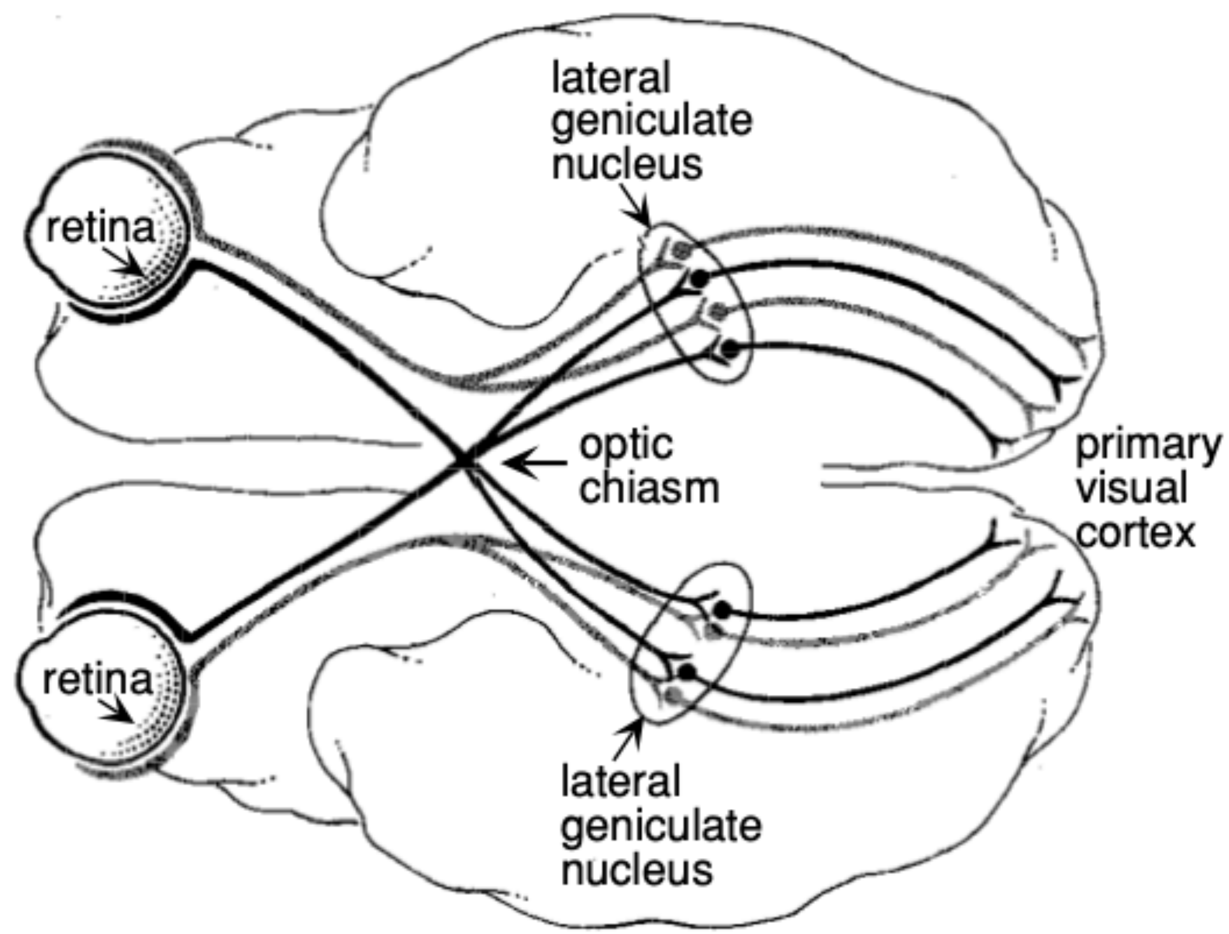
Law of diminished returns



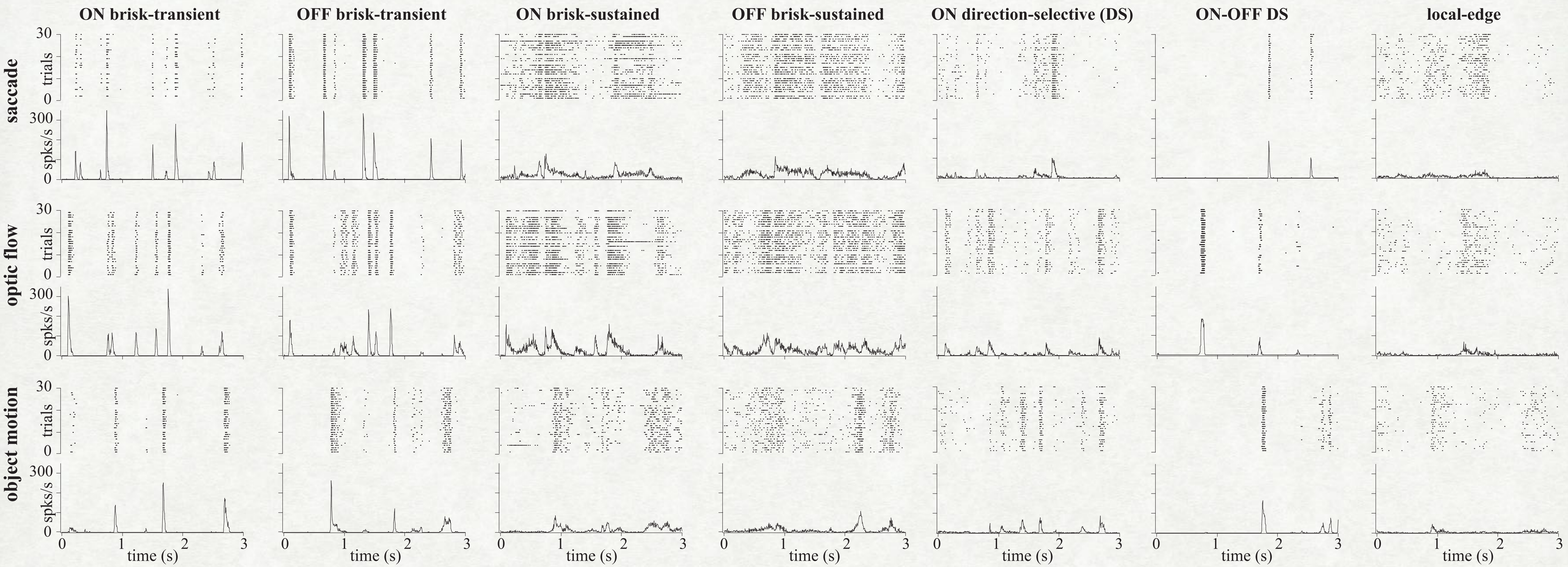


Heterogeneity & efficiency in the brain Vijay Balasubramanian 2015

Perge et al, 2018 How the optic nerve allocates space, energy capacity, and information

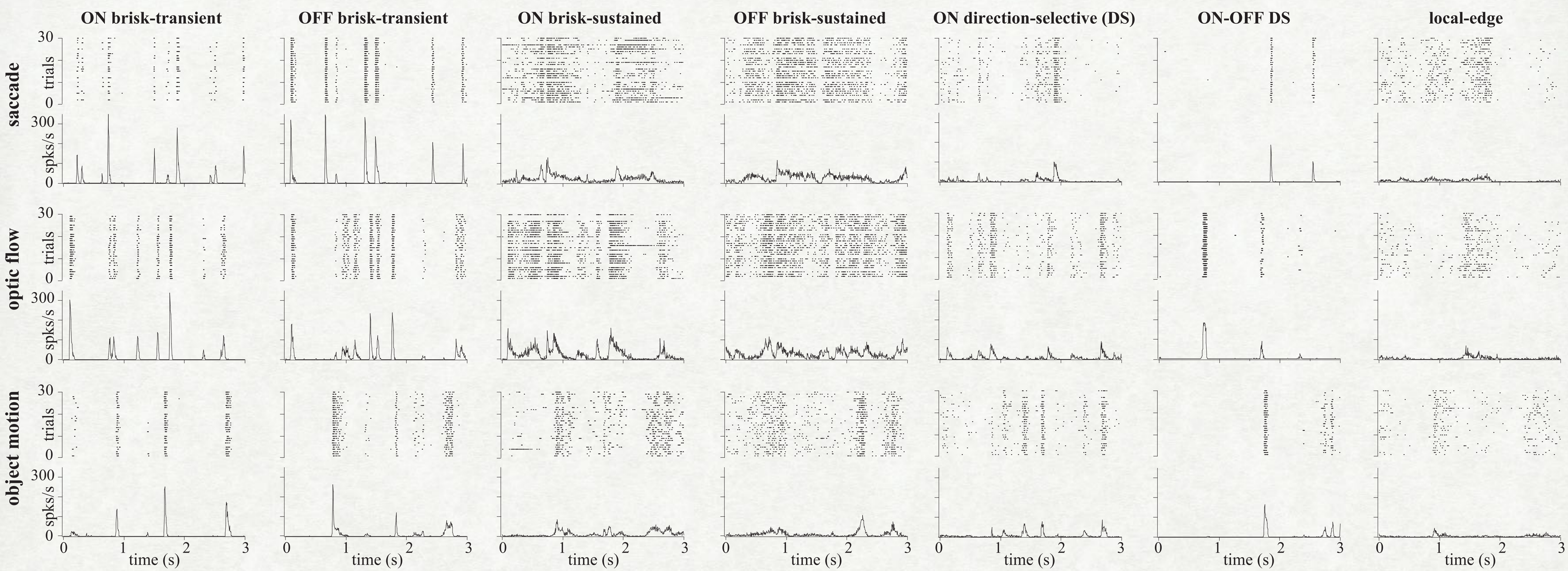

lateral geniculate nucleus
retina
optic chiasm
primary visual cortex
retina
lateral geniculate nucleus

Application: the distribution of information traffic in the optic nerve



Guinea Pig (Koch et al., 2005; Koch et al., 2006 "How much the eye tells the brain")

Application: the distribution of information traffic in the optic nerve

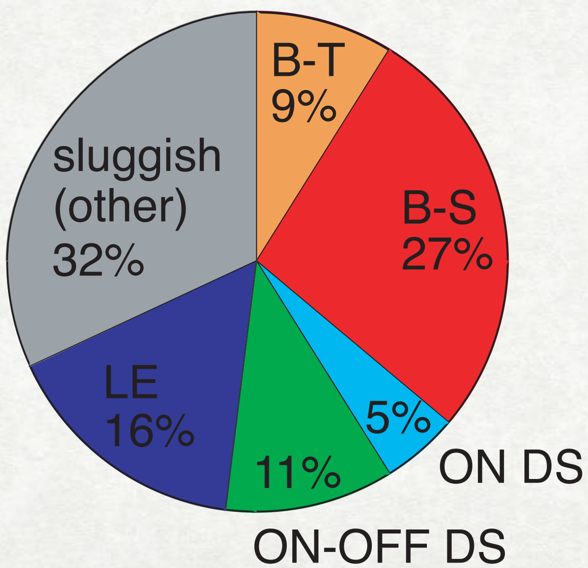


Guinea Pig (Koch et al., 2005; Koch et al., 2006 “How much the eye tells the brain”)

How and why is the total information traffic divided up between so many different types of channels?

Information traffic along the optic nerve

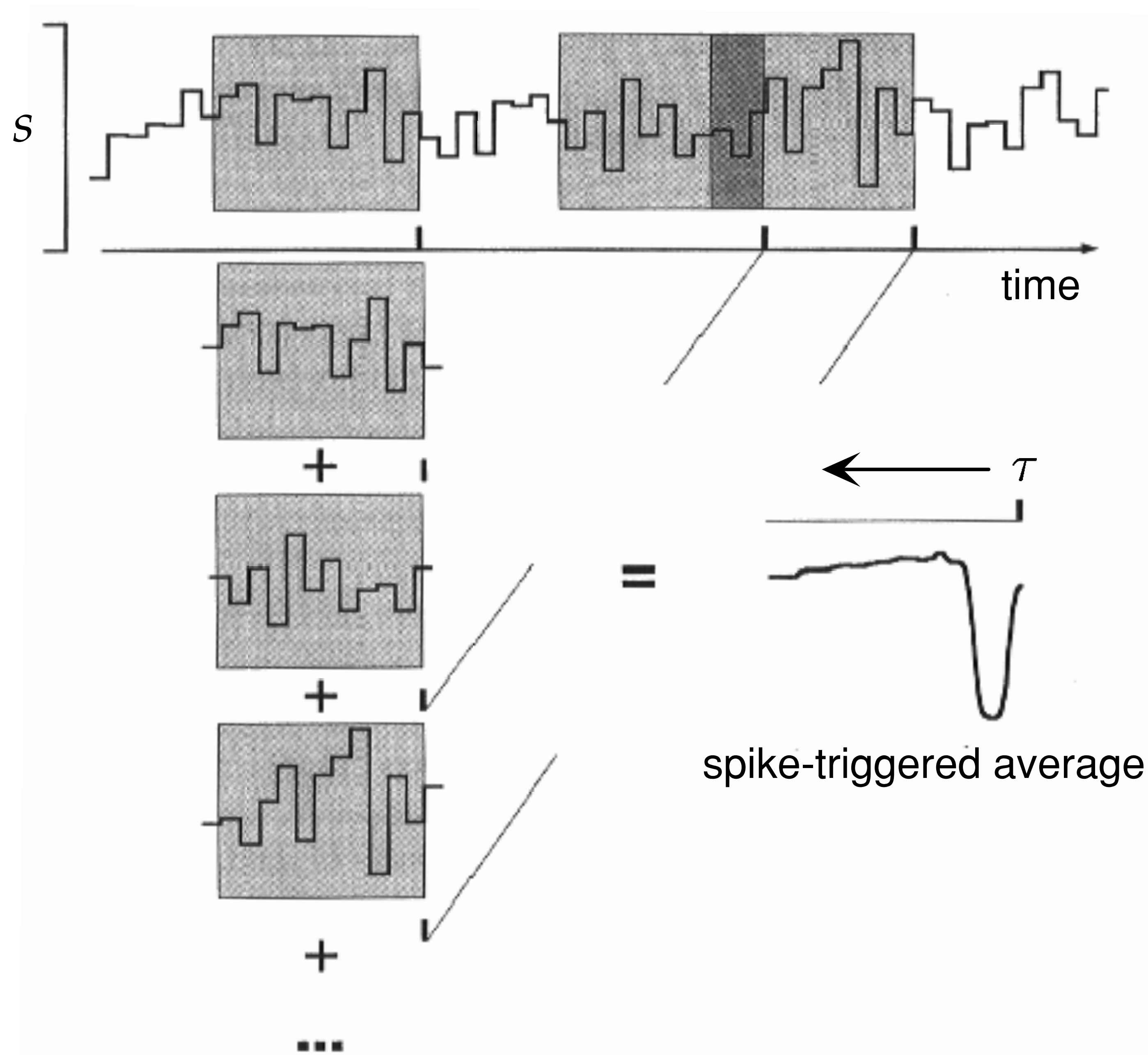
cell type	bits/s	bits/spike	cells	bits	spikes
Brisk-transient	13	1.9	6,000	78,000	41,000
Brisk-sustained	10	1.8	24,000	240,000	133,000
ON DS	6	2.2	7,000	42,000	19,000
ON-OFF DS	8	2.2	12,000	96,000	44,000
Local-edge	7	2.1	20,000	140,000	67,000
Sluggish (other)	9	2.2	31,000	279,000	127,000
Total			**100,000**	**875,000**	**431,000**



- Messages are transmitted asymmetrically - less studied sluggish cells account for most of the traffic

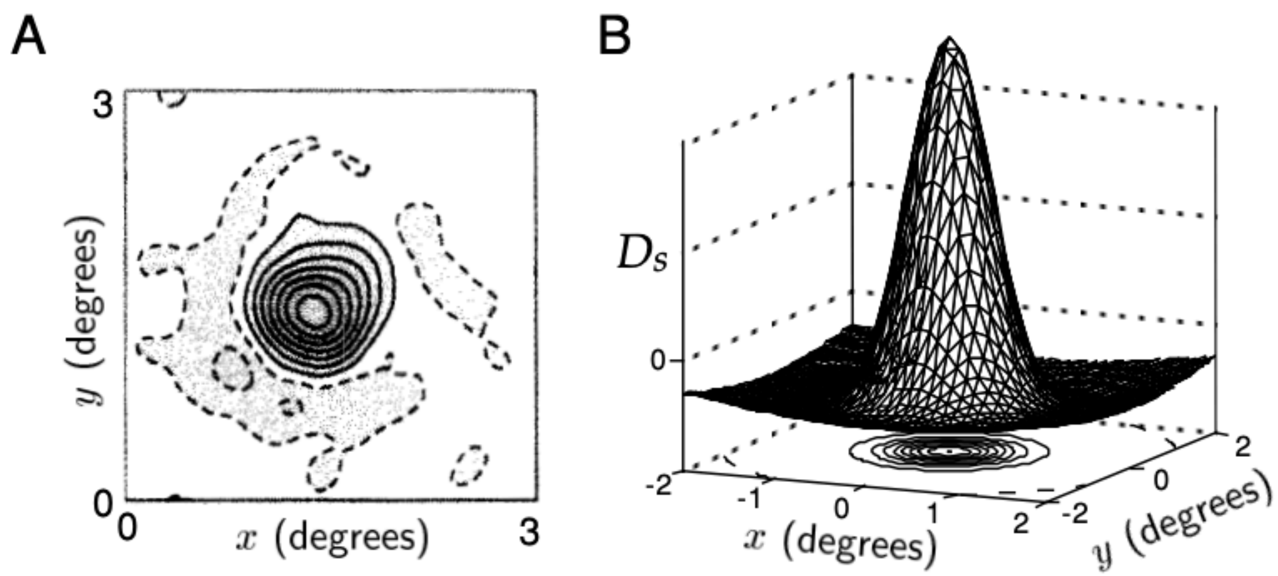
- Scaling up to human optic nerve (million axons) gives a traffic of order an Ethernet cable. This is the same order of magnitude as the amount of information in natural scenes according to Ruderman, 1994.

What kind of information a spike train represent?



Linear response theory and optimal kernel

Receptive field of retinal ganglion cells



Differences between Gaussians

$$D_s(x, y) = \pm\left(\frac{1}{2\pi\sigma_{\text{cen}}^2}\exp\left(-\frac{x^2+y^2}{2\sigma_{\text{cen}}^2}\right) - \frac{B}{2\pi\sigma_{\text{sur}}^2}\exp\left(-\frac{x^2+y^2}{2\sigma_{\text{sur}}^2}\right)\right).$$

Receptive field of simple cells in the visual cortex

$$D_s(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\Big(-\frac{x^2}{2\sigma_x^2}-\frac{y^2}{2\sigma_y^2}\Big)\cos(kx-\phi)$$

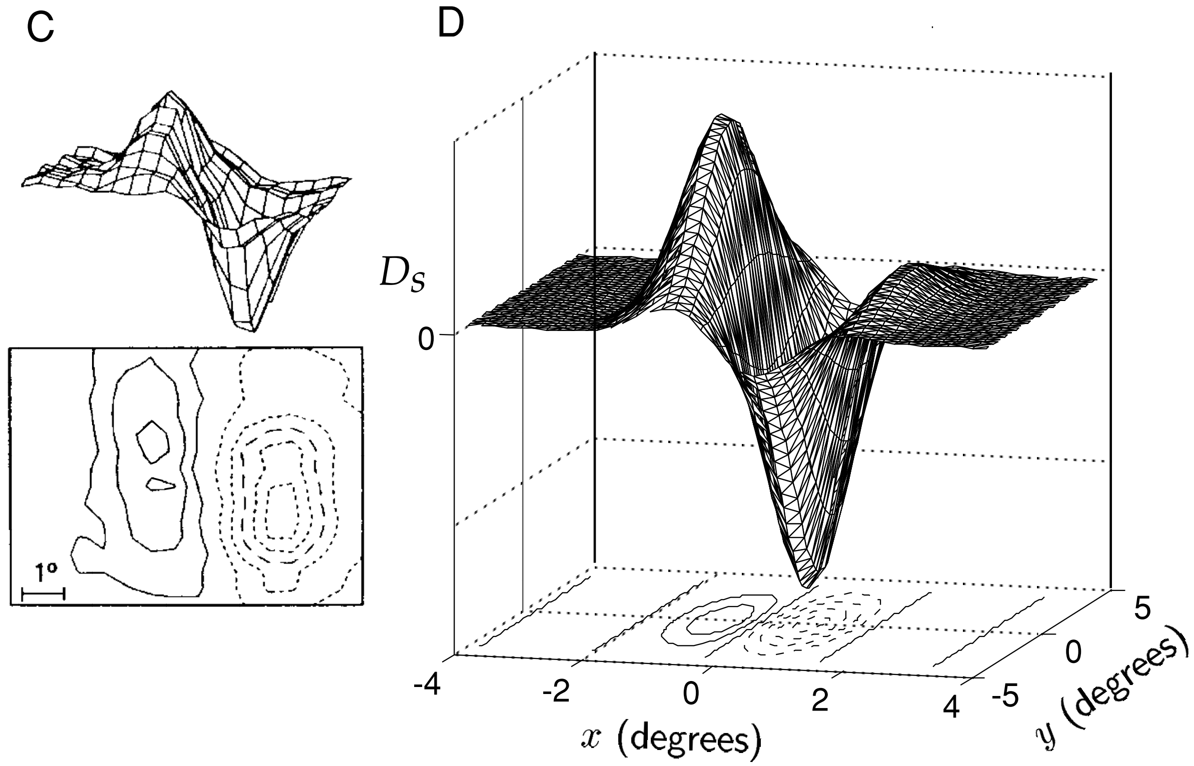
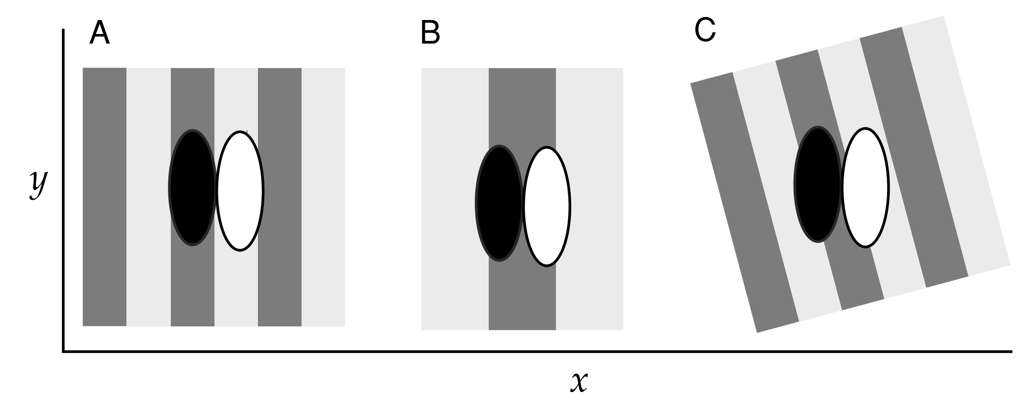


Figure 2.10 Spatial receptive field structure of simple cells. (A) and (C) Spatial structure of the receptive fields of two neurons in cat primary visual cortex determined by averaging stimuli between 50 ms and 100 ms prior to an action potential. The upper plots are three-dimensional representations, with the horizontal dimensions acting as the x-y plane and the vertical dimension indicating the magnitude and sign of $D_s(x,y)$. The lower contour plots represent the x-y plane. Regions with solid contour curves are ON areas where $D_s(x,y) > 0$, and regions with dashed contours are OFF areas where $D_s(x,y) < 0$. (B) and (D) Gabor functions (equation 2.27) with $\sigma_x = 1°$, $\sigma_y = 2°$, $1/k = 0.56°$, and $\phi = 1 - \pi/2$ (B) or $\phi = 1 - \pi$ (D), chosen to match the receptive fields in A and C. (A and C adapted from Jones and Palmer, 1987a.)



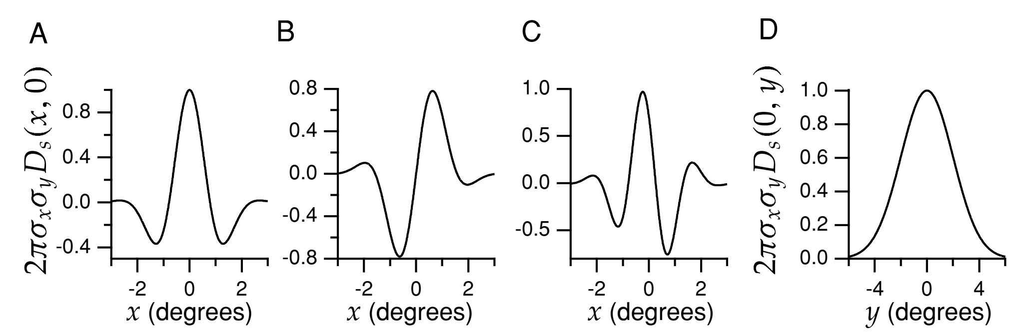
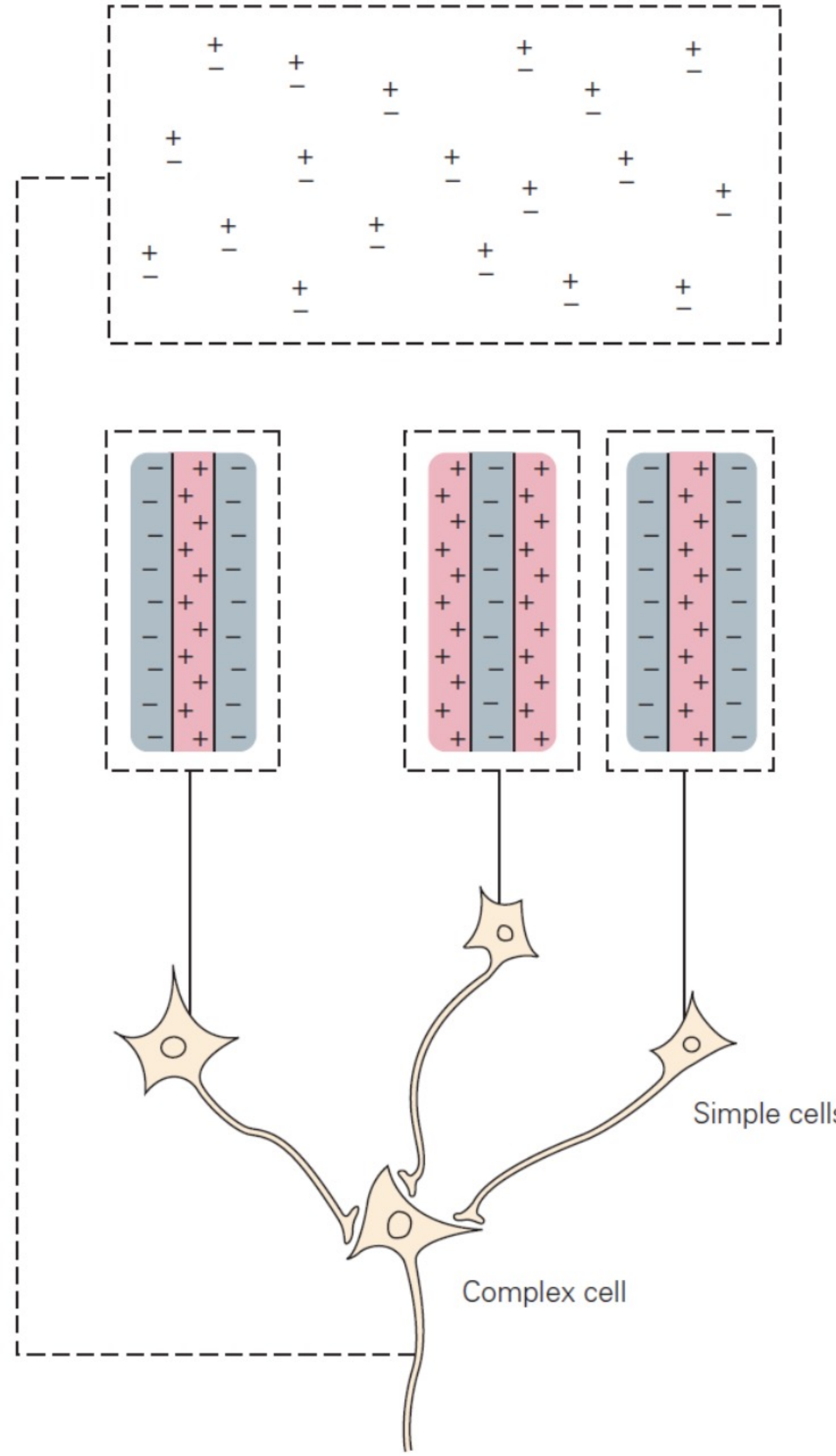


Figure 2.12 Gabor functions of the form given by equation 2.27. For convenience we plot the dimensionless function $2\pi\sigma_x\sigma_y D_s$. (A) A Gabor function with $\sigma_x = 1°$, $1/k = 0.5°$, and $\phi = 0$ plotted as a function of x for $y = 0$. This function is symmetric about $x = 0$. (B) A Gabor function with $\sigma_x = 1°$, $1/k = 0.5°$, and $\phi = \pi/2$ plotted as a function of x for $y = 0$. This function is antisymmetric about $x = 0$ and corresponds to using a sine instead of a cosine function in equation 2.27. (C) A Gabor function with $\sigma_x = 1°$, $1/k = 0.33°$, and $\phi = \pi/4$ plotted as a function of x for $y = 0$. This function has no particular symmetry properties with respect to $x = 0$. (D) The Gabor function of equation 2.27 with $\sigma_y = 2°$ plotted as a function of y for $x = 0$. This function is simply a Gaussian.

复杂细胞

Torsten N. Wiesel   David H. Hubel

1981 Nobel prize



Hubel-Wiesel model of orientation selectivity

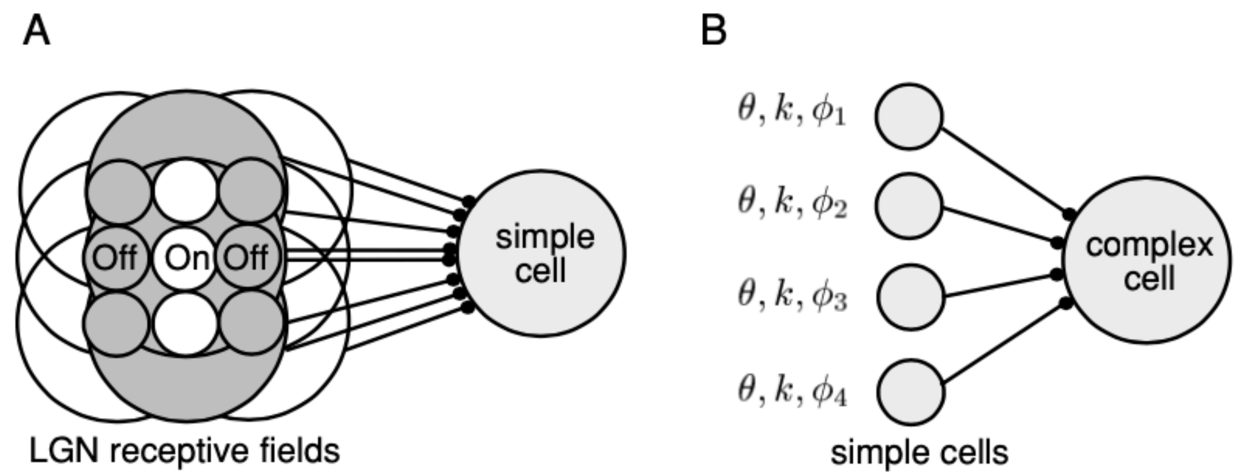


Figure 2.27 (A) The Hubel-Wiesel model of orientation selectivity. The spatial arrangement of the receptive fields of nine LGN neurons are shown, with a row of three ON-center fields flanked on either side by rows of three OFF-center fields. White areas denote ON fields and gray areas, OFF fields. In the model, the converging LGN inputs are summed by the simple cell. This arrangement produces a receptive field oriented in the vertical direction. (B) The Hubel-Wiesel model of a complex cell. Inputs from a number of simple cells with similar orientation and spatial frequency preferences (θ and k), but different spatial phase preferences (ϕ_1, ϕ_2, ϕ_3, and ϕ_4), converge on a complex cell and are summed. This produces a complex cell output that is selective for orientation and spatial frequency, but not for spatial phase. The figure shows four simple cells converging on a complex cell, but additional simple cells can be included to give a more complete coverage of spatial phase.

Temporal receptive field

$$D_t(\tau) = \alpha \exp(-\alpha\tau)\left[\frac{(\alpha\tau)^5}{5!} - \frac{(\alpha\tau)^7}{7!}\right]$$

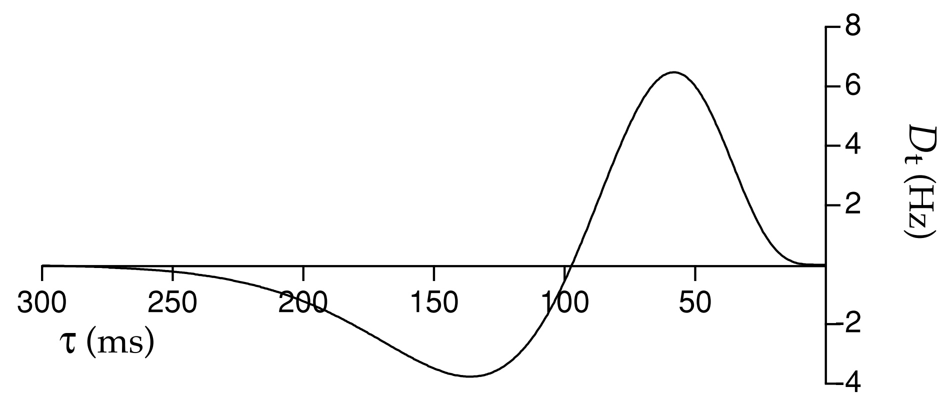
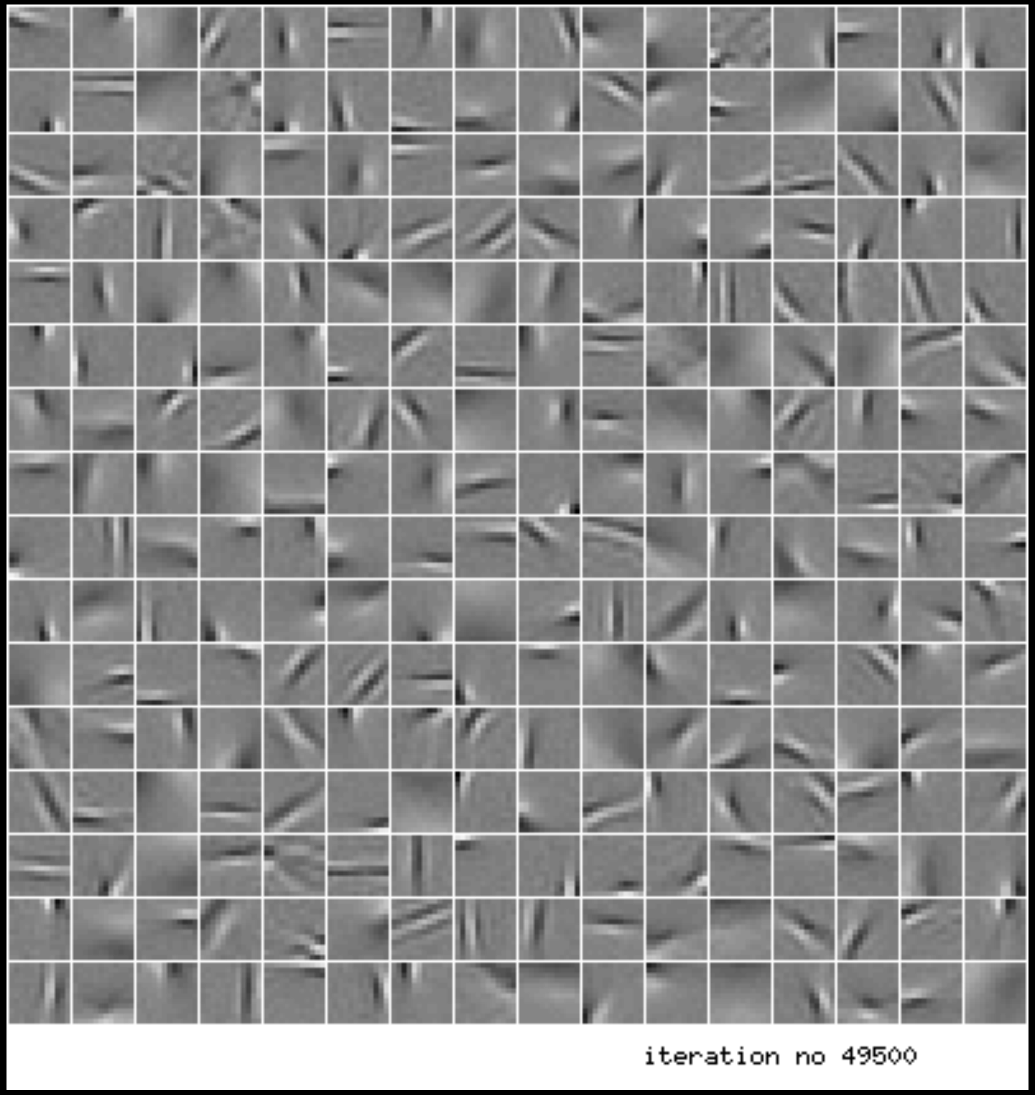


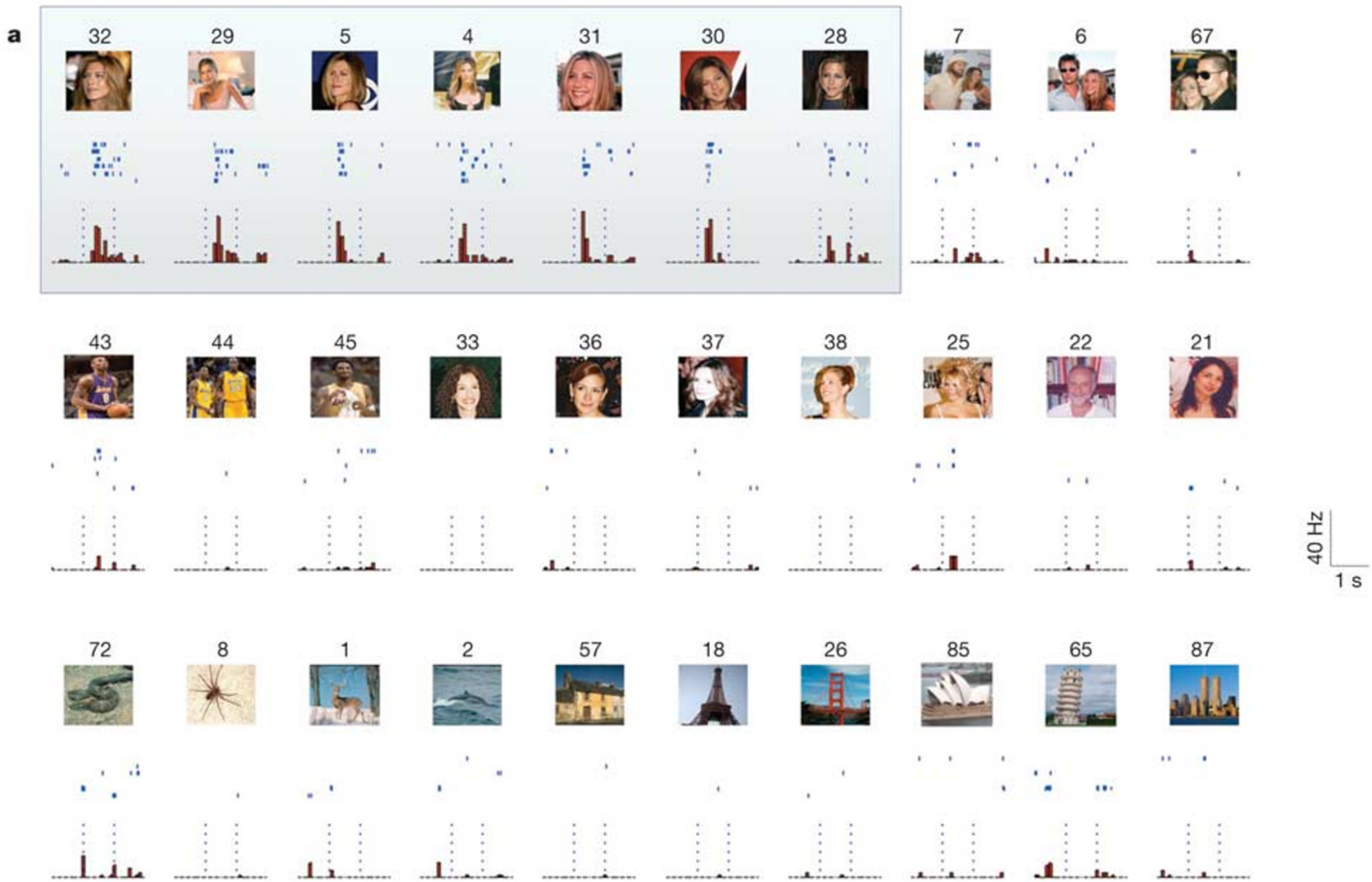
Figure 2.14 Temporal structure of a receptive field. The function $D_t(\tau)$ of equation 2.29 with $\alpha = 1/(15\text{ ms})$.

Convolutional neural net (CNN) was inspired by information processing in human visual pathway



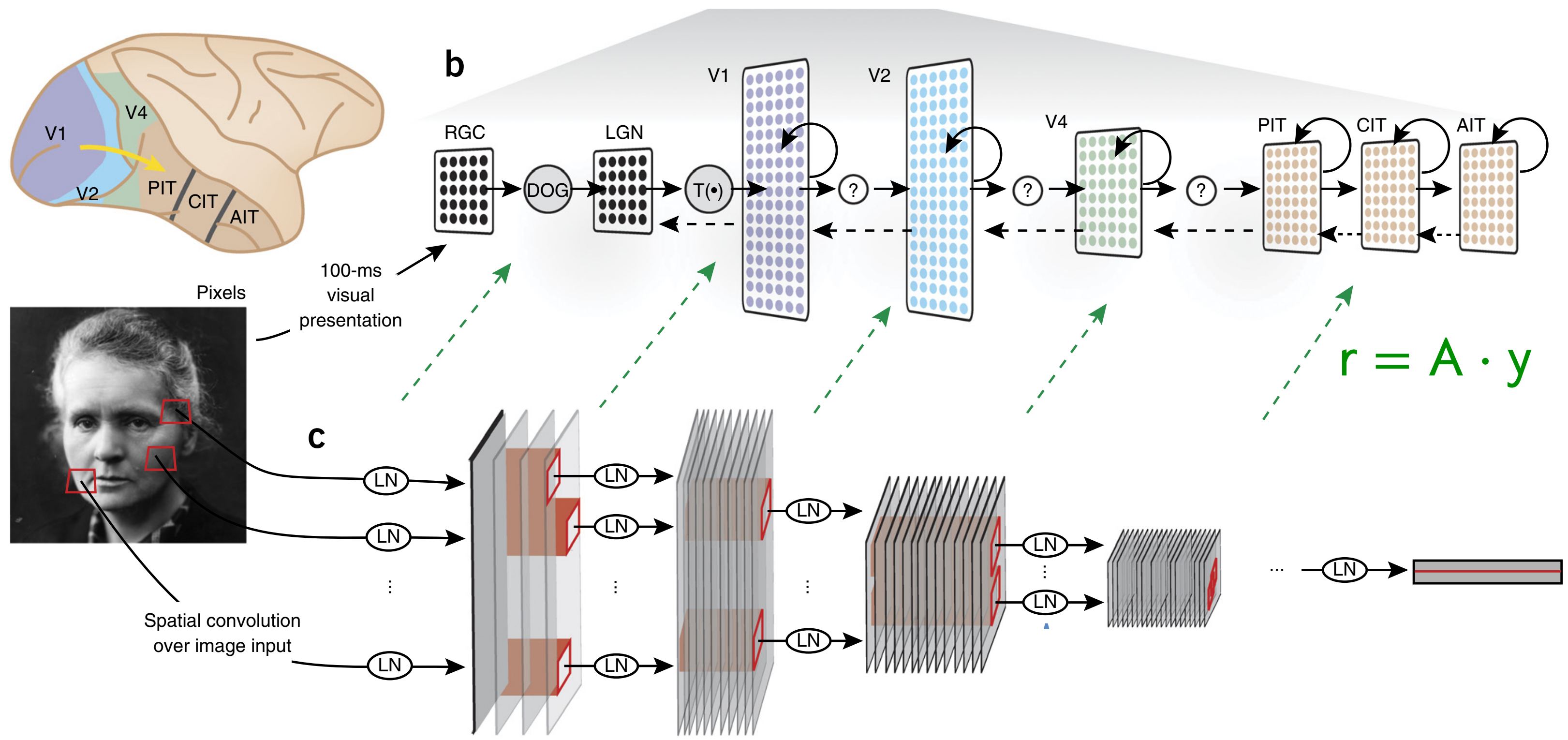
In the first layer of CNN, neurons can generate receptive field just like simple cells in visual cortex

The Jennifer Aniston cell



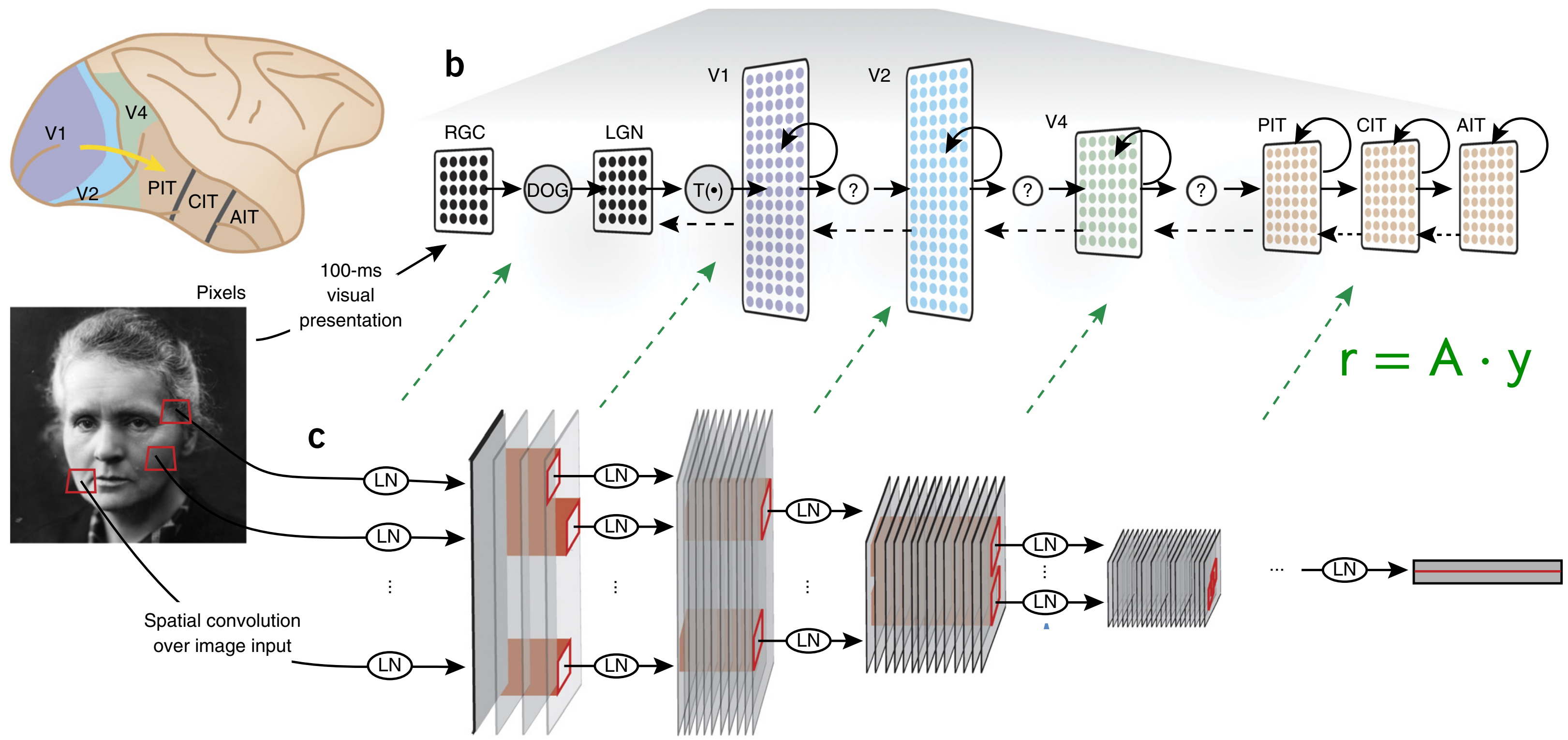
R. Quinn Quiroga et al (2005). Nature

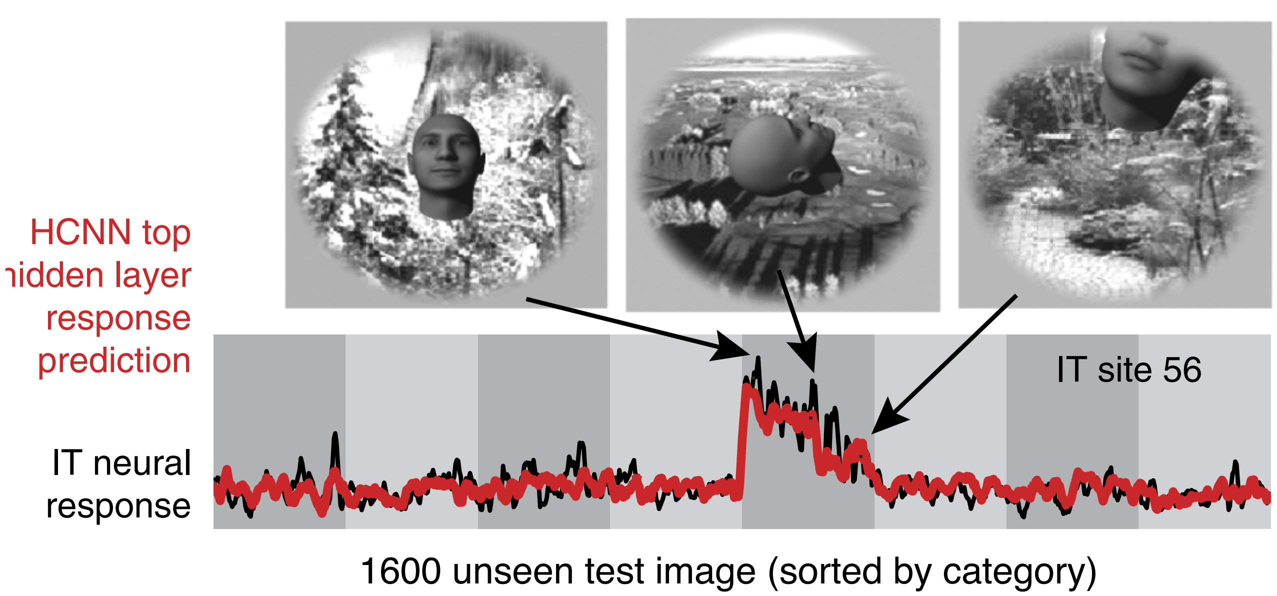
Deep neural network and biological neurons

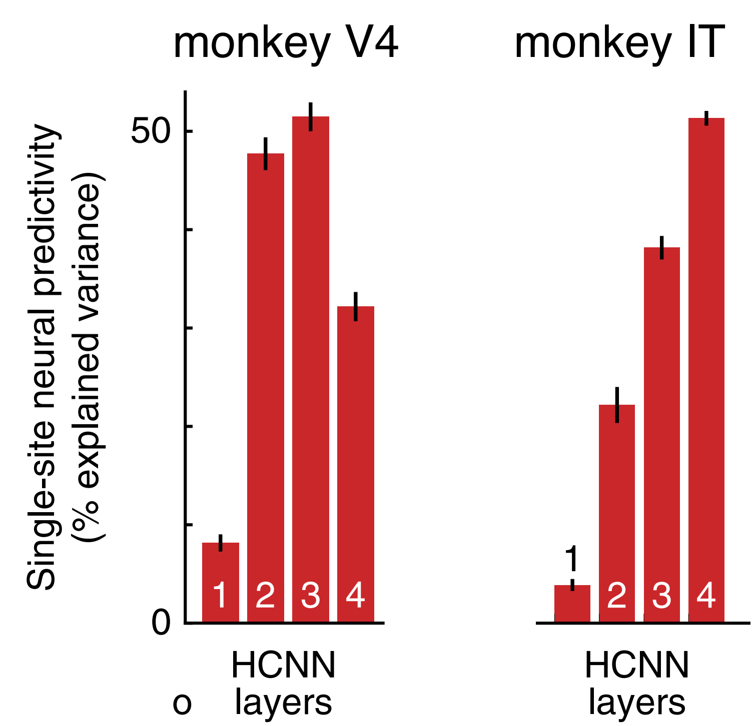


Daniel L K Yamins & James J DiCarlo (2016). Nature Neuroscience

Deep neural network and biological neurons



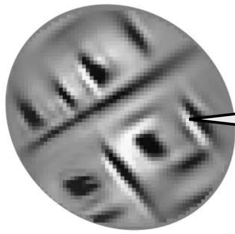




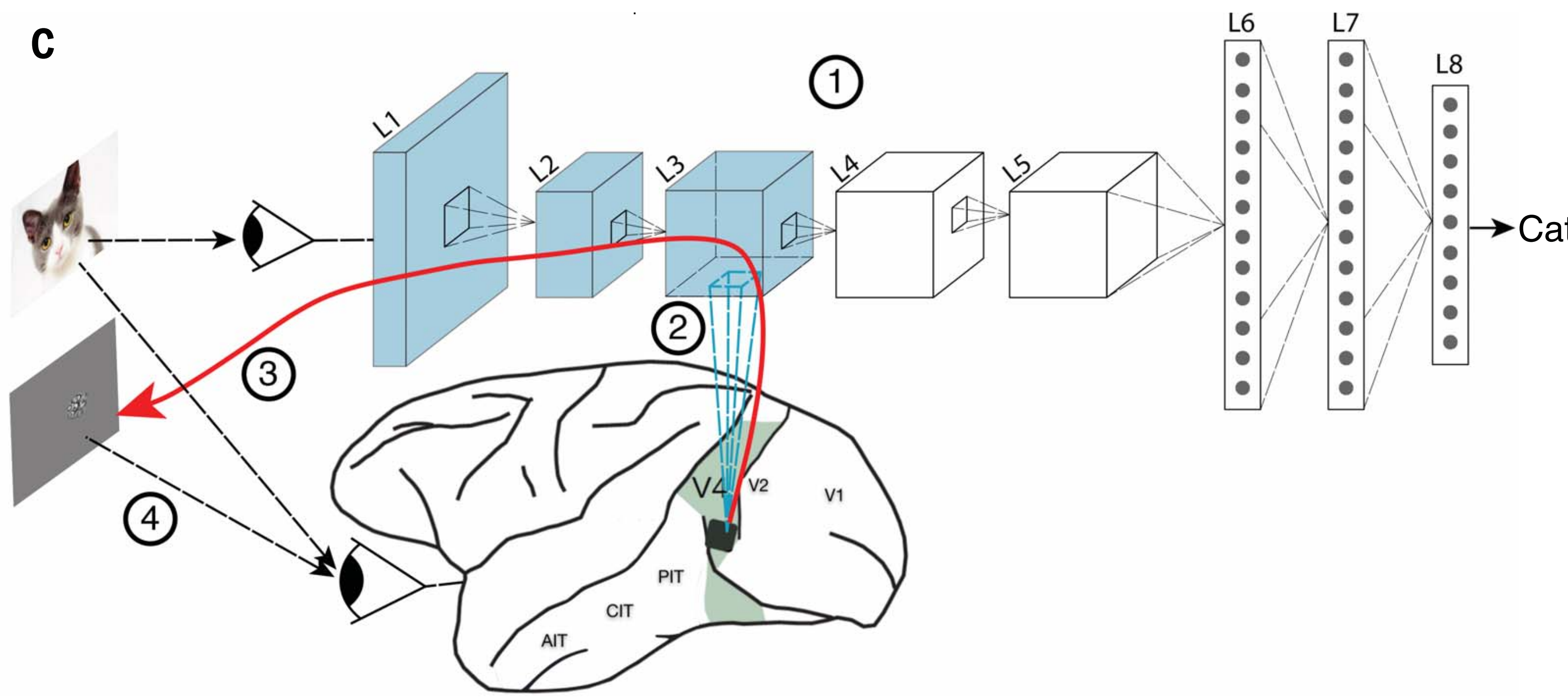
Daniel L K Yamins & James J DiCarlo (2016). Nature Neuroscience

Test deep neural networks on V4 neurons

syntethetic stimuli

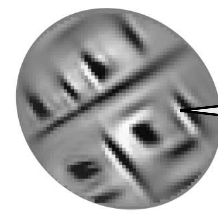


engineered to maximize response in Deep Neural Network

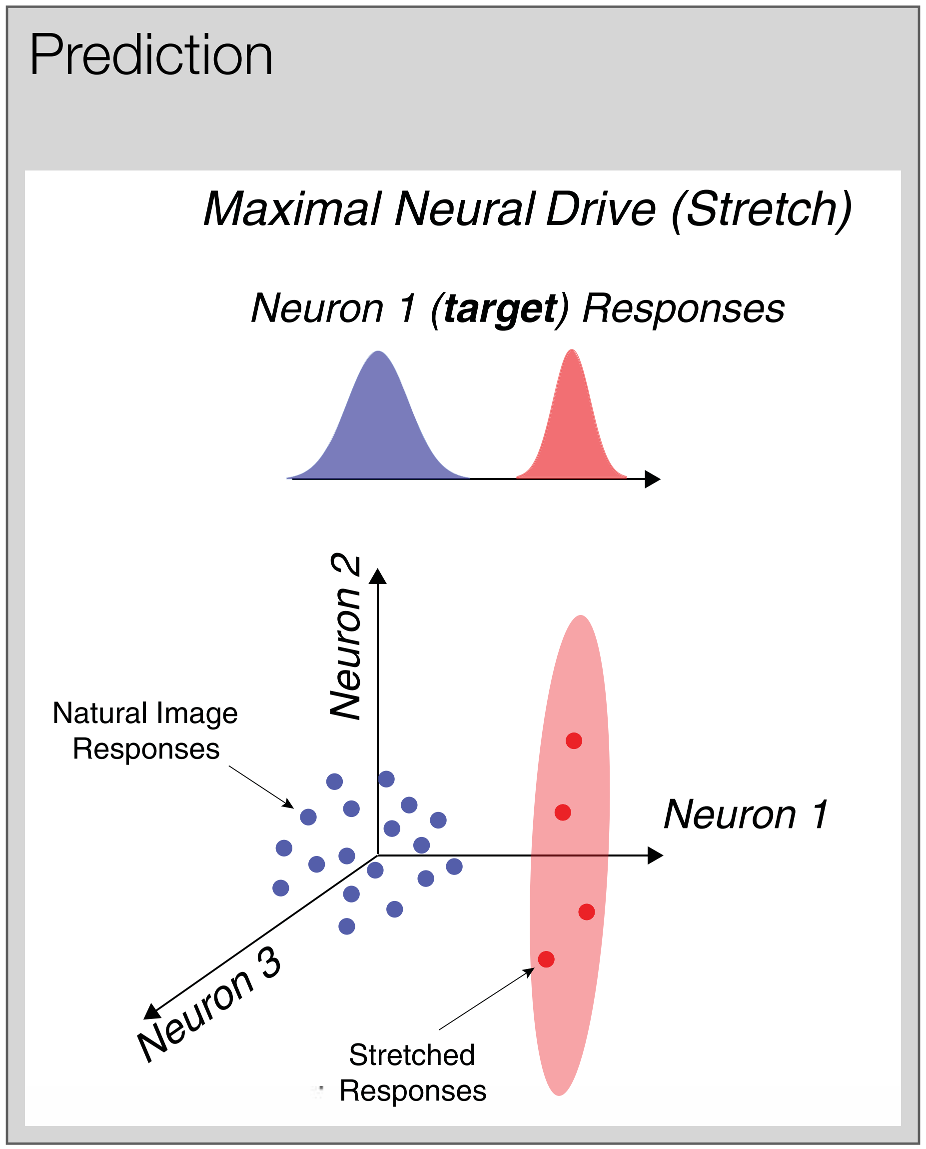


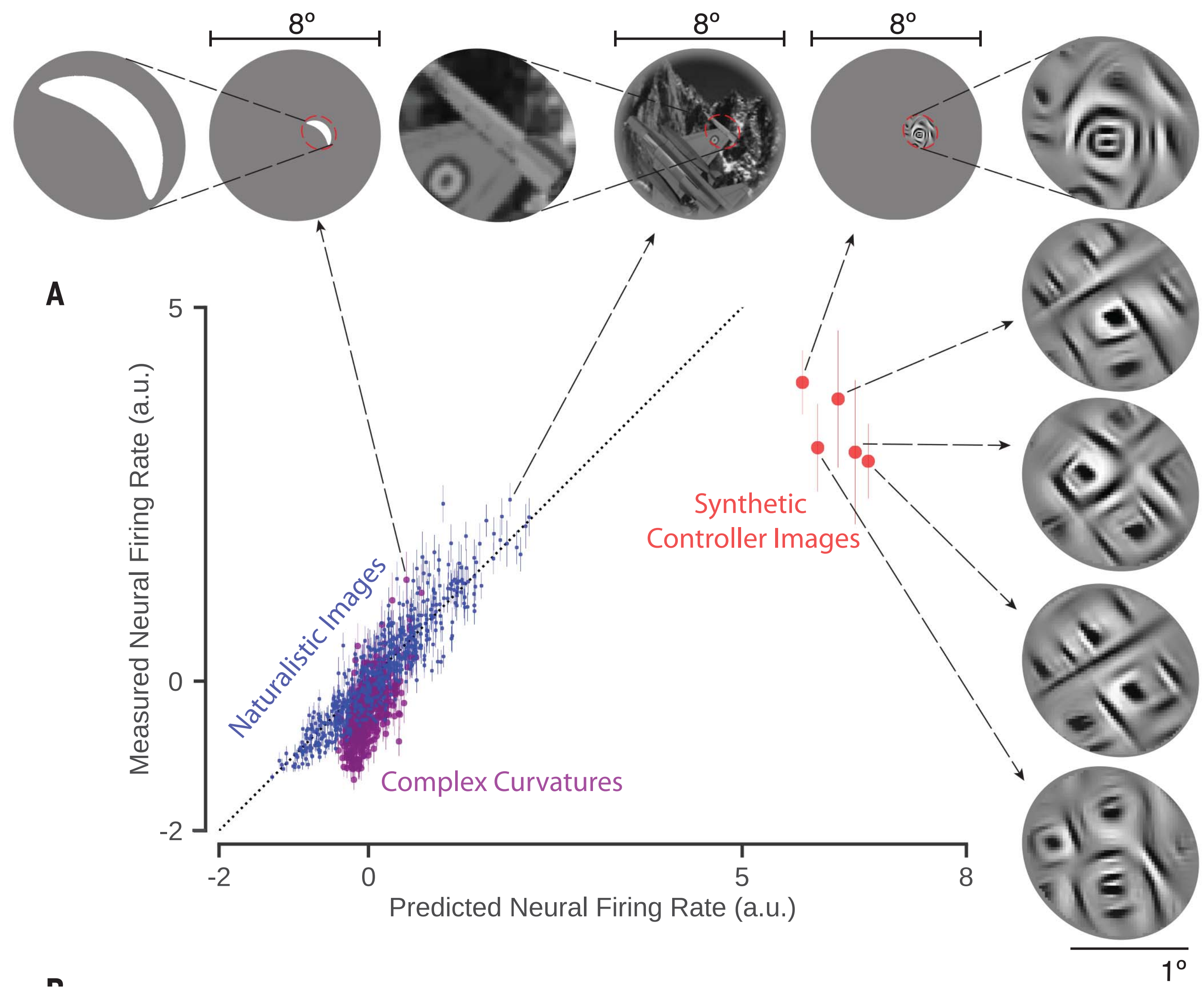
Test deep neural networks on V4 neurons

synthetethic stimuli



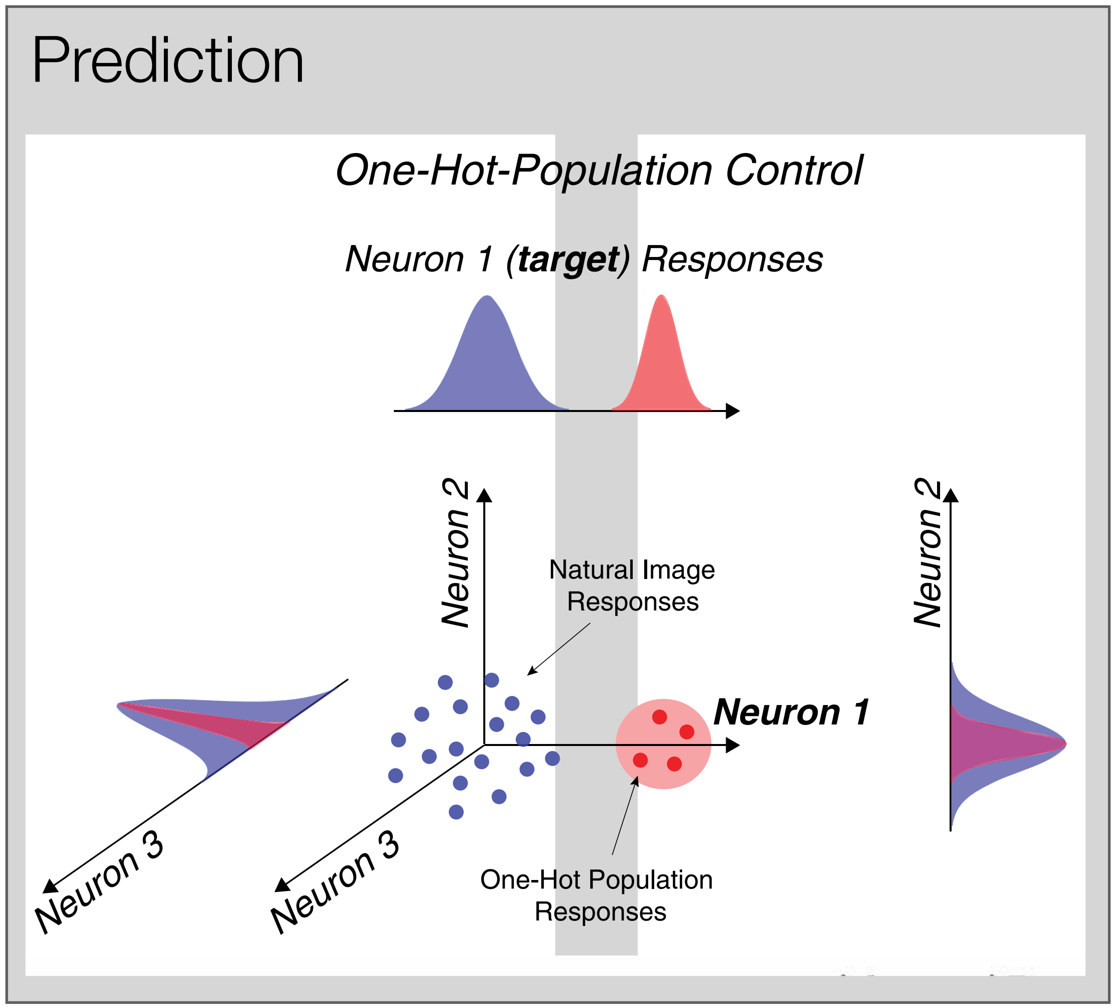
engineered to maximize response in Deep Neural Network

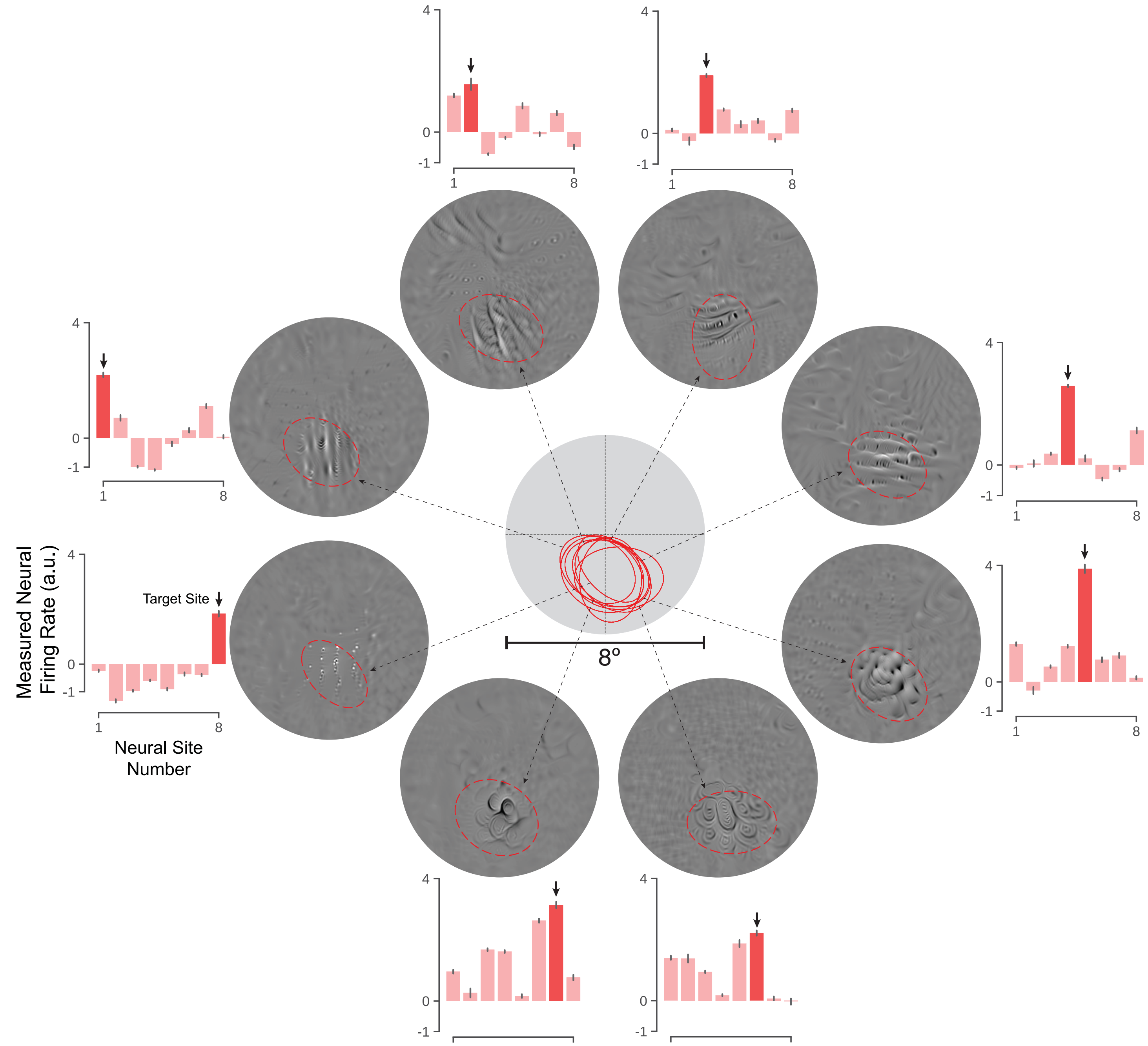




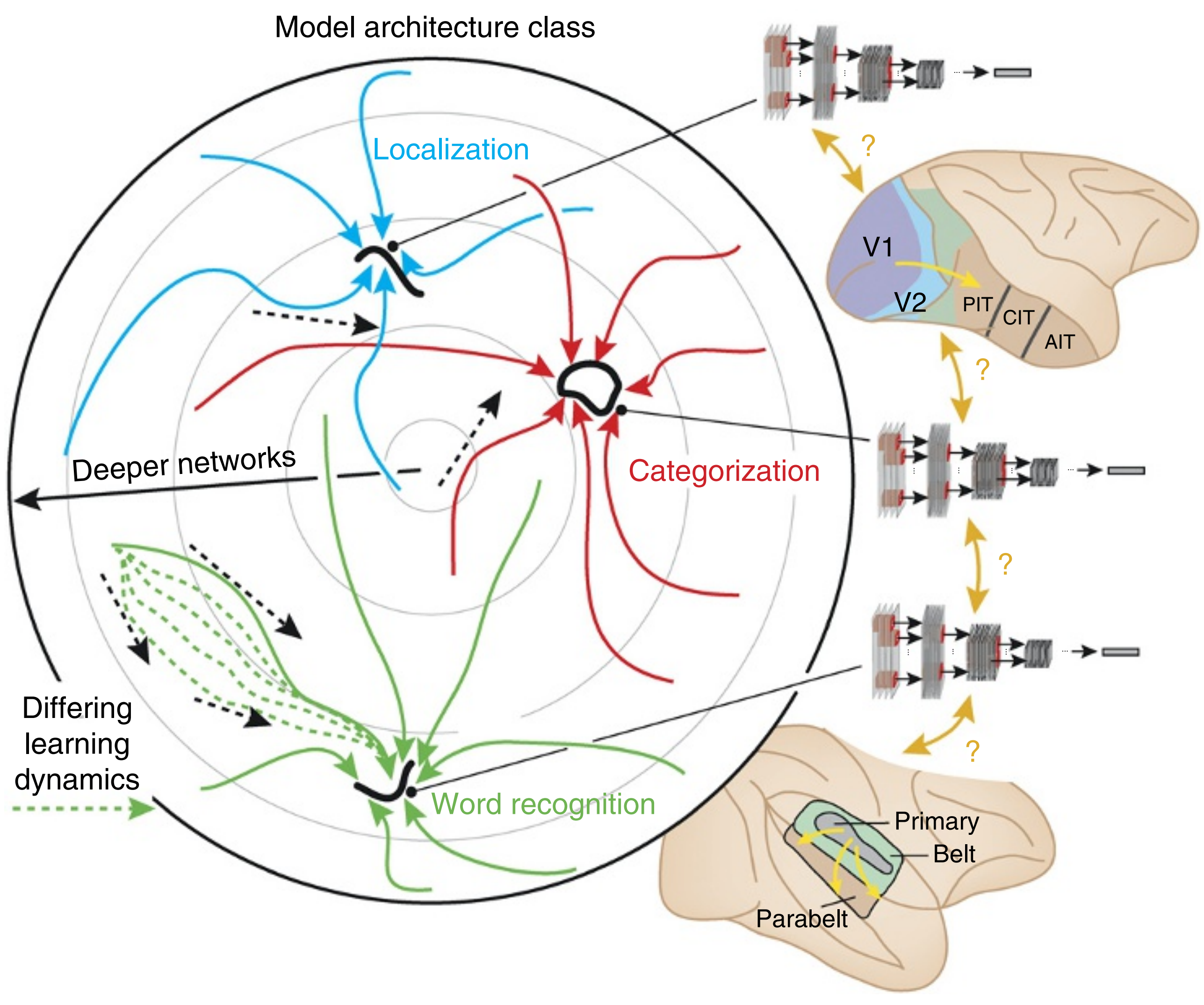
Bashivan, Kar, DiCarlo (2019) Science

Test deep neural networks on V4 neurons



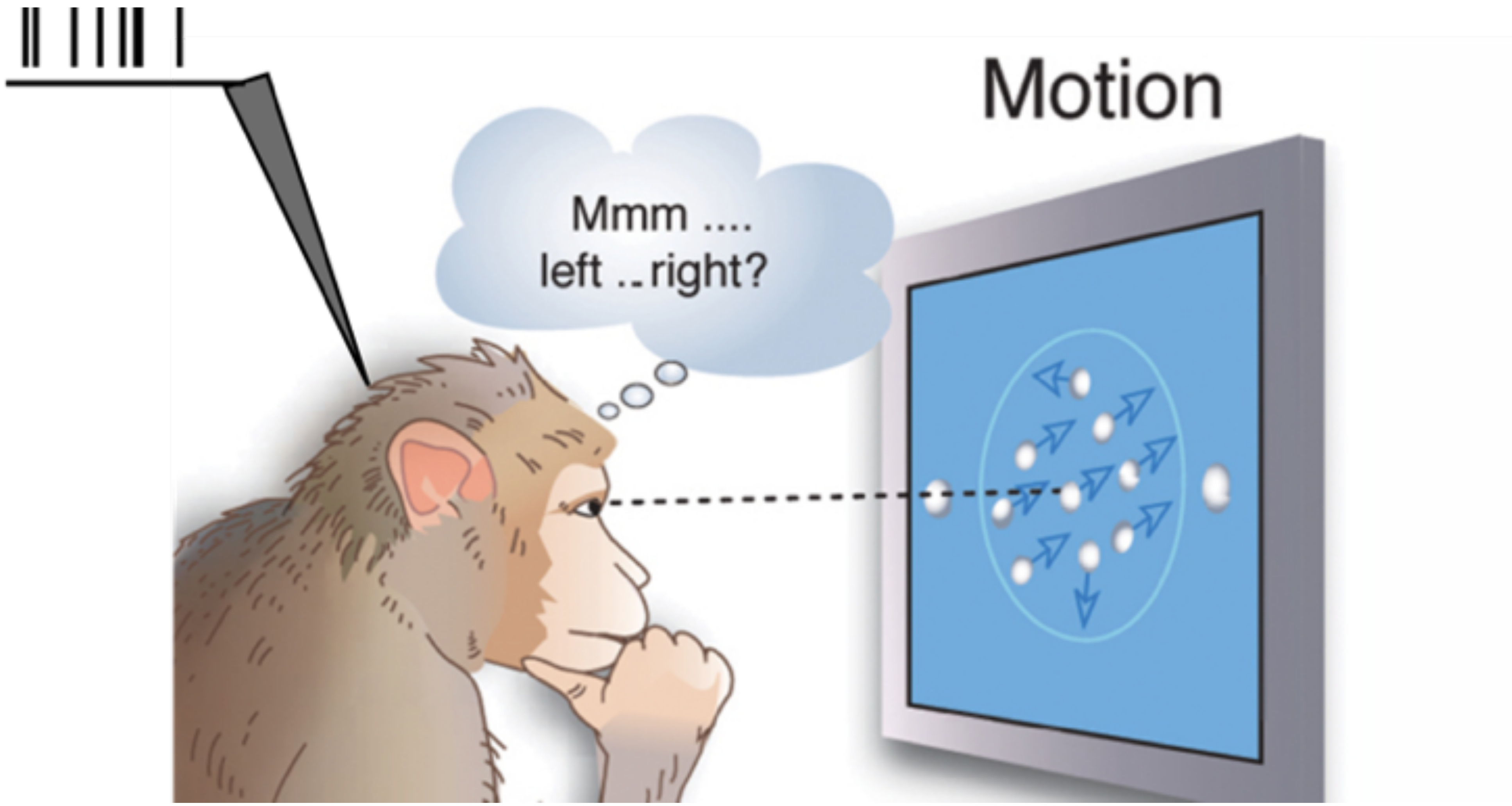


Task specific deep neural networks

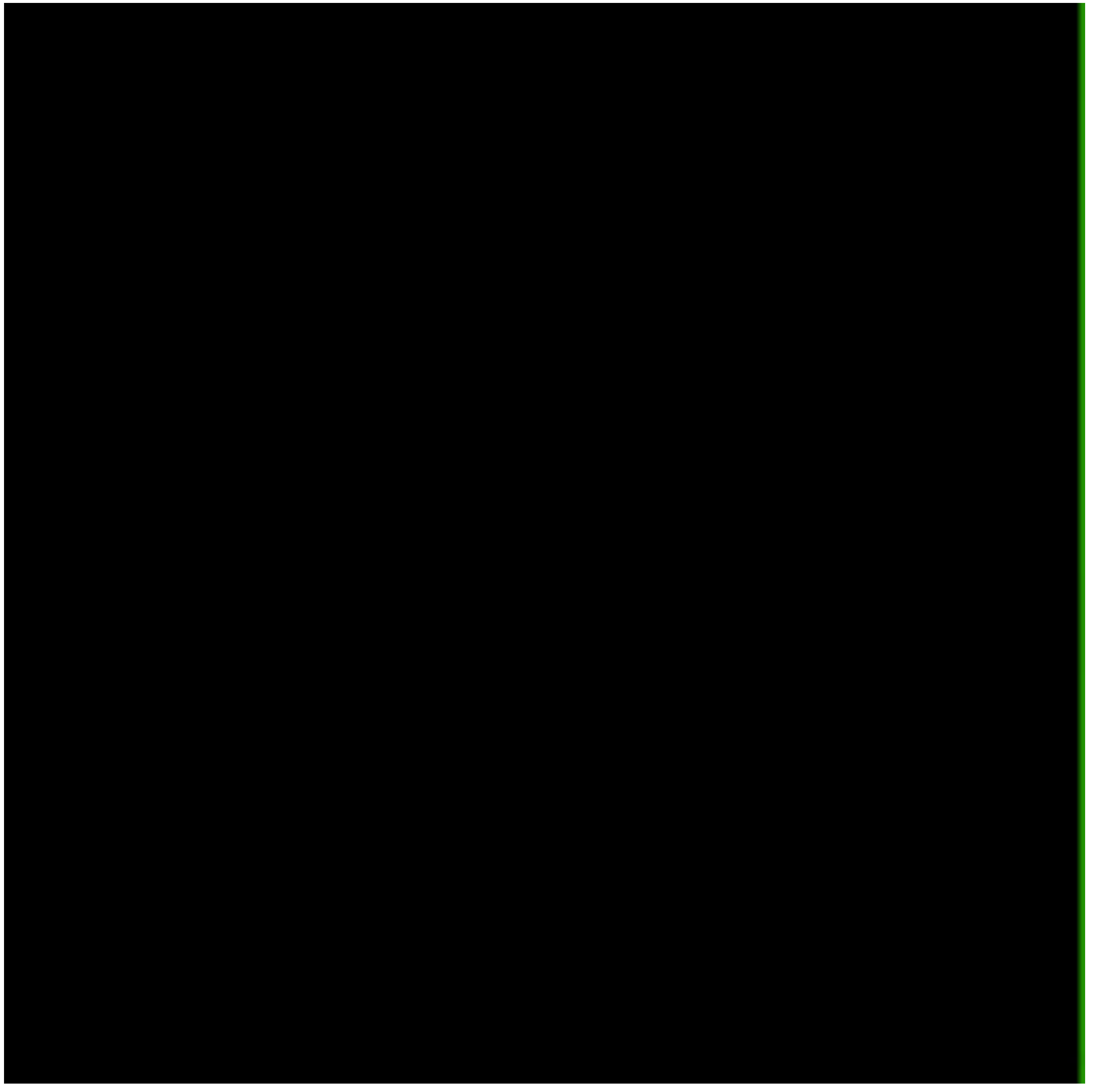


Neuron Decoding

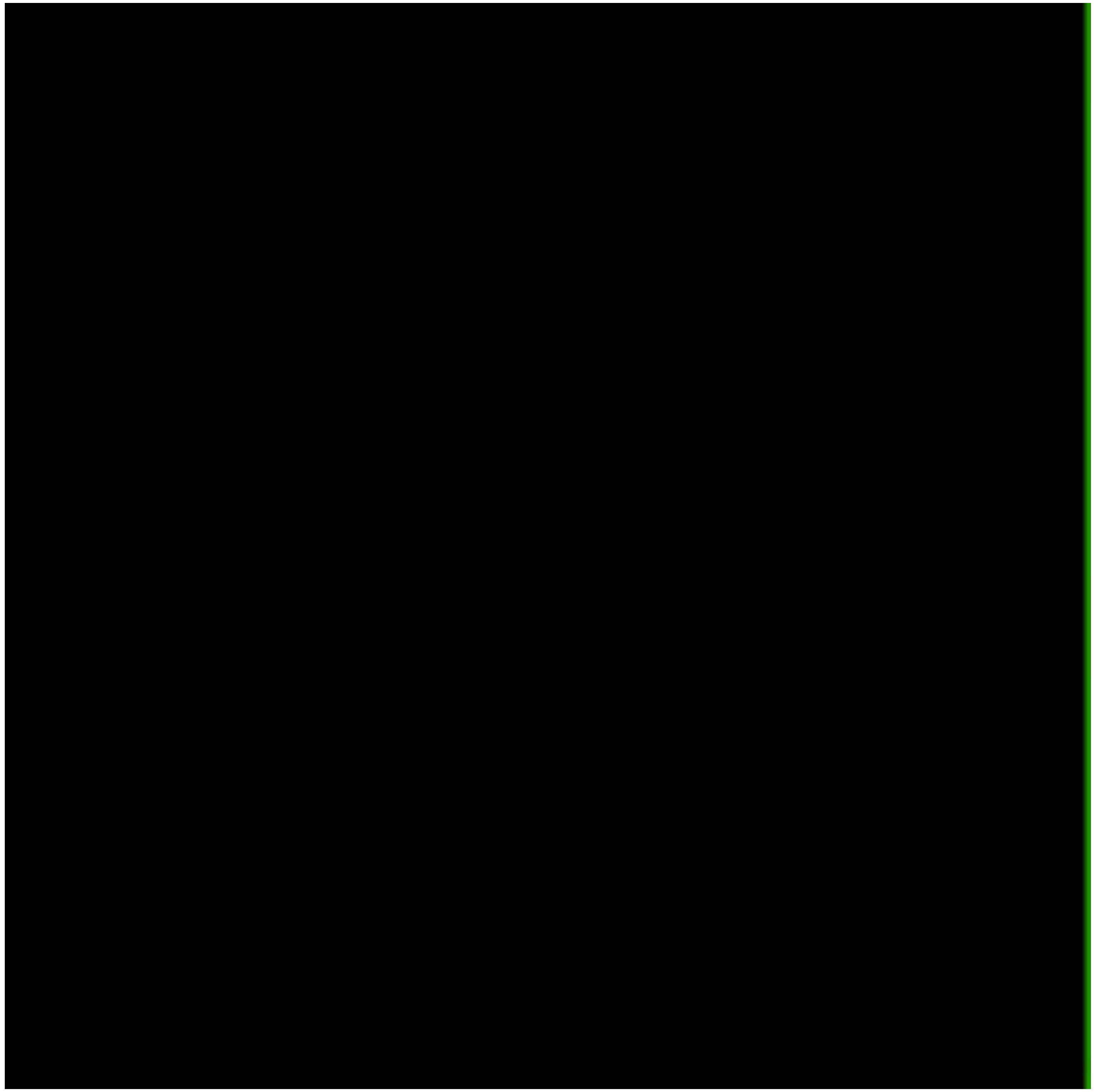
Random dots motion discrimination task



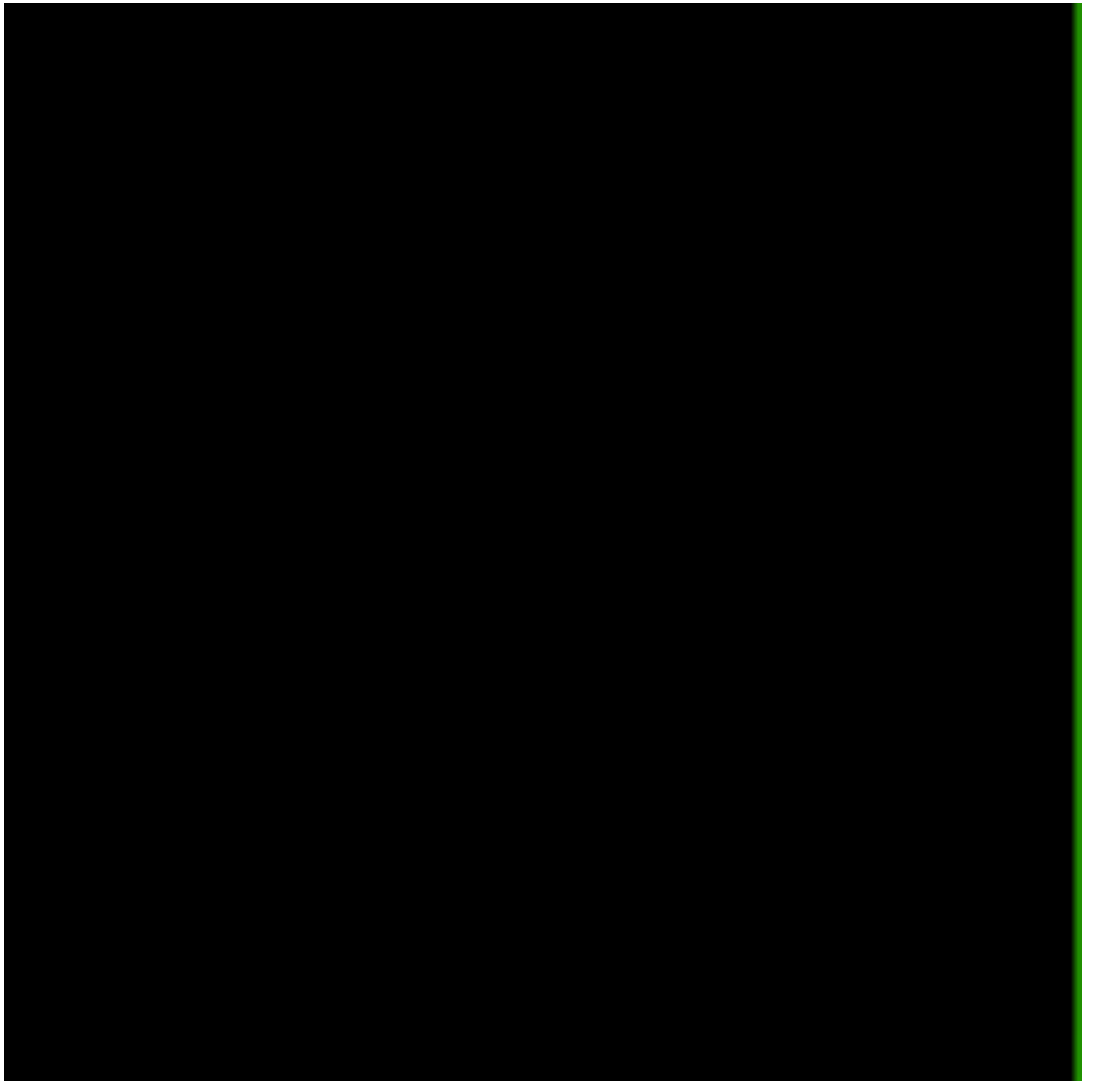
This slide and the following movies are adapted from Professor Tianming Yang's lectures



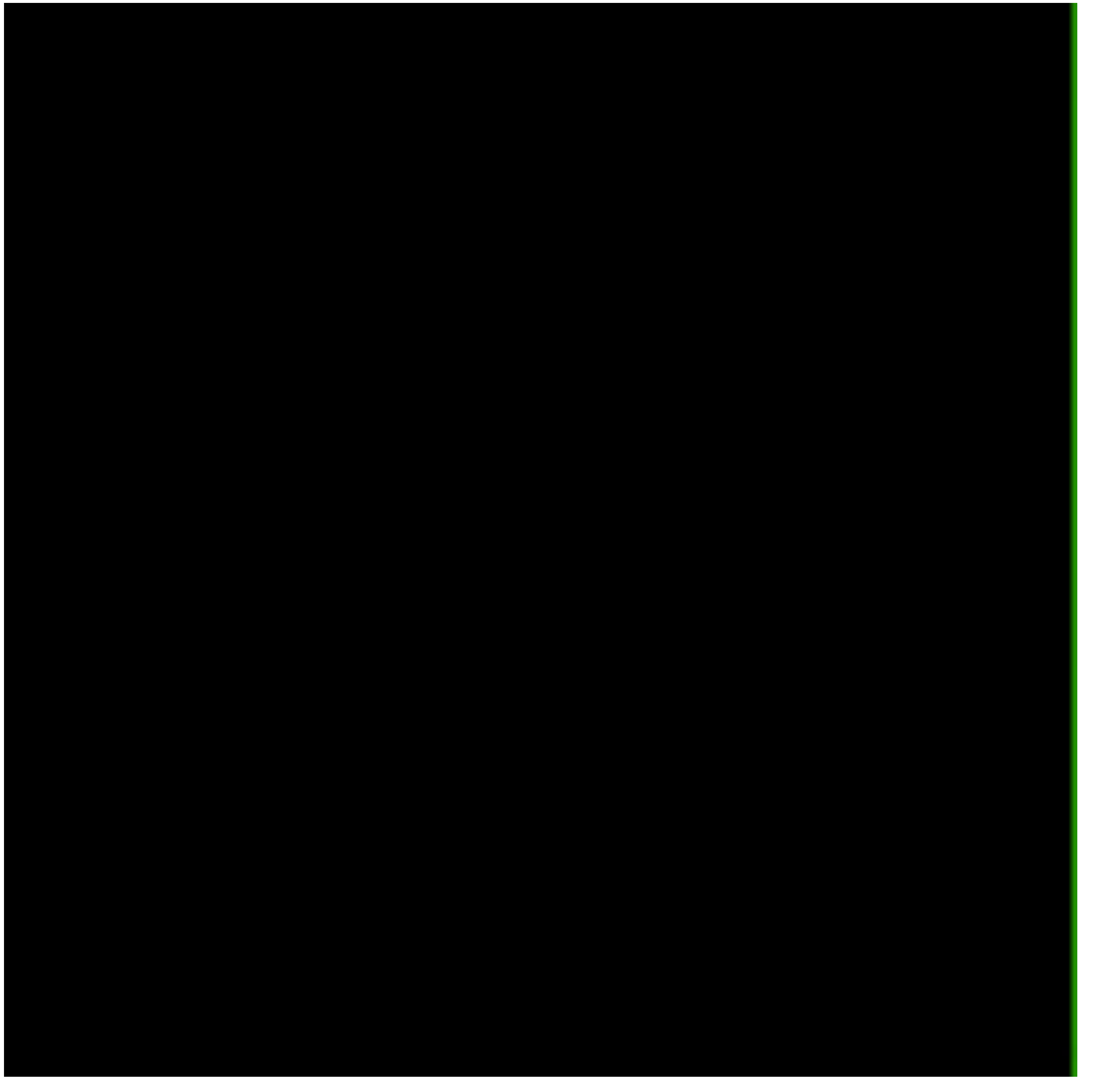
100%



51.2%

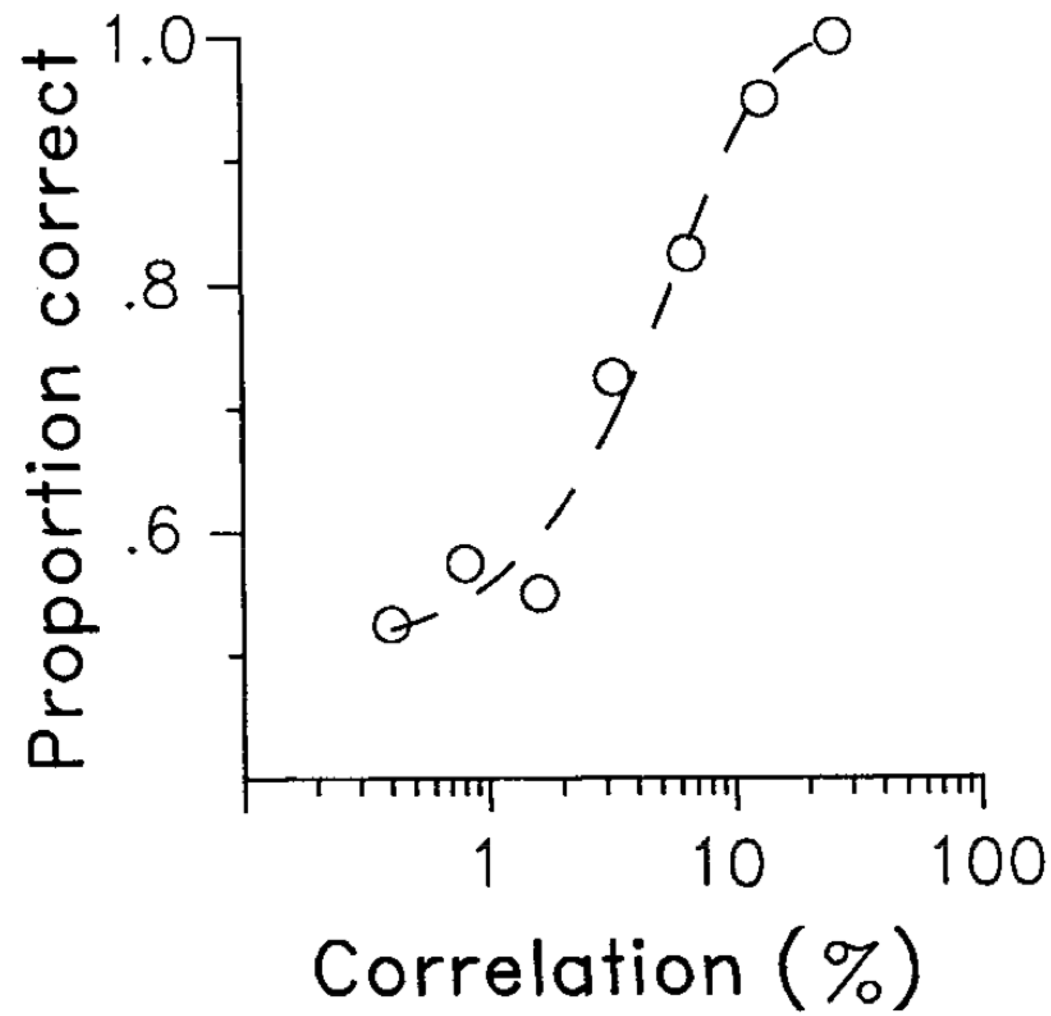


12.8%



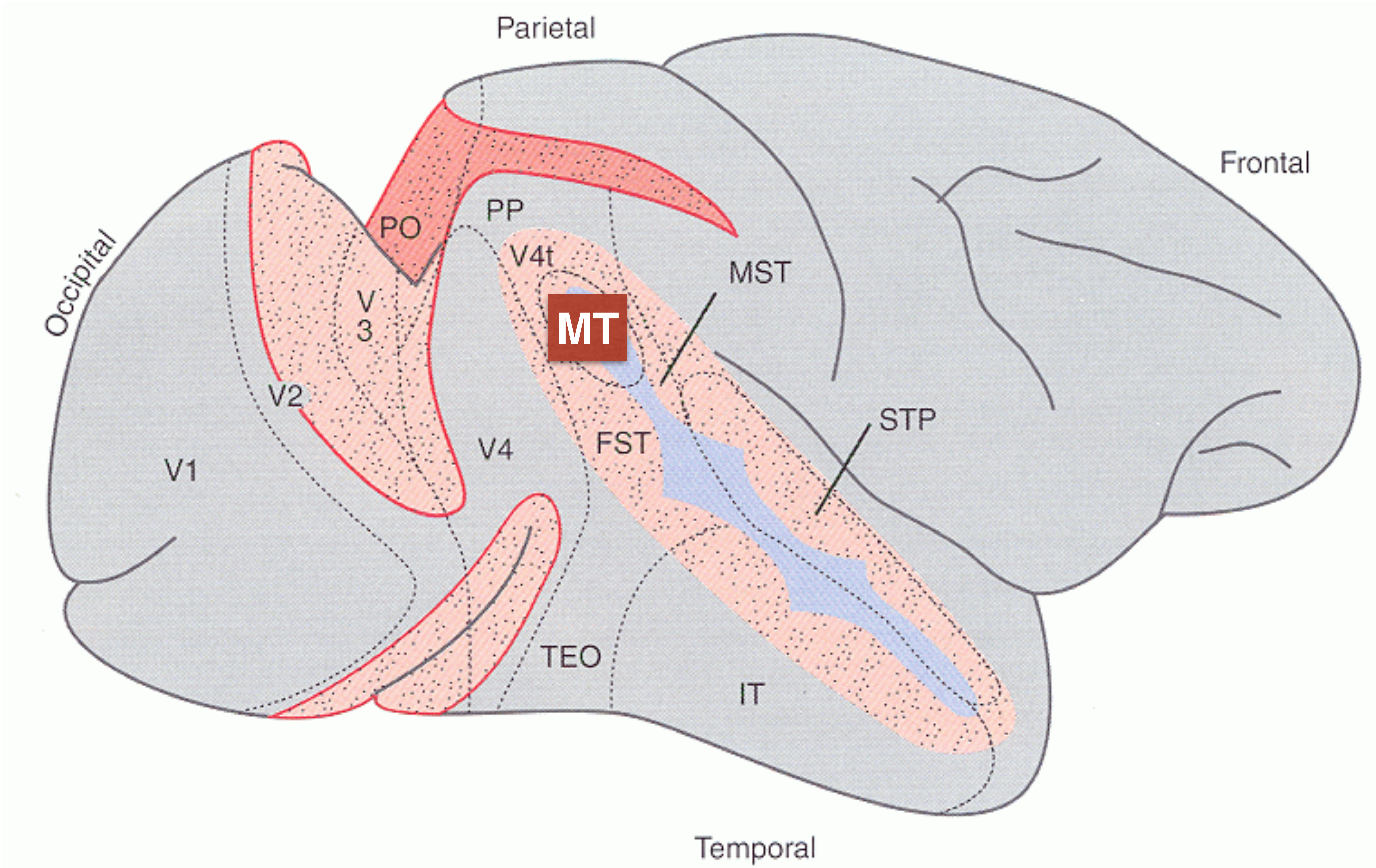
0%

Behavior Performance

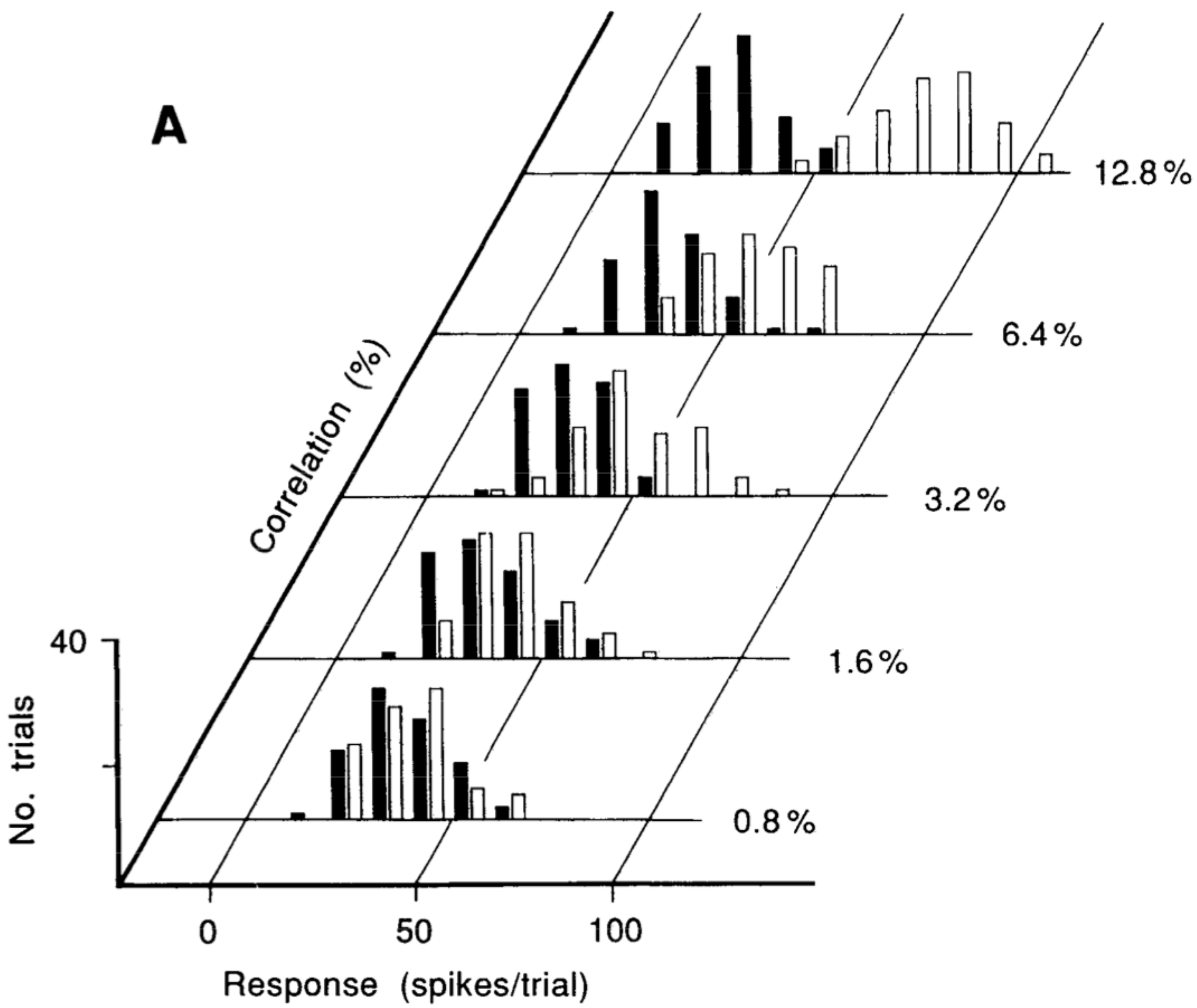


Britten, Shadlen, Newsome and Movshon, J Neurosci., 1992

Measuring neural activity in MT



http://fourier.eng.hmc.edu/e180/lectures/figures/macaquebrain.gif

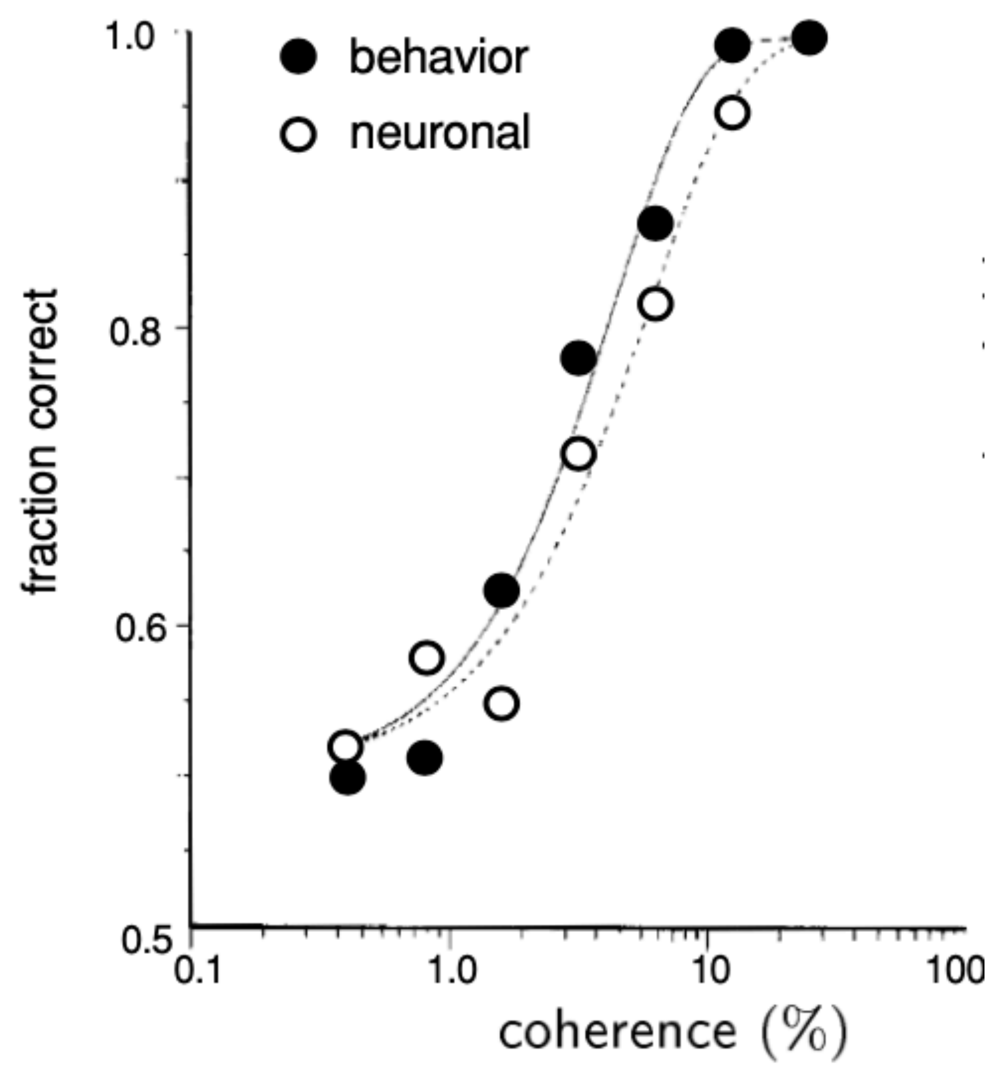


$$d = \frac{\langle r \rangle_+ - \langle r \rangle_-}{\sigma}$$

$$P(\text{correct}) = \frac{1}{\sqrt{\pi}} \int_{-d/2}^{\infty} dx \exp(-x^2)$$

Britten, Shadlen, Newsome and Movshon, J Neurosci., 1992

Neural Correlates with Behavior

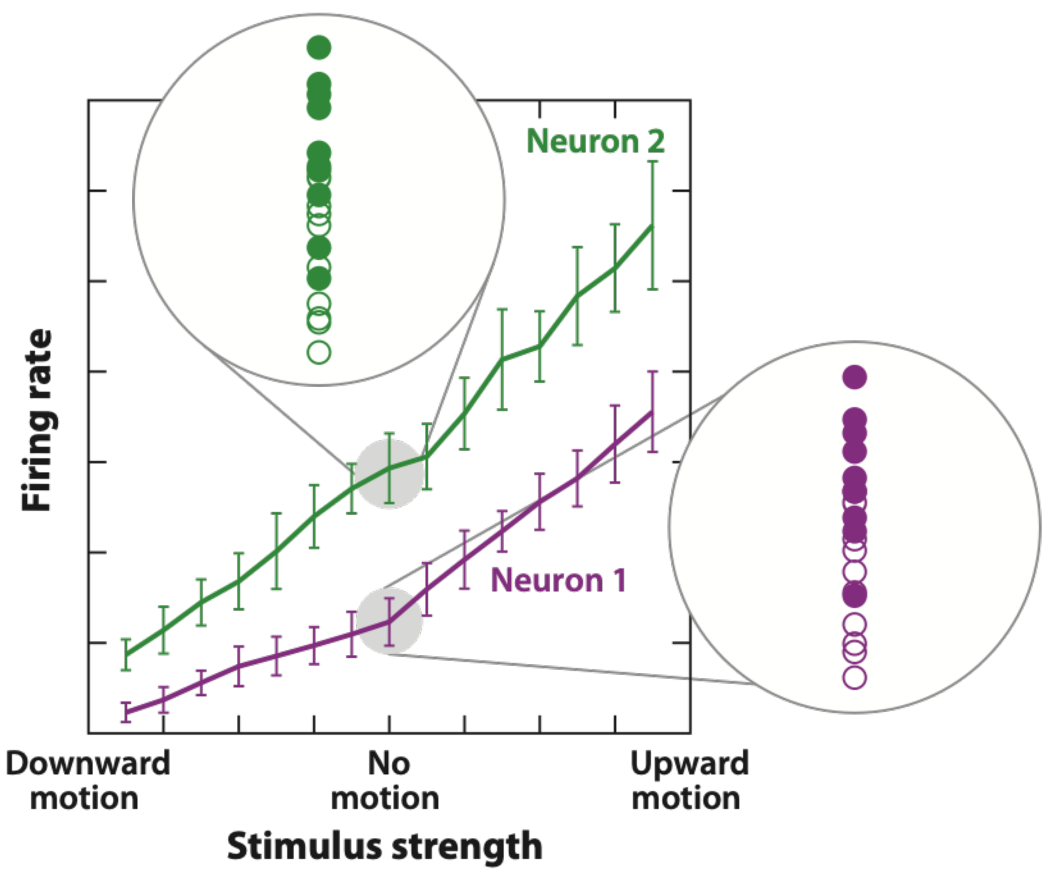


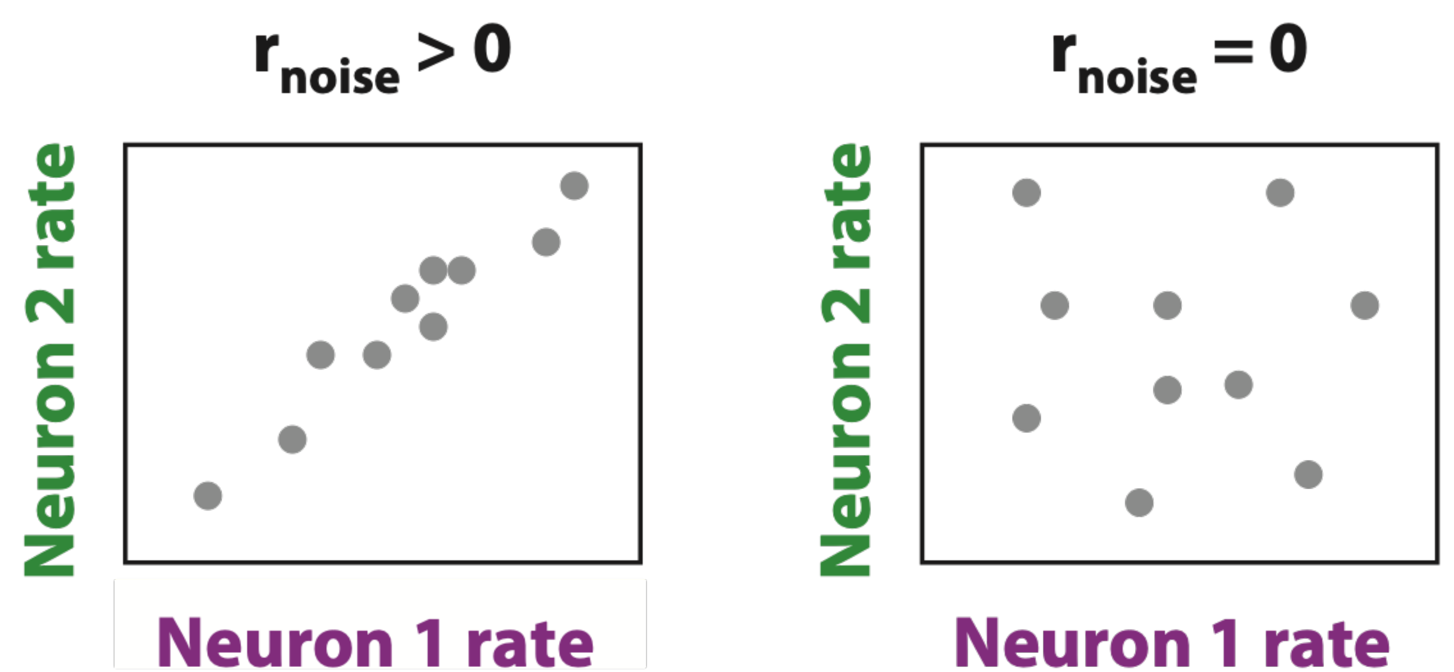
Population decoding

$$k_{+} = \sum_{i=1}^{N} r_{+}^{i} \qquad\qquad k_{-} = \sum_{i=1}^{N} r_{-}^{i}$$

$$d^2 = \frac{\big(\langle k_{+}\rangle - \langle k_{-}\rangle\big)^2}{\langle\big(k_{+} - \langle k_{+}\rangle\big)^2\rangle}$$

Population decoding with correlated neurons

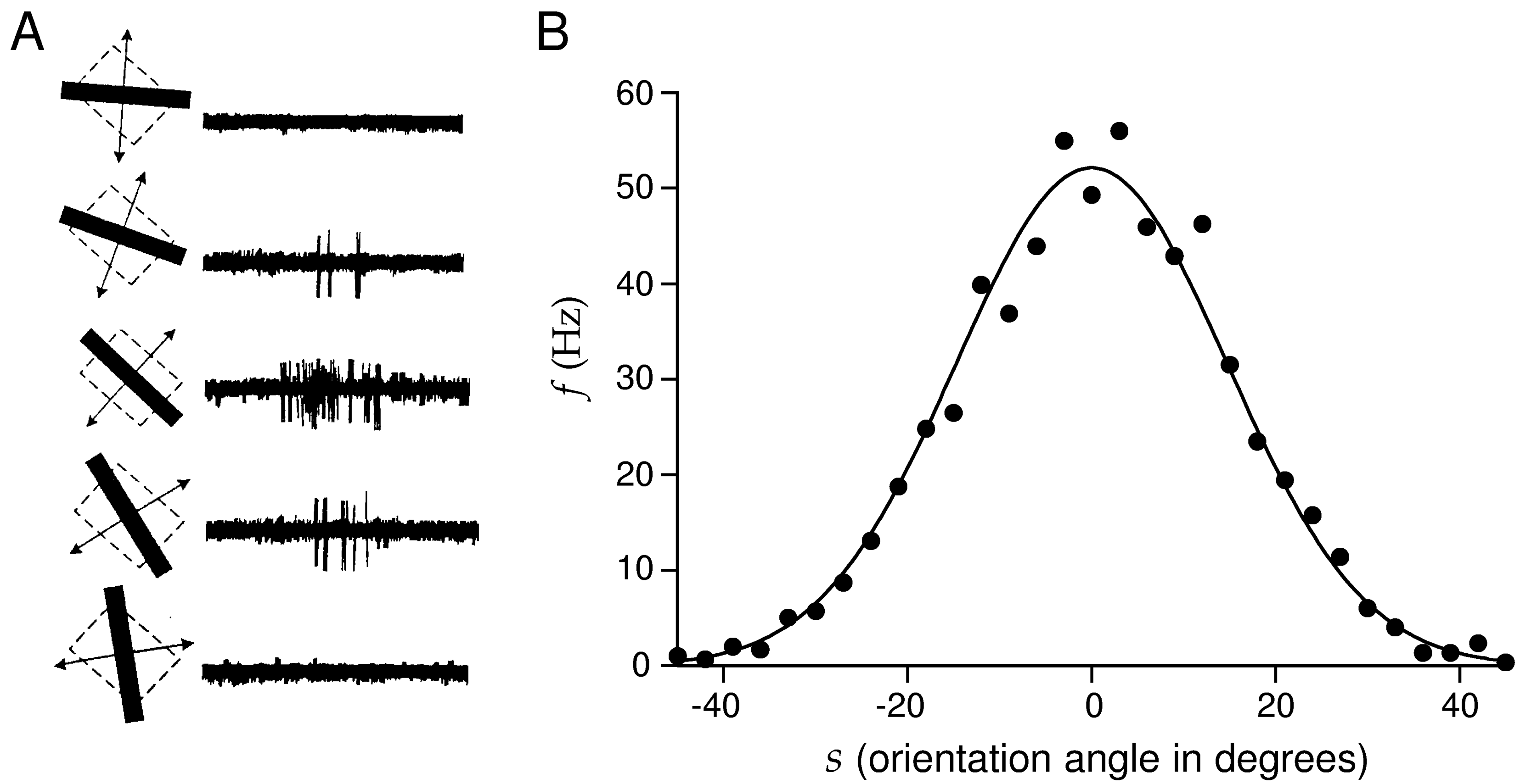




Signal Correlation

Noise Correlation

Orientation selectivity of simple cells in the visual cortex

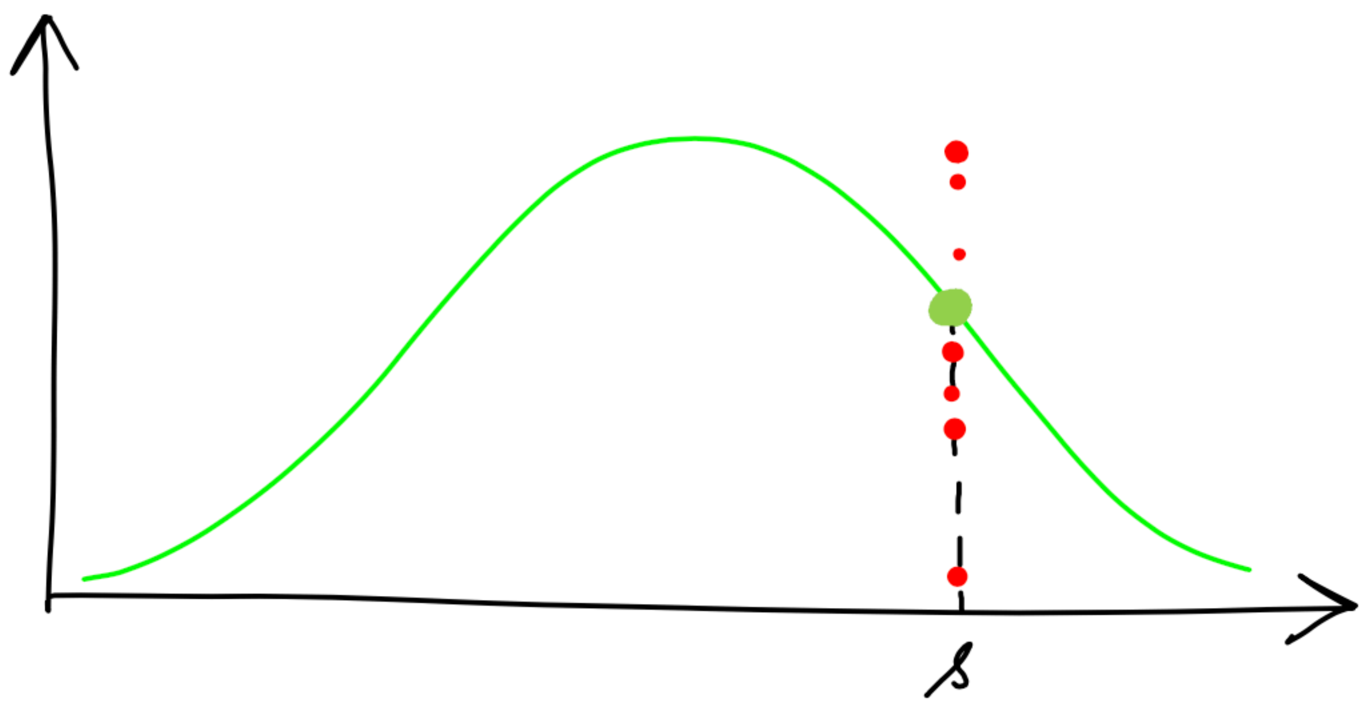


Gaussian tuning curve of a neuron in the primary visual cortex (V1)

Bayesian decoding method

Variability

$$r = m(s) + \xi$$



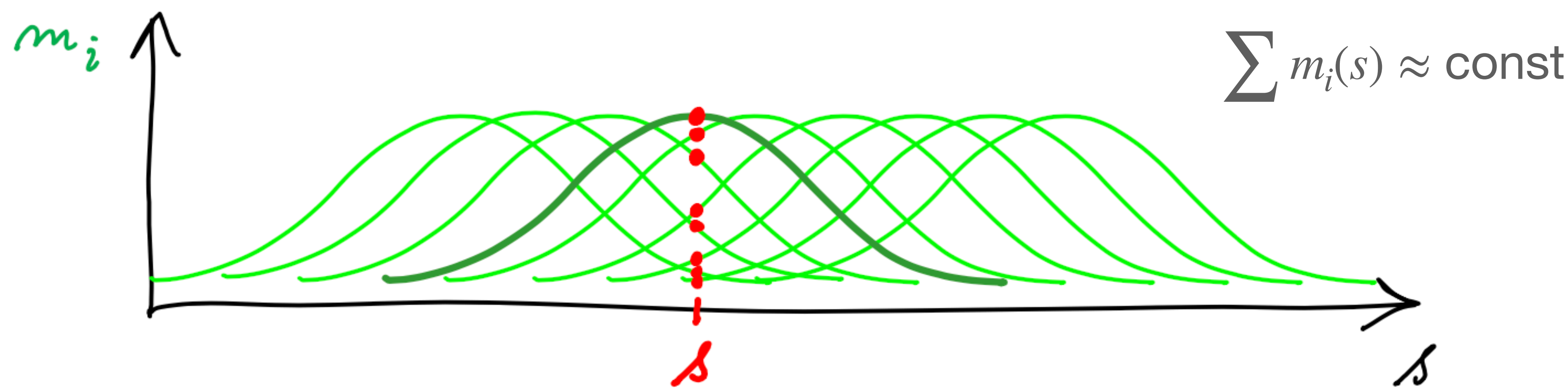
Likelihood Prior

$$p(s\,|\,r) = \frac{p(r\,|\,s)p(s)}{p(r)}$$

Normalization factor

$$m(s) = r_{max}\exp\left(-\frac{1}{2}(s-s_i)^2/\sigma_i^2\right)$$

Population decoding



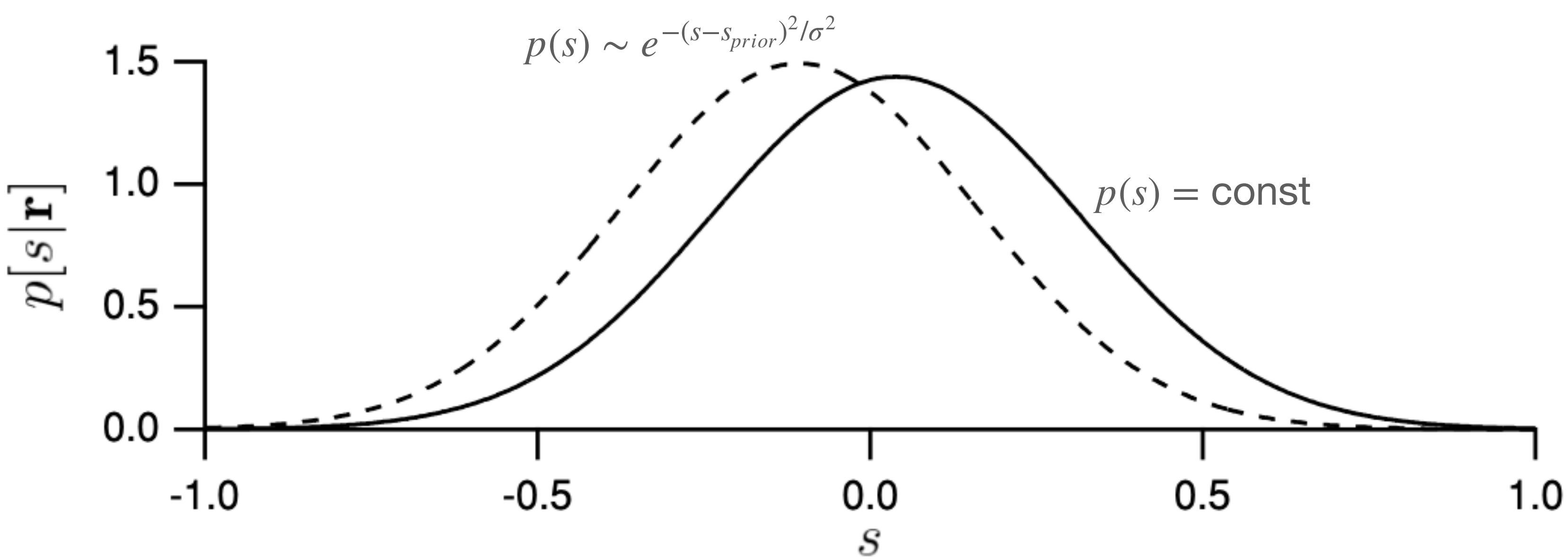
$$p(n_i \,|\, s) = \frac{[m_i(s)T]^{n_i}}{n_i!} \exp(-m_i(s)T)$$

$$\operatorname*{argmax}_s \; p(\mathbf{r} \,|\, s) = \prod_{i=1}^{N} p(n_i \,|\, s)$$

$$m_i'(s)/m_i(s) = (s_i - s)/\sigma_i^2$$

$$\sum_i^N r_i \frac{m_i'(s)}{m_i(s)} = 0$$

$$s = \frac{\sum r_i s_i/\sigma_i^2}{\sum r_i/\sigma_i^2}$$



$$s - \langle s_{est} \rangle = b_{est}$$

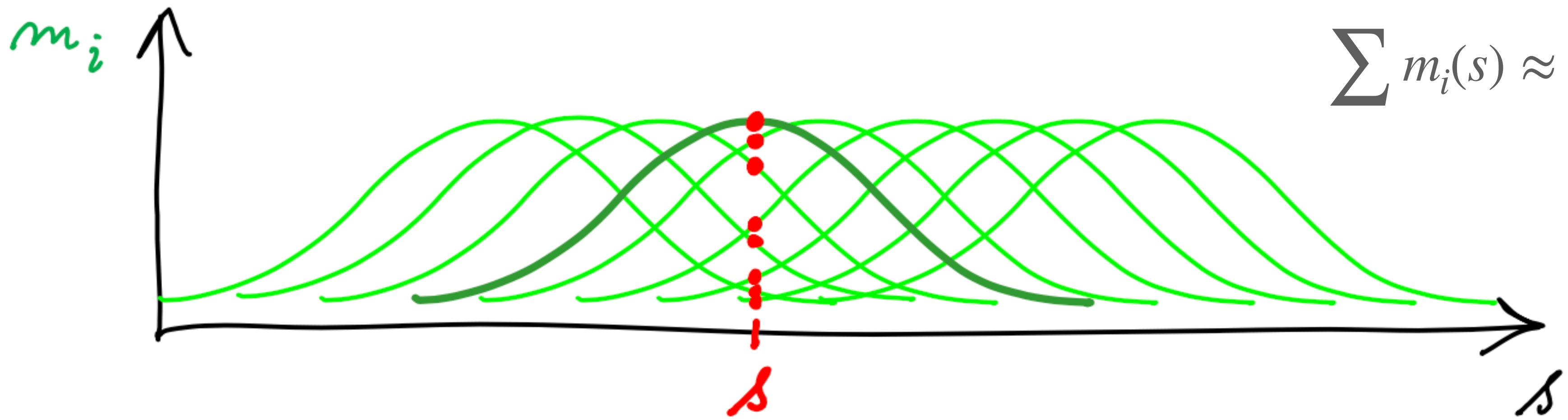
$$\langle (s - s_{est})^2 \rangle = \langle (s - \langle s_{est} \rangle + \langle s_{est} \rangle - s_{est})^2 \rangle = b_{est}^2 + \sigma_{est}^2$$

Cramer-Rao bound and Fisher information

$$\sigma_{est}^2 \geq \frac{(1 + b_{est})^2}{I_F}$$

$$I_F = \left\langle -\frac{\partial^2 \log p(r\,|\,s)}{\partial s^2} \right\rangle = -\int dr p(r\,|\,s) \frac{\partial^2 \log p(r\,|\,s)}{\partial s^2}$$

Population decoding



$\sum m_i(s) \approx \text{const}$

$$I_F = T \sum_i \frac{\left(m_i'(s)\right)^2}{m_i(s)}$$