COMS30127/COMSM2127
Computational Neuroscience

Lecture 12: V1 and sparse coding (g)

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What we will cover today

- V1 single cell responses: simple vs complex cells.
- The cortical microcircuit.
- Topographic maps.
- Sparse coding.

Primary visual cortex

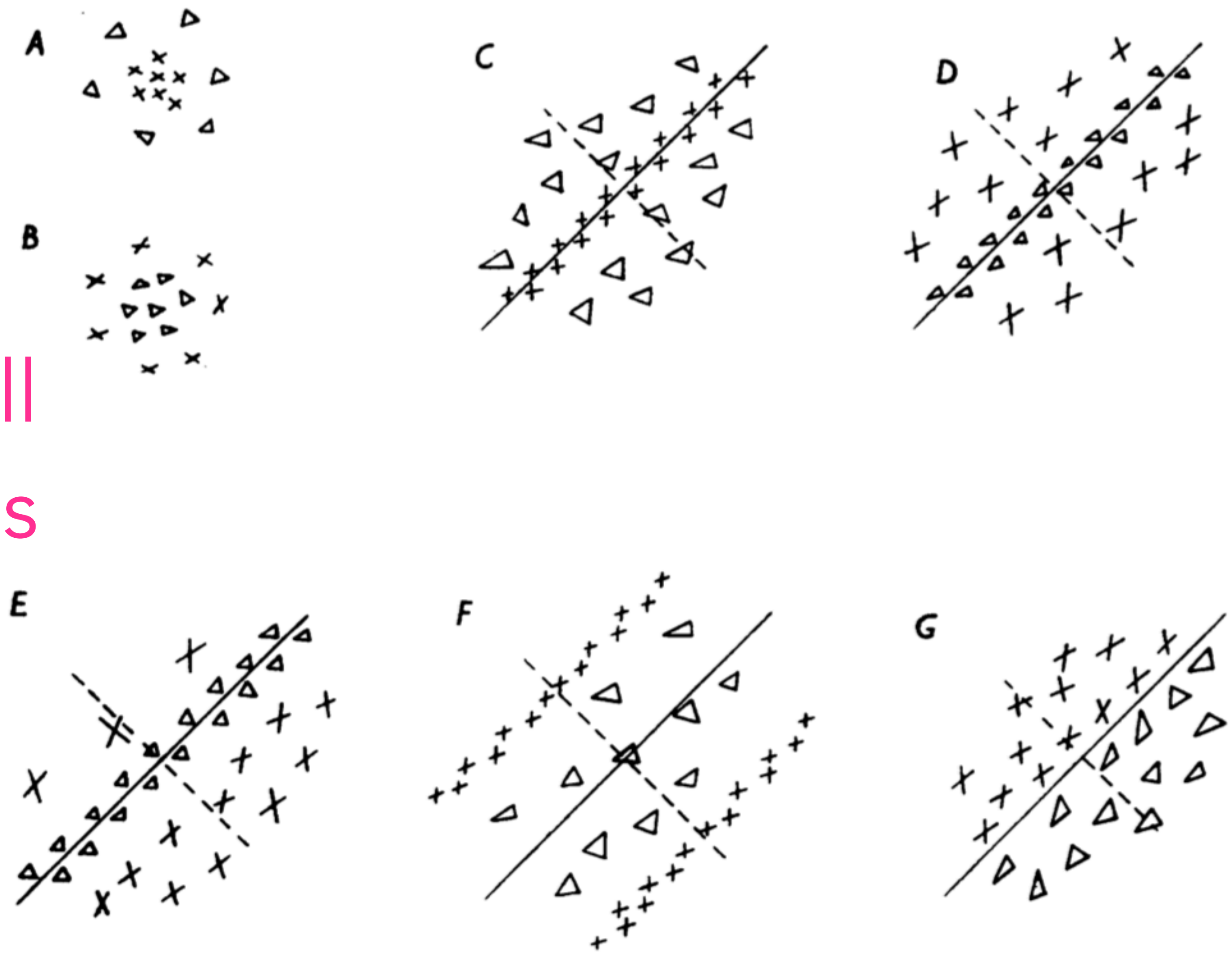
- First place visual information arrives in the cortex.
- Variously known as V1, primary visual cortex, or striate cortex.
- Single V1 neurons tend to respond to basic features of the visual stimulus, like oriented edges.
- Often thought of as a canonical cortical region.

Simple vs complex cells

- Classical neurophysiologists distinguished two dominant types of single cell responses in V1.
- “Simple cells” respond to oriented edge/grating stimuli in a specific part of visual field only.
- “Complex cells” also respond to oriented stimuli, but exhibit some degree of spatial invariance. They will respond similarly no matter where the stimulus is located within the receptive field.

Simple vs complex cells

Simple cell receptive fields

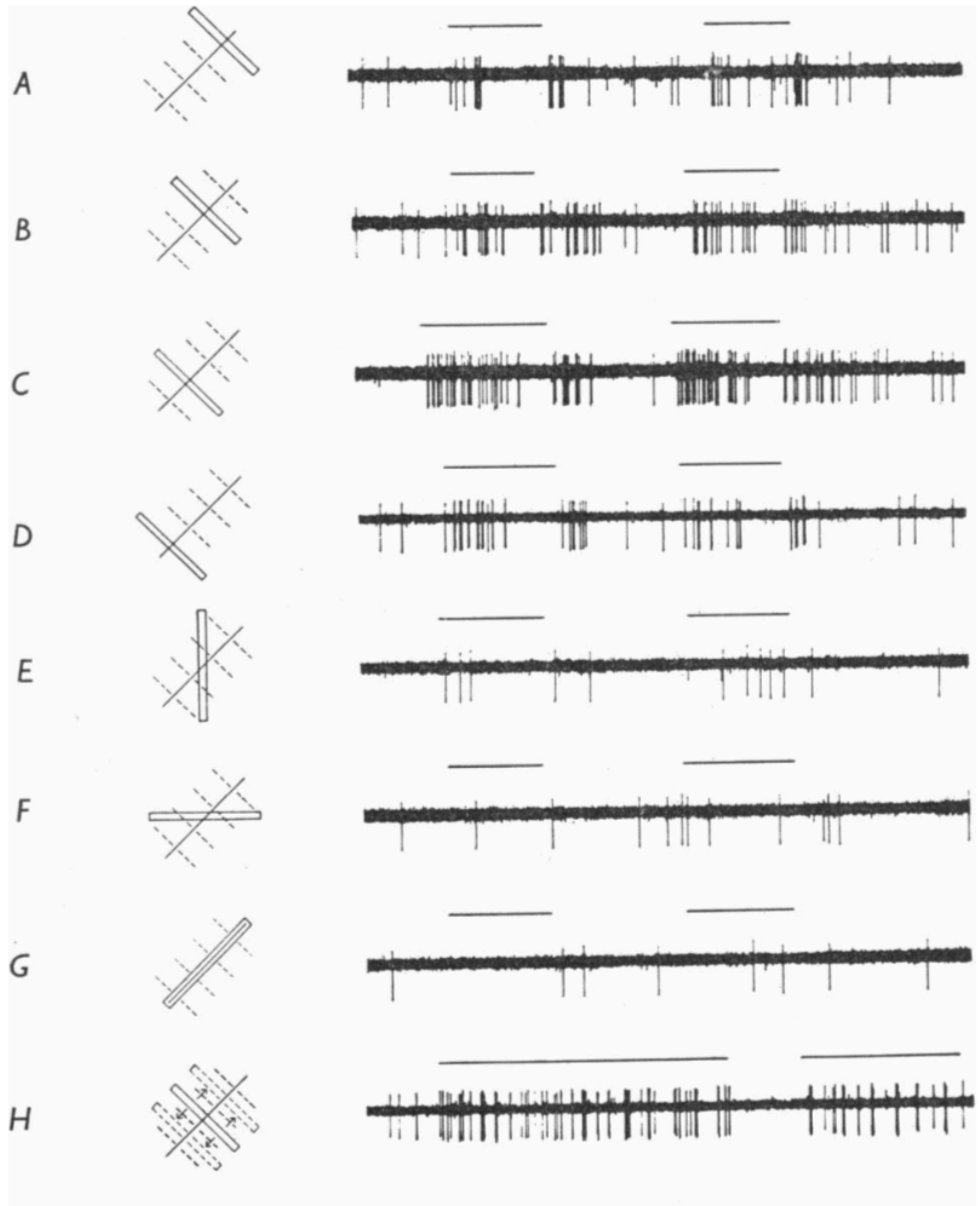


Text-fig. 2. Common arrangements of lateral geniculate and cortical receptive fields. *A*. 'On'-centre geniculate receptive field. *B*. 'Off'-centre geniculate receptive field. *C–G*. Various arrangements of simple cortical receptive fields. ×, areas giving excitatory responses ('on' responses); △, areas giving inhibitory responses ('off' responses). Receptive-field axes are shown by continuous lines through field centres; in the figure these are all oblique, but each arrangement occurs in all orientations.

[Hubel and Wiesel, J Physiol, 1962]

Simple vs complex cells

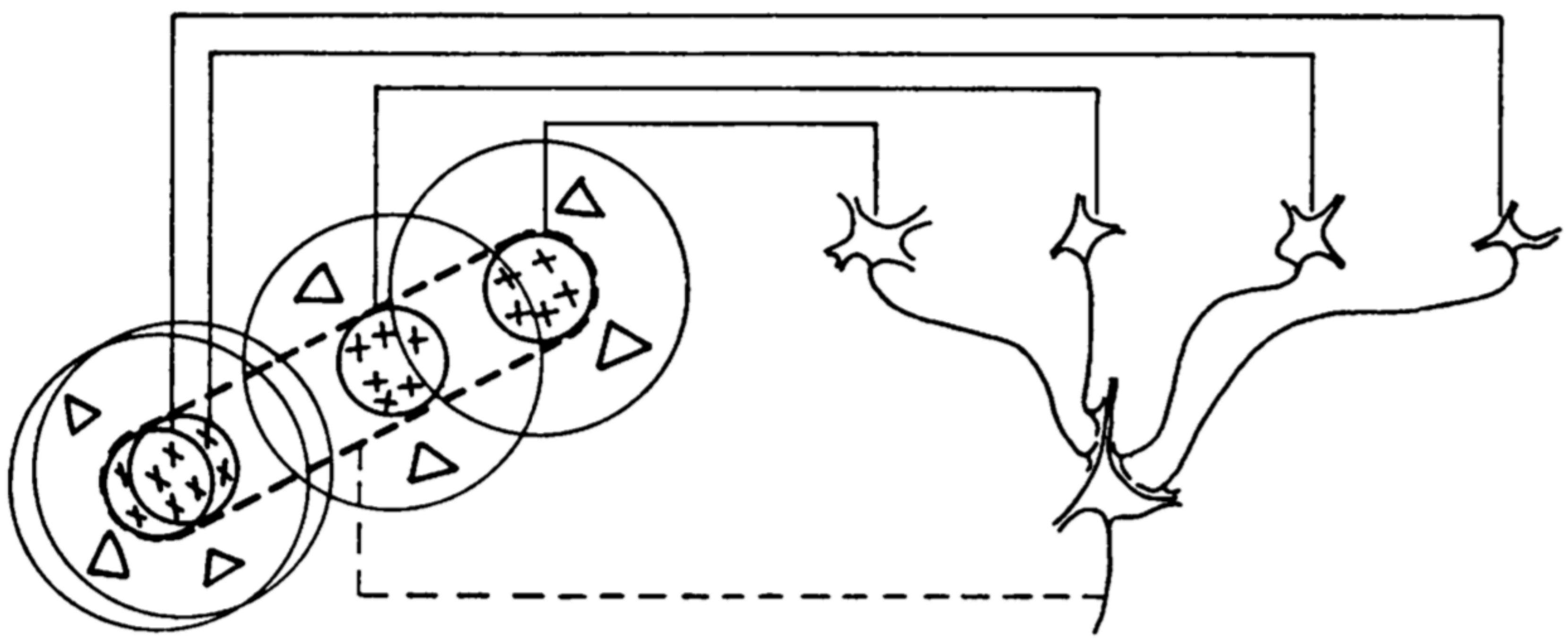
Complex cell responses



Text-fig. 4. Responses of a cell with a complex field to stimulation of the left (contralateral) eye with a slit $\frac{1}{8} \times 2\frac{1}{2}°$. Receptive field was in the area centralis and was about $2 \times 3°$ in size. *A–D*, $\frac{1}{8}°$ 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.

[Hubel and Wiesel, J Physiol, 1962]

Hubel and Wiesel's model for orientation tuning



Text-fig. 19. Possible scheme for explaining the organization of simple receptive fields. A large number of lateral geniculate cells, of which four are illustrated in the upper right in the figure, have receptive fields with 'on' centres arranged along a straight line on the retina. All of these project upon a single cortical cell, and the synapses are supposed to be excitatory. The receptive field of the cortical cell will then have an elongated 'on' centre indicated by the interrupted lines in the receptive-field diagram to the left of the figure.

[Hubel and Wiesel, J Physiol, 1962]

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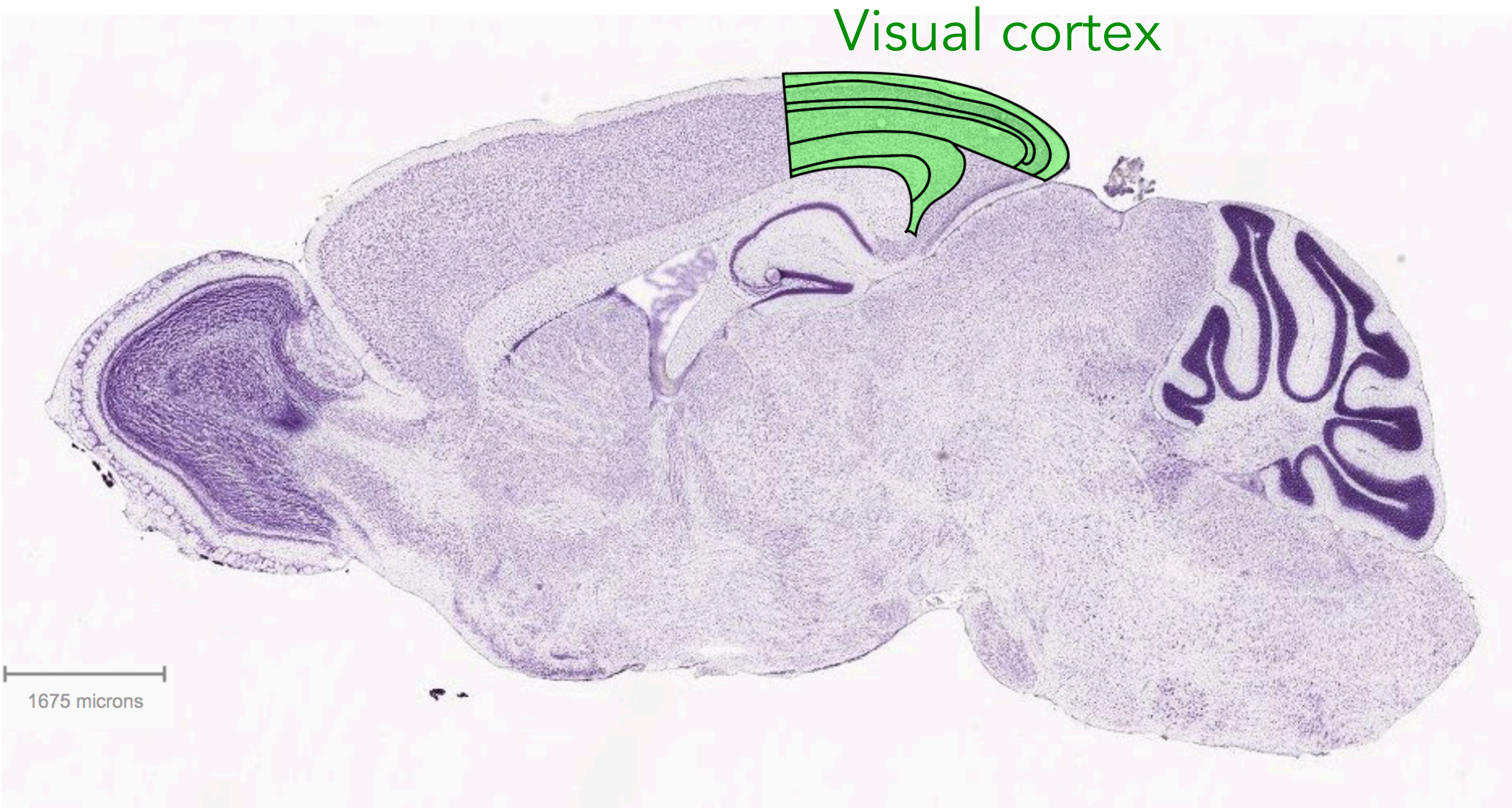
Cortical microcircuit



Allen Institute: http://atlas.brain-map.org

Cortical microcircuit

- The mammalian neocortex is fairly homogeneous: most parts of it look similar (with some key exceptions).
  - Therefore the hope is that if we could understand how V1 works, then we can generalise those principles to the rest of cortex.

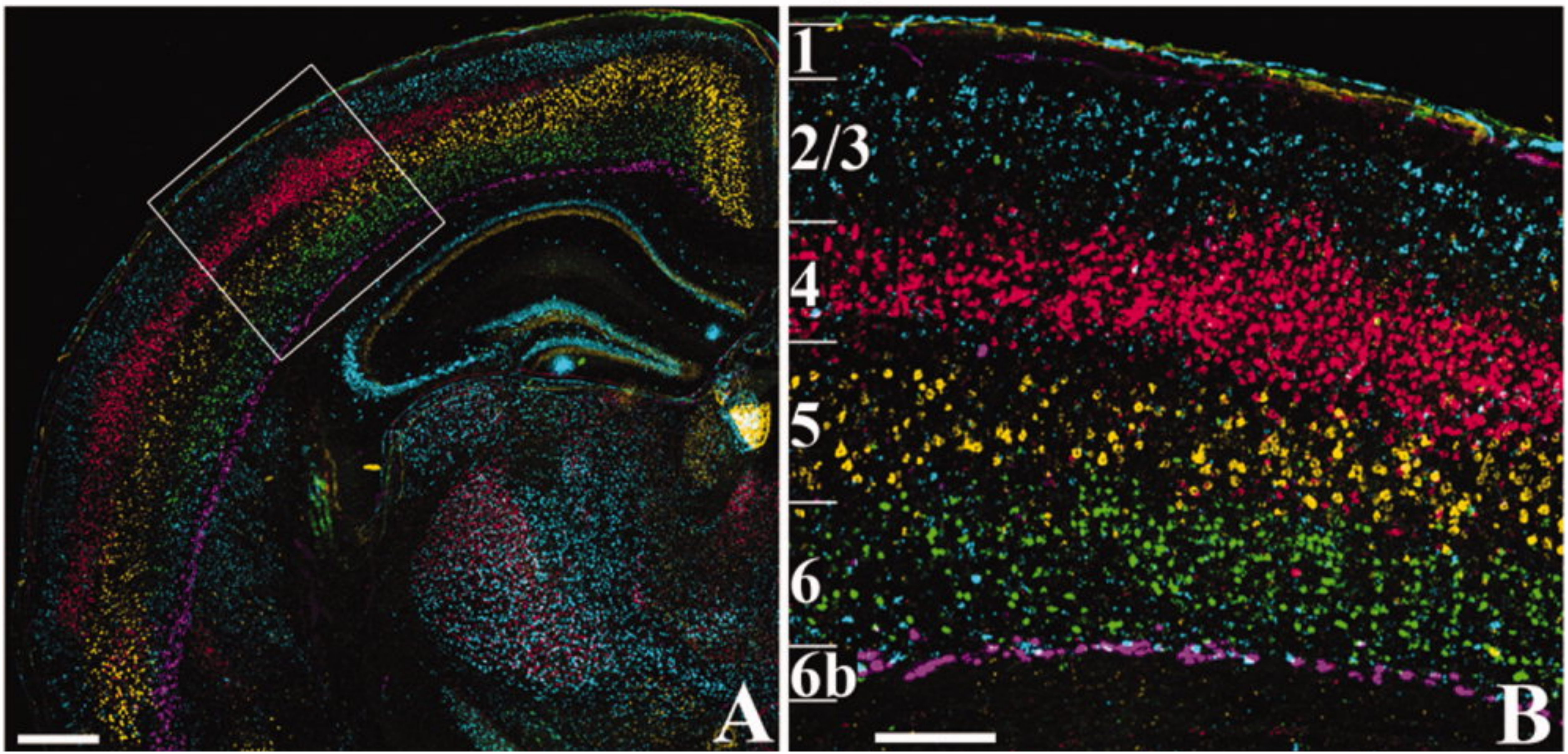
- V1 has six layers, numbered from 1–6 starting at the brain surface (i.e. layer 1 is the most superficial, layer 6 is the deepest.

- Each layer has a mix of distinct excitatory and inhibitory cell types.
  - There are numerically more excitatory neurons than inhibitory neurons (around a 80/20% split), but there are many more subtypes of inhibitory neuron (around 10–20) than excitatory neuron (around 4–6).

- The classic route for information flow is:
  Thalamus → layer 4 → layer 2/3 → layer 5 → other parts of the brain.

Cortical microcircuit

Layers

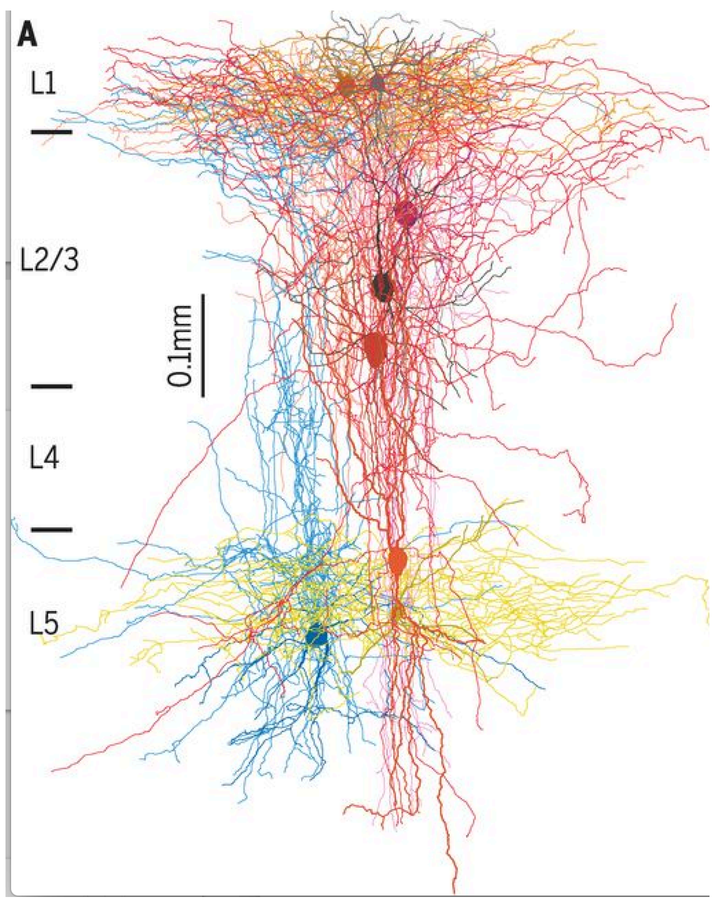


[Boyle et al., *J Neurosci*, 2011]

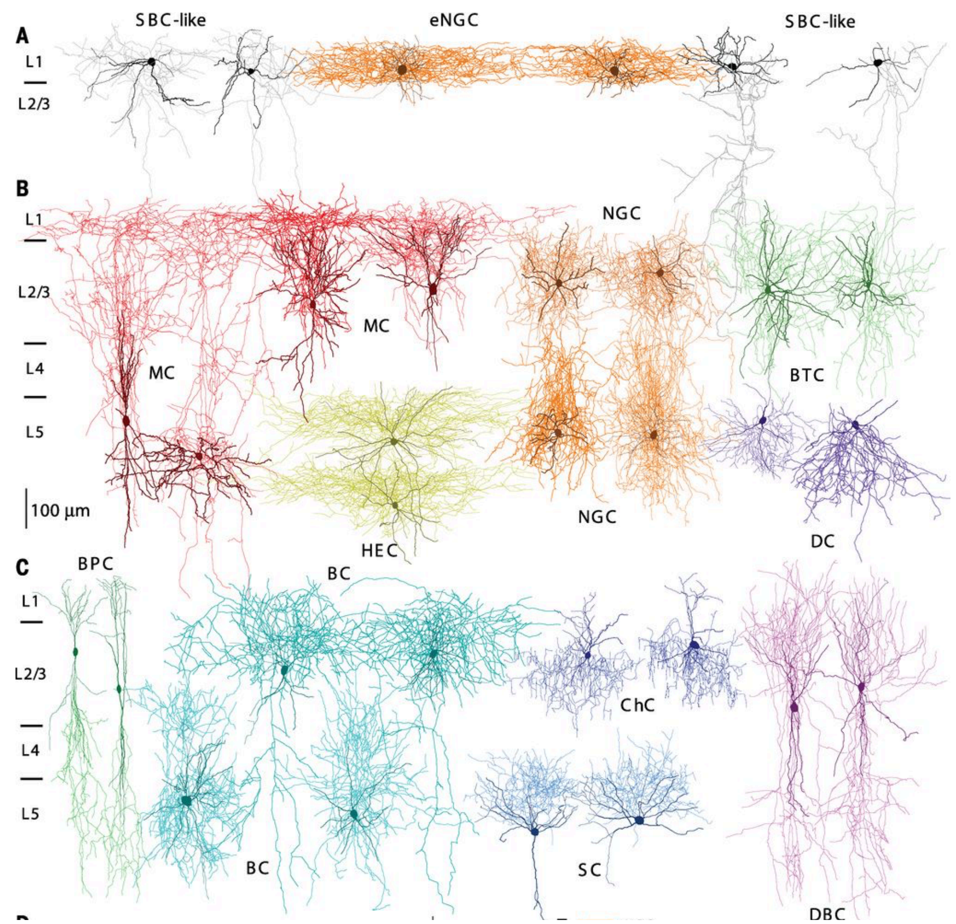
Cortical microcircuit

The circuit diagram

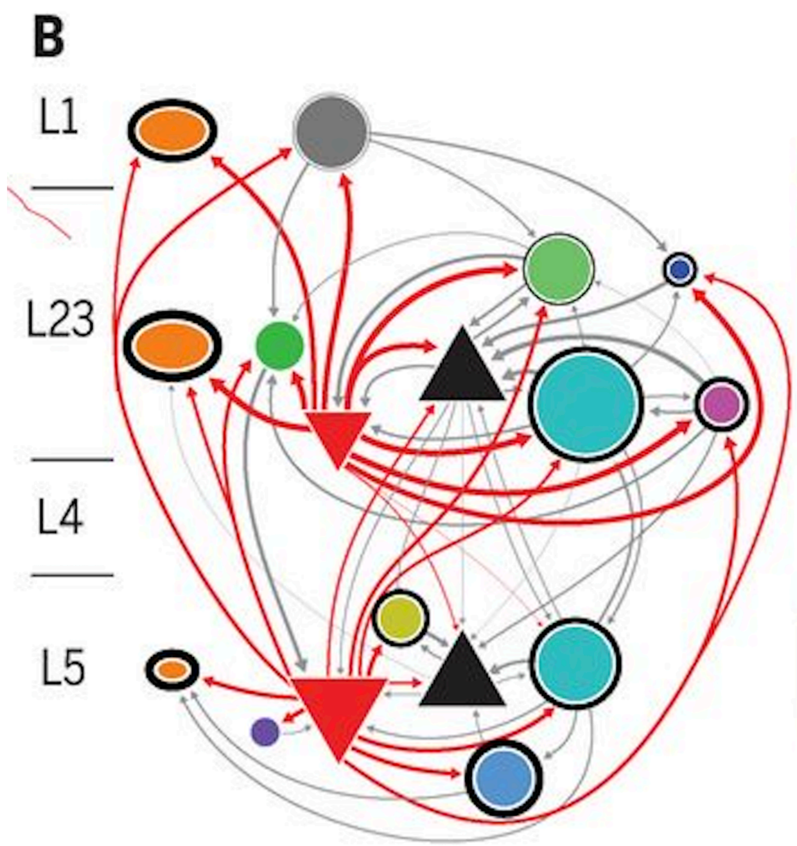
Excitatory (pyramidal) neurons



Inhibitory neurons

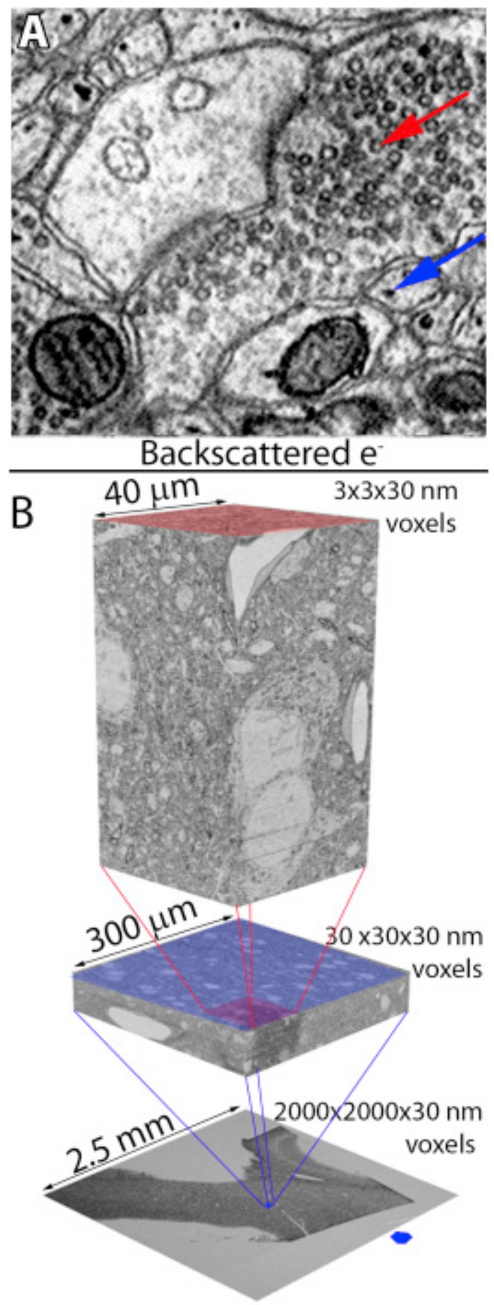


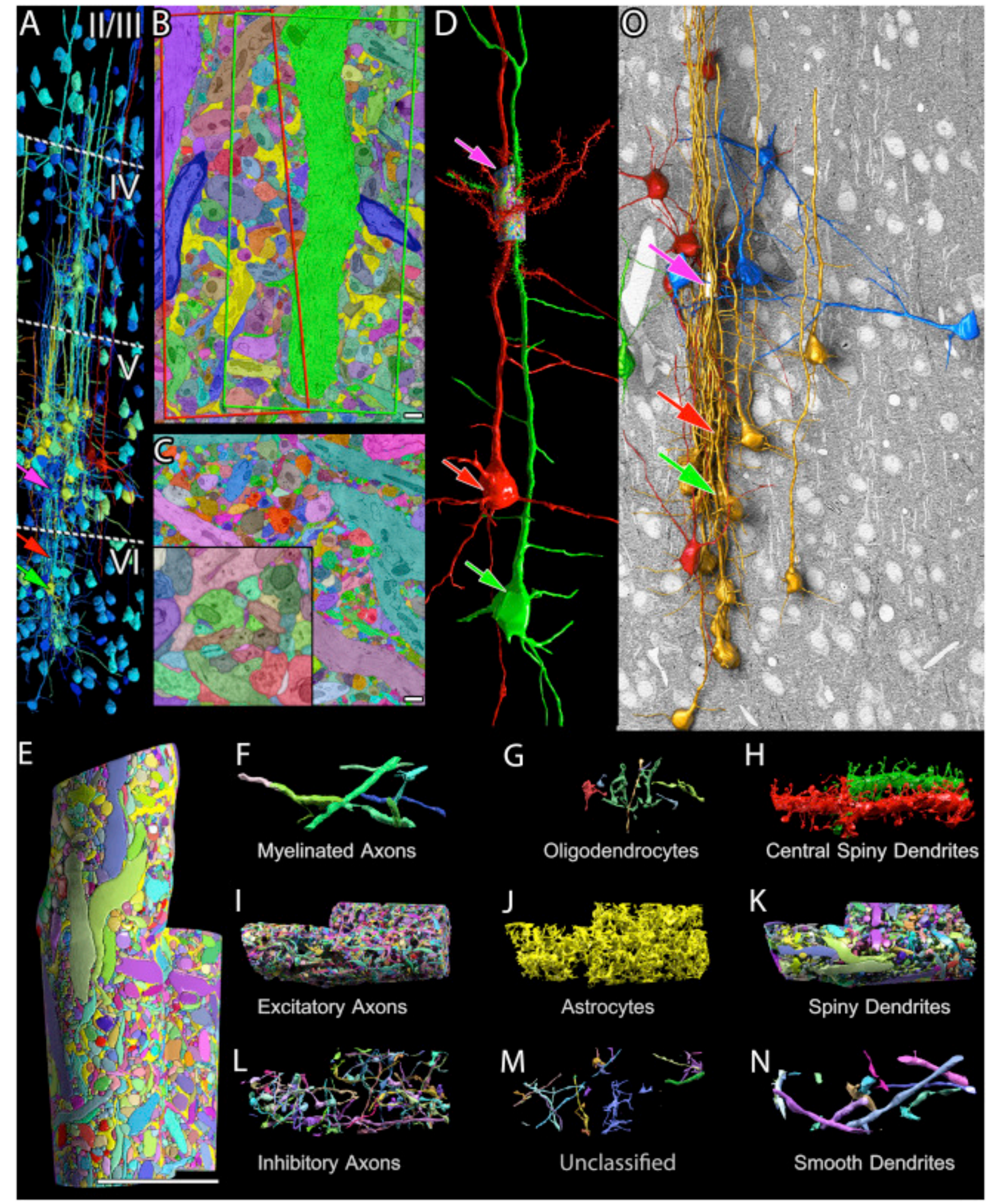
Circuit diagram



[Jiang et al., *Science*, 2015]

Cortical microcircuit





Links for movies on labeling and flythrough.

Large-scale electron-microscopy to reconstruct cortical circuit at nm resolution.

[Kasthuri et al., *Cell*, 2015]

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Topographic maps

- Topographic maps are when anatomically nearby neurons in cortex demonstrate similar functional properties.

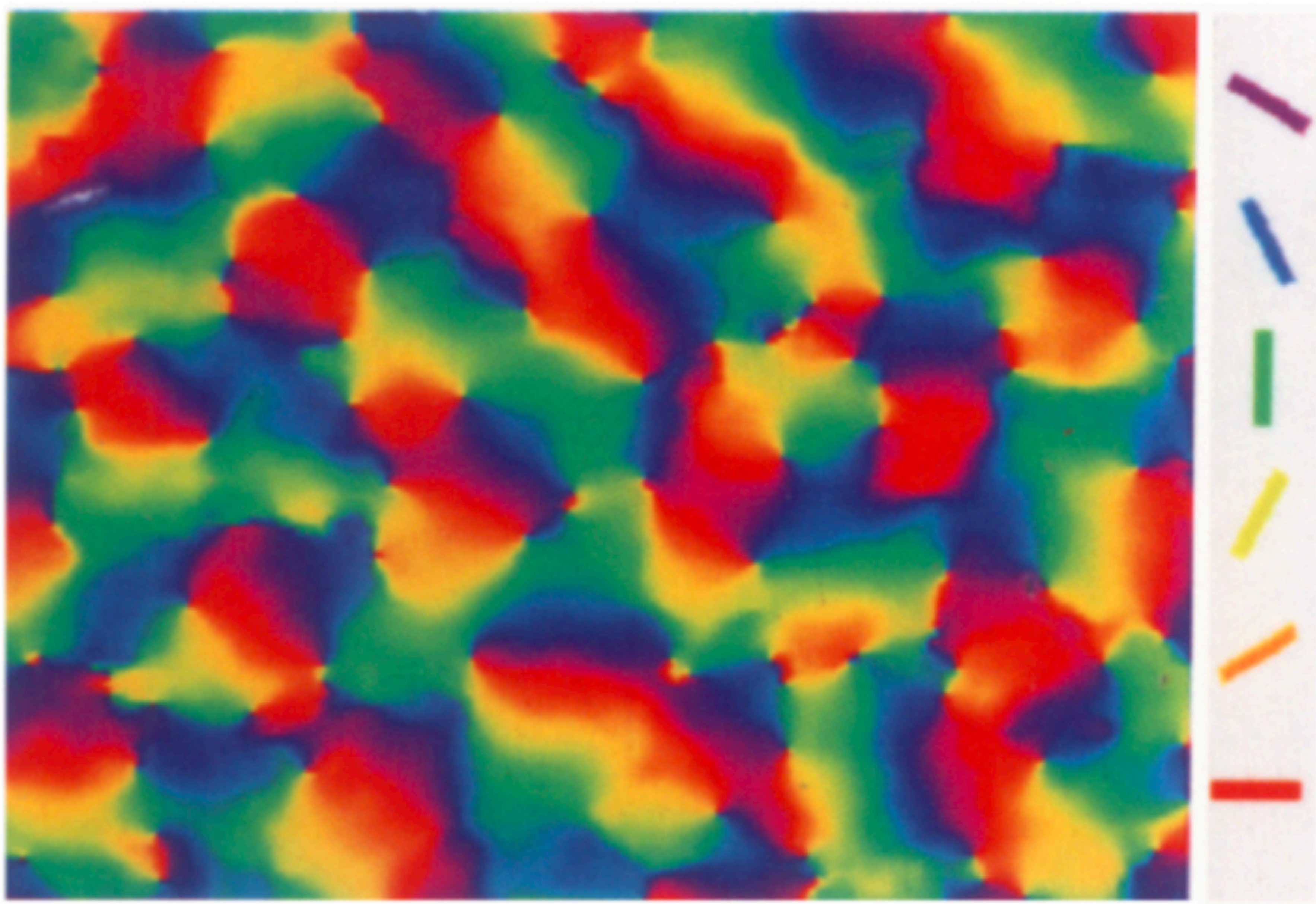
- First described by Vernon Mountcastle (*J Neurophysiol*, 1957).

- The retinotopic map (nearby locations in the visual field map to anatomically nearby locations in cortex) is one example.

- The visual cortex in most mammals has multiple topographic maps superimposed, according to: orientation preference, ocular dominance, motion direction preference, spatial frequency sensitivity, etc.

- Also exist in other parts of the brain: auditory cortex has a tonotopic map, somatosensory cortex has a somatotopic map, etc.

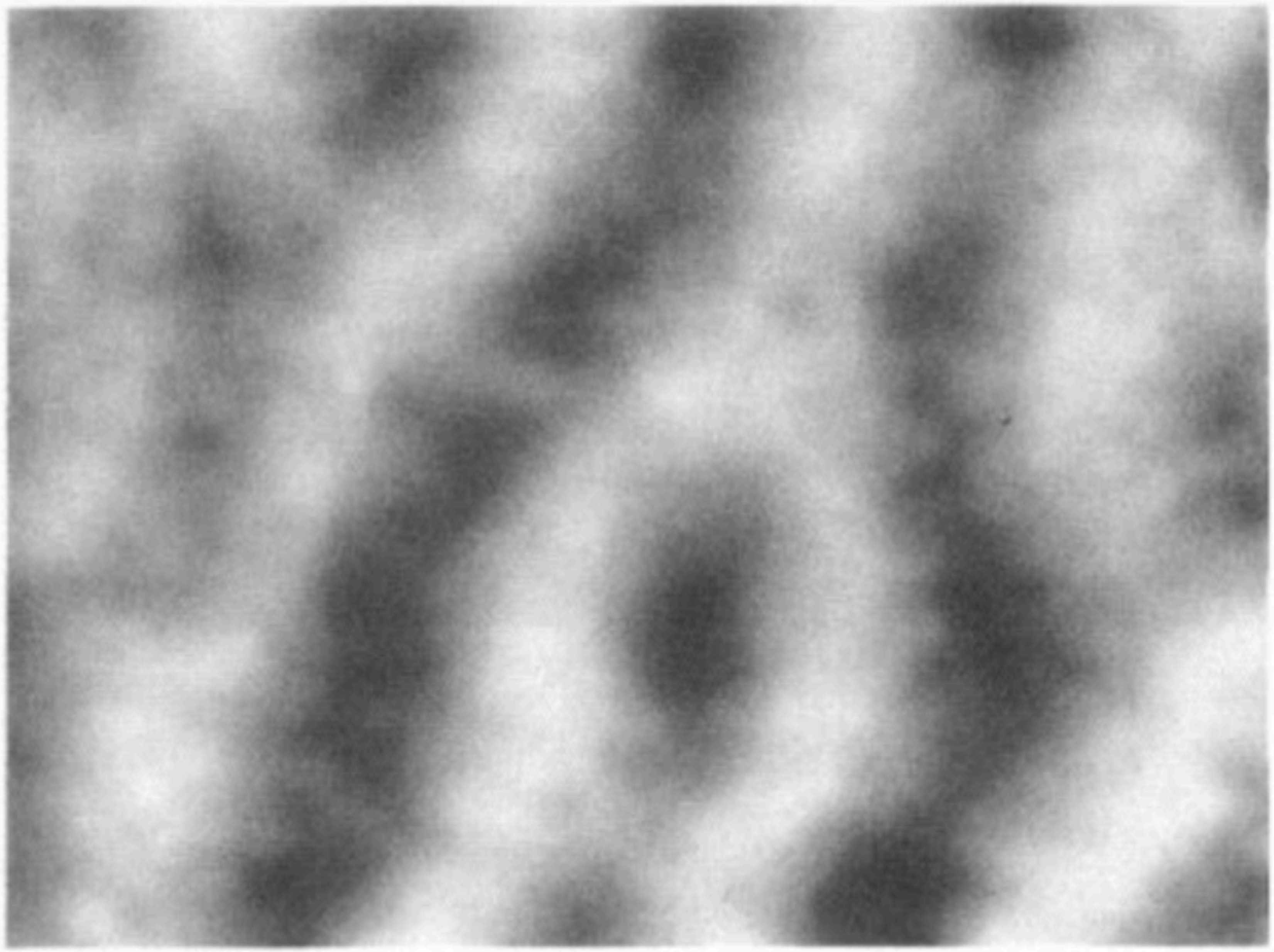
Orientation preference maps



Intrinsic imaging of orientation preference patches at the surface of macaque V1.

Blasdel, *J Neurosci* (1992)

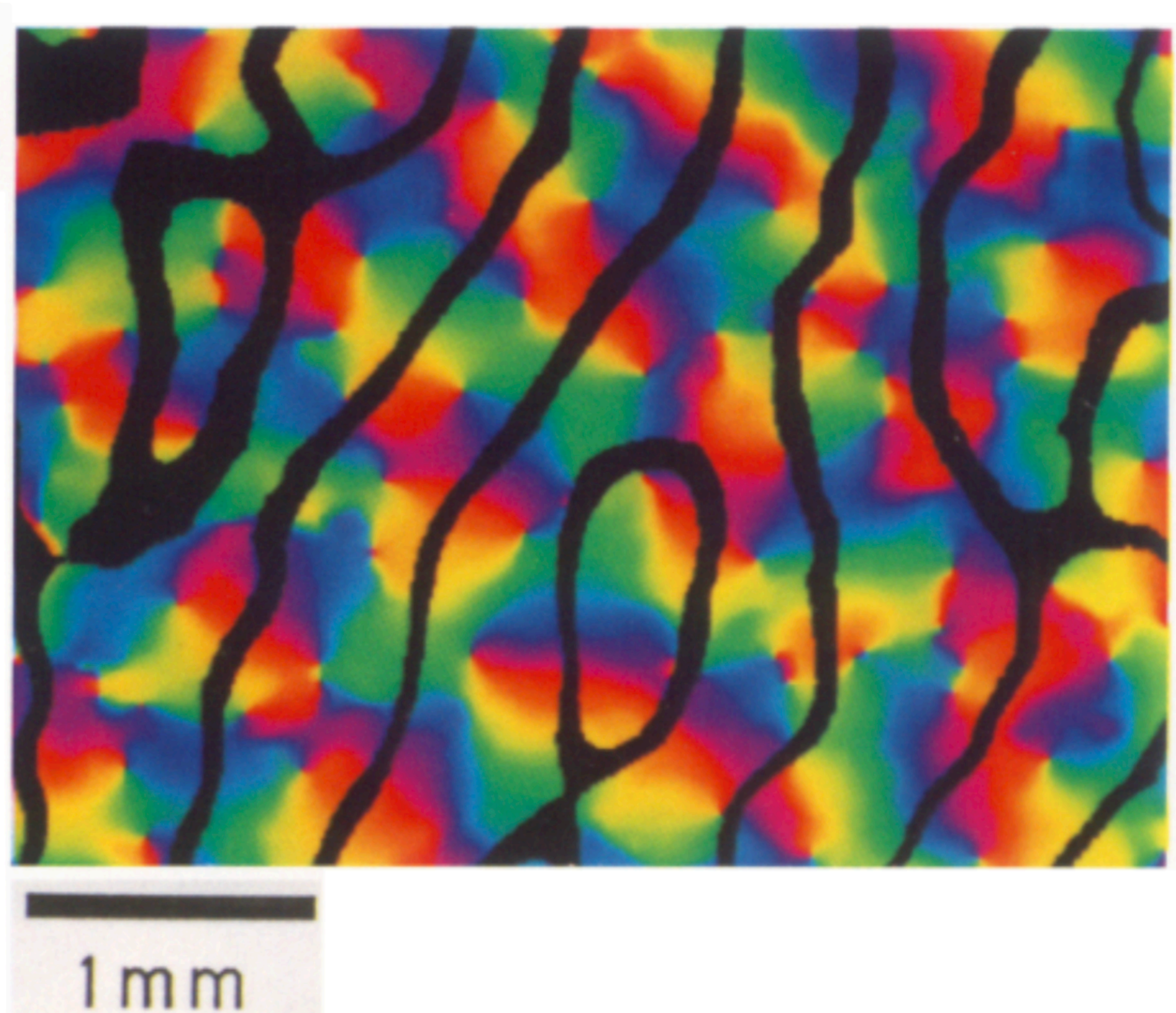
Ocular dominance maps



Intrinsic imaging of ocular dominance patches at the surface of macaque V1.

Blasdel, *J Neurosci* (1992)

Interaction between OR and OD maps



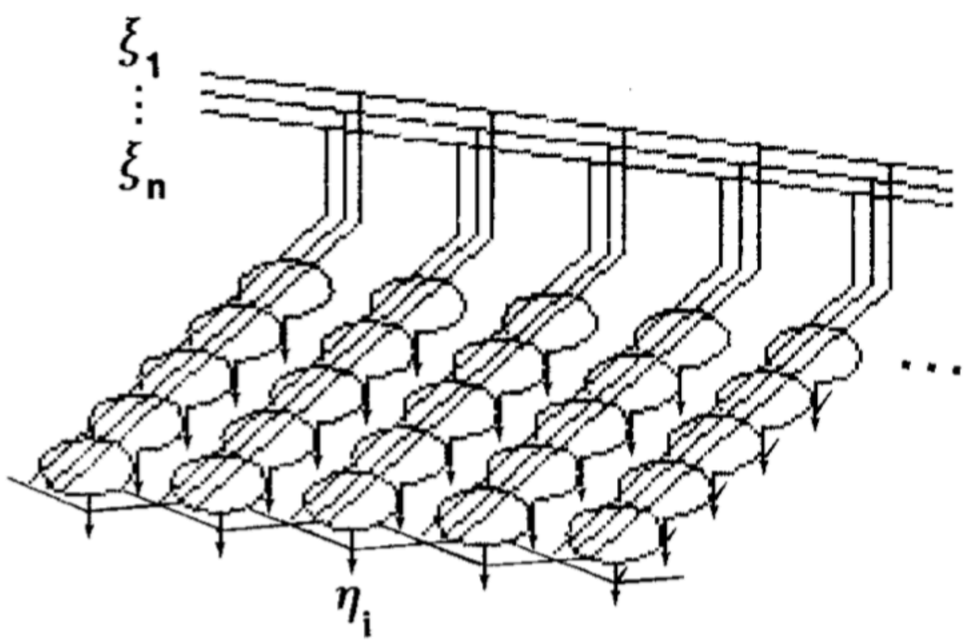
Blasdel, *J Neurosci* (1992)

Models of V1 development

- Various computational models have been proposed to explain aspects of visual cortex development.
- Ocular dominance columns classic example (Kenneth Miller). Requires symmetry-breaking.
- Kohonen map (a.k.a. self-organising map) can generically explain topographic map formation.

Kohonen map

Algorithm for learning self-organised maps



- Neuron i's output y_i is a weighted sum of inputs x_js
  $$y_i = \sum_j w_{ij} x_j$$
- Present an input pattern $x^{(t)}$ (indexed by t), find the most active neuron in the array, $\max(\boldsymbol{x}^{(t)})$
- Only update the weights of the most active neuron plus its nearest neighbours in the grid, according to the rule:
  $$w^{(t+1)} = \frac{w^{(t)} + \alpha x^{(t)}}{C}$$
  where C is a normalising constant to keep the weight vectors of unit length.
- Repeat from step 2. This results in the weights of neighbouring units becoming more similar with training.

Kohonen, *Biol Cybern* (1982)

Kohonen map

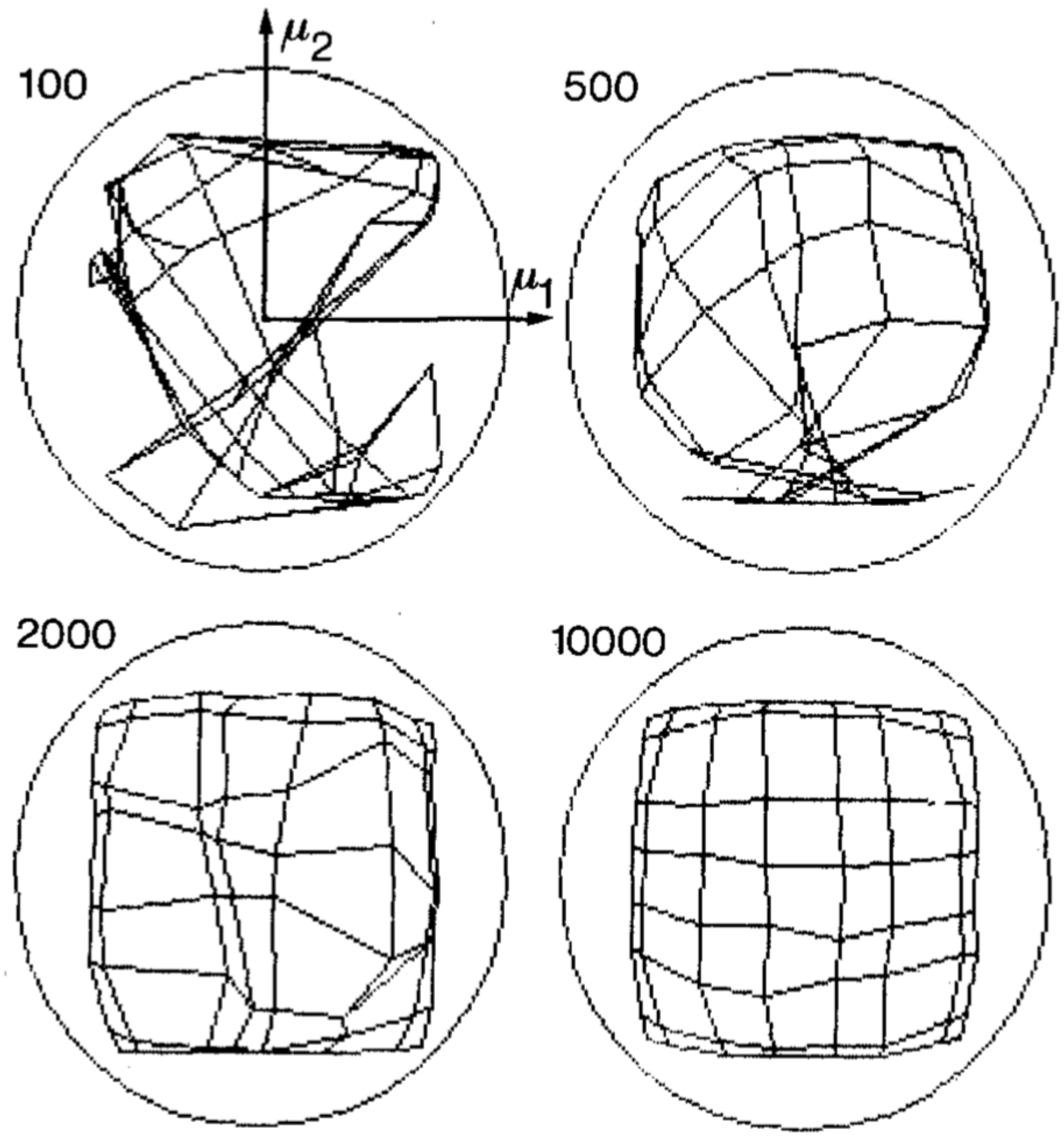


Fig. 4. Distribution of the weight vectors $m_i(t)$ at different times. The number of training steps is shown above the distribution. Interaction between nearest neighbours only

Kohonen, *Biol Cybern* (1982)

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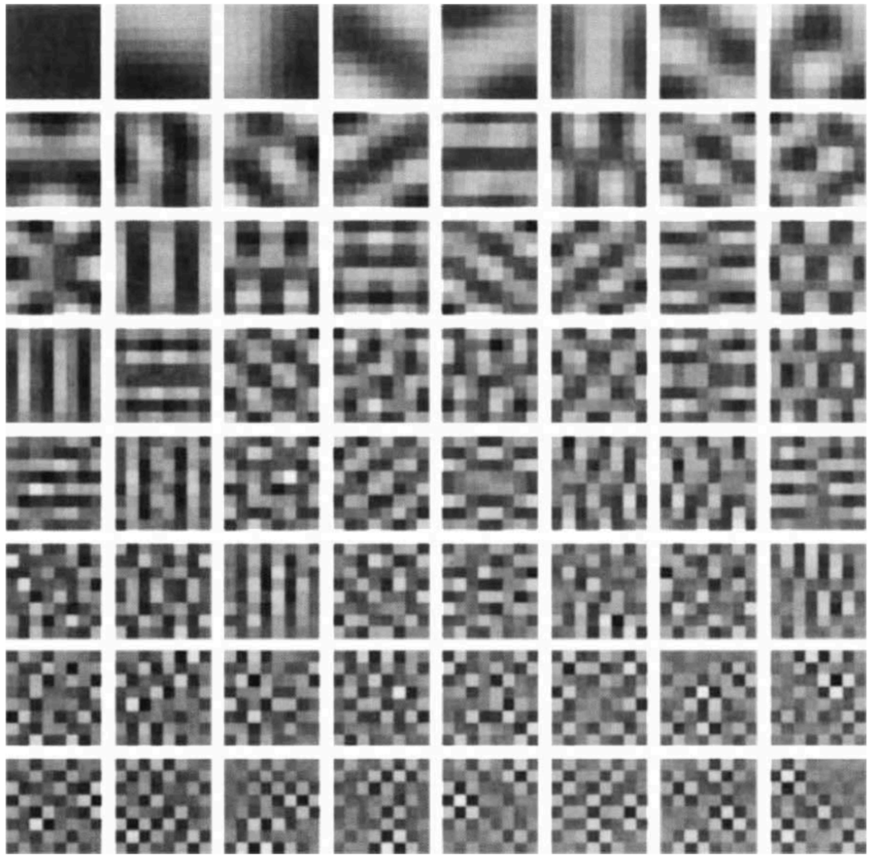
Sparse coding

- The activity in many brain regions is sparse: many neurons are often silent.
- Sparse codes sit somewhere between dense codes (all neurons participate in all patterns) and fully local codes (only one neuron active for each type of sensory signal).
- Sparsity may resolve a tradeoff between energy efficiency and representational capacity.
- Theoretical neuroscientists have found that sparse coding can also provide computational benefits:
  - Sparsity can enhance discriminability; less overlap between patterns.
  - Sparsity can act as a form of regularisation; many signals in the outside world are inherently sparse, so sparse brain coding can speed up learning of sensory signal statistics.
- Further reading: http://www.scholarpedia.org/article/Sparse_coding and Olshausen and Fields, *Curr Opin Neurbiol*, 2004.

Sparse coding encourages V1-like receptive fields

- A computer science approach: find a set of basis functions that we can linearly sum to reconstruct an image: $I(x,y) = \sum_i a_i \phi_i(x,y)$
- Principal components analysis (PCA) is a classic method, but when applied to a set of natural images gives basis functions that look nothing like V1 receptive fields.



PCA components

Olshausen and Field, *Nature* (1996)

Sparse coding encourages V1-like receptive fields

- Olshausen and Field searched for basis functions that can be combined to reconstruct images, but also have a sparseness penalty that encourages the a_i terms to be small or zero.
- Want to minimise: $E = -[\text{preserve information}] - \lambda[\text{sparseness of } a_i]$

$$[\text{preserve information}] = -\sum_{x,y}\left[I(x,y) - \sum_i a_i \phi_i(x,y)\right]^2$$

Encourages good reconstructions

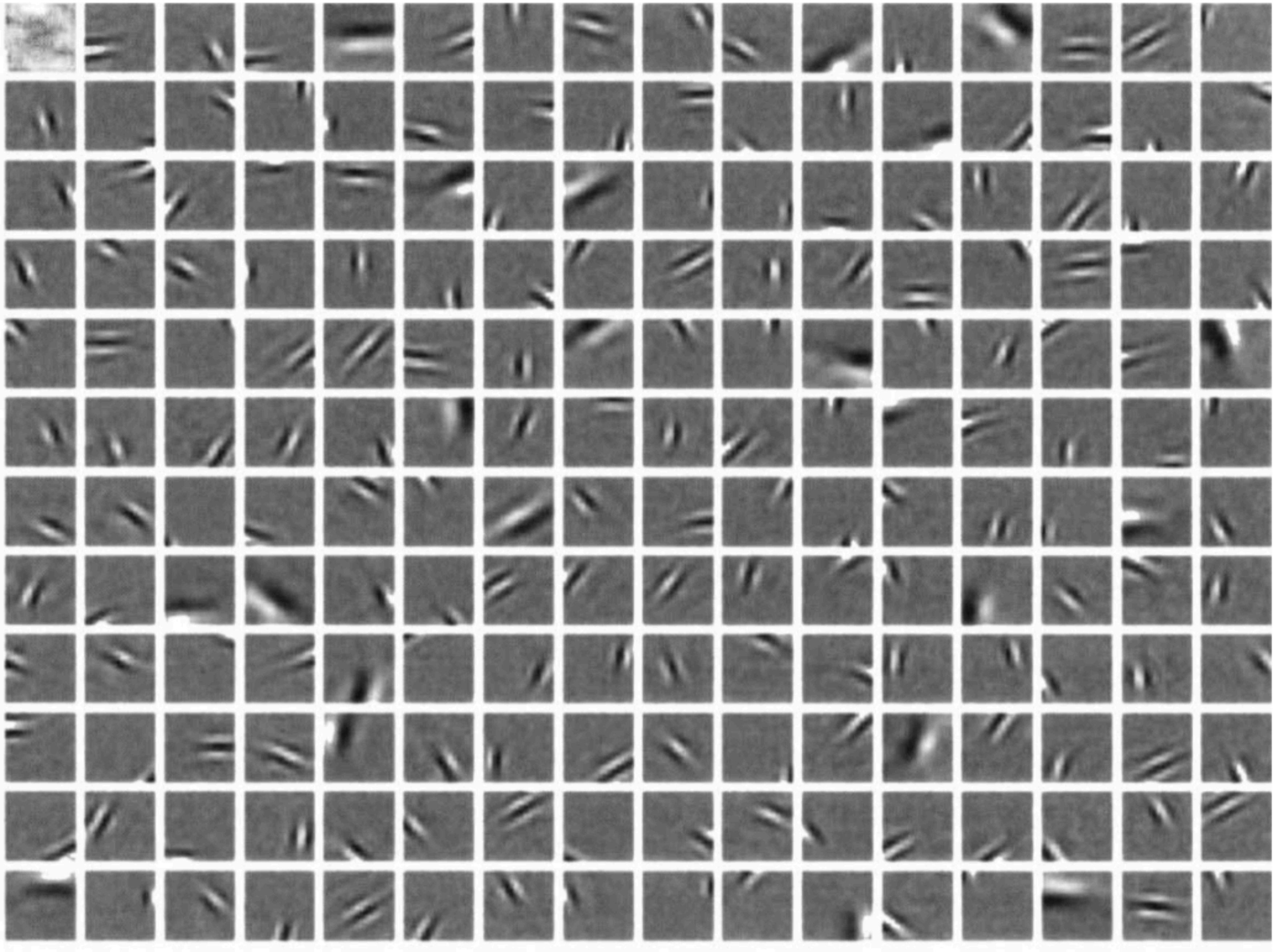
$$[\text{sparseness of } a_i] = -\sum_i S\left(\frac{a_i}{\sigma}\right)$$

Encourages a_is to be small

- This results in finding a sparse, "overcomplete" basis set where components are typically localised, oriented, and bandpass.

Olshausen and Field, *Nature* (1996)

Sparse coding encourages V1-like receptive fields



Gabor-like basis functions learned from a set of natural images from the Amercian Northwest, by including a penalty term that encourages sparseness.

Olshausen and Field, *Nature* (1996)

End