

Visual Object Recognition

Computational Models and Neurophysiological Mechanisms

Neurobiology 130/230. Harvard College/GSAS 78454

Web site: <http://tinyurl.com/visionclass>

→ Class notes, Class slides, Readings Assignments

Location: Biolabs 2062

Time: Mondays 03:00 – 05:00

Lectures:

Faculty: Gabriel Kreiman and invited guests

TA: Emma Giles

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Visual Object Recognition

Computational Models and Neurophysiological Mechanisms

Neurobiology 230. Harvard College/GSAS 78454

Class 1 [09/10/2018]. Introduction to pattern recognition [Kreiman]

Class 2 [09/17/2018]. Why is vision difficult? Natural image statistics. The retina. [Kreiman]

Class 3 [09/24/2018]. Lesions and neurological studies [Kreiman].

Class 4 [10/01/2018]. Psychophysics of visual object recognition [[Sarit Szpiro](#)]

October 8: University Holiday

Class 5 [10/15/2018]. Primary visual cortex [[Hartmann](#)]

Class 6 [10/22/2018]. Adventures into *terra incognita* [[Frederico Azevedo](#)]

Class 7 [10/29/2018]. High-level visual cognition [[Diego Mendoza-Haliday](#)]

Class 8 [11/05/2018]. Correlation and causality. Electrical stimulation in visual cortex [Kreiman]

Class 9 [11/12/2018]. Visual consciousness [Kreiman]

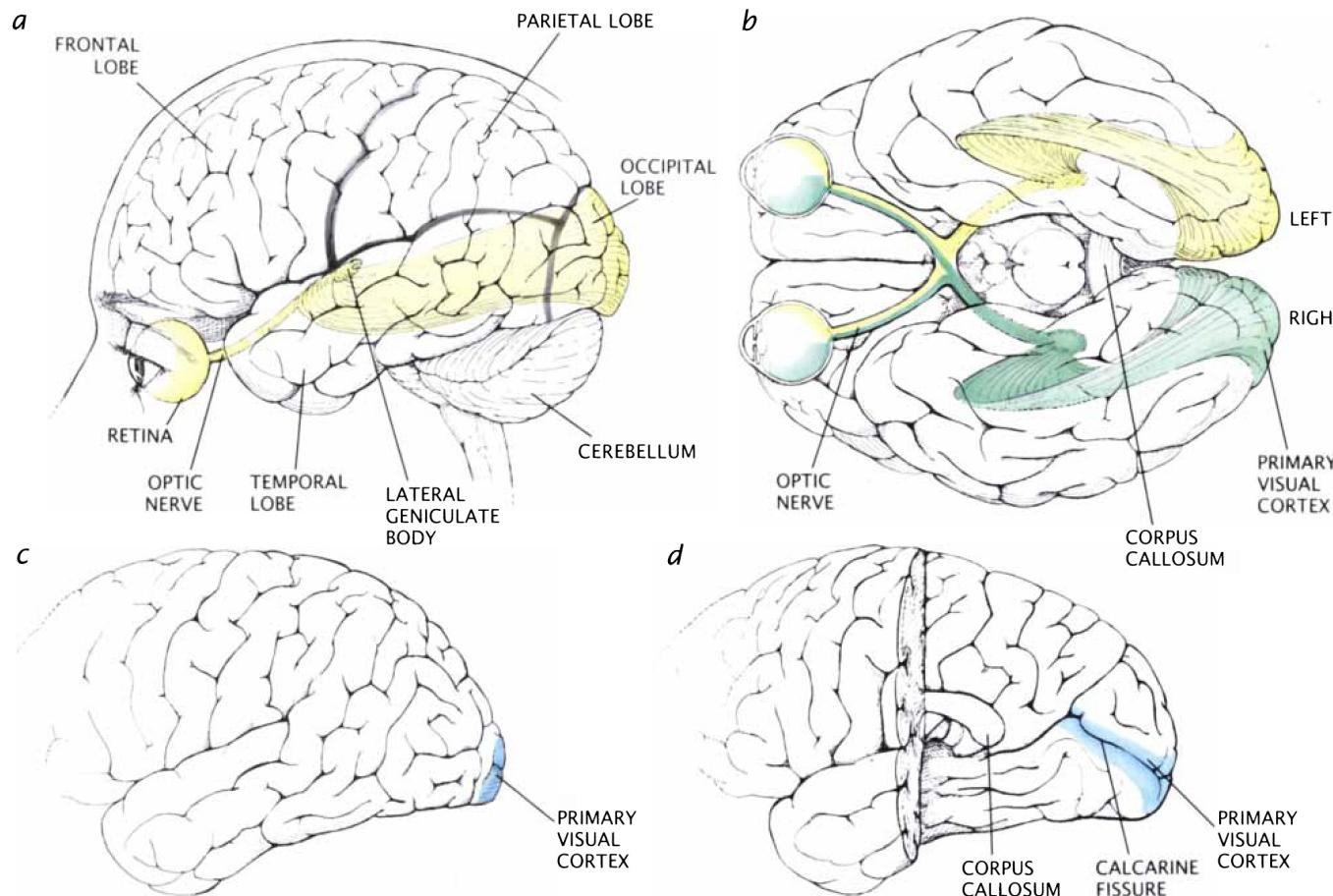
Class 10 [11/19/2018]. Computational models of neurons and neural networks. [Kreiman]

Class 11 [11/26/2018]. Computer vision. Artificial Intelligence in Visual Cognition [[Bill Lotter](#)]

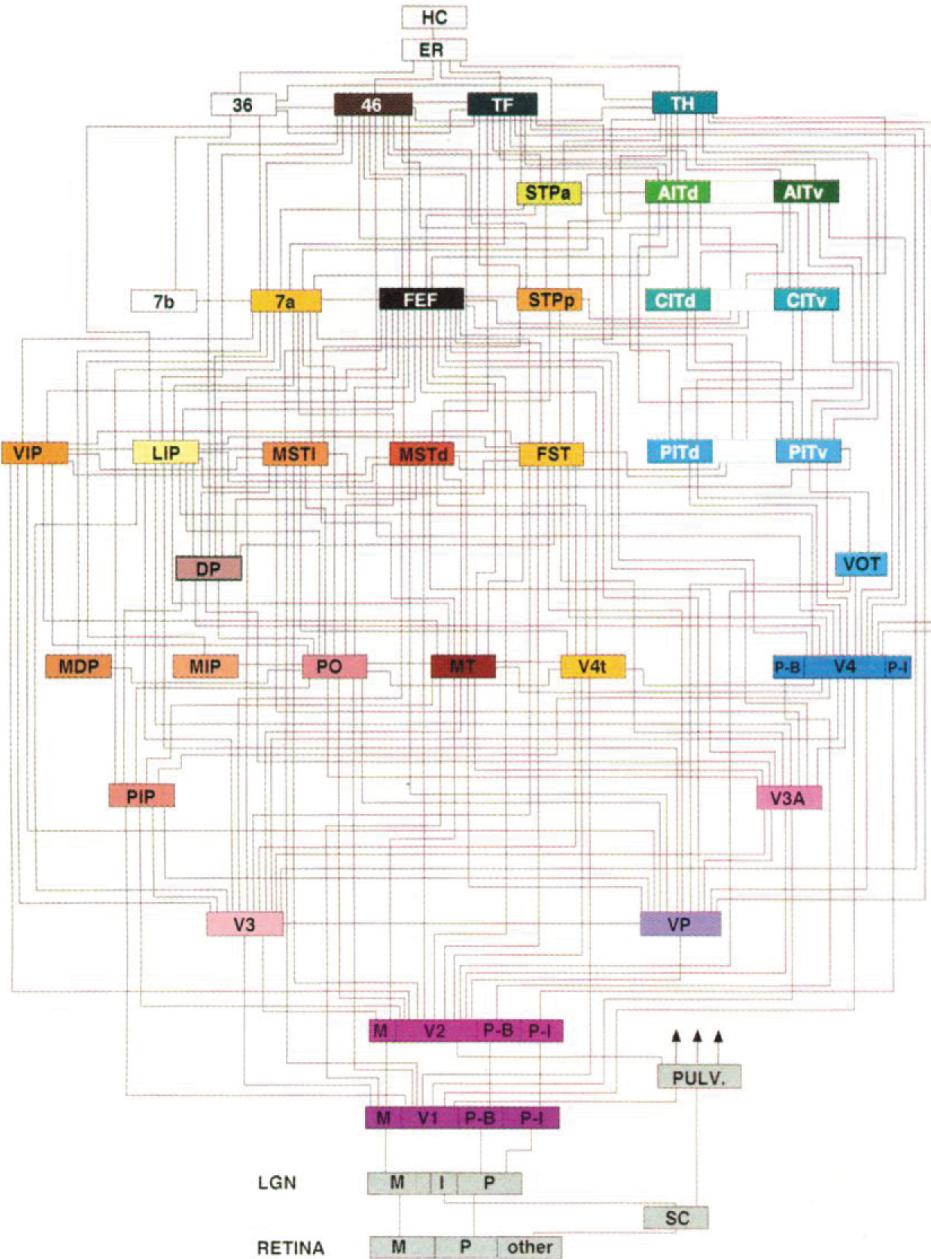
Class 12 [12/03/2018]. The operating system for vision. [[Xavier Boix](#)]

FINAL EXAM, PAPER DUE 12/13/2018. No extensions.

From the retina to cortex

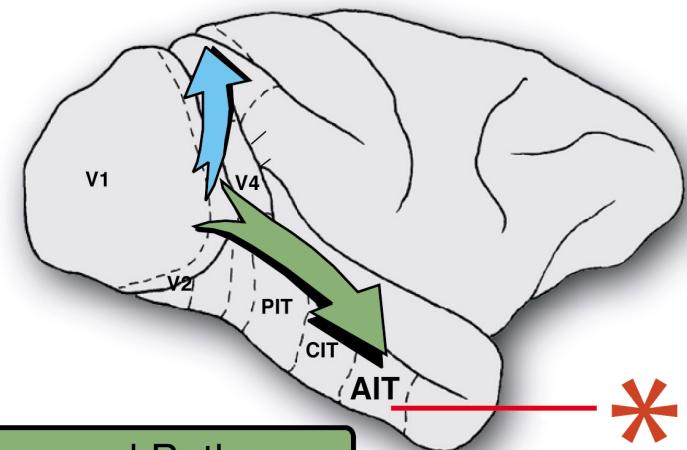


Glickstein, M. (1988). The discovery of the visual cortex. *Scientific American*



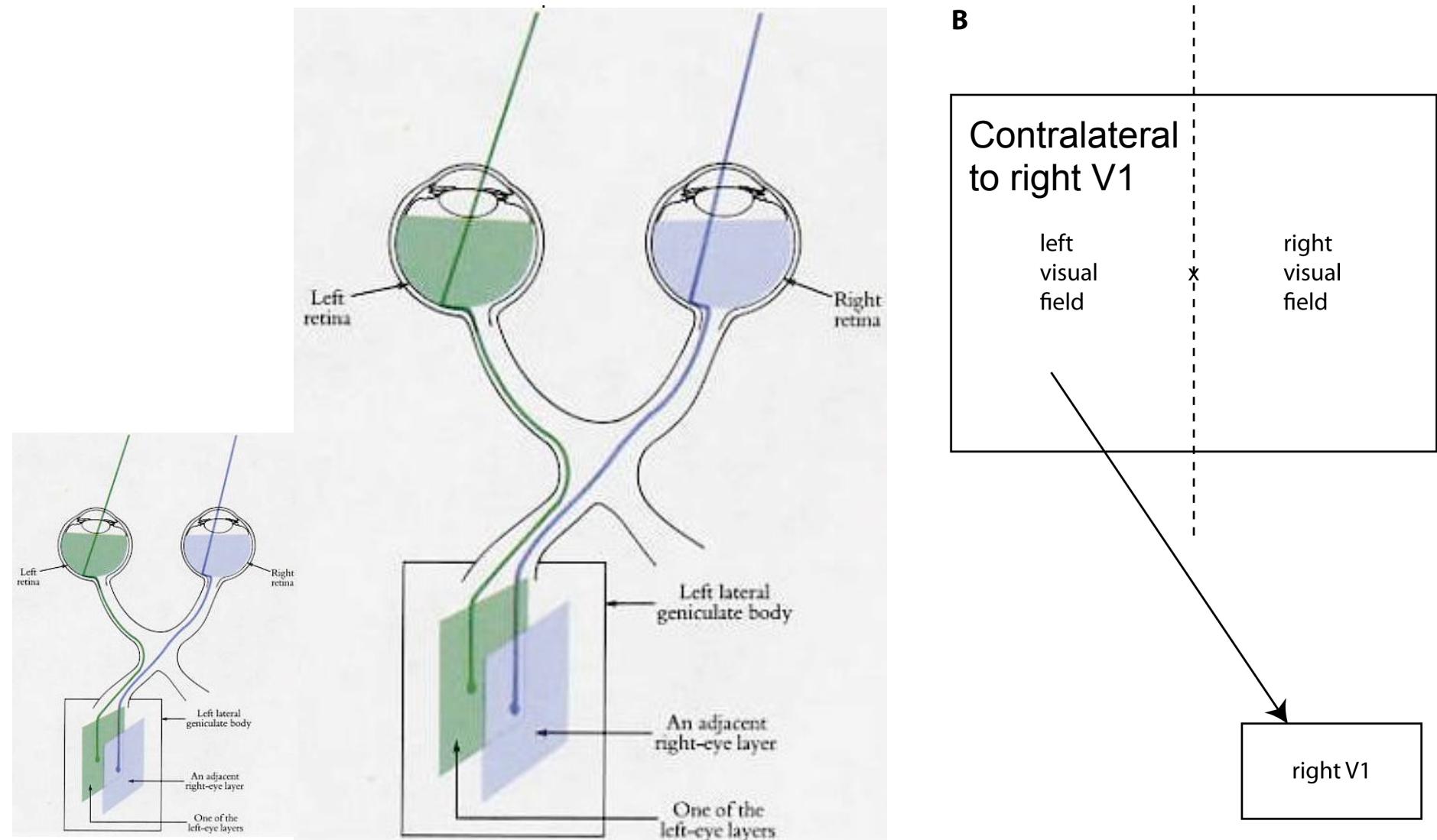
Visual system circuitry

Parietal Pathway

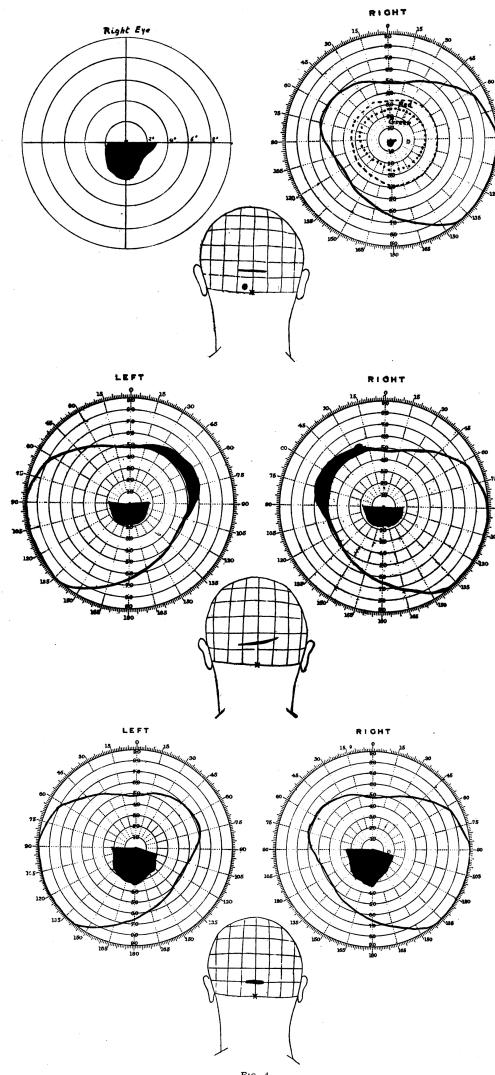
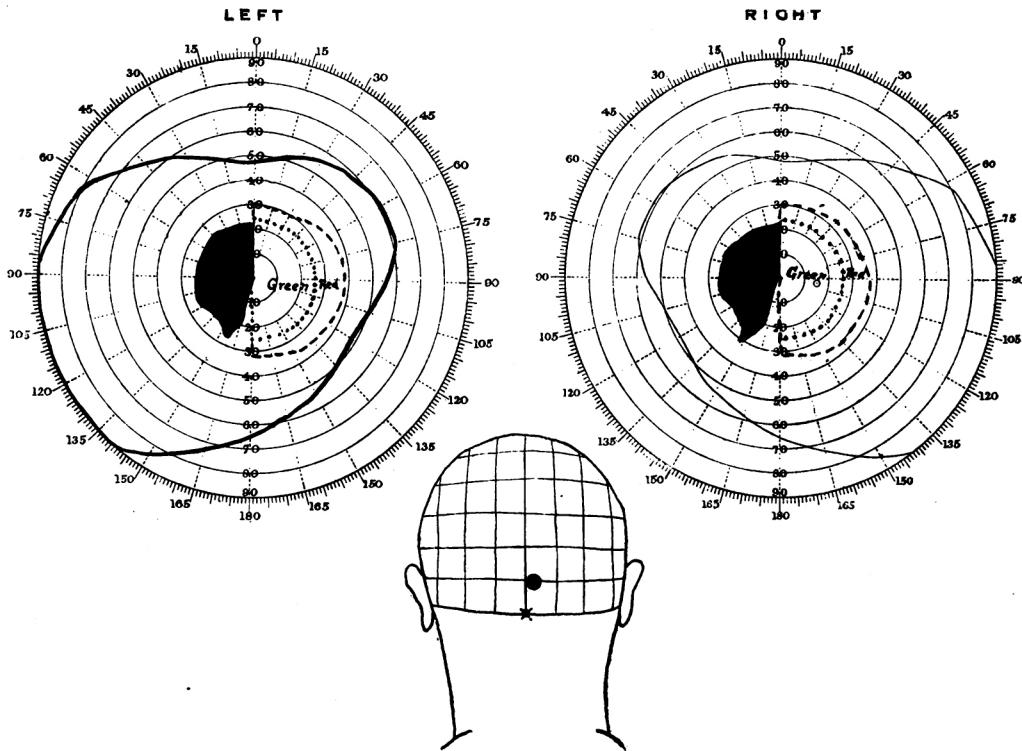


Temporal Pathway

V1 in each hemisphere represents the *contralateral* visual field

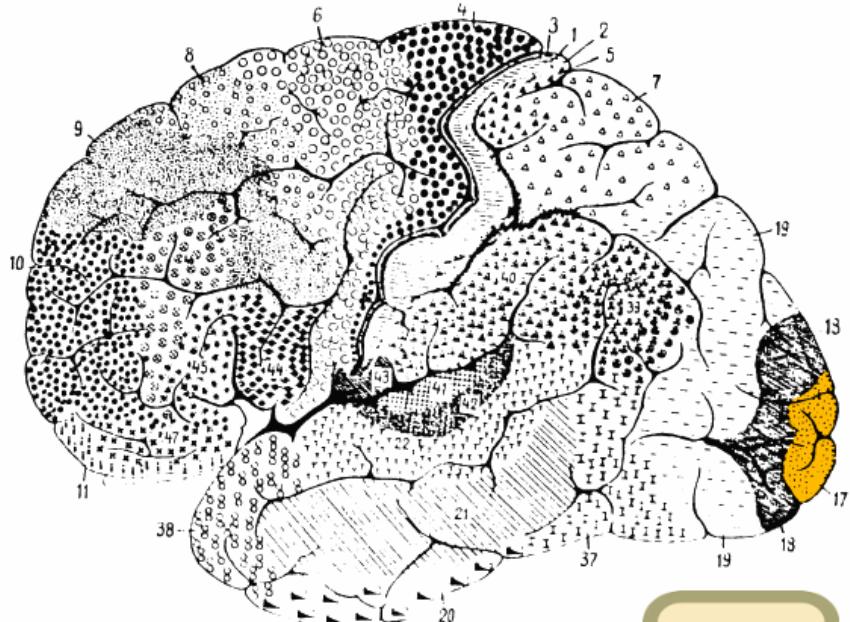


Studies of gunshot lesions revealed topographic visual deficits

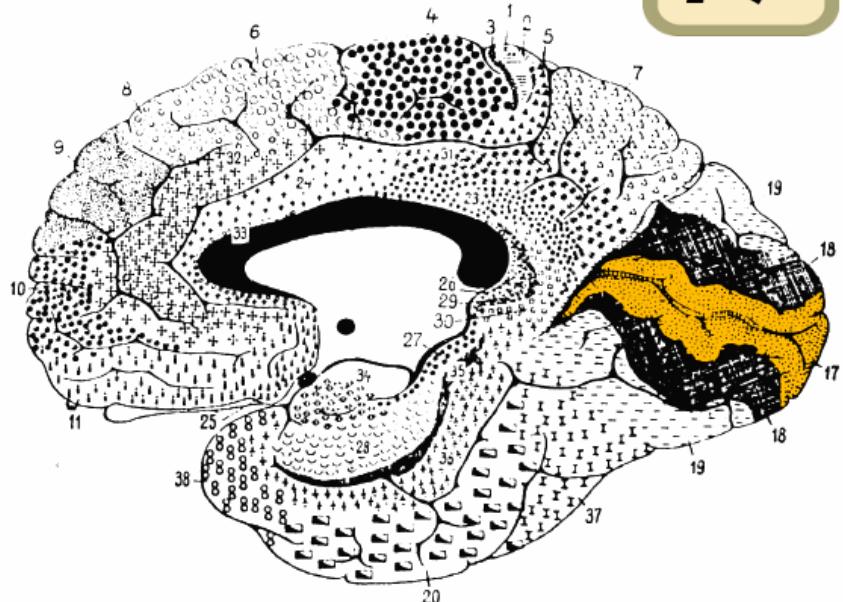


Holmes, G. (1918). Disturbances of vision by cerebral lesions. British Journal of Ophthalmology 2, 353-384.

Primary visual cortex in Brodmann's map



17



Brain shown from the side, facing left.
Above: view from outside, below: cut
through the middle. Orange = Brodmann
area 17 (primary visual cortex)

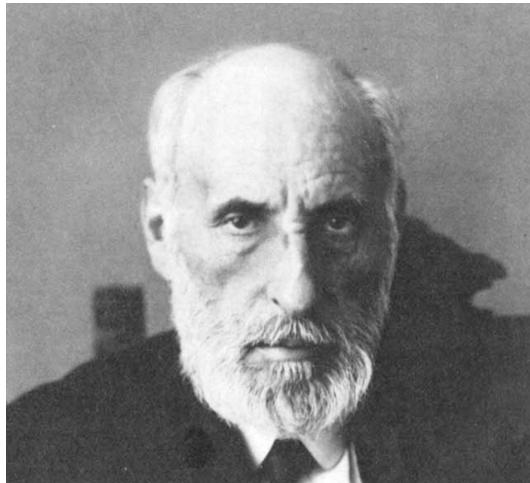
Acuity is much higher at the fovea

Fixate here

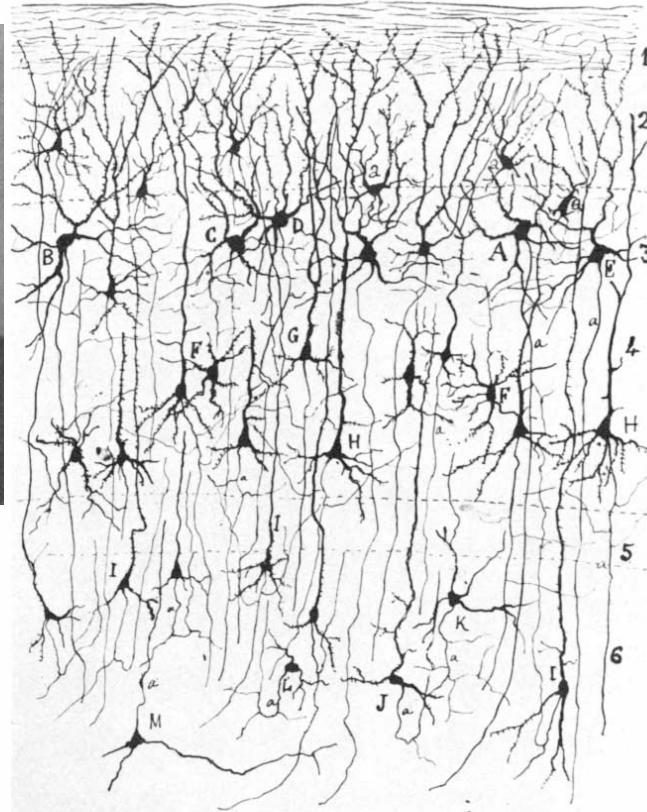


TRY READING THIS [44]
Retinal photoreceptor density [36]
Cortical magnification factor [28]
Why is it that we do not see things upside down? [20]
Or the split between the two hemifields? [12]
And do not forget about the importance of crowding! [8]

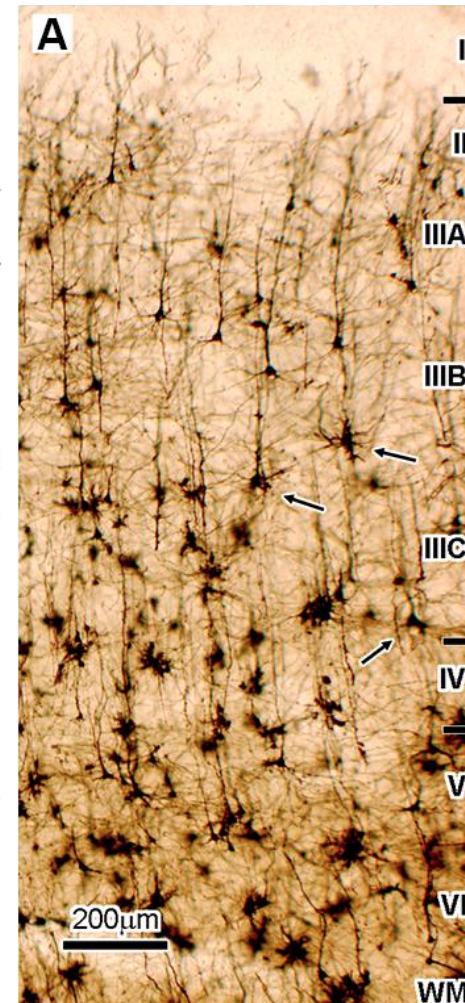
The complex circuitry of cortex as drawn by Ramon y Cajal



Ramon y Cajal
[1852-1934]



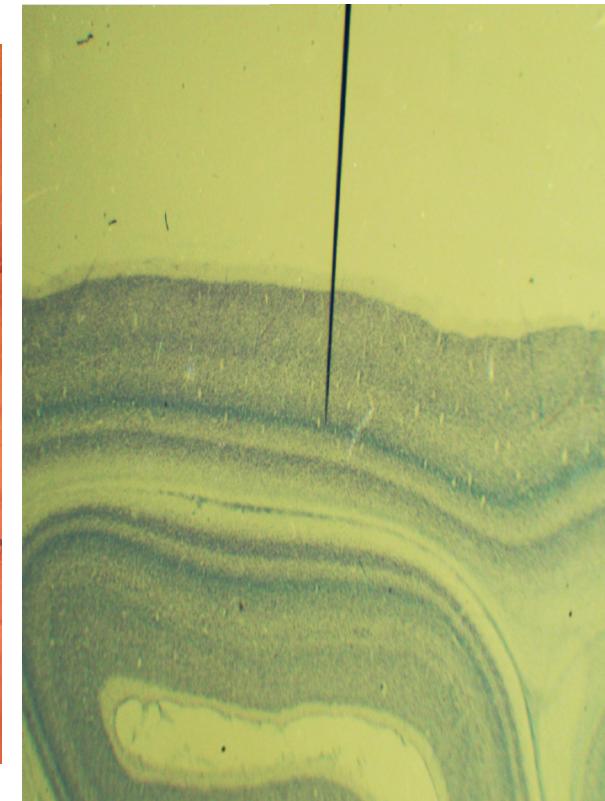
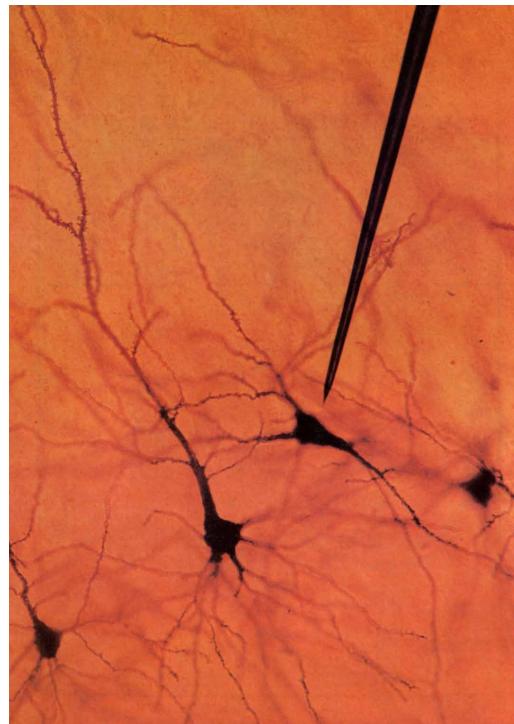
GOLGI-STAINED NERVE TISSUE from the visual cortex of a rat was sketched by Cajal in 1888. The numbers along the right-hand margin identify cellular layers; the capital letters label individual neurons. One of Cajal's most important contributions to neurobiology was to establish the neuron as a discrete, well-defined cell rather than as part of a continuous network.



The gold standard to examine neuronal activity: microelectrode recordings

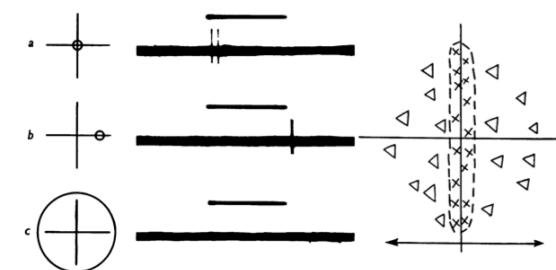
Edgar Adrian 1926

Neuronal resolution
Sub-millisecond temporal resolution
Direct examination of action potentials



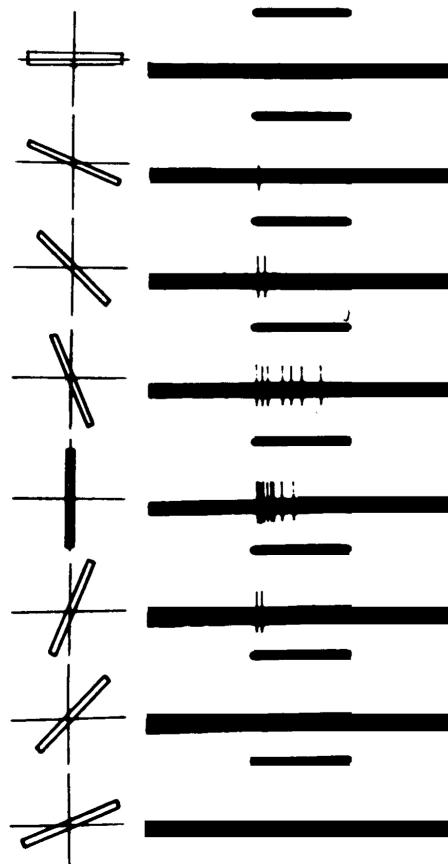
Hubel, D. (1979). The Visual Brain.
SCIENTIFIC AMERICAN 241, 45-53.

Neurophysiological recordings from primary visual cortex

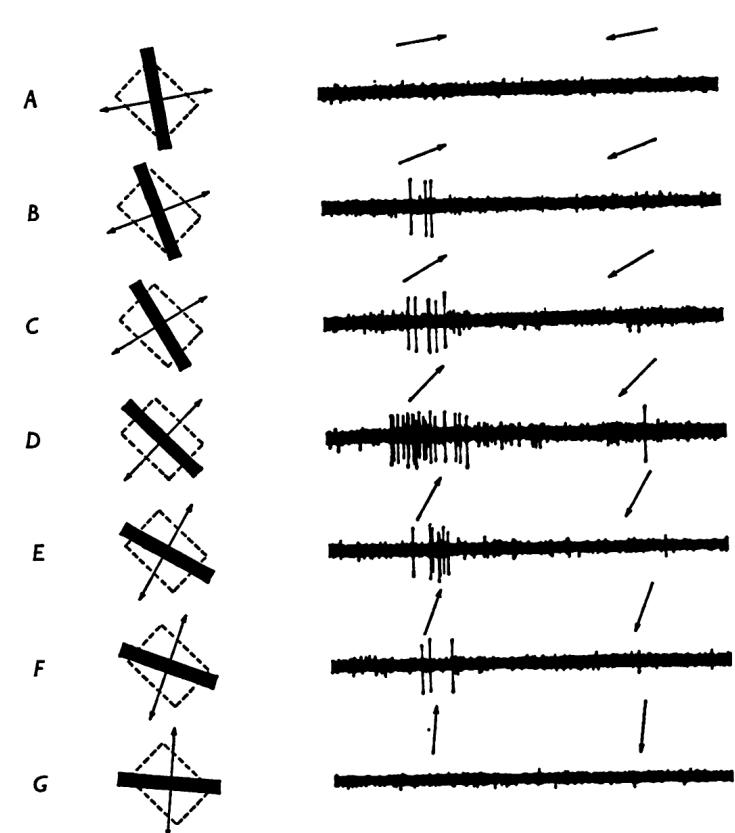


Hubel & Wiesel
J. Physiol. 1959

Orientation selectivity



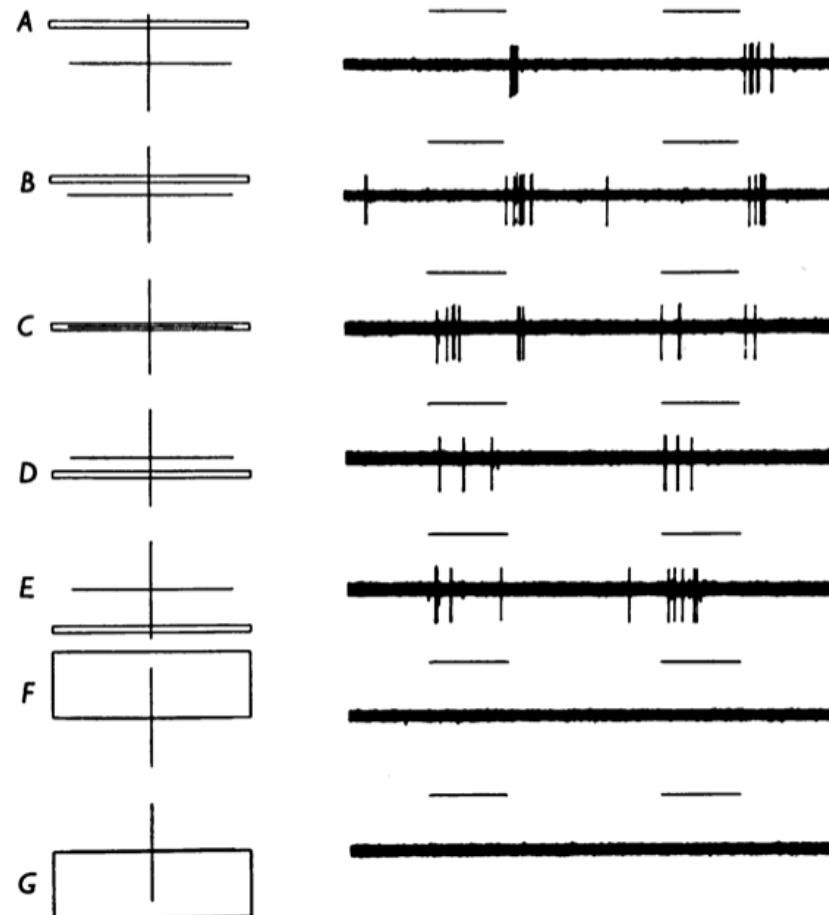
Direction selectivity



Hubel – Nobel Lecture

Hubel and Wiesel 1968

Selectivity and tolerance of complex fields

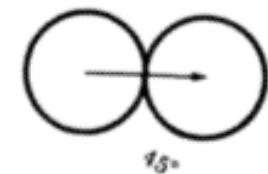
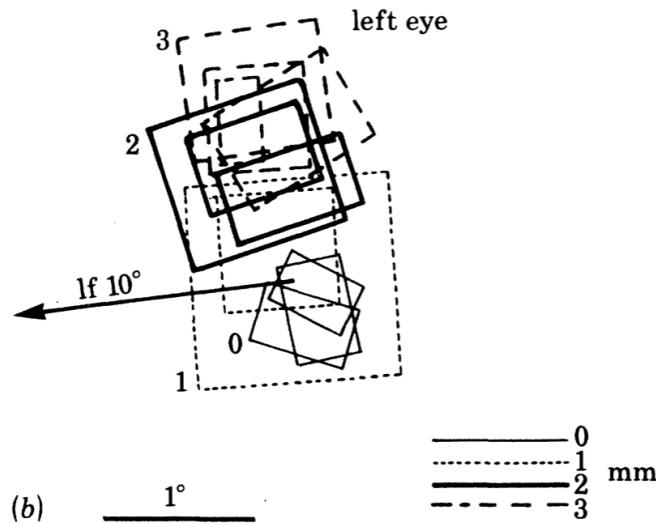
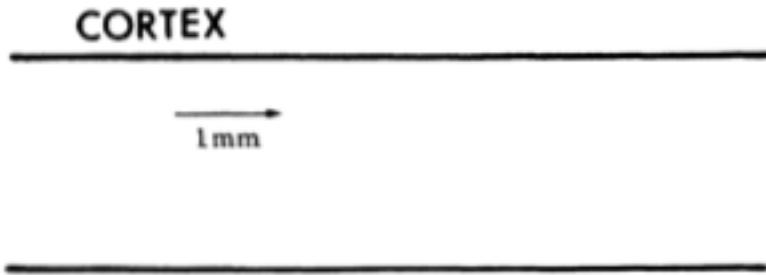


Hubel and Wiesel. J. Physiol. 1962

Video of Hubel and Wiesel

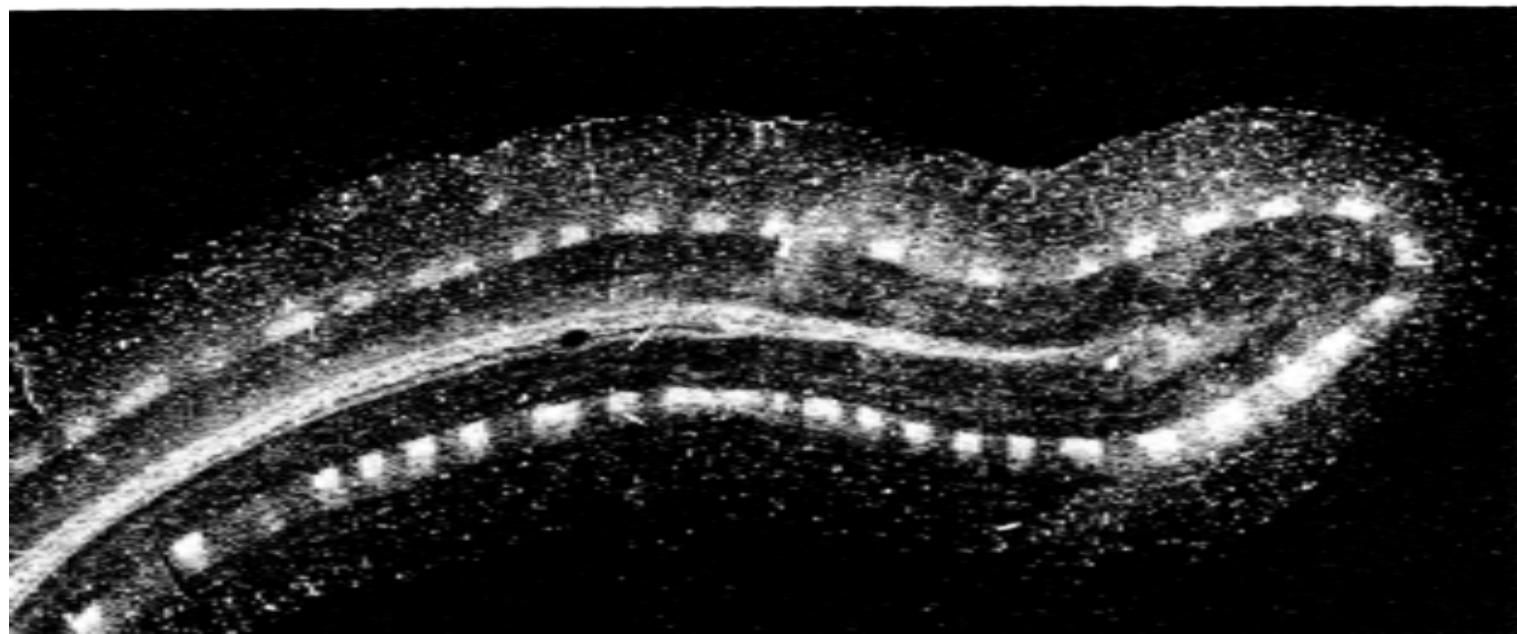
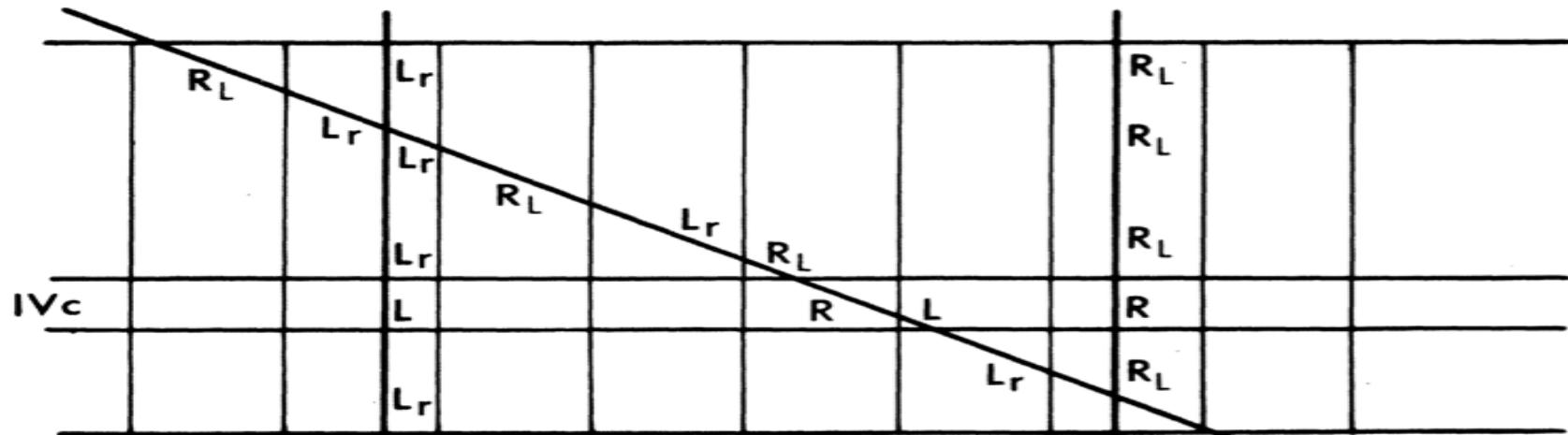
<http://www.youtube.com/watch?v=8VdFf3egwfg>

Retinotopical map in cortex

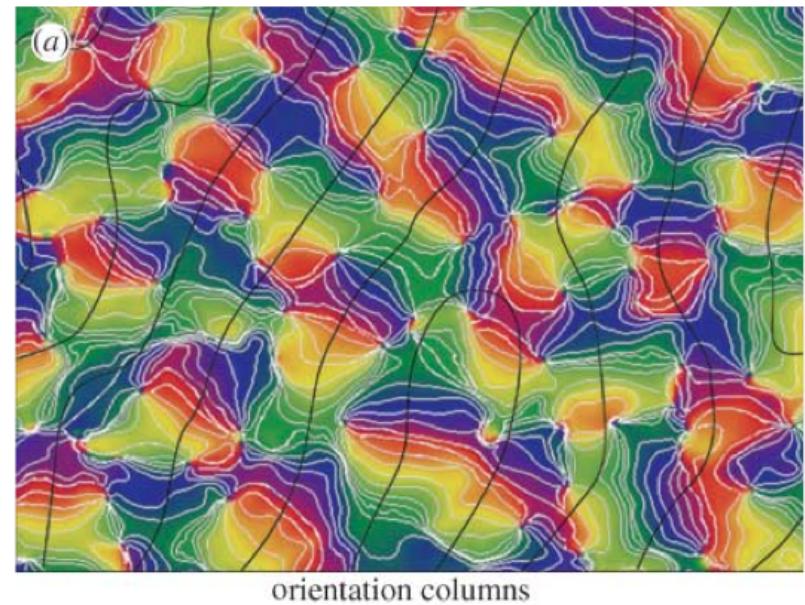
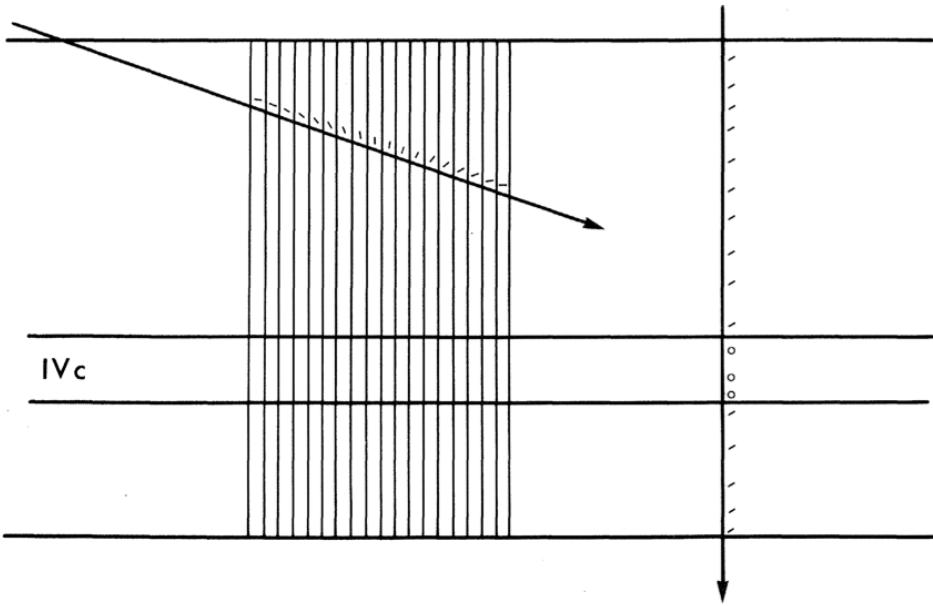


Ocular dominance columns

Hubel & Wiesel, Proc. R. Soc. Lond. B, 1977



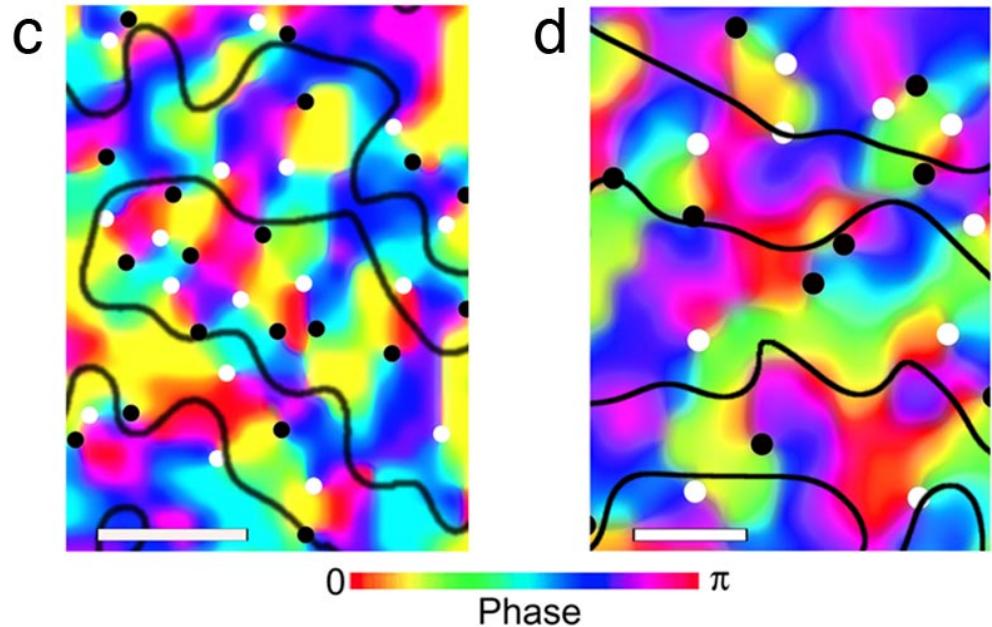
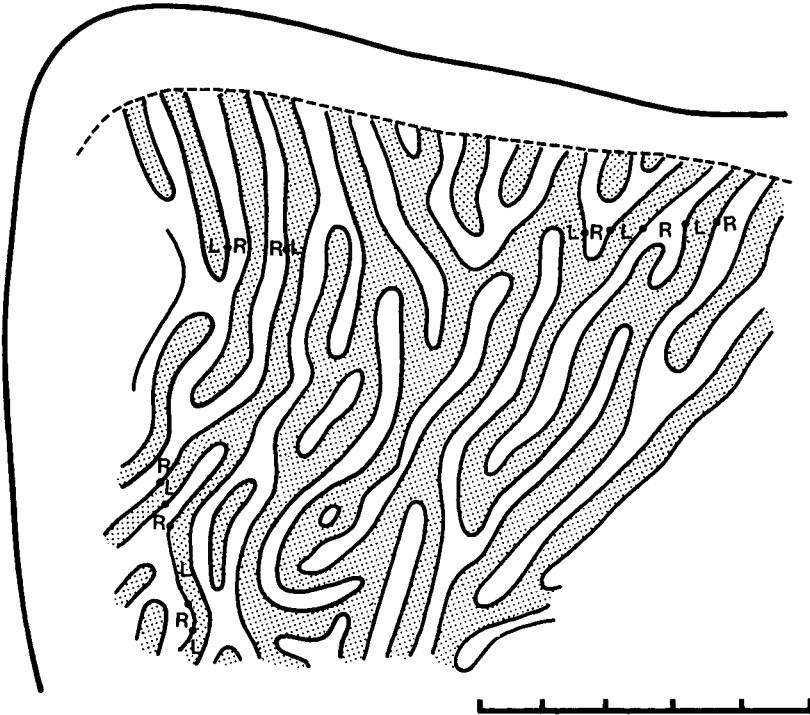
Visual orientation columns



Hubel & Wiesel, Proc. R. Soc. Lond. B, 1977

Horton & Adams, Phil. Trans. R. Soc. B, 2005

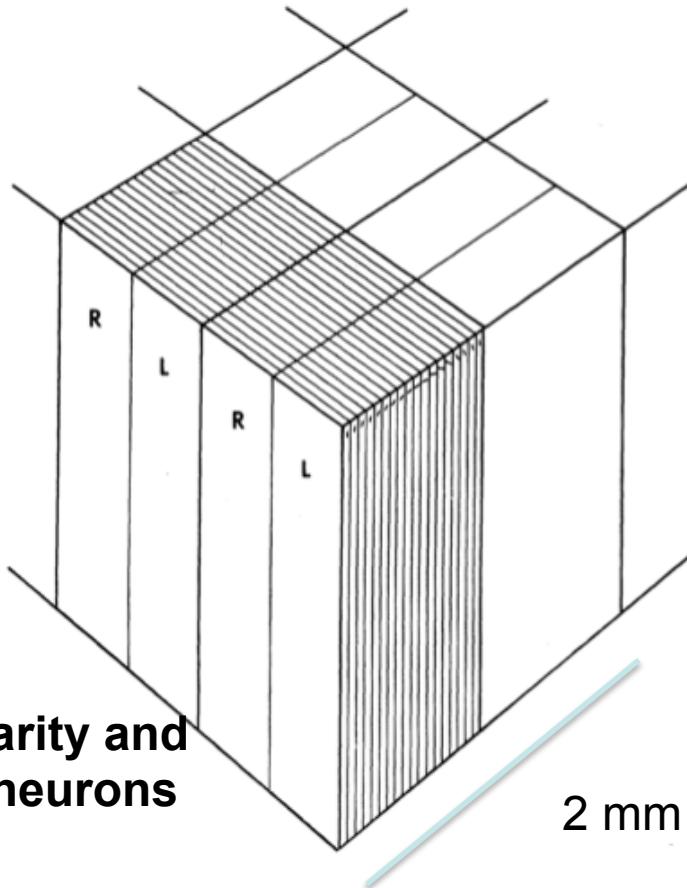
Columnar organization of primary visual cortex



LeVay, Hubel, & Wiesel, 1975

Yacoub, Harel, & Uğurbil, 2008

Putting it all* together: the “hypercolumn”



***all is more than ocularity and orientation. Many V1 neurons are also selective for:**

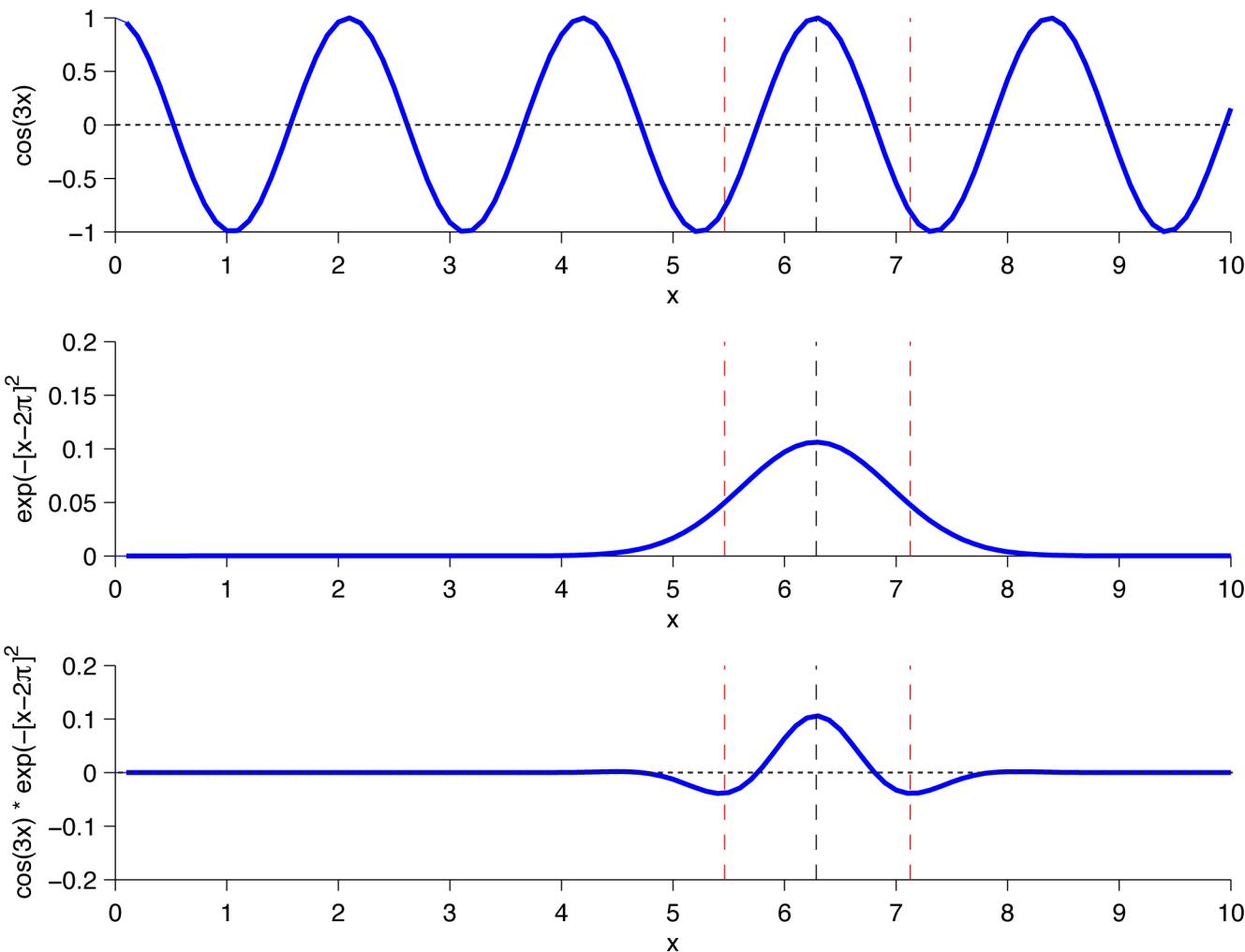
- Direction & speed
- Depth
- Color

Hubel & Wiesel, Proc. R. Soc. Lond. B, 1977

Different primary visual cortex neurons show a variety of interests

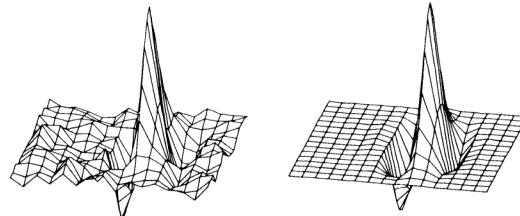
- Orientation selectivity
- Direction selectivity
- Speed selectivity
- Typically monotonic response with contrast
- Spatial frequency preferences
- Color

Interlude 1: Multiplying a cosyne and a Gaussian function



Receptive fields for simple cells in V1

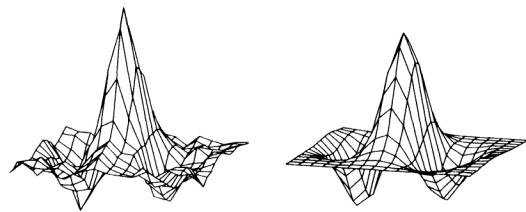
Spatial receptive field Gabor fit



Cell 1

Gabor function

$$D(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{x^2}{2\sigma_x^2} - \frac{y^2}{2\sigma_y^2}\right] \cos(kx - \phi)$$



Cell 2

Spatial receptive field

Cat primary visual cortex (area 17)

Jones and Palmer 1987

Interlude 2: MATLAB

An easy way to write computer code

- <http://www.mathworks.com/index.html>
- “High-level” computer programming language
- Quite powerful!

```
theta_rad=(2*pi/360)*theta;
x=(-2*sigma_x):bin:(2*sigma_x);nx=length(x);
y=(-2*sigma_y):bin:(2*sigma_y);ny=length(y);
```

```
factor1=1/(2*pi*sigma_x*sigma_y);
```

```
for i=1:nx
```

```
    for j=1:ny
```

```
        curr_x=x(i)*cos(theta_rad)+y(j)*sin(theta_rad);
```

```
        curr_y=y(j)*cos(theta_rad)-x(i)*sin(theta_rad);
```

```
        factor2=exp(-curr_x^2/(2*sigma_x^2)-curr_y^2/(2*sigma_y^2));
```

```
        factor3=cos(k*curr_x-phi);
```

```
        Ds(i,j)=factor1*factor2*factor3;
```

```
    end
```

```
end
```

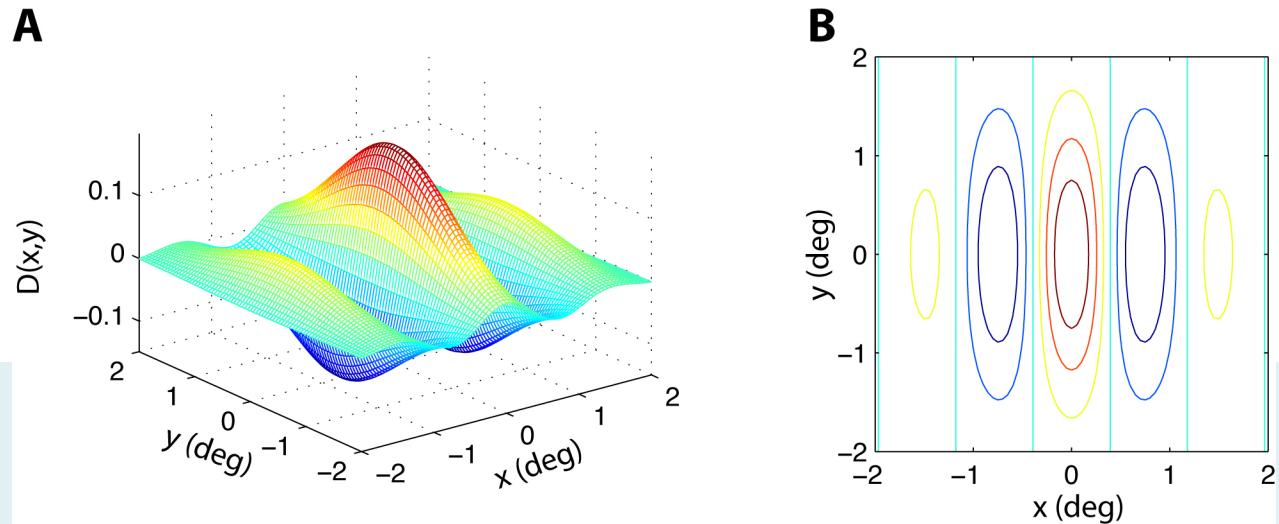
```
% theta angle in radians  
% define x axis  
% define y axis
```

$$D(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{x^2}{2\sigma_x^2} - \frac{y^2}{2\sigma_y^2}\right] \cos(kx - \phi)$$

Interlude 2: MATLAB

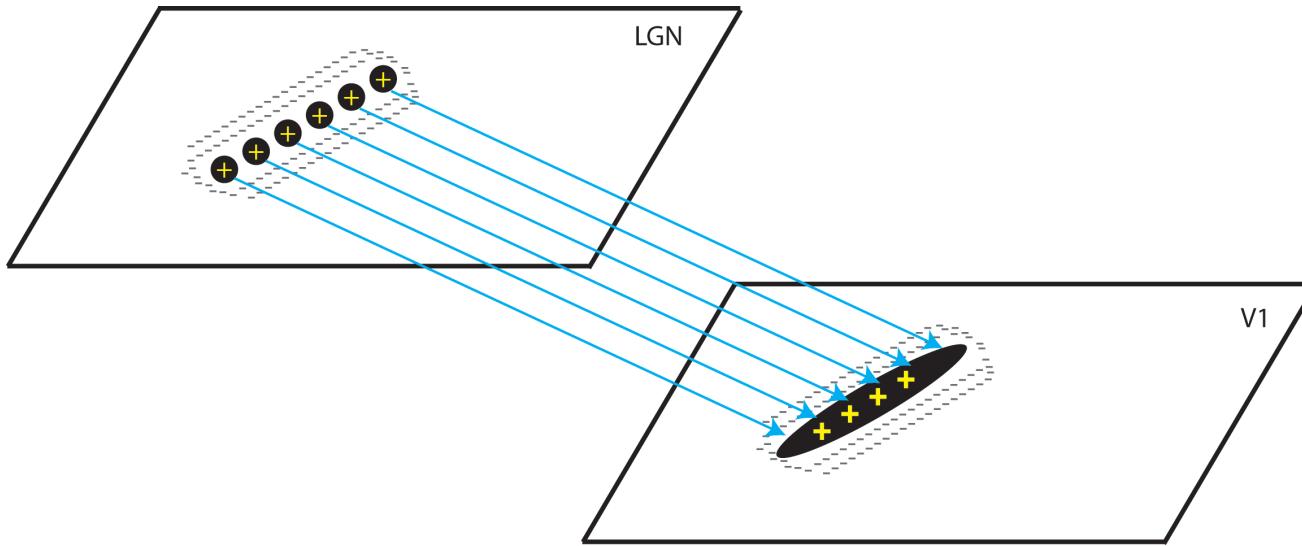
An easy way to make plots

```
sigma_x=1;  
sigma_y=1;  
bin=0.05;  
k=1/0.25;  
theta=0;  
i=0;  
phi=0;  
[Ds,x,y]=mygabor1(sigma_x,sigma_y,k,phi,theta,bin);  
subplot(2,2,1);  
mesh(x,y,Ds');  
axis([min(x) max(x) min(y) max(y) min(Ds(:)) max(Ds(:))]);  
subplot(2,2,2);  
contour(x,y,Ds');  
axis square;
```



$$D(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{x^2}{2\sigma_x^2} - \frac{y^2}{2\sigma_y^2}\right] \cos(kx - \phi)$$

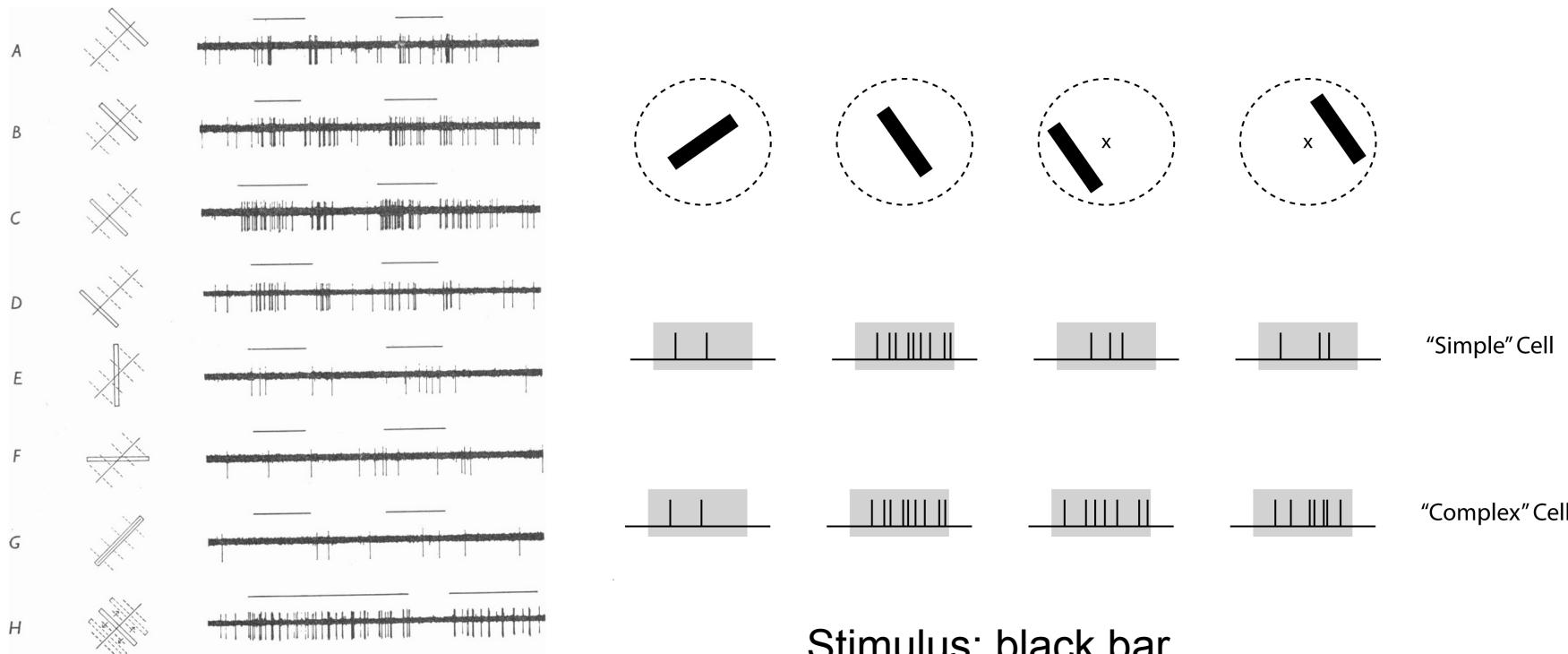
A model for orientation tuning in simple cells



A feed-forward model for orientation selectivity in V1
(by no means the only model)

Wandell (1995), Foundations of Vision. Sinauer Books
Dayan and Abbott. (2001) Theoretical Neuroscience. The MIT Press

Complex cells show position tolerance



Text-fig. 4. Responses of a cell with a complex field to stimulation of the left (contralateral) eye with a slit $\frac{1}{8} \times 2\frac{1}{2}^\circ$. Receptive field was in the area centralis and was about $2 \times 3^\circ$ in size. A-D, $\frac{1}{8}^\circ$ wide slit oriented parallel to receptive field axis. E-G, slit oriented at 45 and 90° to receptive-field axis. H, slit oriented as in A-D, is on throughout the record and is moved rapidly from side to side where indicated by upper beam. Responses from left eye slightly more marked than those from right (Group 3, see Part II). Time 1 sec.

Simple and complex cells in V1 show distinct responses to drifting gratings

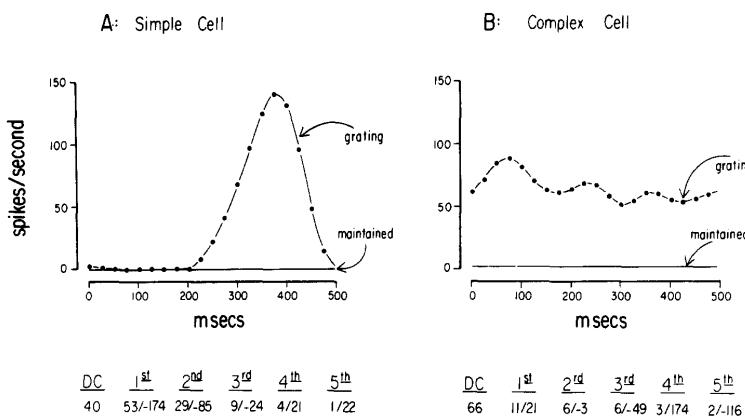


Fig. 1. Response patterns of a representative simple cell (A) and complex cell (B) to gratings drifted across their receptive fields. The response (peri-stimulus time histogram, PSTH) averaged over 20 repetitions of the sinusoidal stimulus is shown above a printout of the d.c. (mean rate of firing) and the first five harmonic components (amplitude/phase). The average maintained discharge in the absence of any visual stimulus is also displayed for each cell. Note that the simple cell's response to the drifting grating shows a discharge pattern which modulates in synchrony with the fundamental temporal cycle of the stimulus, therefore most of the power appears in the 1st harmonic. The complex cell's response, on the other hand, shows an overall increase in the mean rate of firing with little modulation, therefore the response appears in the d.c. component with little power in the harmonics.

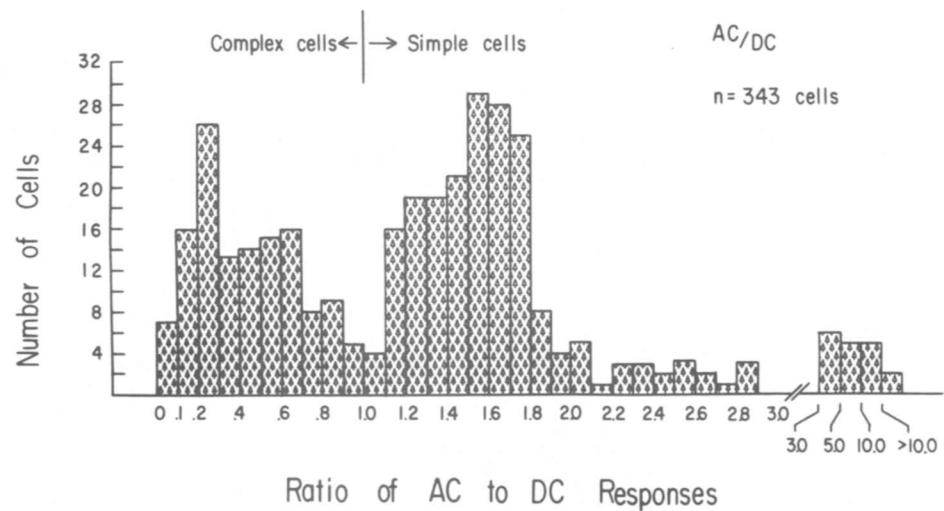
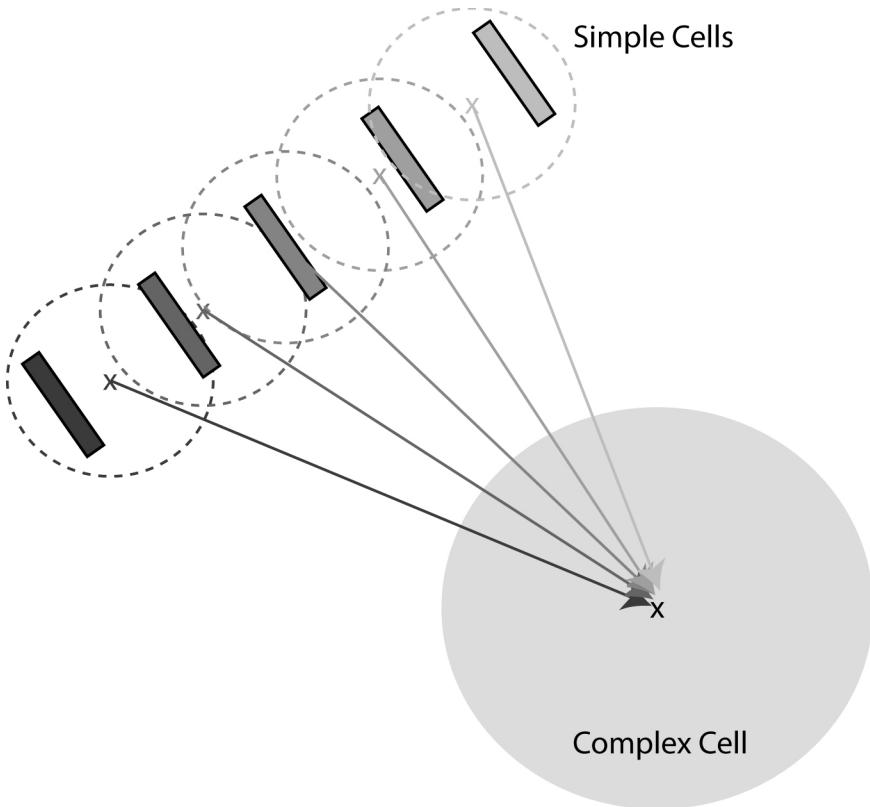


Fig. 3. Distribution of the a.c./d.c. ratio for all cells measured ($n = 343$). Those cells whose d.c. is larger than the a.c. (that is, Y cells) fall between 0.0 and 1.0; those cells whose a.c. is larger than the d.c. fall above 1.0. It is clear that the distribution is best described as bimodal indicating the presence of two distinct populations of cells.

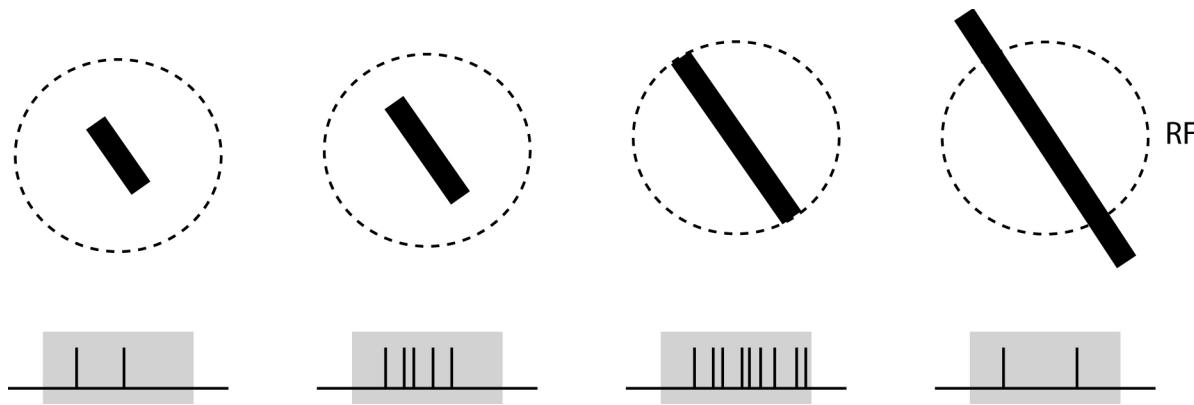
A model to describe tolerance in complex cells



A feed-forward model
describing the responses of
complex cells arising from
non-linear (e.g. OR) adding
of inputs from multiple simple
cells
(by no means the only model)

Wandell (1995), Foundations of Vision. Sinauer Books
Dayan and Abbott. (2001) Theoretical Neuroscience. The MIT Press

End stopping

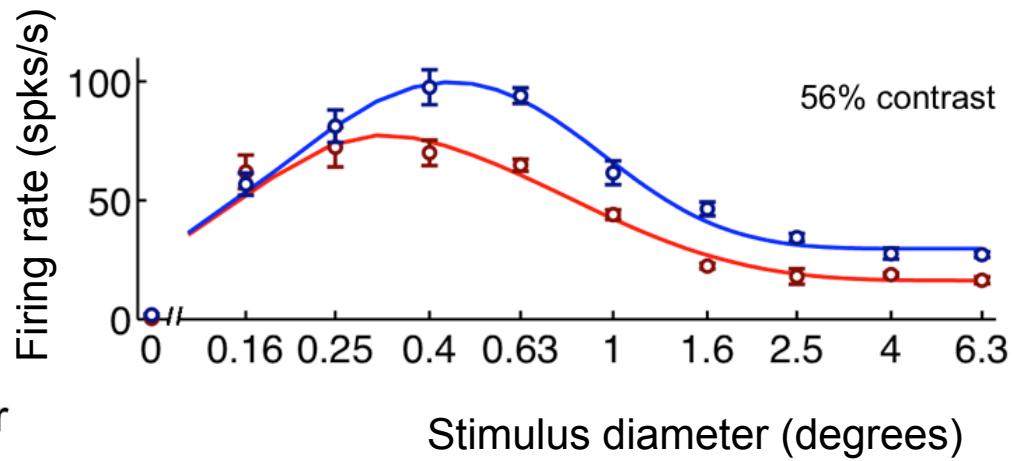
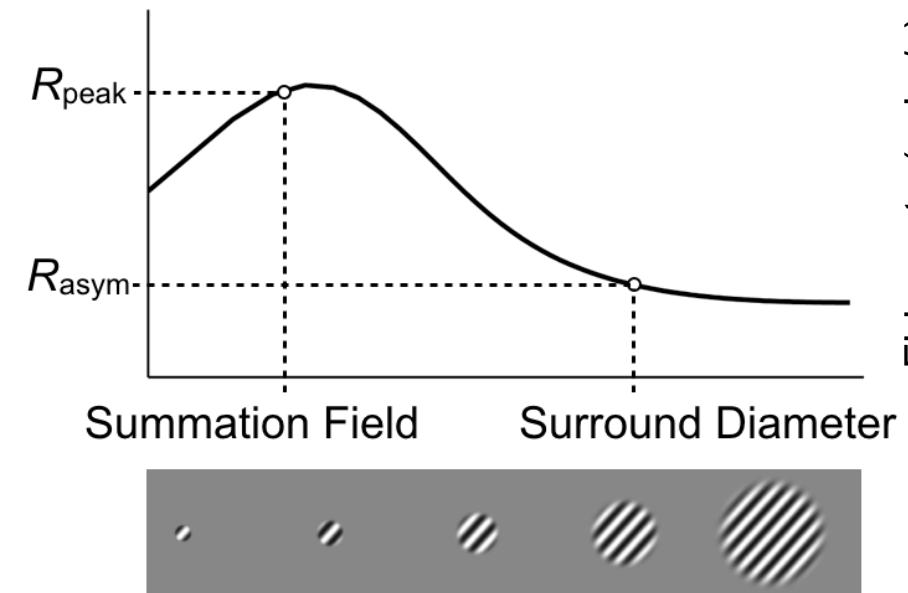


Stimulus: bar with preferred orientation

Stimulus presentation time

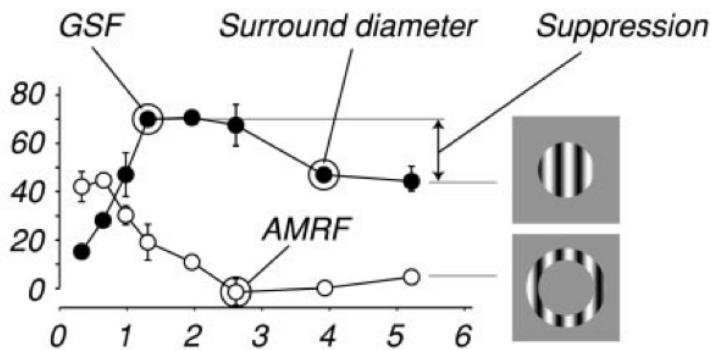
Receptive field

More is not necessarily better: the surround can inhibit the responses of neurons in V1

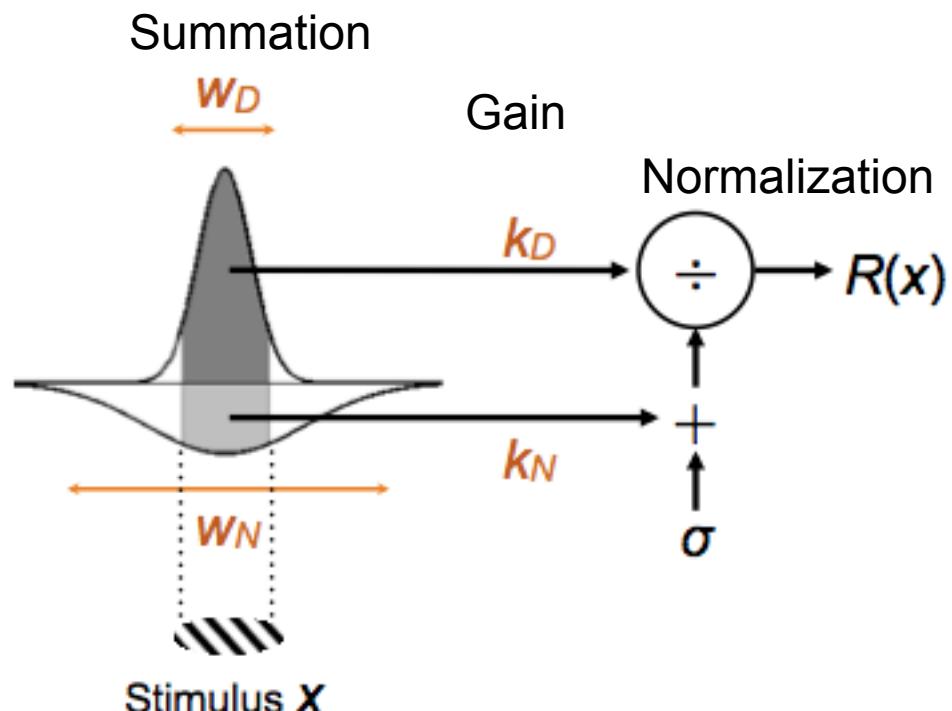


More is not necessarily better: the surround can inhibit the responses of neurons in V1

A



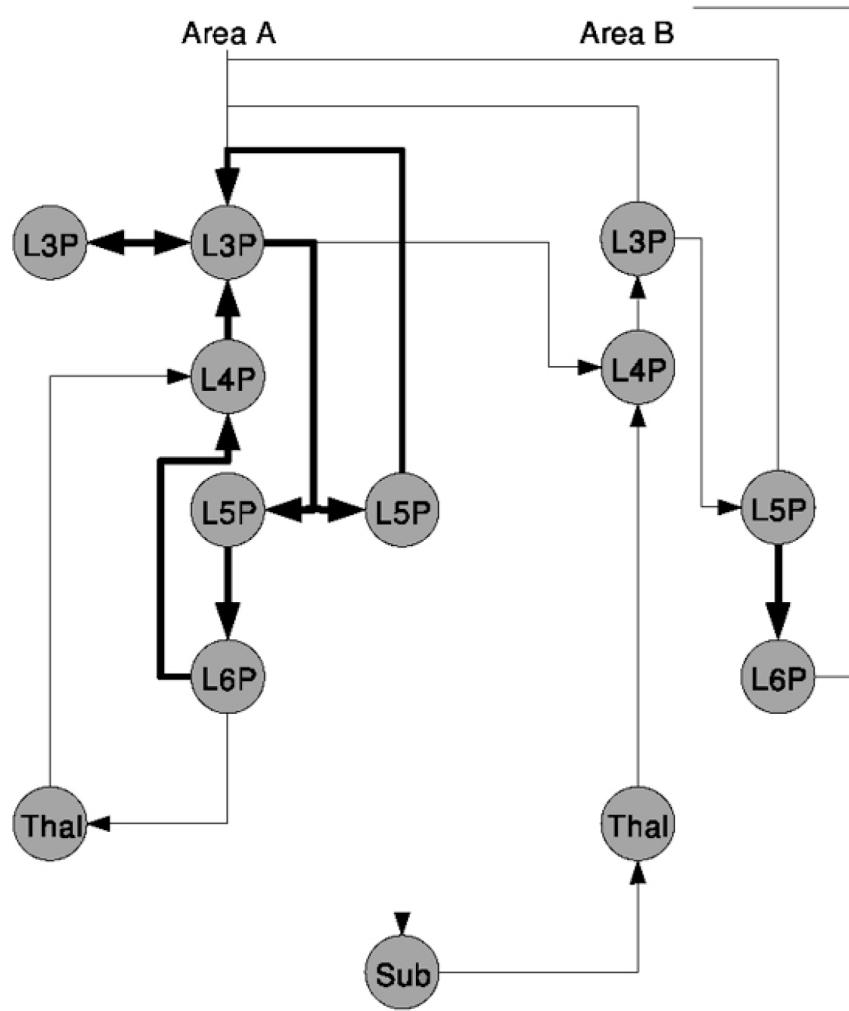
Cavanaugh et al J.
Neurophys 2002



$$R_{\text{ROG}}(x) = R_0 + \frac{k_D [w_D \operatorname{erf}(x/2w_D)]^2}{\sigma + k_N [w_N \operatorname{erf}(x/2w_N)]^2}$$

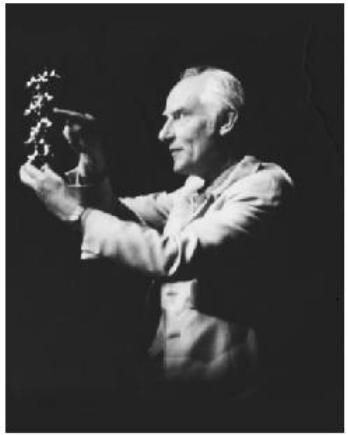
Nassi et al Front. Syst. Neurosci. 2014

“Canonical” microcircuits in neocortex



Felleman and Van Essen 1991
Douglas and Martin 2004

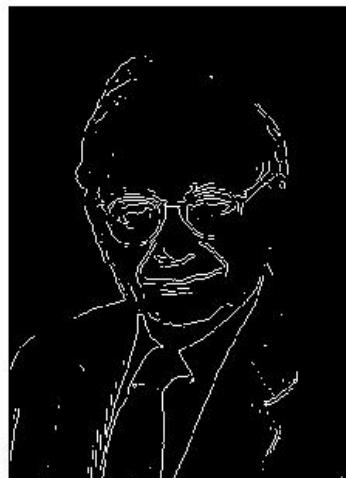
Edges can take us a long way towards object recognition



1.9% of pixels > 0



2.9% of pixels > 0



MATLAB:

I: image

I_edges = edge(I);

Different methods:

Sobel, Prewitt, Roberts,
Laplacian of Gaussian,
Canny

(determining how the
gradients of I are
computed)

Note: this is a major
oversimplification. The output
of V1 does not simply
represent the image edges

Do we know what the early visual system does?

Up to 85% of “V1 function” has yet to be accounted for (Olshausen and Field 2005)

- Biased sampling of neurons
- Biased stimuli
- Biased theories
- Contextual effects
- Internal connections and feedback
- Joint activity

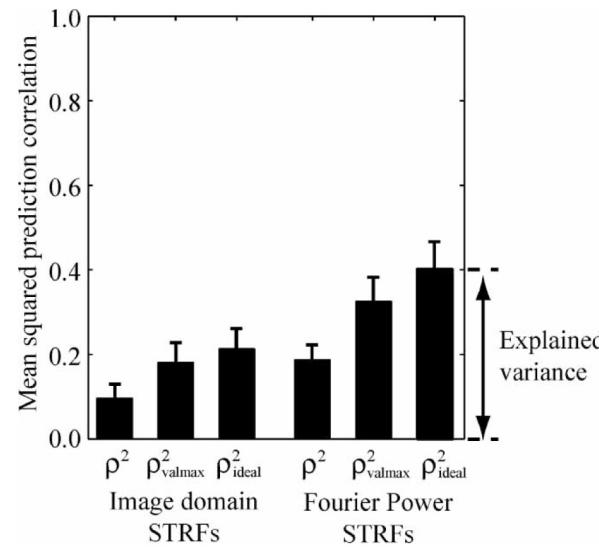


Figure 8. Summary of the effect of finite sampling on predictions. Each bar indicates mean squared prediction correlation for the 49 neurons with greater than 2000 stimulus-response samples (error bars indicate standard error). Data for image domain STRFs are shown at left, and for Fourier power STRFs at right. ρ^2 indicates the mean squared prediction correlation actually measured for the STRFs. ρ^2_{valmax} indicates mean prediction after correcting for finite sampling of validation data. ρ^2_{ideal} indicates the mean prediction after correcting for finite sampling of both estimation and validation data. Fourier power STRFs perform consistently better than image domain STRFs. After correcting for sampling limitations, Fourier power STRFs can account for an average of 40% of the response variance in V1. The remaining portion of the response results from nonlinear response properties ('unexplained variance') not included in the Fourier power model.

David and Gallant, J.L. Network (2005)

Further reading

Further reading

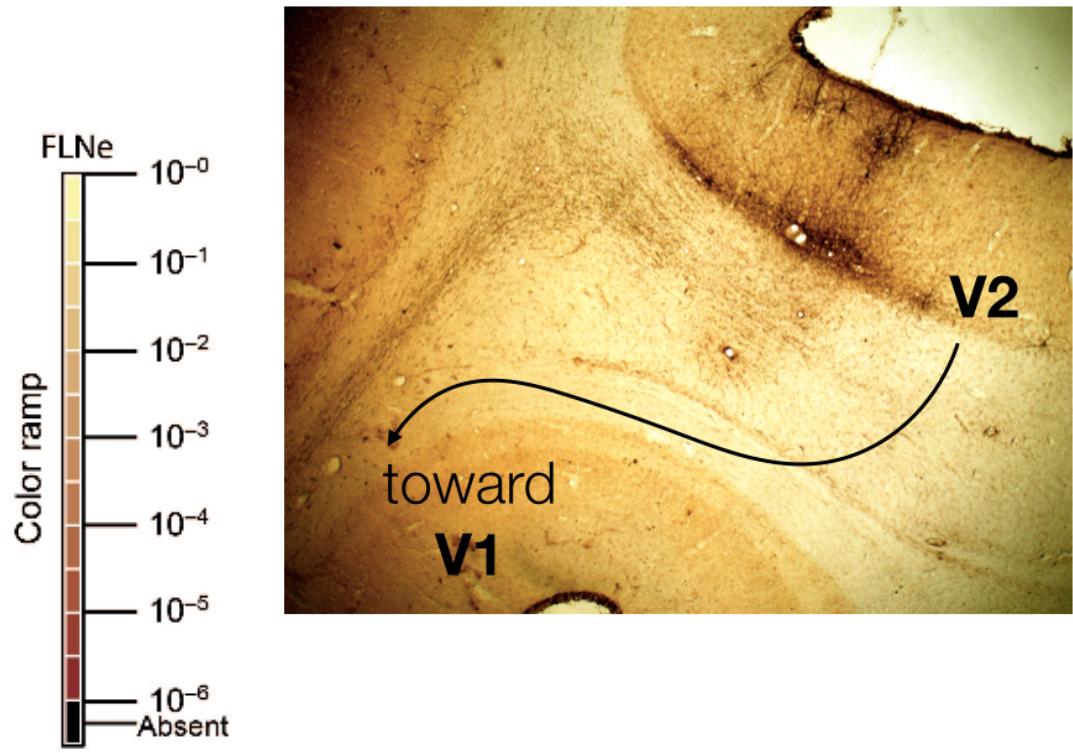
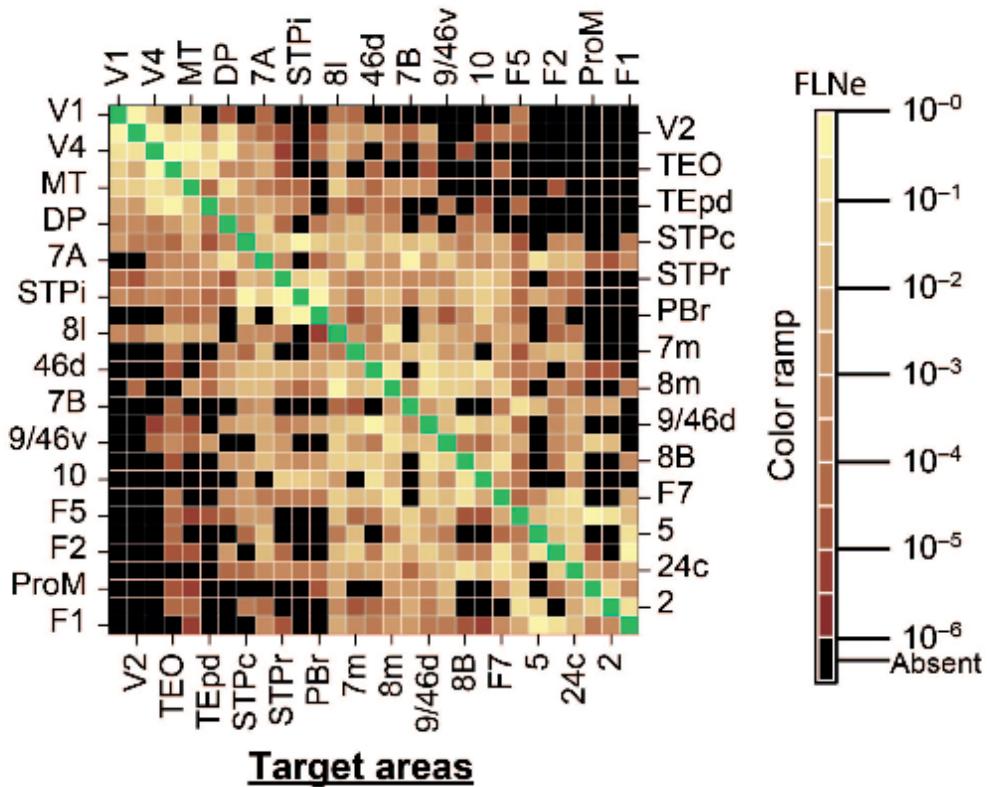
- Wandell B. Foundations of Vision. Sinauer Books 1995.
- Dayan and Abbott. Theoretical Neuroscience. MIT Press 2001.

Original articles cited in class

- Simoncelli and Olshausen. Annual Review of Neuroscience 2001
- Hubel and Wiesel. Journal of Physiology 1968.
- Carandini et al. Journal of Neuroscience 2005.
- Keat et al. Neuron 2001.
- Felleman and Van Essen. Cerebral Cortex 1991.
- Douglas and Martin. Annual Review of Neuroscience 2004.
- De Valois et al. Vision Research 1982

There are more top-down connections than bottom-up ones

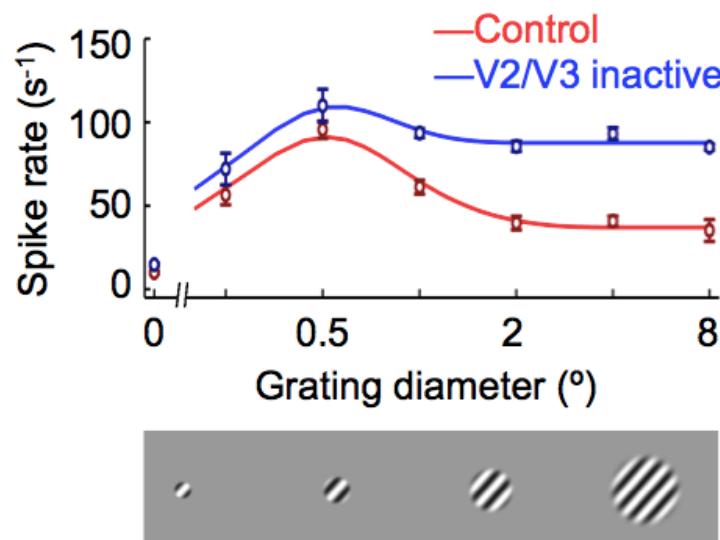
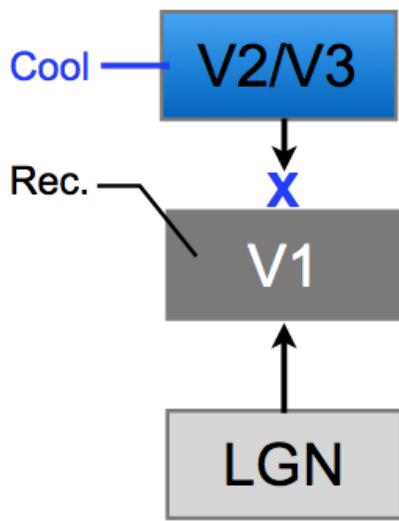
B



Markov et al.

Cerebral Cortex 2014

Inactivating feedback to V1 leads to less surround suppression



Cited works

- Carandini, M., Demb, J. B., Mante, V., Tolhurst, D. J., Dan, Y., Olshausen, B. A., Gallant, J. L., & Rust, N. C. (2005). Do we know what the early visual system does?. *The Journal of neuroscience*, 25(46), 10577-10597.
- David, S. V., & Gallant, J. L. (2005). Predicting neuronal responses during natural vision. *Network: Computation in Neural Systems*, 16(2-3), 239-260.
- Dayan, P., and Abbott, L. (2001). *Theoretical Neuroscience* (Cambridge: MIT Press).
- De Valois, R. L., Albrecht, D. G., & Thorell, L. G. (1982). Spatial frequency selectivity of cells in macaque visual cortex. *Vision research*, 22(5), 545-559.
- Douglas, R. J., & Martin, K. A. (2004). Neuronal circuits of the neocortex. *Annu. Rev. Neurosci.*, 27, 419-451.
- Felleman, D. J., & Van Essen, D. C. (1991). Distributed hierarchical processing in the primate cerebral cortex. *Cerebral Cortex*, 1(1), 1-47.
- Glickstein, M. (1988). The discovery of the visual cortex. *Scientific American*, 259(3), 84-91.
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