



Deep neural networks in brains and machines

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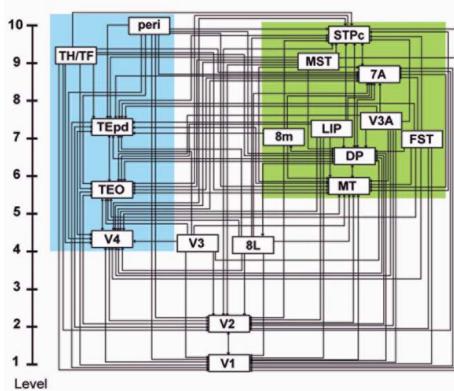
Lecturer in Computational Neuroscience

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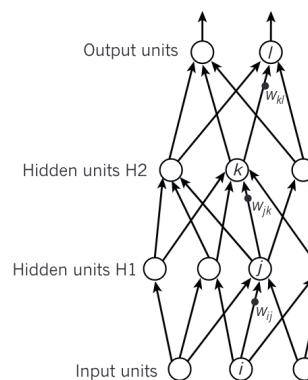
Just how similar are deep neural networks in brains and machines?

Monkey brain



Markov et al., *J. Comp. Neurol.*, 2014

Artificial neural network



LeCun et al., *Nature*, 2015

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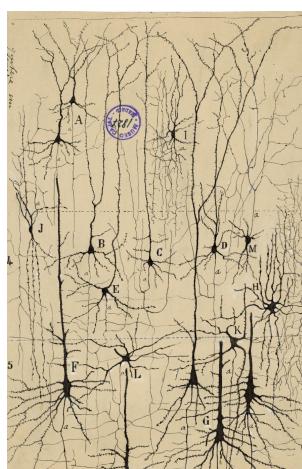
Intended Learning Outcomes

- By the end of this video you will be able to:
 - Describe the major types of neurons in the brain
 - Describe how distinct features of the brain's anatomy and physiology change along a deep hierarchy of areas
 - Illustrate the basic architecture of deep neural networks
 - Critically compare the similarities and differences of deep and convolutional neural networks in brains and machines

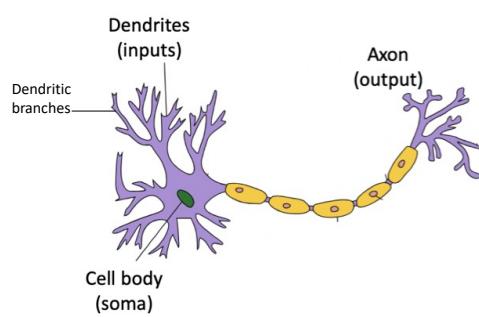
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The anatomy of a single biological neuron



Ramón y Cajal



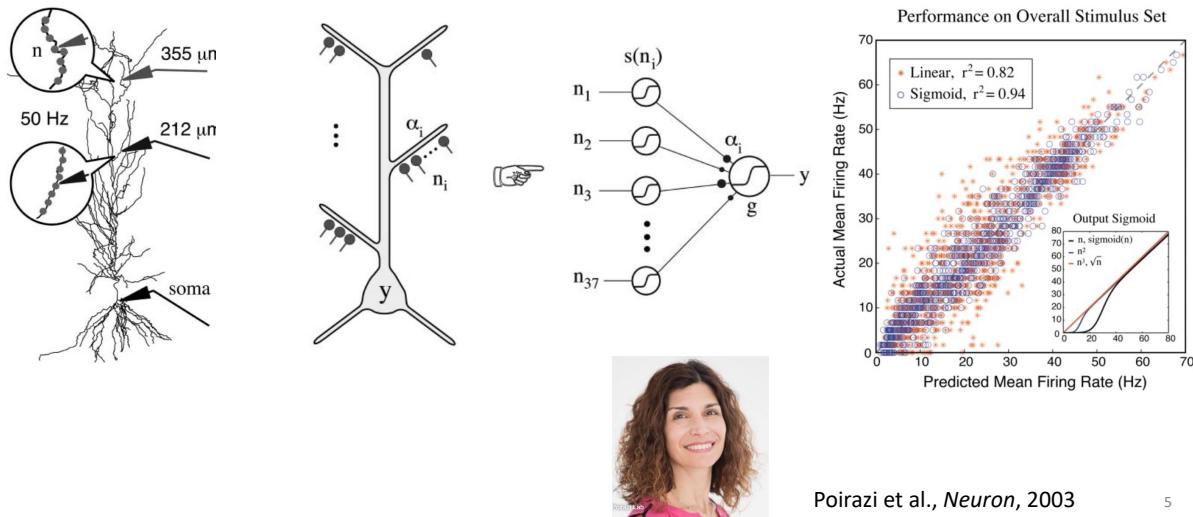
Quasar Jarosz, Wikimedia Commons

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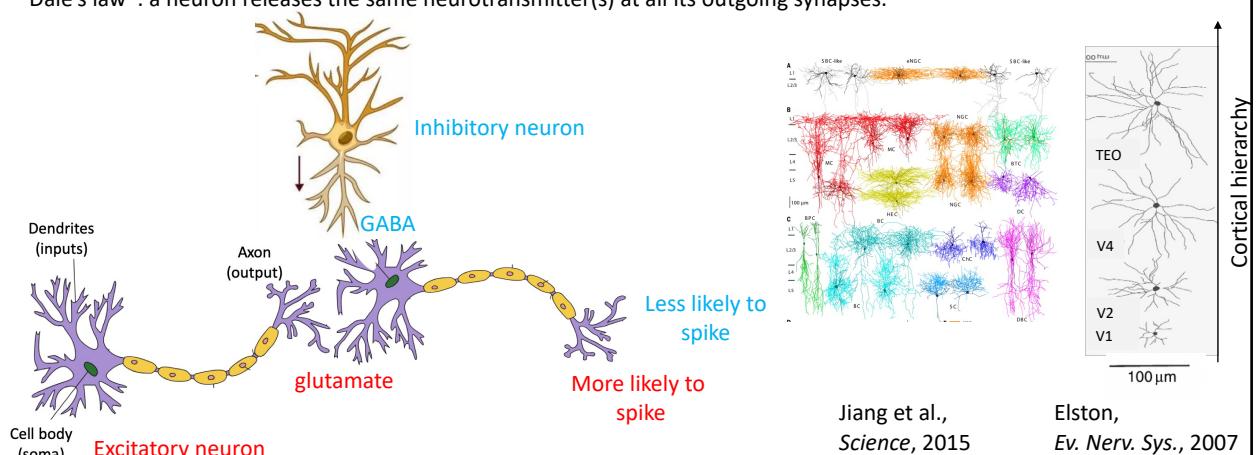
A biological *neuron* as a two-layer artificial neural network?



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Neurons are not all the same

The main division of neurons is between excitatory and inhibitory neurons
 "Dale's law": a neuron releases the same neurotransmitter(s) at all its outgoing synapses.*



* Laws in biology never strictly work, there are always exceptions! However, Dale's law is still a good first approximation to reality.

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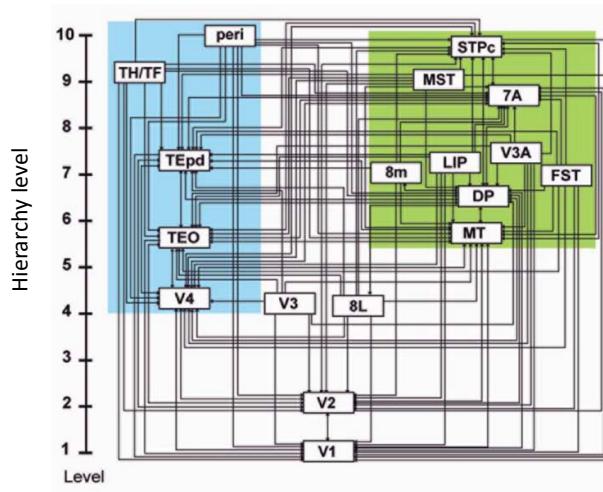
Quiz

- Compare and contrast biological neurons and units (neurons) in artificial neural networks. What may be some functional implications of these differences?

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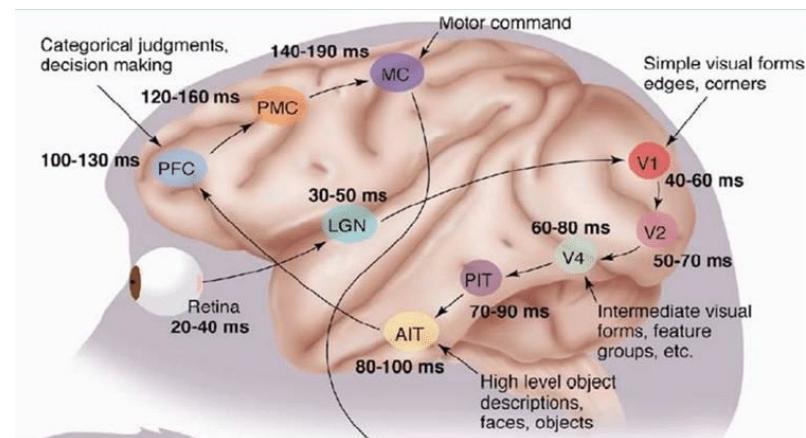
Sensory cortex has a deep hierarchical structure. What changes as you step up the hierarchy?



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The time for a neuron to respond to a stimulus increases

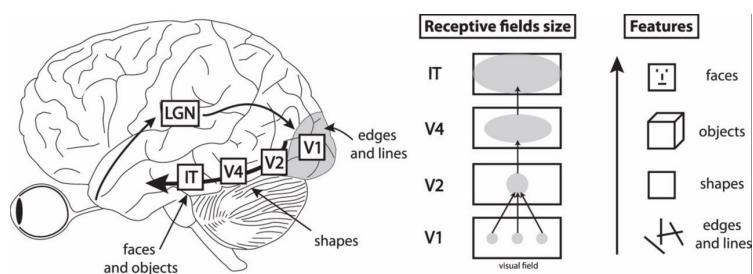
Thorpe & Faber-Thorpe, *Science*, 2001

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The types of stimuli that activate a neuron change

- As you move up the cortical hierarchy, the 'preferred' stimuli of a neuron
 - Can occupy more positions in visual space
 - Become more complex (from lines, to people)

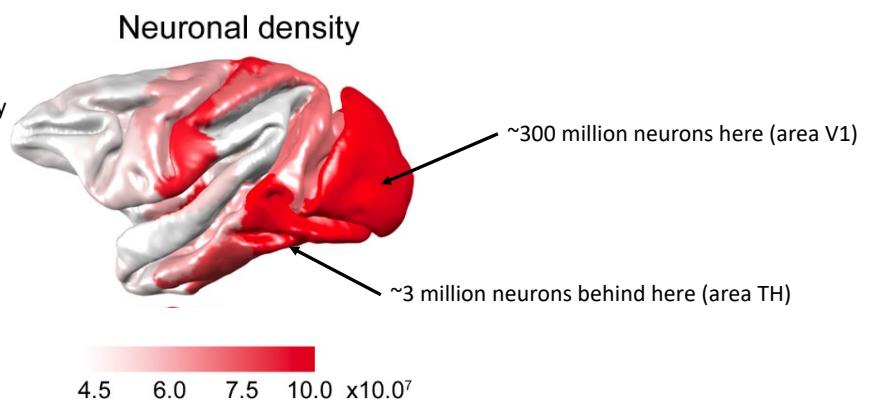
Manassi et al., *J. Vision*, 2013

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The number of neurons per area goes down

- This suggests that the sensory information is compressed higher up the cortical hierarchy



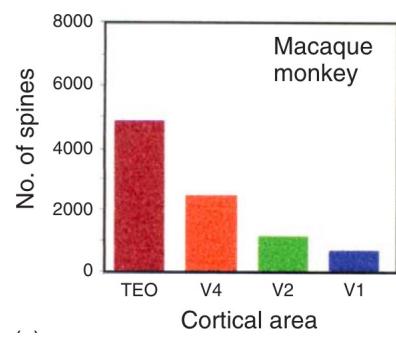
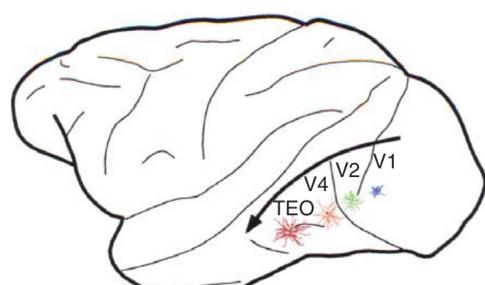
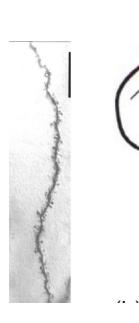
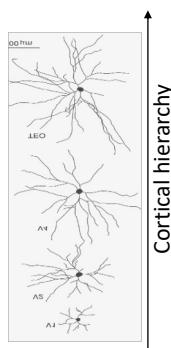
Froudast-Walsh et al., *eLife*, 2018

Collins et al., *PNAS*, 2010

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Increased number of inputs

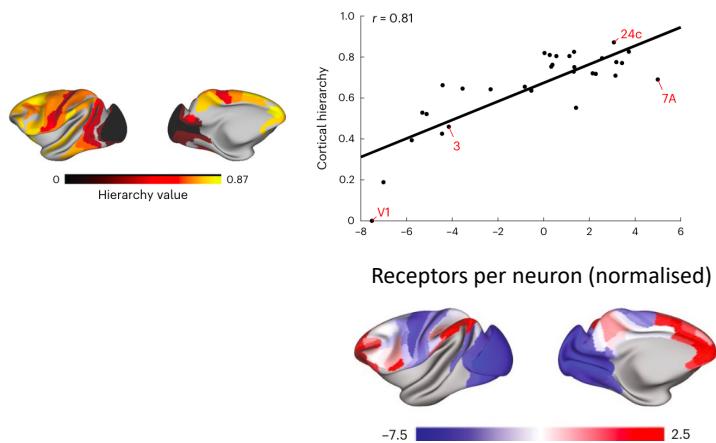


Elston, *Evolution of Nervous Systems*, 2007

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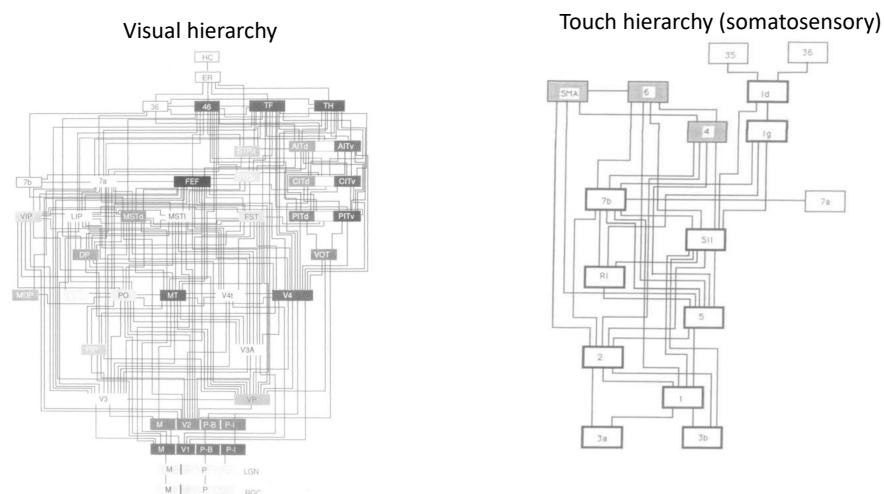
Increased capacity for modulation

Froudist-Walsh et al., *Nature Neuroscience*, 2023

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Different sensory modalities, different hierarchies

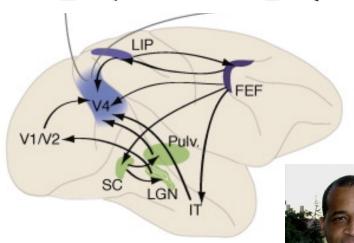
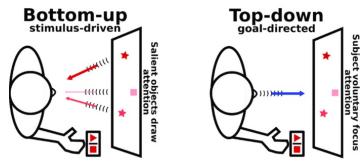
Felleman & Van Essen, *Cerebral Cortex*, 1991

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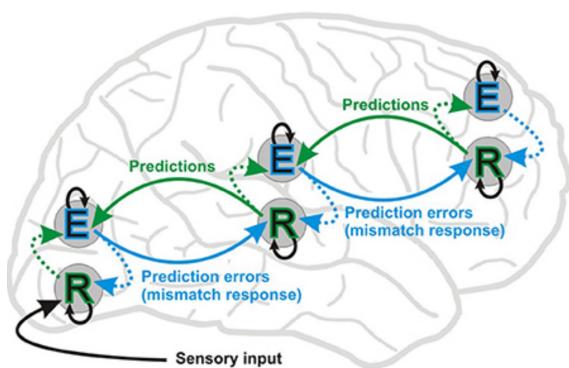
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Feedback connections

Selective attention



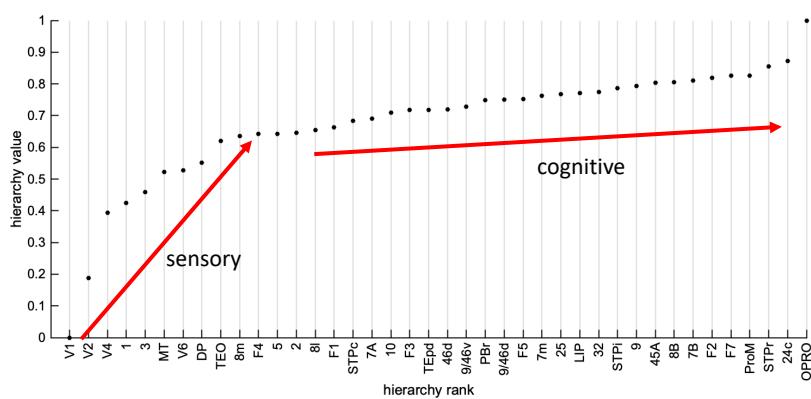
Predictions



Stefanics et al., *Front. Hum. Neurosci.*, 2014
Rao & Ballard, *Nature Neuroscience*, 1999

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If we are interested in modeling cognition,
should we build models with a different
architecture?



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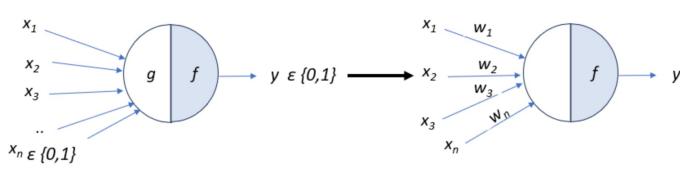
Quiz

- How do neurons at the bottom and top of the hierarchy differ in the brain and in machines? What (if any) could be the benefits of incorporating more of the missing biological features into artificial neural networks?

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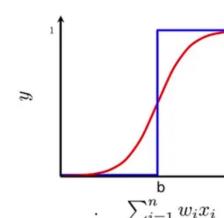
A neuron (unit) in an artificial neural network



$$y = f(g(x)) = \begin{cases} 1 & \text{if } g(x) \geq \theta \\ 0 & \text{otherwise} \end{cases}$$

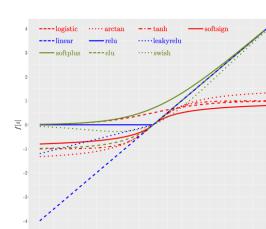
Where θ is the *thresholding parameter*/

McCulloch & Pitts, Bull. Math. Biophys., 1943



$$y = \frac{1}{1+e^{-(w^T x+b)}}$$

Niranjan Kumar

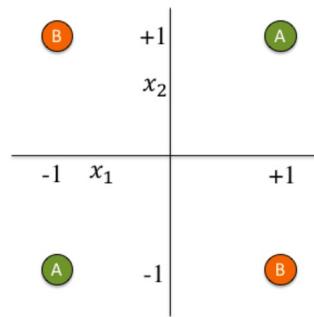


Lederer, arXiv, 2021

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XOR – linear decoding & AI winter

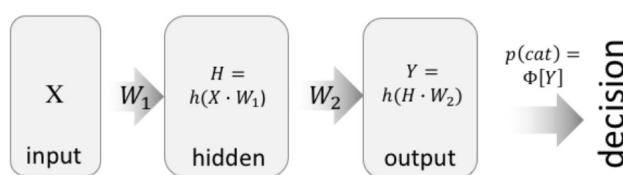


Summerfield, 2018

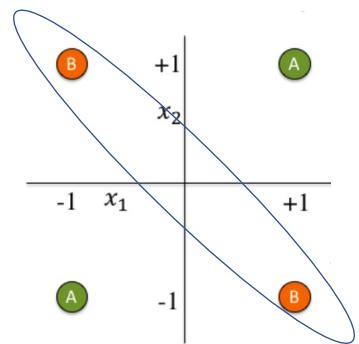
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Introducing depth (hidden layers)



- Depth & non-linearities helps the network solve complex classification problems.
- The output Y is now computed not directly from X , but by passing H through another set of weights.

Summerfield, *How to build a brain from scratch*, 2018 20

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A dog is a dog, wherever it is

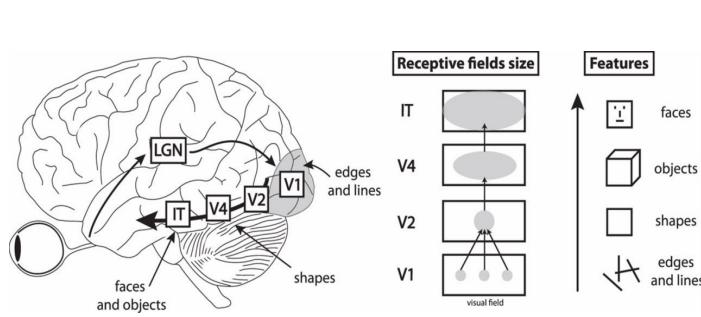


- Neurons in the dog-sensing part of the brain respond to dogs whether they are close, far, or at any position in space. This is called *translation invariance*, as the response won't vary much (invariance) if you move (translate) the dog.
 - Neurons in feedforward neural networks that are fully connected (such as those studied so far) do not have translation invariance emerge naturally.

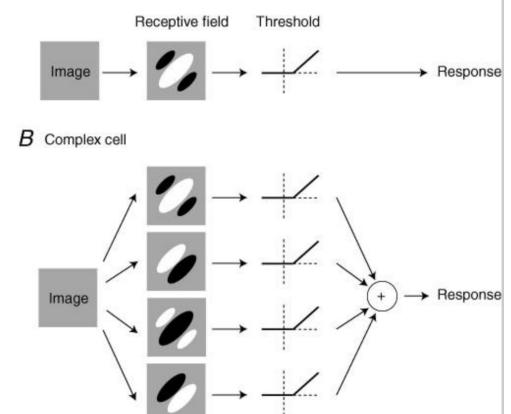
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How the brain builds translation invariance



A Simple cel



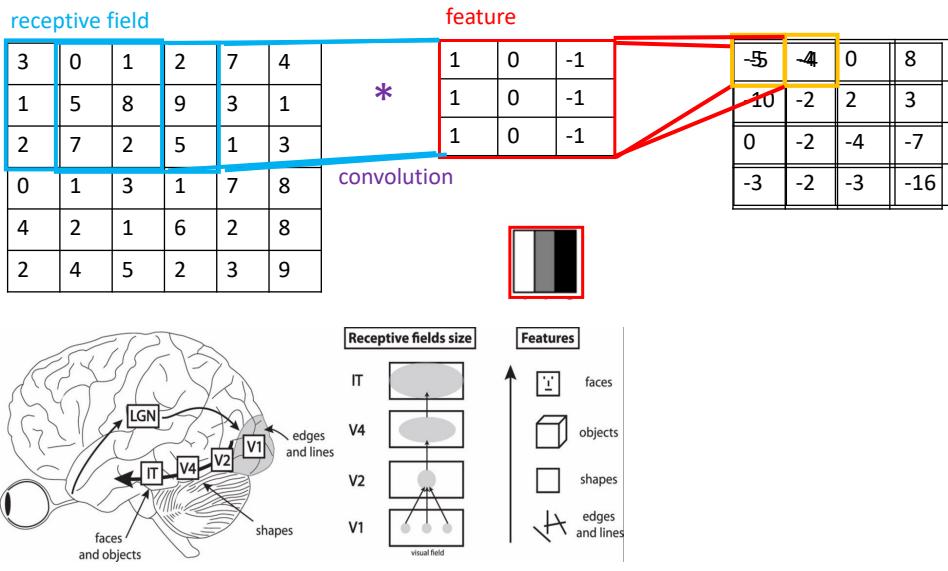
Manassi et al., *J. Vision*, 2013

Carandini, *J. Physiol.*, 2006; Movshon et al., *J. Physiol.*, 1978a,b

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Convolutions – receptive fields and features



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Conv Nets – Pooling & Normalisation

3	0	1	2
1	5	8	9
0	1	3	1
2	4	5	2

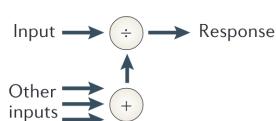
Max pooling

5	9
4	5



Reducing dimensionality?

Normalisation



Divide by average of nearby neurons – accentuate differences

$$b_i = \frac{a_i}{(k + \alpha \cdot \sum a_j^2)^\beta}$$

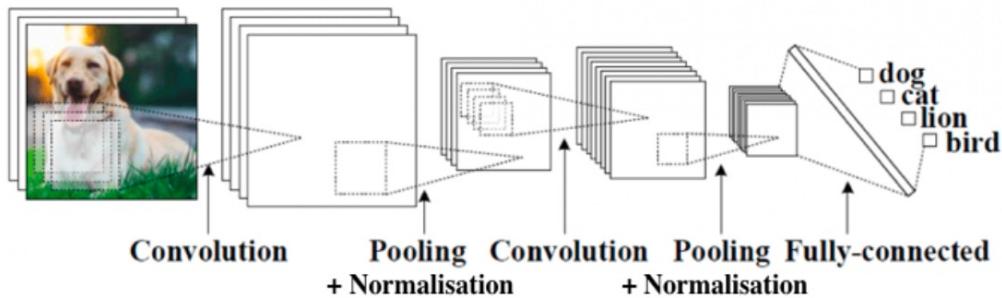
Carandini & Heeger, *Nature Reviews Neuroscience*, 2012

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A full convolutional neural network



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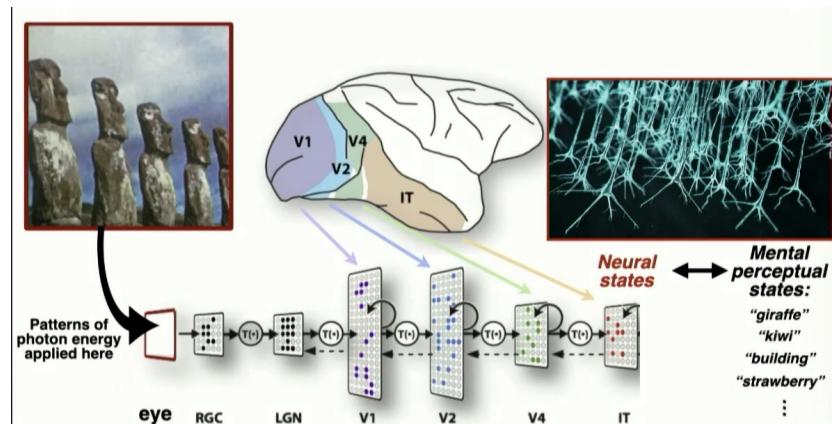
Quiz

- Practically, convolutional neural networks seem to be less likely to overfit the training data, and generalize better to new data, compared to fully-connected deep neural networks. Why do you think this is?

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Coming soon: training deep neural networks and comparisons with brains



video: James DiCarlo (MIT)
Yamins et al., PNAS, 2014

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Recap

- Biological neurons are capable of more computation than artificial neurons (units) in neural networks
- Biological neurons are diverse, with many different excitatory and inhibitory types with different connectivity patterns
- There are different sensory hierarchies in the cortex
- As you move up these hierarchies from early sensory cortex to higher areas
 - Response time increases
 - Receptive field gets bigger
 - The preferred stimulus gets more complex
 - The number of neurons gets smaller (dimensionality goes down)
 - The number of inputs per neuron goes up
 - The capacity for modulation goes up
- It is debated whether there is a hierarchy among higher cognitive parts of the cortex
- Depth & non-linearities allow neural networks to solve complex classification problems
- Convolutional neural networks are directly inspired by features of biological vision processing including
 - Hierarchical structure
 - Receptive fields
 - Feature detectors

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Still curious? You can dive in deeper to any of today's topics:

- Hierarchies in the brain's anatomical connections
 - Felleman, Daniel J., and David C. Van Essen. "Distributed hierarchical processing in the primate cerebral cortex." *Cerebral cortex (New York, NY: 1991)* 1, no. 1 (1991): 1-47.
 - Markov, Nikola T., Julien Vezoli, Pascal Chameau, Arnaud Falchier, René Quilodran, Cyril Huissoud, Camille Lamy et al. "Anatomy of hierarchy: feedforward and feedback pathways in macaque visual cortex." *Journal of Comparative Neurology* 522, no. 1 (2014): 225-259.
- Biological neurons as 2-layer neural networks
 - Poirazi, Panayiotis, Terrence Brannon, and Bartlett W. Mel. "Pyramidal neuron as two-layer neural network." *Neuron* 37, no. 6 (2003): 989-999.
- Predictive coding
 - Rao, Rajesh PN, and Dana H. Ballard. "Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects." *Nature neuroscience* 2, no. 1 (1999): 79-87.
- Selective attention
 - Noudoost, Behrad, Mindy H. Chang, Nicholas A. Steinmetz, and Tirin Moore. "Top-down control of visual attention." *Current opinion in neurobiology* 20, no. 2 (2010): 183-190.
- Increased number of inputs per neuron along the cortical hierarchy
 - Elston, Guy N. "Specialization of the neocortical pyramidal cell during primate evolution." *Evolution of nervous systems* (2007): 191-242.
- Convolutions in the brain
 - Carandini, Matteo. "What simple and complex cells compute." *The Journal of physiology* 577, no. Pt 2 (2006): 463.
- Normalisation
 - Carandini, Matteo, and David J. Heeger. "Normalization as a canonical neural computation." *Nature Reviews Neuroscience* 13, no. 1 (2012): 51-62.
- McCullough - Pitts model
 - McCulloch, Warren S., and Walter Pitts. "A logical calculus of the ideas immanent in nervous activity." *The bulletin of mathematical biophysics* 5 (1943): 115-133.
- The first paper on Convolutional Neural Networks trained with backpropagation
 - LeCun, Yann, Bernhard Boser, John Denker, Donnie Henderson, Richard Howard, Wayne Hubbard, and Lawrence Jackel. "Handwritten digit recognition with a back-propagation network." *Advances in neural information processing systems* 2 (1989).

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