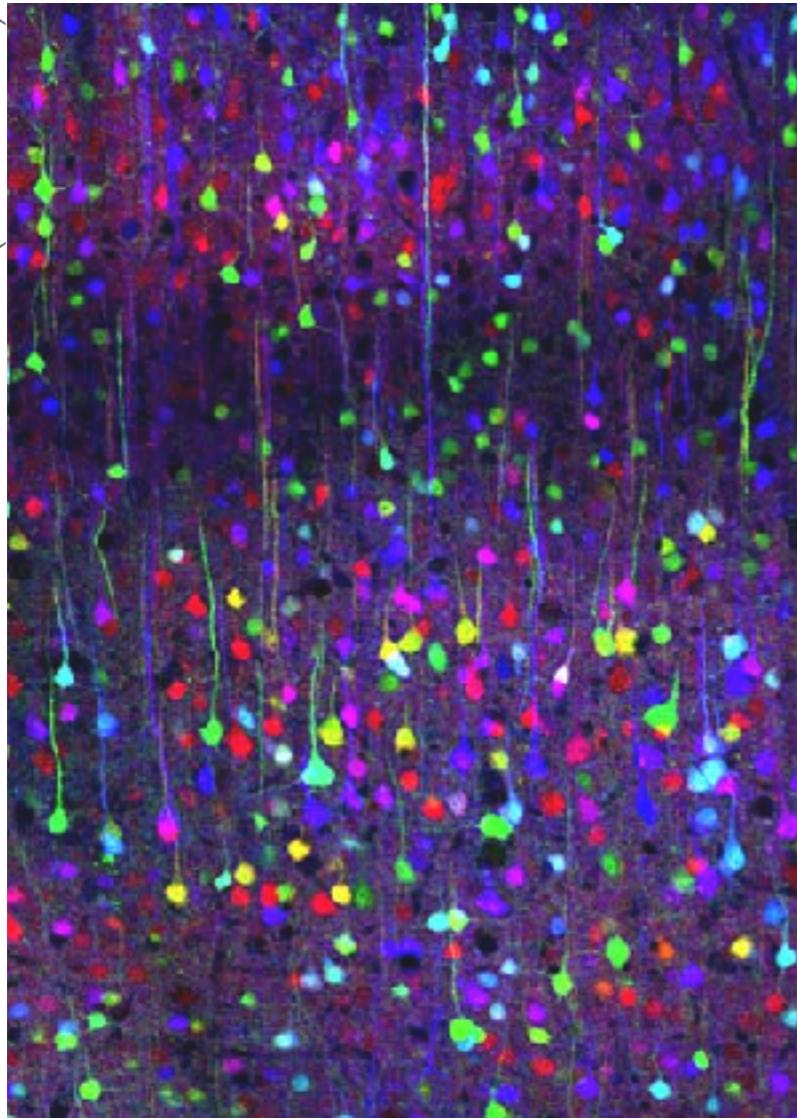


Neural Information Processing 2018/2019



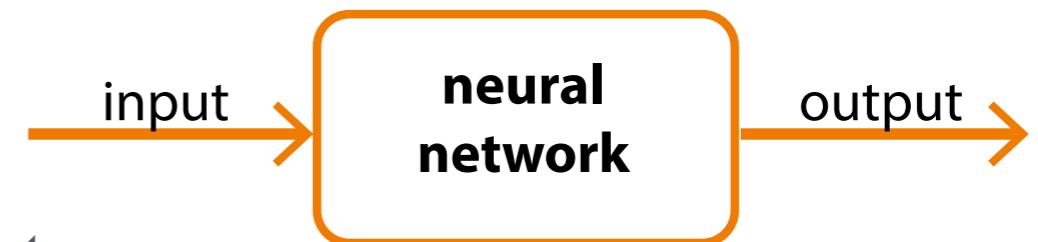
Brainbow (Litchman Lab)



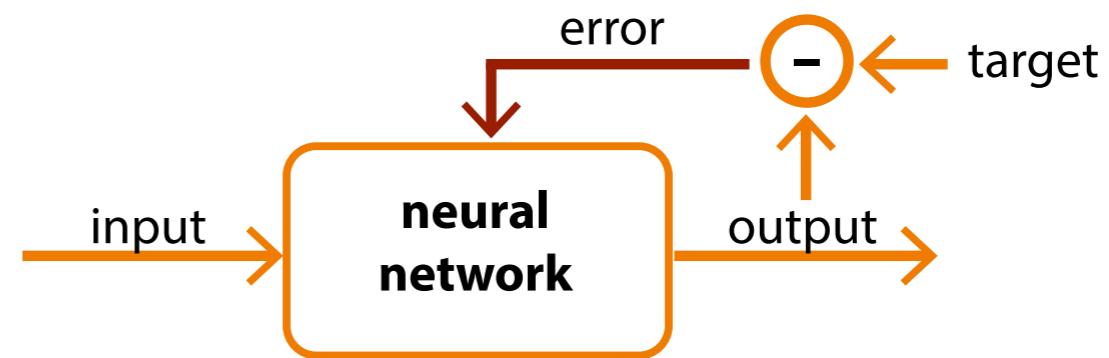
Lecture 11 Neural circuits: Visual cortex and convolutional nnets

Previously on Neural Information Processing...

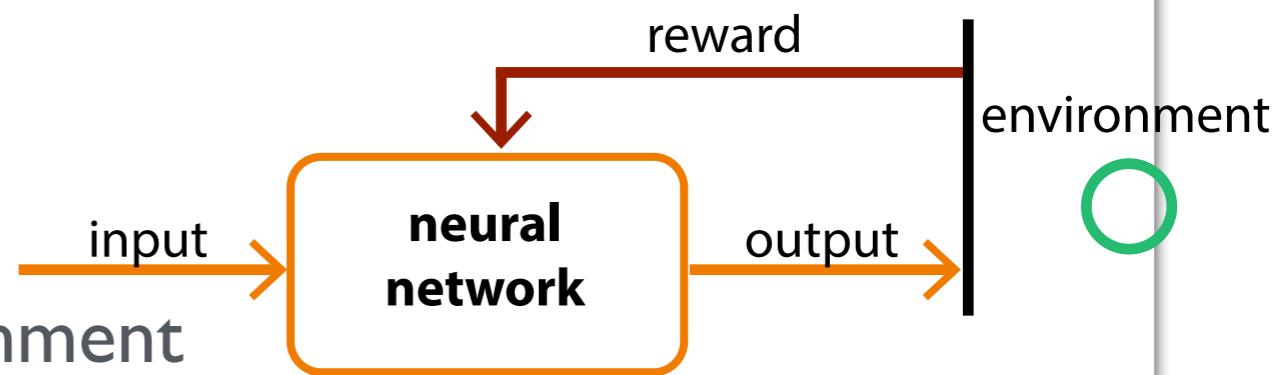
Unsupervised Learning:
Extracts useful representations of input



Supervised Learning:
Relies on a teaching signal

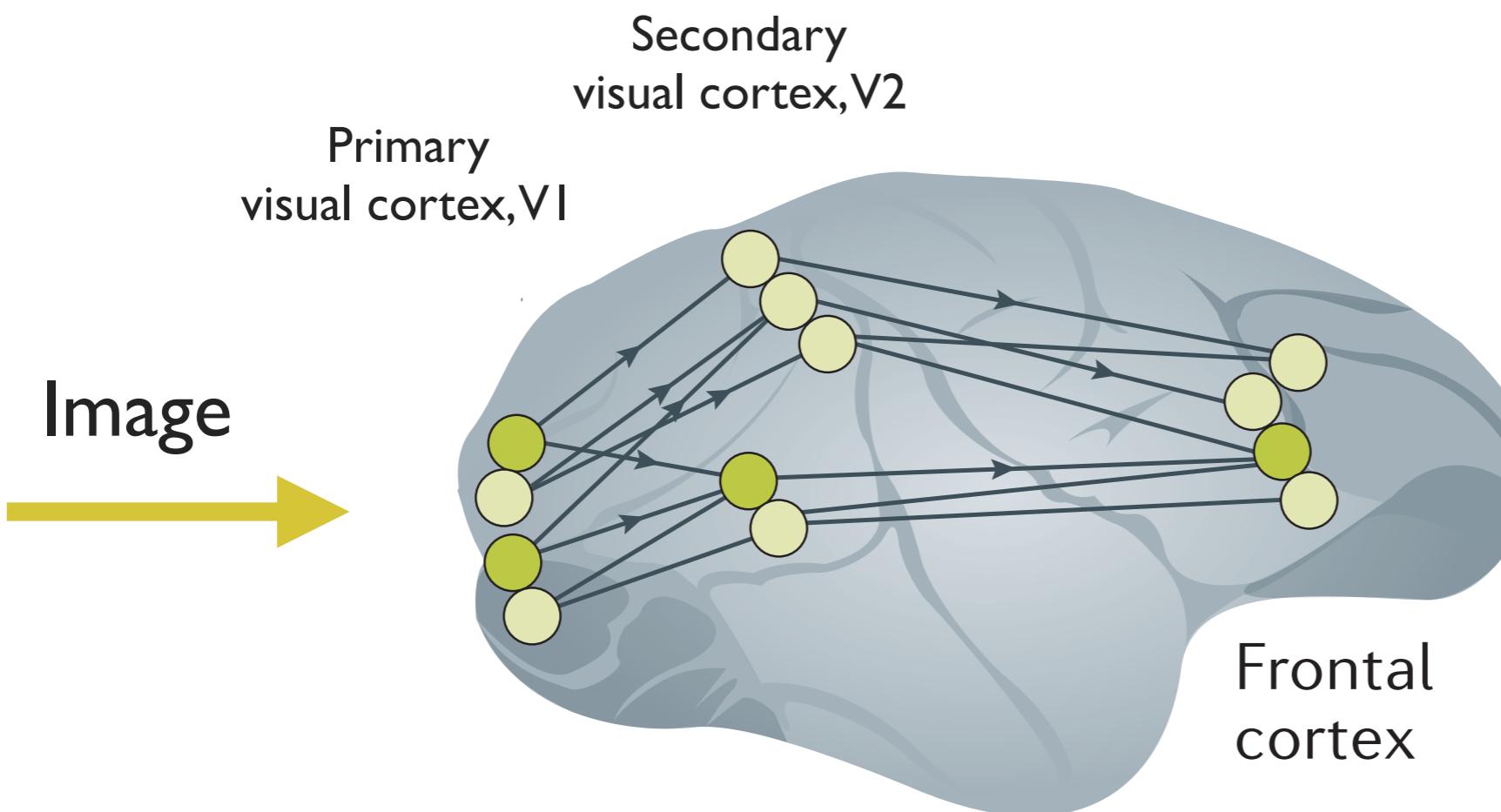


Reinforcement Learning:
Learn to navigate/survive an environment



But, what to learn?

How to connect the different elements in the brain!
for example: the visual cortex

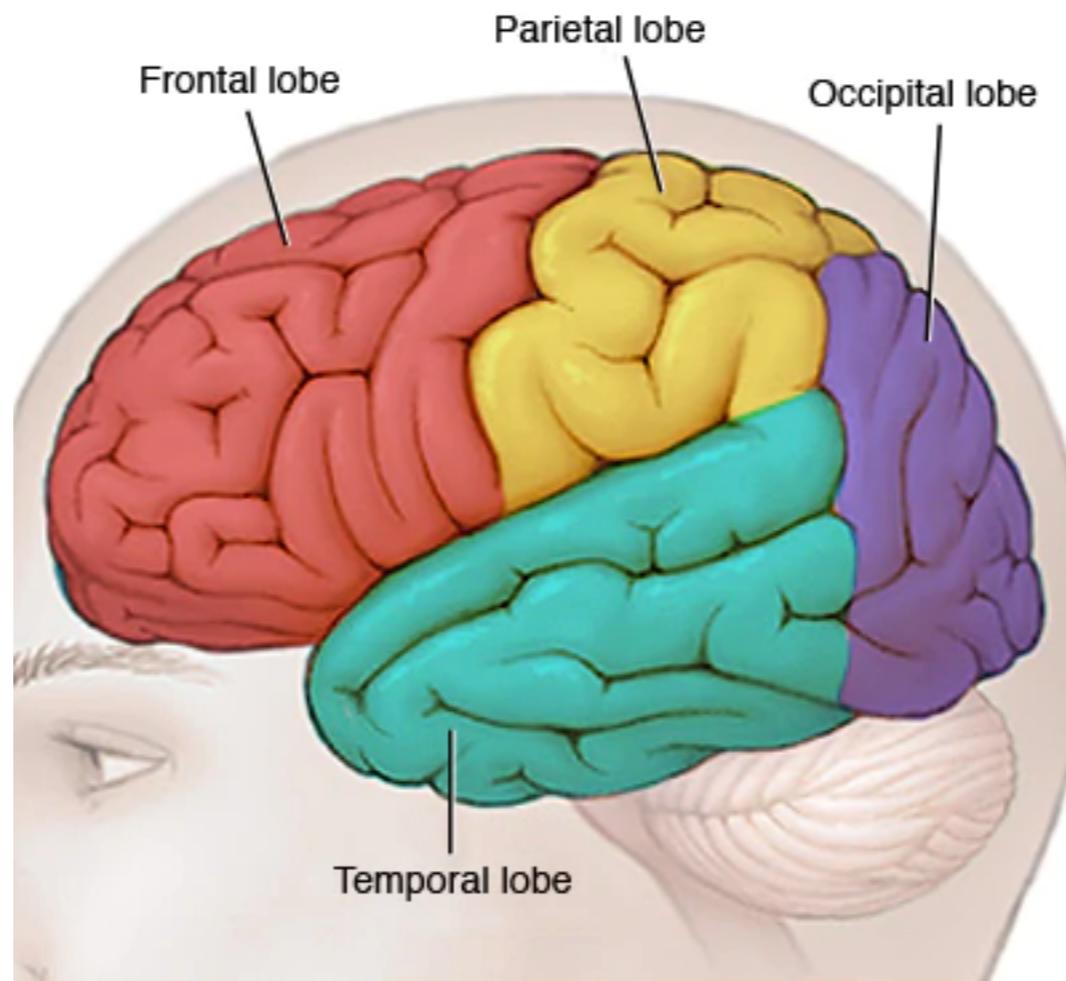


Roelfsema et al., Nature Neuroscience Rev (2018)

Outline

- I. Visual cortex: structure**
- 2. Visual cortex: receptive fields**
- 3. Convolutional neural networks as models of visual system**

Brain structure

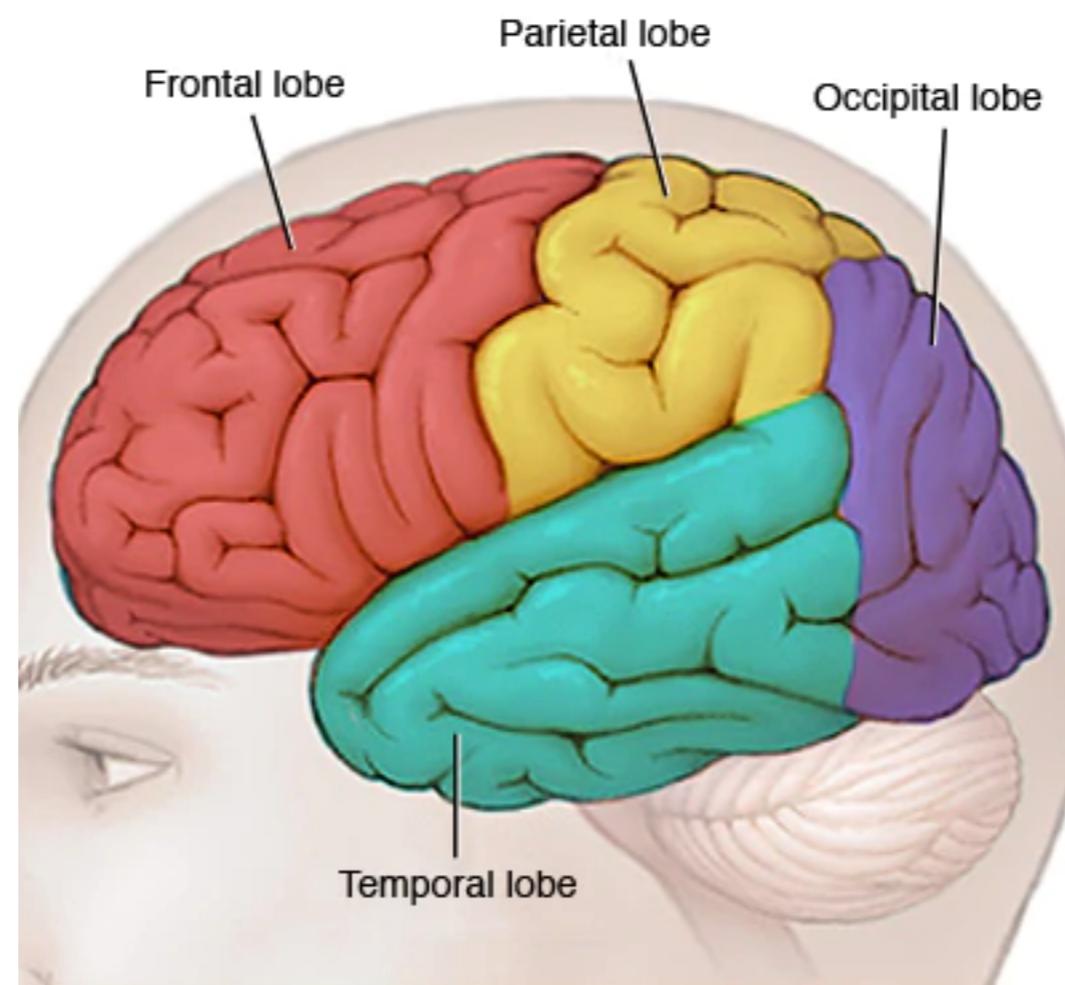


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adult learning material

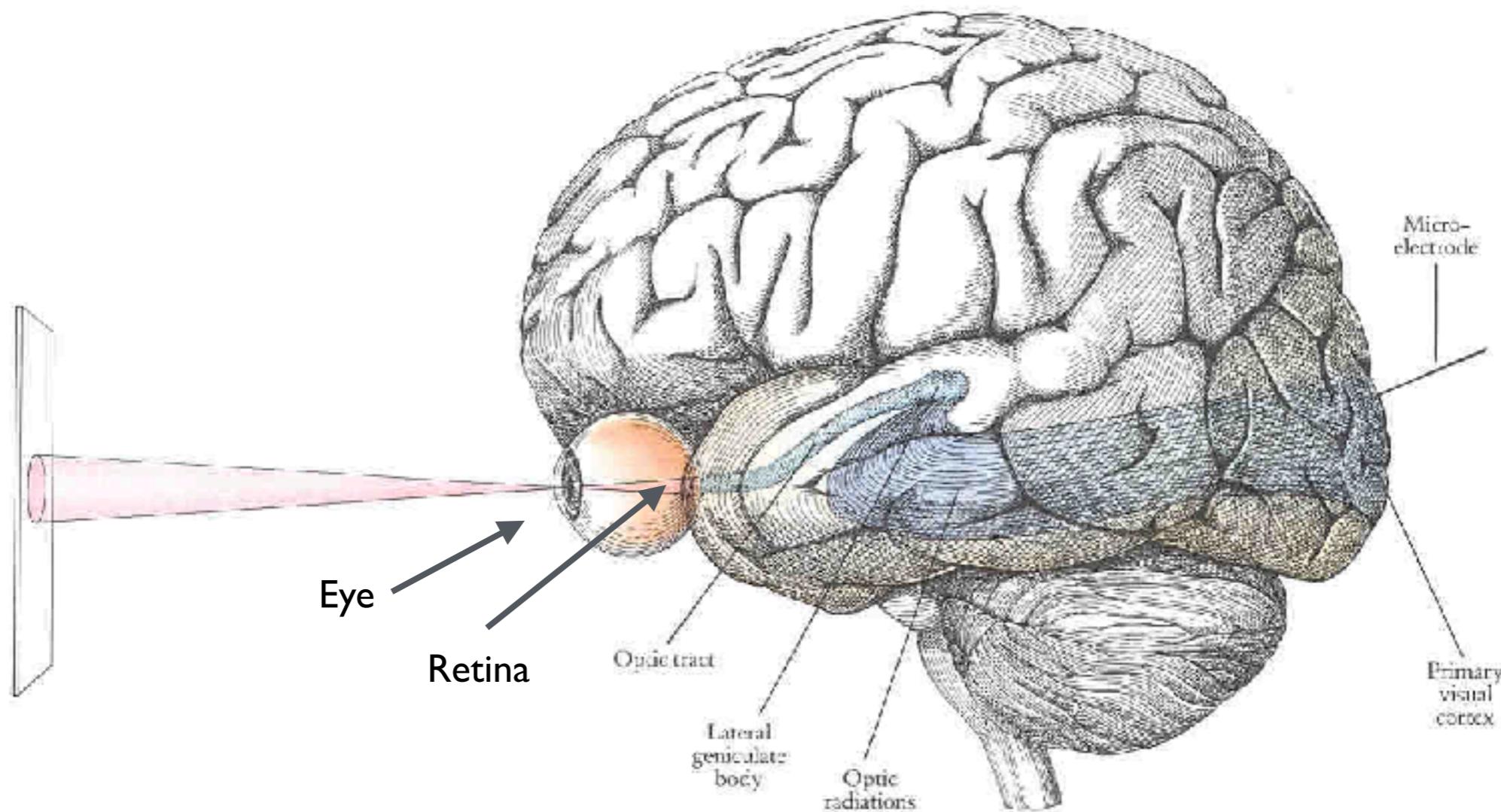
The visual cortex



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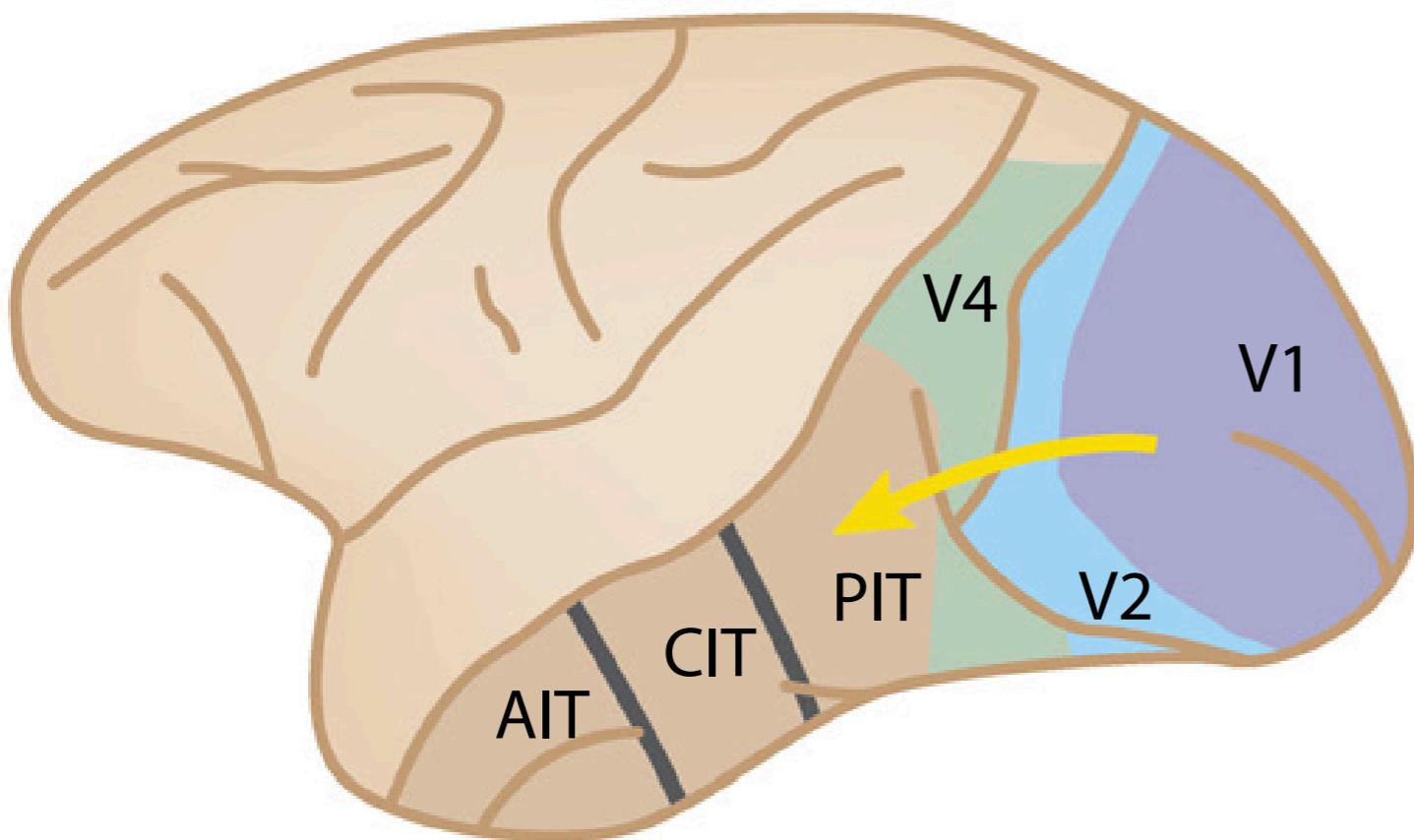
adult learning material

The visual system



[[http://www.cog.brown.edu/courses/cg0001/
lectures/visualpaths.html](http://www.cog.brown.edu/courses/cg0001/lectures/visualpaths.html)]

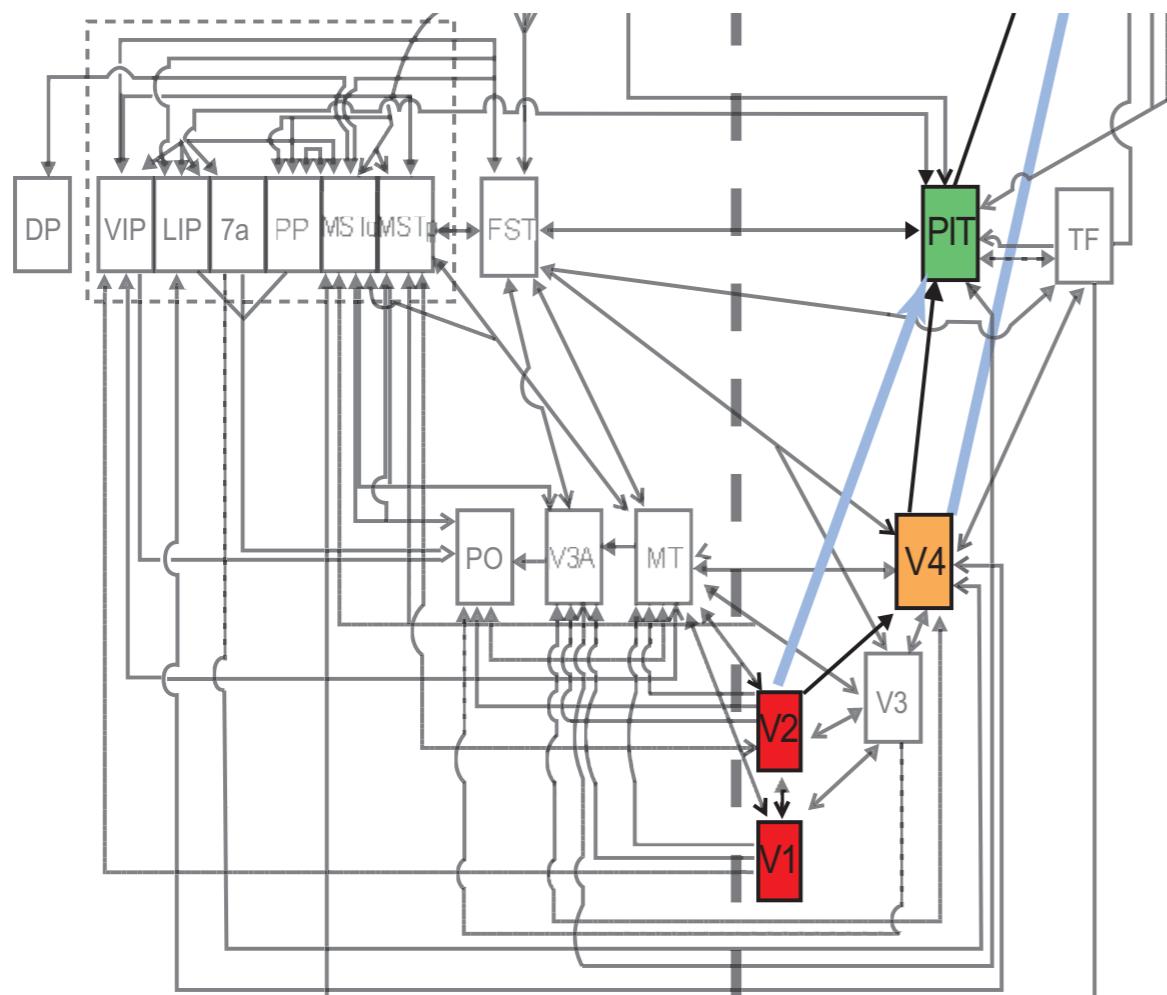
Visual cortex: multiple sub-areas



- V1: Primary visual cortex
- V2: Secondary visual cortex
- IT: Inferior temporal cortex

Yamins and DiCarlo, Nature Neuroscience (2016)

Visual cortex: what and where pathways



dorsal stream
'where' pathway

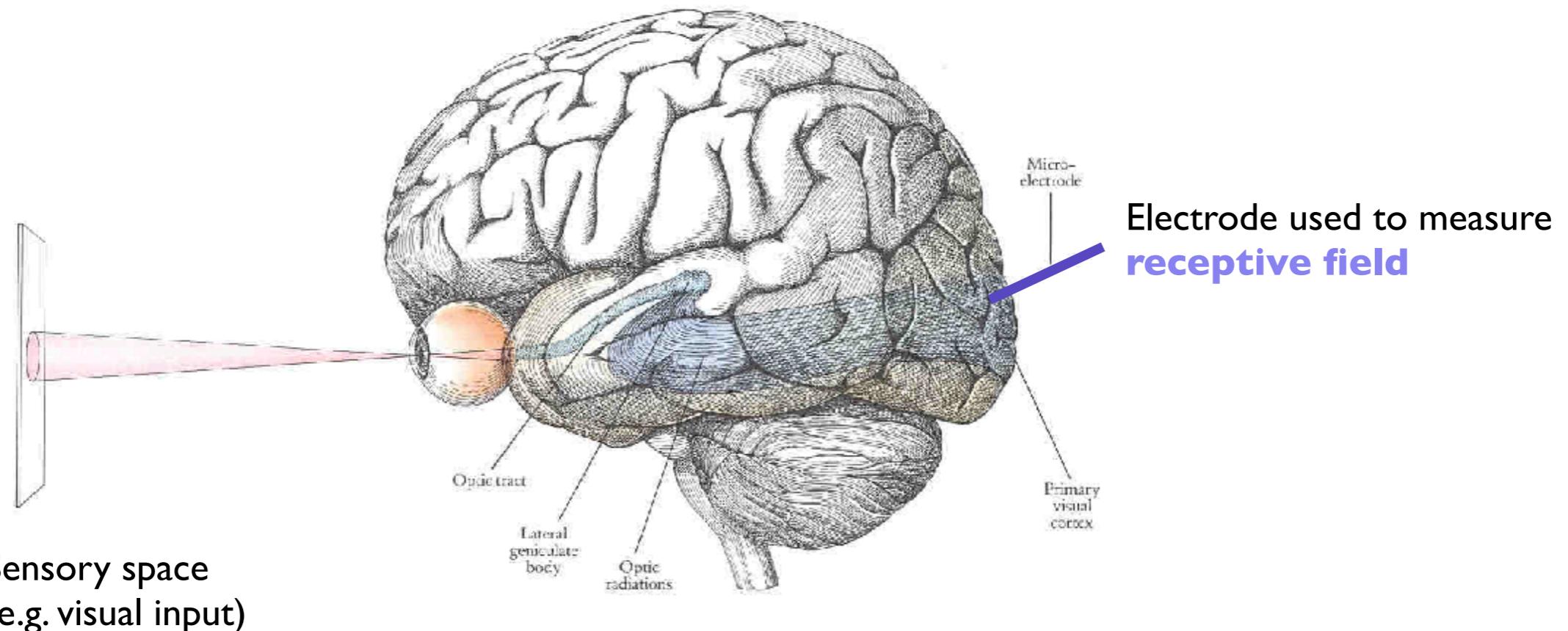
ventral stream
'what' pathway'

- **'What' pathway:** Relevant to detect what is in the image (e.g. lion vs eagle?)

- **'Where' pathway:** Processes the spatial location of objects (e.g. top vs bottom)

Serre et al., PNAS (2007)

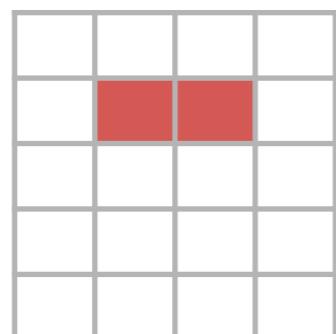
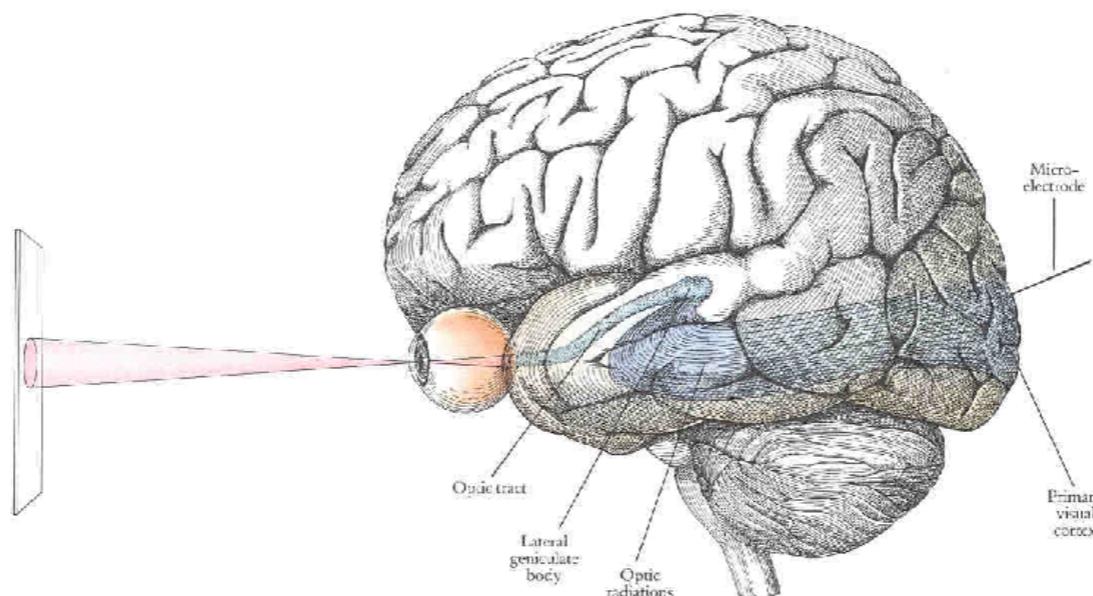
Visual cortex function receptive fields



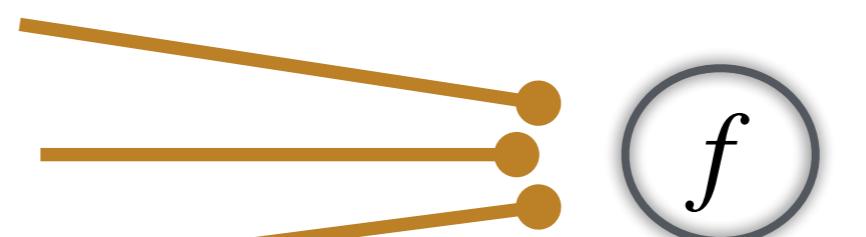
Receptive field: Region of sensory space in which a stimulus modifies (i.e. increases or decreases) the firing of the neuron.

Visual cortex function

a simple model of receptive field



Visual input, u



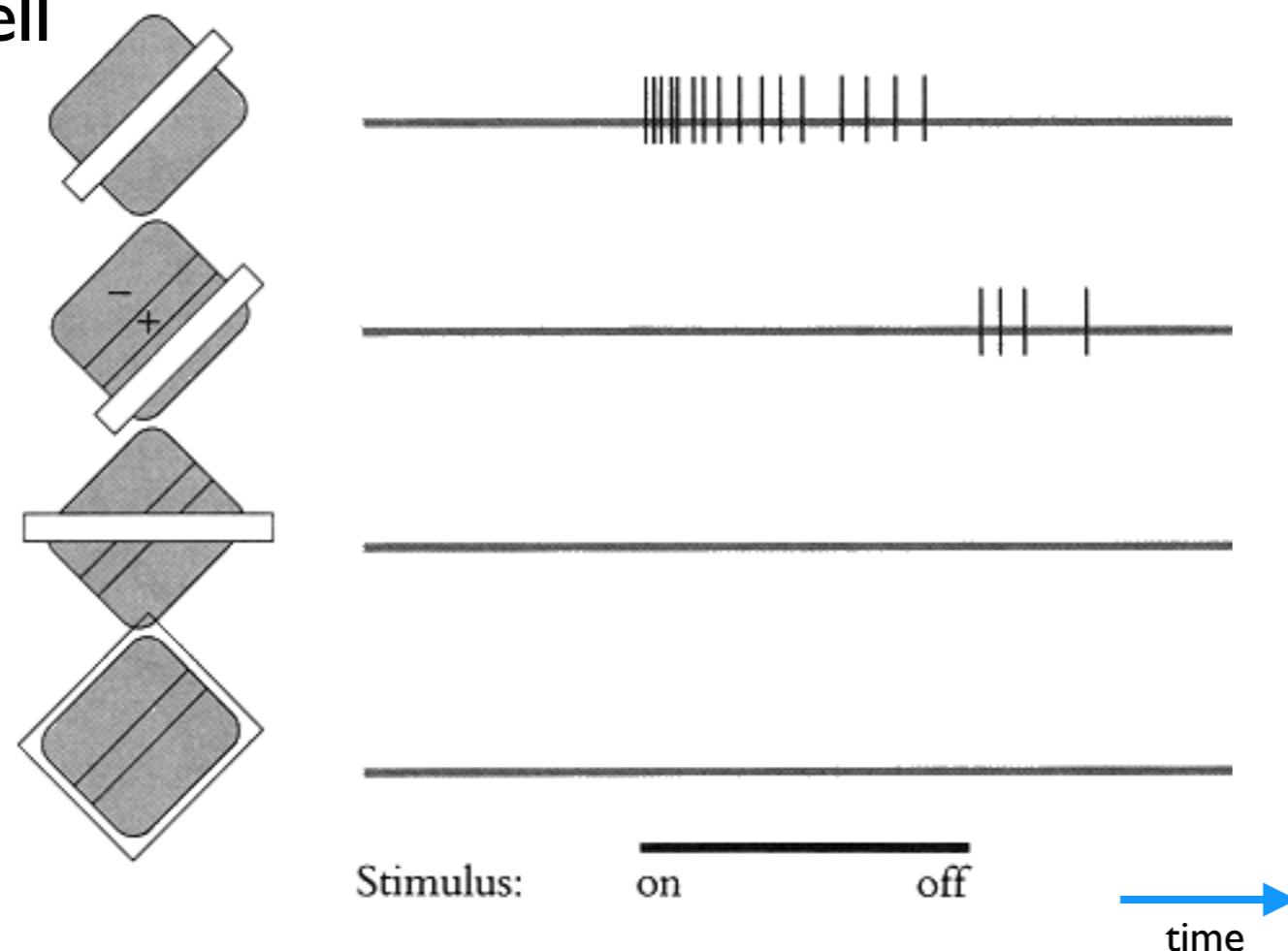
weights, w

Visual cortex
neuron, v

$$v = f(wu)$$

Classical receptive field: simple cells in primary visual cortex

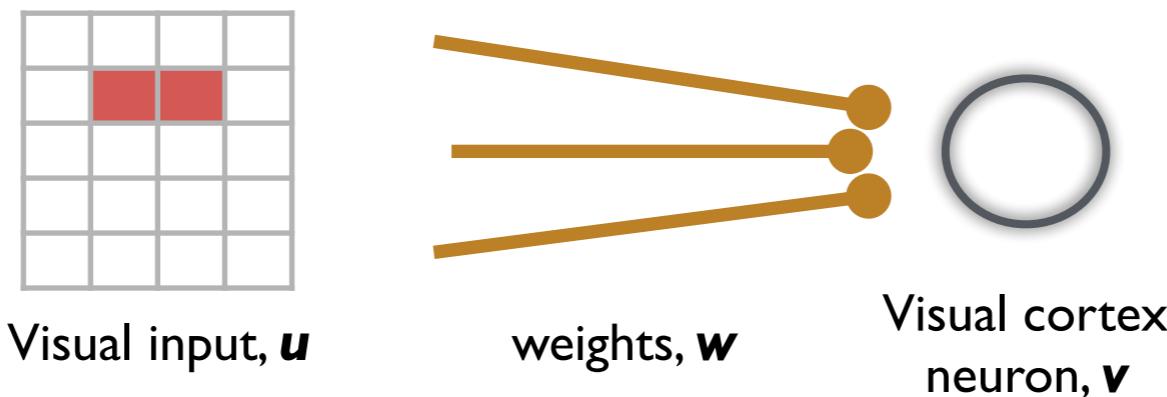
Simple cell



Video of Hubel & Wiesel experiments:
<https://youtu.be/8VdFf3egwfg>

Hubel and Wiesel, J Physiol (1962)

Classical receptive field: Gabor filter as a model of simple cells



where w can be approximated by a Gabor filter:

$$w \sim g(x, y; \lambda, \theta, \phi, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda} + \phi\right),$$

Classical receptive field: Gabor filter as a model of simple cells

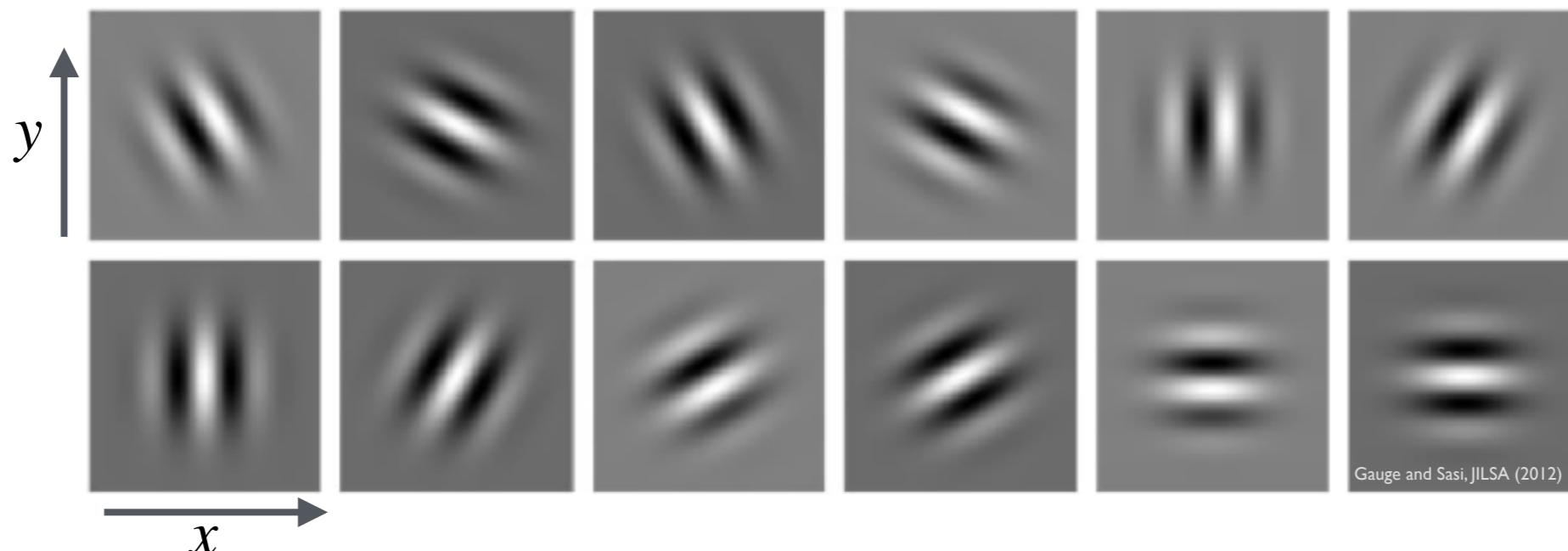
A Gabor filter is a product of a Gaussian and a sinusoid that can model a periodic pattern similar to simple cells.

$$w \sim g(x, y; \lambda, \theta, \phi, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda} + \phi\right),$$

$$y' = -x \sin \theta + y \cos \theta.$$

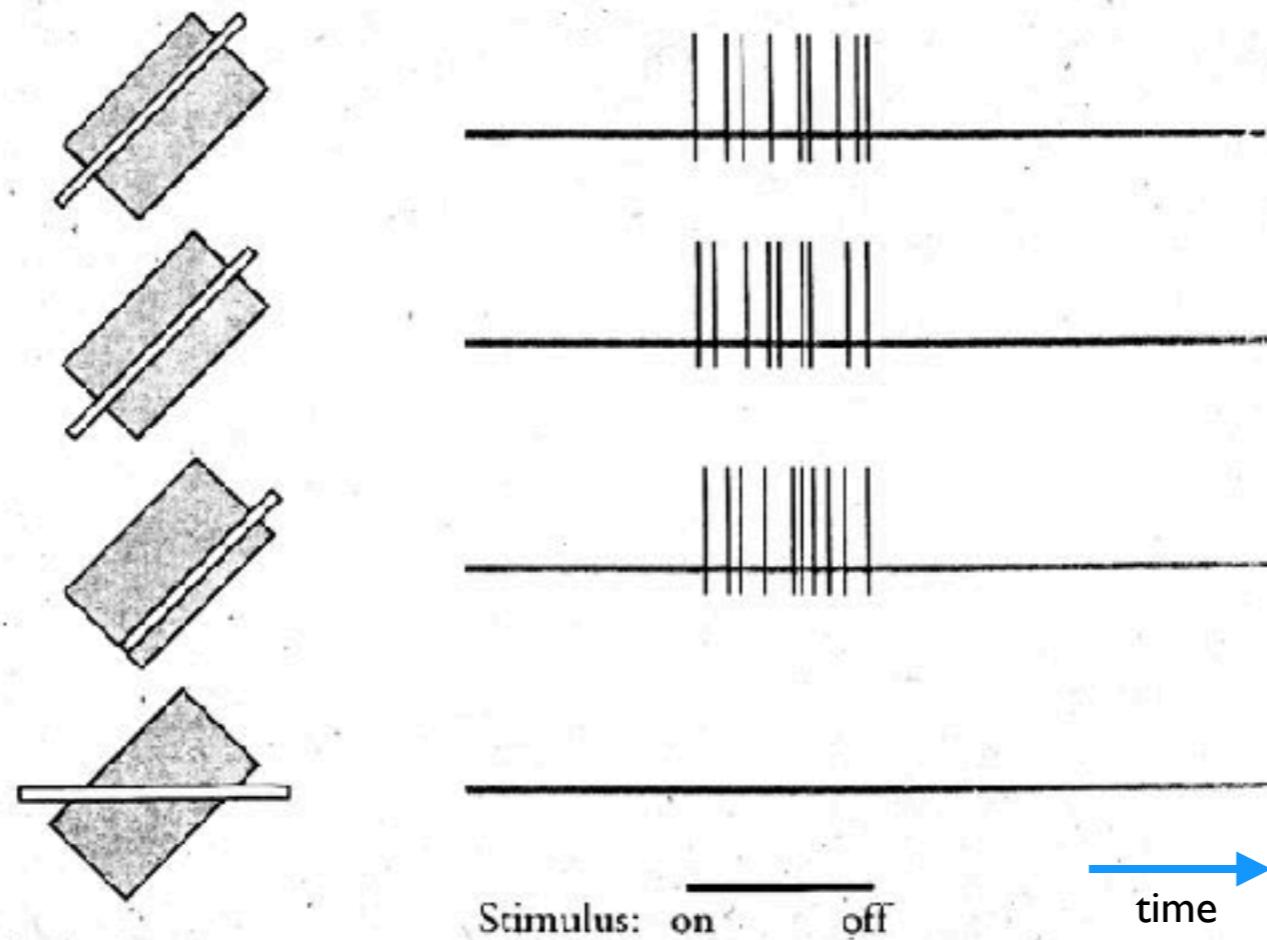
$$x' = x \cos \theta + y \sin \theta,$$

Gabor filters for different θ :



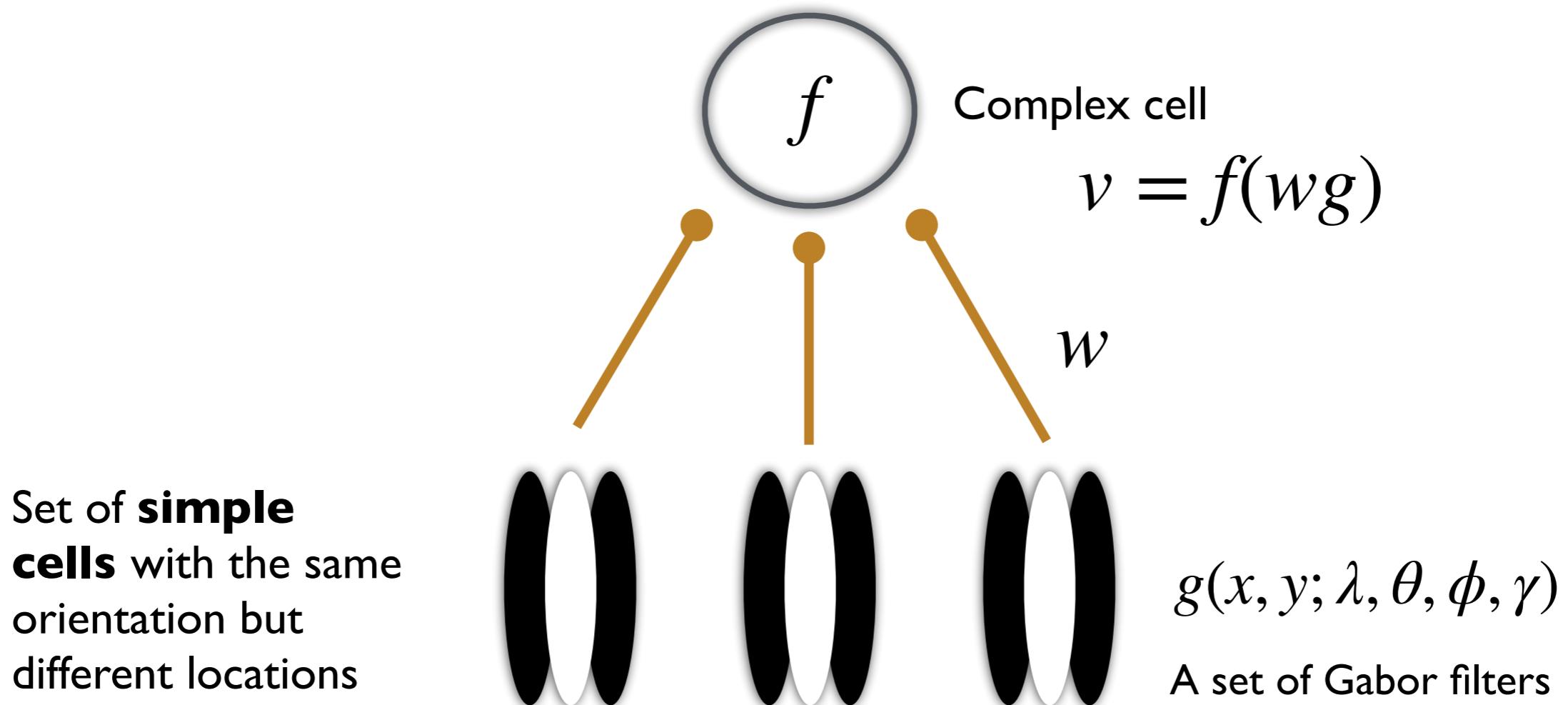
Visual cortex: complex cells

Complex cell



Hubel and Wiesel, J Physiol (1962)

Visual cortex: complex cells, a model



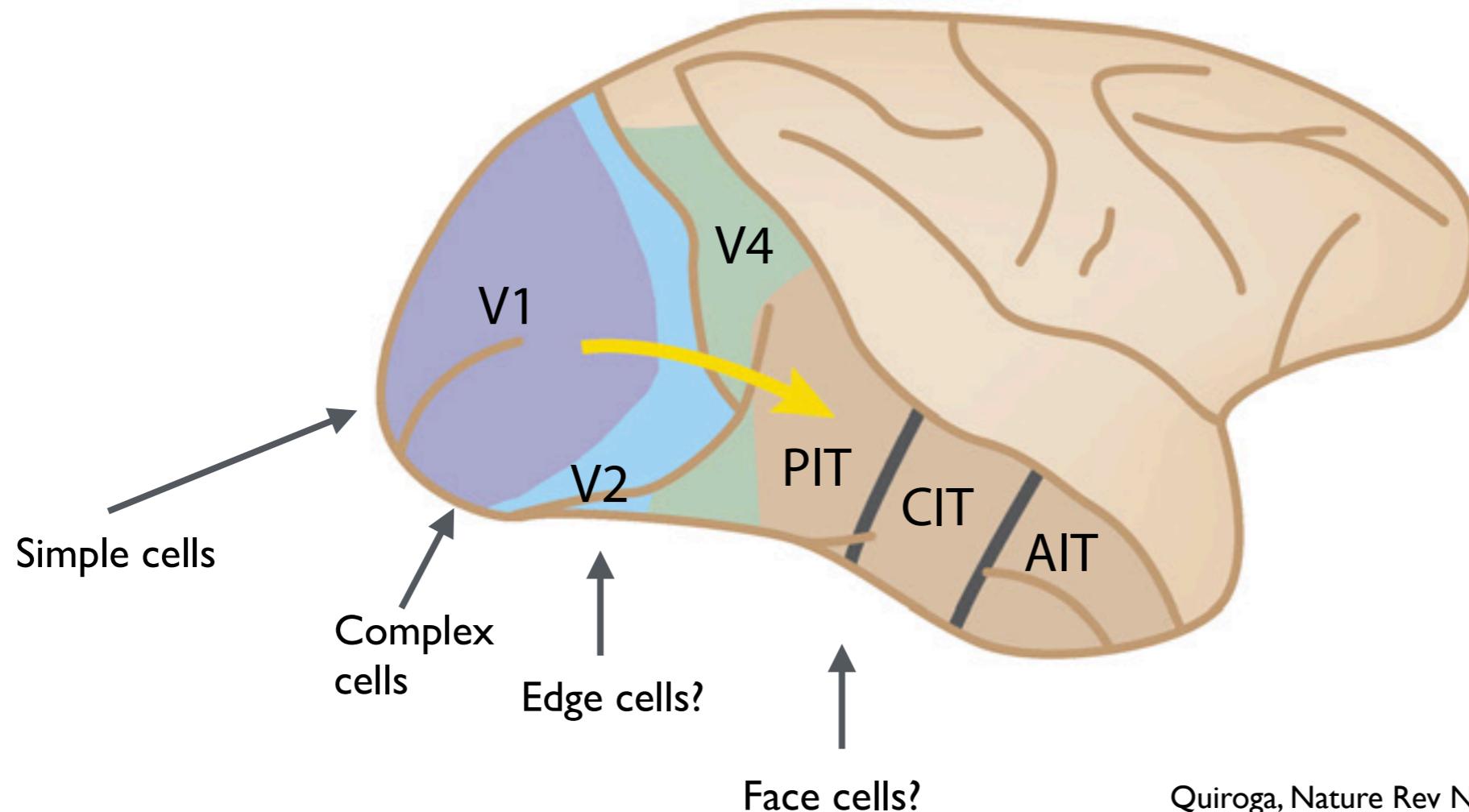
Group discussion

groups of 2-3 (5 min)

- **What other receptive fields would be useful for the visual cortex to have?**

Hint: look around you for common visual features

Visual cortex: Higher order representations



Quiroga, Nature Rev Neurosci (2012)

Yamins and DiCarlo, Nature Neuroscience (2016)

Visual cortex:

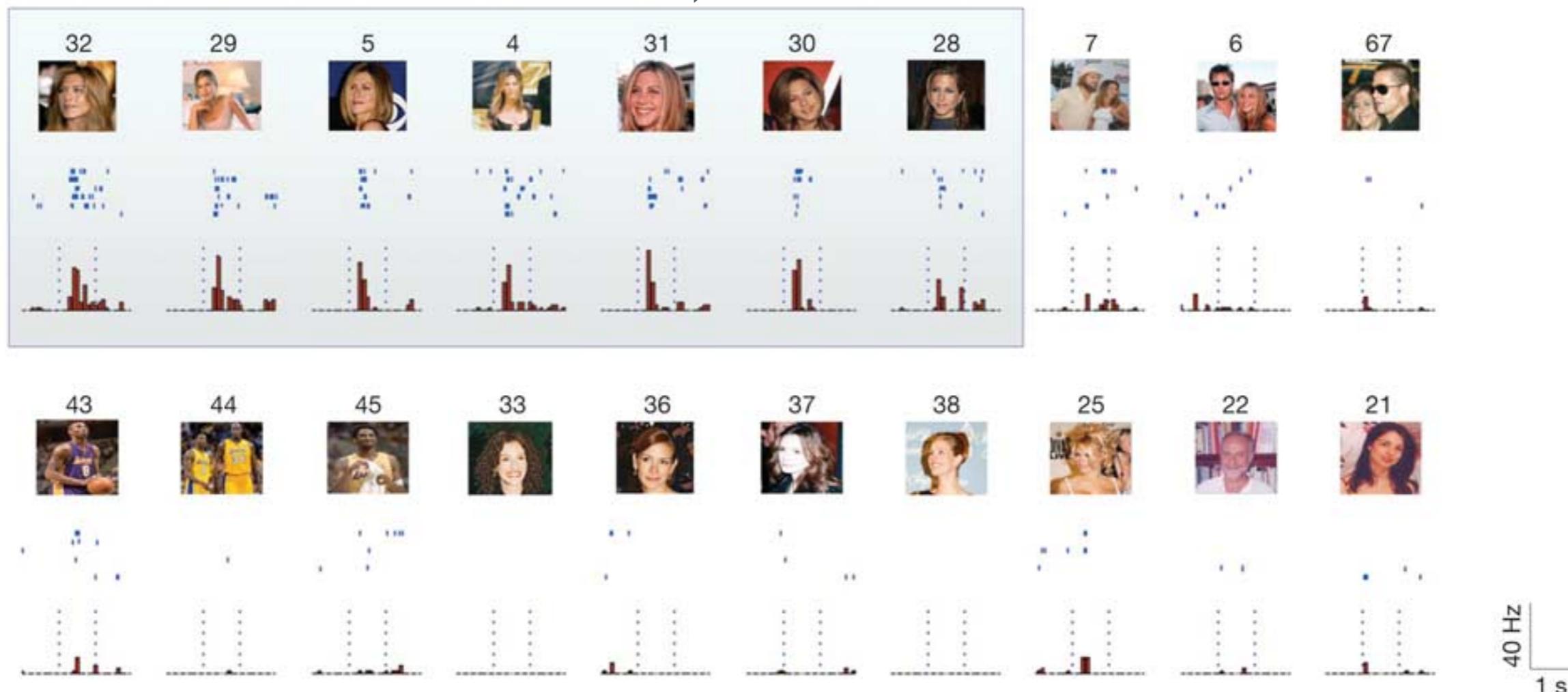
Grandmother cell (e.g. the Jennifer Aniston cell)

Grandmother cell: The idea that here are neurons responding specifically when you see people that you are familiar with.

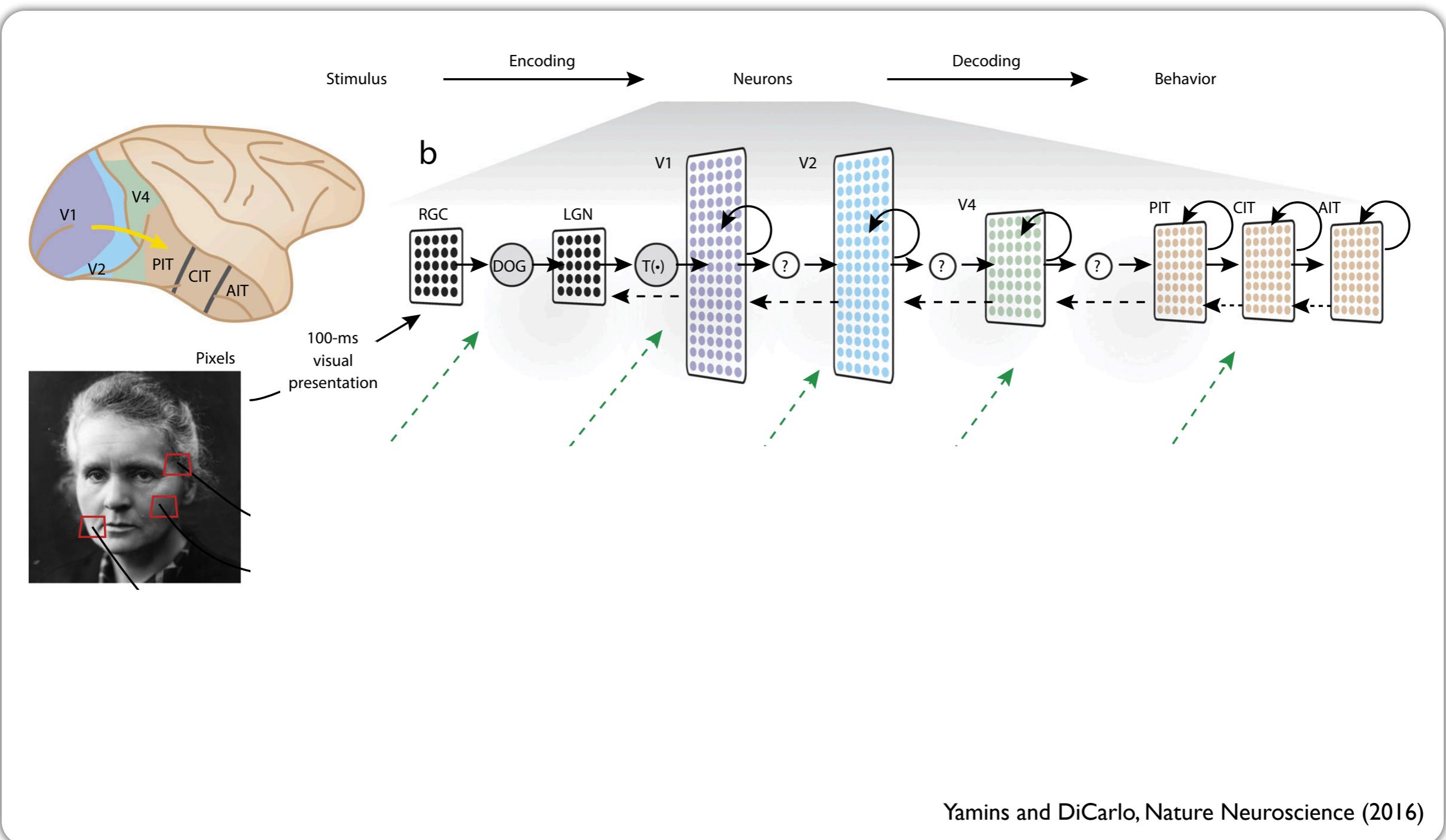
A neuron responding to images of Jennifer Aniston recorded in Medial Temporal Lobe in humans (epilepsy patients):



Quiroga et al., Nature (2005)

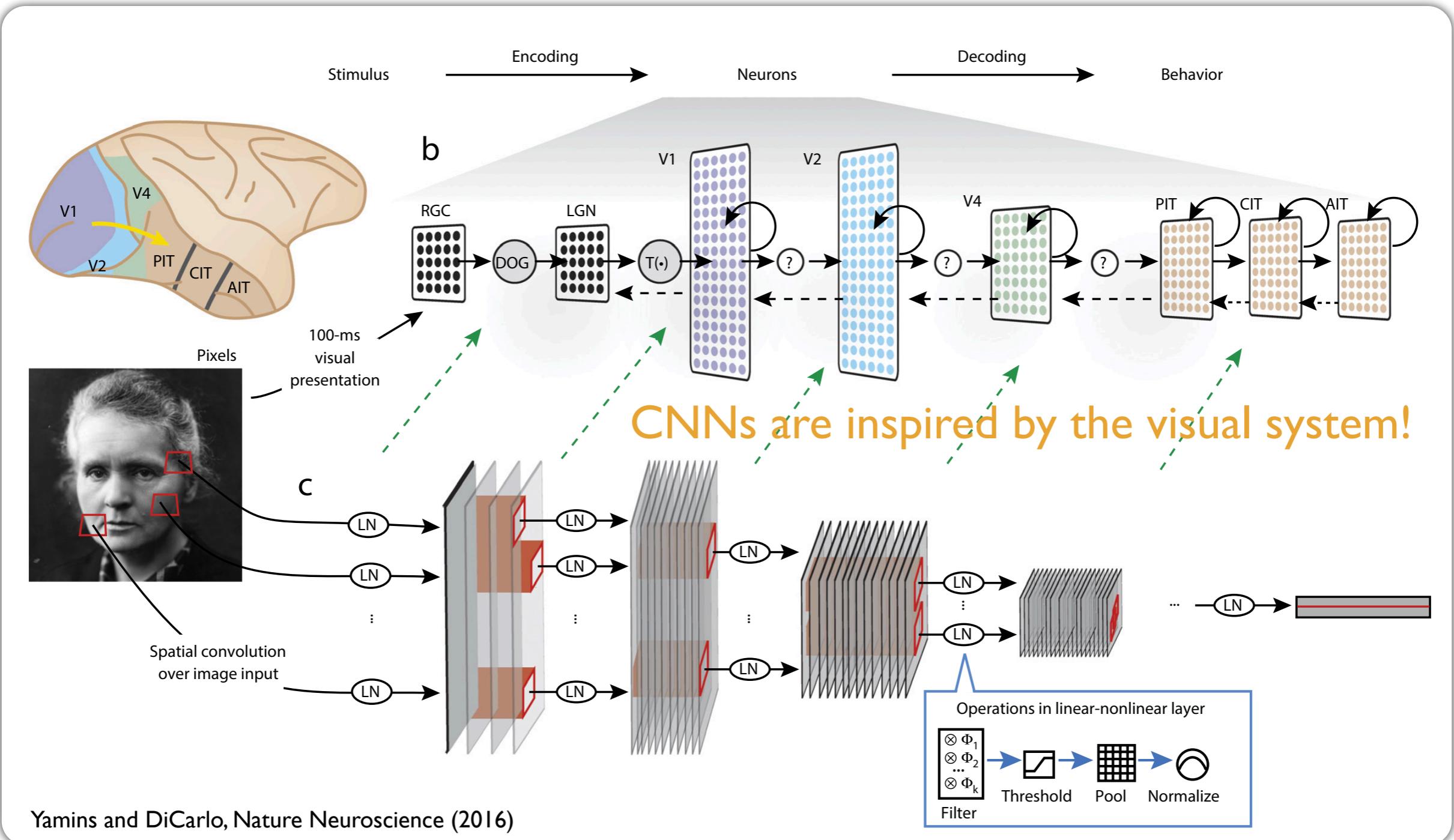


Convolutional neural networks (CNNs) as a model of the visual system

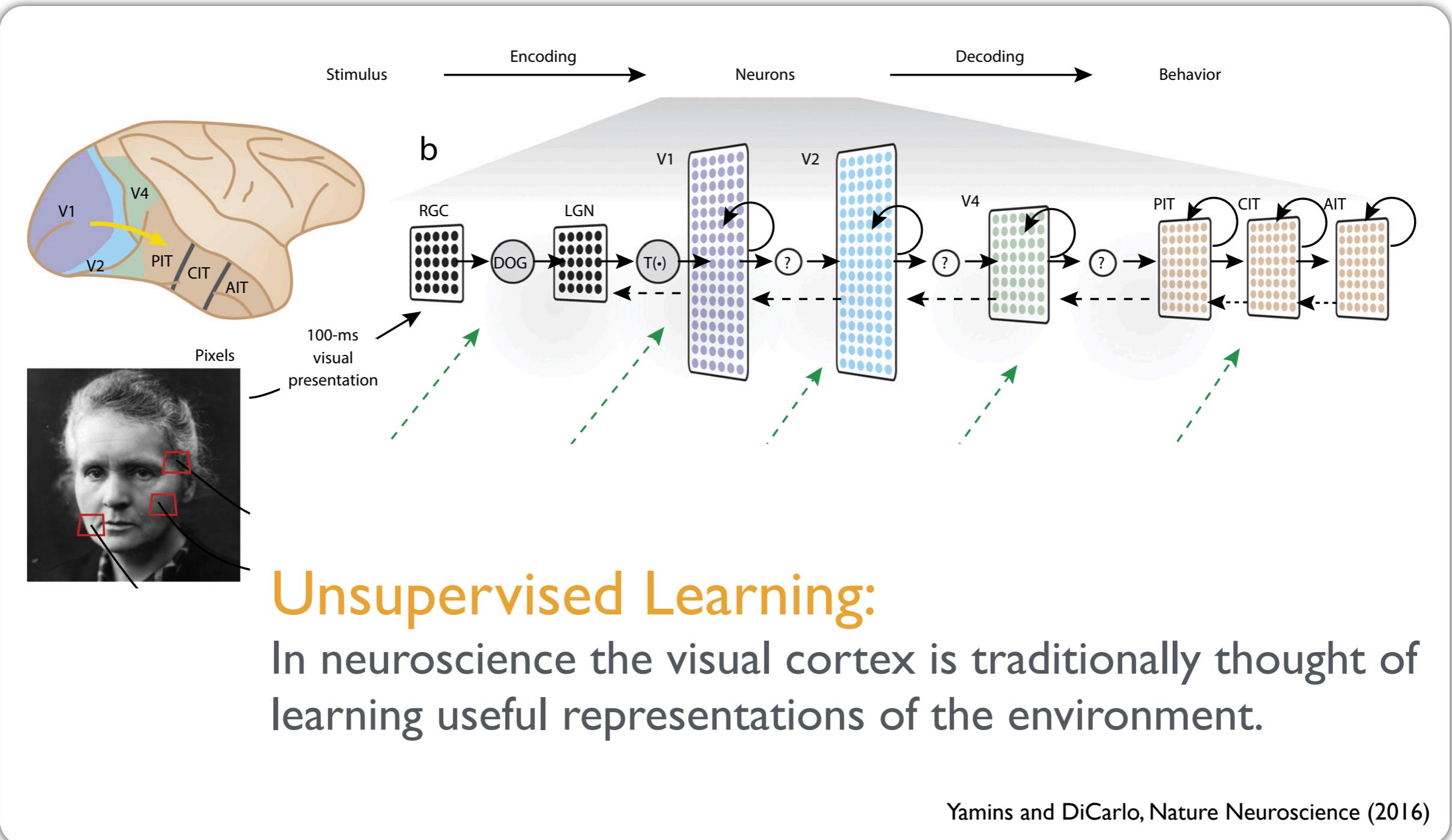


Yamins and DiCarlo, Nature Neuroscience (2016)

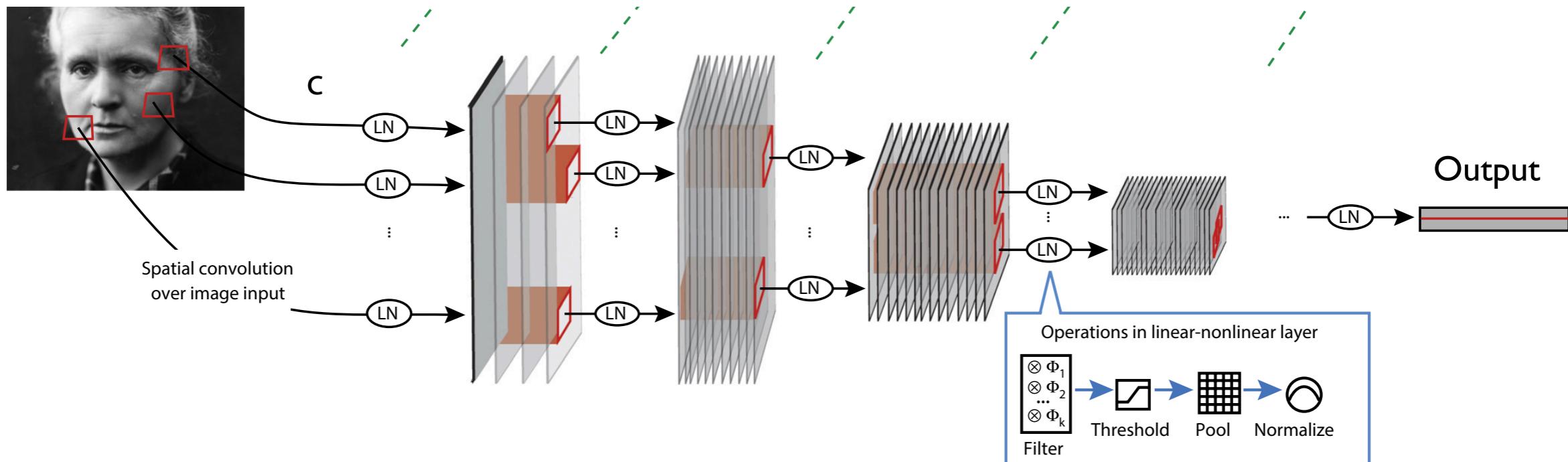
Convolutional neural networks (CNNs) as a model of the visual system



Convolutional neural networks (CNNs) as a model of the visual system



Convolutional neural networks (CNNs) as a model of the visual system

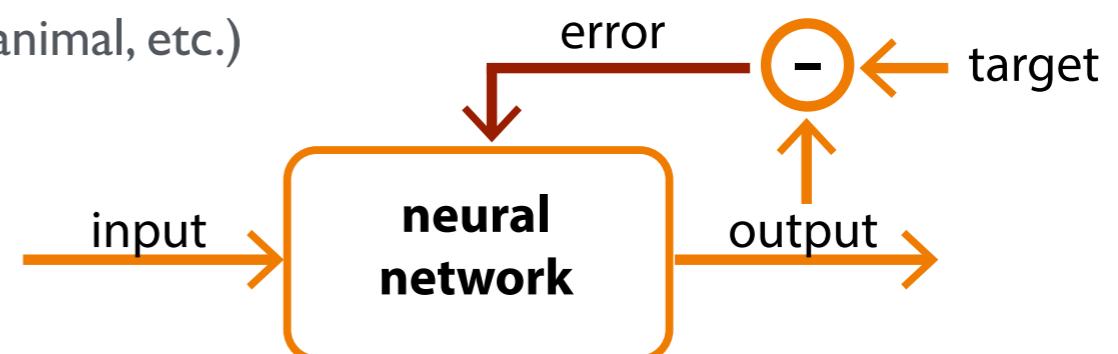


But CNNs rely on **Supervised Learning**:

CNNs are trained with the backprop algorithm (see next lecture)

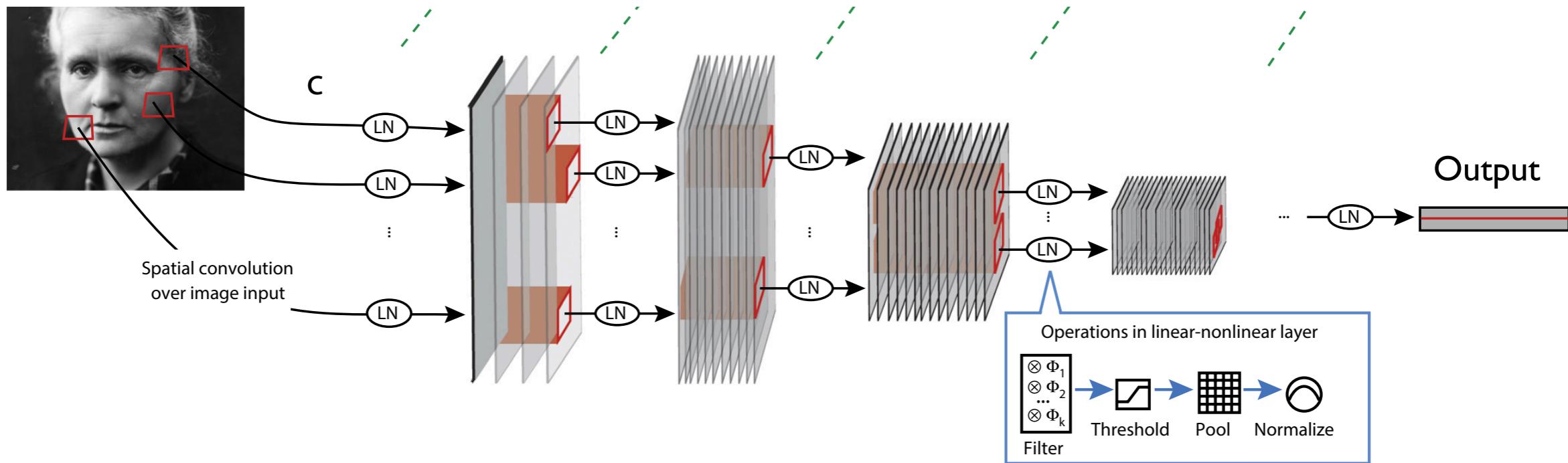
Target: Image label/category (e.g. person, animal, etc.)

CNNs have revolutionised computer vision!



Yamins and DiCarlo, Nature Neuroscience (2016)

Convolutional neural networks (CNNs) as a model of the visual system



Two key operations:

Spatial convolution: Scanning the image with a filter (red squares)

Pooling: Subsampling input (e.g. max operation: selecting most active unit)

Others: Thresholding and normalisation

Yamins and DiCarlo, Nature Neuroscience (2016)

Convolutional neural networks (CNNs)

Convolution operator

Example of filter:

1	0	1
0	1	0
1	0	1

Convolutional operation:

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

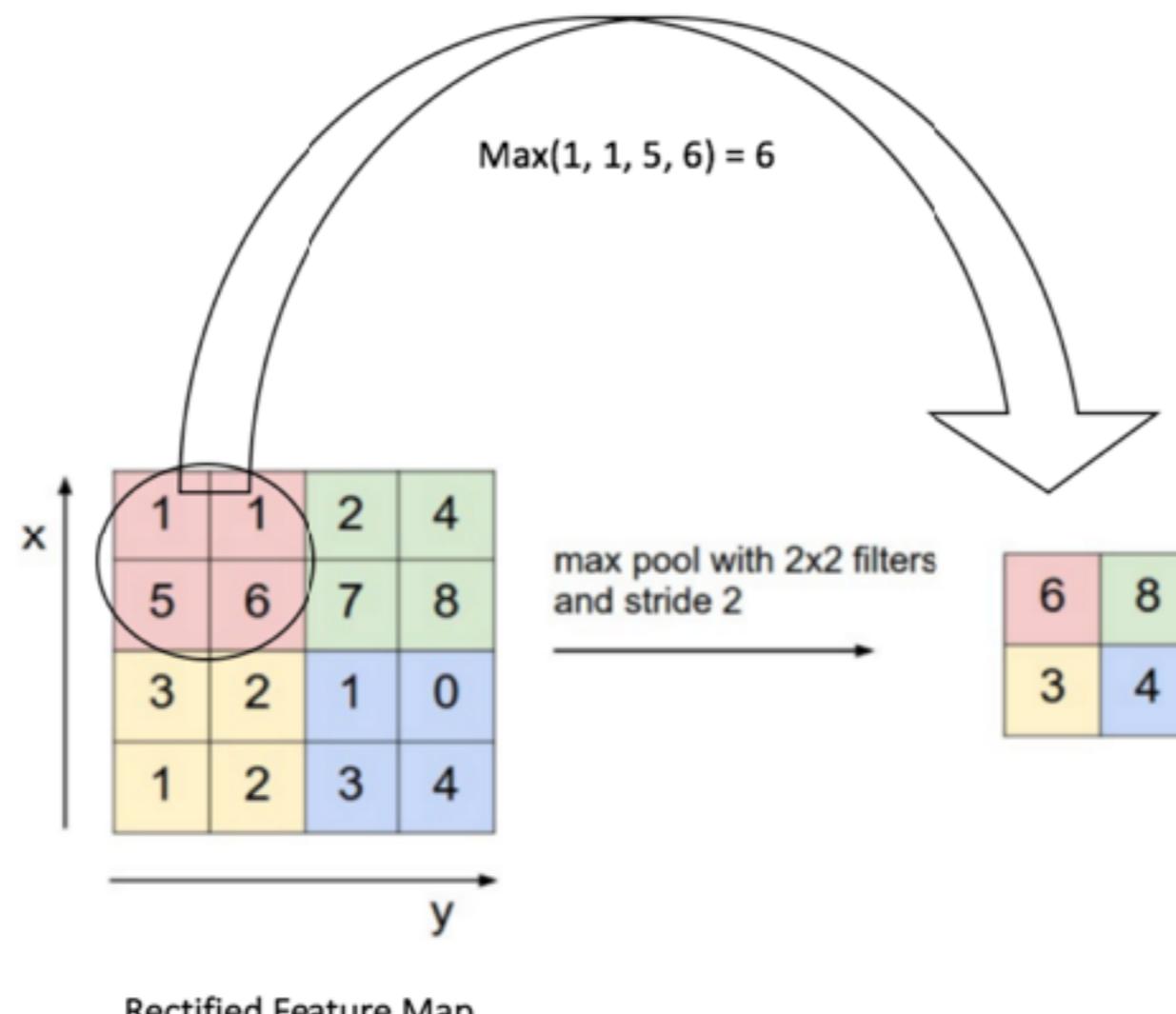
Convolved
Feature

<https://uijwalkarn.me/2016/08/11/intuitive-explanation-convnets>

Convolutional neural networks (CNNs)

Pooling

(Max) Pooling:



<https://uijwalkarn.me/2016/08/11/intuitive-explanation-convnets>

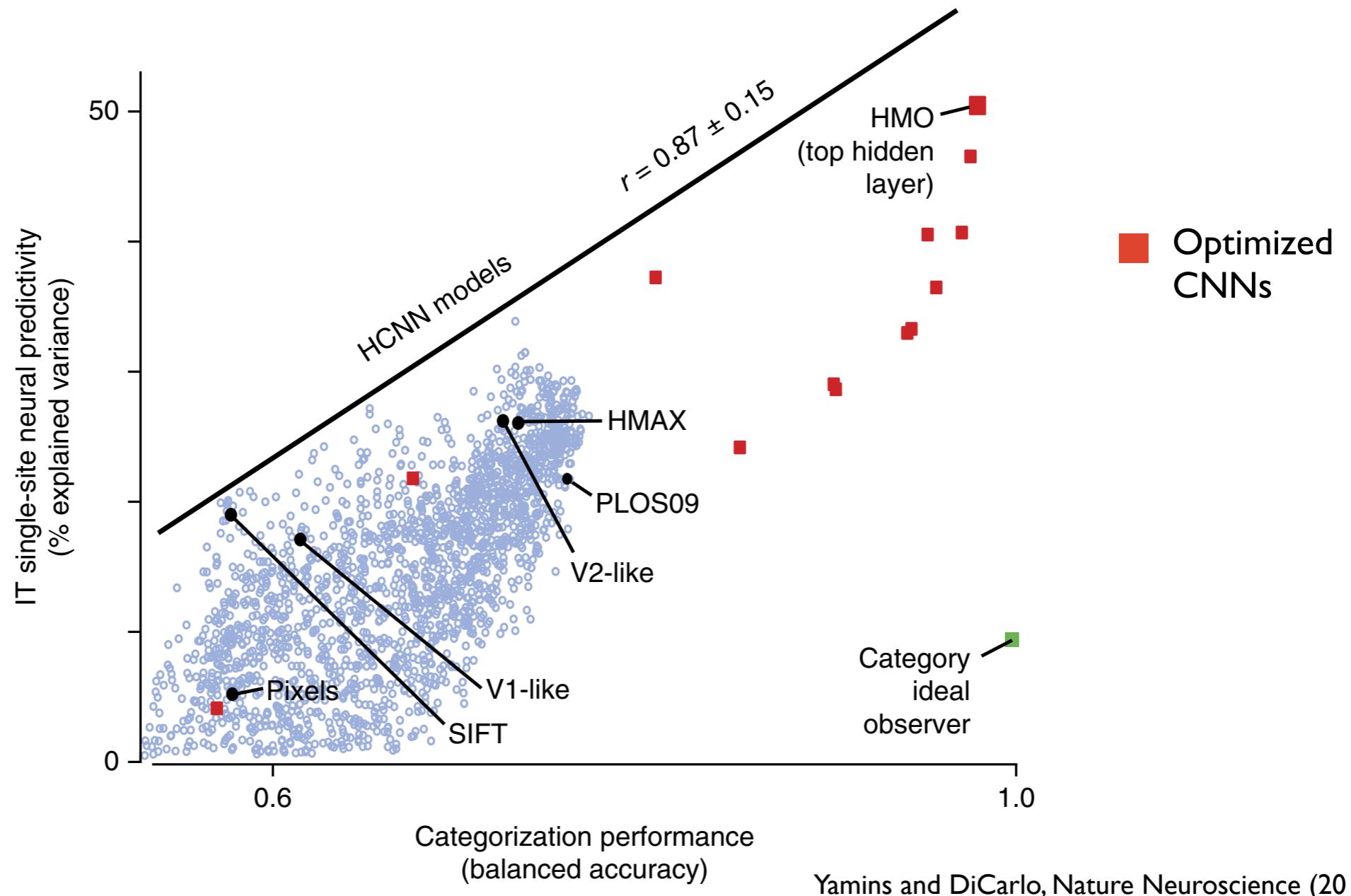
Convolutional neural networks (CNNs) as a model of the visual system

A comparison between CNNs and the visual system:

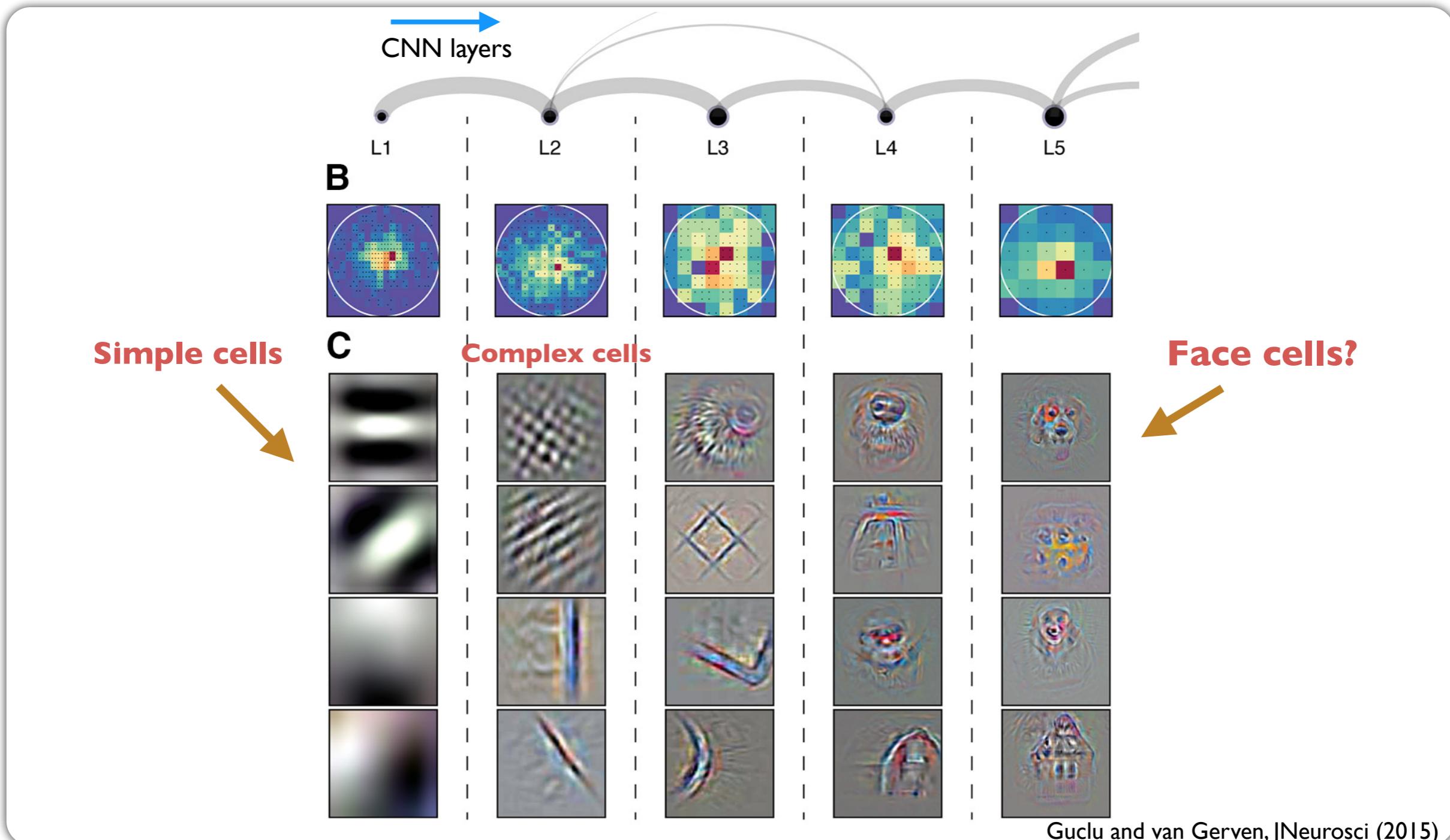
CNNs (machine learning)	Visual system (neuroscience)	Example model
Filter	Simple cells	w
Convolution	Complex cells	$w * u$
Thresholding	Neuron Threshold	ReLU: $v = \max(w * u, 0)$
Pooling/Subsampling	Connectivity between and within brain areas	$\max(v)$ $\text{average}(v)$
Layers	Brain areas (e.g. V1, V2, etc.)	$f(w_2 * f(w_1 * u))$

* : convolution operator

CNNs performance predicts visual cortex responses



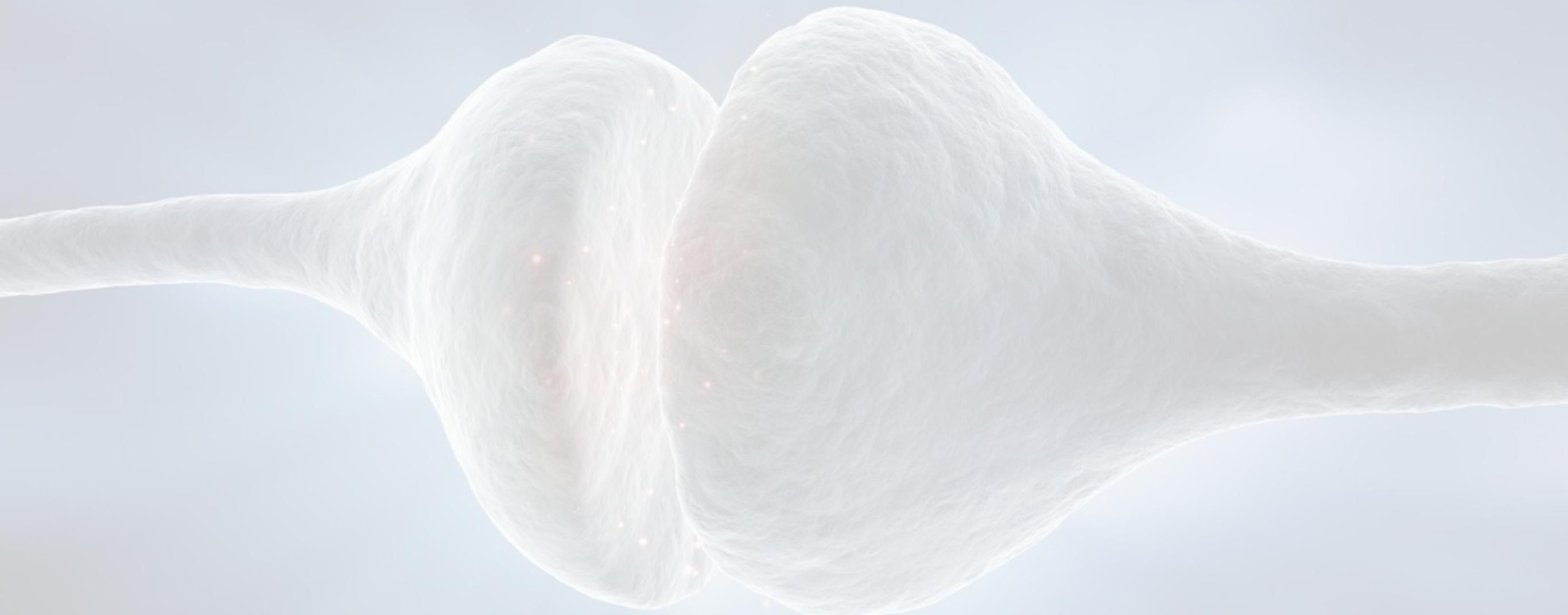
CNNs learn hierarchical features similar to the ones found in the brain



Summary

1. **Visual cortex: spread across multiple areas (V1, V2..)**
2. **Receptive fields of increasing complexity: simple, complex, face and grandmother cells**
3. **Mathematical models of simple and complex cells (e.g. gabor filters)**
4. **Convolutional neural networks as hierarchical models of the visual system**

Questions?



References

Text books:

Theoretical neuroscience: Dayan and Abbott (Chapter 2: receptive fields in the visual system)

Deep Learning by Courville, Goodfellow and Bengio

Recommended: <https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets>

Relevant papers:

- Yamins and DiCarlo, Nature Neuroscience (2016) (review on how well CNNs capture neural data)
- Hubel and Wiesel, J Physiol (1962) (seminal work measuring receptive fields in visual cortex)
- Quiroga, Nature Rev Neurosci (2012) (review on concept/grandmother cells in the cortex)

Upcoming lectures

- Neural circuits and learning (L10)
- Neural circuits: sensory processing
 - L11: Visual cortex
 - L11: Convolutional neural networks
 - L12: Supervised learning: The backpropagation algorithm/cerebellum
 - L13: Unsupervised learning: Sparse coding
- Temporal processing in the brain
 - L14: Auditory cortex and recurrent neural networks
 - L15: Gated recurrent neural networks
- Reinforcement learning in the brain
 - L16: Temporal difference learning/dopamine
 - L16: Q-learning and deep RL