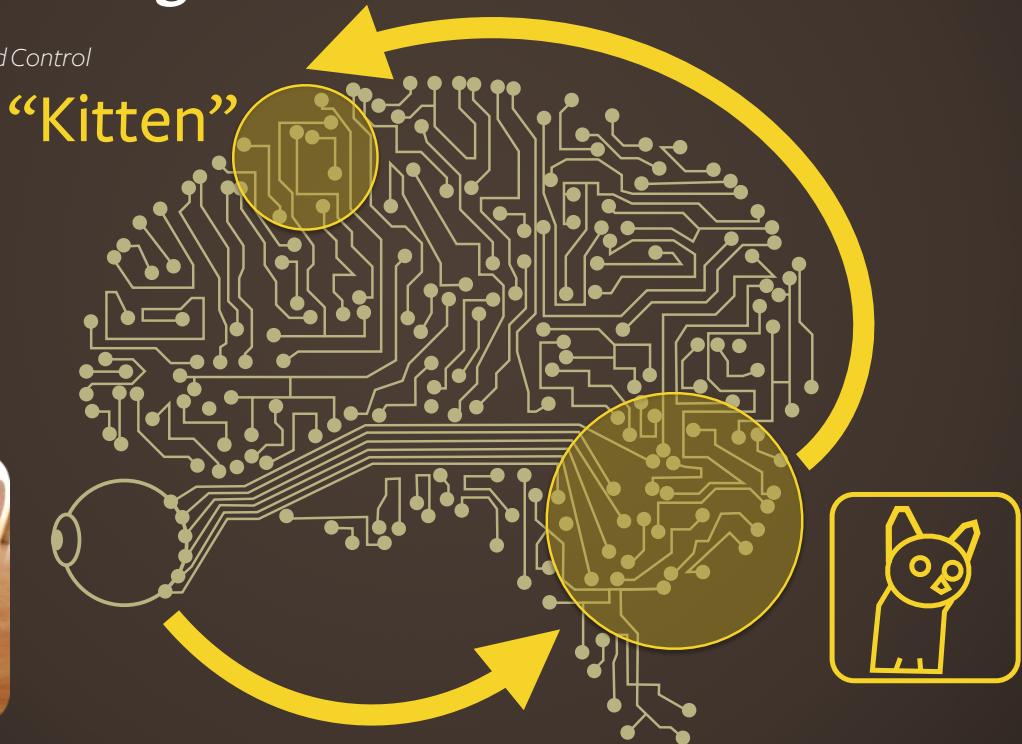
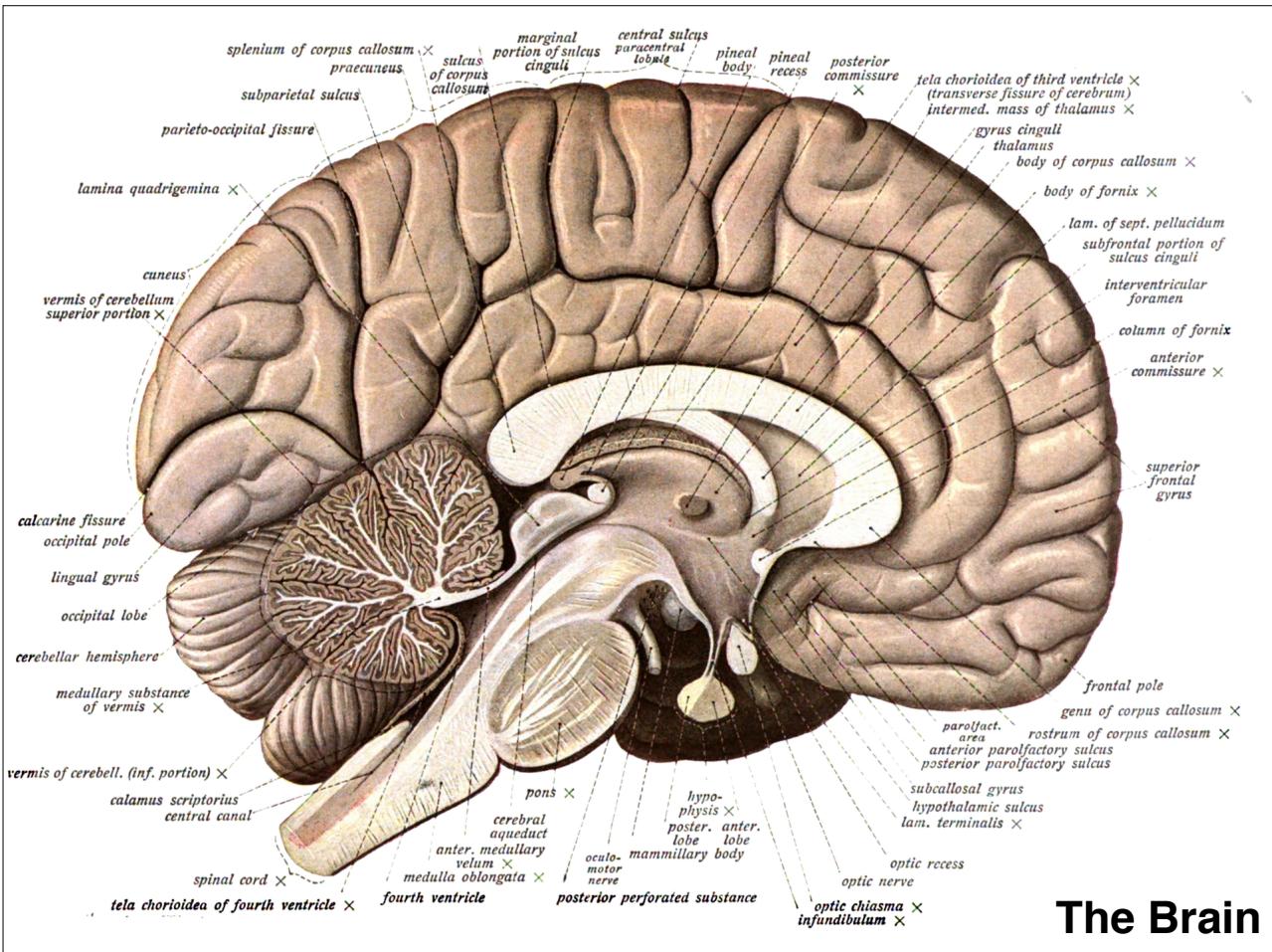


The biological inspiration and motivation of Deep Learning

Dr Jonathon Hare
Vision, Learning and Control

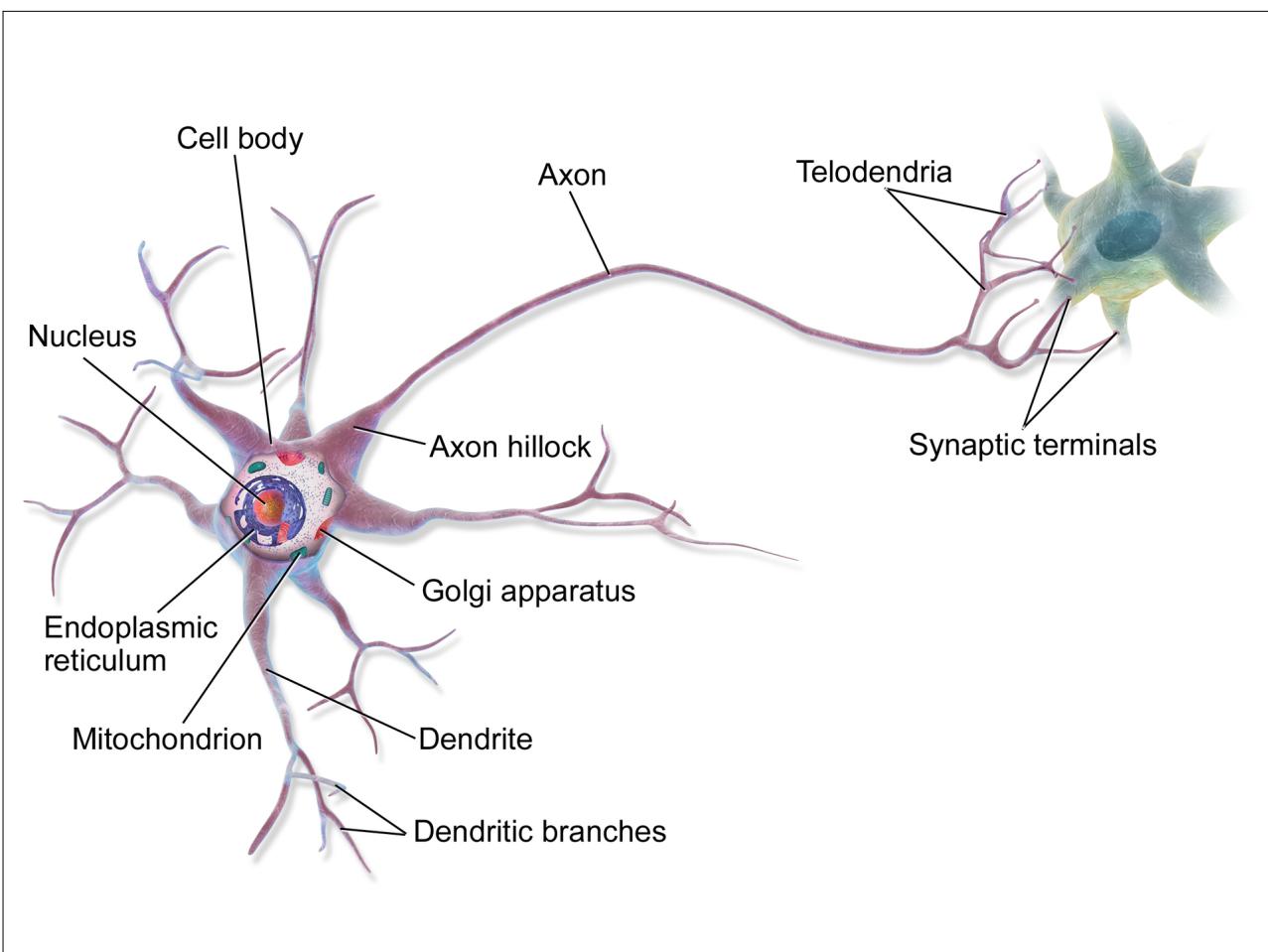
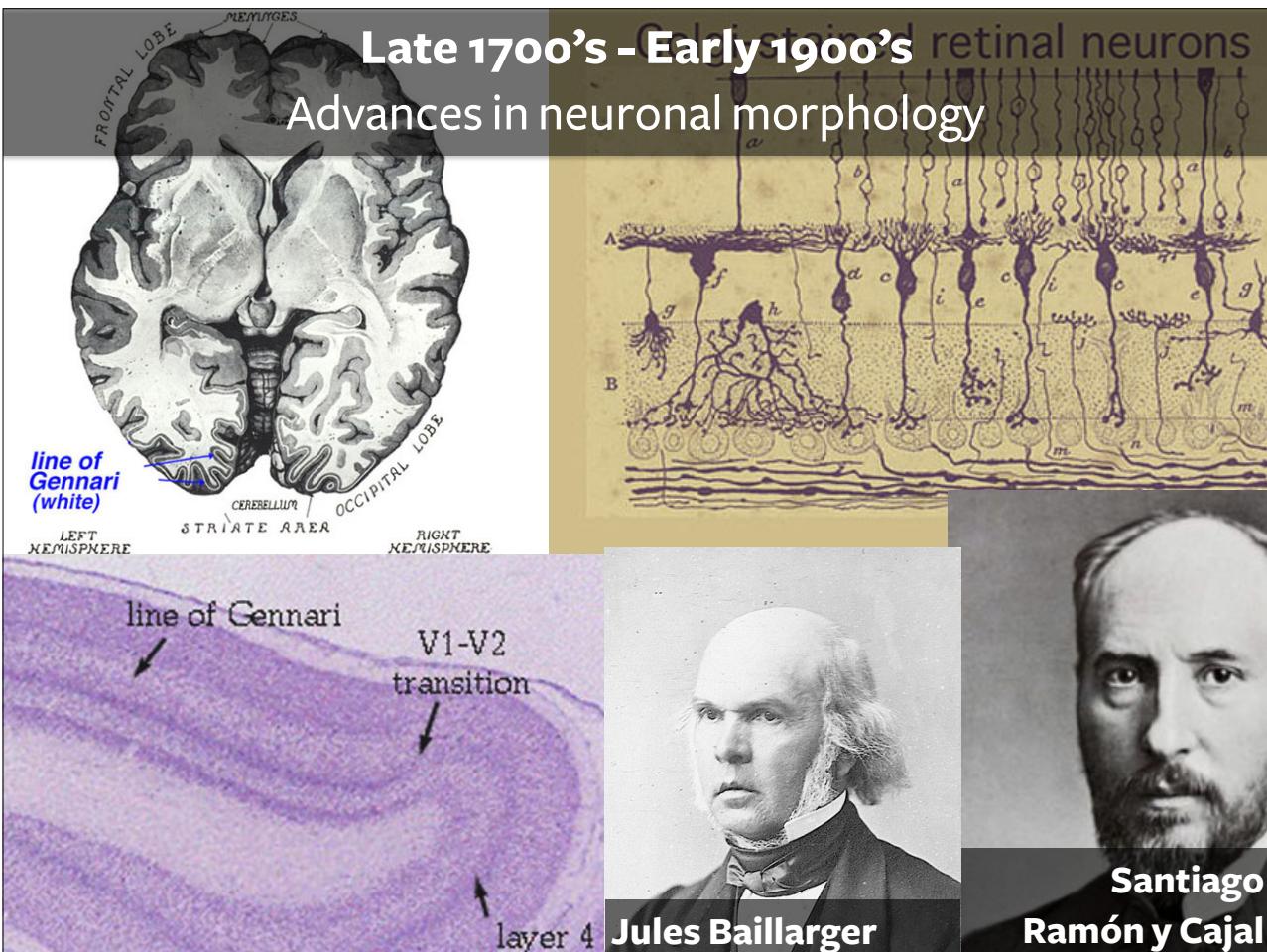


- Biological systems, neuroscience and psychology have long served as inspiration and motivation for Artificial Intelligence
- There is no argument that current deep learning models and approaches are **not biologically plausible.**
- But, throughout the development of neural networks and deep learning, biology has played a role...



The Brain

Biological Neurons



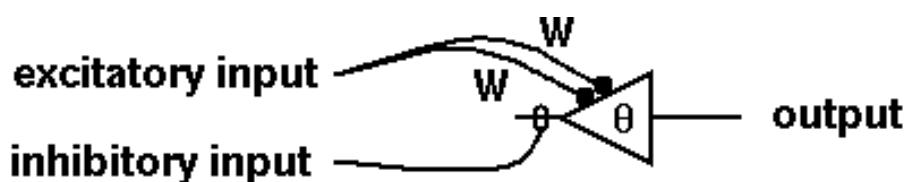
- Biological Neurons “spike”
 - If sufficient spikes are received by the dendrites within a time period the neuron fires its “action potential”
 - Some inputs are inhibitory - they reduce the potential of the neuron to fire
- Once it has fired there is a short refractory period which inhibits firing again
- There are also a number of other interesting dynamical properties
 - e.g. short-term synaptic depression

A Formalism for Approaching the Operation of a Single Neuron

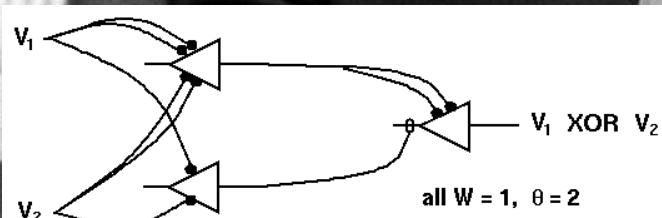
1943

McCulloch-Pitts Artificial Neuron

$$V_i = \begin{cases} 1 & : \sum_j W V_j \geq \theta \text{ AND no inhibition} \\ 0 & : \text{otherwise} \end{cases}$$



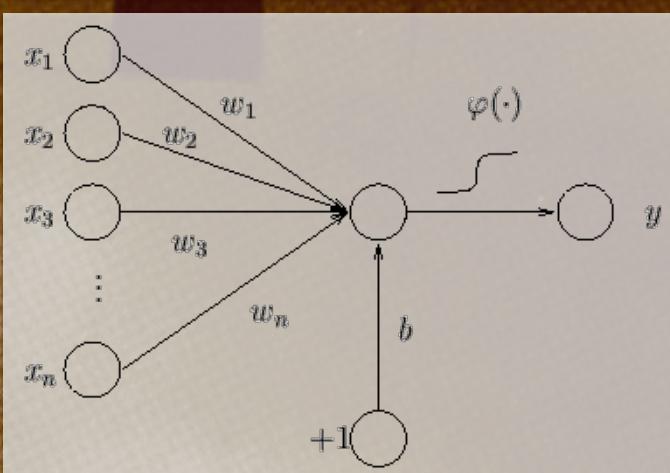
Warren
McCulloch



Walter
Pitts

1958

Rosenblatt's Perceptron

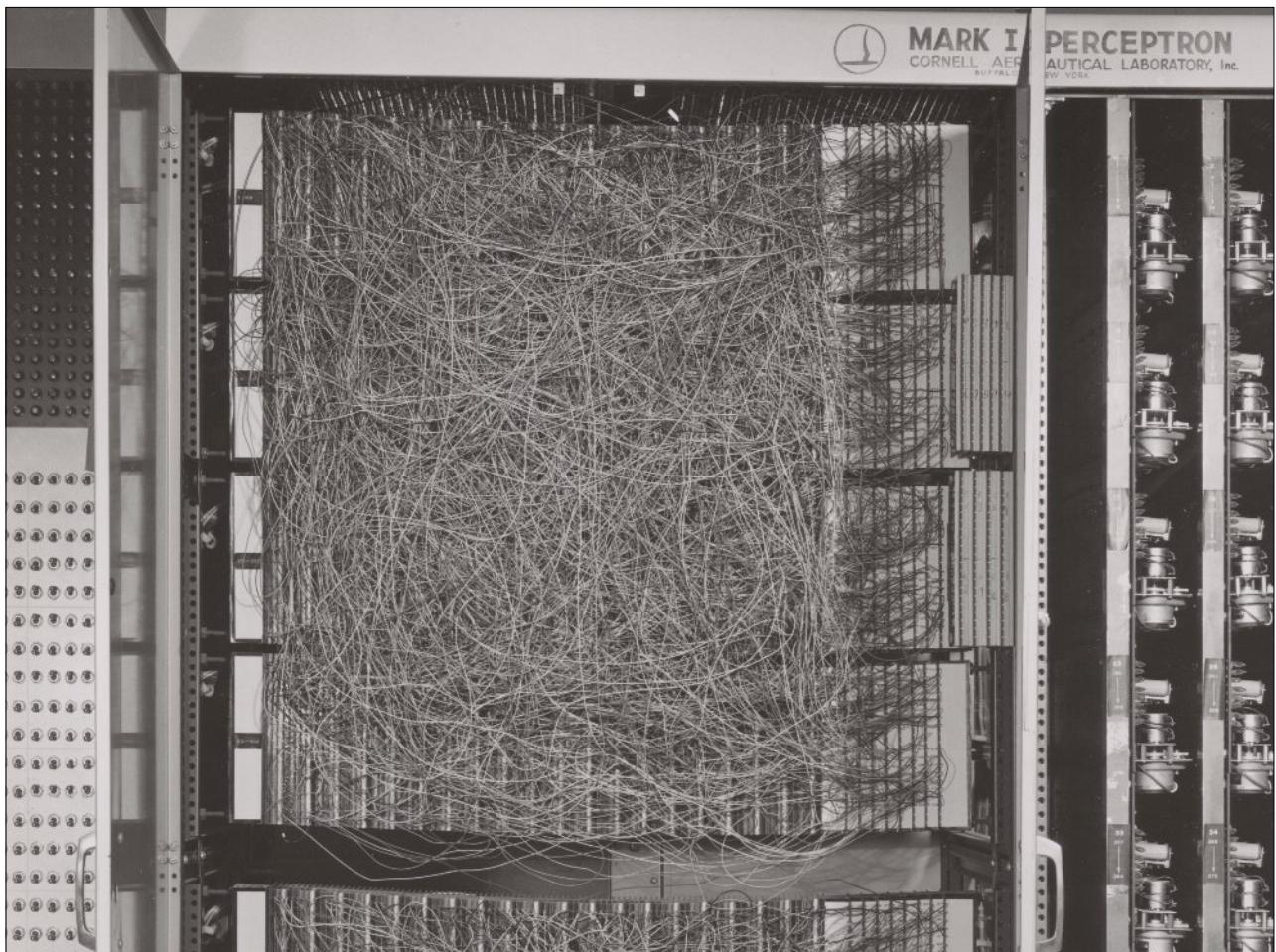


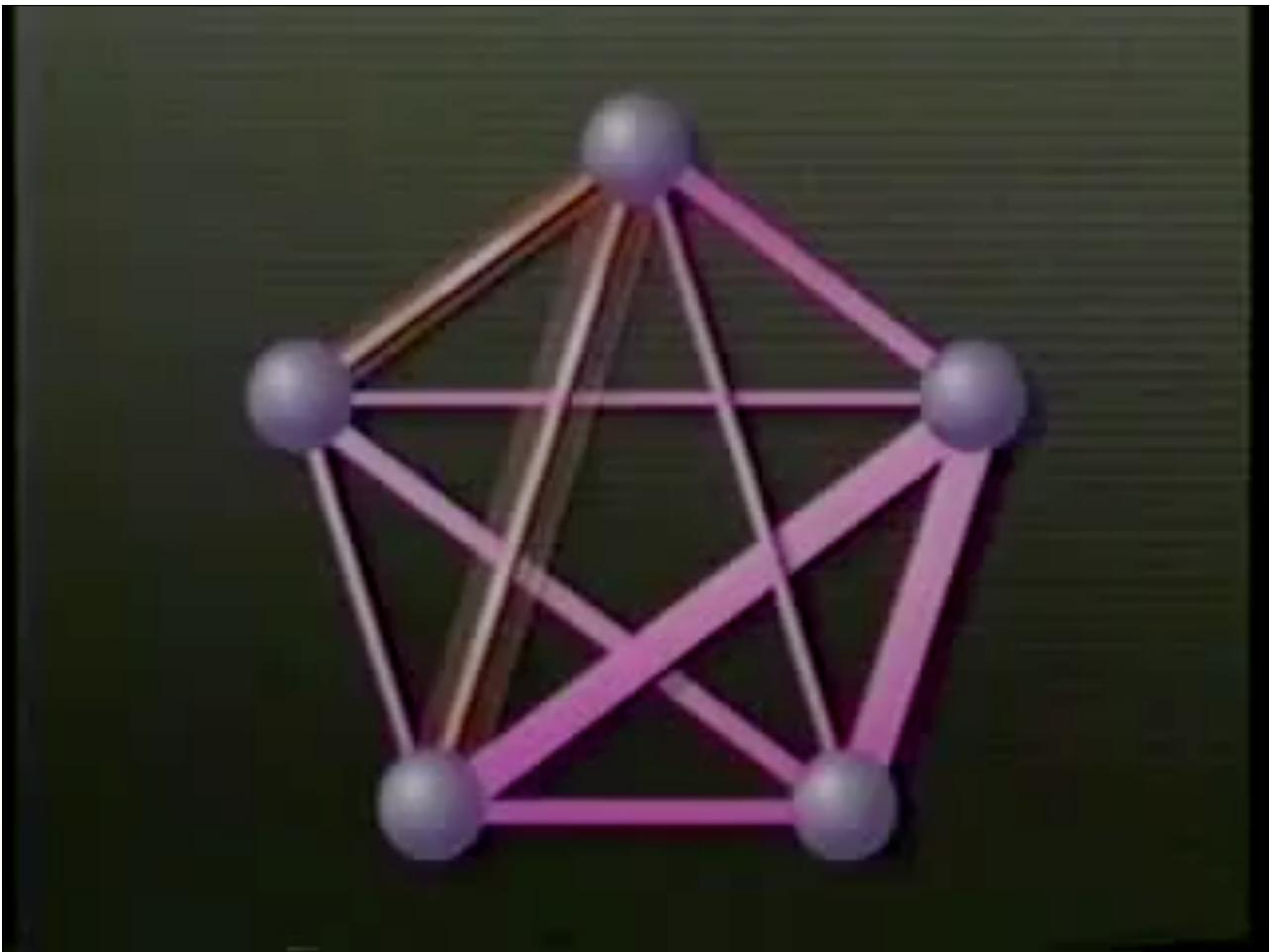
Frank Rosenblatt

$$y = \varphi\left(\sum_{i=1}^n w_i x_i + b\right) = \varphi(\mathbf{w}^T \mathbf{x} + b)$$

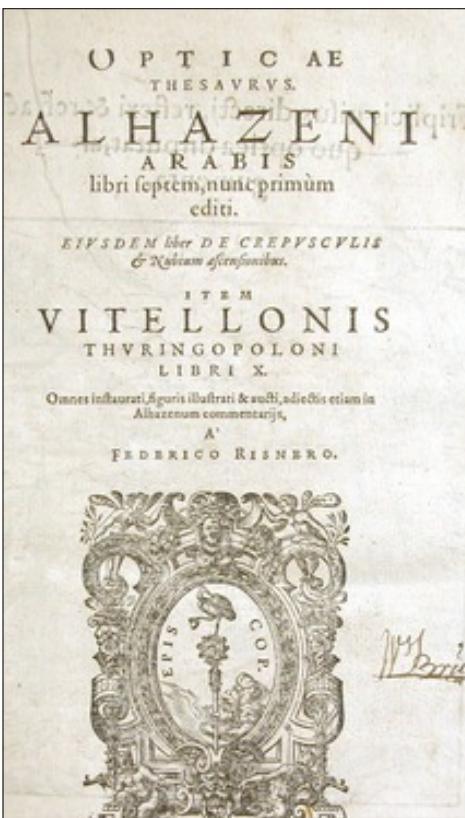
$$y = \varphi\left(\sum_{i=1}^n w_i x_i + b\right) = \varphi(\mathbf{w}^T \mathbf{x} + b)$$

- Rosenblatt's model captures many of the key points of a biological neuron:
 - Output is a function of the sum of inputs
 - Negative weights account for inhibitory connections
 - The “activation function” can ensure that output is only produced once a threshold is exceeded (although we use many variants of these days)





Back to a real brain: The
visual system



Com priuilegio Cesariorum Regum Gallie ac Scotorum.

BASILEAE,
PER EPIS.

Circa AD 100 - 1000

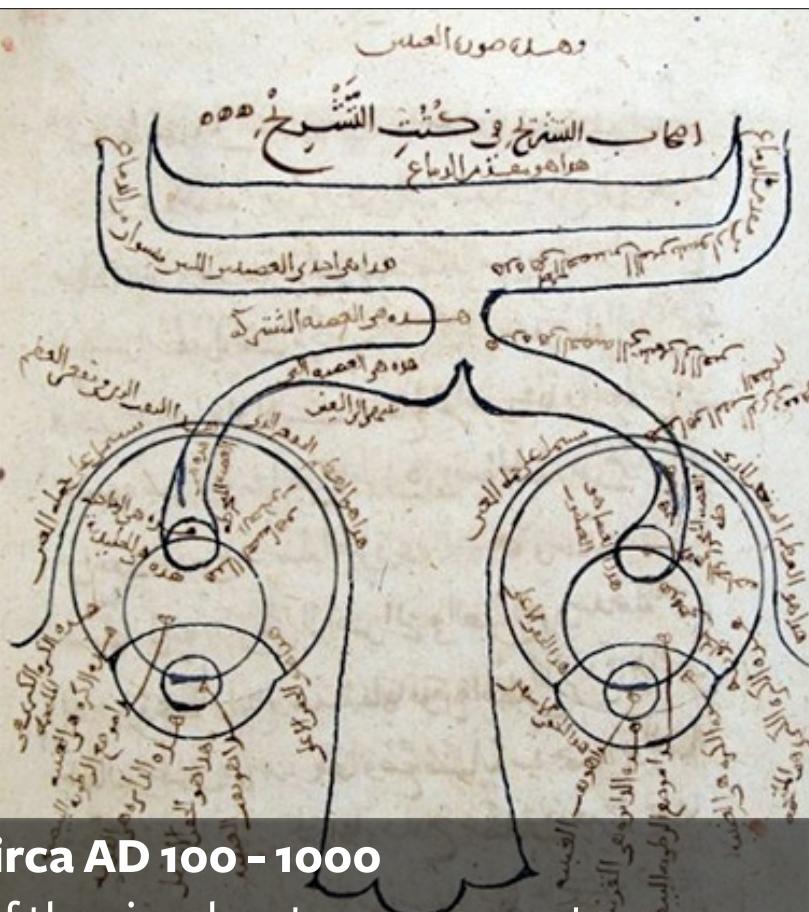
Understanding of the visual system gross anatomy

Circa AD 1500

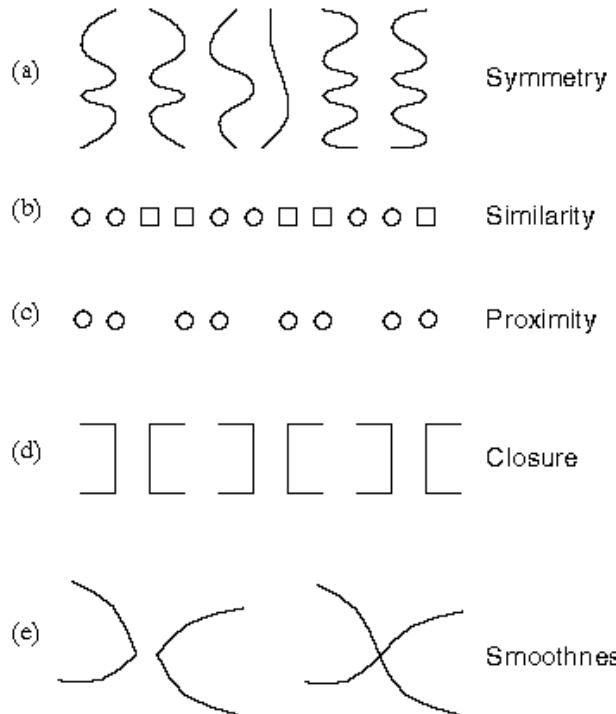
Foveal and peripheral vision

“The function of the human eye ... was described by a large number of authors in a certain way. But I found it to be completely different.”

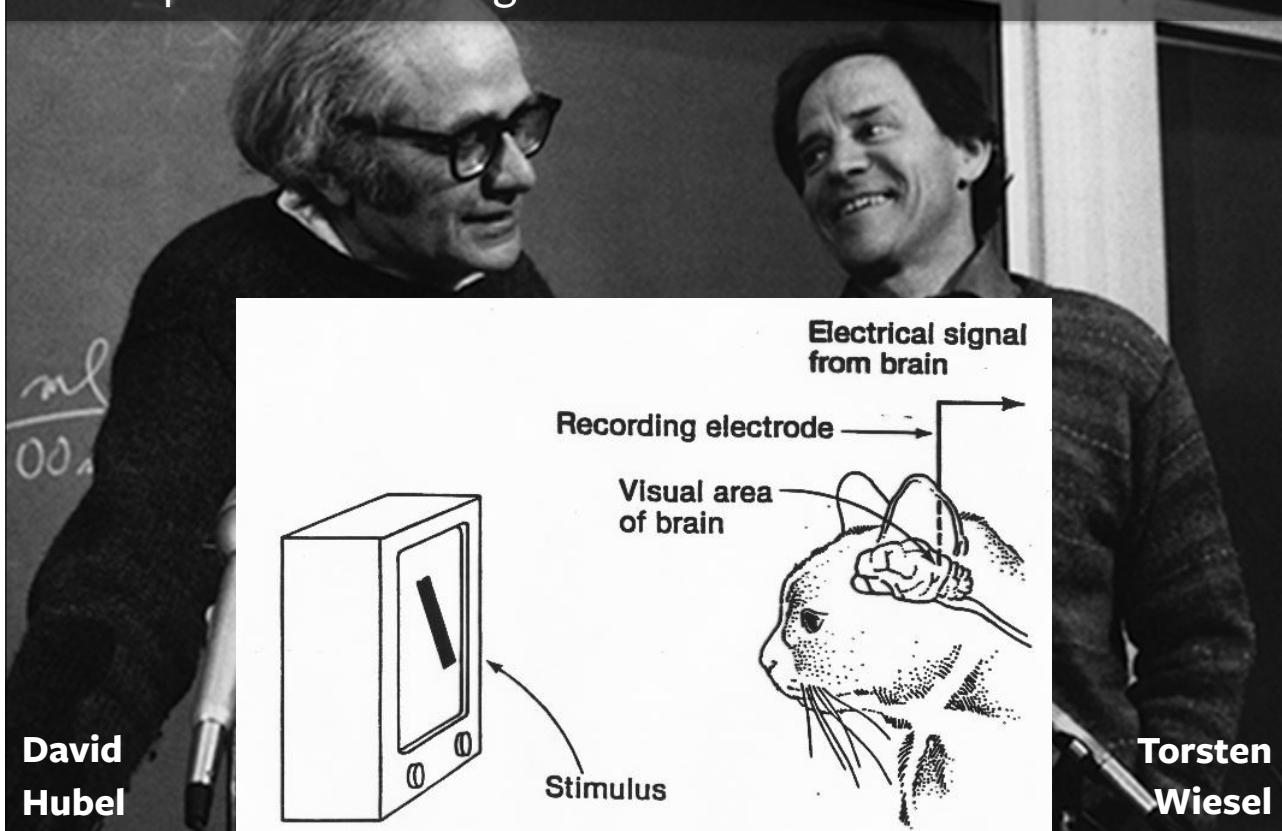
—Leonardo Da Vinci



1930's
Gestalt Laws of Perceptual Grouping



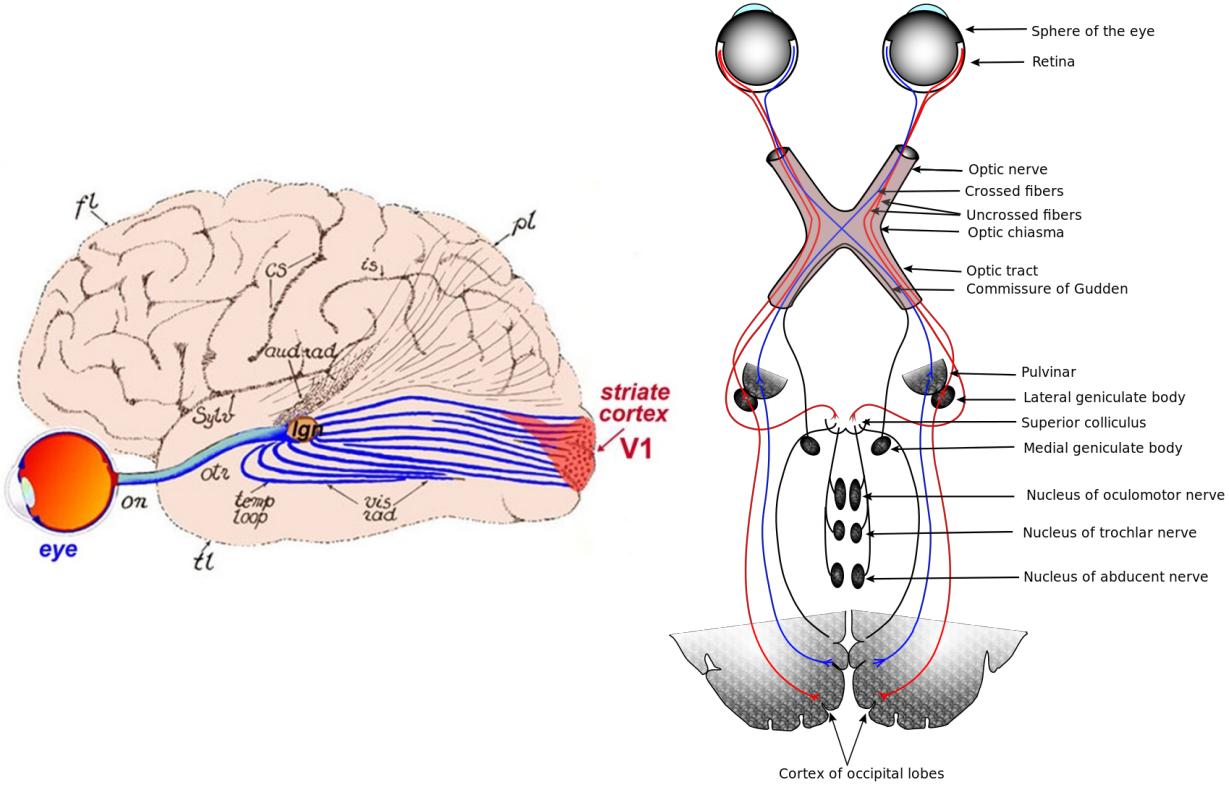
1959
Receptive Fields of Single Neurons in the Cat's Striate Cortex



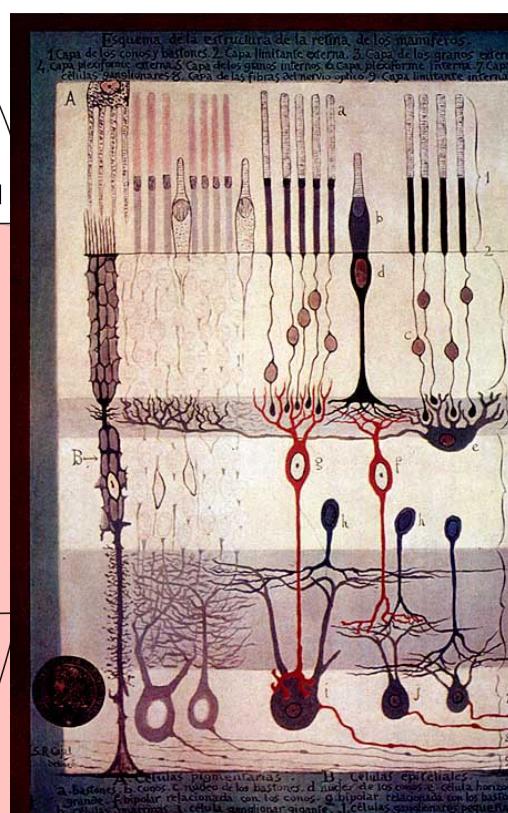
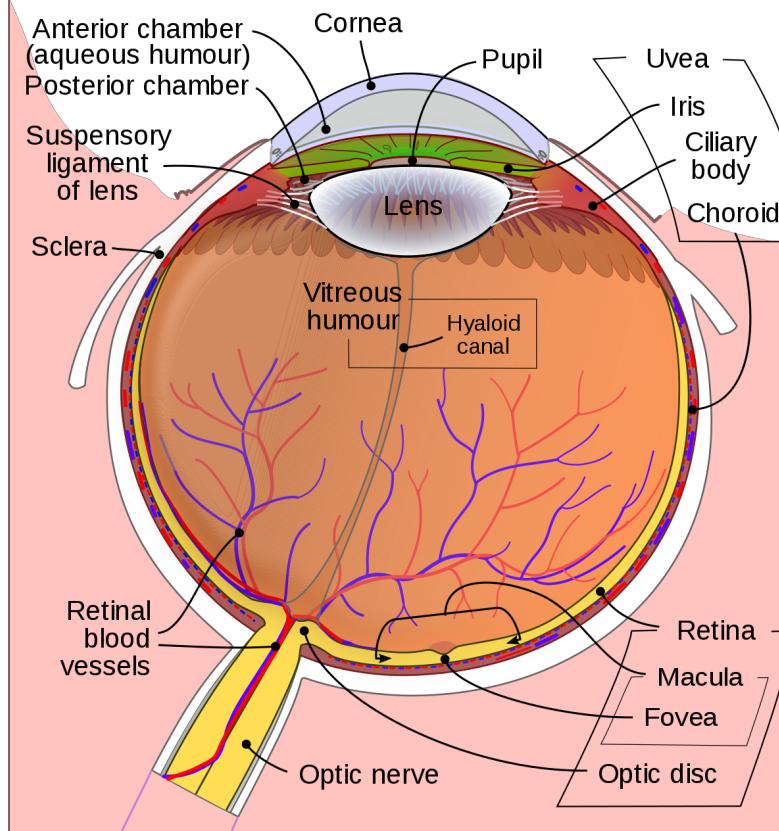


A modern understanding of
the visual system

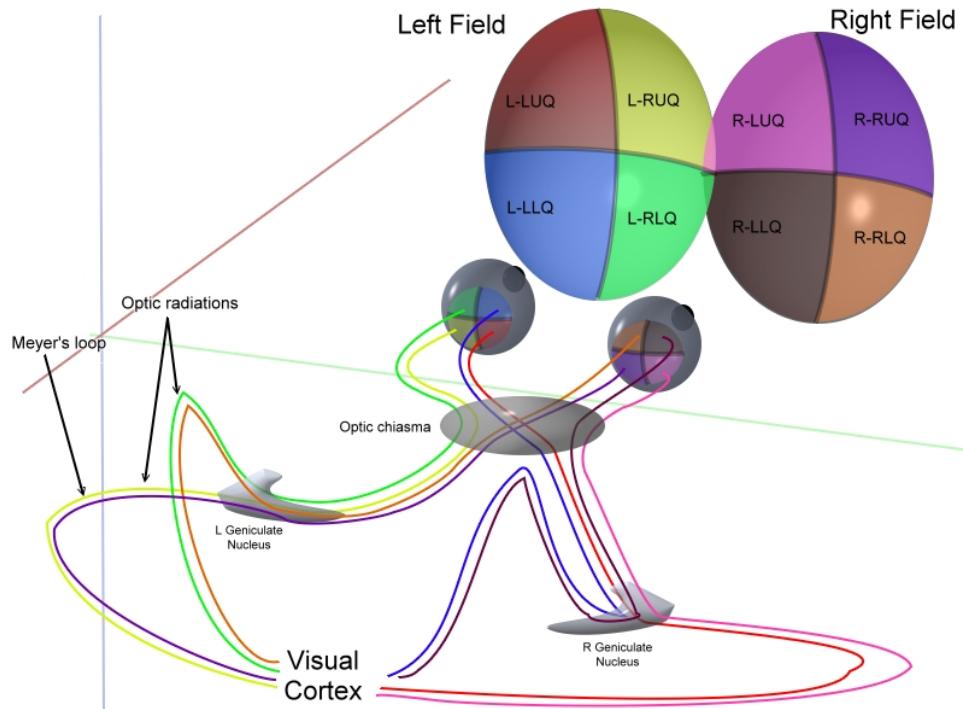
Gross Neuroanatomical Features



Neuroanatomy: the retina



Neuroanatomy: information flow along the optic nerve



Bandwidth of the optic nerve

- Estimated to be 8960 kbps (<https://www.newscientist.com/article/dn9633-calculating-the-speed-of-sight/>)
 - ~1.1 megabytes per second
 - An uncompressed 640*480 8-bit RGB image is $640*480*3$ bytes = 0.92 megabytes

Neuroanatomy: the striate cortex (aka primary visual cortex or V1)

- Receives information from the LGN, with retinotopic mapping preserved
- Characterised by a layered structure of cells organised into “hypercolumns”
 - Small “receptive fields”
 - Neurons adapted to firing on relatively simple features like edges of specific orientations

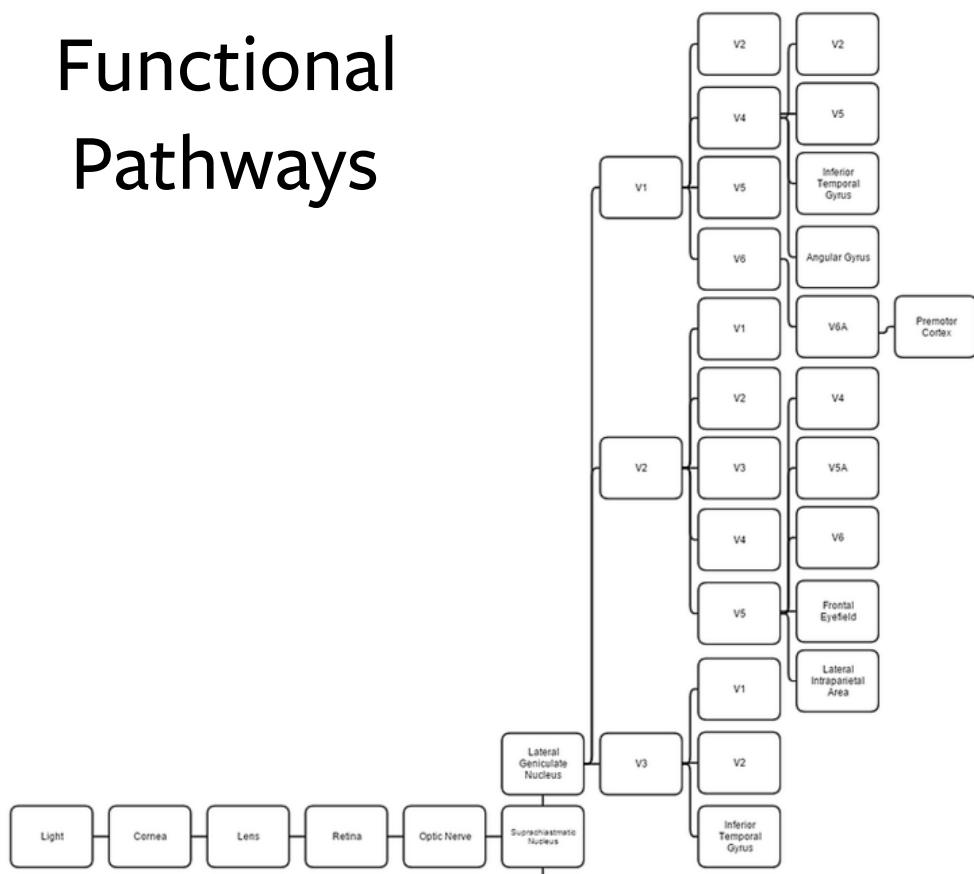
Neuroanatomy: the extrastriate cortex (aka V2-V5)

- V2: local receptive fields, forward connections to V3, V4 and V5, backward connections to V1
 - Cells tuned to moderately complex patterns
- V3: lots of controversy to what the extent of this bit is & what it does!
- V4: attentional modulation; tuned to moderately complex object features
- V5/Middle Temporal: cells sensitive to movement and direction
- V6/Dorsomedial: processing of ego-motion

Neuroanatomy: the Inferior Temporal Cortex (IT)

- Cells sensitive to specific types of high-level features
- For example cells that fire when a face is present in the visual field

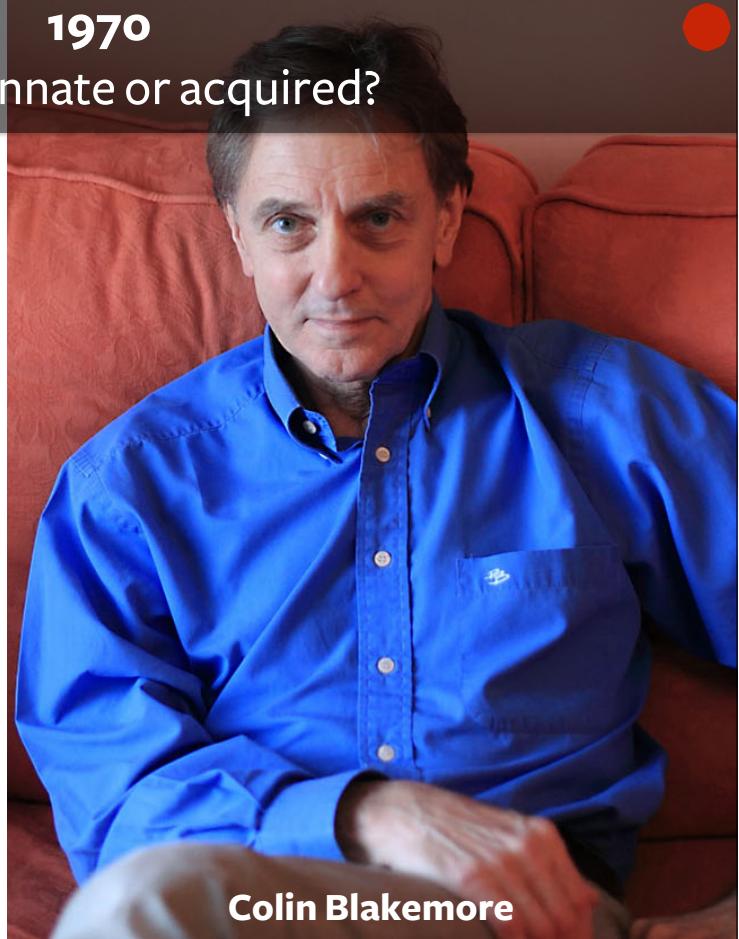
Functional Pathways



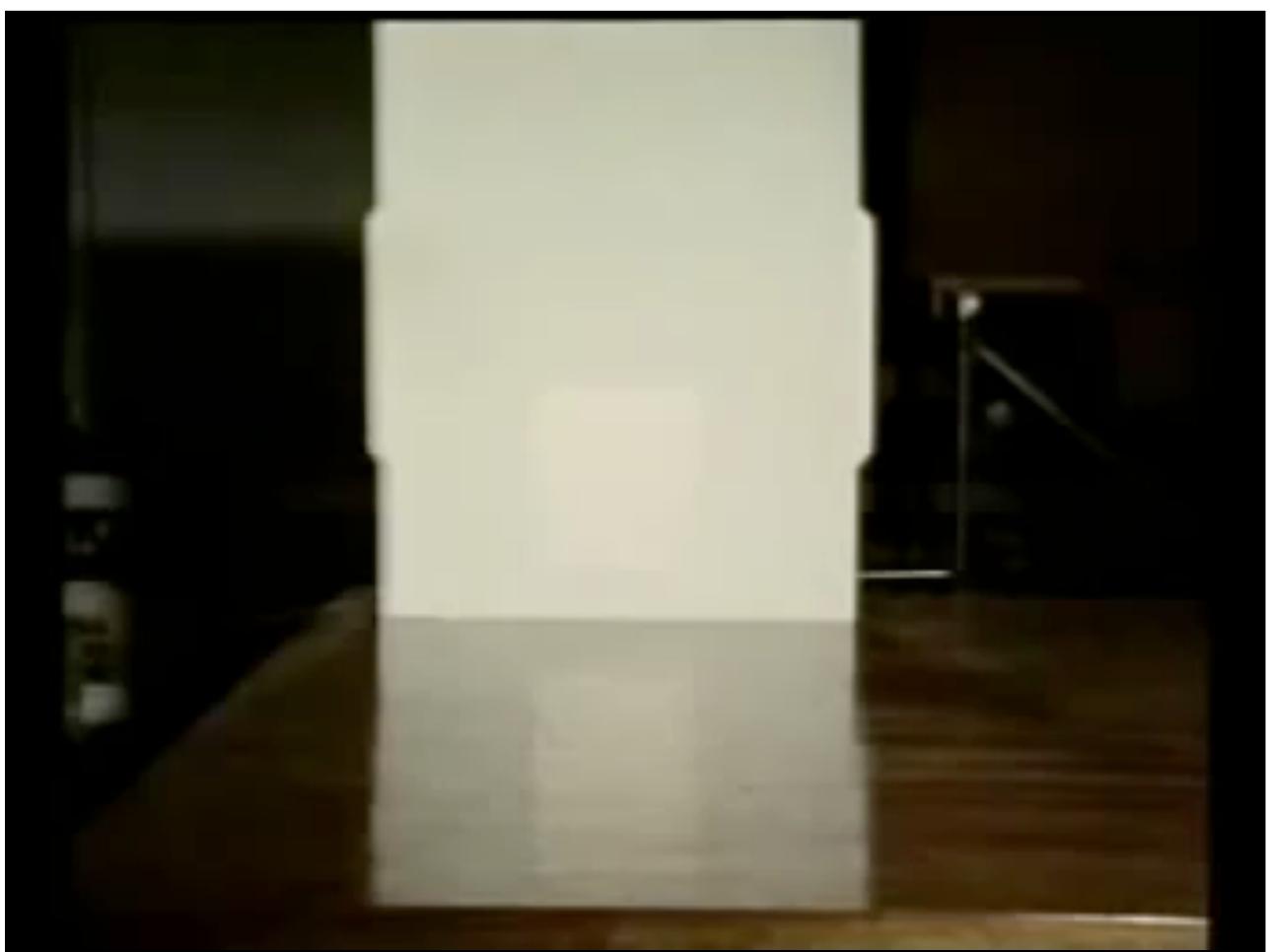
Nature or nurture... Do we “learn” to see?

1970

Is vision innate or acquired?



Colin Blakemore

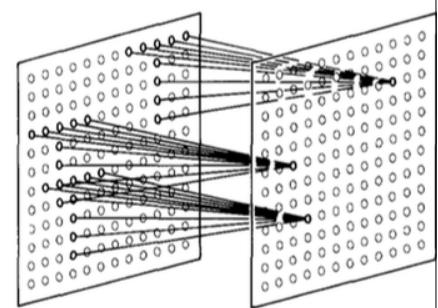
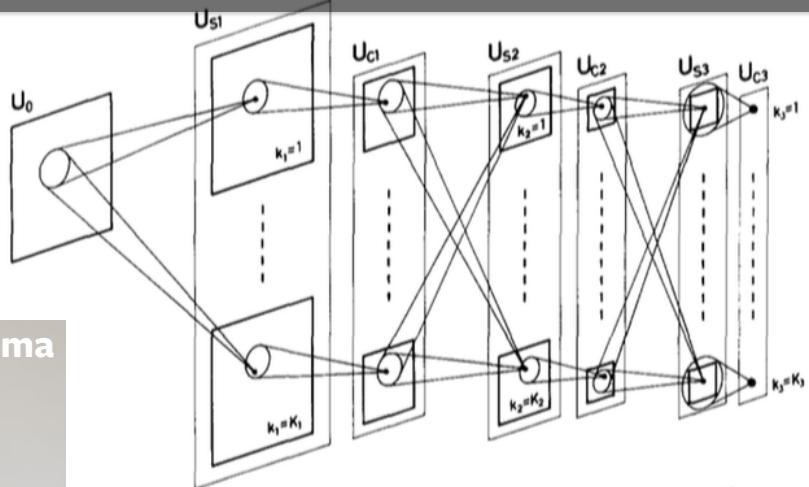


Back to computational models: feature learning, local receptive fields and preserved spatial mappings

1979

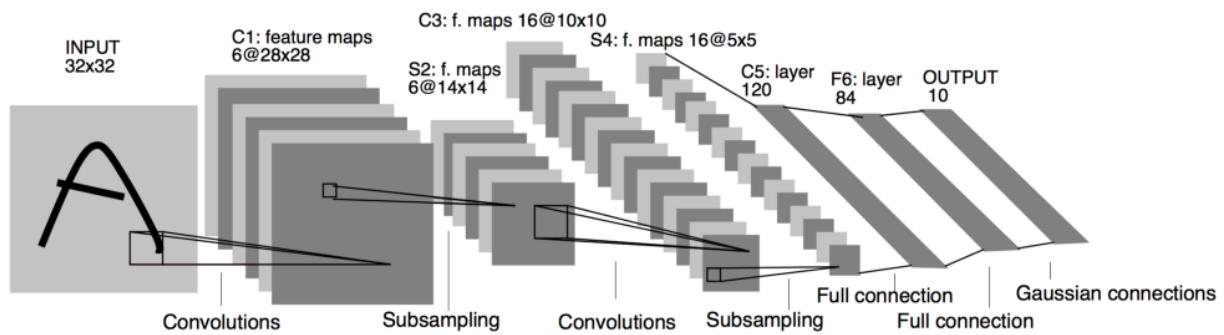
Neocognitron

Kunihiro Fukushima



1998

LeNet-5: Convolutional Neural Networks



A word of warning from
Marvin Minsky about learning
features



Parting words

- Deep learning architectures are definitely not biologically plausible, but they do take ideas from our understanding of the brain.
- We haven't talked about learning... is backprop biologically plausible?
 - Does all learning need to involve gradients?