

Brain-Inspired Artificial Intelligence

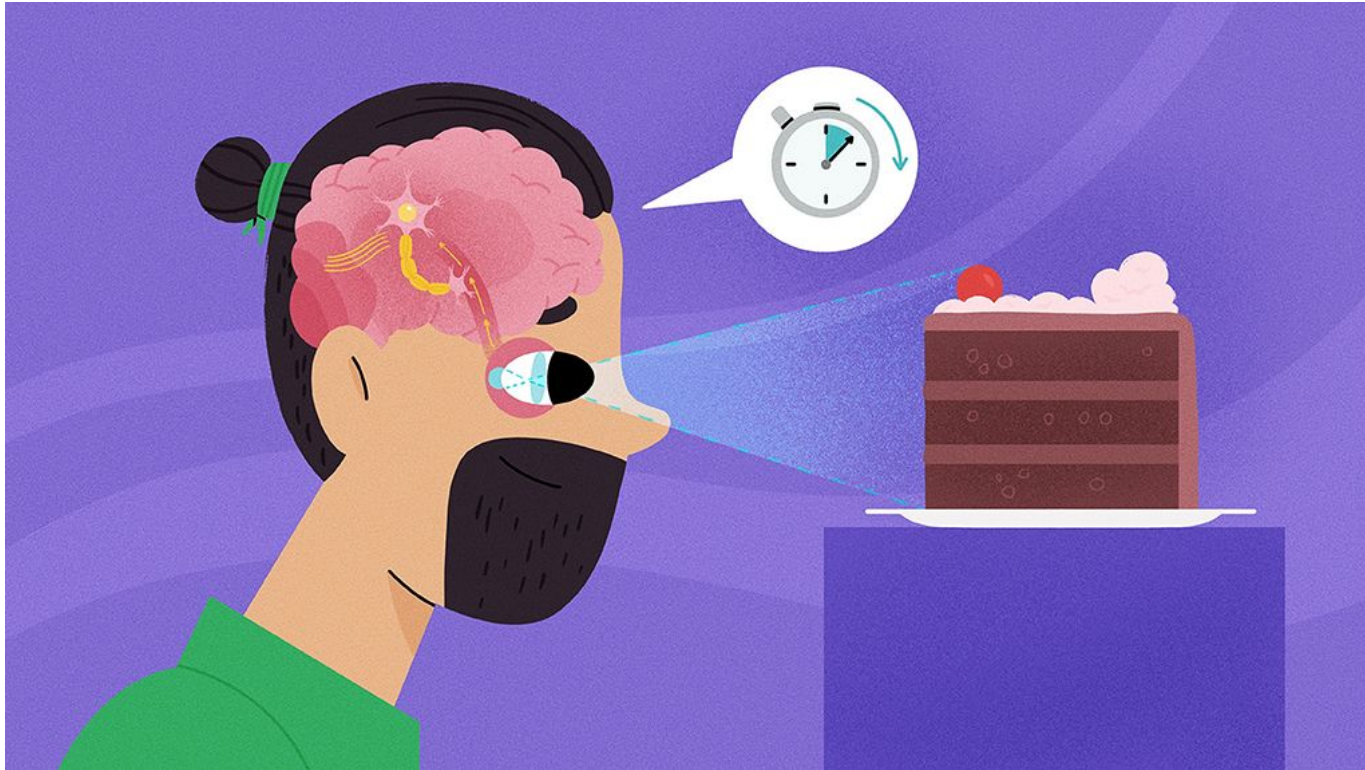
Naiti Bhatt
University of Edinburgh

Roadmap

- Pre-reading Discussion
- Introduction to Vision
- Neurobiological Visual System
- Introduction to Neural Networks
- Convolutional Neural Networks

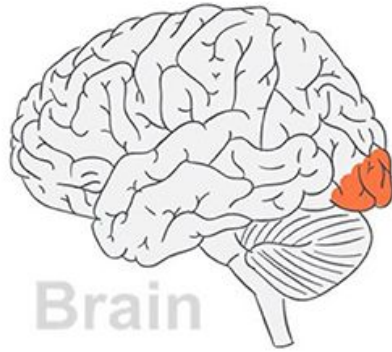
Pre-Reading Discussion

How Does the Brain Allow the Eyes to See?



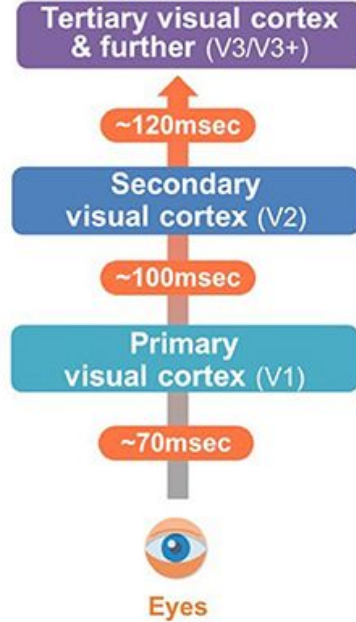
Levels of the visual system and their information processing times.

A

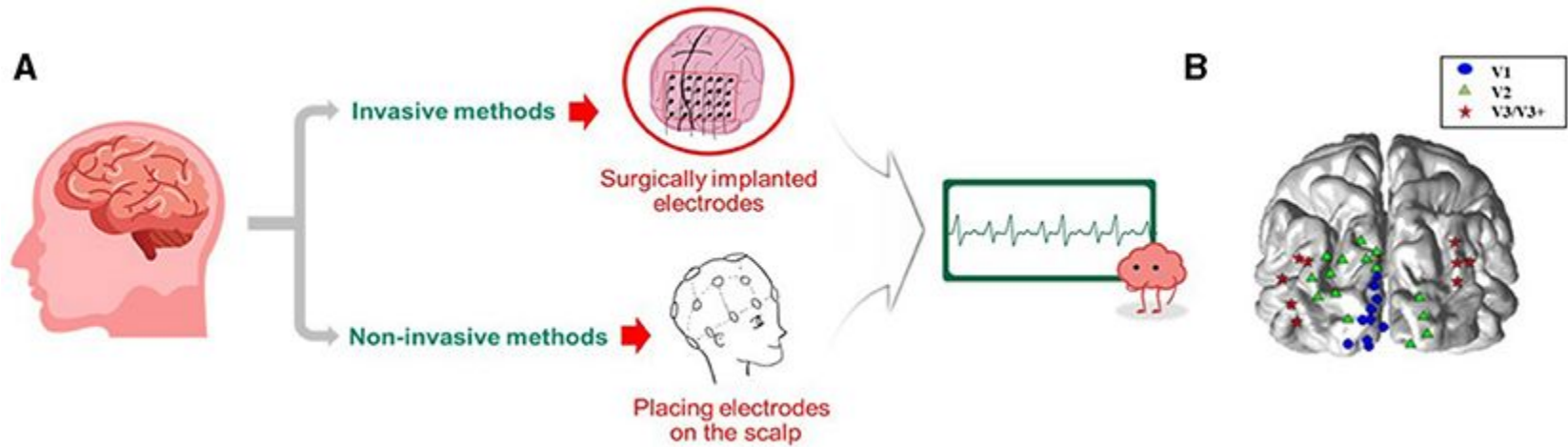


Visual Cortex

B

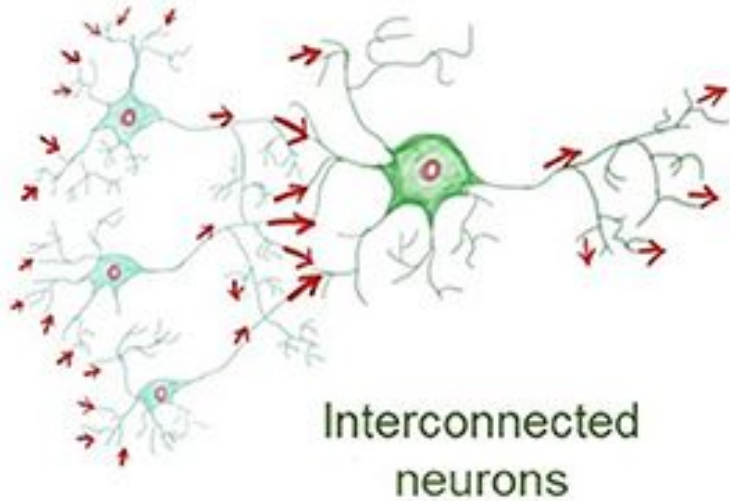


Measuring neural activity in visual cortex using electrodes

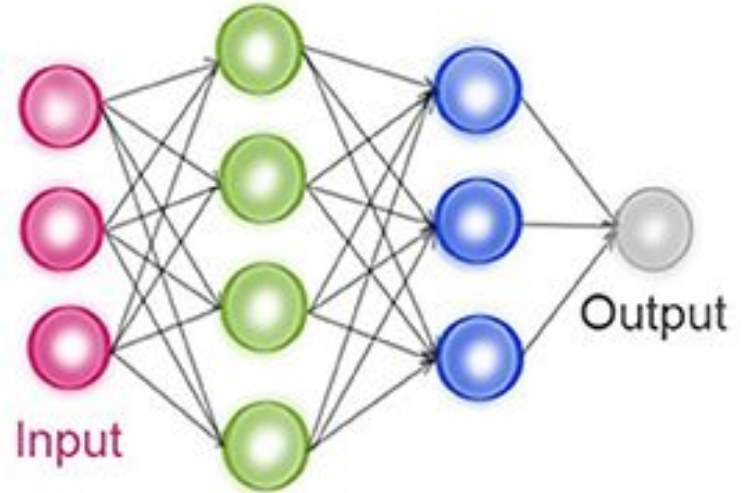


Neurons and neural networks

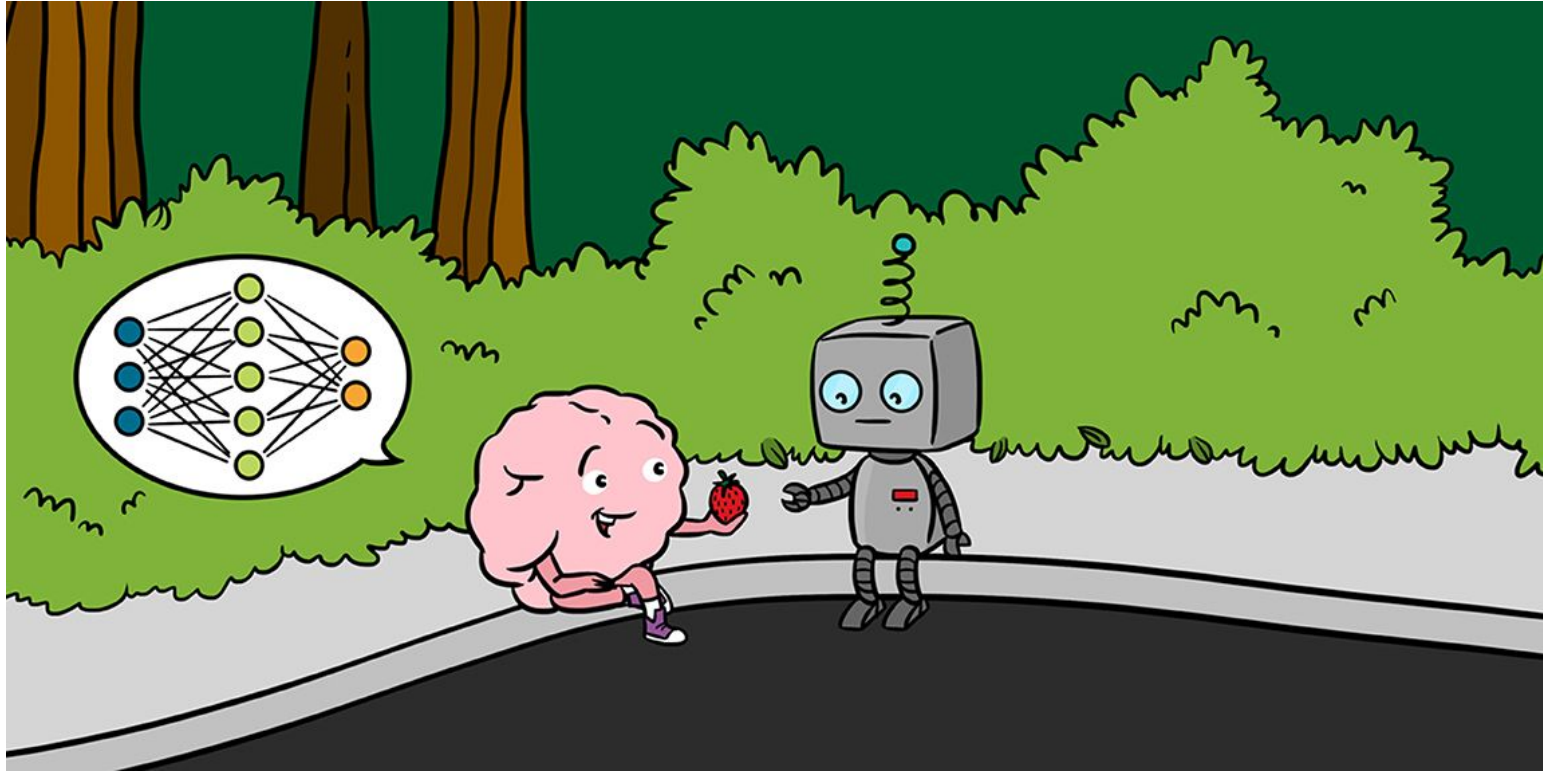
A



B

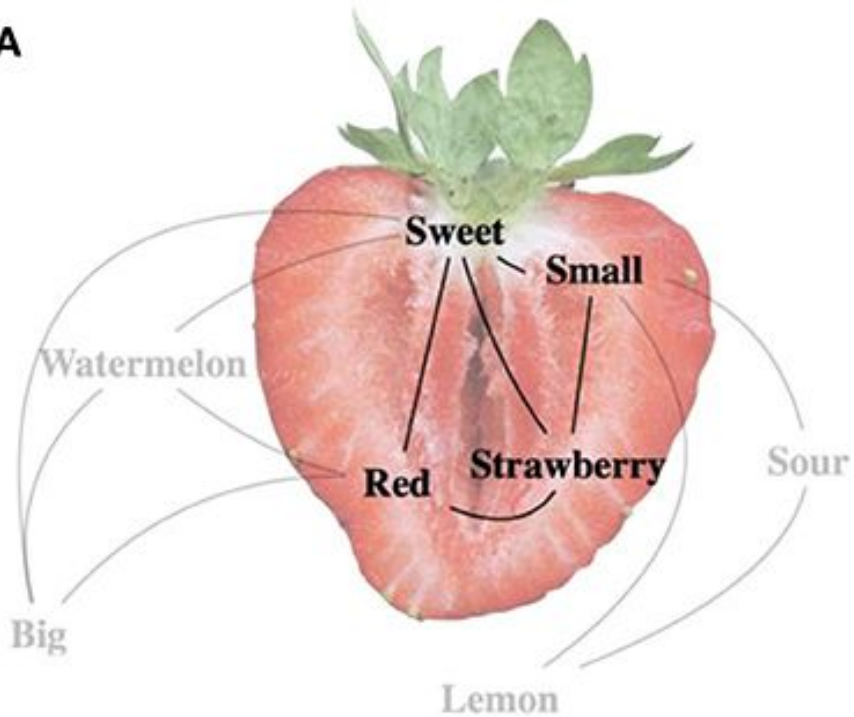


How Are Nerve Cells And Artificial Intelligence Similar?

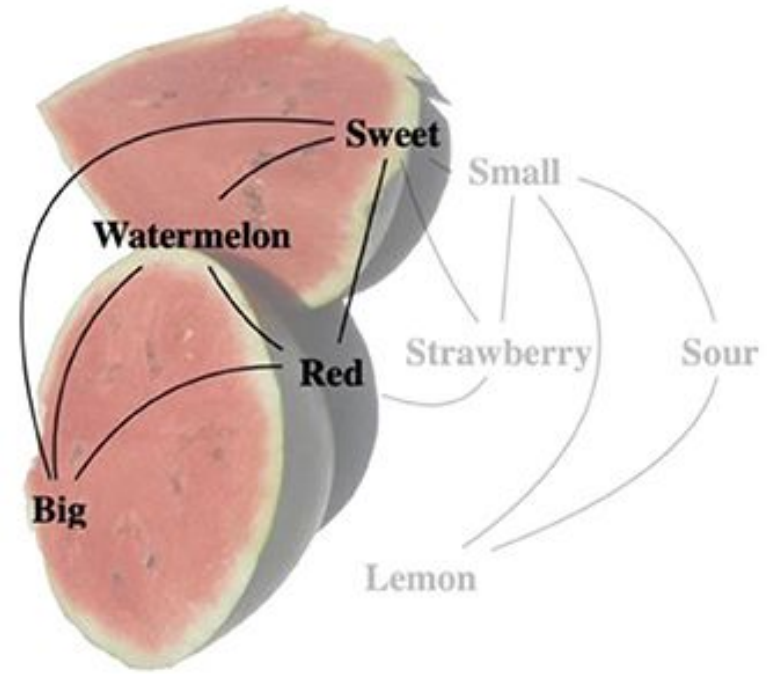


Thinking as traversing the edges of a conceptual network

A

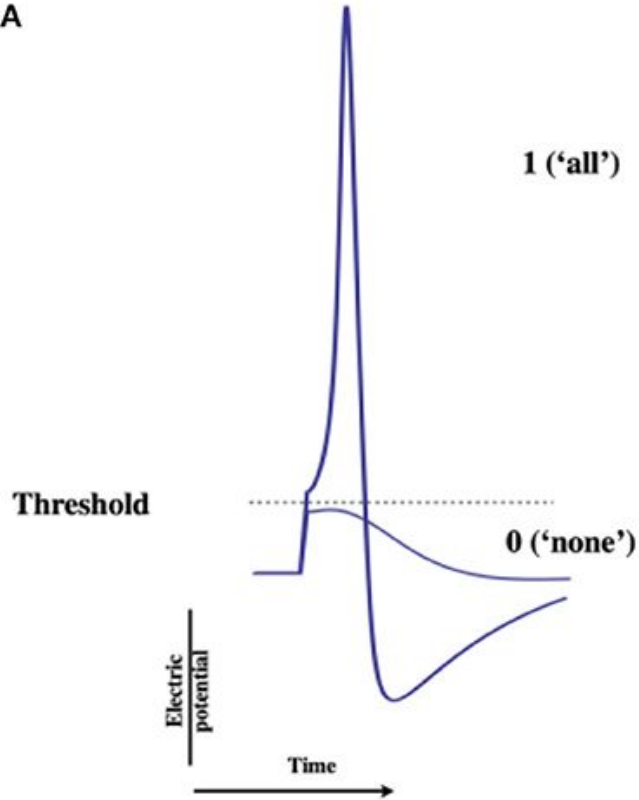


B

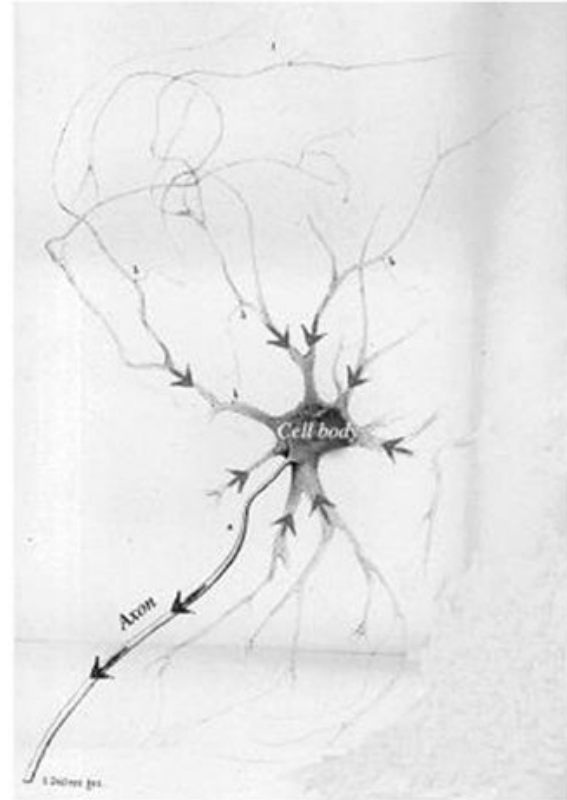


Action Potentials in a Neuron (Nerve Cell)

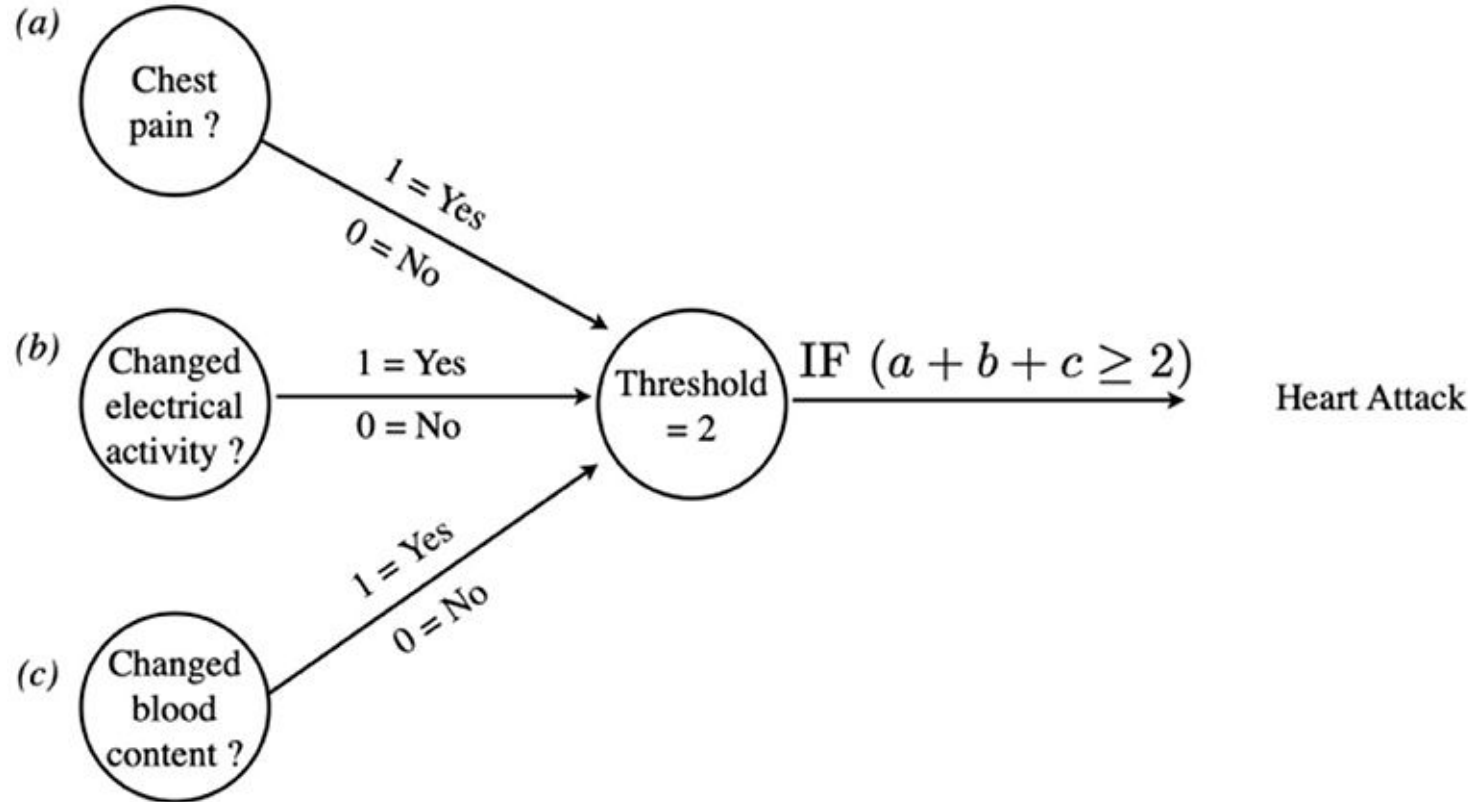
A



B



Artificial Neural Networks



Introduction to Vision



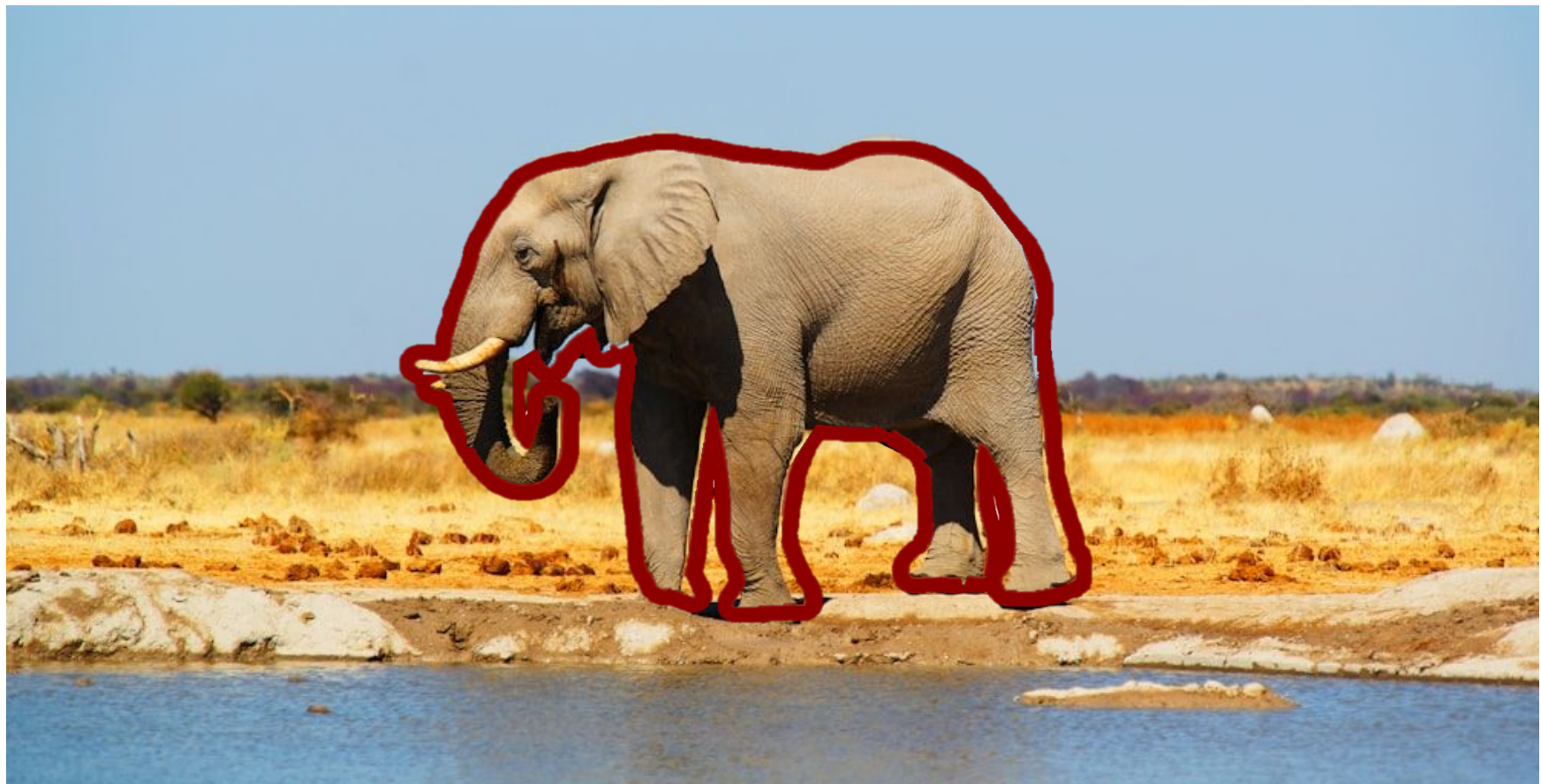
A photograph of an African elephant standing on a rocky bank next to a watering hole. The elephant is facing left, with its trunk curled. The background shows a savanna landscape with dry grass and scattered trees under a clear blue sky. The image is framed by a white border with a dark red outer edge.

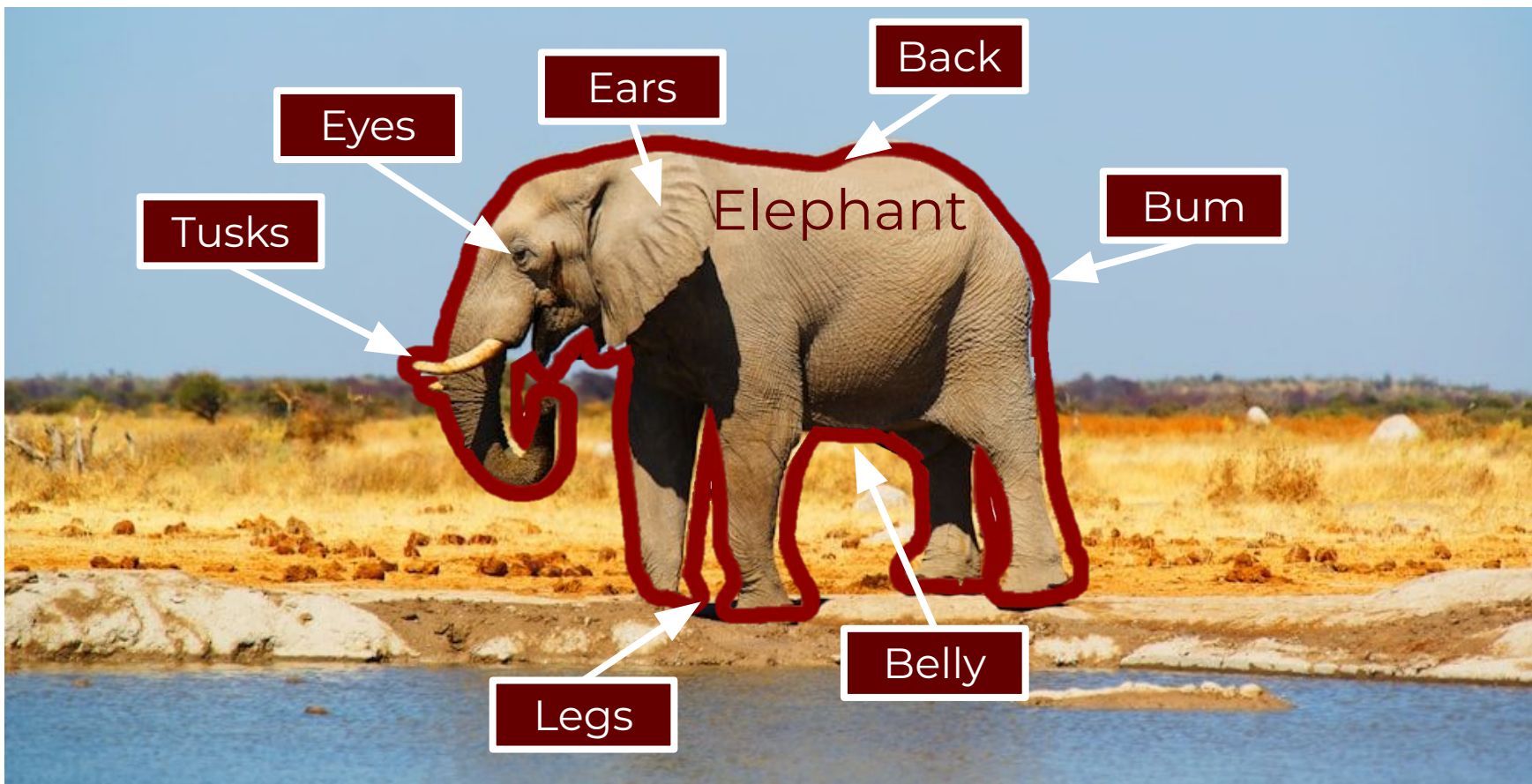
Sky

Elephant

Grass

Water





Eyes

Tusks

Ears

Back

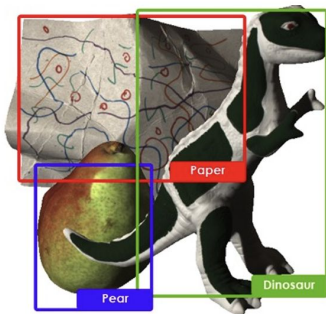
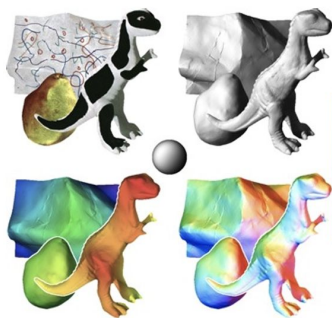
Elephant

Bum

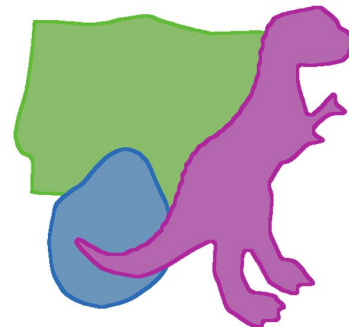
Belly

Legs

Three R's of Vision

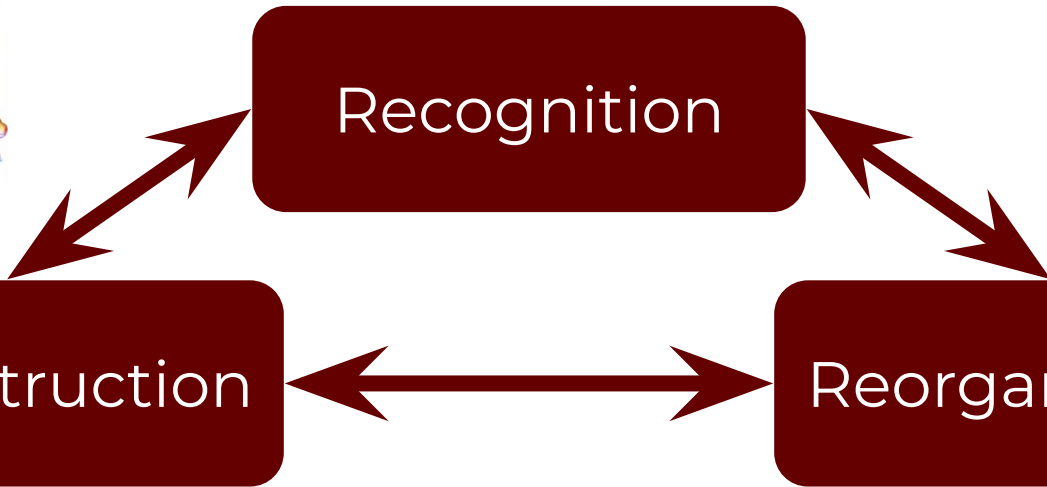


Recognition



Reconstruction

Reorganization



Aspects of Vision

→ **Perceptual**

- ◆ Predict what a human would perceive in an image

→ **Neuroscientific**

- ◆ Understand the mechanisms in the retina and the brain

→ **Functional**

- ◆ How laws of optics, and the statistics of the world we live in, make certain interpretations of an image more likely to be valid

Aspects of Human ↔ Computer Vision

→ **Perceptual**

- ◆ Computer should be **interpretable & consistent** with human

→ **Neuroscientific**

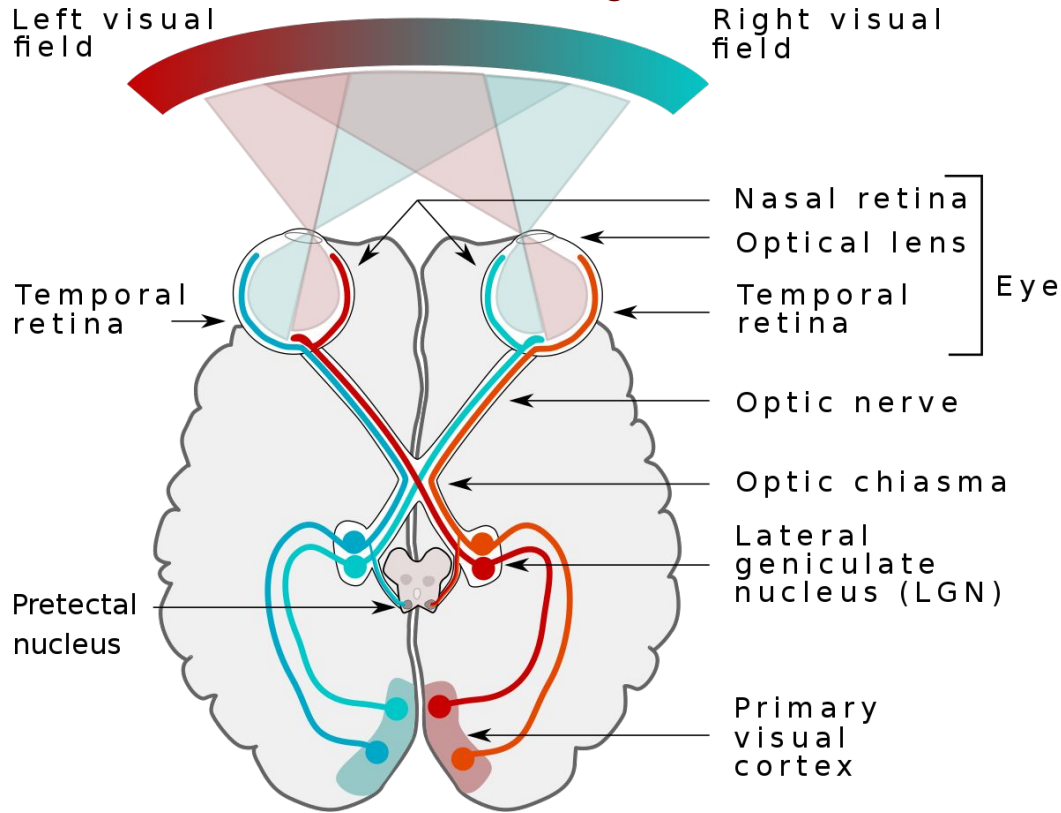
- ◆ Human system is **source of ideas** for computer vision models

→ **Functional**

- ◆ Human ↔ Computer **match is strongest** at this level

Neurobiological Visual System

Overview of Human Visual System



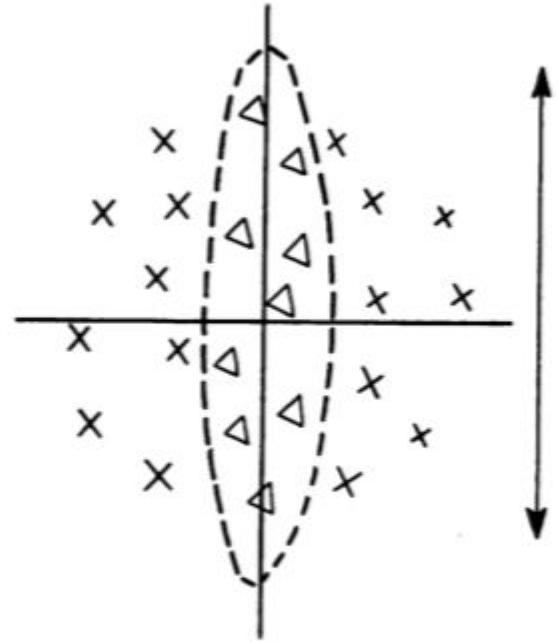
Receptive Fields (RFs)

Receptors

The receptive field of a receptor is simply the area in which light strikes that receptor.

Neurons, etc.

For any other cell in the visual system, the receptive field is the area in which receptors connect to the cell in question.



Hubel & Wiesel: 1959

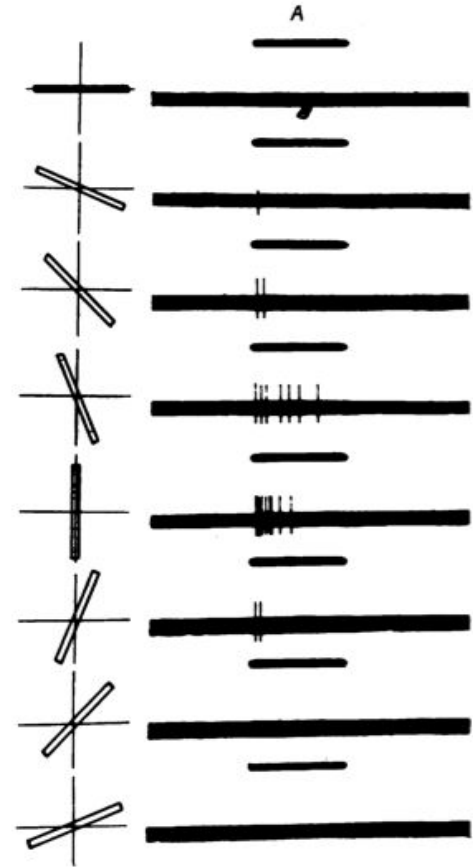
Measured neuronal responses in cat striate cortex (V1)

Receptive fields...

respond depending on the orientation of input light

contain excitatory and inhibitory regions

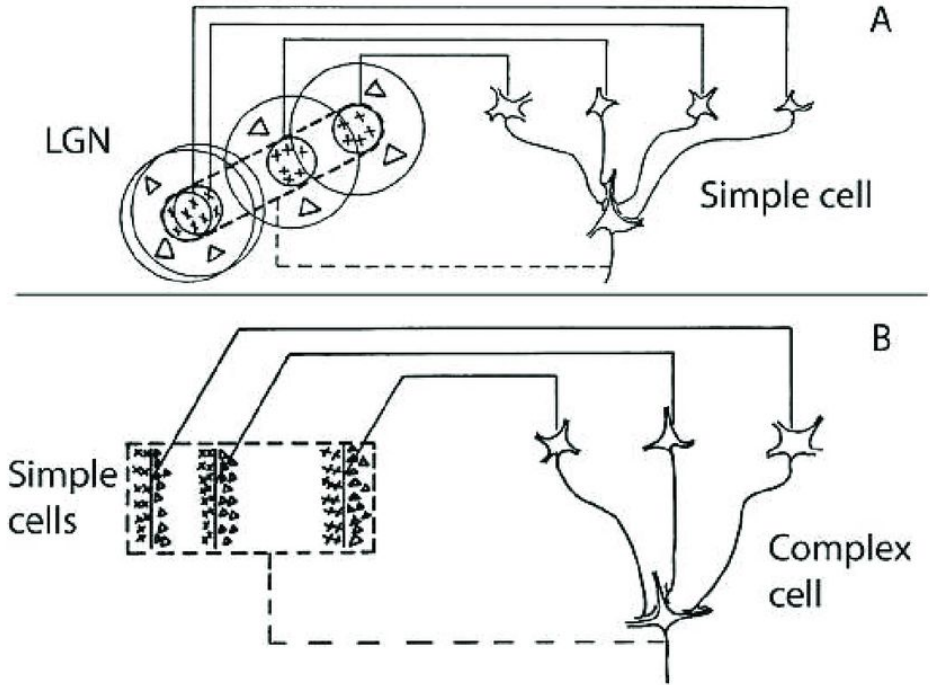
are oriented in a horizontal, vertical, or oblique manner



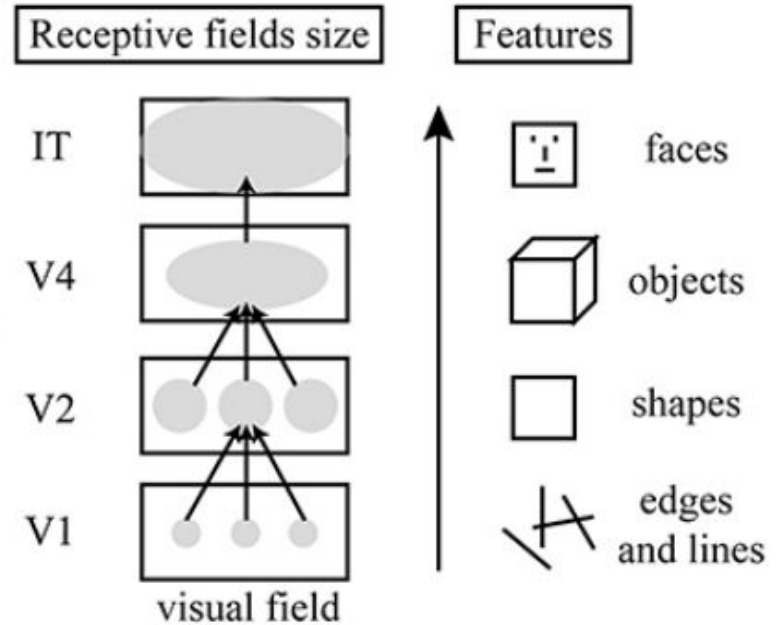
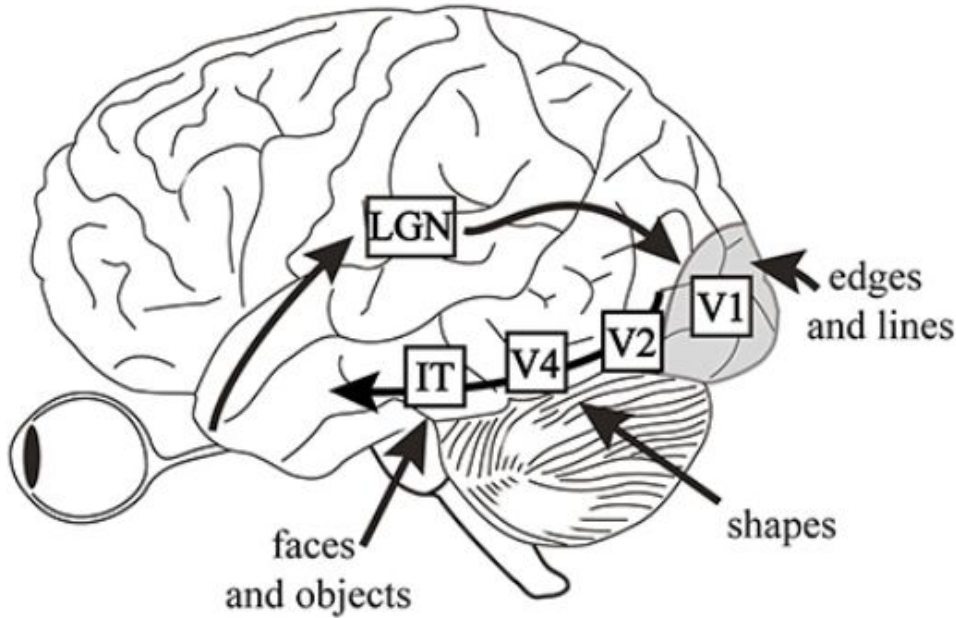
Hubel & Wiesel: 1962

Striate cortex (V1) contains two cell types:

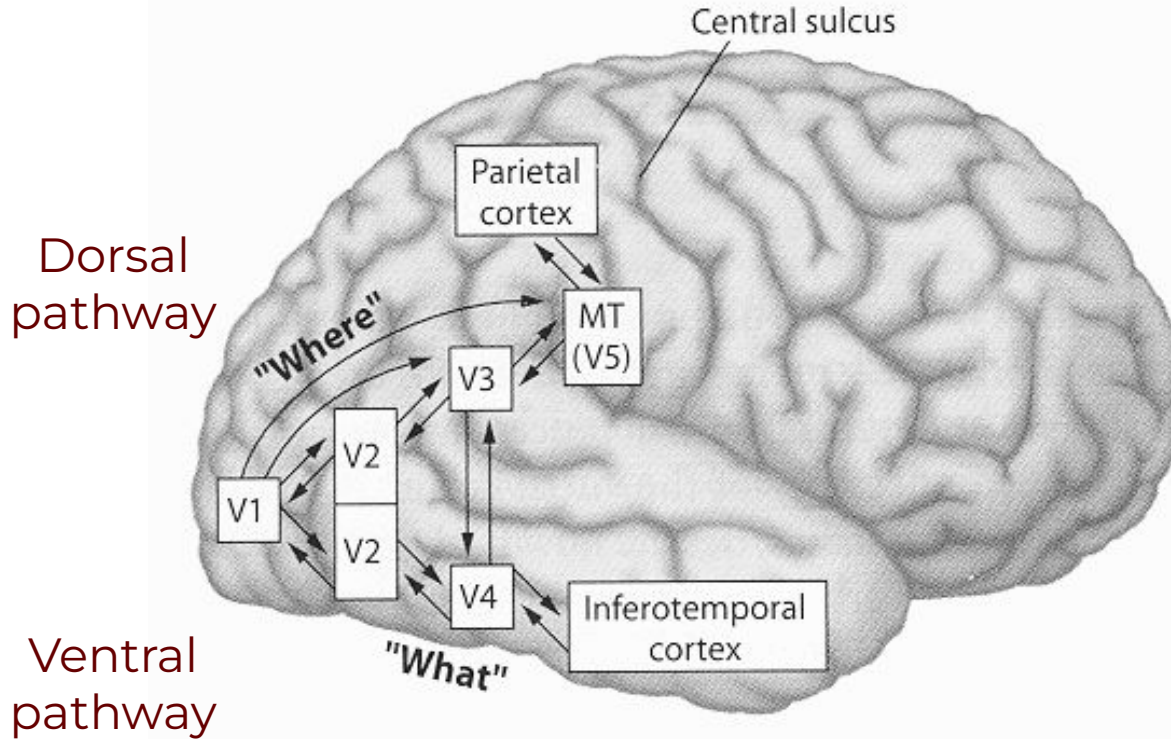
- Simple (S) cells
 - Encode and elongate retinal RFs
 - Susceptible to fuzziness and noise
- Complex (C) cells
 - Fine-tune and orient S-cell RFs
 - Robust against S-cell shortcomings



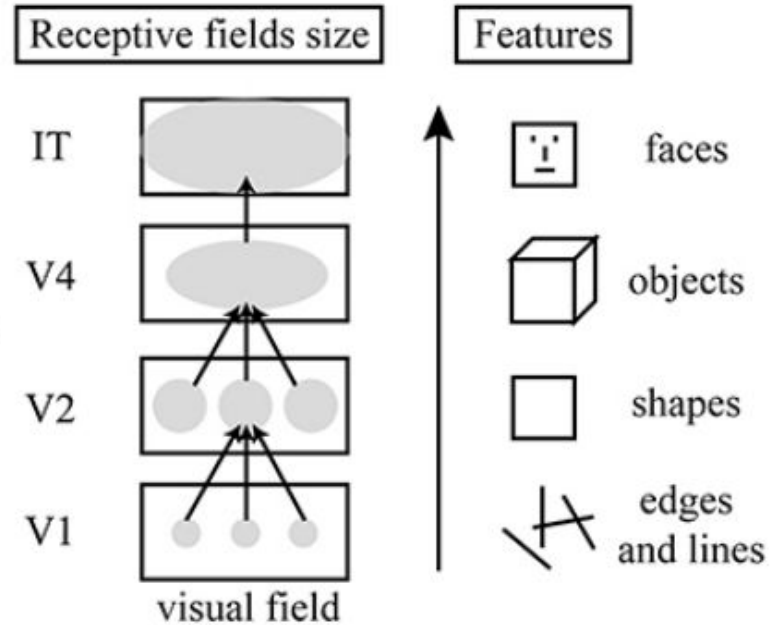
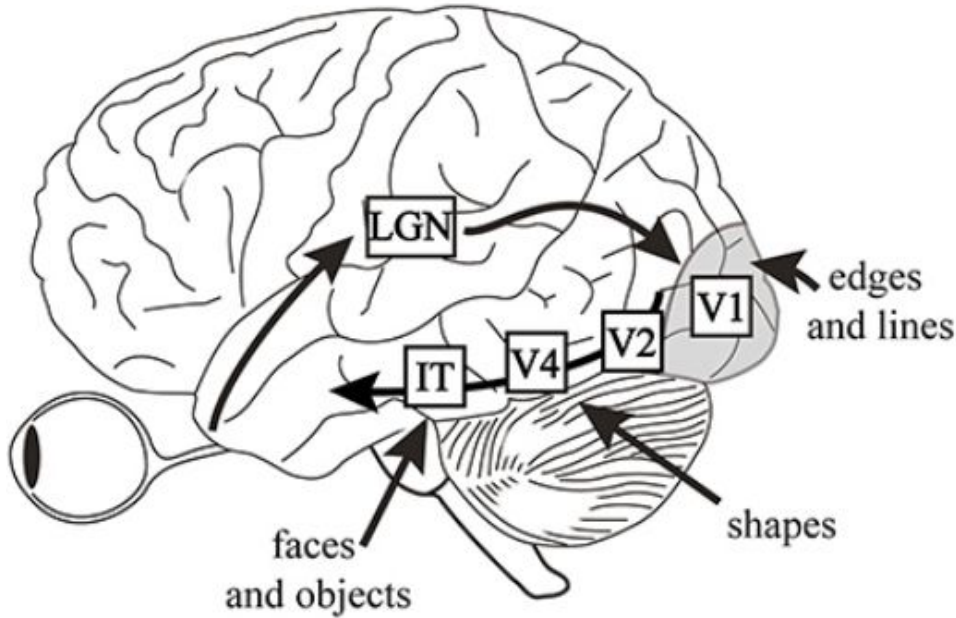
Human Visual Cortex Ventral Pathway



Post-Striatal Processing



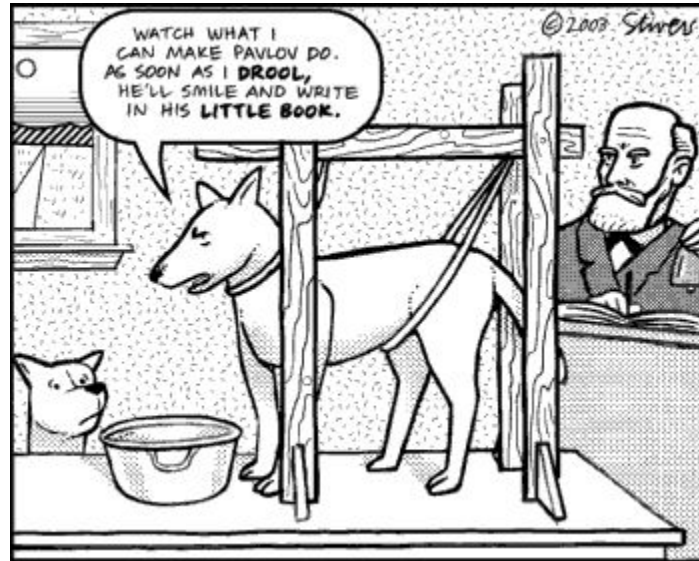
Human Visual Cortex Ventral Pathway



Introduction to Neural Networks

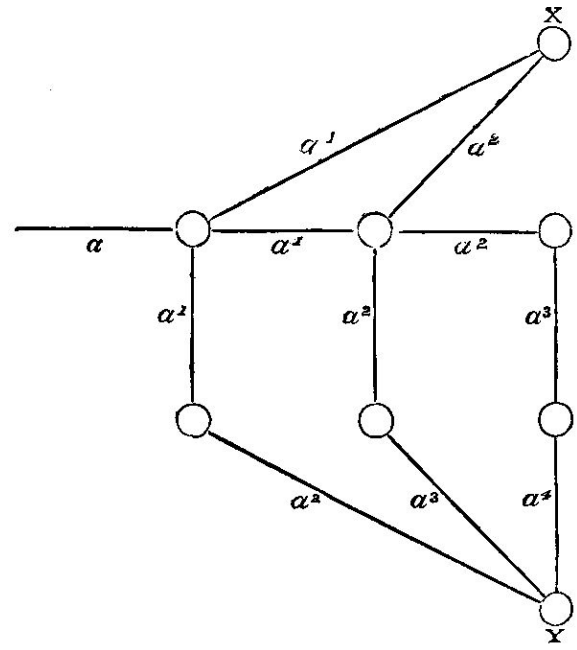
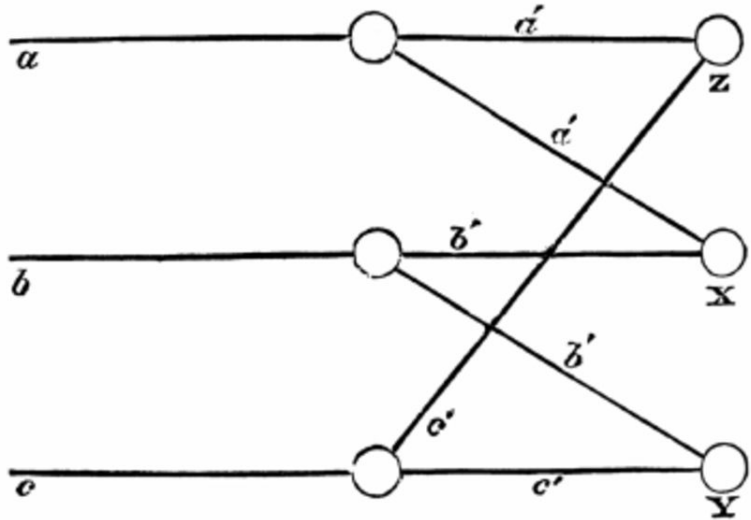
Neural Networks as Cognitive Models

- The earliest model of cognition was associationism
 - Humans learn through association



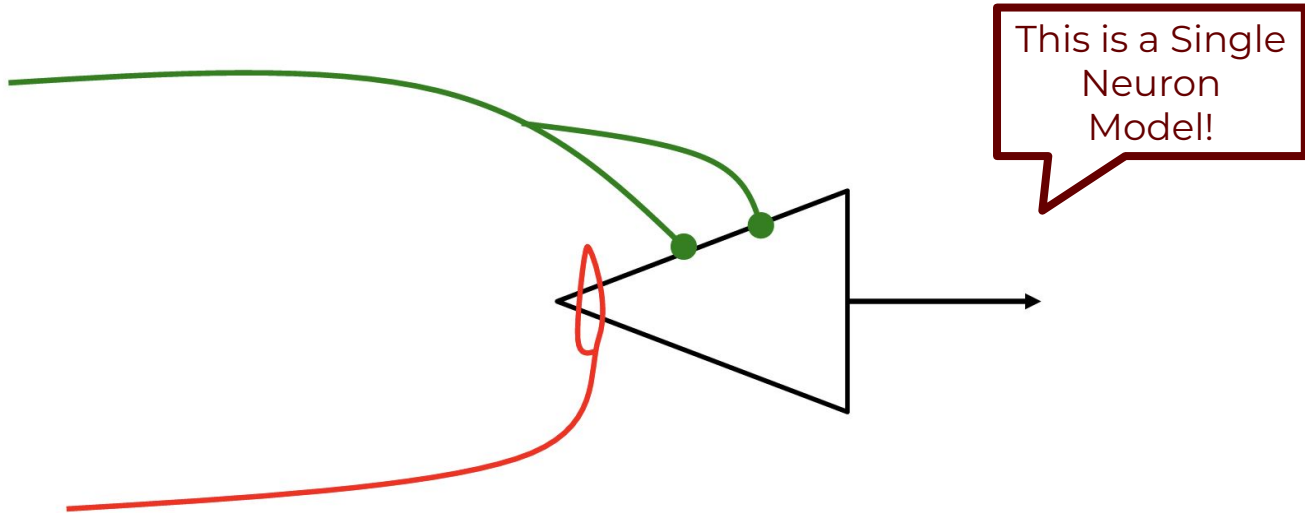
Neural Networks as Cognitive Models

- The more recent model of the brain is connectionist
 - Neurons connect to neurons
 - Information is encoded in connections



Neural Networks as Connectionist Machines

- **McCullough & Pitt Model:** Neurons as Boolean threshold units
 - Models the brain as performing propositional logic
 - No learning rule!



Neural Networks as Connectionist Machines

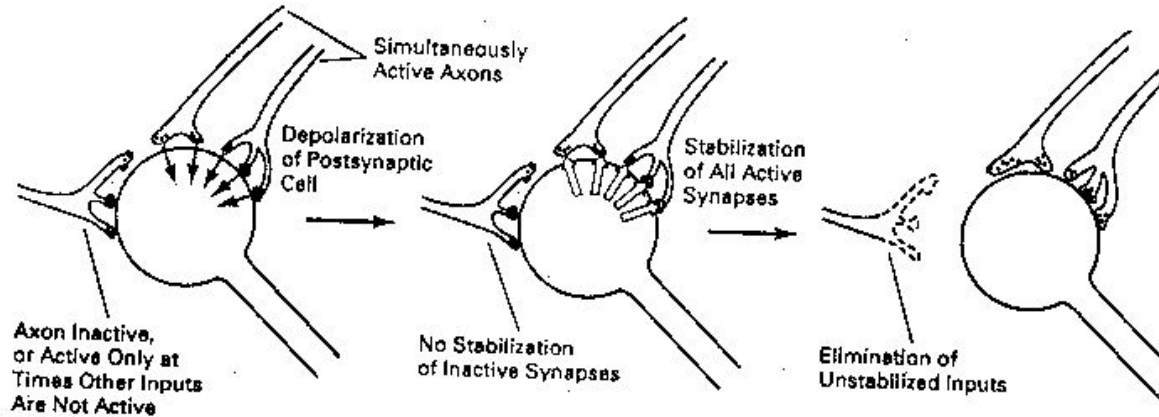
- **Hebb learning rule**

- As neuron x_i repeatedly excites neuron y , its ability to excite y improves

The formulaic basis of many machine learning algorithms!

$$w_i = w_i + \eta x_i y$$

Weight of i^{th} neuron's input to output neuron y

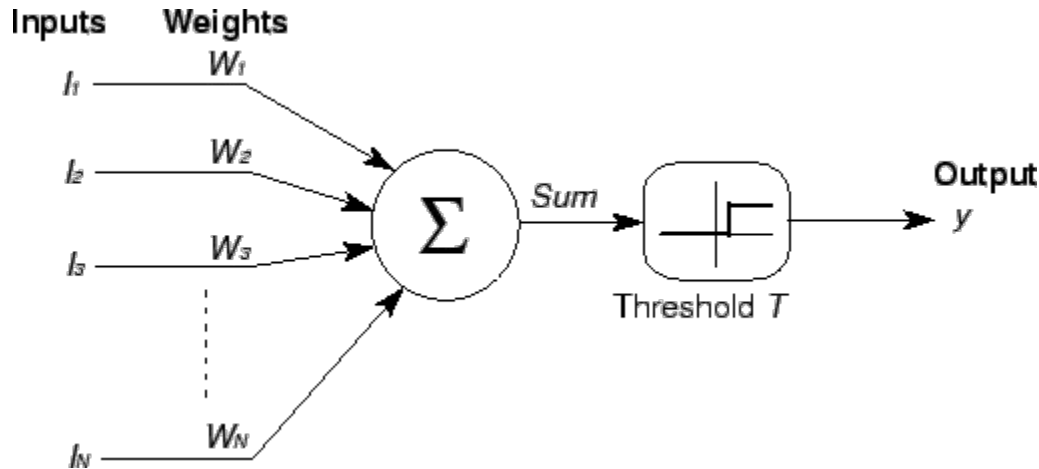


**Neurons that
fire together
wire together!**

Neural Networks as Connectionist Machines

- **Rosenblatt perceptron**

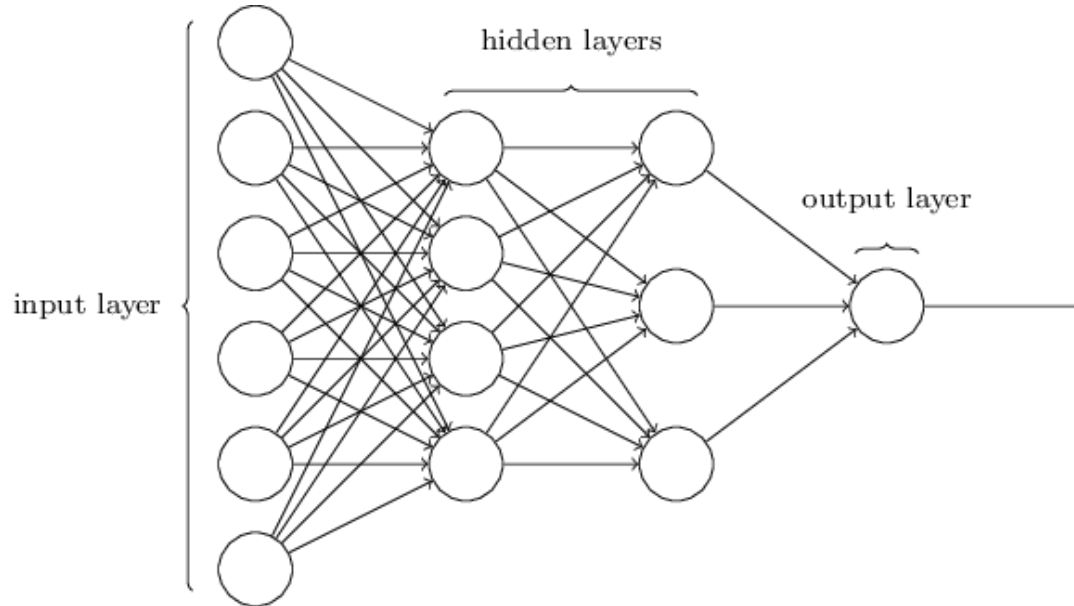
- McCulloch and Pitt neuron with a provably convergent learning rule
- Number of inputs combine linearly
- Threshold logic: Neuron fires if combined input exceeds threshold



Neural Networks as Connectionist Machines

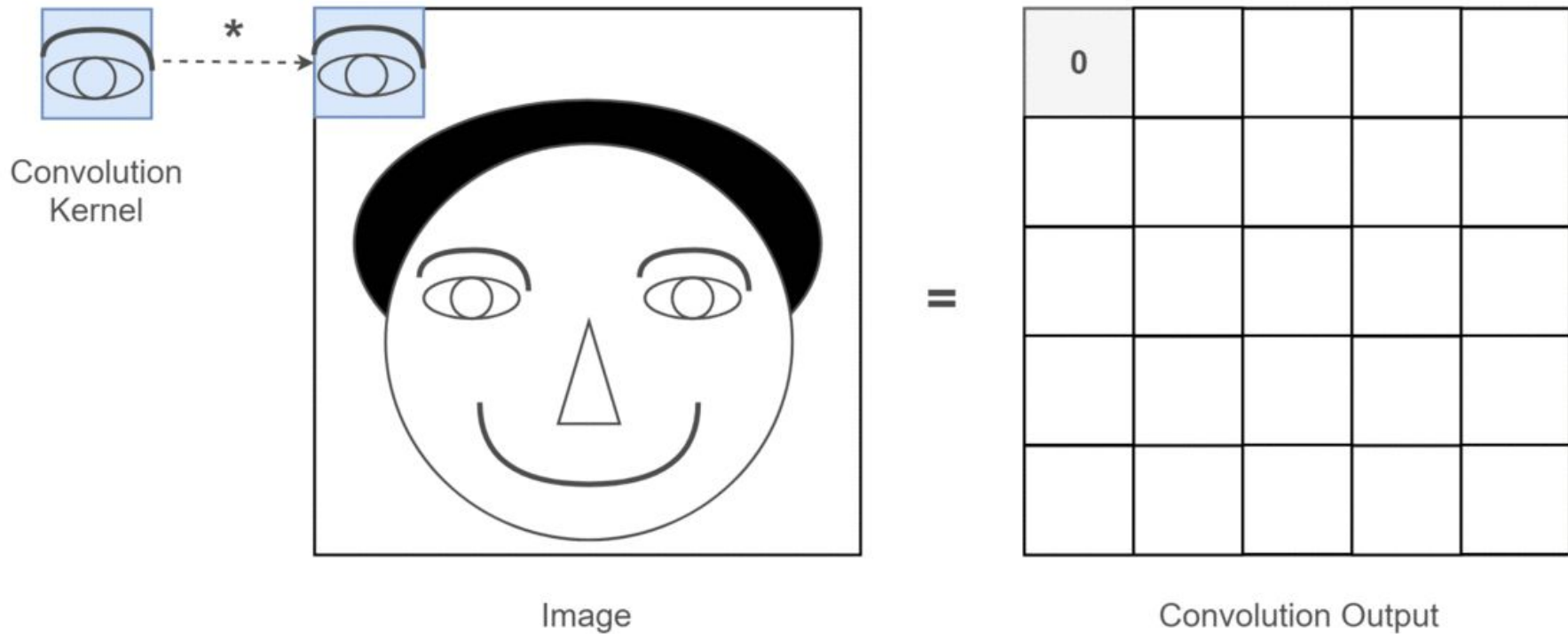
- **Minsky & Papert Multi-Layer Perceptron (MLP)**

- Individual elements are perceptrons that detect features
- Fires if the combination of features match a desired class of signal



Convolutional Neural Networks

Convolution combines two signals to form a third!

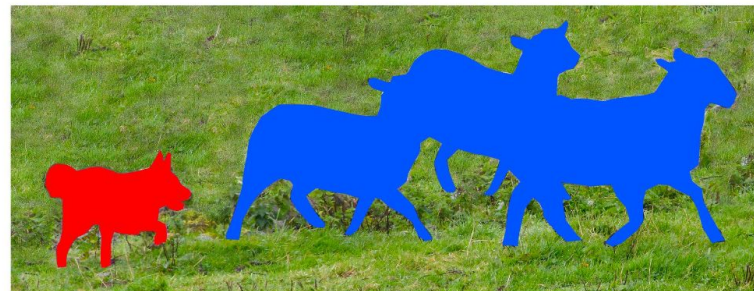


Back to vision...

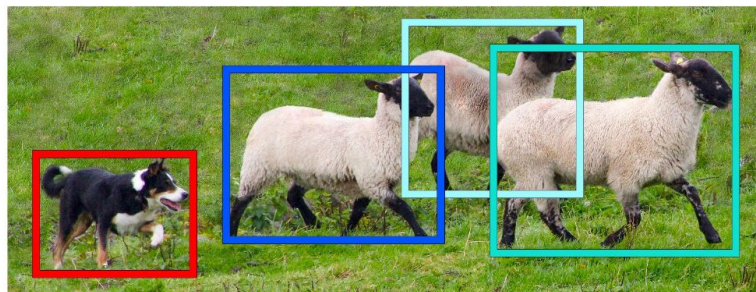
Types of Computer Vision Tasks



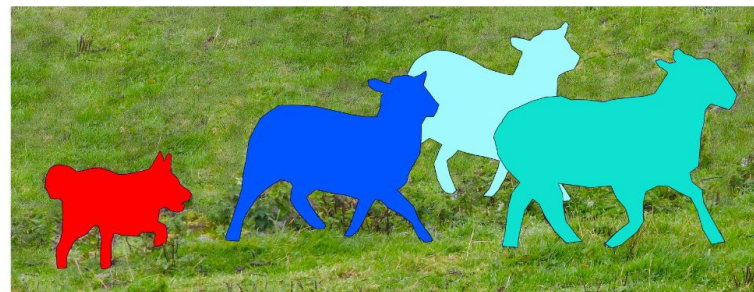
Image Recognition



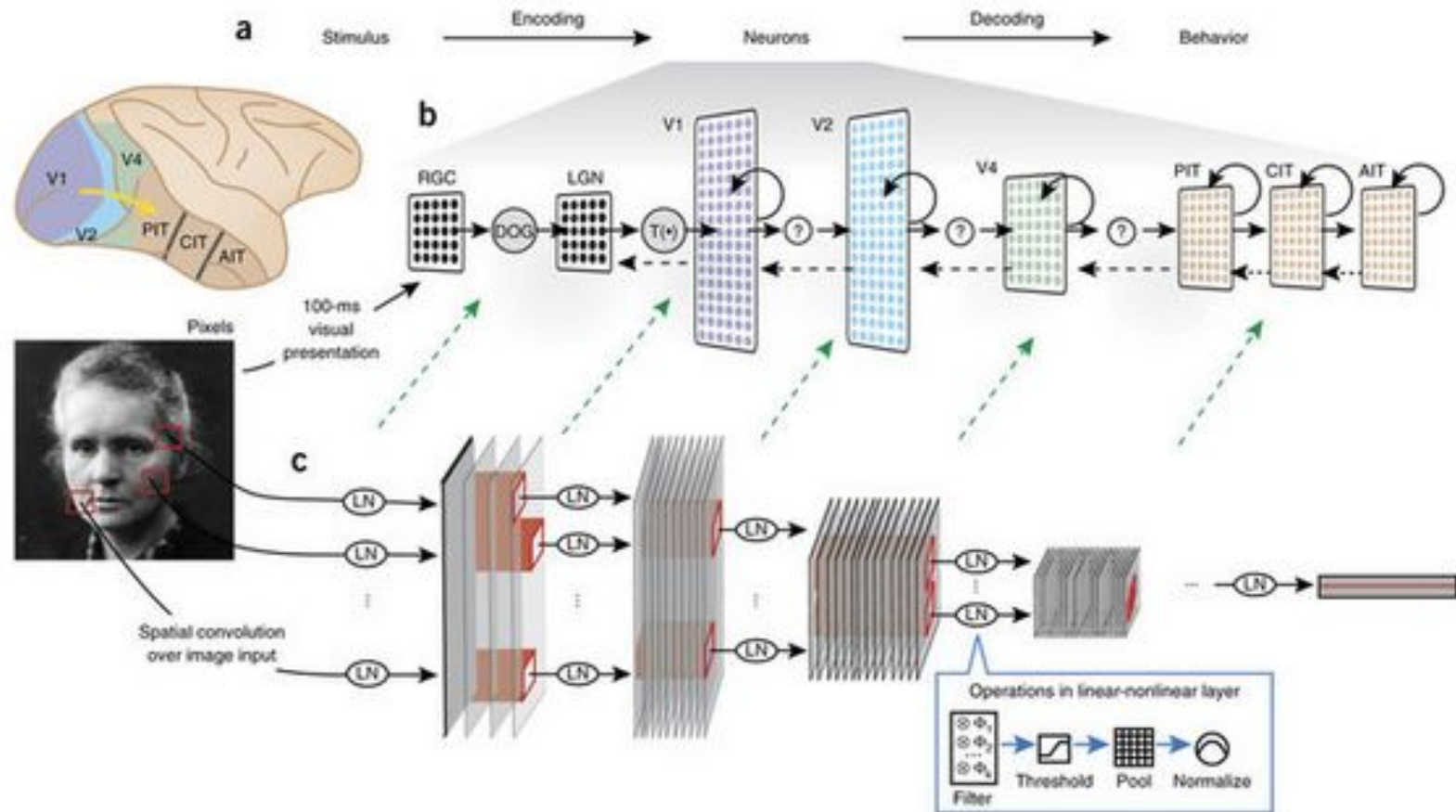
Semantic Segmentation



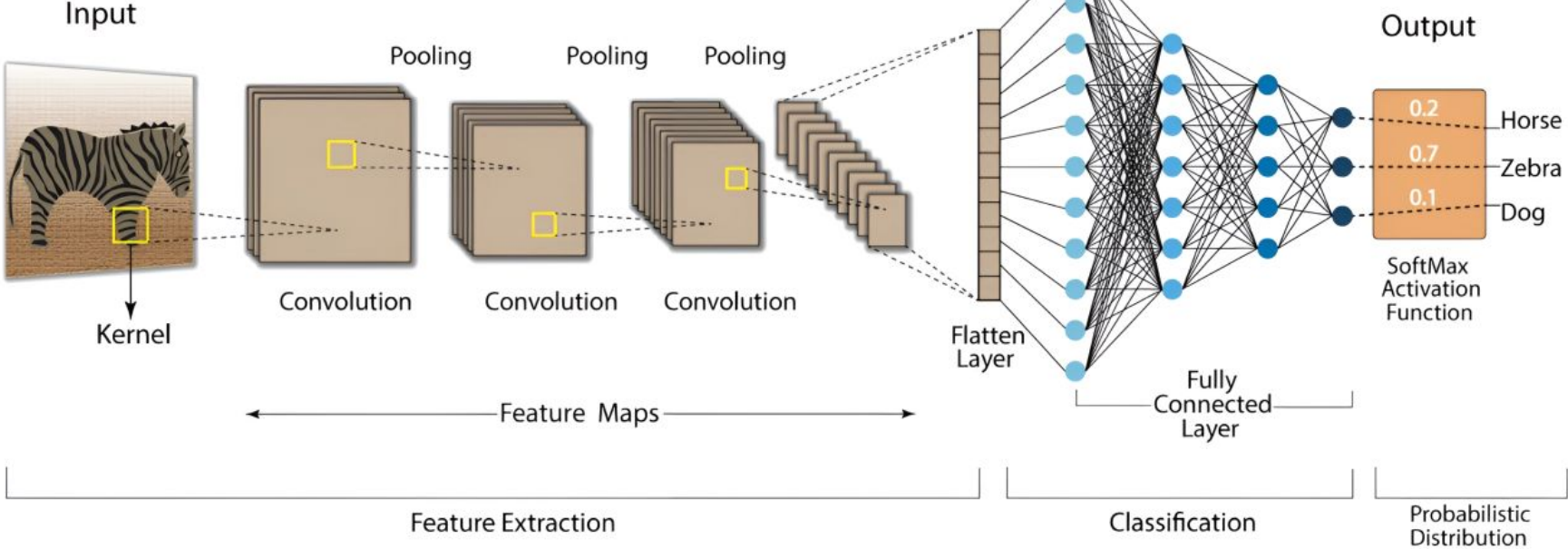
Object Detection



Instance Segmentation



Convolution Neural Network (CNN)



Appendix

Neural Networks as Connectionist Machines

- Neural network models comprise networks of neural units
- McCullough and Pitt model: Neurons as Boolean threshold units
 - Models the brain as performing propositional logic
 - But no learning rule
- Hebb's learning rule: Neurons that fire together wire together
 - Unstable
- Rosenblatt's perceptron: Provably convergent learning rule
 - But individual perceptrons are limited in their capacity
- Multi-layer perceptrons can model arbitrarily complex Boolean functions