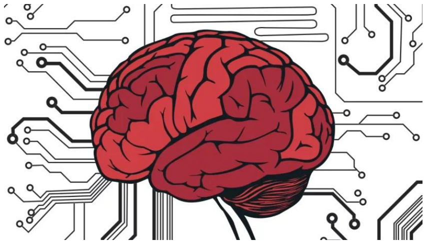
Brain as biological computing machines



complex computational system, consisting of some 100 billion neurons, connected by an estimated 100 trillion synapses

Herculano-Houzel, Suzana. "The remarkable, yet not extraordinary, human brain as a scaled-up primate brain and its associated cost." *Proceedings of the National Academy of Sciences* 109.Supplement 1 (2012): 10661-10668.

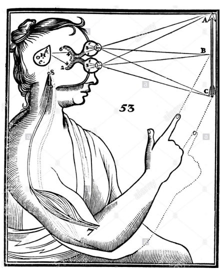
2

Describing brain throughout the history

3

In terms of hydraulic analogies and the movement of fluids

Descartes



Stanford encyclopedia of philosophy. http://plato.stanford.edu/entries/pineal-gland. Accessed: 2014/07/14.

4

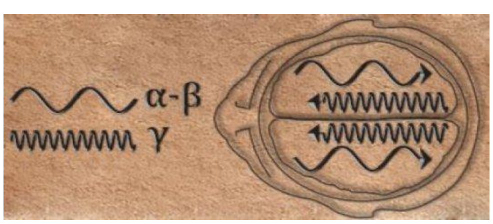
Like a steam engine, distributing and releasing pressure

Freud

D. Leary (Ed.), Metaphors in the History of Psychology, Cambridge University Press, Cambridge (1994)

5

In the era of radio, brains were described in terms of 'channels' and frequencies.



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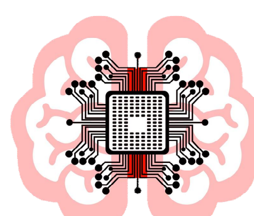
Today

Neuroscientists increasingly speak of neuronal '**computations**' and the '**circuits**' responsible for behaviors; distant brain regions **communicate** to form '**networks**' of activity.



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Brain vs. Silicon

1 mm^3 of cortex:

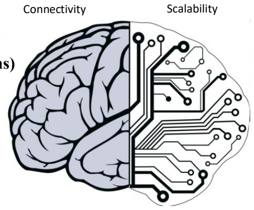
50,000 neurons
1000 connections/neuron
(=> 50 million connections)
4 km of axons

whole brain (2 kg):

10^{11} neurons
10^{14} connections
8 million km of axons
20 watts

Parallelism
Connectivity

Speed
Scalability



1 mm^2 of a CPU:

1 million transistors
2 connections/transistor
(=> 2 million connections)
.002 km of wire

whole CPU:

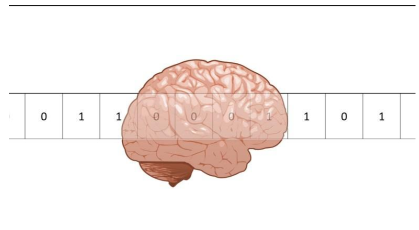
10^9 transistors
2×10^9 connections
2 km of wire
scaled to brain: MW

Bassett, Danielle Smith, and E. D. Bullmore. "Small-world brain networks." *The neuroscientist* 12.6 (2006): 512-523.

Mink, Jonathan W., Robert J. Blumenschine, and David B. Adams. "Ratio of central nervous system to body metabolism in vertebrates: its constancy and functional basis." *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology* 241.3 (1981): R203-R212.

'**Computational**' perspective on neuroscience goes beyond the metaphor of 'the brain is a computer'

computational science provides a rigorous formal framework and tools for reasoning about information-processing systems



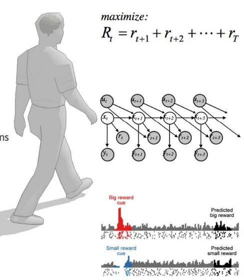
Three levels of description *(David Marr, 1982)*

Computational
Why do things work the way they do?
What is the goal of the computation?
What are the unifying principles?

maximize:
$$R_t = r_{t+1} + r_{t+2} + \cdots + r_T$$

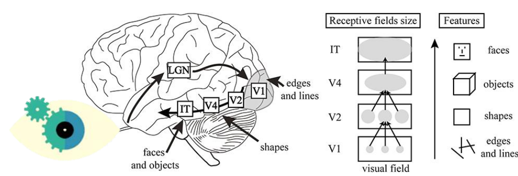
Algorthmic
What representations can implement such computations?
How does the choice of representations determine the algorithm?

Implementational
How can such a system be built in hardware?
How can neurons carry out the computations?



Visual system in brain science and computer vision in machine learning

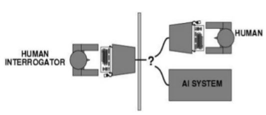
Both of them have played a leading role in their fields



Object recognition provides an interesting test case in the intersection of neuroscience and computing.

The History of Neuroscience in AI

The Turing Test



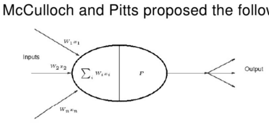
Operational test for intelligent behaviour:
the Imitation Game

"We are not interested in the fact that the brain has the consistency of cold porridge" (Turing 1952)

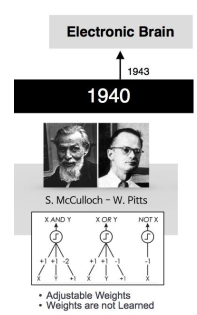
McCulloch and Pitts

A MODEL OF A SINGLE NEURON (UNIT)

- In 1943 McCulloch and Pitts proposed the following idea:

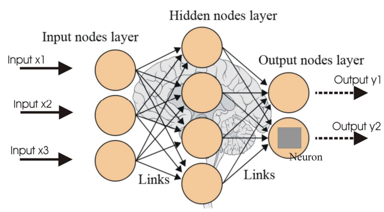


- Denote the incoming signals by $\mathbf{x} = (x_1, x_2, \dots, x_n)$ (the input),
- and the output of a neuron by y (the output $y = f(\mathbf{x})$).



Perceptron; Multi-layers; and back propagation

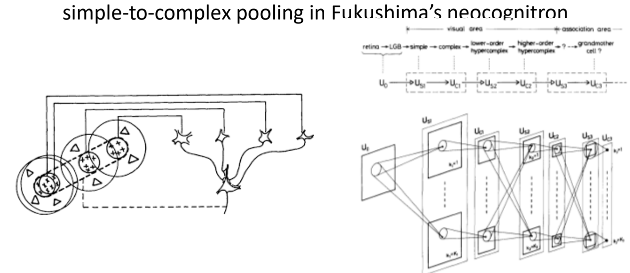
'**Connectionism**' became a popular term for describing the neural networks aimed at solving a wide range of problems, from vision to language.



Rosenblatt, Frank. "The perceptron: a probabilistic model for information storage and organization in the brain." Psychological review 65.6 (1958): 386.
Rumelhart, David E., Geoffrey E. Hinton, and Ronald J. Williams. *Learning internal representations by error propagation.* No. ICS-8506. California Univ San Diego La Jolla Inst for Cognitive Science, 1985.
Bryson, Arthur E., Walter F. Denham, and Stewart E. Dreyfus. "Optimal programming problems with inequality constraints." AIAA journal 1.11 (1963): 2544-2550.

Neocognitron; Emergence of convolutional neural network (1982)

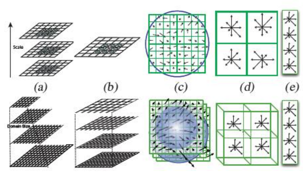
simple-to-complex pooling in Fukushima's neocognitron



Fukushima, Kunihiko, and Sei Miyake. "Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition

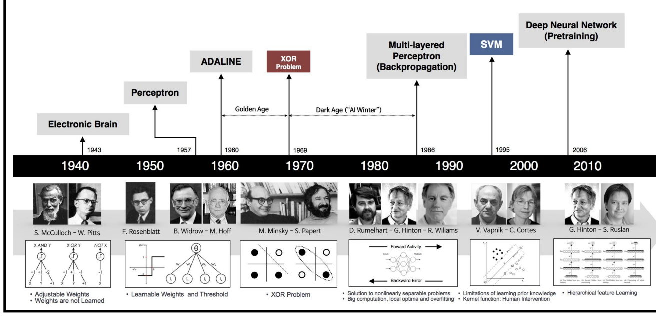
In the winter of AI, community eschewed connections to neuroscience

David Lowe's widely influential Scale Invariant Feature Transform (SIFT) was originally described in analogy to the primate ventral visual pathway

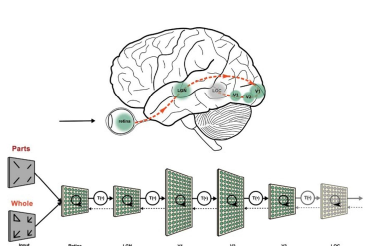


Lowe, David G. "Object recognition from local scale-invariant features." *Computer vision, 1999. The proceedings of the seventh IEEE international conference on.* Vol. 2. Ieee, **1999**.

Deep Learning and the Second A.I. Spring

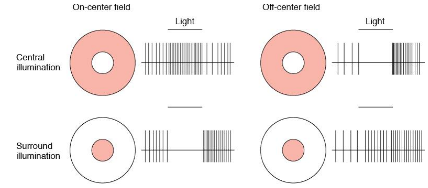


Hierarchical visual processing to to transform images into a better format across many layers



Surround suppression in classical receptive fields

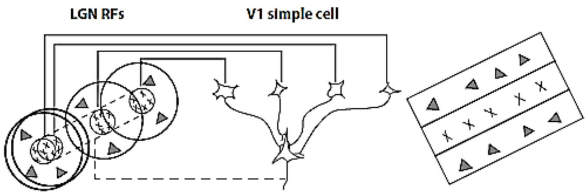
routinely applied in the form of local non-max suppression for edge and contour detectors and localization in object recognition



Source: Barrett KE, Barman SM, Boitano S, Brooks HL: *Ganong's Review of Medical Physiology:* www.accessmedicine.com

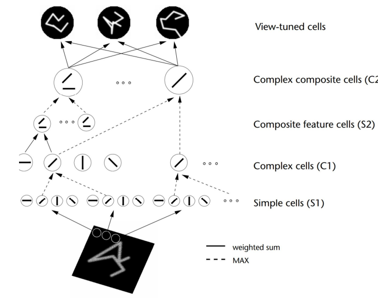
Hyvärinen, Aapo. "Statistical models of natural images and cortical visual representation." *Topics in Cognitive Science* 2.2 (2010): 251-264.

Pooling to make complex feature



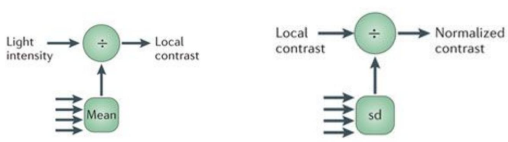
max pooling

Based on neuroscience studies, max pooling has replaced winner-take-all in pooling layers, thereby providing impressive performance gains

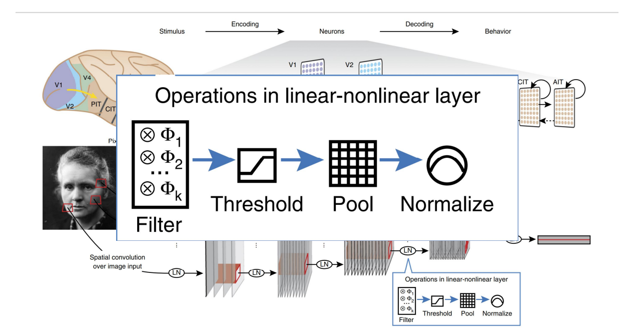


Riesenhuber, Maximilian, and Tomaso Poggio. "Hierarchical models of object recognition in cortex." *Nature neuroscience* 2.11 (1999): 1019.

Normalization operates in a number of neural systems

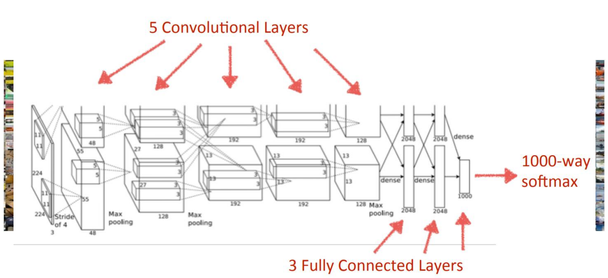


Carandini, Matteo, and David J. Heeger. "Normalization as a canonical neural computation." *Nature Reviews Neuroscience* 13.1 (2012): 51.



Yamins, Daniel LK, and James J. DiCarlo. "Using goal-driven deep learning models to understand sensory cortex." *Nature neuroscience* 19.3 (2016): 356.

Deep learning approaches reached critical mass in 2013



Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

Although theoretical advances have been made, in large part the enabling factor is the availability of **computational power (GPUs)** and of **vast quantities of data**

Geoff Hinton:

It took 17 years to get deep learning right; one year thinking and 16 years of progress in computing, praise be to Intel

The gap between humans and machines is still great

The size of required training datasets:

- Humans and animals can rapidly learn concepts, often from single training examples.

- ImageNet was trained using 1,000 labeled examples each from 1,000 categories of objects, for a total of 1 million labeled images

- The number of visual fixations a human makes in a year (assuming three saccades per second during waking hours),

out-of-set generalization:

- some degree of bias in these benchmark datasets

The nature of representations in humans and deep neural networks are still qualitatively different. There is more that neuroscience can teach deep learning.

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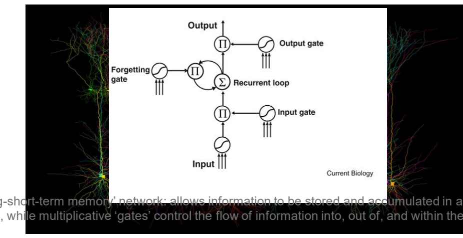
So what's next?

Recurrence and Feedback

Most of the deep networks, are still largely feedforward in their organization. However the real visual cortex contain myriad local recurrent connections and ubiquitous feedback connections between cortical areas



'long-short-term memory' network: allows information to be stored and accumulated in a recurrent loop, while multiplicative 'gates' control the flow of information into, out of, and within the loop

Cox, David Daniel, and Thomas Dean. "Neural networks and neuroscience-inspired computer vision." *Current Biology* 24.18 (2014): R921-R929.

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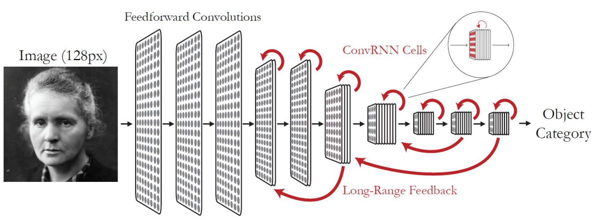
Convolutional Recurrent Models of the Visual System



Nayebi, Aran, et al. "Task-Driven Convolutional Recurrent Models of the Visual System." *arXiv preprint arXiv:1807.00053* (2018).

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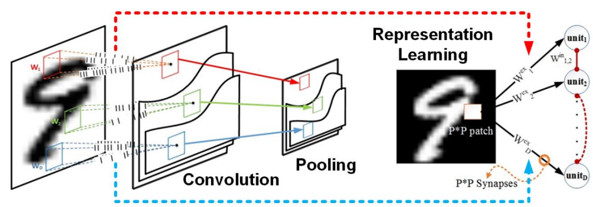
Using spiking networks



Tavanaei, Amirhossein, et al. "Deep Learning in Spiking Neural Networks." arXiv preprint arXiv:1804.08150 (2018).

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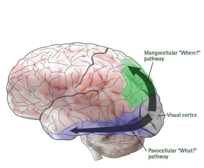
Beyond Still Images

Time-varying signals

There are special mechanism for motion processing in brain (Where pathway)



Simões, Gabriel S., et al. "Movie genre classification with convolutional neural networks." Neural Networks (IJCNN), 2016 International Joint Conference on. IEEE, 2016.

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