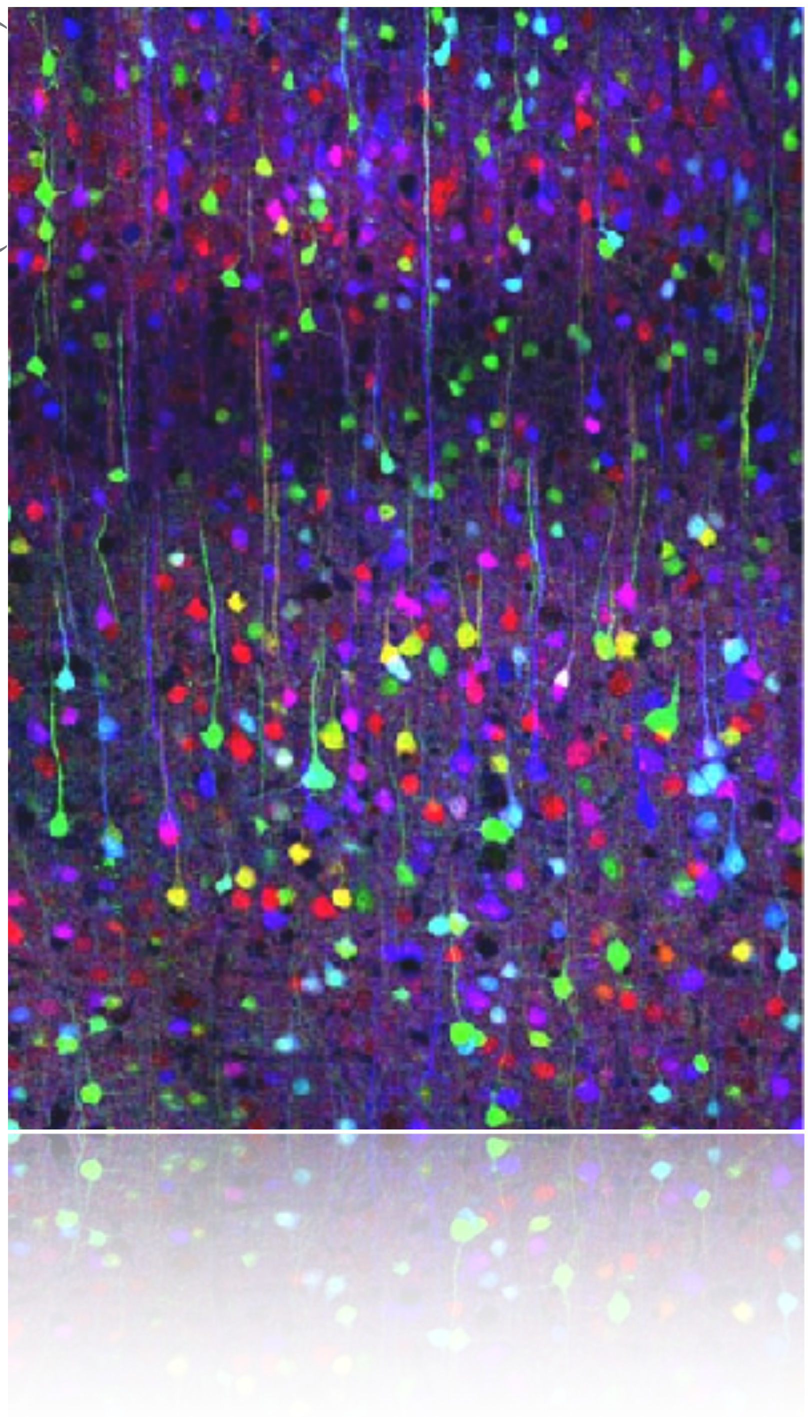
Neural Information Processing 2018/2019

University of
BRISTOL



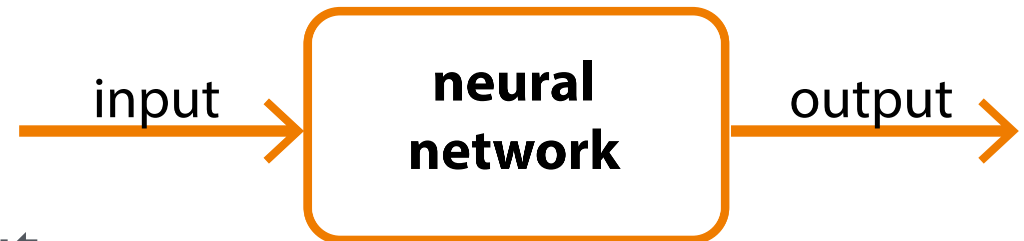
Brainbow (Litchman Lab)

Lecture 11
Neural circuits:
Visual cortex and convolutional nnets

Previously on *Neural Information Processing…*

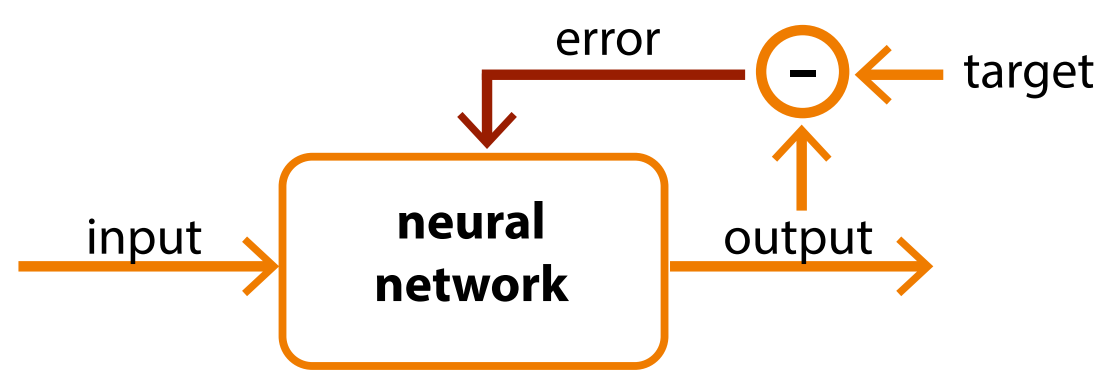
Unsupervised Learning:

Extracts useful representations of input



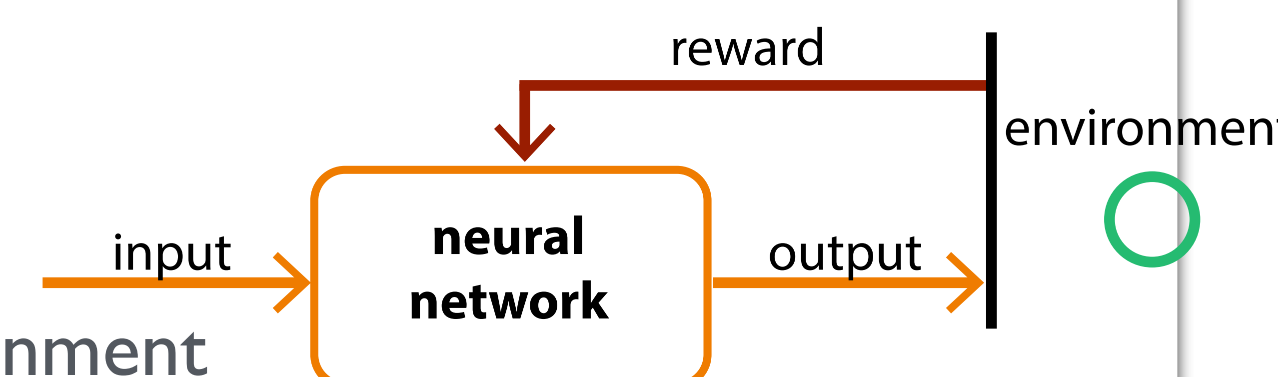
Supervised Learning:

Relies on a teaching signal



Reinforcement Learning:

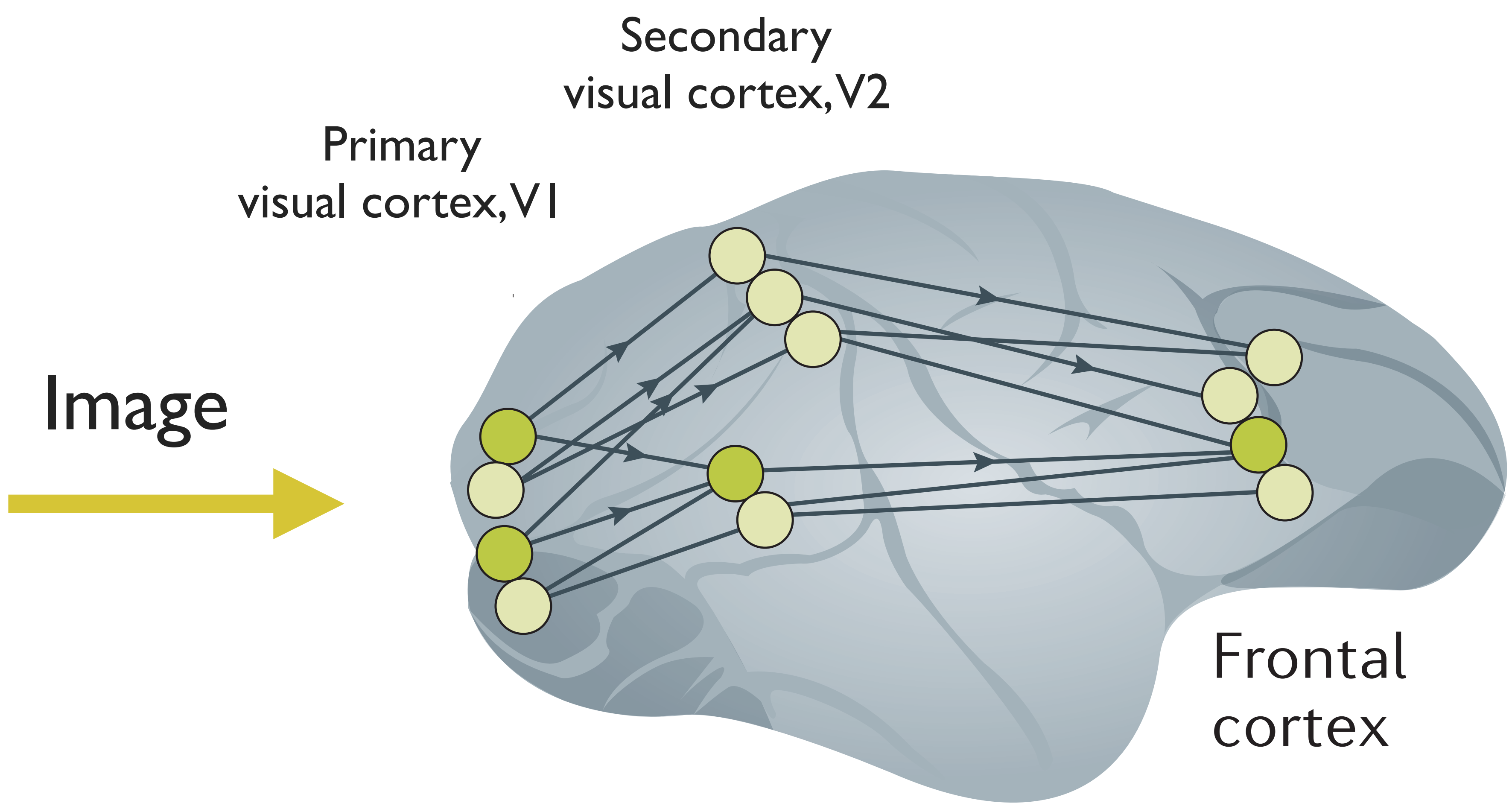
Learn to navigate/survive an environment



But, what to learn?

How to connect the different elements in the brain!

for example: the <u>visual cortex</u>

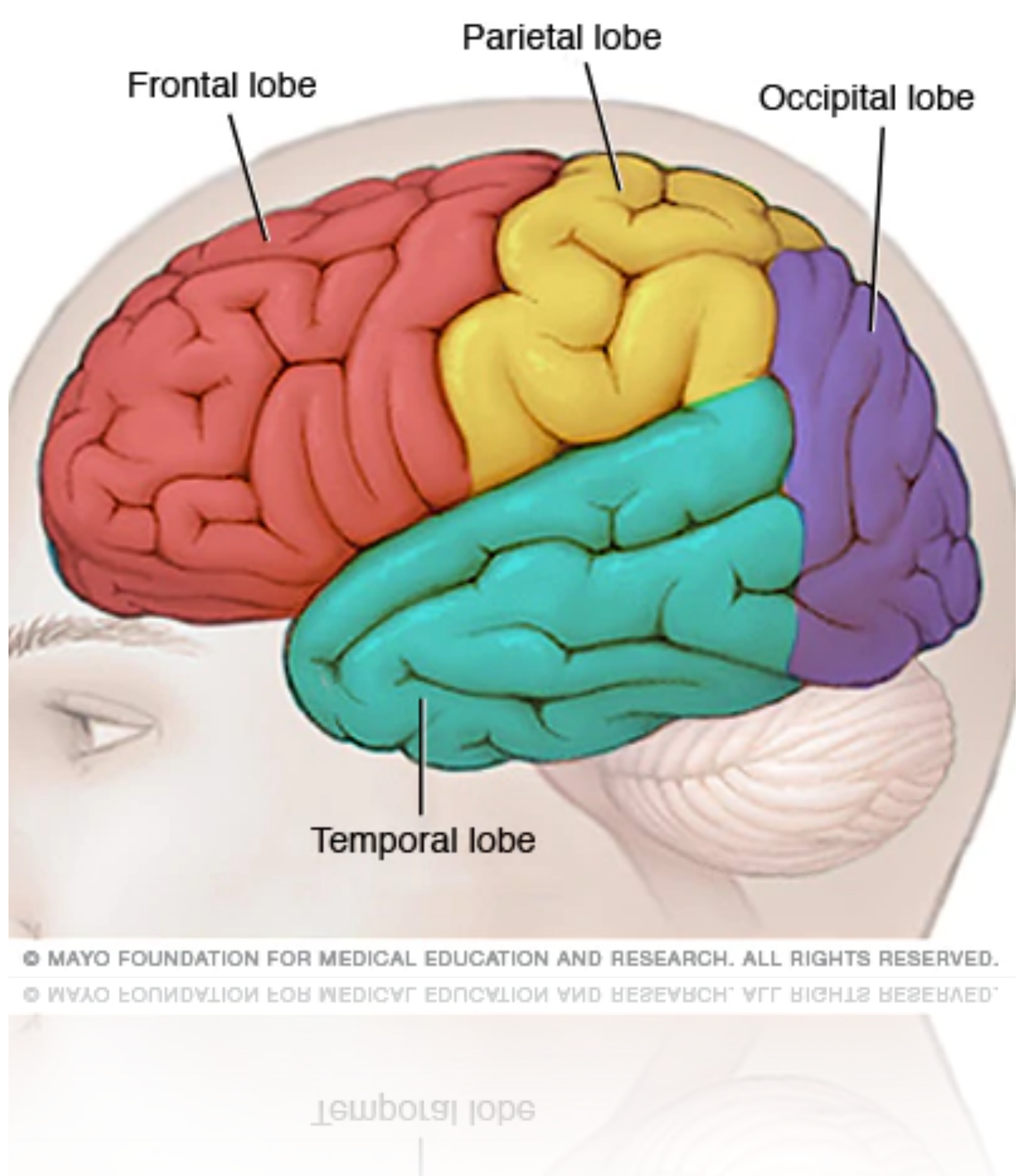


Roelfsema et al., Nature Neuroscience Rev (2018)

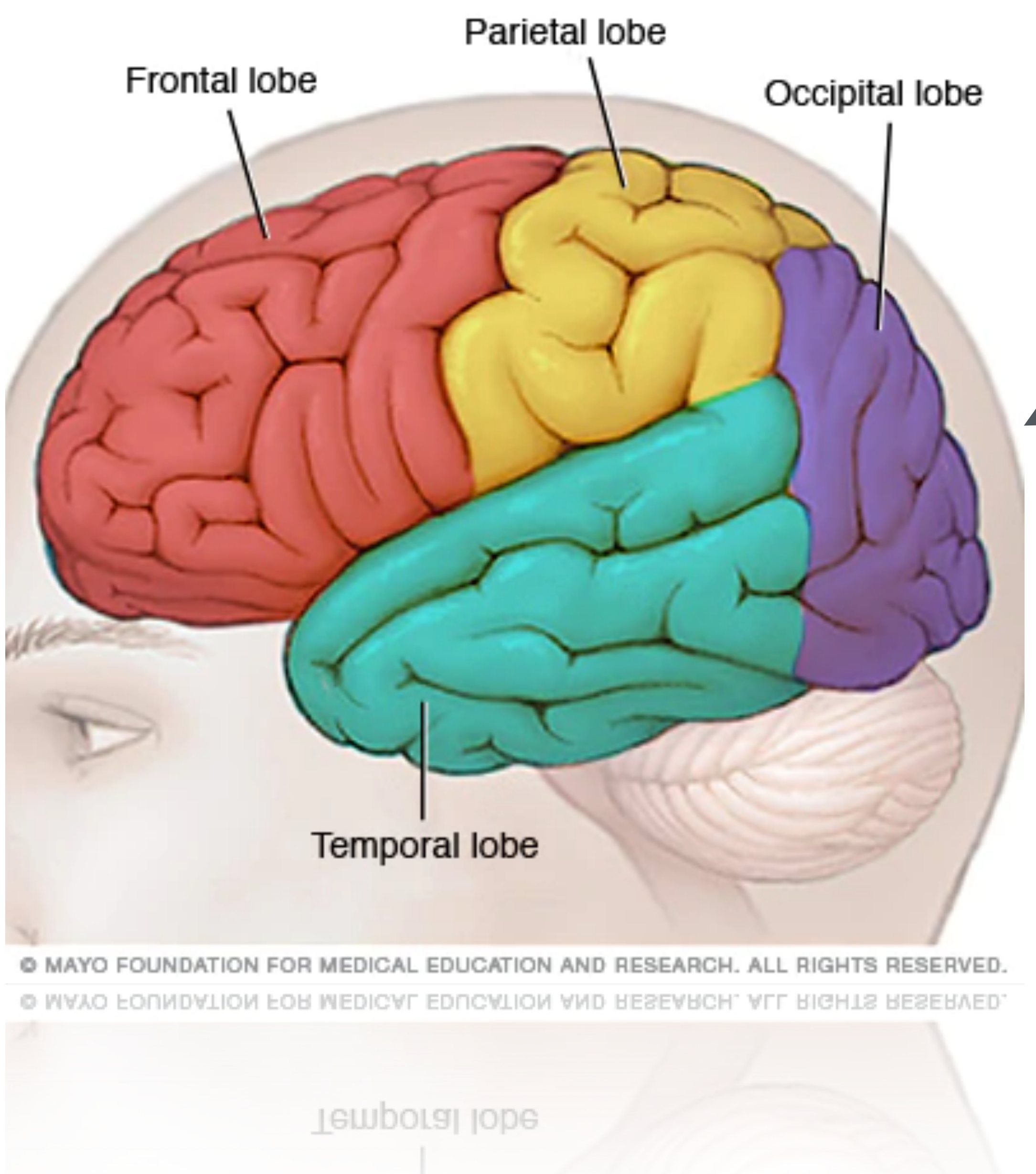
Outline

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

Brain structure

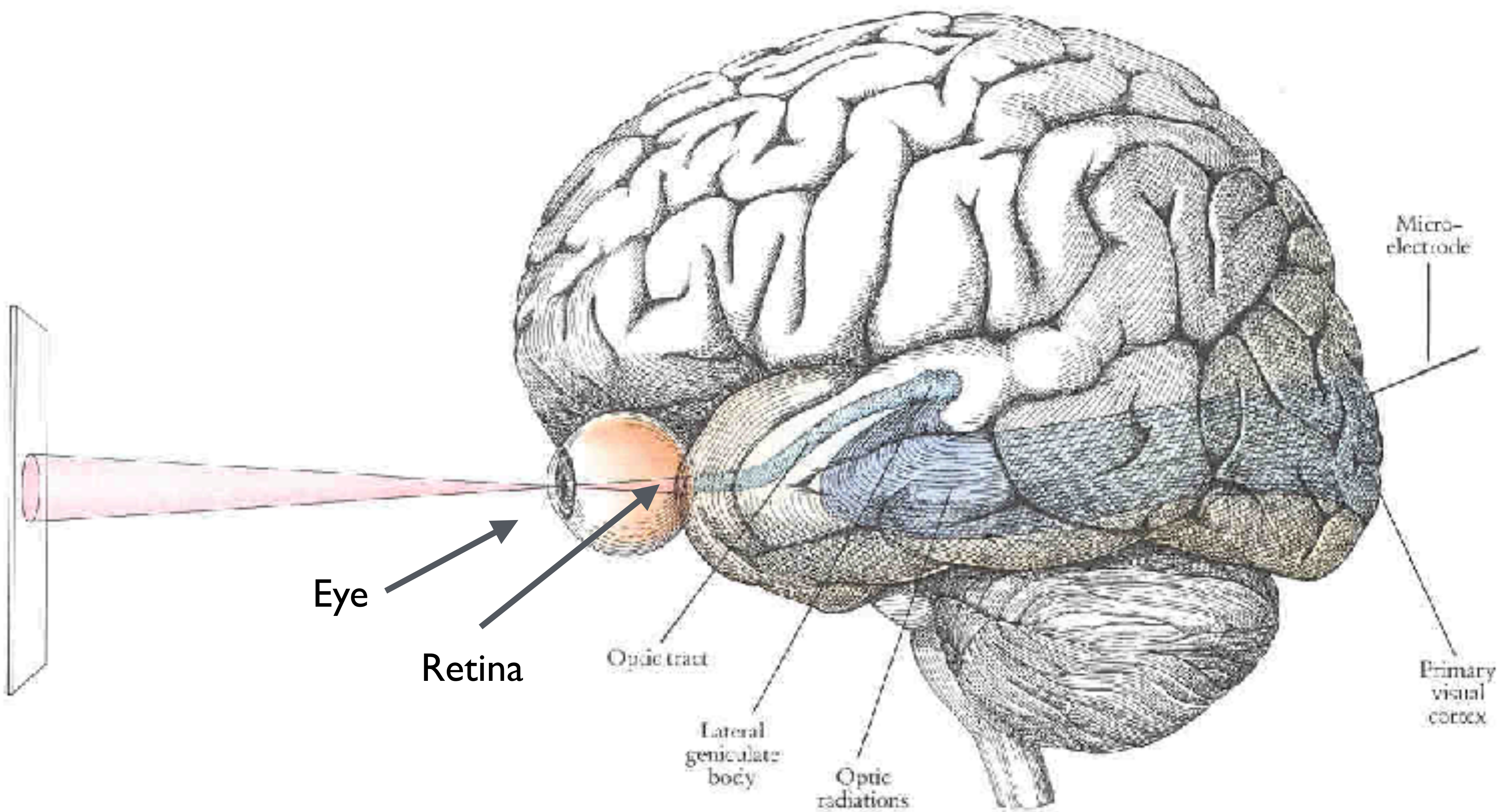


The visual cortex



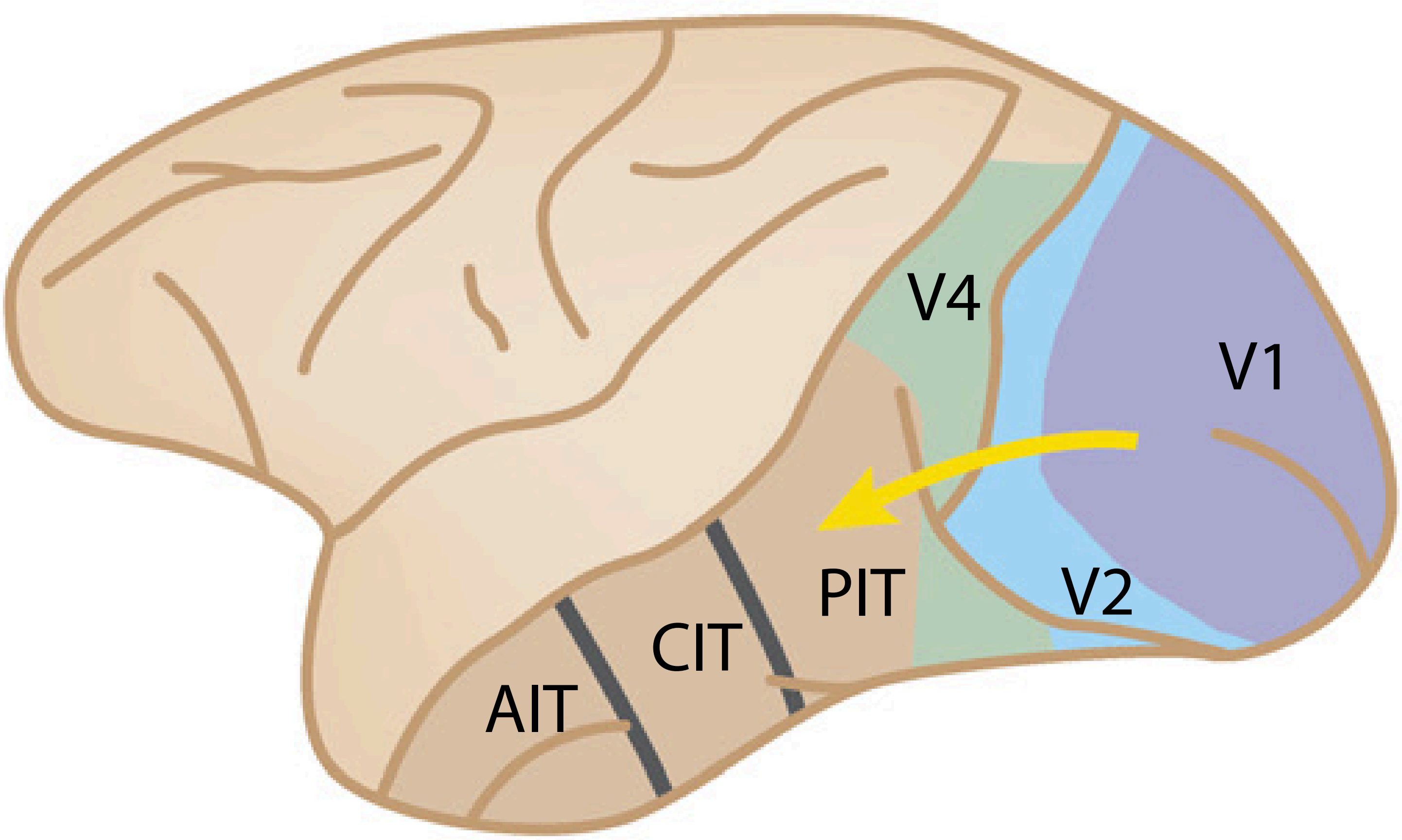
Visual cortex

The visual system



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

Visual cortex: multiple sub-areas

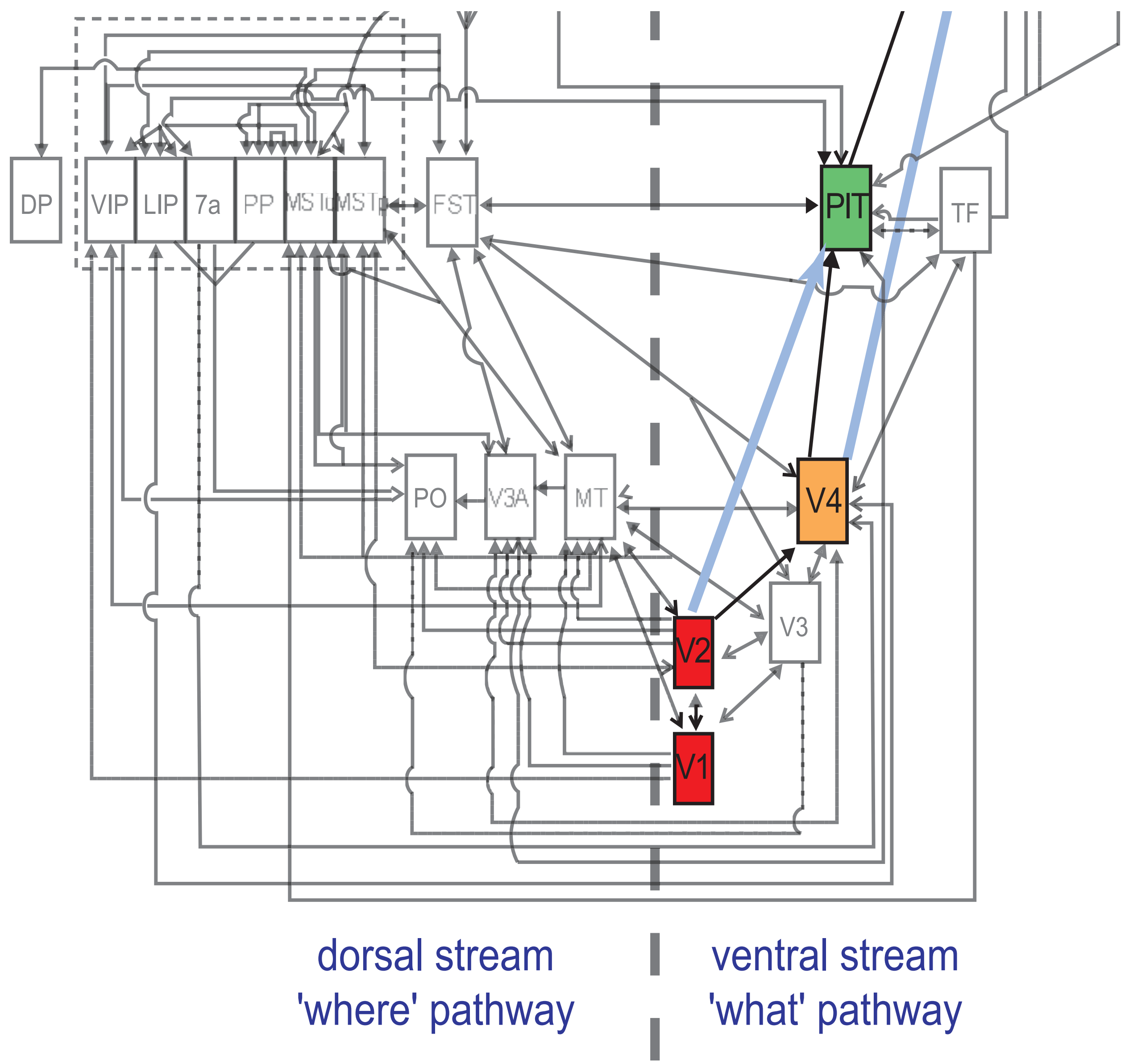


- V1: Primary visual cortex
- V2: Secondary visual cortex

- IT: Inferior temporal cortex

Yamins and DiCarlo, Nature Neuroscience (2016)

Visual cortex: what and where pathways

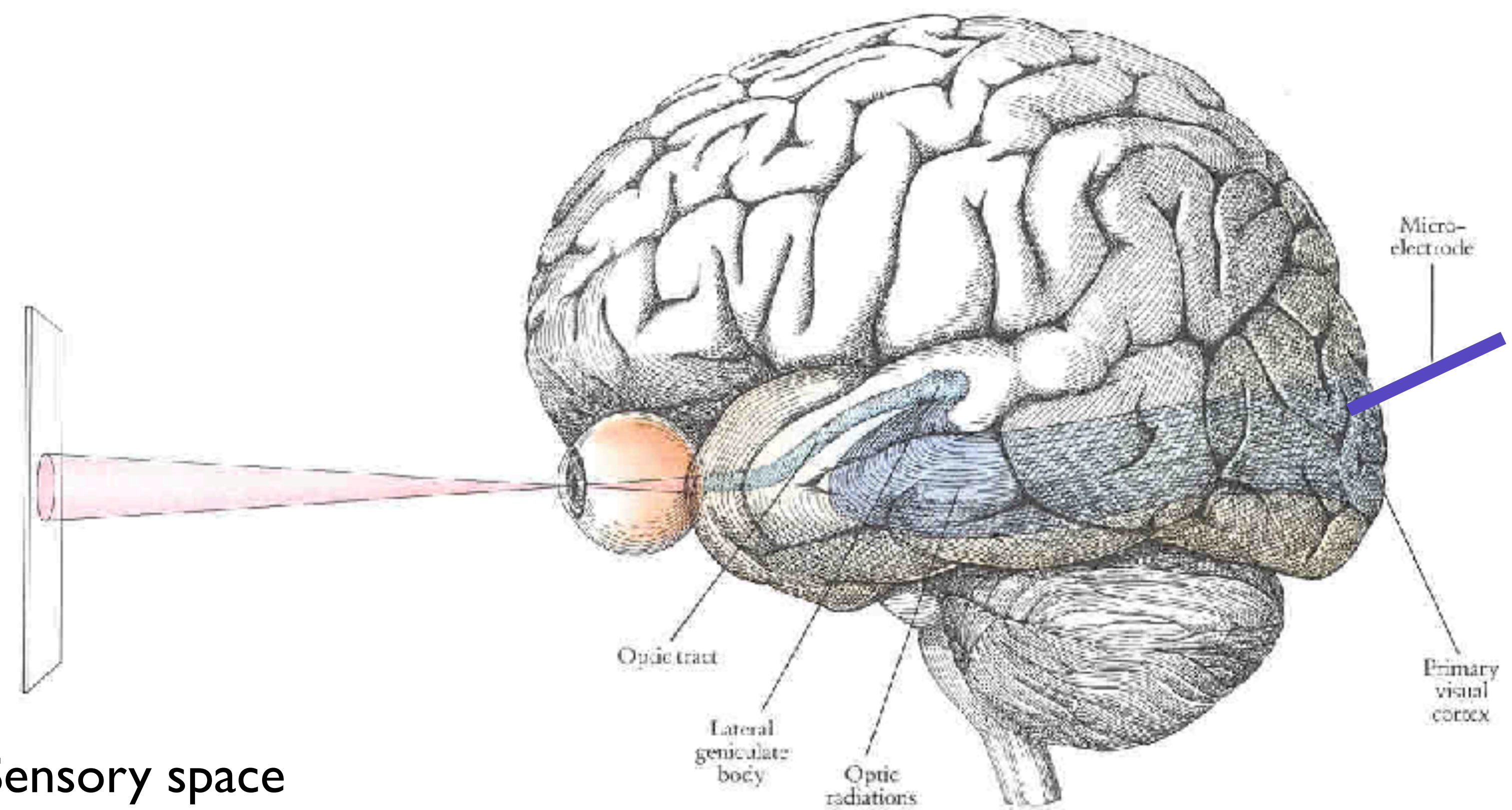


- **'What' pathway:** Relevant to detect what is in the image (e.g. lion vs eagle?)

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

Serre et al., PNAS (2007)

Visual cortex function
receptive fields

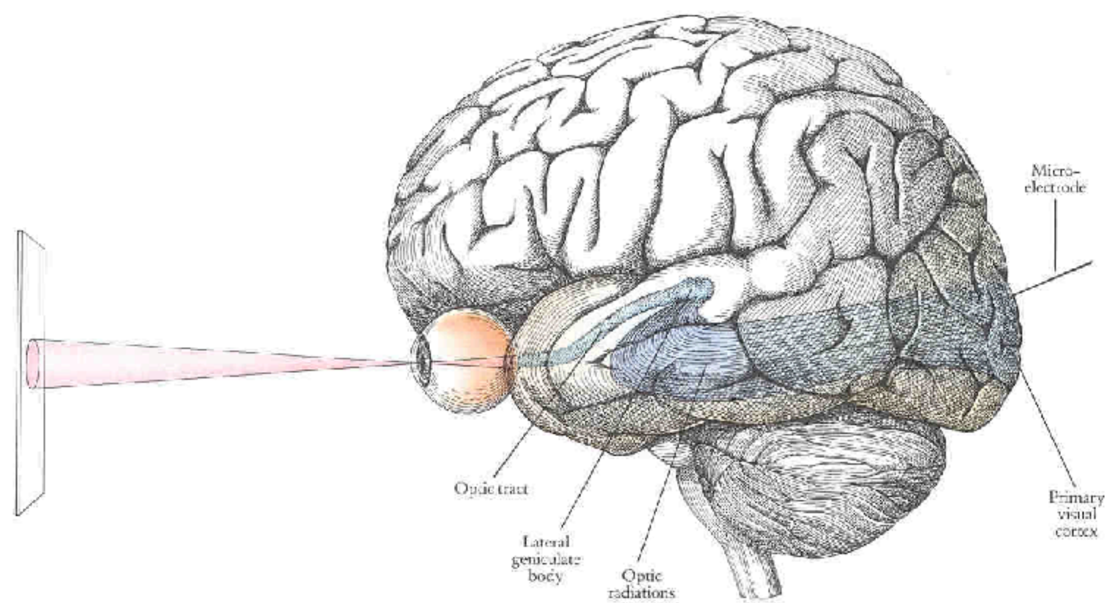


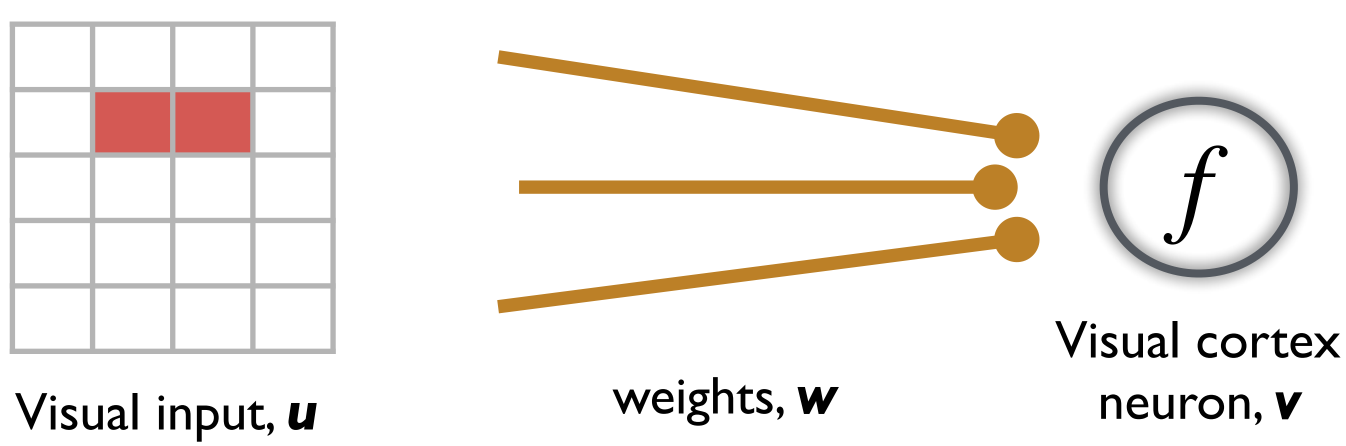
Electrode used to measure **receptive field**

Sensory space
(e.g. visual input)

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

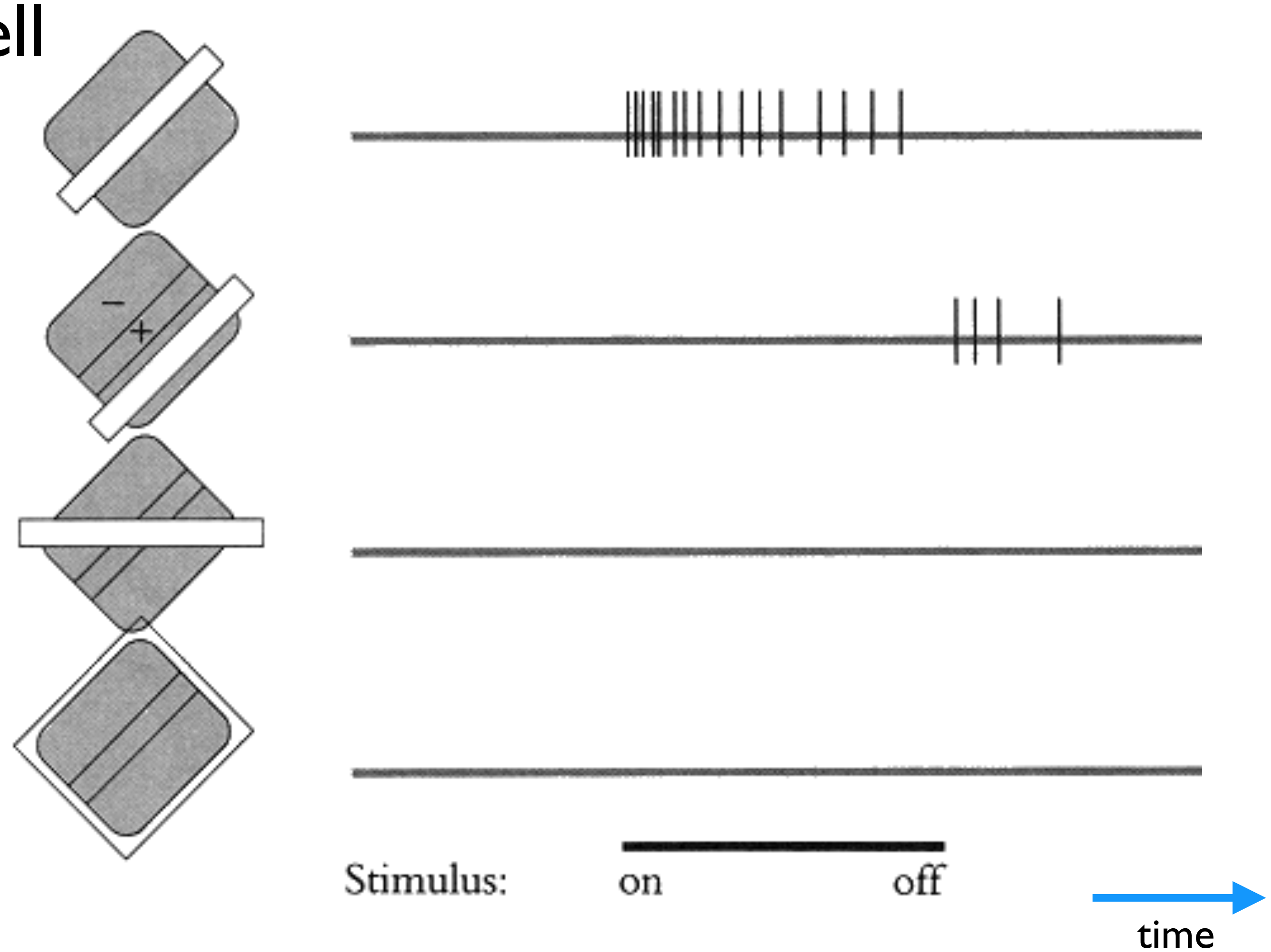




$$v = f(wu)$$

Classical receptive field:
simple cells in primary visual cortex

Simple cell

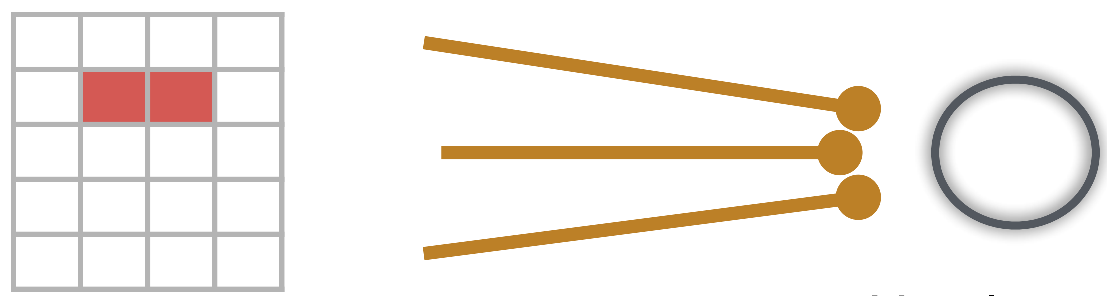


Video of Hubel & Wiesel experiments:
https://youtu.be/8VdFf3egwfg

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:

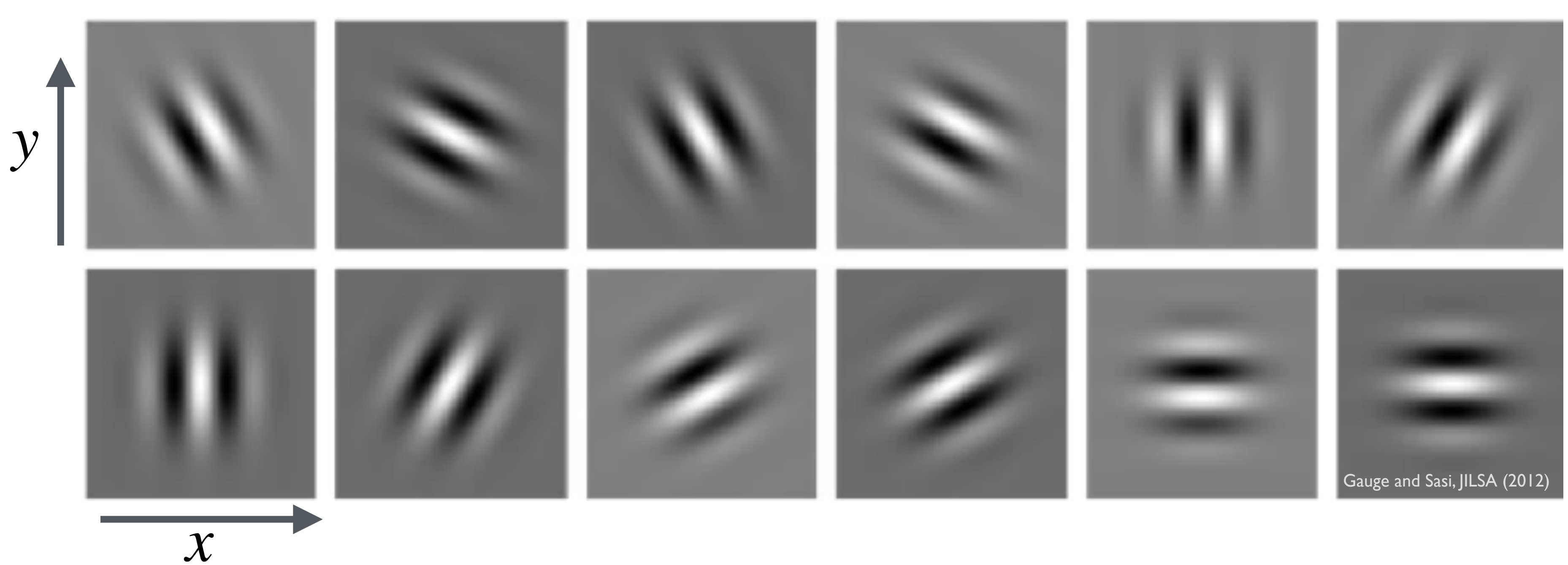
Gabor filter as a model of simple cells

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

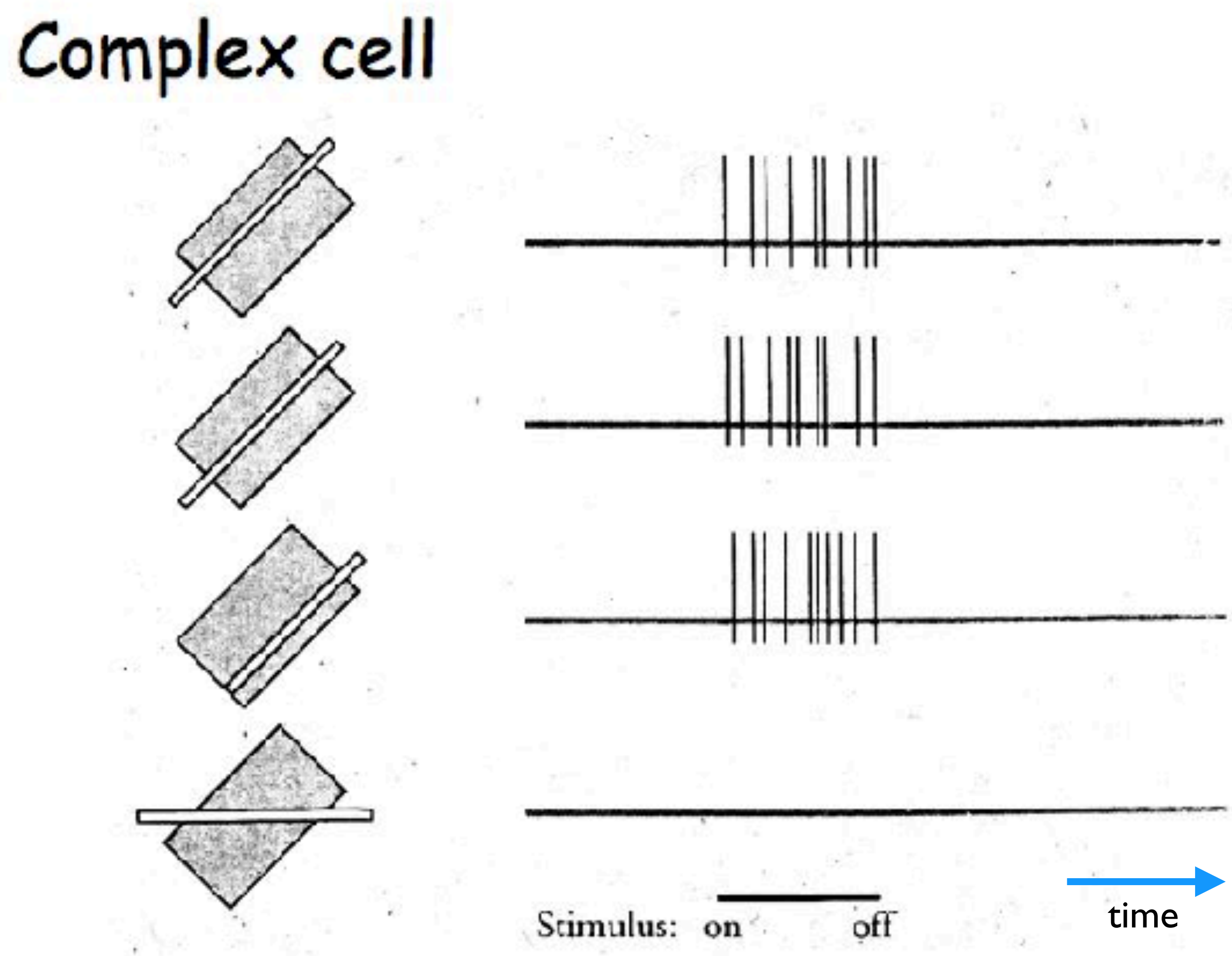
$$w \sim g(x, y; \lambda, \theta, \phi, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2} \right) \cos\left(2\pi \frac{x'}{\lambda} + \phi \right),$$

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

Gabor filters for different θ :

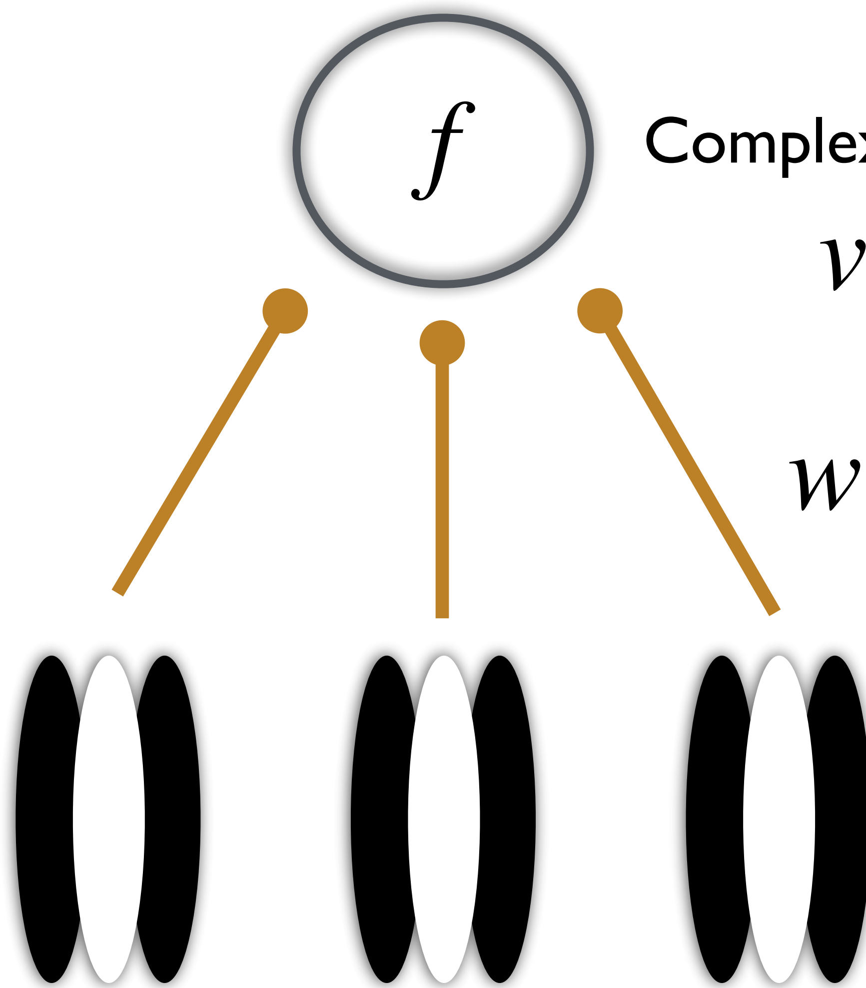


Visual cortex: complex cells



Hubel and Wiesel, J Physiol (1962)

Visual cortex: complex cells, a model



Complex cell

$$v = f(wg)$$

Set of **simple cells** with the same orientation but different locations

$$g(x, y; \lambda, \theta, \phi, \gamma)$$

A set of Gabor filters

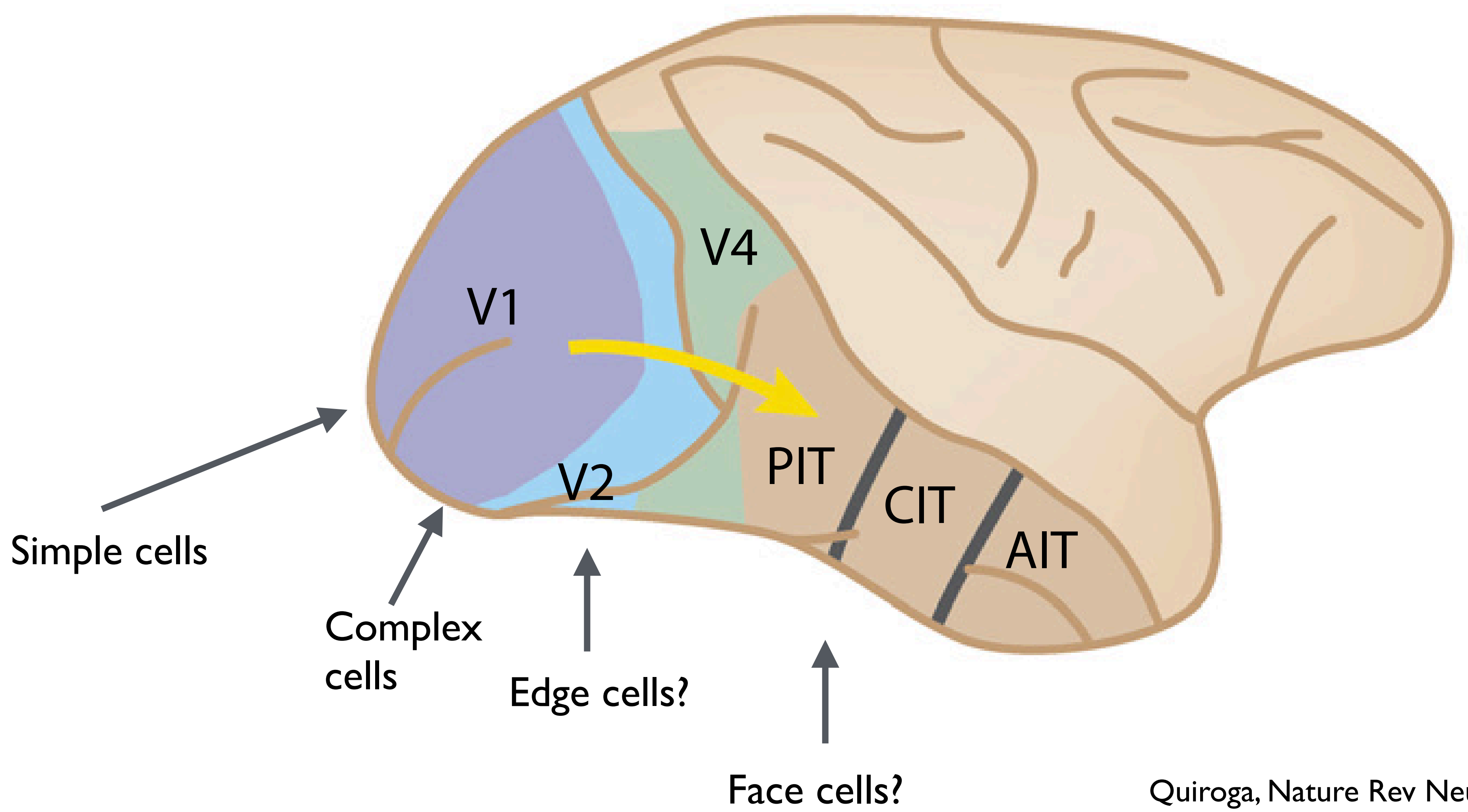
Group discussion

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)

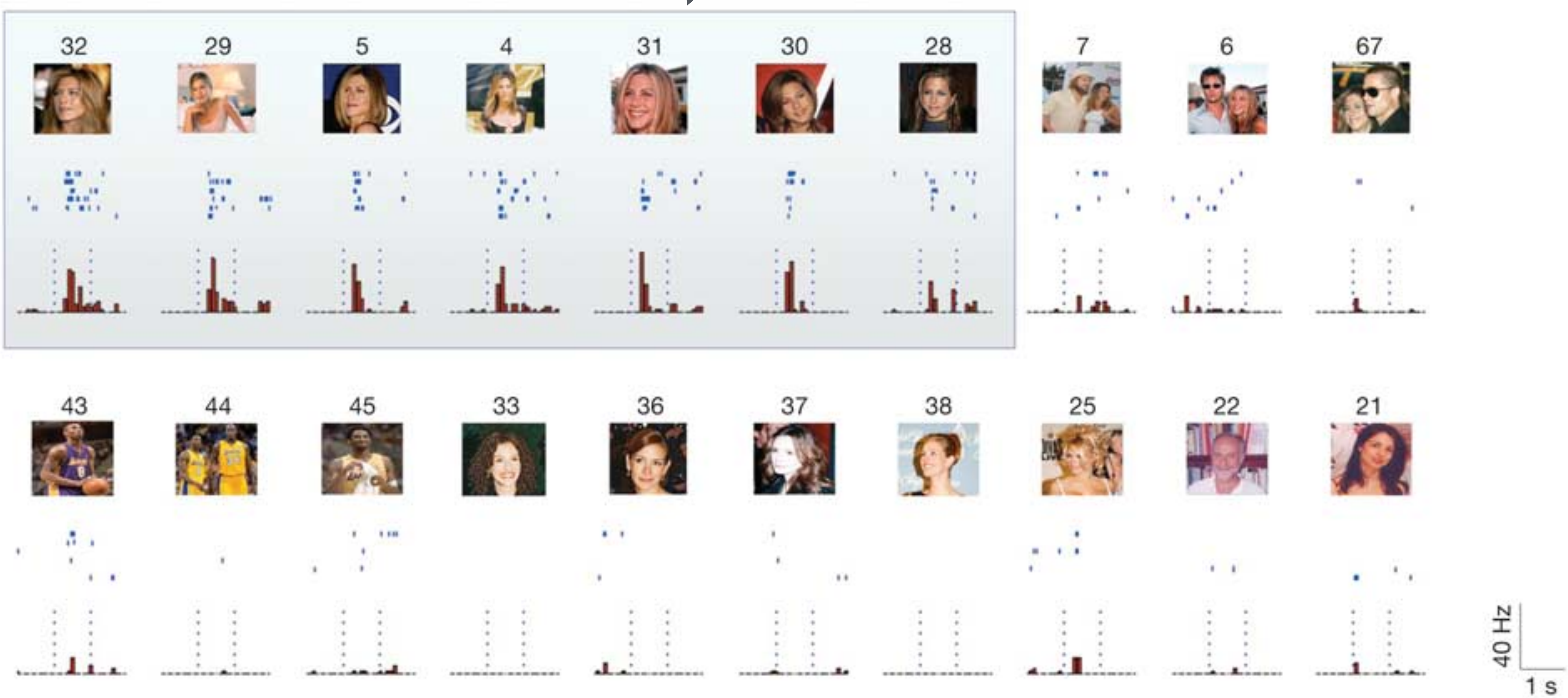
Visual cortex:

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.

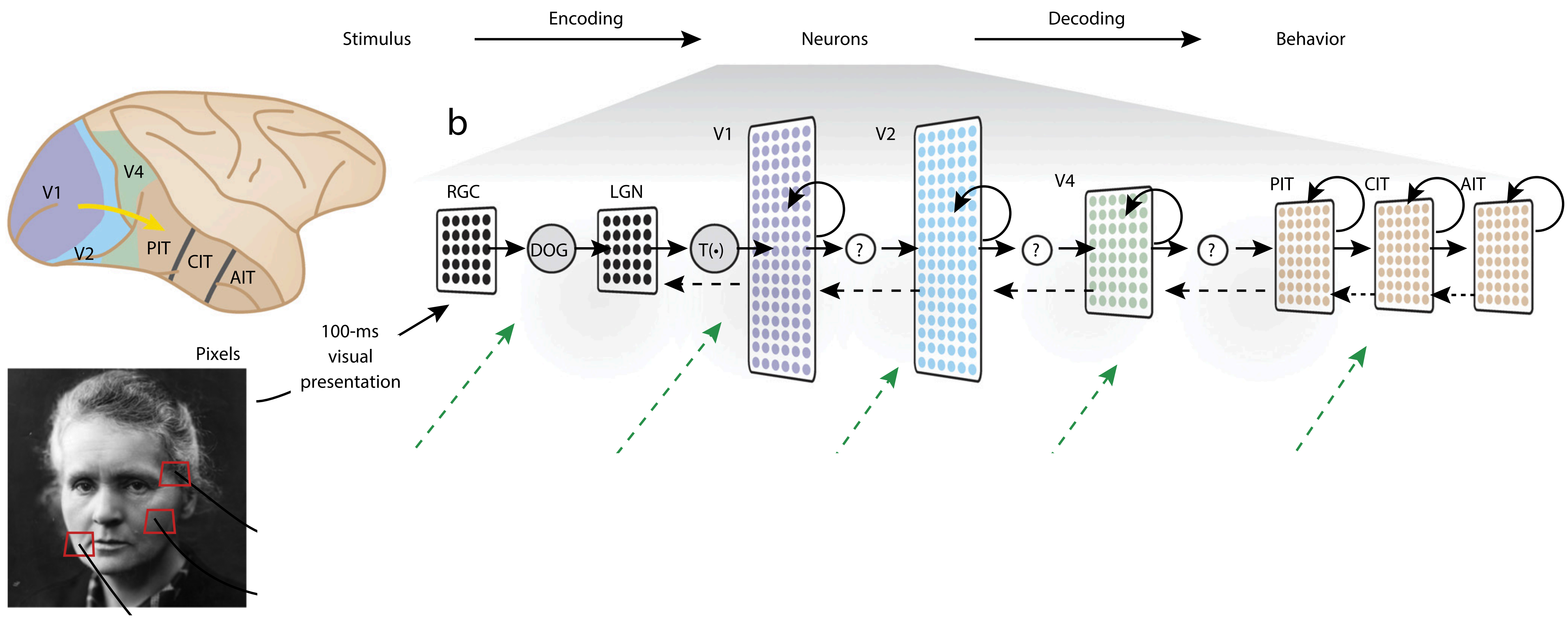
A neuron responding to images of Jennifer Aniston recorded in Medial Temporal Lobe in humans (epilepsy patients):

Quiroga et al., Nature (2005)



Convolutional neural networks (CNNs)

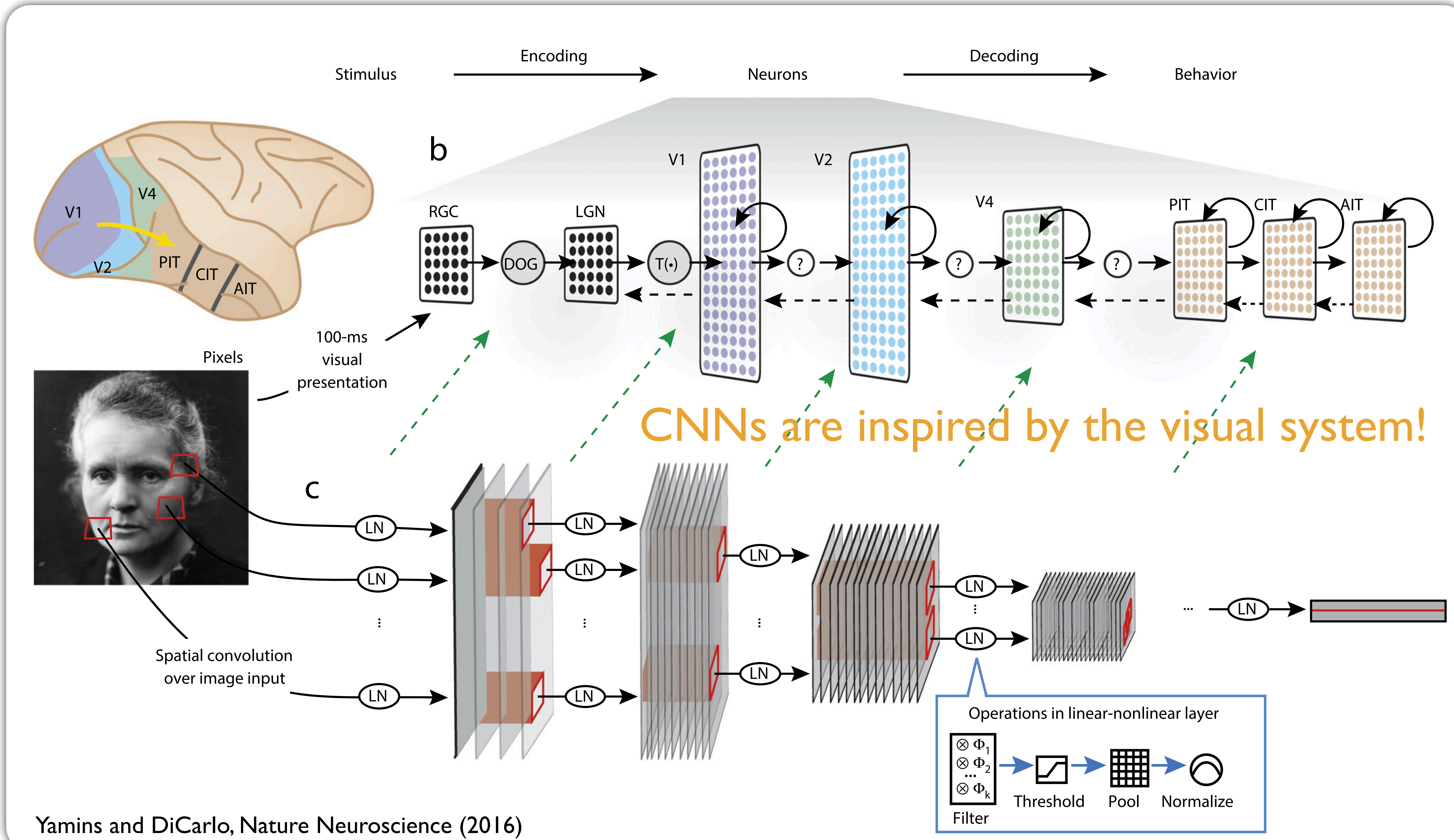
as a model of the visual system



Yamins and DiCarlo, Nature Neuroscience (2016)

Convolutional neural networks (CNNs)

as a model of the visual system

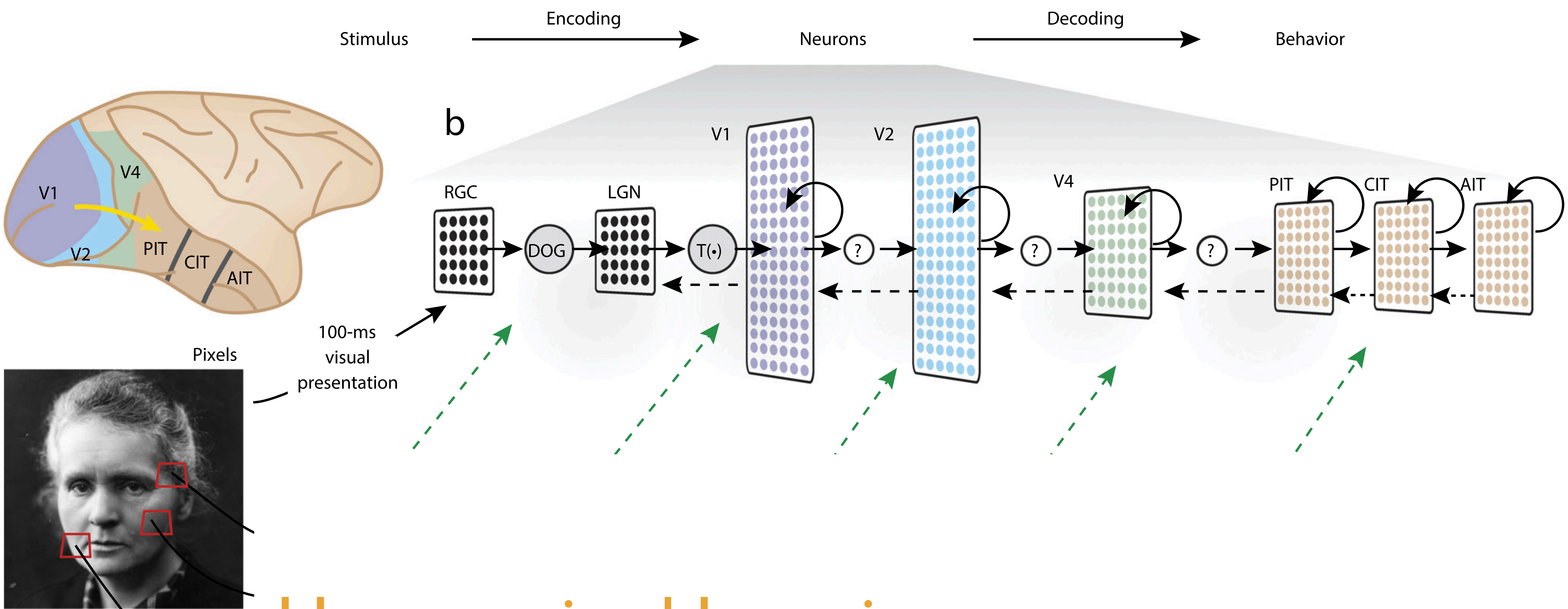


CNNs are inspired by the visual system!

Yamins and DiCarlo, Nature Neuroscience (2016)

Convolutional neural networks (CNNs)

as a model of the visual system



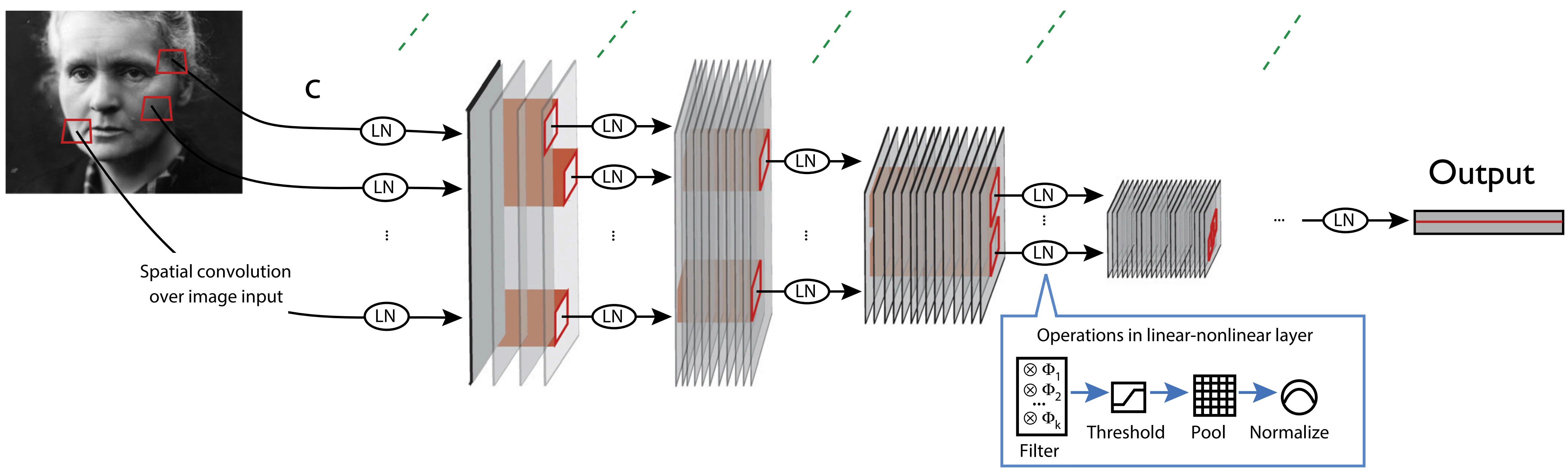
Unsupervised Learning:

In neuroscience the visual cortex is traditionally thought of learning useful representations of the environment.

Yamins and DiCarlo, Nature Neuroscience (2016)

Convolutional neural networks (CNNs)

as a model of the visual system

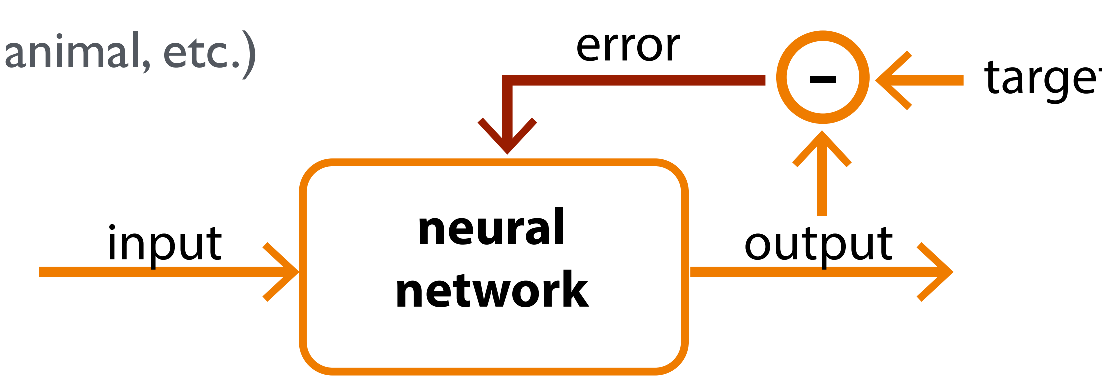


But CNNs rely on **Supervised Learning:**

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

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

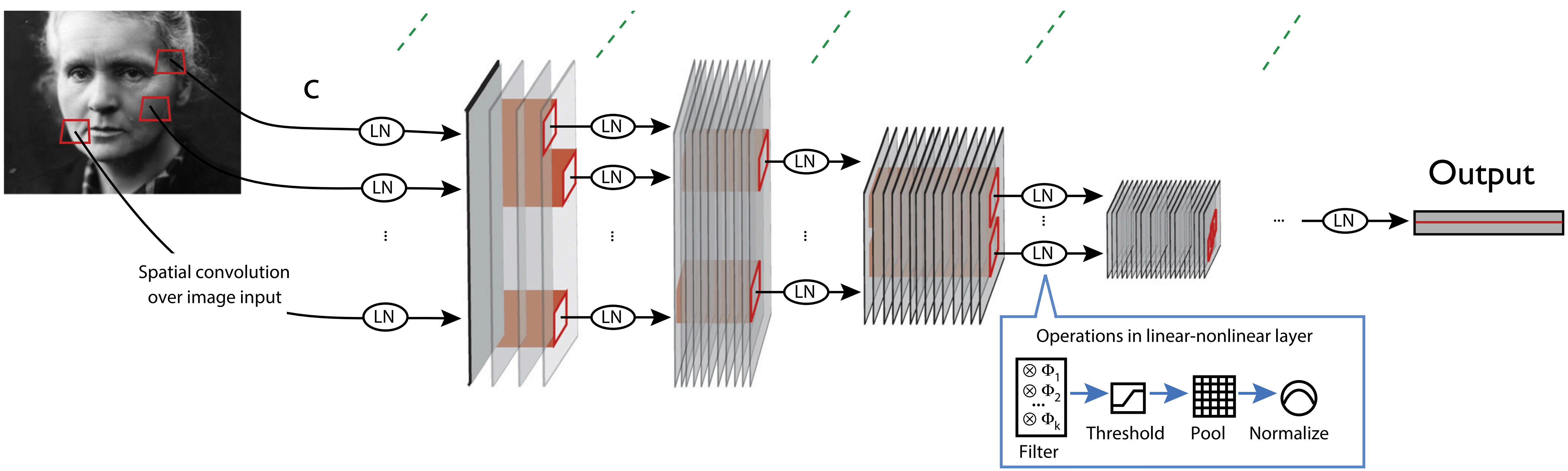
CNNs have revolutionised computer vision!



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)

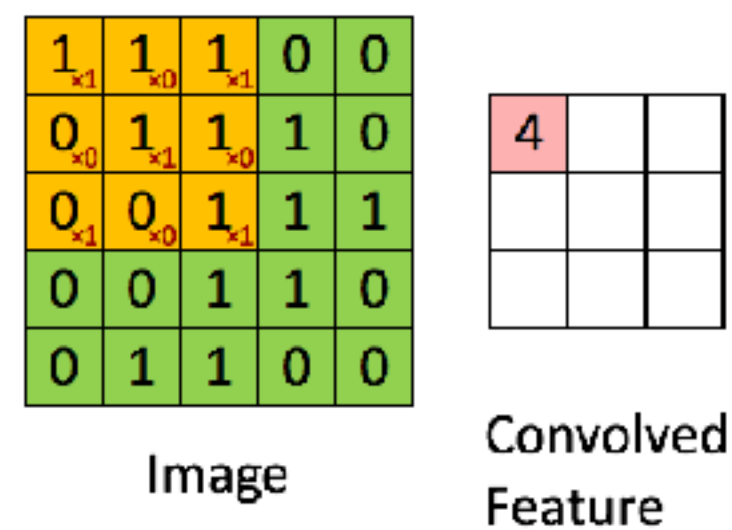
Convolutional neural networks (CNNs)

Convolution operator

Example of filter:

1	0	1
0	1	0
1	0	1

Convolutional operation:

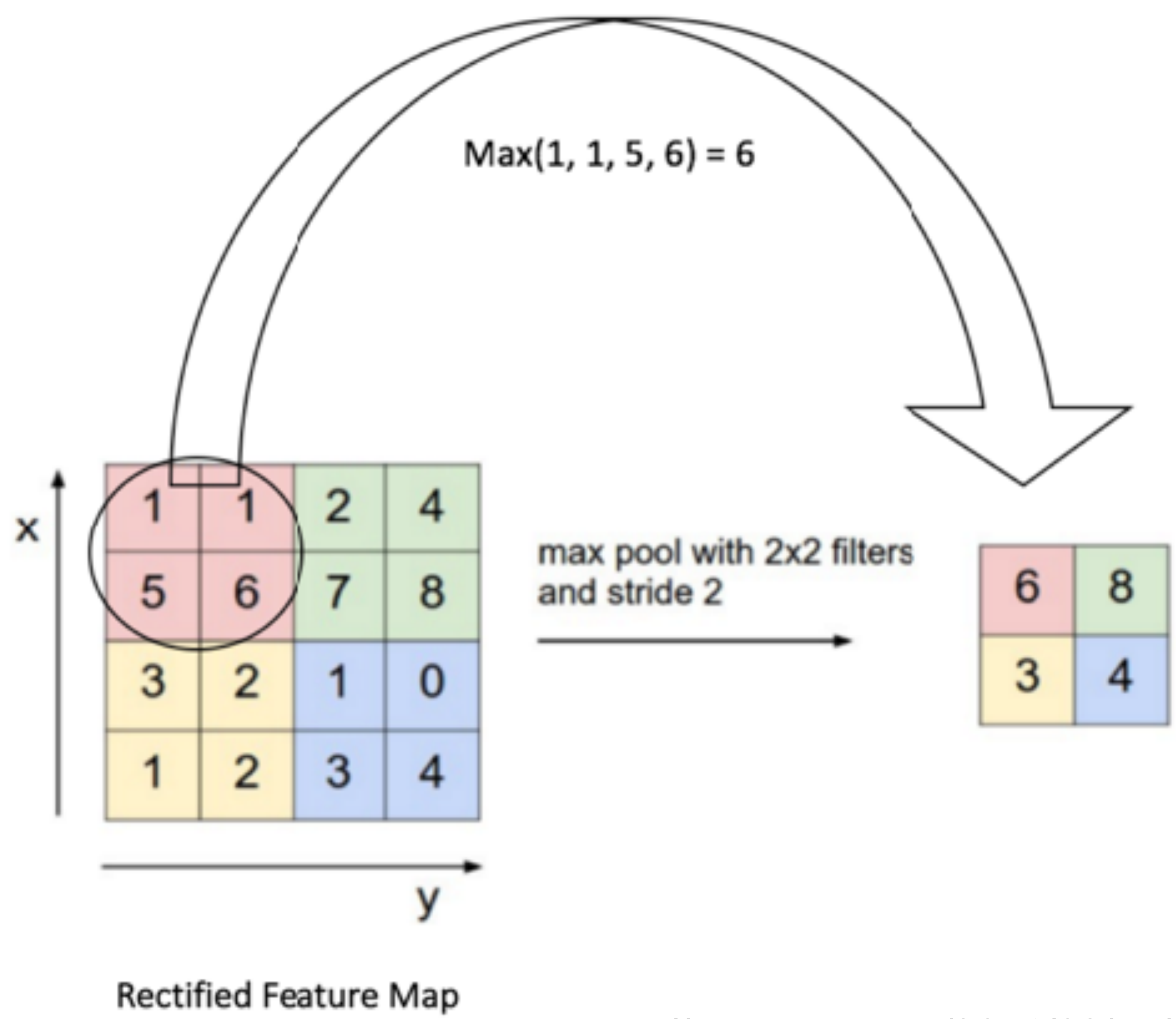


https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets

Convolutional neural networks (CNNs)

Pooling

(Max) Pooling:



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

Convolutional neural networks (CNNs)

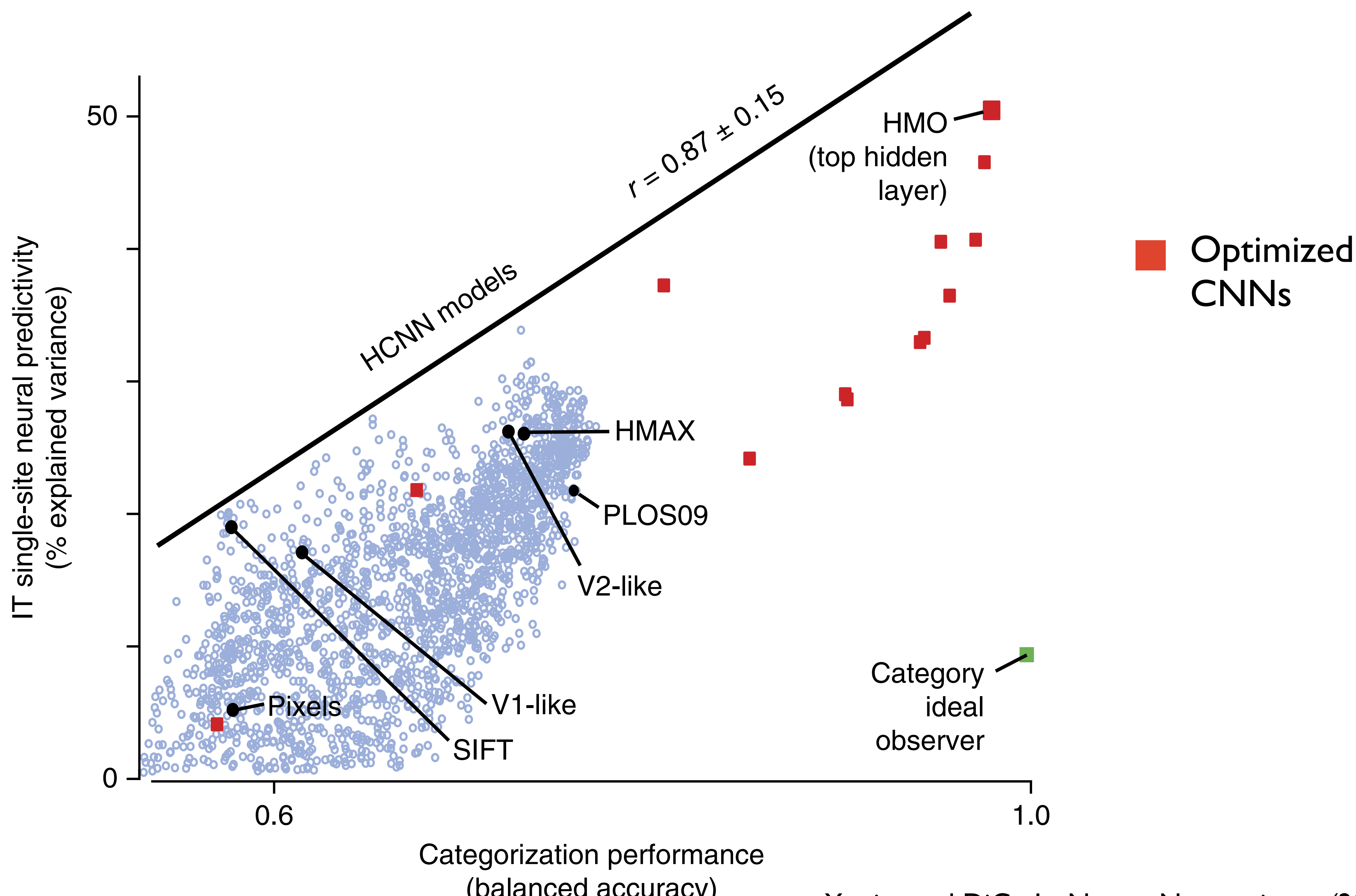
as a model of the visual system

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: $\boldsymbol{v}=\max(w * u, 0)$
Pooling/Subsampling	Connectivity between and within brain areas	$\max(\boldsymbol{v})$ $\mathrm{average}(\boldsymbol{v})$
Layers	Brain areas (e.g. V1, V2, etc.)	$f(w_2 * f(w_1 * u))$

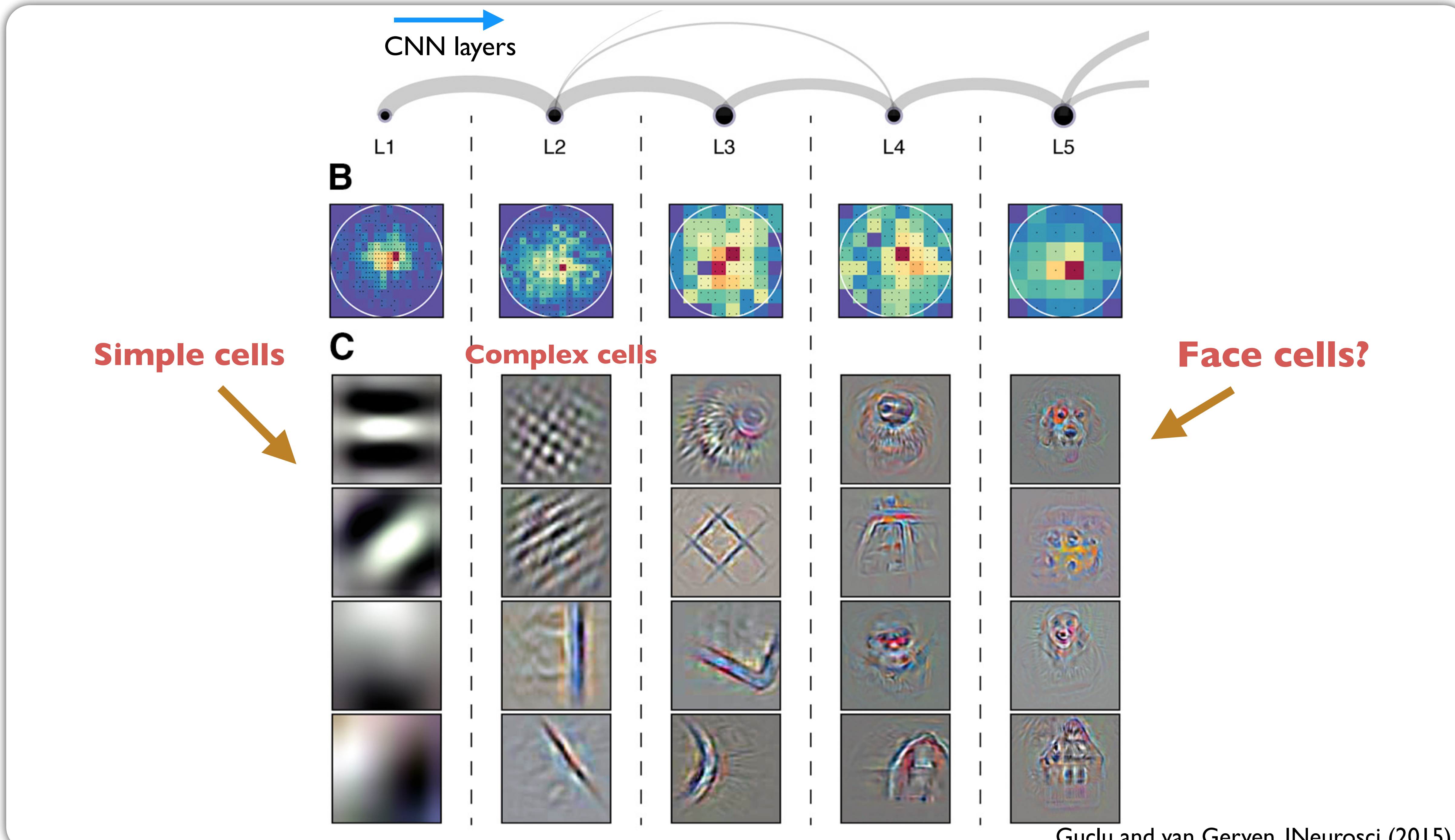
$*$: convolution operator

CNNs performance
predicts visual cortex responses



Yamins and DiCarlo, Nature Neuroscience (2016)

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



Guclu and van Gerven, J Neurosci (2015)

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

- **L10: Neural circuits and learning:** introduction
  - Visual processing
    - L11: Visual cortex
    - L11: Convolutional neural networks
  - Learning in the brain
    - **L12: Supervised learning: The backpropagation algorithm/cerebellum**
    - L13: Unsupervised learning: Sparse coding and Boltzmann Machines
    - L14: Reinforcement learning: TD learning, Q learning, deep RL and dopamine
  - Temporal processing in the brain
    - L14: Auditory cortex and recurrent neural networks
    - L15: Gated recurrent neural networks