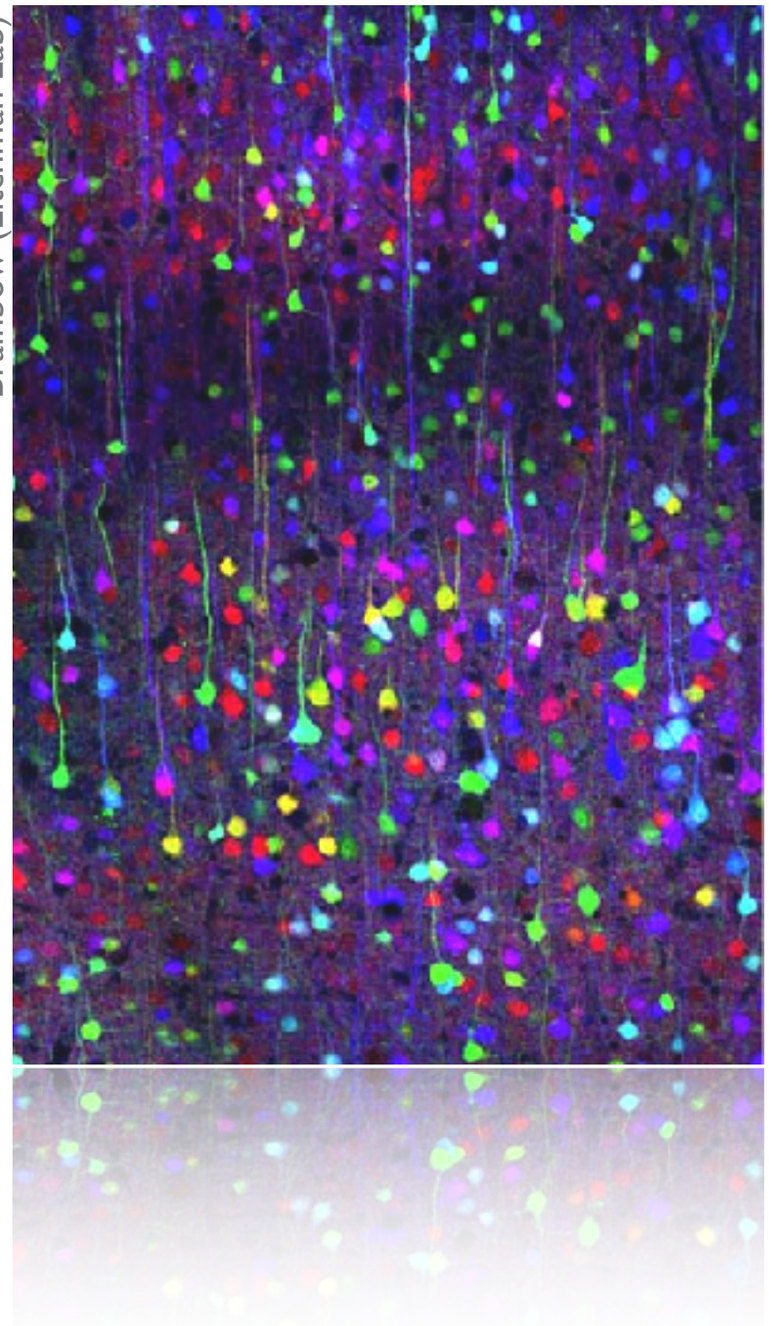
# Information Processing & the Brain 2019/2020

University of BRISTOL



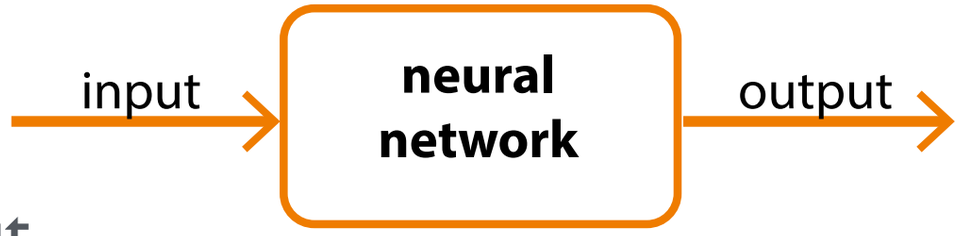
Brainbow (Litchman Lab)

# Lecture 12
# Visual system: deep learning?

# Previously on *IPB*…

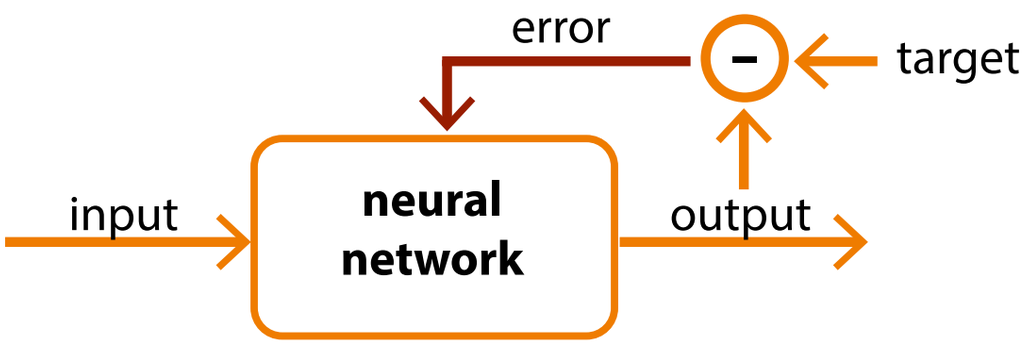
## Unsupervised Learning:

Extracts useful representations of input



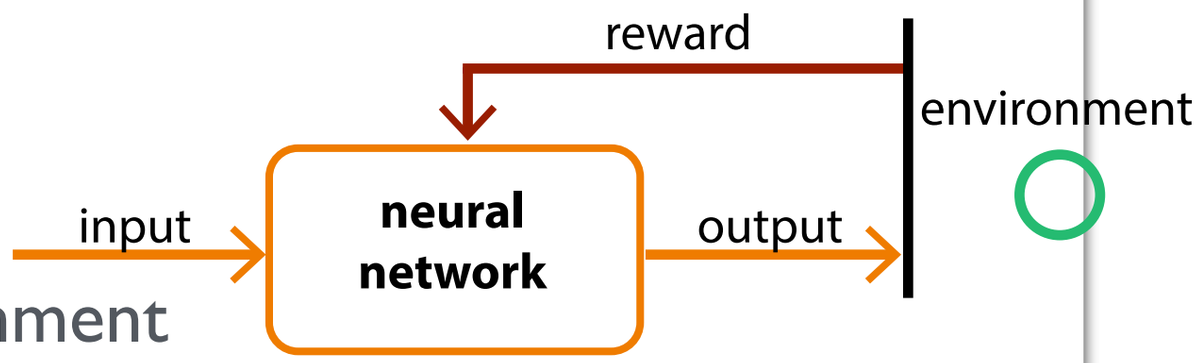

## Supervised Learning:

Relies on a teaching signal




## Reinforcement Learning:

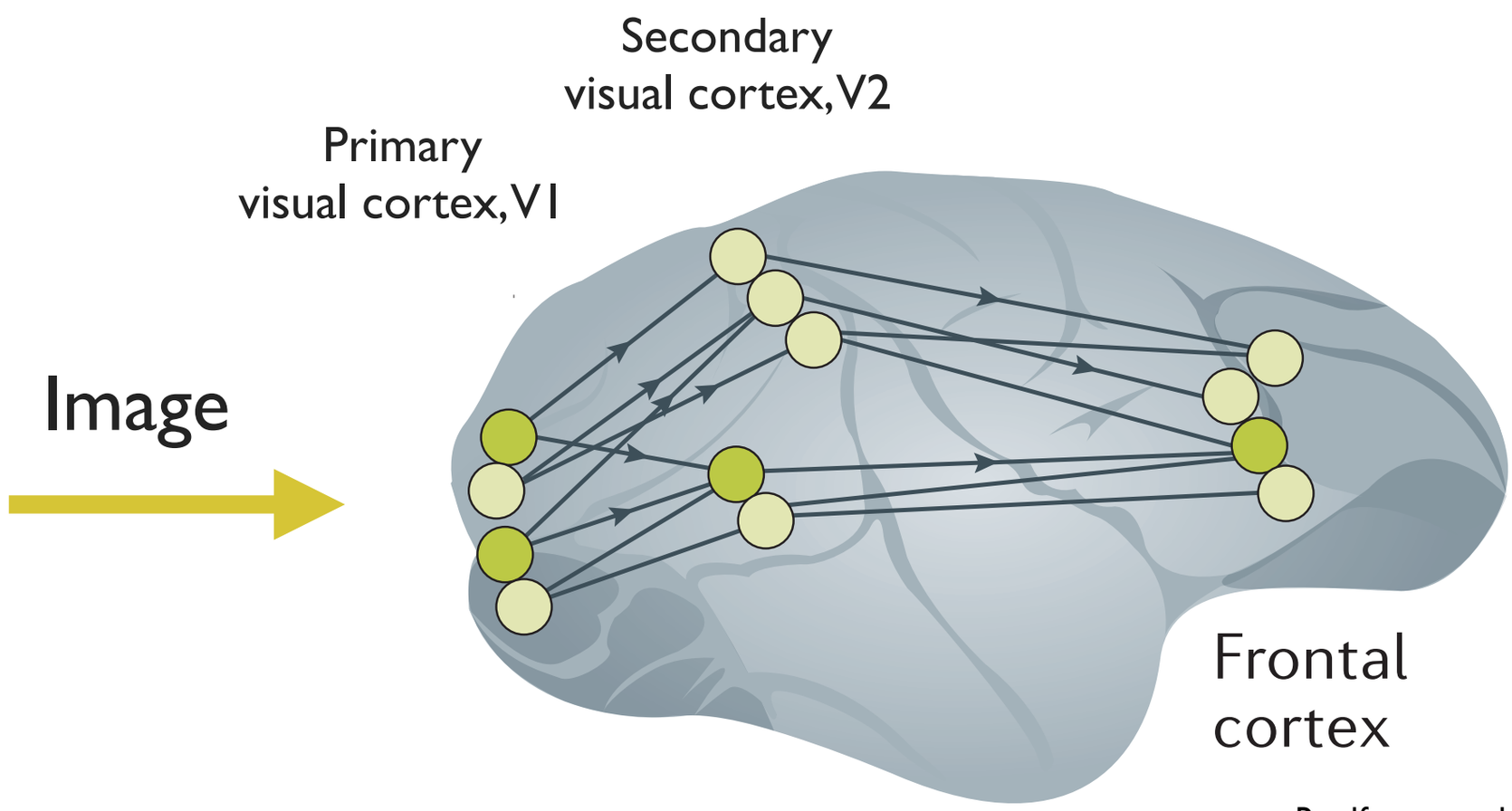
Learn to navigate/survive an environment



# But, what to learn?

**How to connect the different elements in the brain!**

**for example: the visual cortex**

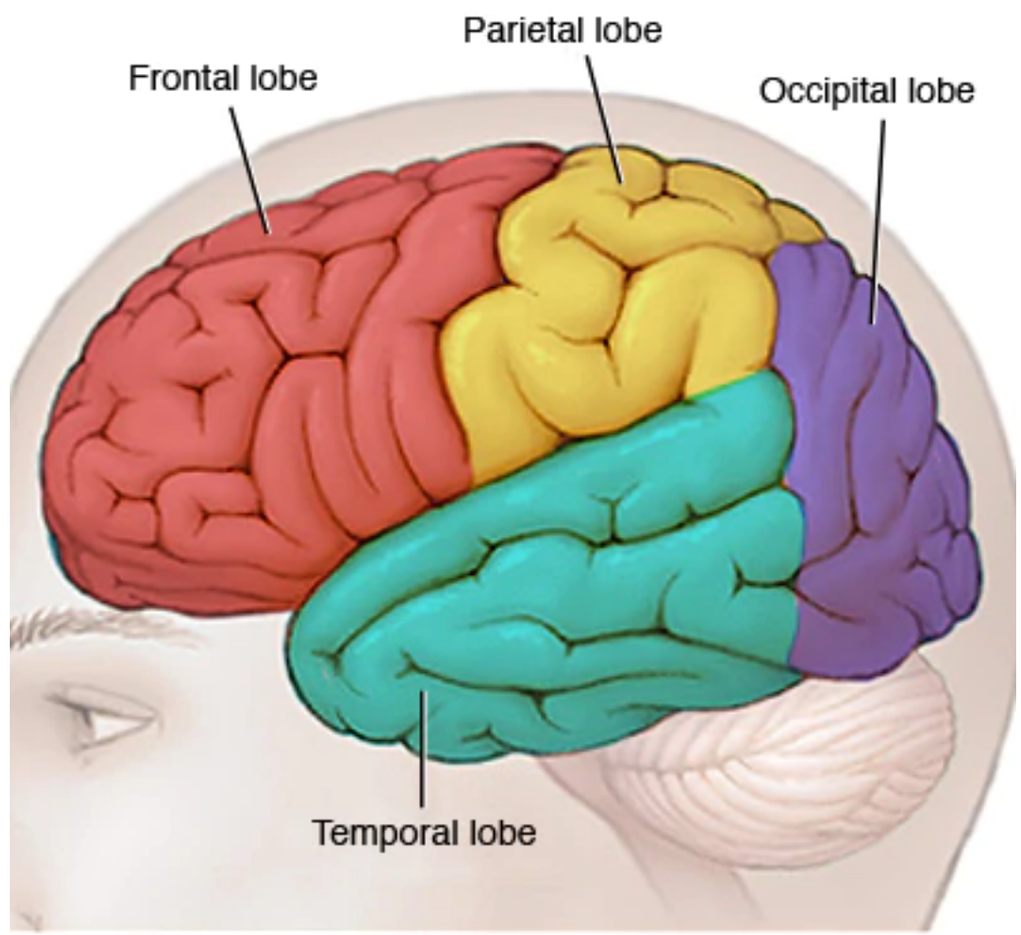



Roelfsema et al., Nature Neuroscience Rev (2018)

# Outline

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

# Brain structure

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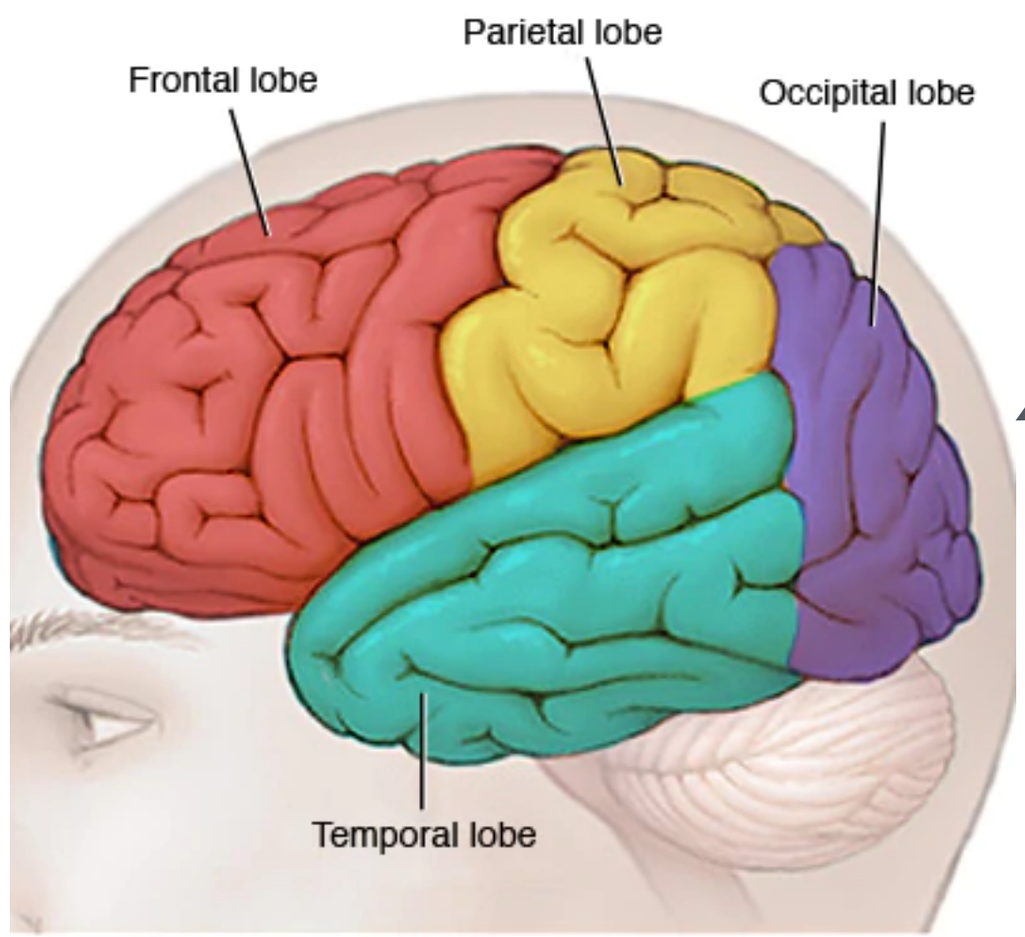
# The visual cortex

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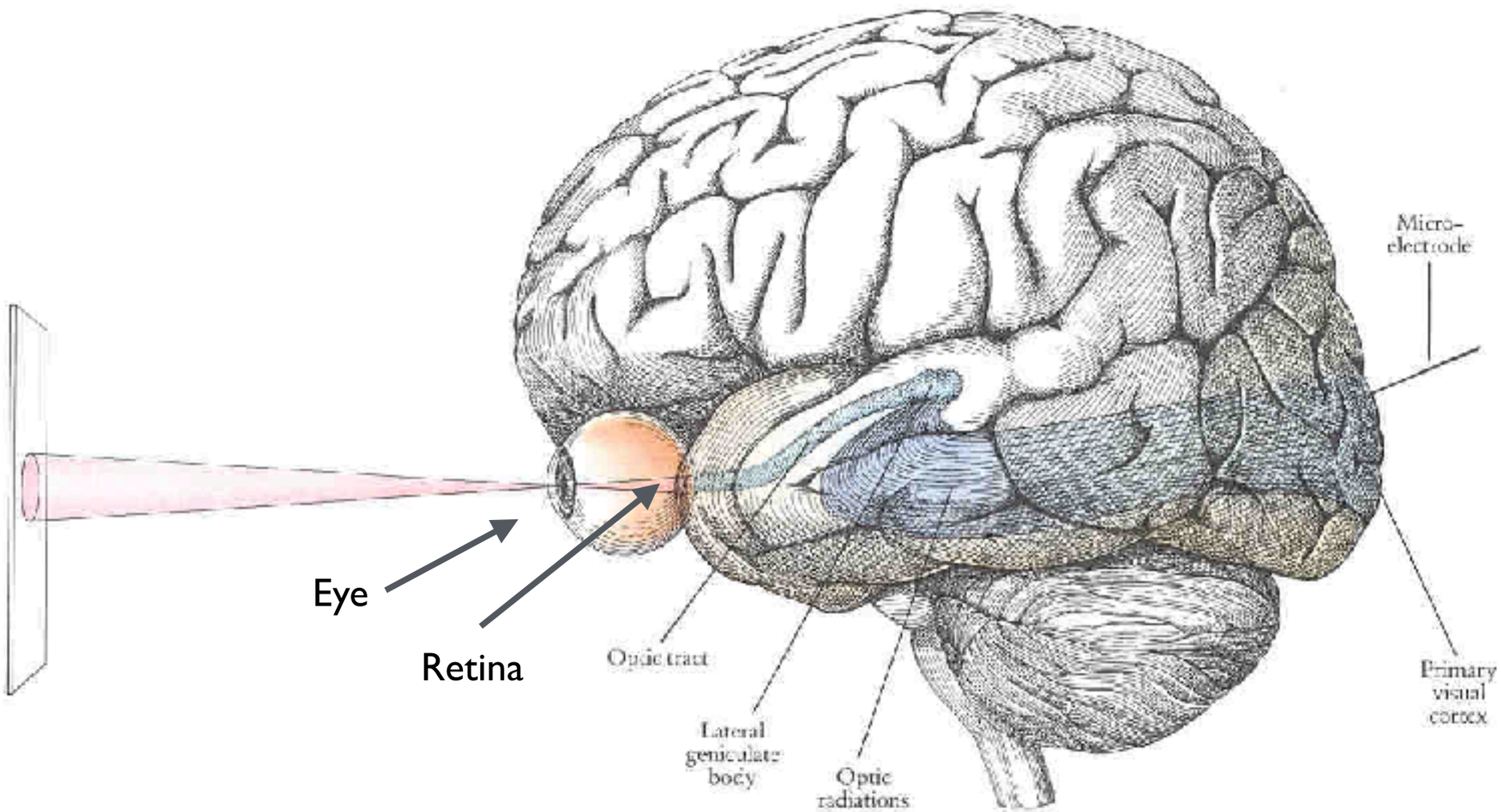
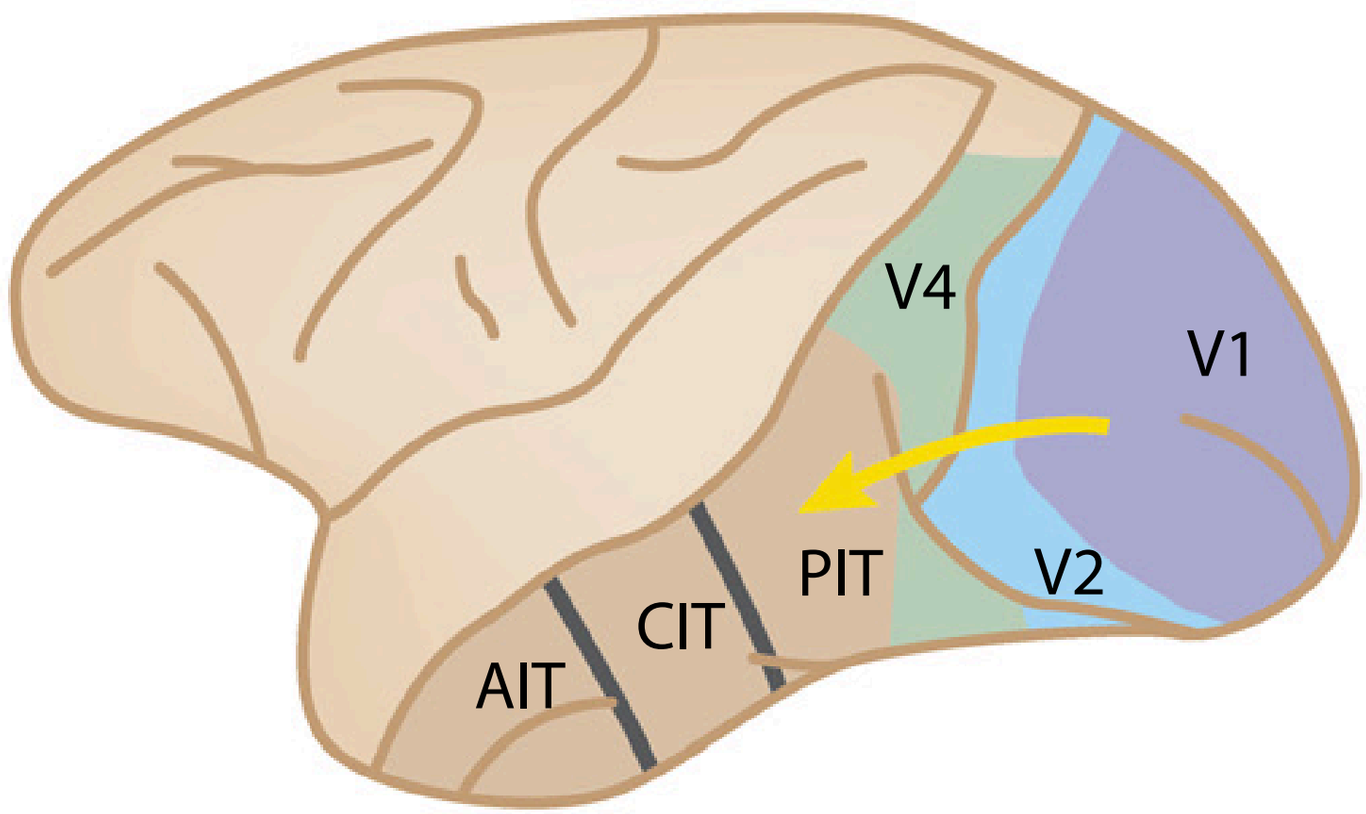
Visual cortex

# The visual system




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

# Visual cortex: multiple sub-areas

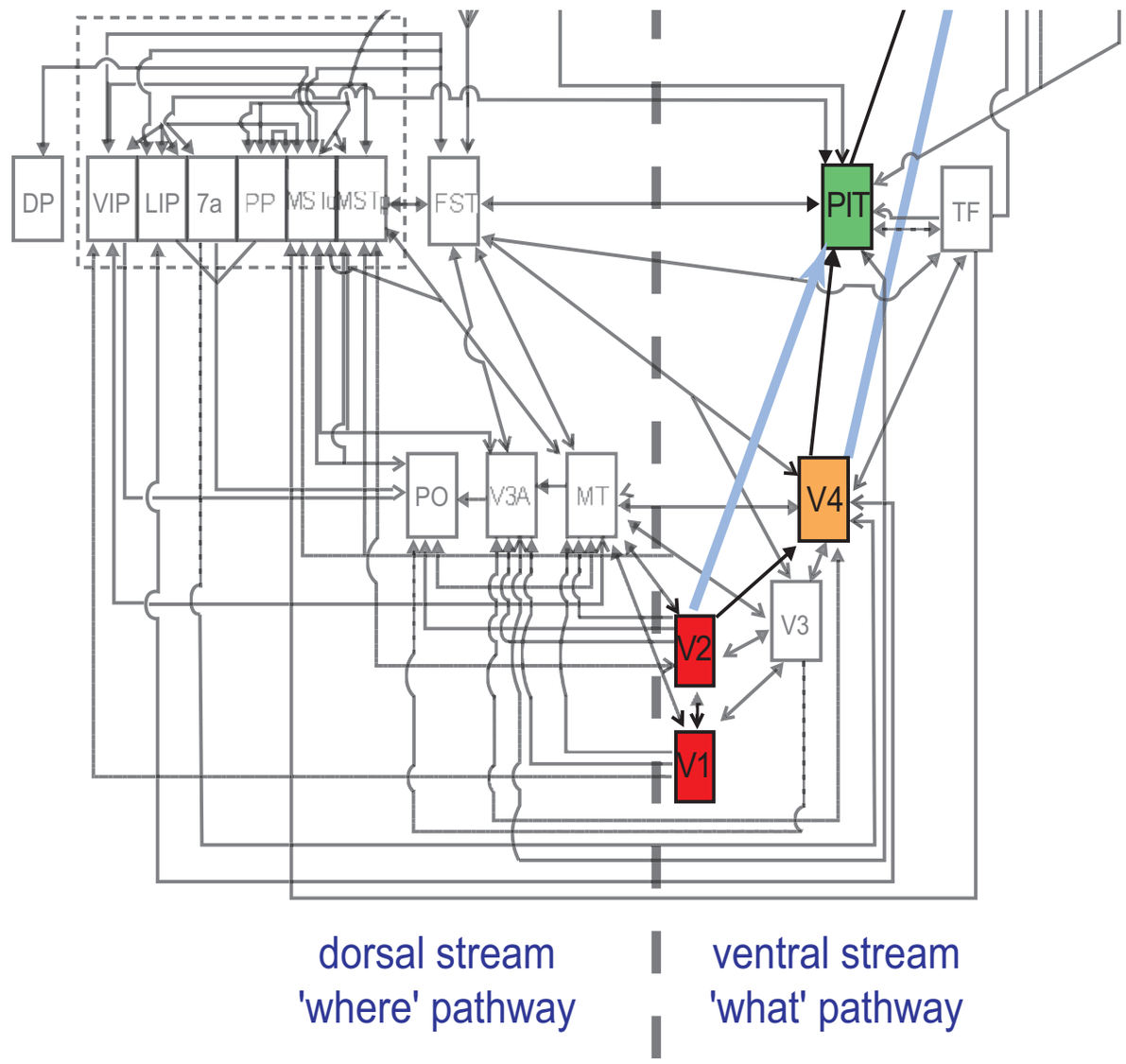



- V1: Primary visual cortex
- V2: Secondary visual cortex

- IT: Inferior temporal cortex

Yamins and DiCarlo, Nature Neuroscience (2016)

# Visual cortex: what and where pathways

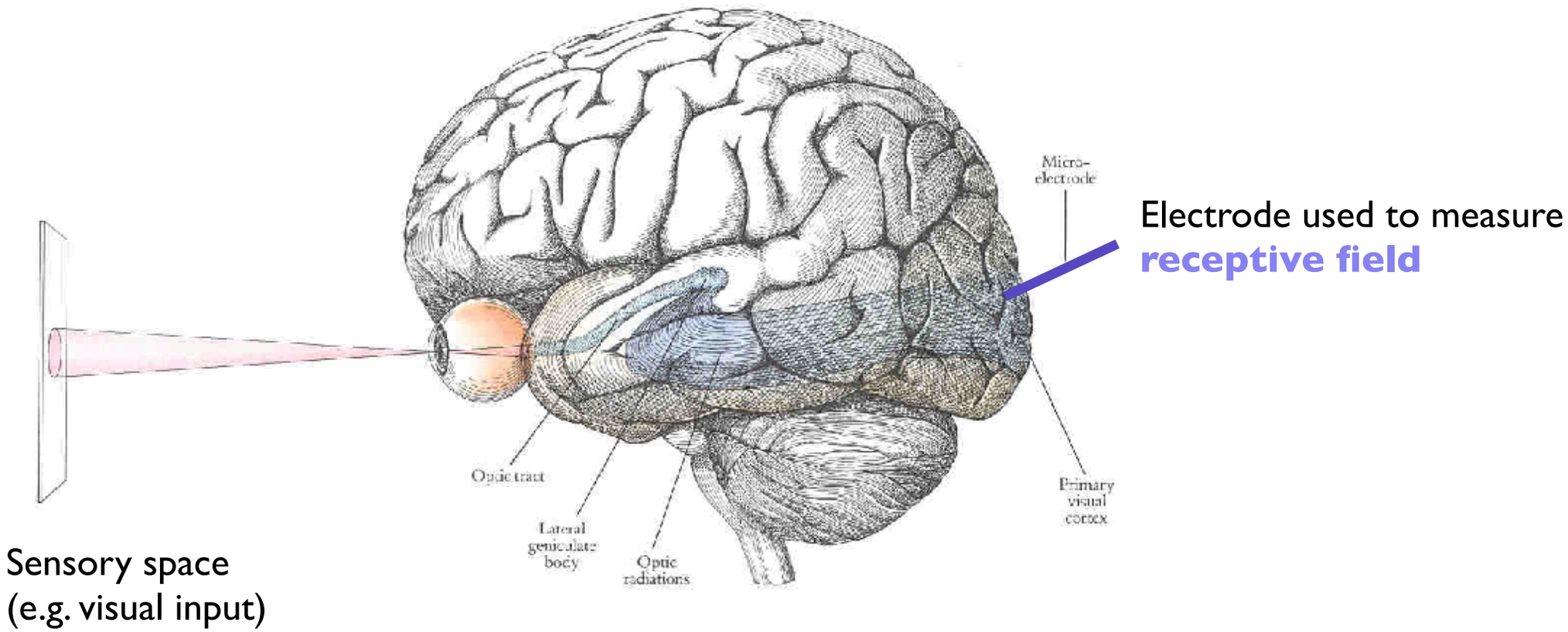



- **'What' pathway:** Relevant to detect what is in the image (e.g. lion vs eagle?)

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

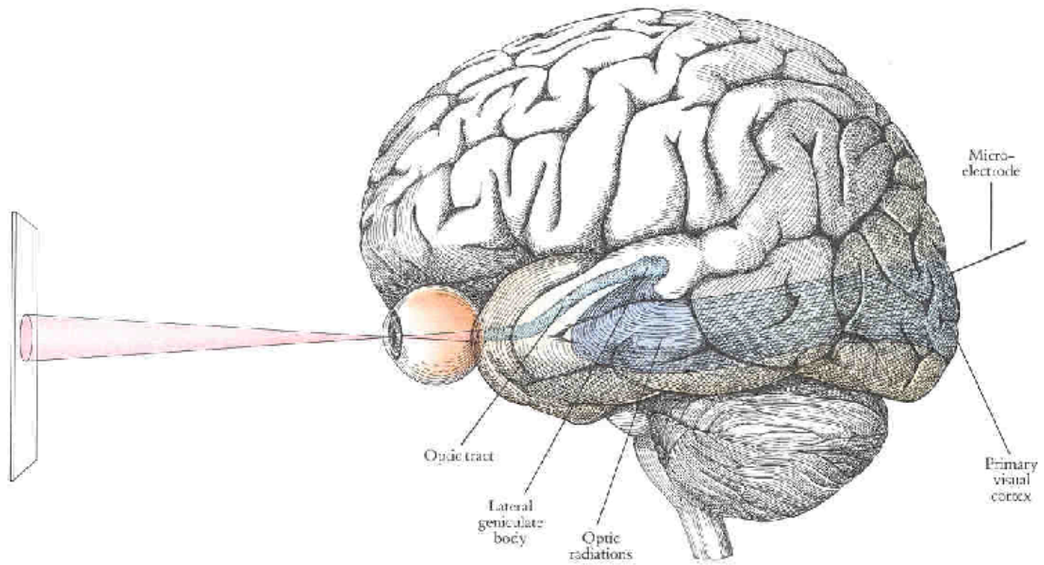
Serre et al., PNAS (2007)

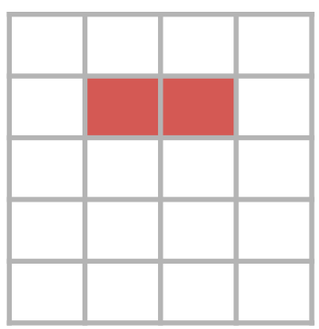
# Visual cortex function
# receptive fields



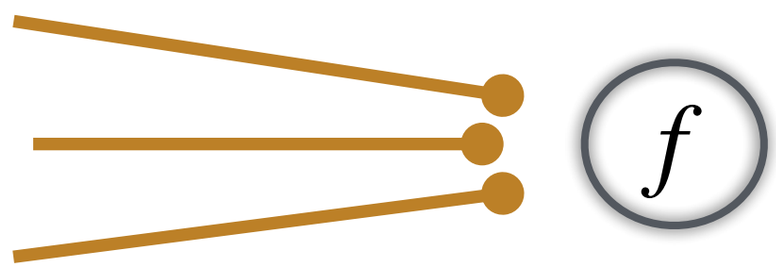

**Receptive field**: Region of sensory space in which a stimulus modifies (i.e. increases or decreases) the firing of the neuron.

# Visual cortex function
# a simple model of receptive field



Visual input, ***u***



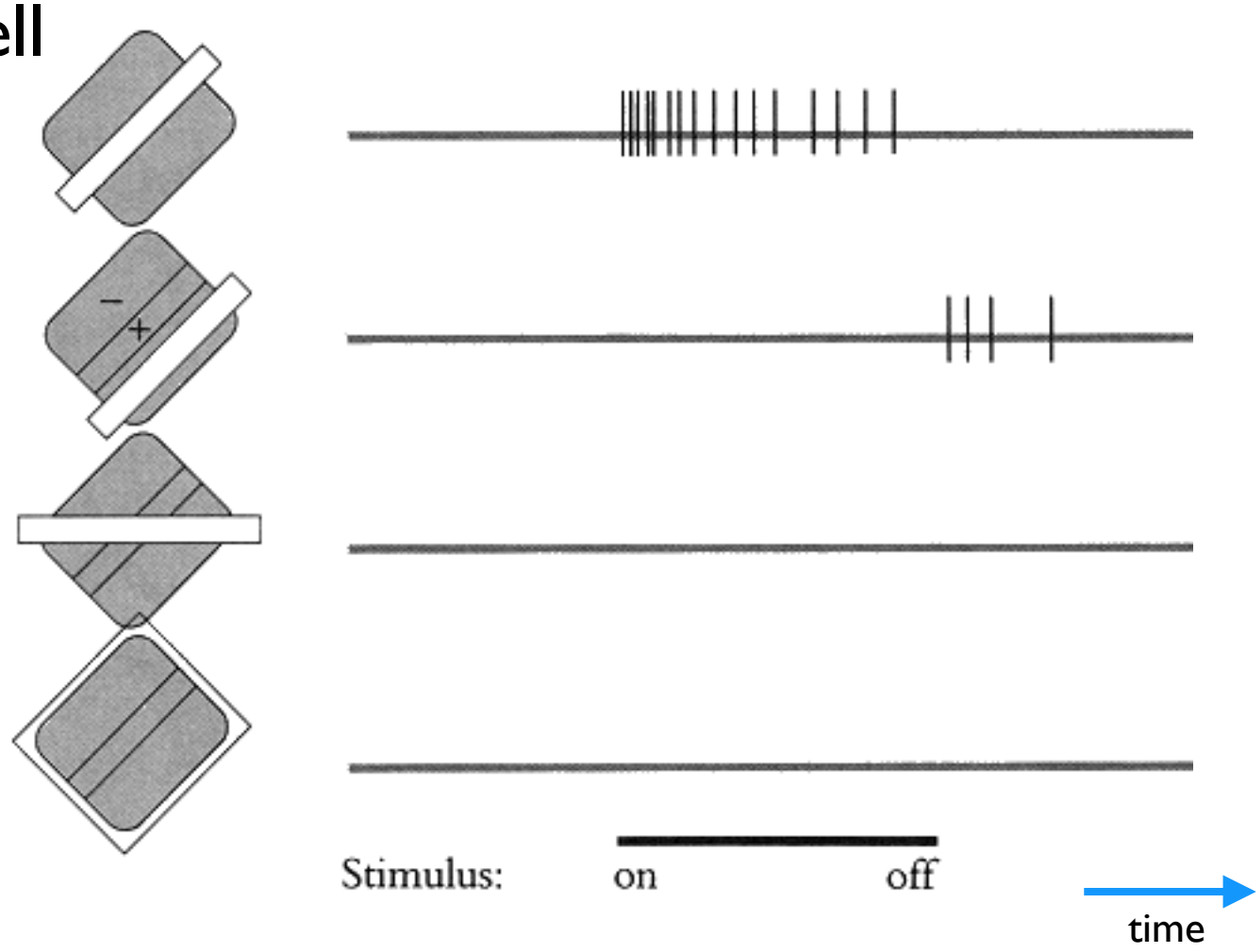

weights, ***w***

Visual cortex
neuron, ***v***

$$v = f(wu)$$

# Classical receptive field:
## simple cells in primary visual cortex

Simple cell

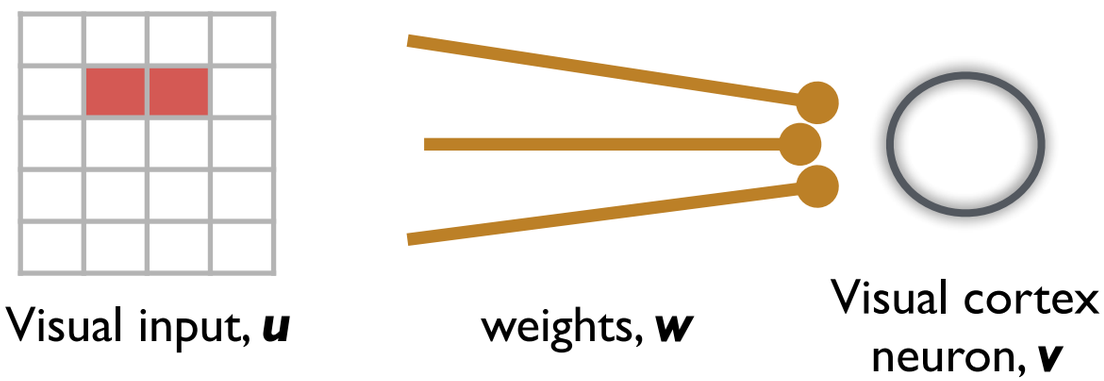



Video of Hubel & Wiesel experiments:
https://youtu.be/8VdFf3egwfg

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:

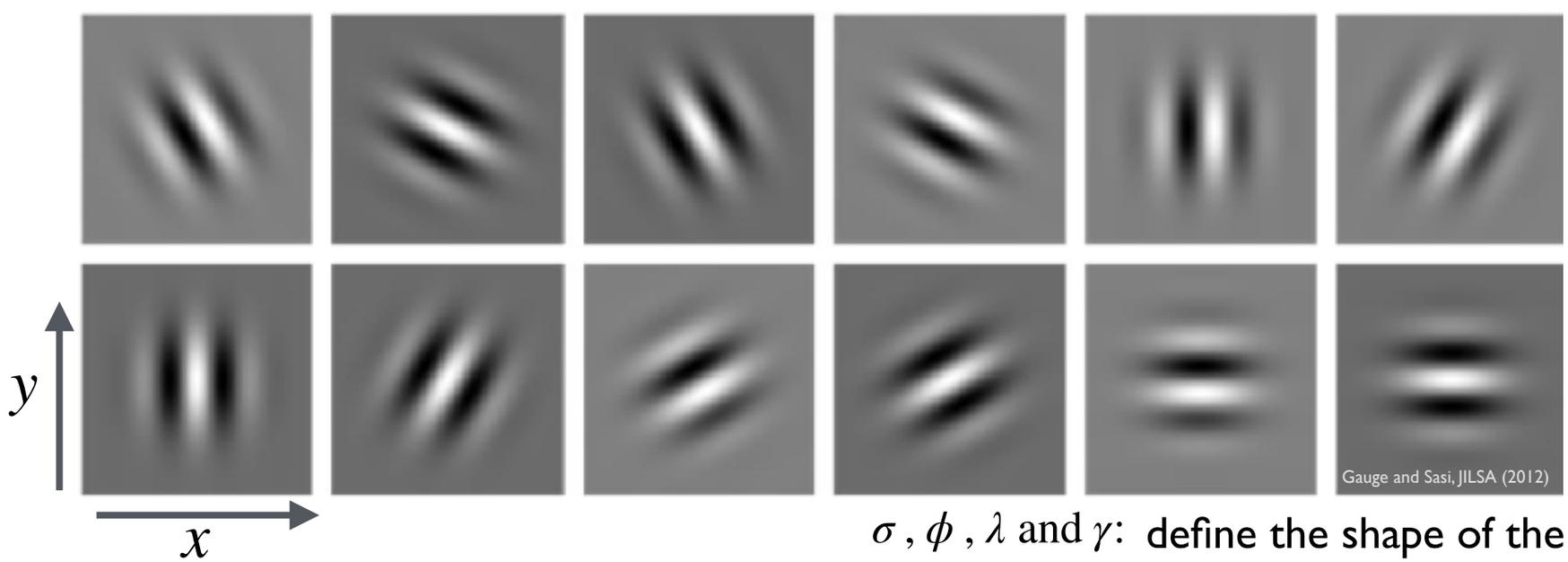
## Gabor filter as a model of simple cells

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

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

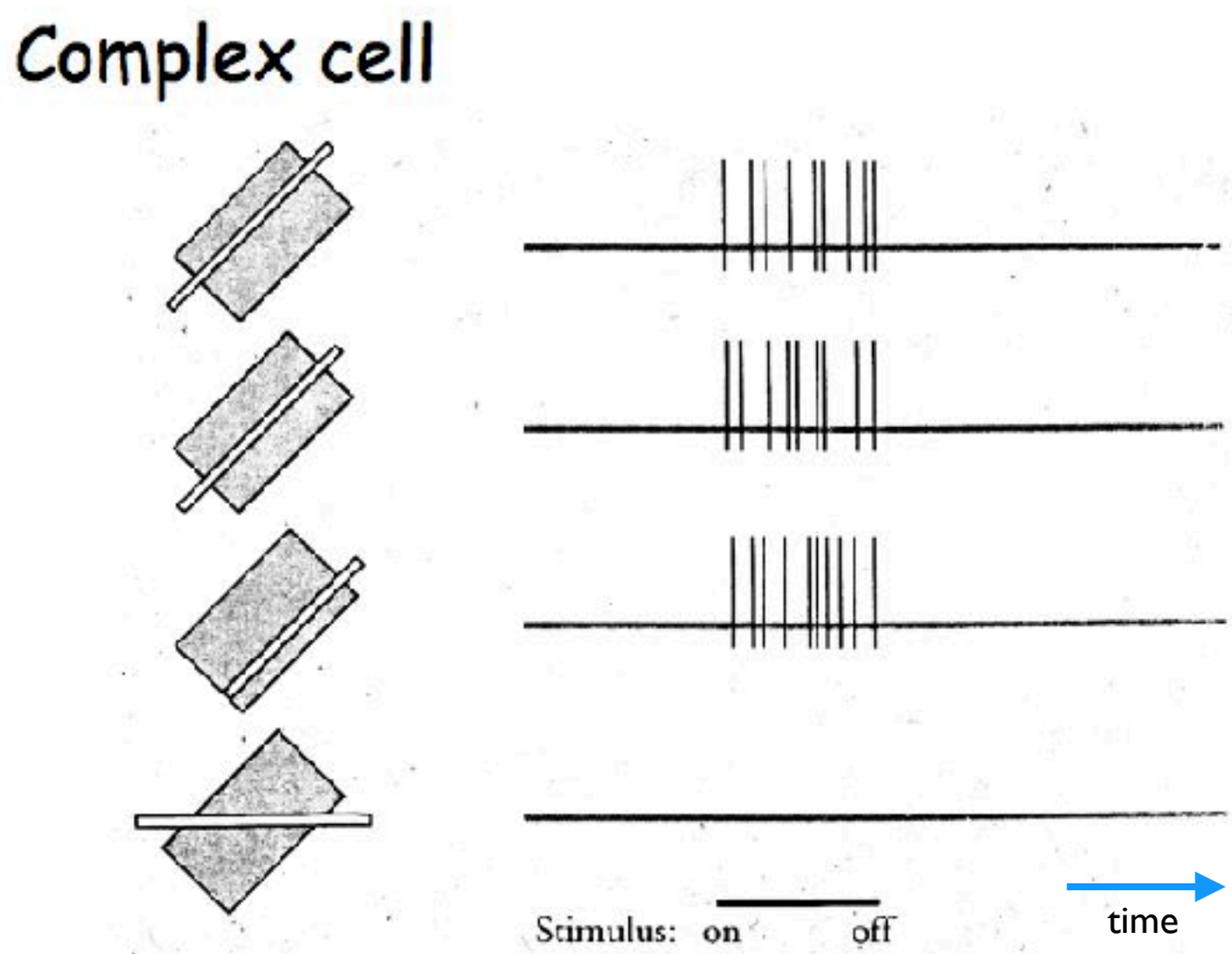
$$y' = -x \sin\theta + y \cos\theta\,.$$
$$x' = x \cos\theta + y \sin\theta,$$

Gabor filters for different angles $\theta$ :



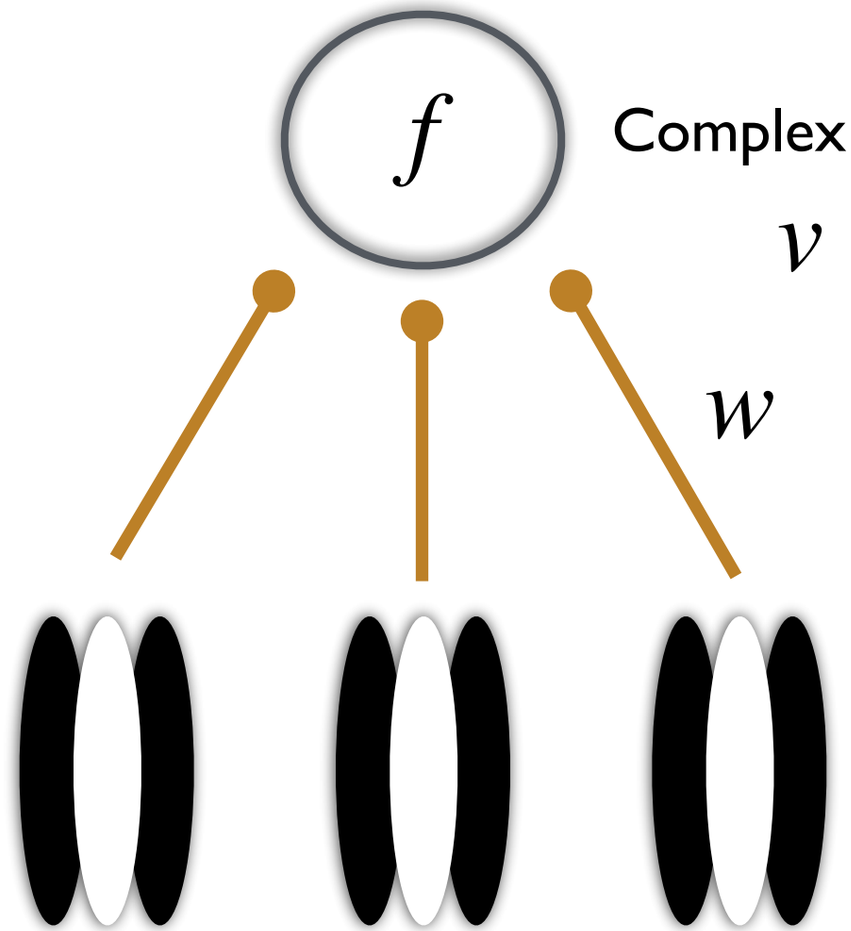

$\sigma$ , $\phi$ , $\lambda$ and $\gamma$: define the shape of the Gabor filter.

# Visual cortex: complex cells




Hubel and Wiesel, J Physiol (1962)

# Visual cortex: complex cells, a model




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

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

E.g.:
A set of Gabor filters

# Group discussion

groups of 2-3 (5 min)

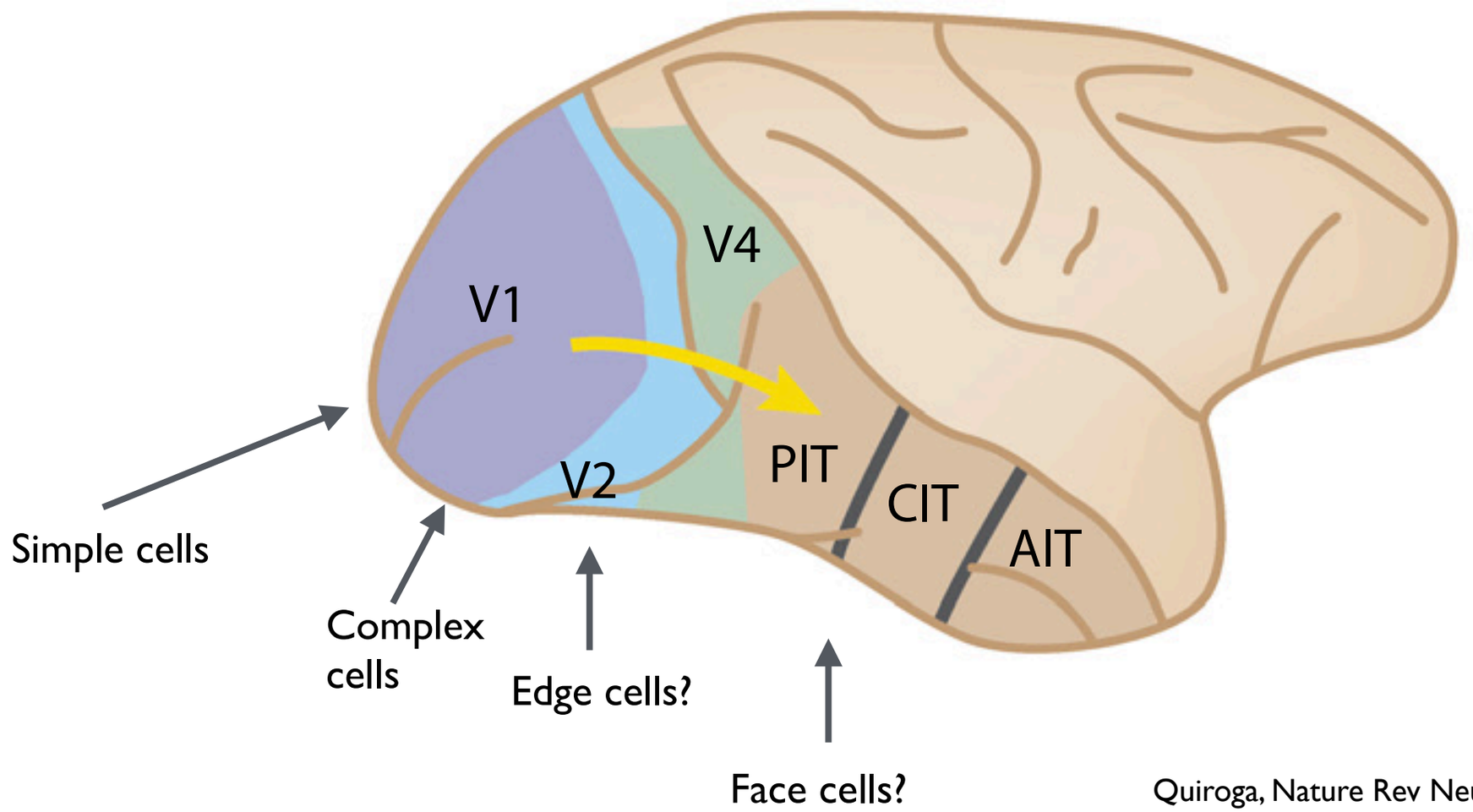
- **What other receptive fields/features would be useful for the visual cortex to encode?**

**Hint**: look around you for common visual features

Go to www.menti.com

Code: 27 81 19

# Visual cortex:
# Higher order representations




Quiroga, Nature Rev Neurosci (2012)

Yamins and DiCarlo, Nature Neuroscience (2016)

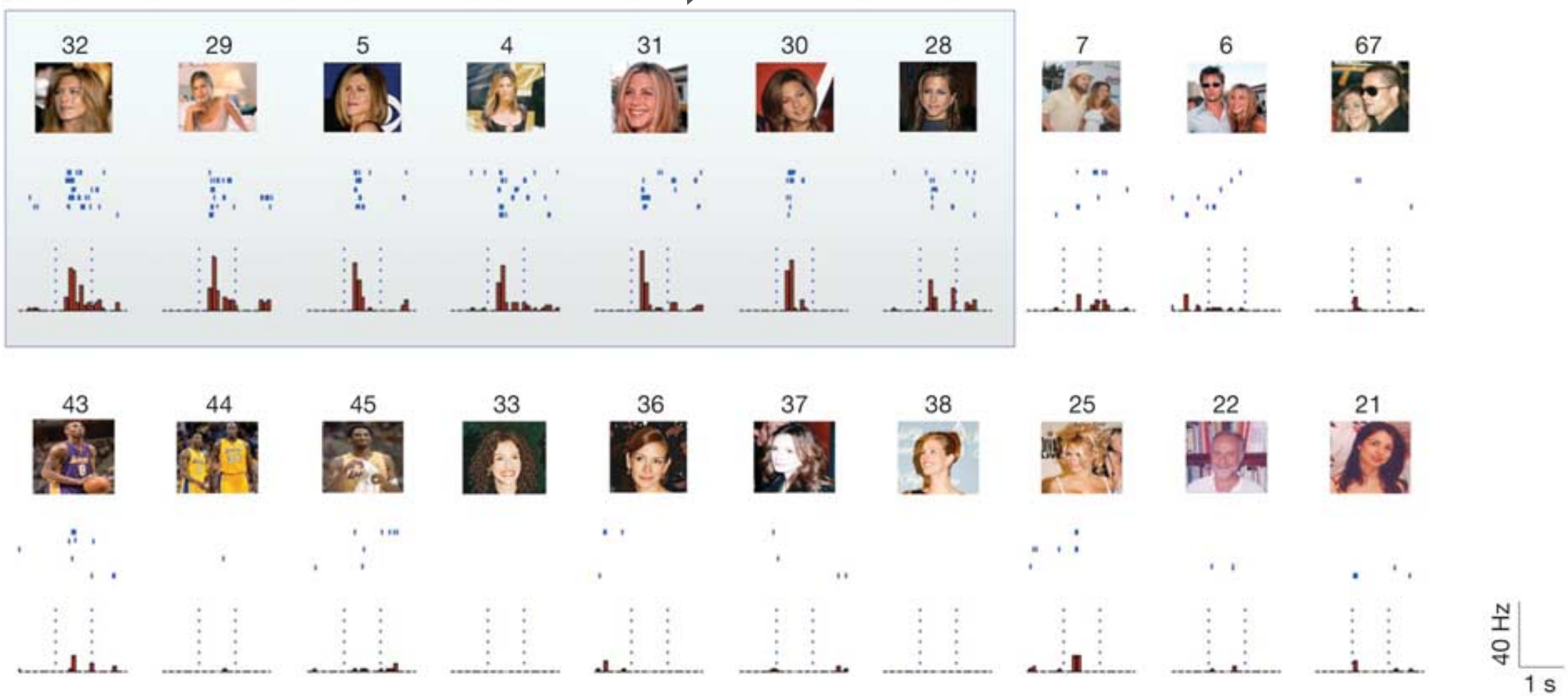
# Visual cortex:

## 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.

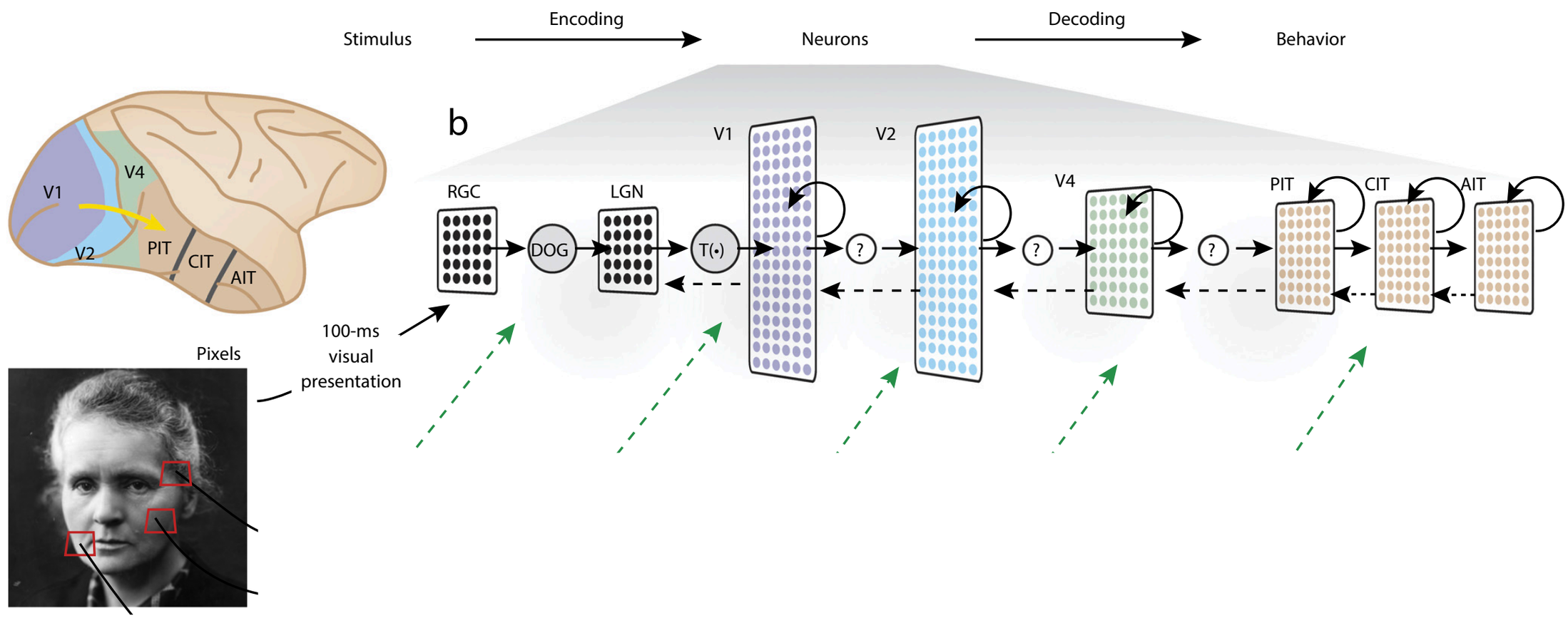
A neuron responding to images of Jennifer Aniston recorded in Medial Temporal Lobe in humans (epilepsy patients):

Quiroga et al., Nature (2005)



# Convolutional neural networks (CNNs)

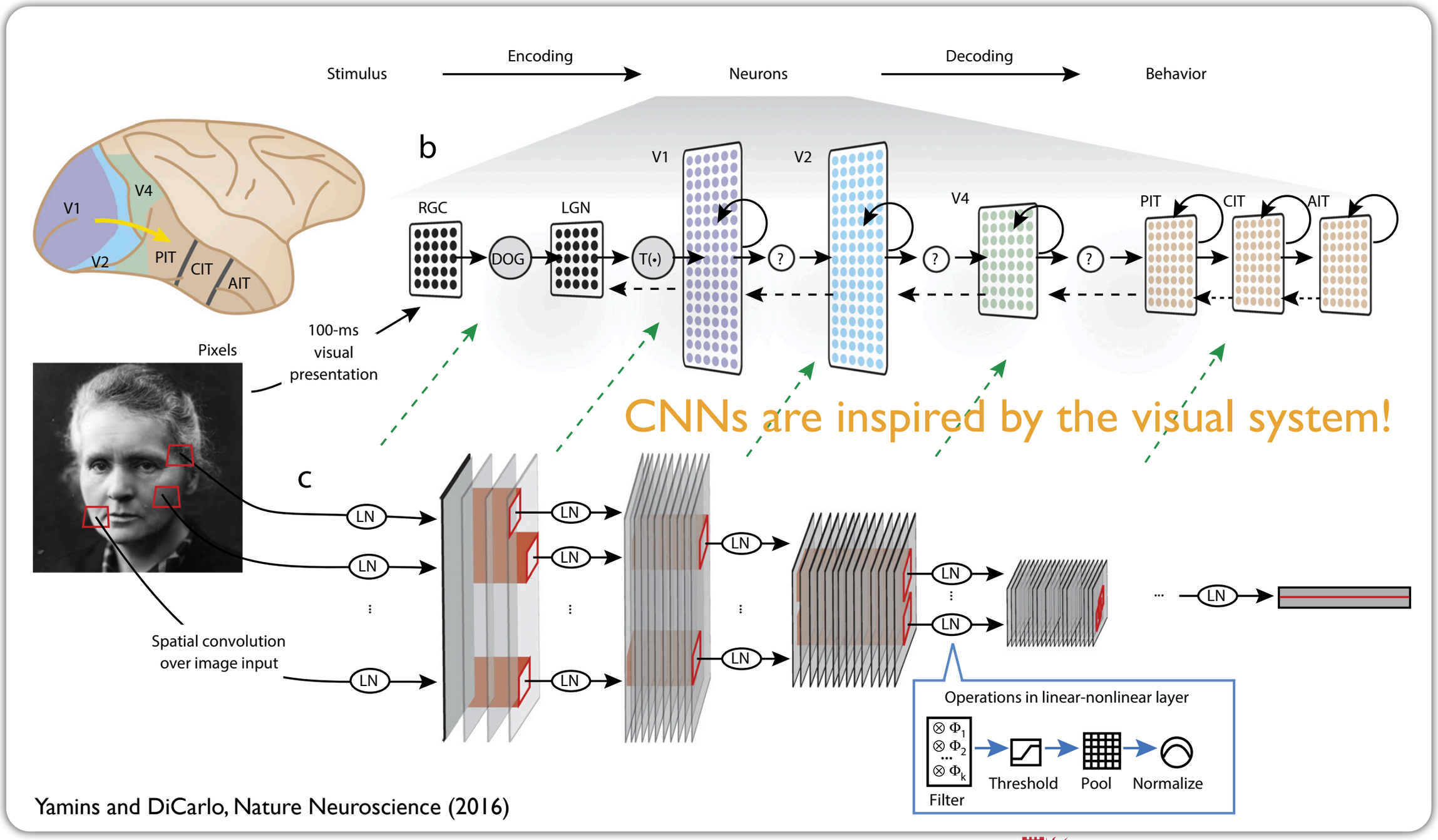
## as a model of the visual system




Yamins and DiCarlo, Nature Neuroscience (2016)

# Convolutional neural networks (CNNs)

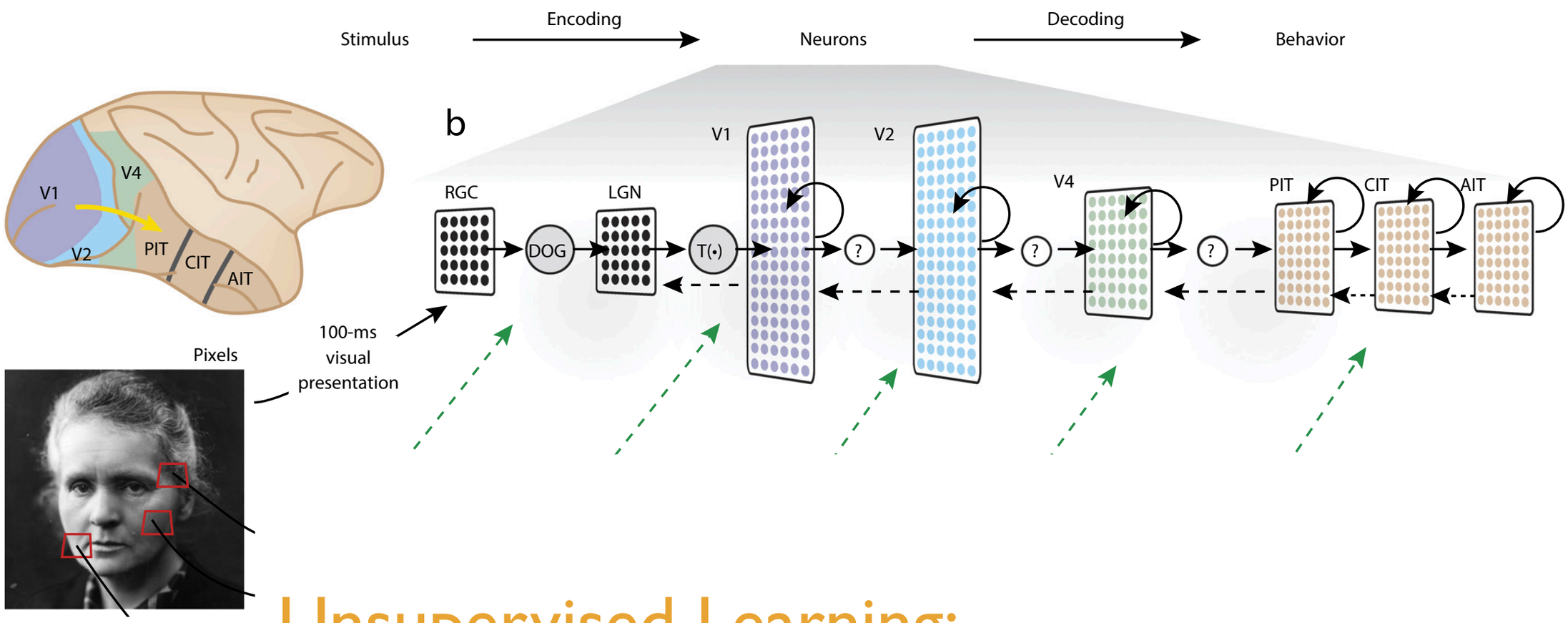
## as a model of the visual system




Yamins and DiCarlo, Nature Neuroscience (2016)

# Convolutional neural networks (CNNs)

## as a model of the visual system



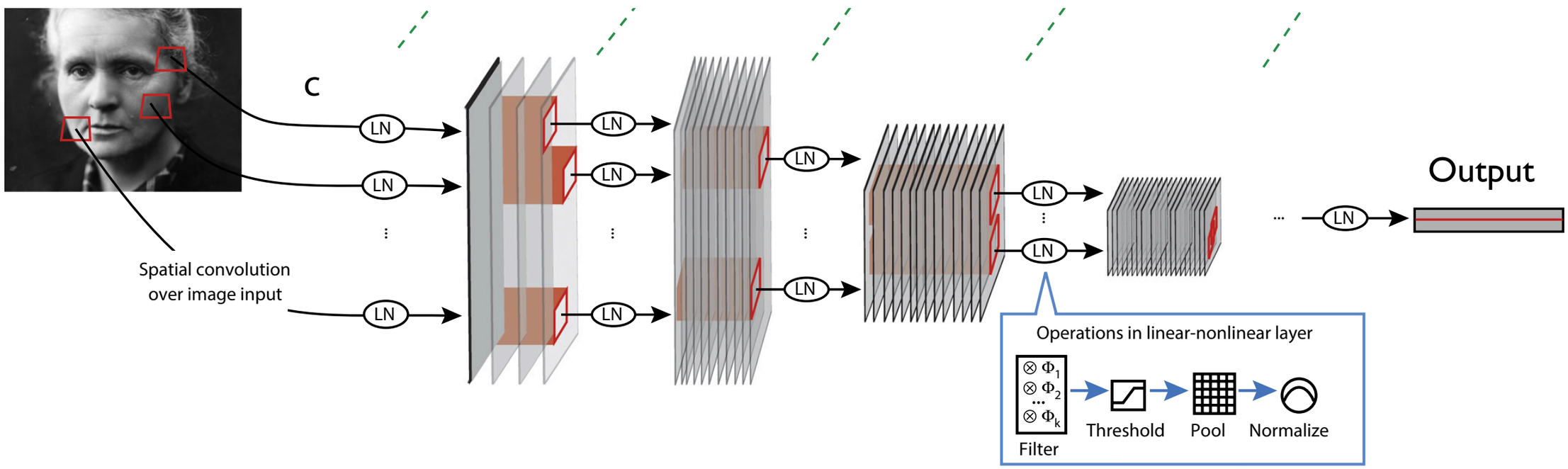

## Unsupervised Learning:

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

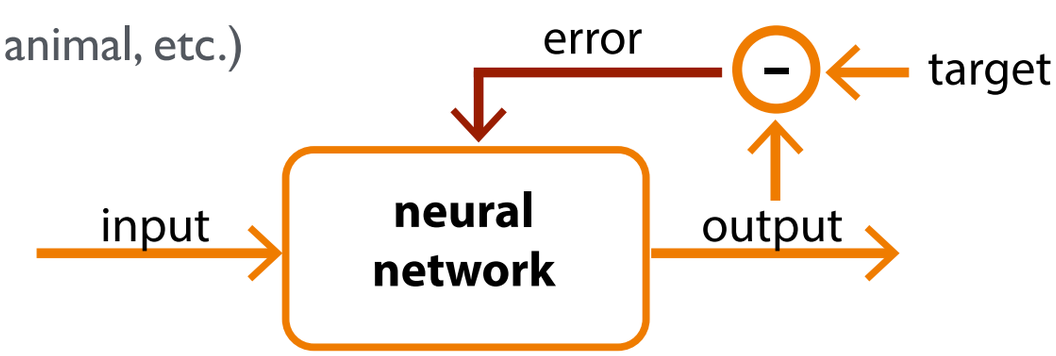



But CNNs rely on Supervised Learning:

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

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

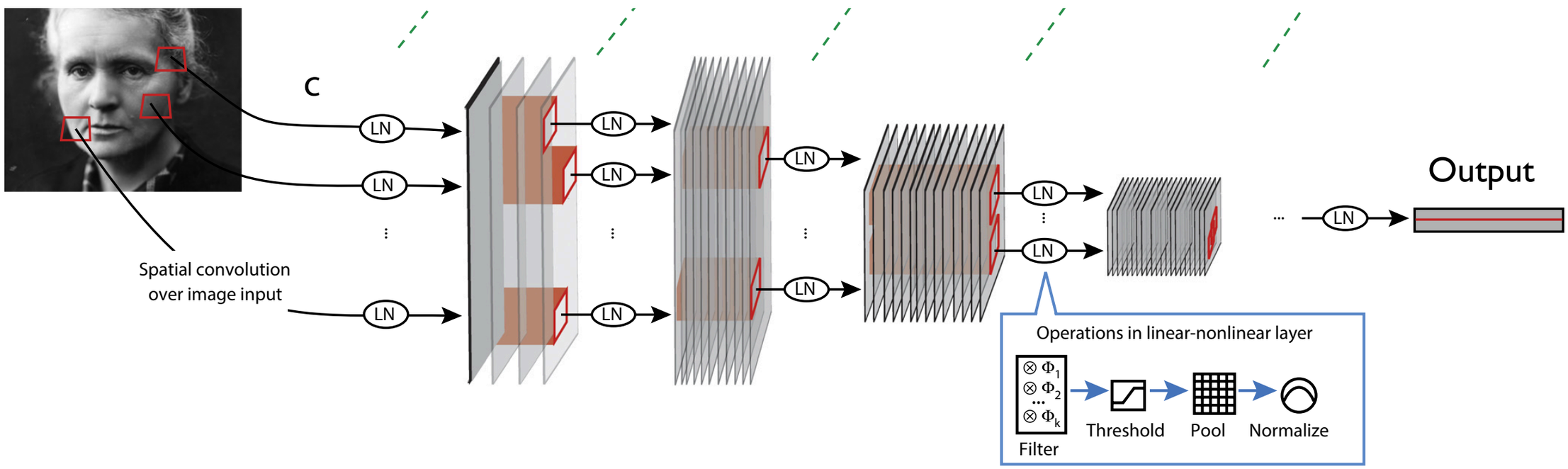
CNNs have revolutionised computer vision!




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)

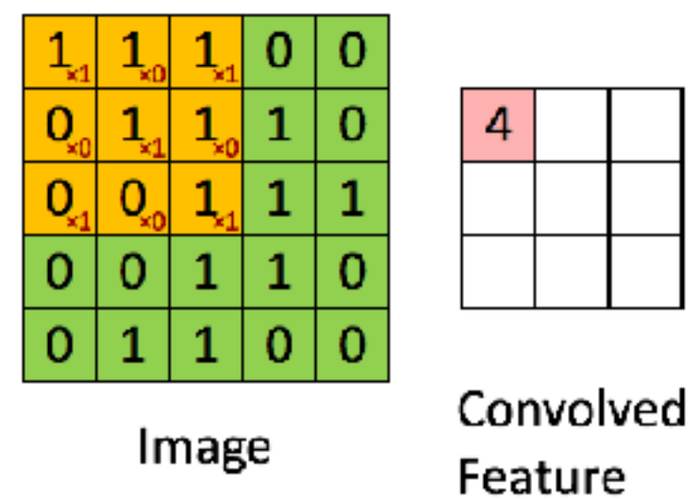
# Convolutional neural networks (CNNs)

## Convolution operator

Example of filter:

| | | |
|---|---|---|
| 1 | 0 | 1 |
| 0 | 1 | 0 |
| 1 | 0 | 1 |

Convolutional operation:

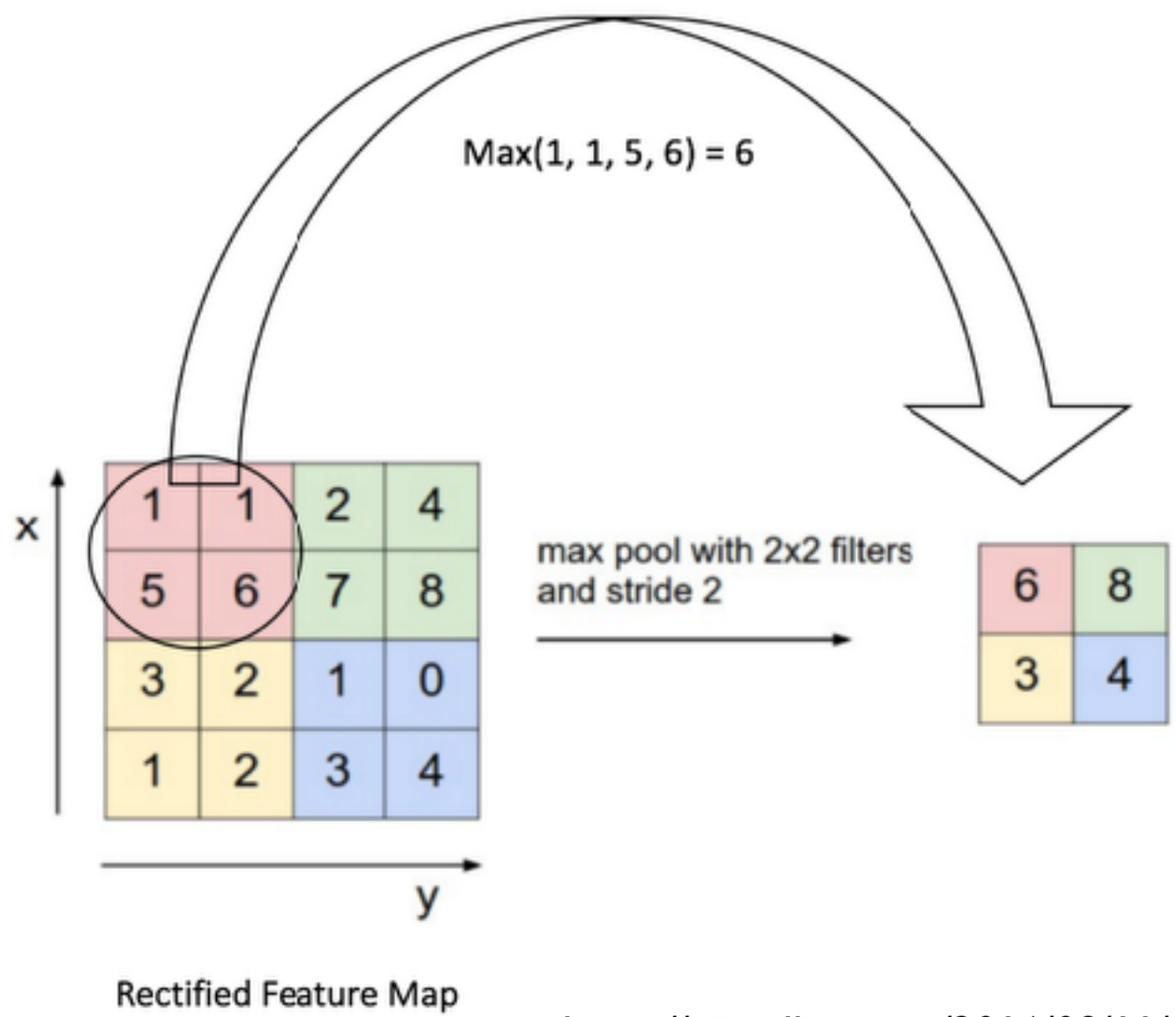



https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets

# 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

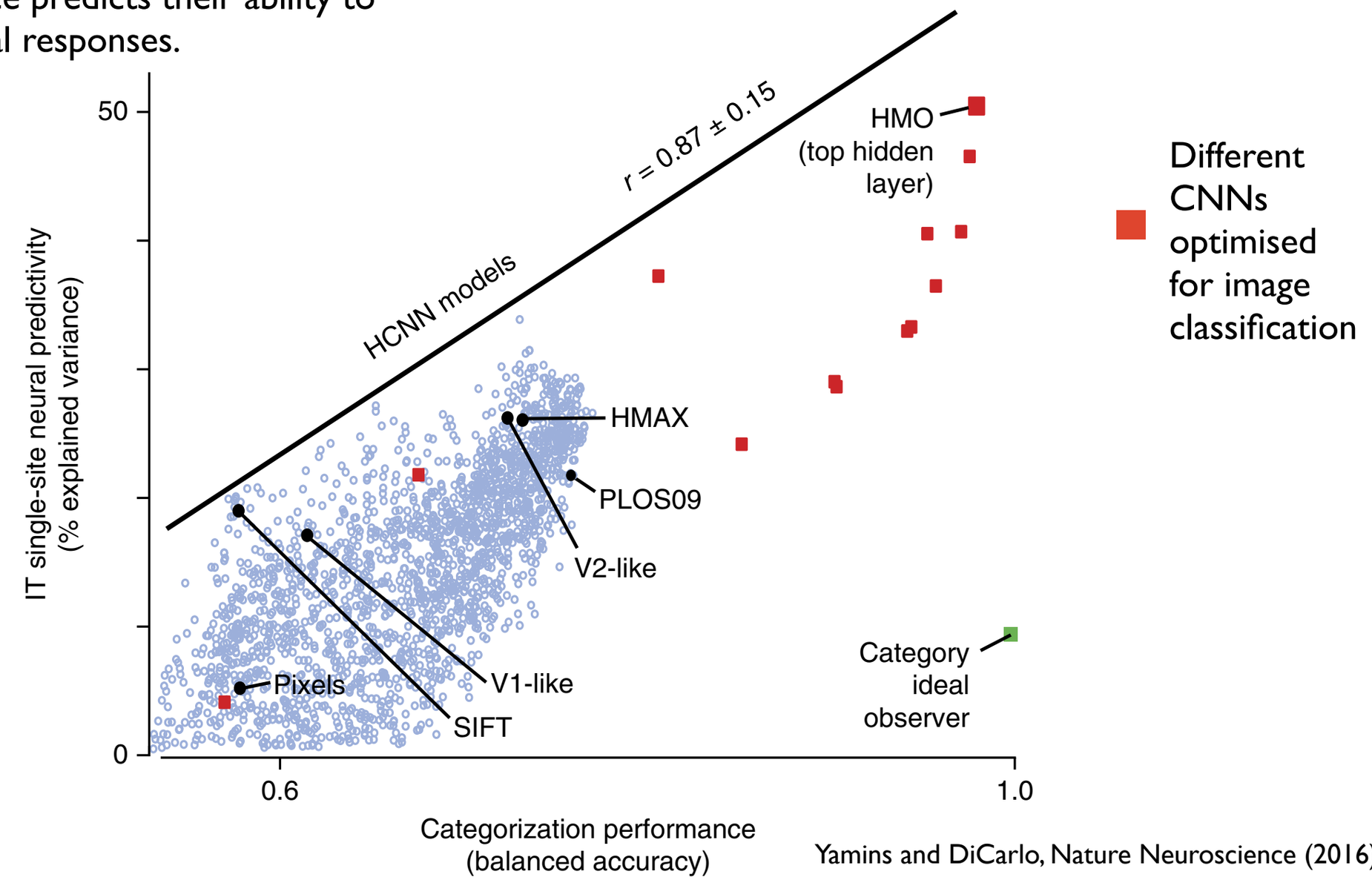
A comparison between CNNs and the visual system:

| **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 | $\max(\boldsymbol{v})$ $\text{average}(\boldsymbol{v})$ |
| Layers | Brain areas (e.g. V1, V2, etc.) | $f(w_2 * f(w_1 * u))$ |

$*$ : convolution operator

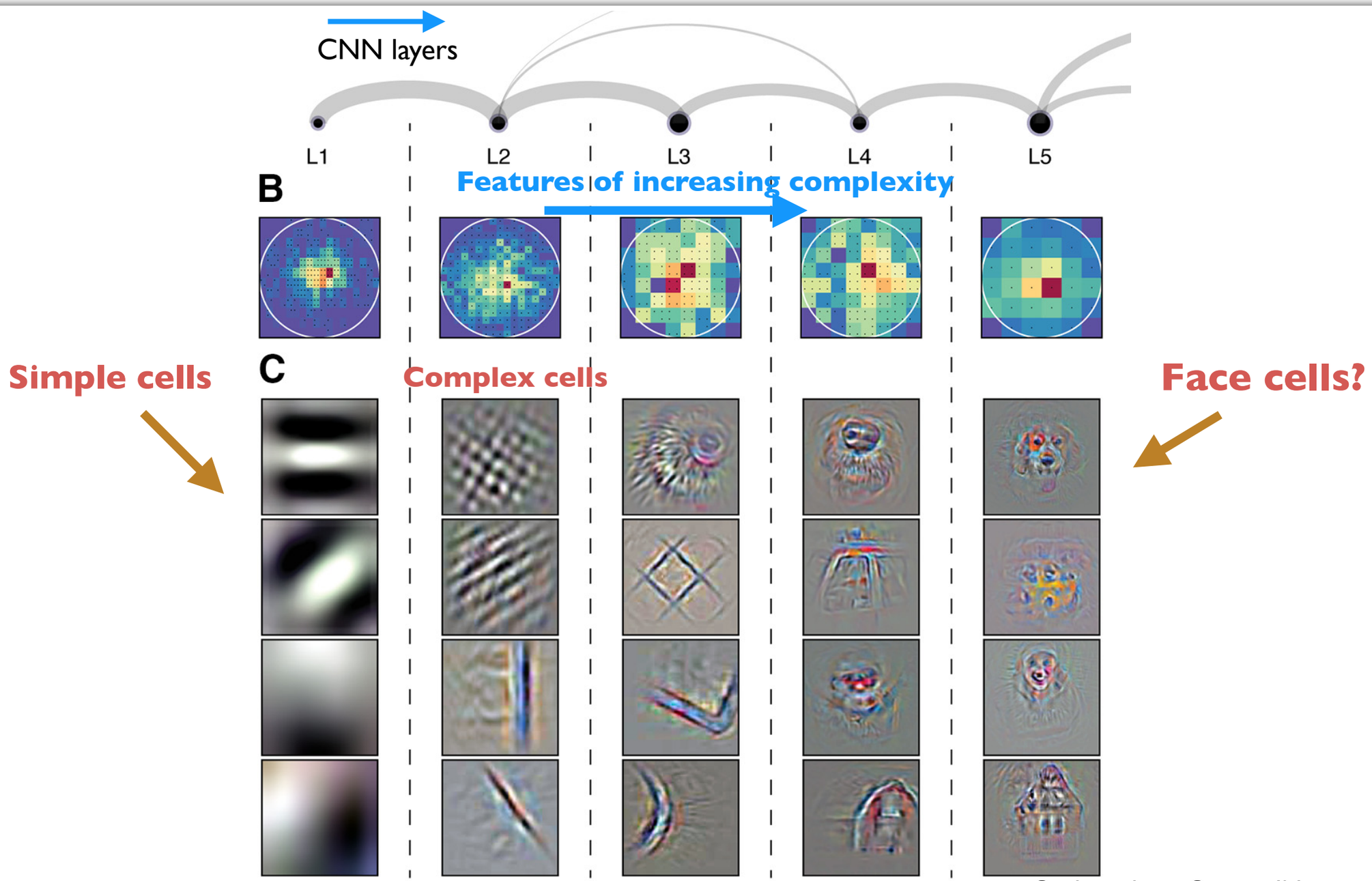
# CNNs performance predicts visual cortex responses

CNNs were trained to classify natural images.
Their performance predicts their ability to explain real neural responses.




Yamins and DiCarlo, Nature Neuroscience (2016)

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




Guclu and van Gerven, JNeurosci (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, 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

- L11[6]: Neural circuits and learning: introduction
- L12[6]: Visual system: deep learning?
- **L13[7]: Supervised learning & backprop**
- L14[7]: Unsupervised learning
- L15[9]: Reinforcement learning
- L16[9]: Temporal processing & recurrent neural networks
- L17[10]: Recurrent neural networks
- L18[10]: Brain vs machine: meta-learning and inductive bias
- L19-20[11]: Neural data analysis (by Cian)
- L21-22[12]: Revision week