Machine Learning and NeuroEngineering

机器学习与神经工程

Lecture 1 – Introduction to brain (neuroscience)

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BMEB212, Spring term, 2021

Goals of this course

- Understand the neural basis of how our brain works
  - visual system
  - motor system
  - language
  - emotion
  - …
- Learn some basic computational models and machine learning methods
  - basic parameter estimation techniques
  - maximum likelihood estimation (MLE)
  - Bayesian parameter estimation
  - model comparisons
  - neural networks
  - …
- Do a course project
  - work on a specific scientific/technical question
  - use some machine learning methods or NeuroEngineering techniques
  - make a course presentation
  - write a final report

Please feel free to ask questions any time.

Logistics

Neural Computing Control

神经计算与控制实验室
NCC lab

NCC lab
微信公众号

NCC lab
B站账号

- Class hours:
  - Monday, 10:20-12:10 (each week, 一教108)
  - Wednesday, 19:00-20:50 (even weeks, 一教108)
- Lecturer: Quanying Liu
  - My Office hours: Wednesday, 13:00-14:00, Taizhou hall(台州楼) 310
  - Lunch hours: you are welcome to make an appointment by email (liuqy@sustech.edu.cn).
- Class INFO is on blackboard platform: bb.sustech.edu.cn
- Textbooks: Computational Modelling of Cognition and Behavior, by Simon Farrell and Stephan Lewandowsky
- Extra reading (not necessary):
  - Neuroscience - Exploring the Brain, by Mark F. Bear, Barry W. Connors, Michael A. Paradiso
  - Machine Learning: A Probabilistic Perspective, by Kevin P. Murphy
- Some reading materials will be recommended at the class.

Logistics

- TA:
  - Youzhi Qu (曲由之)
  - Zhichao Liang (梁智超)

Taizhou hall(台州楼) 306

梁智超

曲由之

- Scoring:
  - No exams!!!
  - **10%** Quiz during classes (Please attend the class!)
  - **20%** assignments (10% mid-term, 10% final)
  - **30%** course project
    - 10% form a team with 3-4 members, 20% mid-way report
  - **40%** final presentation
    - 20% oral presentation/demo, 20% final report

  - Mimic a peer-review process (a prize for the best project)
  - Possibly a conference/journal submission (with bonus scores)

Machine Learning & NeuroEngineering (ML&NE) in 2020

1 - Introduction to NeuroScience
2 - Introduction to ML
3 - Random Walk Model
4 - Basic Parameter Estimation 1
5 - Basic Parameter Estimation 2
6 - Probability Overview
7 - Combining Data
8 - Bayesian Parameter Estimation
9 - MCMC
10 - Gibbs Sampling & JAGS
11 - Hierachical Modeling
12 - Model Comparison
13 - Bayesian Model Comparison
14 - A brief introduction to GAN
15 - Gradient Descent & Error BackPropagation
16 - CNN & Tips to train DNNs
17 - Tips to train DNNs
18 - unsupervised learning (PCA)
19 - unsupervised learning (Deep Auto-encoder)
20 - RNN

Computational modelling

Neuroengineering techniques are integrated into the models.

Deep learning

Machine Learning & NeuroEngineering (ML&NE) in 2020

选课人数：13

教评评分：96.92

预计的改进方法：

1. 多布置作业和课后编程练习
2. 在课程中refresh先修课上的相关内容
3. 事先提供所需安装的软件（R, python）
4. 适当增加神经工程相关内容

98	刘老师会每节课问问大家课程知识吸收的如何，然后会根据大家的反馈实时查漏补缺，给大家再解释不太懂的地方。 课程作业方面可以多布置一些，设置些阅读作业的respone 相比线下，大家无法一起做proj，效率不高，同时课程设置上无法进行有助教在场的lab课，编程只能自学
100	课程有趣 课程所需软件安装不便
74	我概率忘了很多，复杂概念有点没跟上
100	老师能根据学生的需求调整讲课内容，会尽量讲一些我们想知道的知识。
100	老师备课、讲课很用心。
94	好的地方：内容丰富
100	老师人很好
100	刘老师第一次授课讲这么好，原本比较担心听不太懂后面发现还好
100	无
94	期末项目可以提前布置，并且多设置一些编程练习的时间。理论课希望可以留一些习题巩固学到的知识。
100	nothing
100	刘老师人很好，讲课也很仔细。就是对于没有相关基础知识的同学接受起来，可能还是有点难度，希望之后刘老师可以更系统的讲授神经工程相关内容，而不是下半学期这样一节课一个板块的机器学习内容。
100	no

研究生课程 BME5012：人脑智能与机器智能（Brain Intelligence & Artificial Intelligence）

选课人数：57

1 - Introduction to BI & AI
2 - Visual System & tensorflow configuration
3 - GD & BP & CNN & LeNet hands-on
4 - What does AI/Brain learn?
5 - Loss function & Tips to train CNN
6 - EEG data analysis 1 & CNN visualization hands-on
7 - EEG data analysis 2
8 - Data for supervised deep learning
9 - RNN
10 - Oddball & RNN hands-on
11 - how to write a literature review
12 - Auditory system 1
13 - Auditory system 2
14 - somatosensory system
15 - motor system 1
16 - motor system 2
17 - emotion
18 - sleep & dreaming
19 - language
20 - SEEG and fMRI data analsysi
21 - overview

AI

AI hands-on

BI

Neural signal processing

Any questions so far?

Machine learning and NeuroEngineering

↓ generalize

Computational models and Neuroscience (brain)

1. Why do we model our brain?

"The purpose of models is not to fit the data but to sharpen the questions."

-- Samuel Karlin

2. How do we model our brain?

"Everything should be made as simple as possible, but not simpler."

-- Albert Einstein

An example: visual process

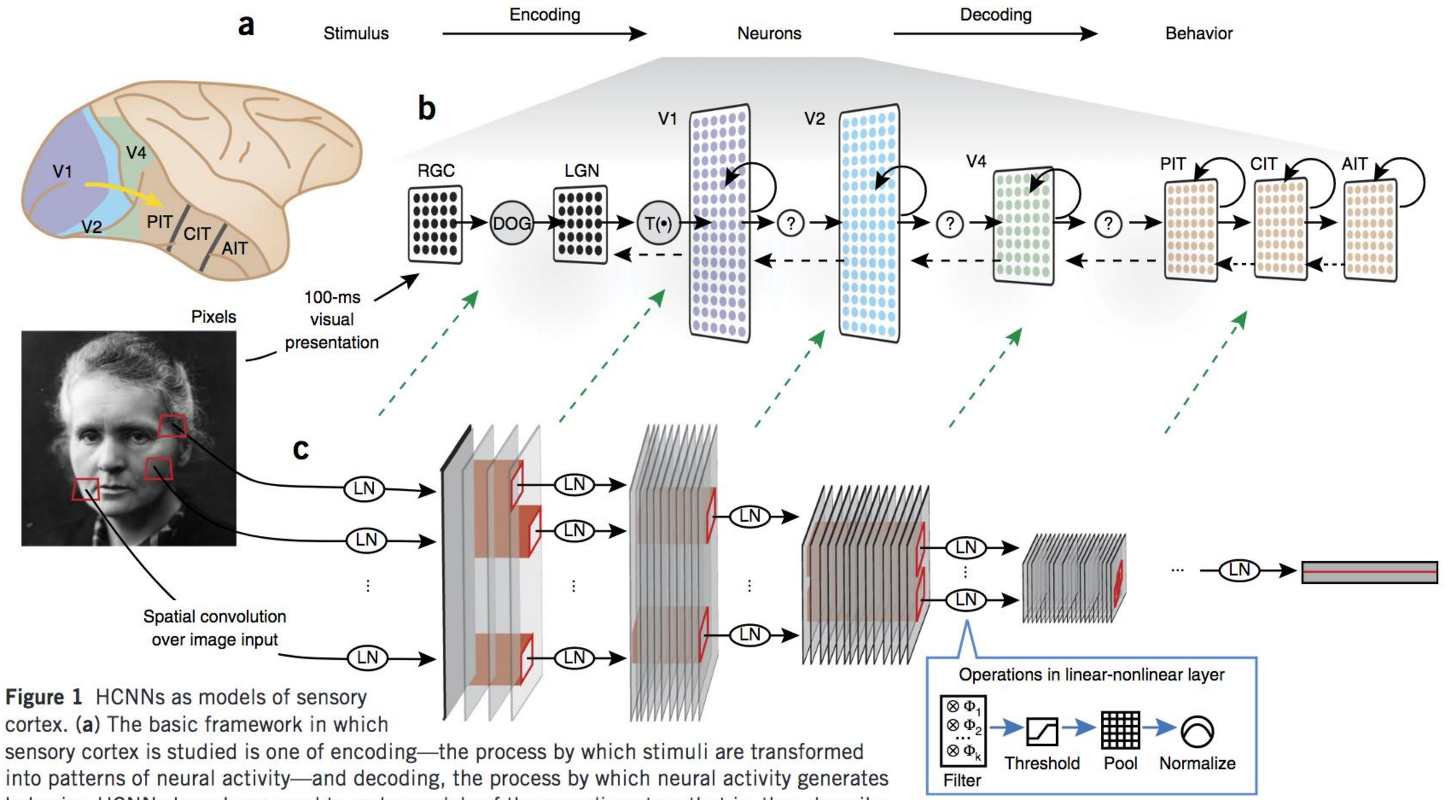


Figure 1 HCNNs as models of sensory cortex. (**a**) The basic framework in which sensory cortex is studied is one of encoding—the process by which stimuli are transformed into patterns of neural activity—and decoding, the process by which neural activity generates behavior. HCNNs have been used to make models of the encoding step; that is, they describe the mapping of stimuli to neural responses as measured in brain. (**b**) The ventral visual pathway is the most comprehensively studied sensory cascade. It consists of a series of connected cortical brain areas (macaque brain shown). PIT, posterior inferior temporal cortex; CIT, central; AIT, anterior; RGC, retinal ganglion cell; LGN, lateral geniculate nucleus. DoG, difference of Gaussians model; T(•), transformation. (**c**) HCNNs are multilayer neural networks, each of whose layers are made up of a linear-nonlinear (LN) combination of simple operations such as filtering, thresholding, pooling and normalization. The filter bank in each layer consists of a set of weights analogous to synaptic strengths. Each filter in the filter bank corresponds to a distinct template, analogous to Gabor wavelets with different frequencies and orientations; the image shows a model with four filters in layer 1, eight in layer 2, and so on. The operations within a layer are applied locally to spatial patches within the input, corresponding to simple, limited-size receptive fields (red boxes). The composition of multiple layers leads to a complex nonlinear transform of the original input stimulus. At each layer, retinopy decreases and effective receptive field size increases. HCNNs are good candidates for models of the ventral visual pathway. By definition, they are image computable, meaning that they generate responses for arbitrary input images; they are also mappable, meaning that they can be naturally identified in a component-wise fashion with observable structures in the ventral pathway; and, when their parameters are chosen correctly, they are predictive, meaning that layers within the network describe the neural response patterns to large classes of stimuli outside the domain on which the models were built.

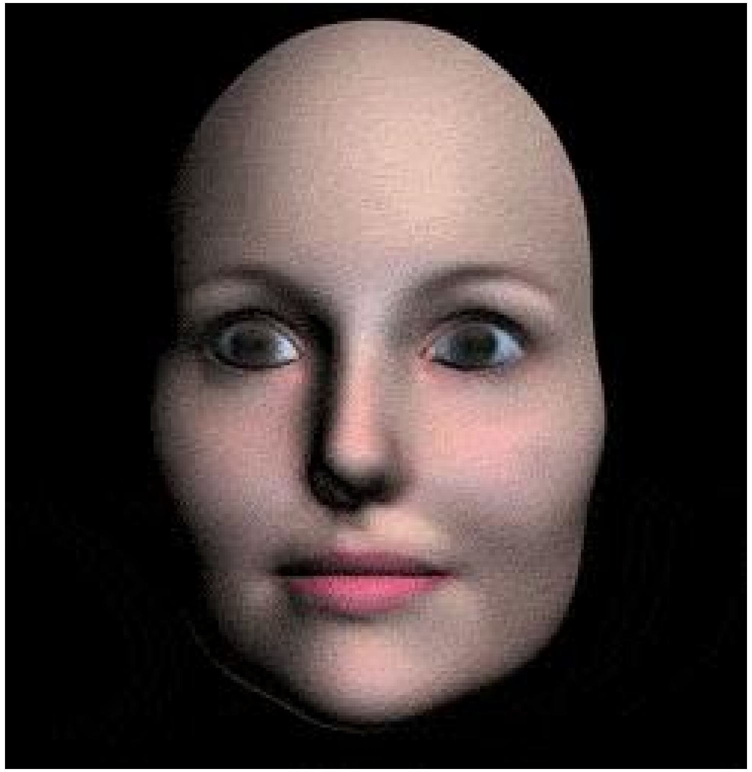
Neuronal populations along the ventral visual processing stream

V1 -> V2 -> V4 -> PIT -> CIT -> AIT

Felleman and Van Essen (1991) Cereb. Cortex;
DiCarlo and Cox (2007) TiCS;
Yamins (2016) Nature Neurosci

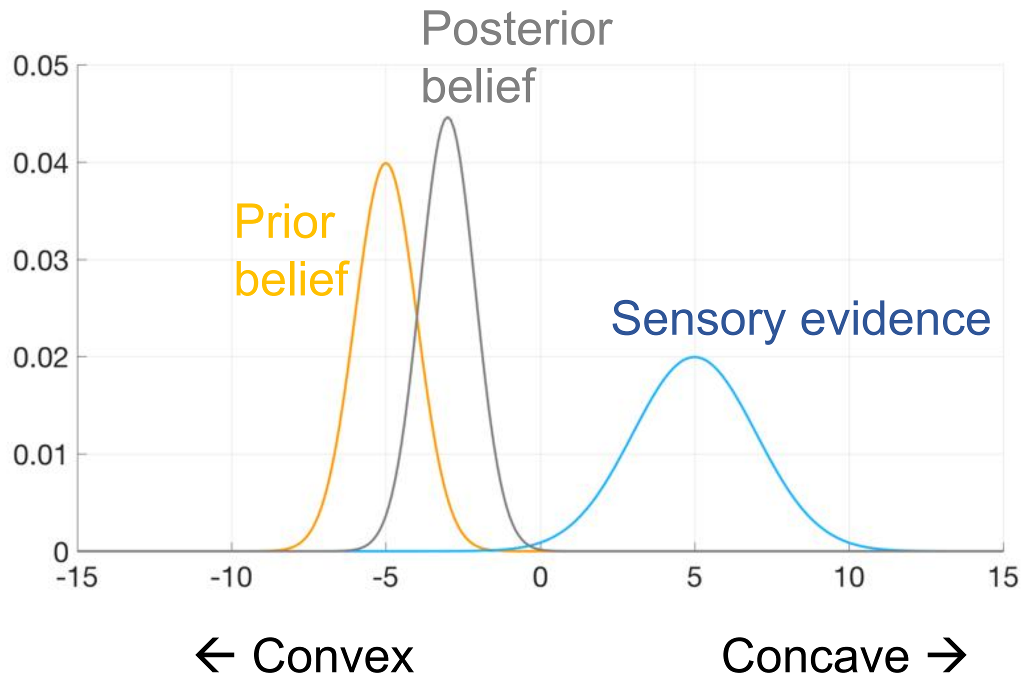
Another example: cognition

Hollow-face illusion



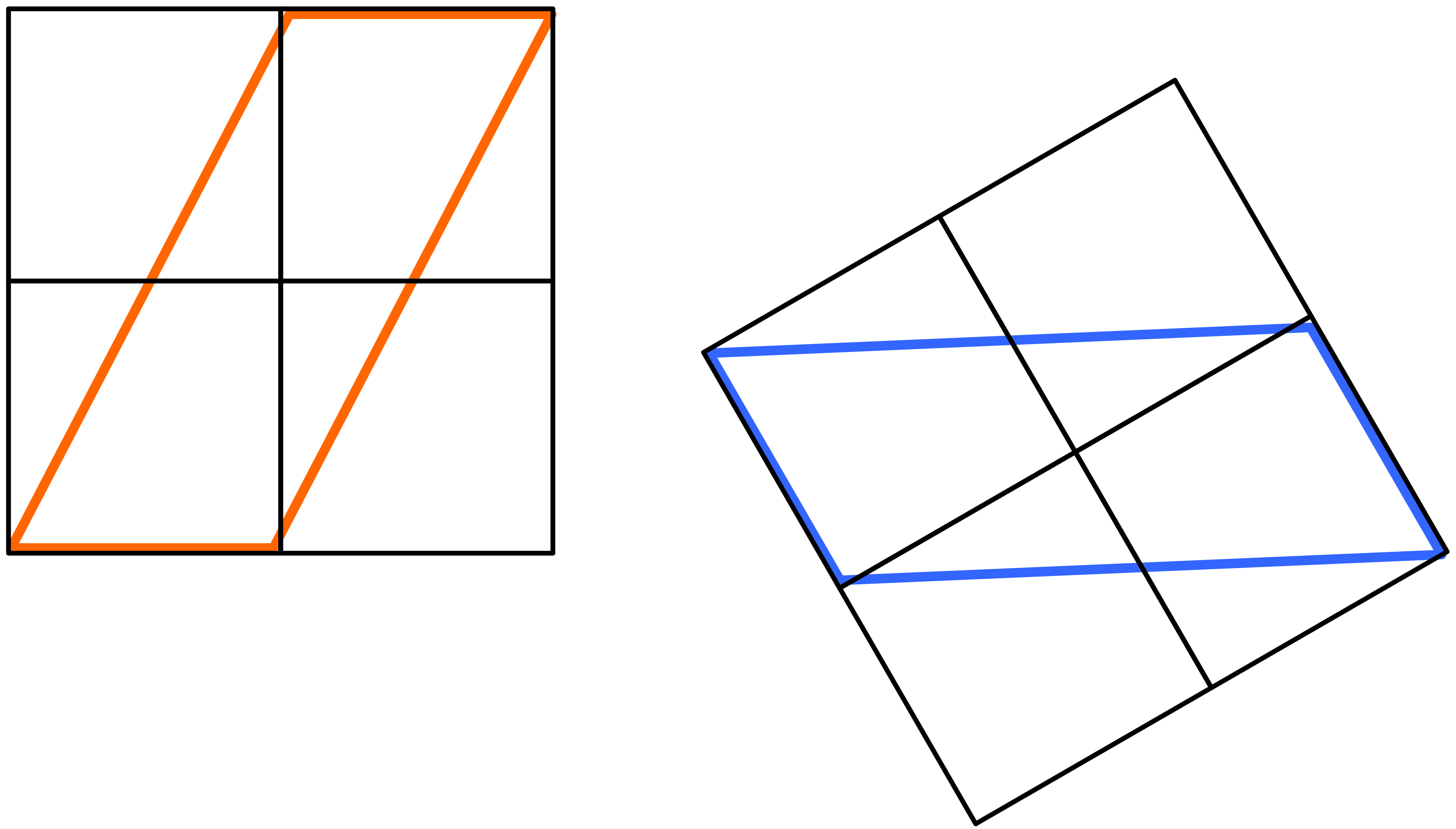
Why do we see the hollow face as convex?

Prior x likelihood ∝ posterior probability



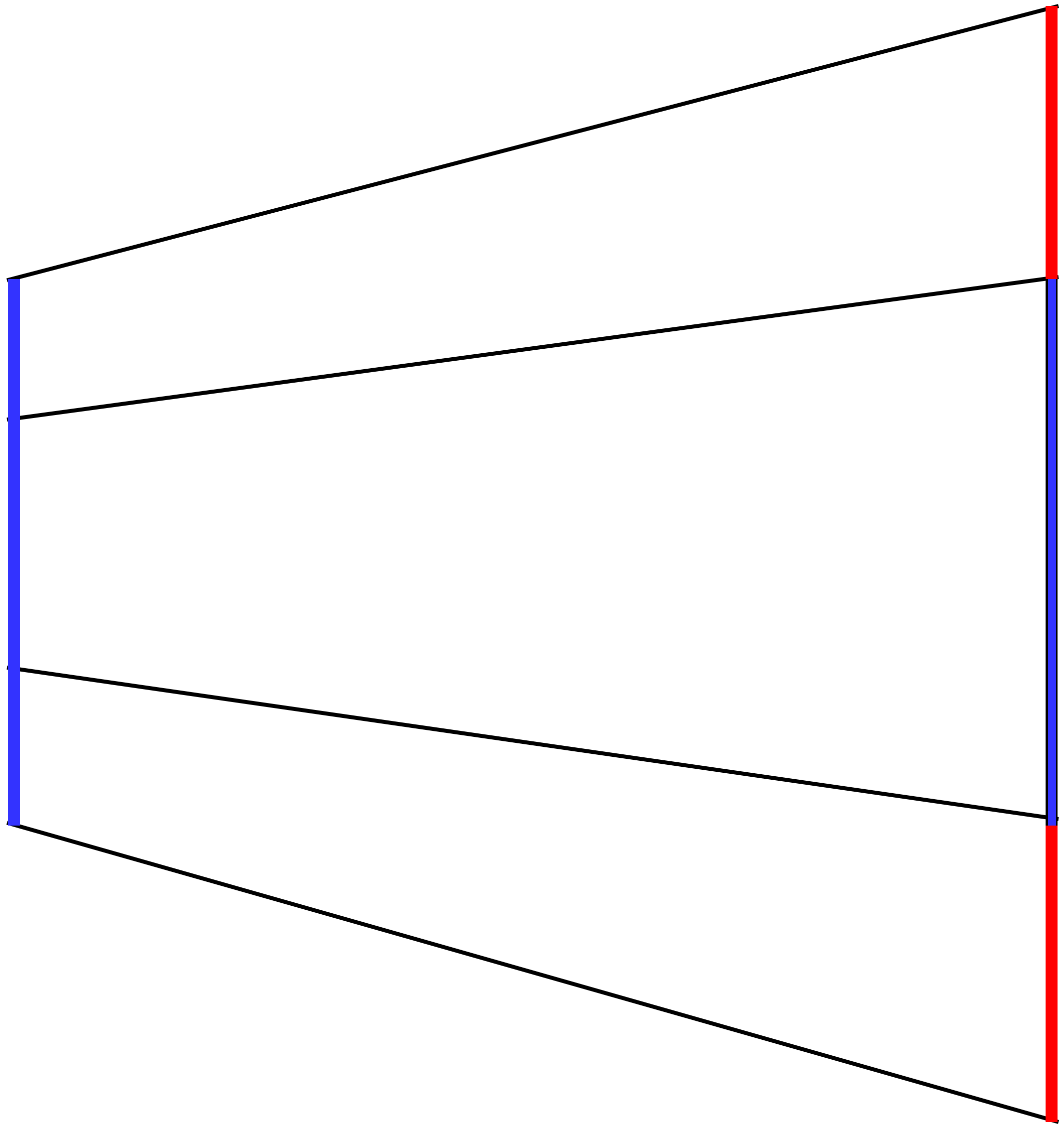
Some other visual illusions

Same size?

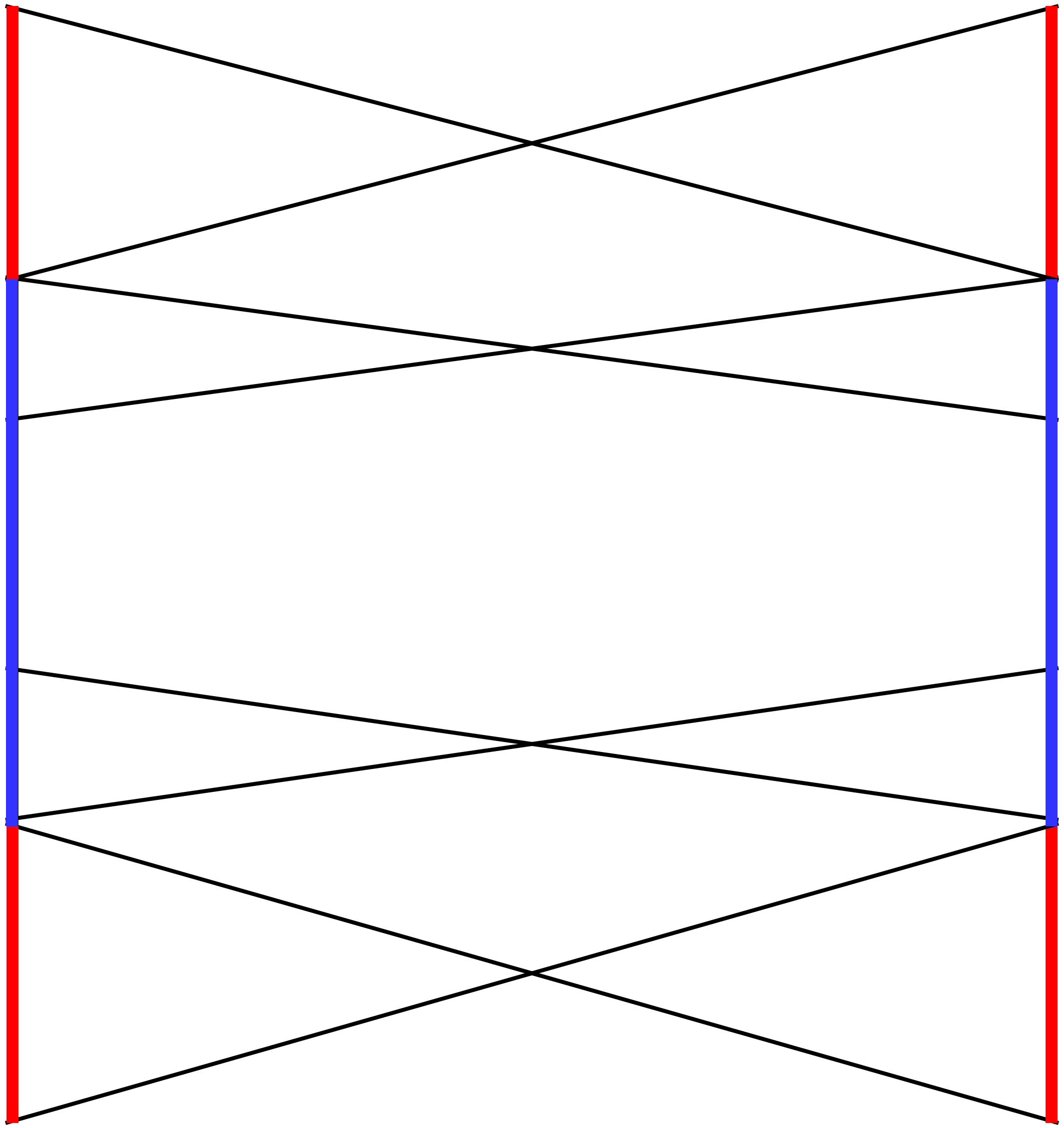


Which blue line is longer?

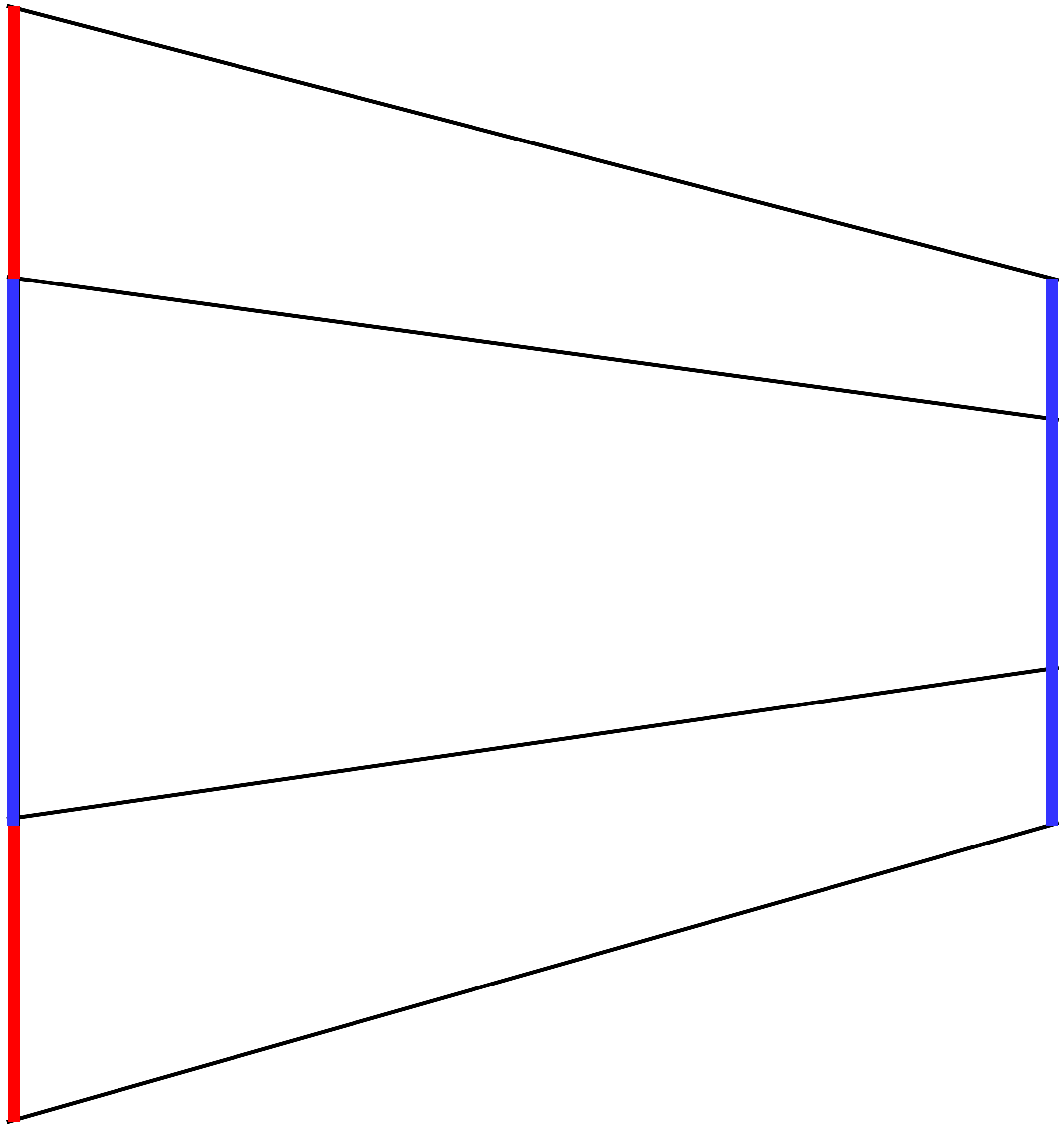
Which blue line is longer?



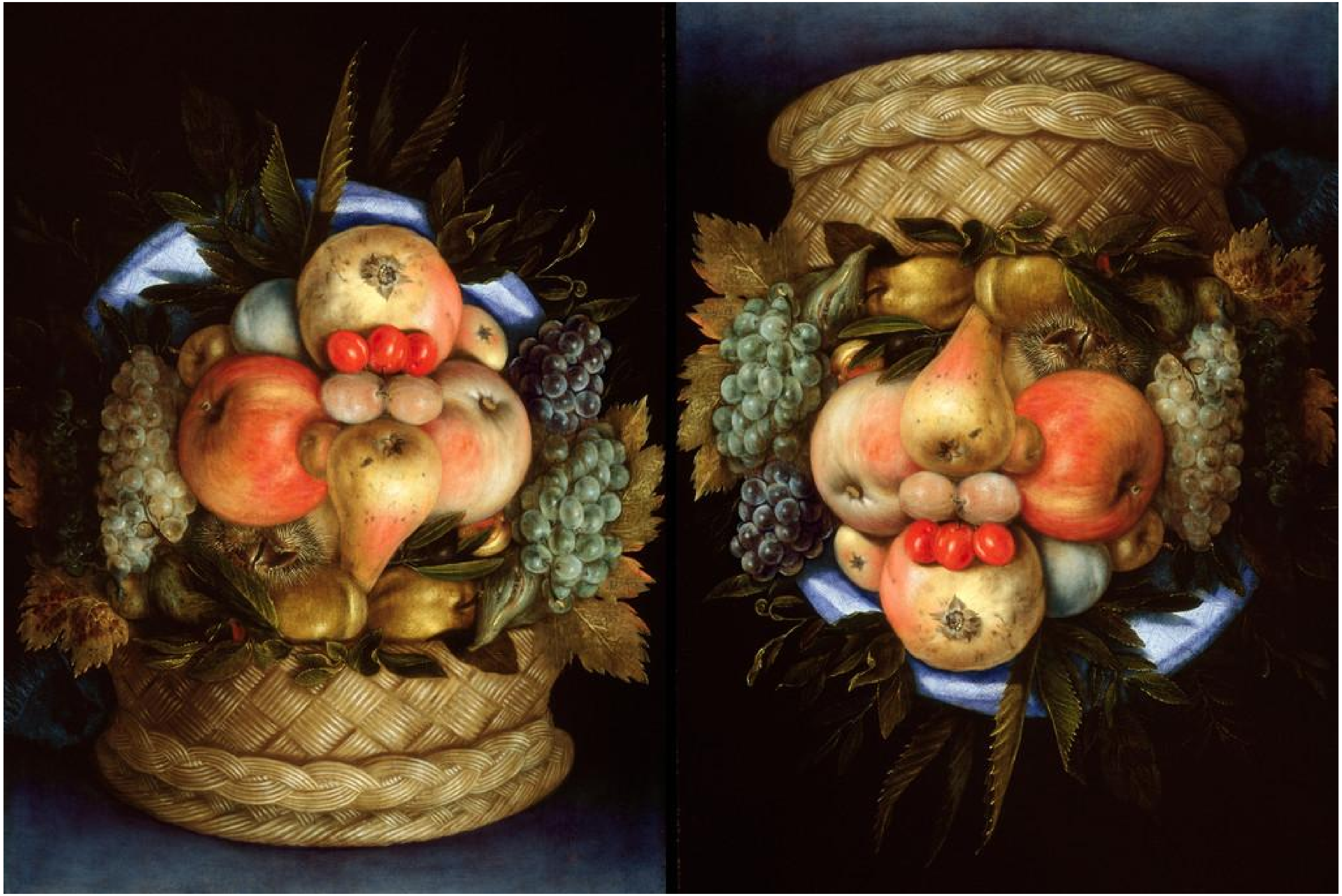
Which blue line is longer?



Which blue line is longer?



Which blue line is longer?



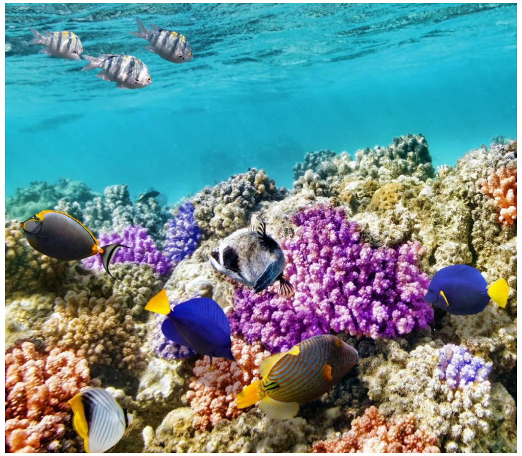
Any ideas about how to **explain** these effects?

Any ideas about how to **model** these effects?

Another example: availability of extreme events

Availability bias: people over-estimate the probability of events that come to mind easily (Tversky & Kahneman, 1973)

I am going to the ocean tomorrow.
I am thinking about …



vs.

I have a fever now.
I am thinking about…

I have a cold.

vs.

I got COVID-19.

Extreme events come to mind easily.

Any other examples?

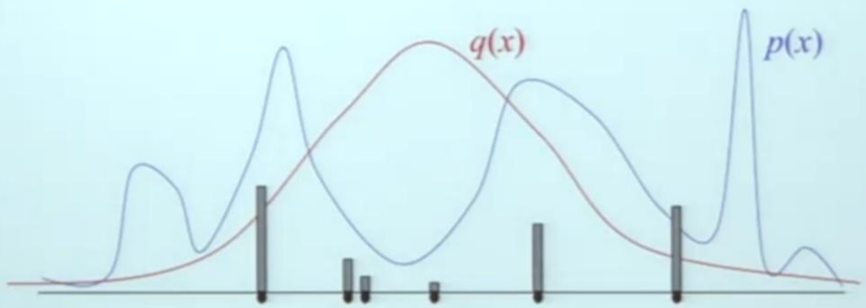
An explanation: availability of extreme events

- **Task:** Estimate the expected utility of an action

$$E[U] = \int u(x)p(x)dx$$

- **Architecture:** Generate (weighted) samples of possible outcomes of the action
- **Cost:** Increases linearly in the number of samples (as with opportunity cost)

Importance sampling



$$w^{(i)} = \frac{p(x^{(i)})}{q(x^{(i)})} \qquad E[U] \approx \frac{\sum_i w^{(i)} u(x^{(i)})}{\sum_i w^{(i)}}$$

The optimal distribution

- Variance is minimized by…

$$q(x) \propto p(x)\left|u(x) - E[U]\right|$$

- But, the result is biased: with small samples, we will over-represent extreme events

(Lieder, Hsu, & Griffiths, 2014)

External World (stimuli)

A deep Neural Network to encode (simulate) neural signals?

80 billions of neurons in human brain

Another deep Neural Network to decode neural signals?

Behavior (action)
Emotion
Cognition
…

What is the problem of NN here?

Not possible to record all neurons (10^{12})
No enough training datasets
No enough computational power to fit data

Even though we can do all these, we know nothing from the model.

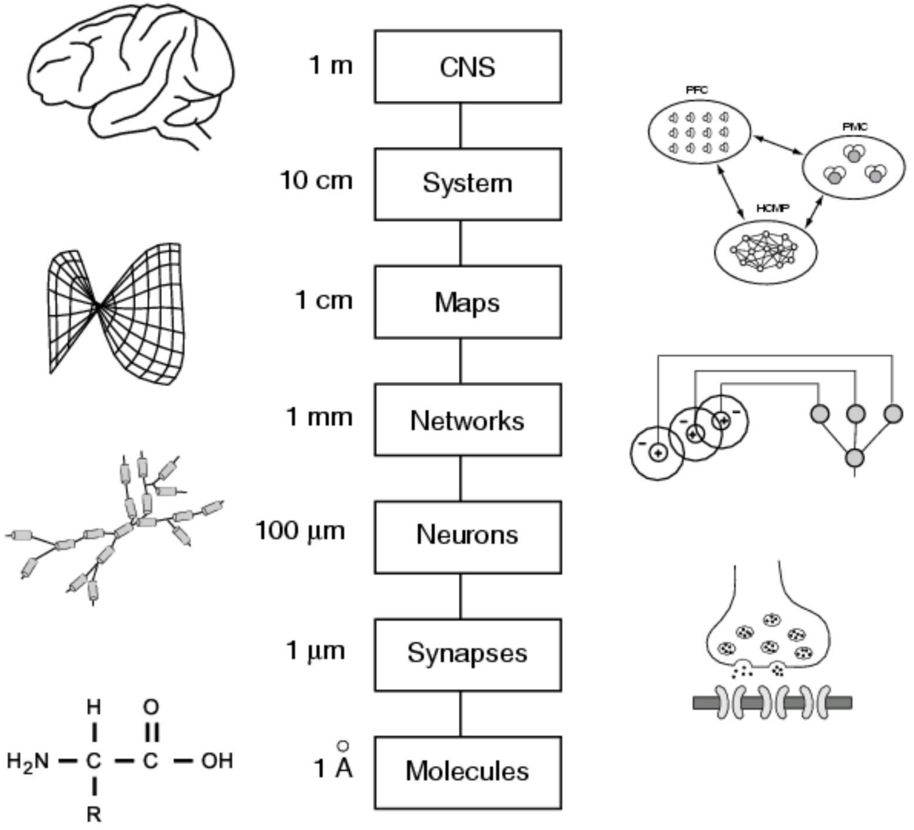
A good model shall not only fit the data, but also provide insights to explain the underlying mechanisms.

Once again,
The purpose of models is not to fit the data but to sharpen the questions.

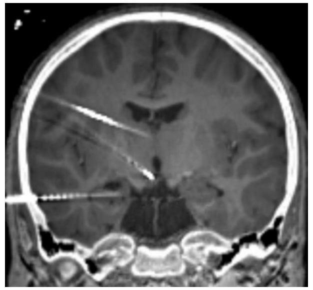
Electrophysiological and Neuroimaging techniques

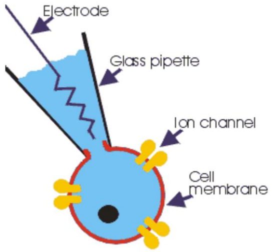
help to see what is happening in the brain

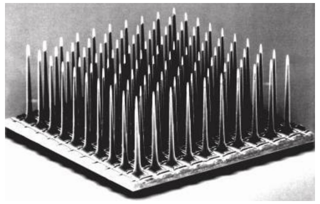
Different levels

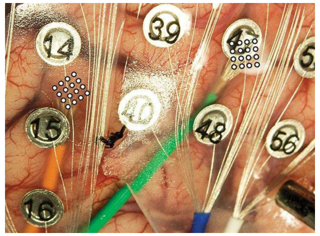


- MRI, fMRI
- EEG, MEG
- SEEG
- ECoG
- Local field potential (extracellular)
- Utah Array
- Patch clamp (intracellular recording)



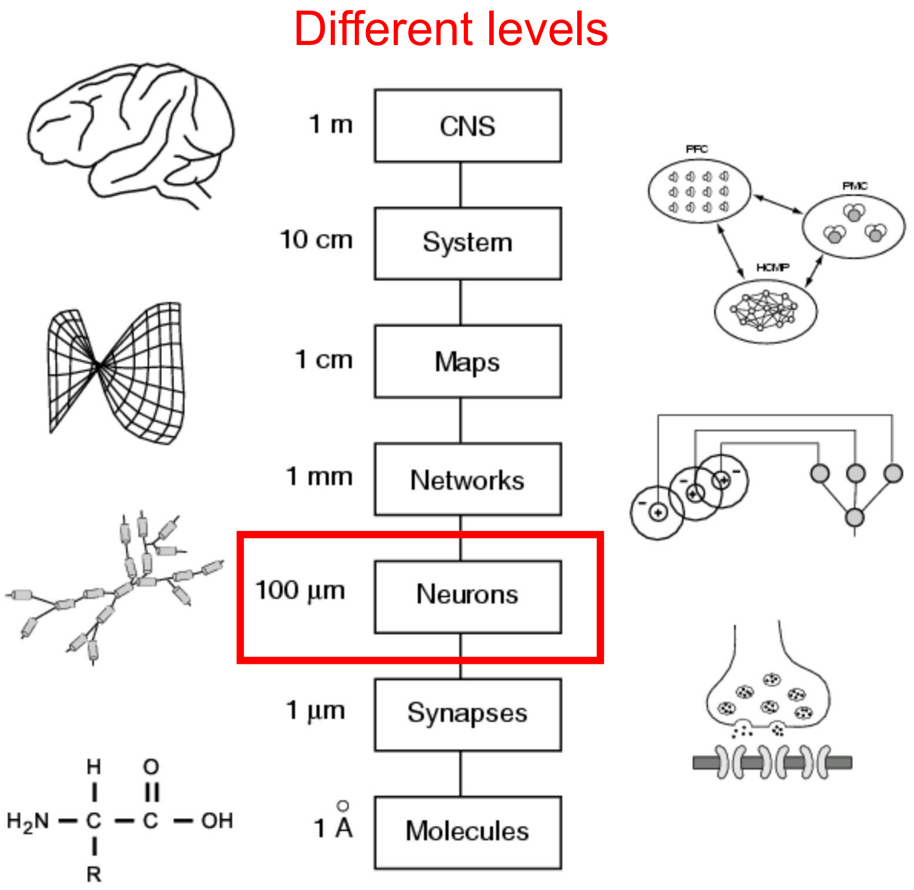


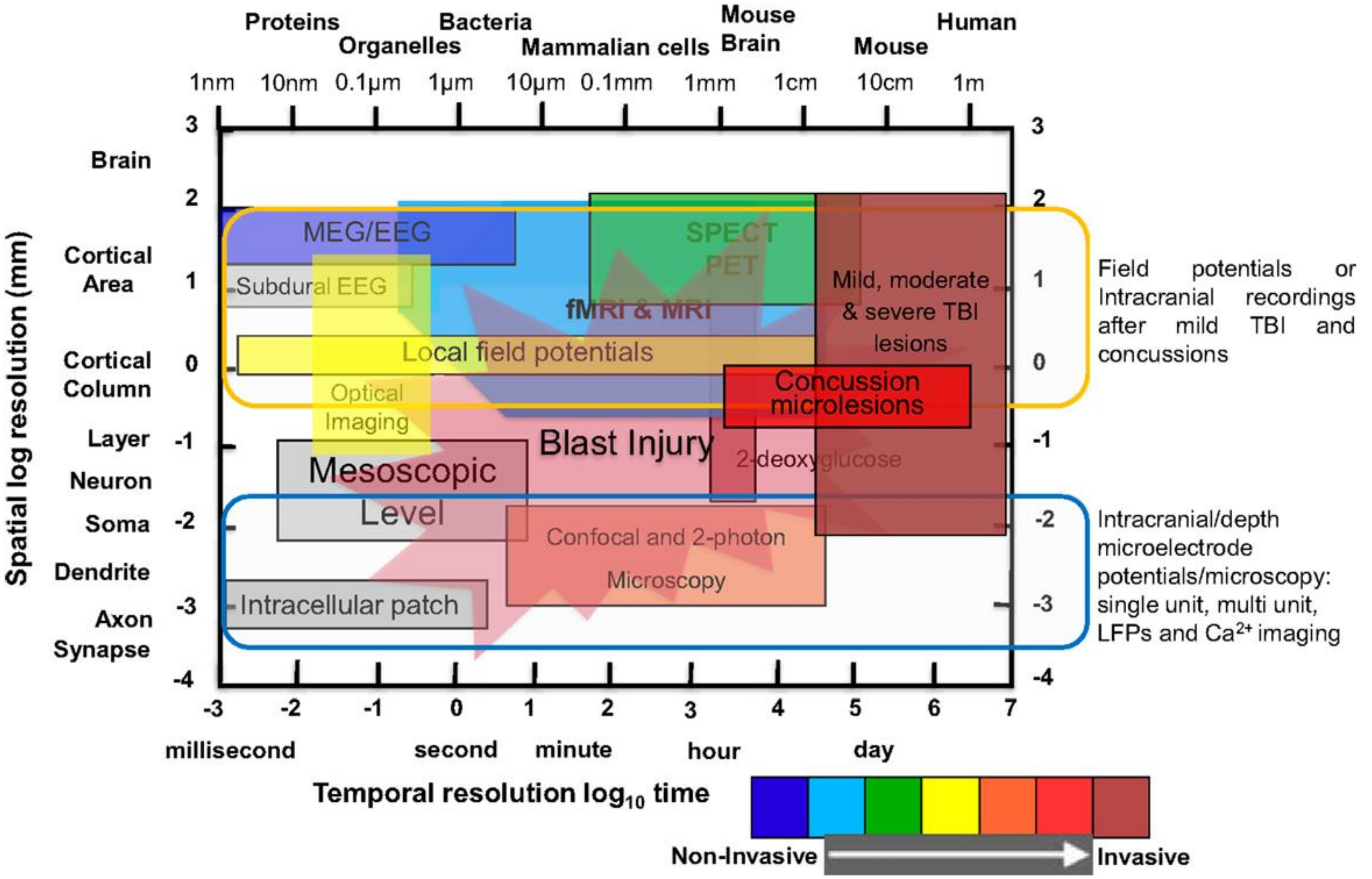




Electrophysiological and Neuroimaging techniques

help to see what is happening in the brain

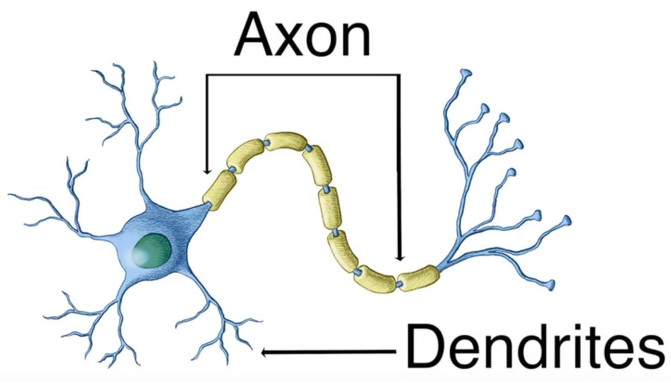




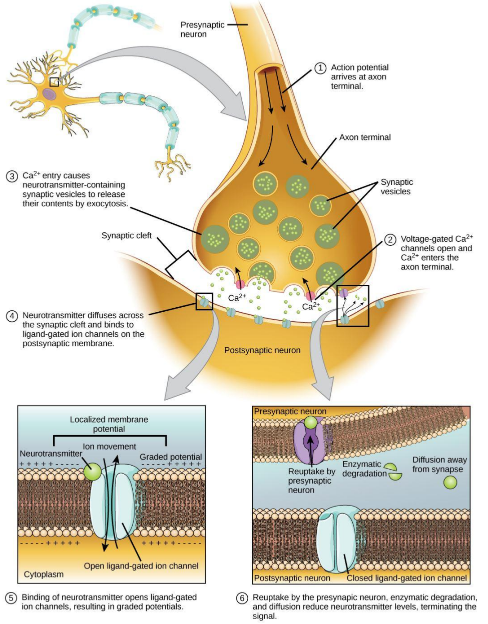
Manoj Kumar Jaiswal, Front Neurol 2015

Neuron and Action potential

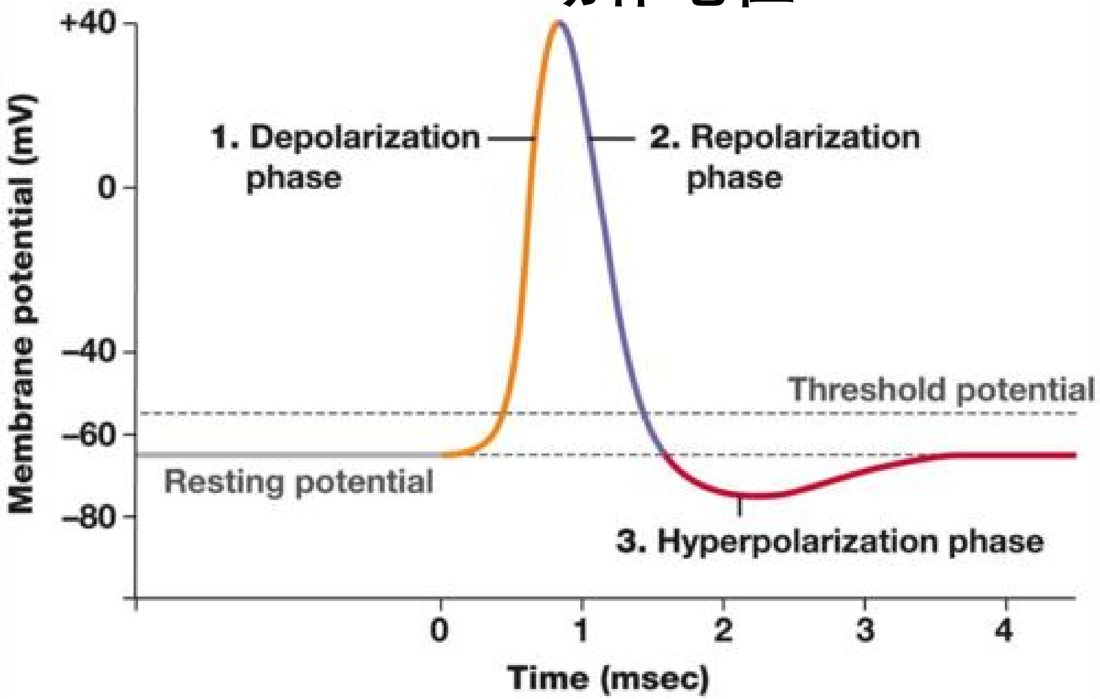
Neuron
神经元



Synapse
突触



Action potential (spike)
动作电位



binary code: 0 1 0 0 0

Cell Membrane

Membrane potential : -70 mV
(outside membrane as the ground)

Discovery of neurons

1906 Nobel Prize in Physiology or Medicine

"in recognition of their work on the structure of the nervous system."

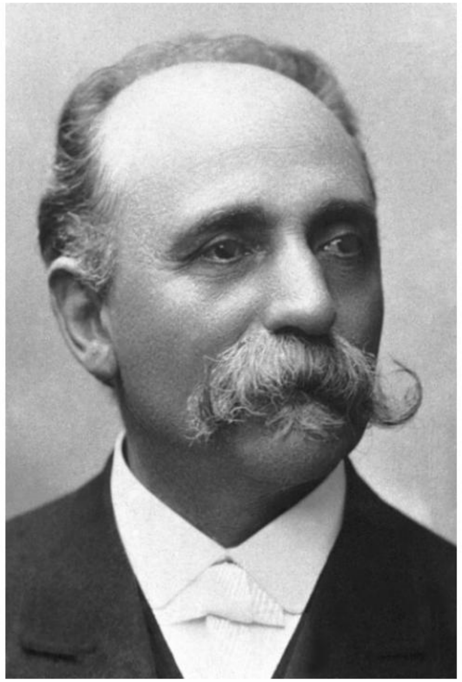


Photo from the Nobel Foundation archive.

Camillo Golgi

Prize share: 1/2

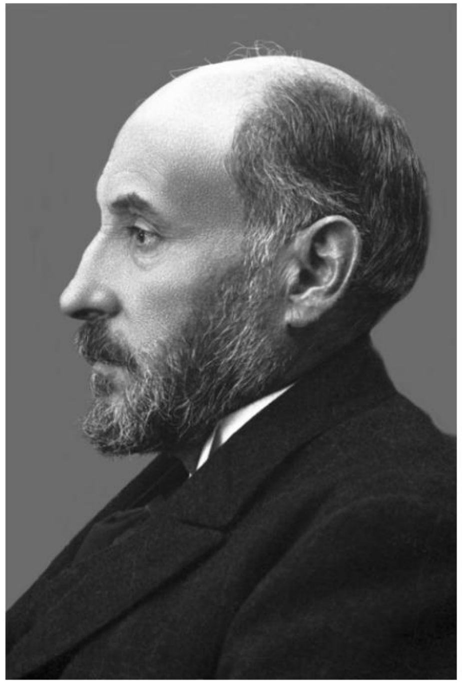
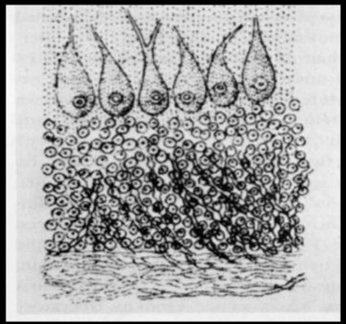
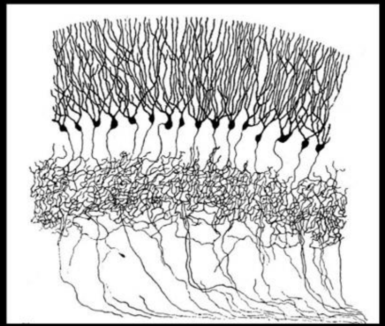


Photo from the Nobel Foundation archive.

Santiago Ramón y Cajal

Prize share: 1/2

They discovered that nerve cells could be stained with silver nitrate.
However, they support two different theories.

Neuron doctrine	Reticular theory
Cells 1 nucleus/cell	Syncytium Multiple nuclei
Evidence:	Evidence:
Golgi stain showed individual neurons	Neural tissue hard to observe
	

Discovery of action potential

1963 Nobel Prize in Physiology or Medicine

"for their discoveries concerning the ionic mechanisms involved in excitation and inhibition in the peripheral and central portions of the nerve cell membrane."

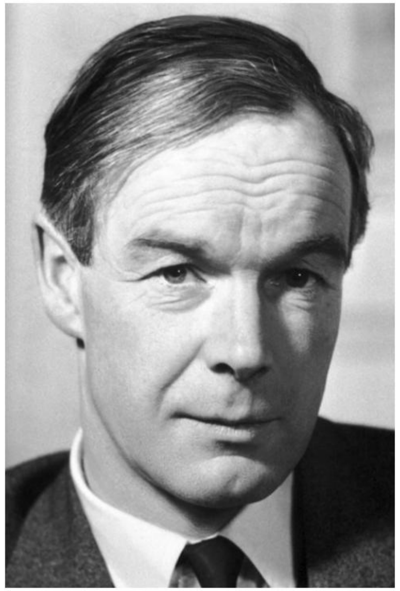


Photo from the Nobel Foundation archive.

Alan Lloyd Hodgkin

Prize share: 1/3

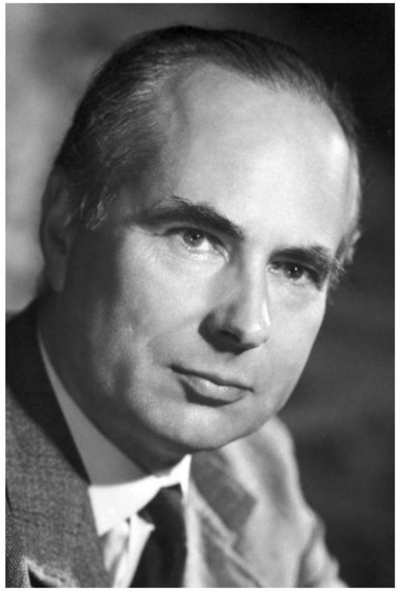
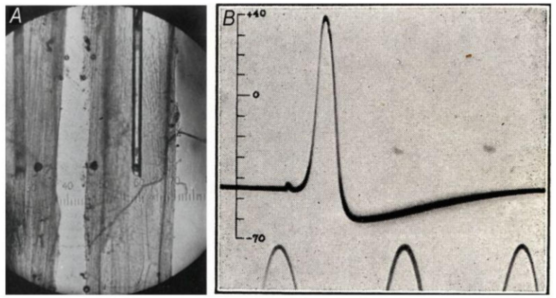
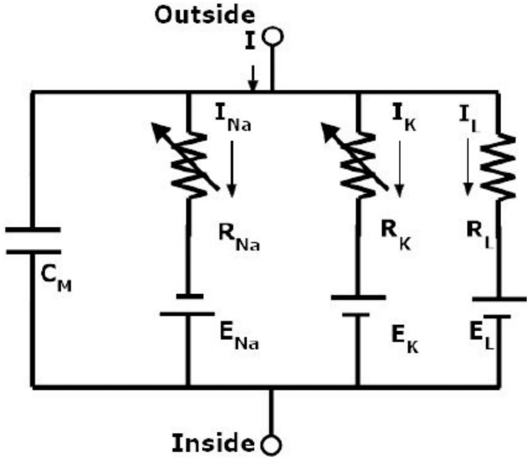


Photo from the Nobel Foundation archive.

Andrew Fielding Huxley

Prize share: 1/3





Kirchhoff Law:

$$I = I_c + I_i = C_m \frac{dV}{dt} + I_i$$

$$I_i = I_{Na} + I_K + I_l$$

$$I_{ion} = g_{ion}(V - E_{ion})$$

Hodgkin-Huxley model:

$$C_m \frac{dV}{dt} = -g_{Na}(V - E_{Na}) - g_K(V - E_K) - g_l(V - E_l) + I$$

Hodgkin AL & Huxley AF (1939). Action potentials recorded from inside a nerve fibre. Nature 144, 710–711.

Representation of Perceptual Information in Neurons

1981 Nobel Prize in Physiology or Medicine

"for their discoveries concerning information processing in the visual system."

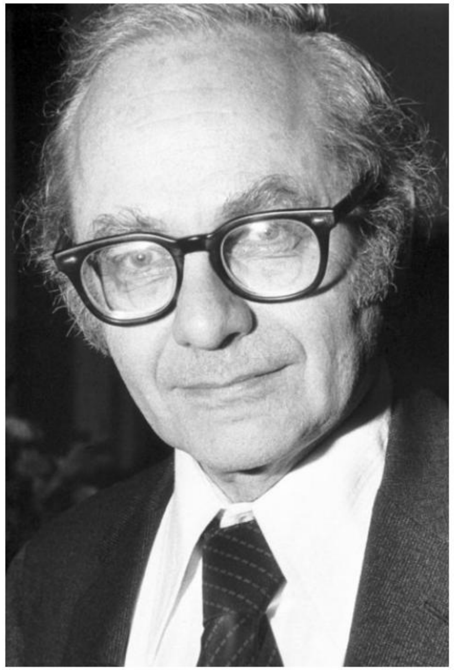


Photo from the Nobel Foundation archive.

David H. Hubel

Prize share: 1/4

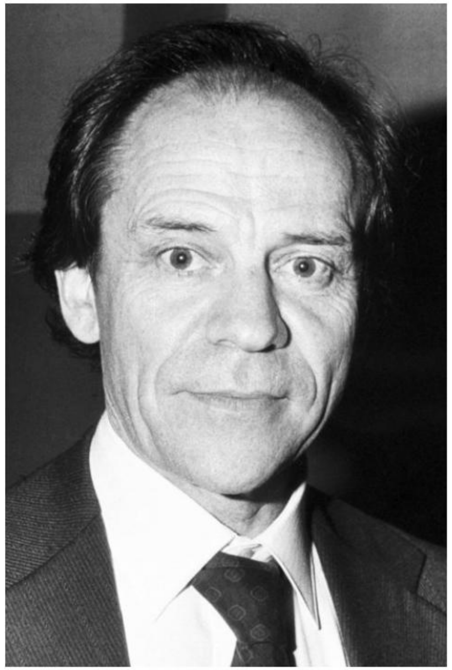
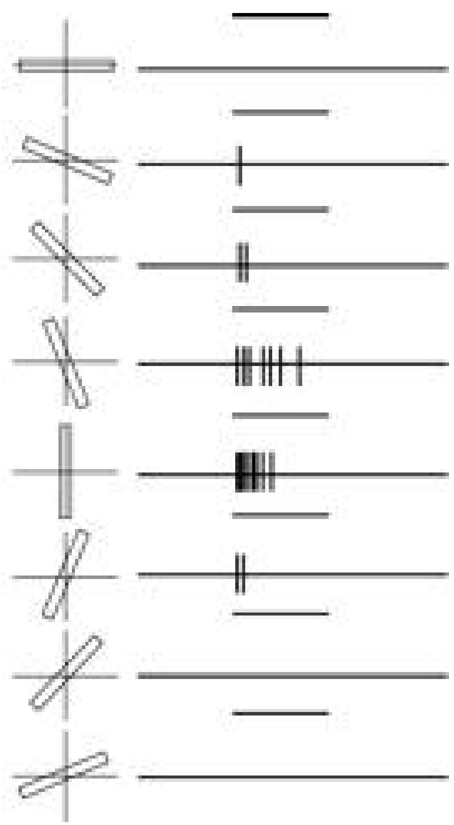


Photo from the Nobel Foundation archive.

Torsten N. Wiesel

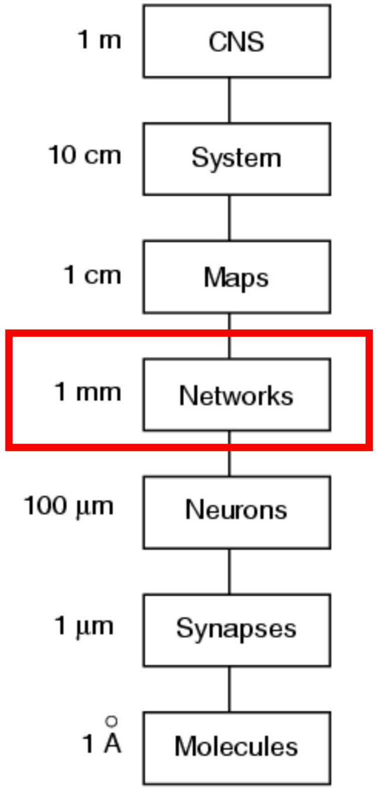
Prize share: 1/4

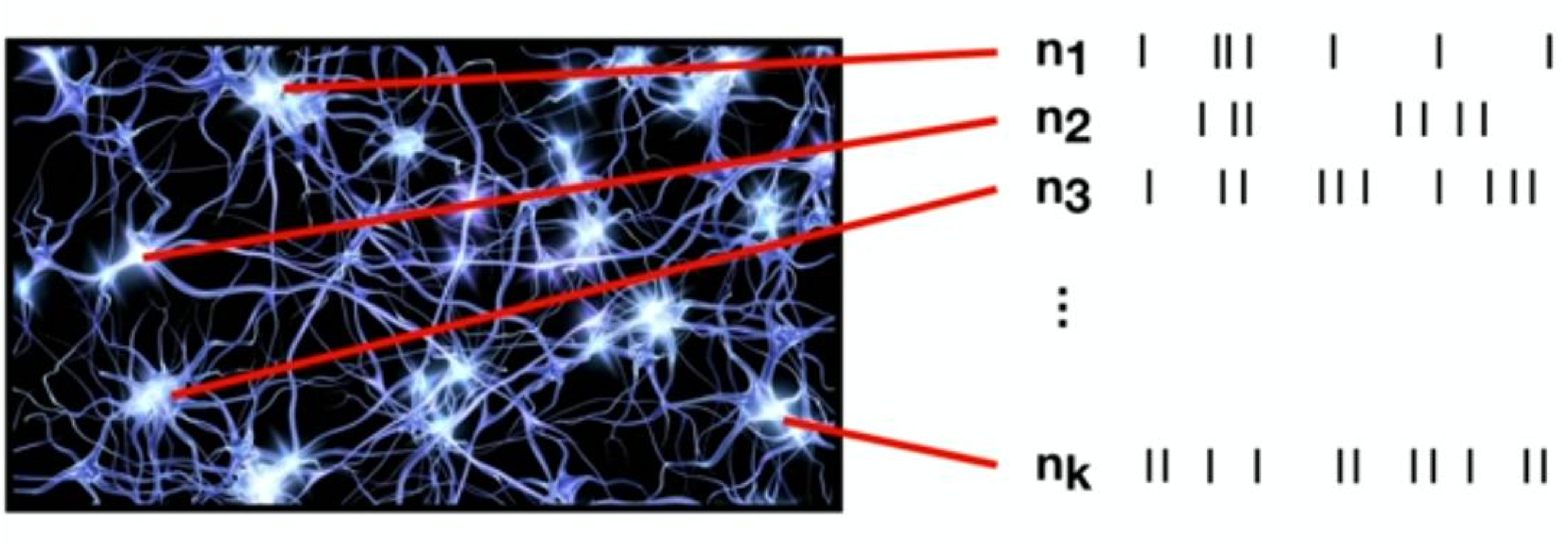


- Neurons as ‘perceptual predicates’
  - ‘There’s an edge of orientation q at position [x,y]’
- Higher firing rate = stronger support *or* better fit
- Controversial, but perhaps useful?

Hubel and Wiesel (1968)- Receptive fields and functional architecture of monkey striate cortex. J. Physiol.

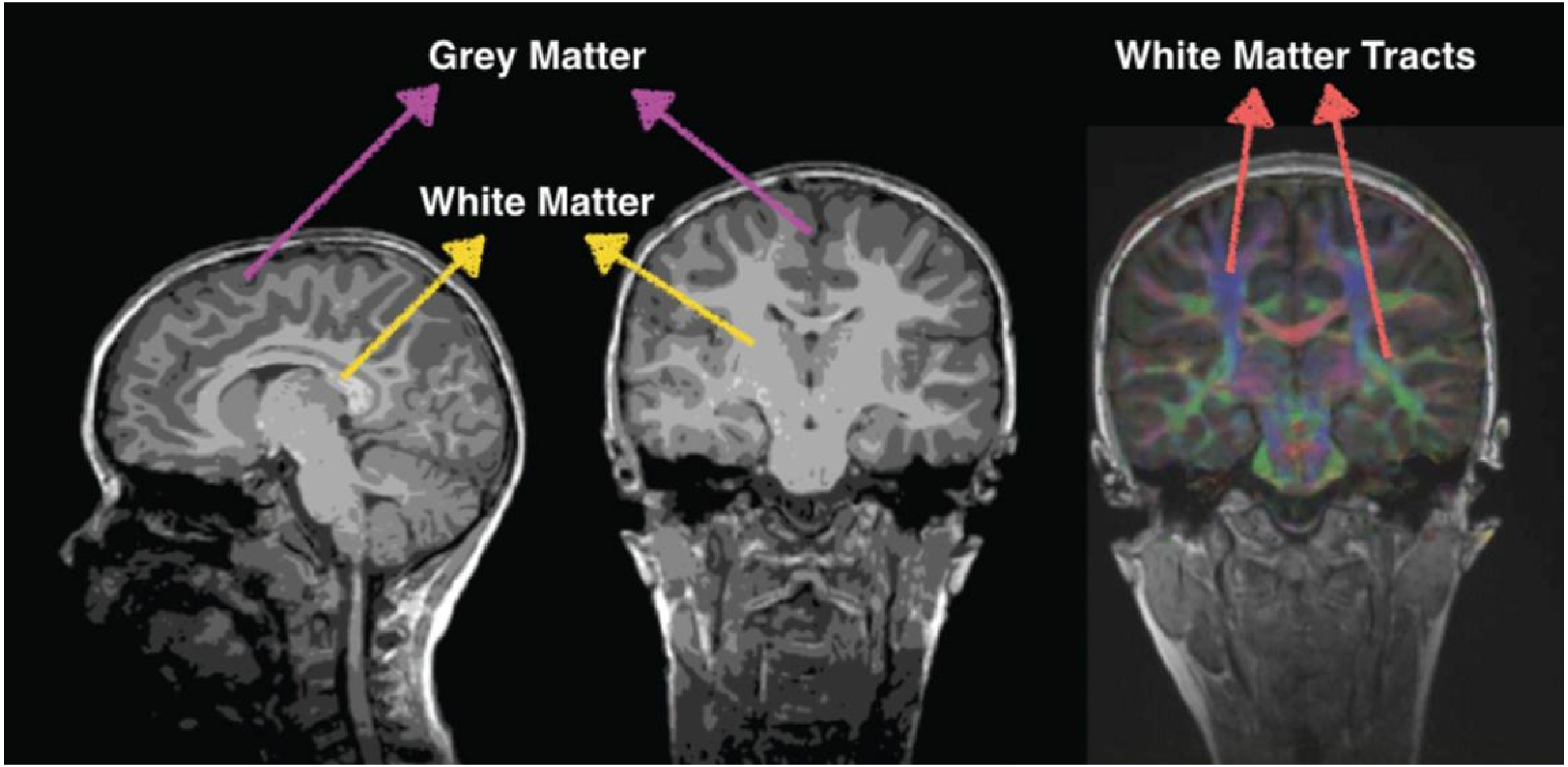
Real neural network



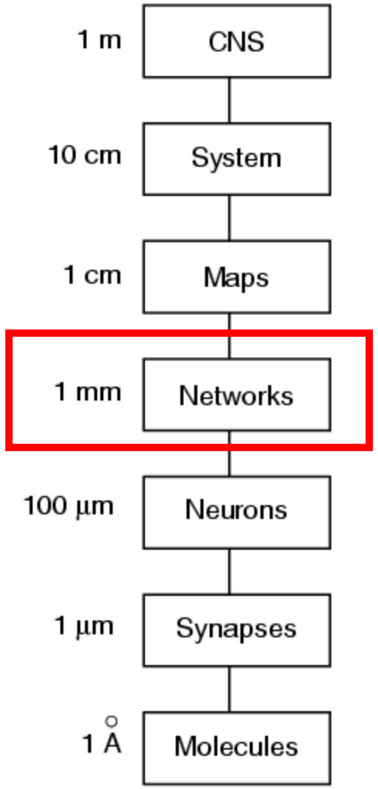


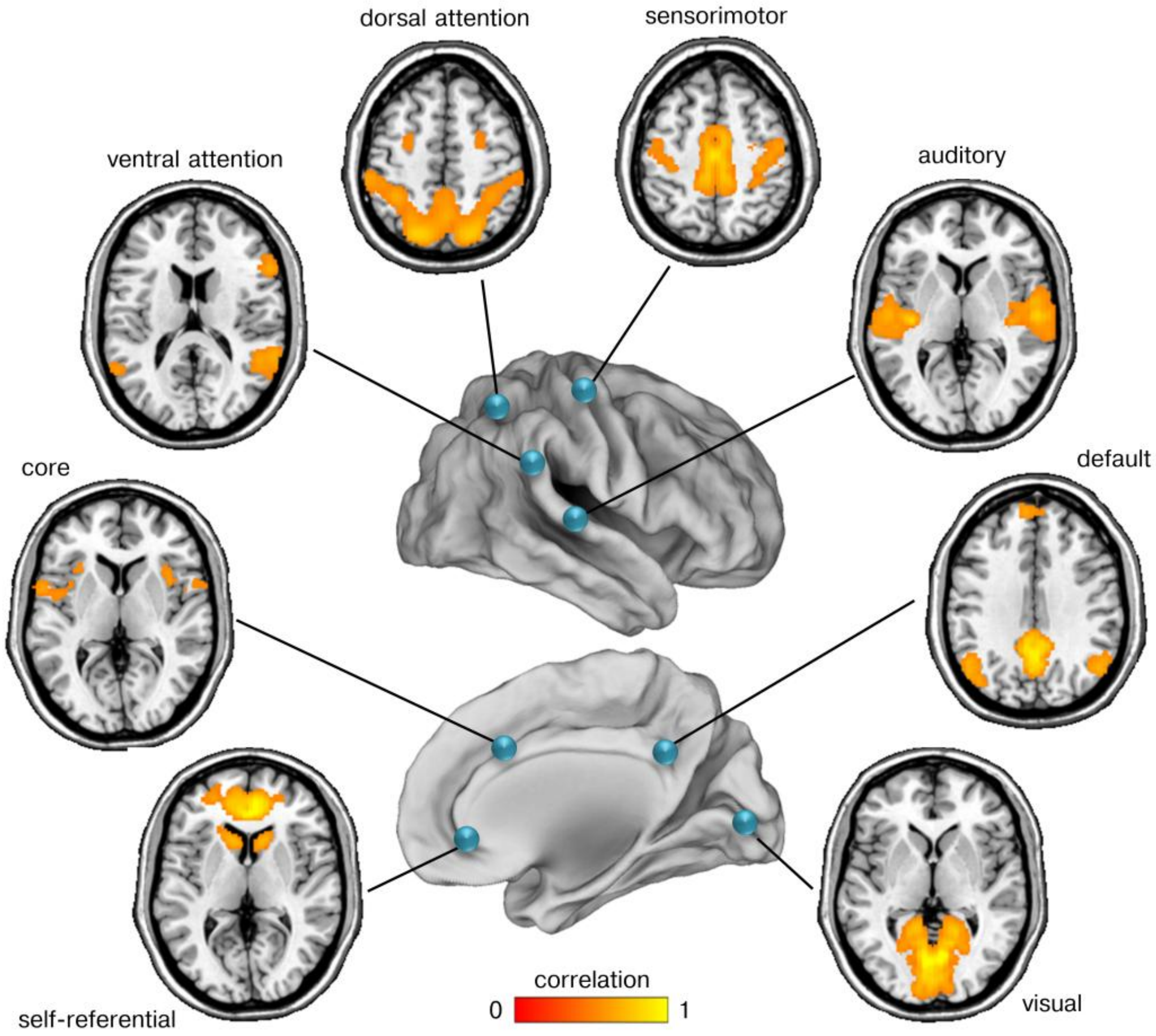
Real neural network ⟺ Artificial neural network

Grey Matter (cell body) & White Matter (axons)



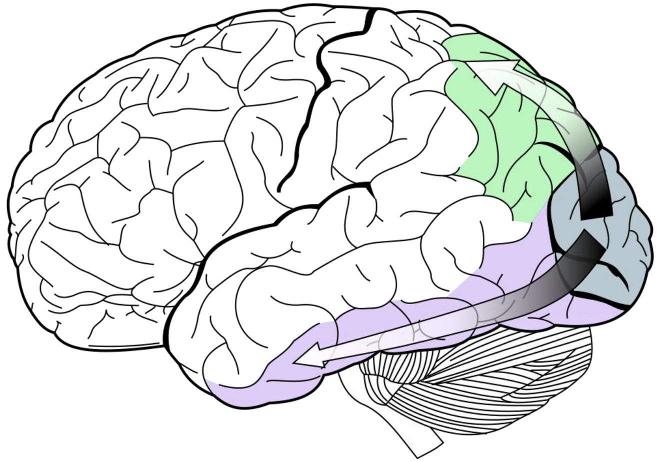
Brain functional networks





Gillebert and Mantini, *The Neuroscientist* 2013

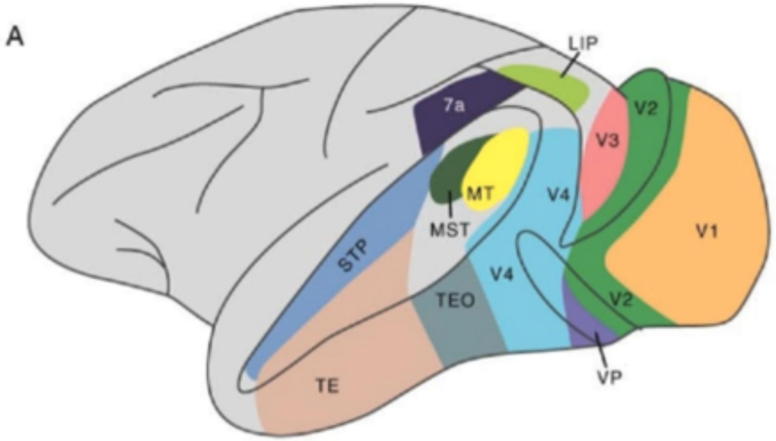
Perceptual integration: dorsal and ventral streams



dorsal ‘where’ pathway

&

ventral ‘what’ pathway



‘Where’: object localisation

the motion and spatial location

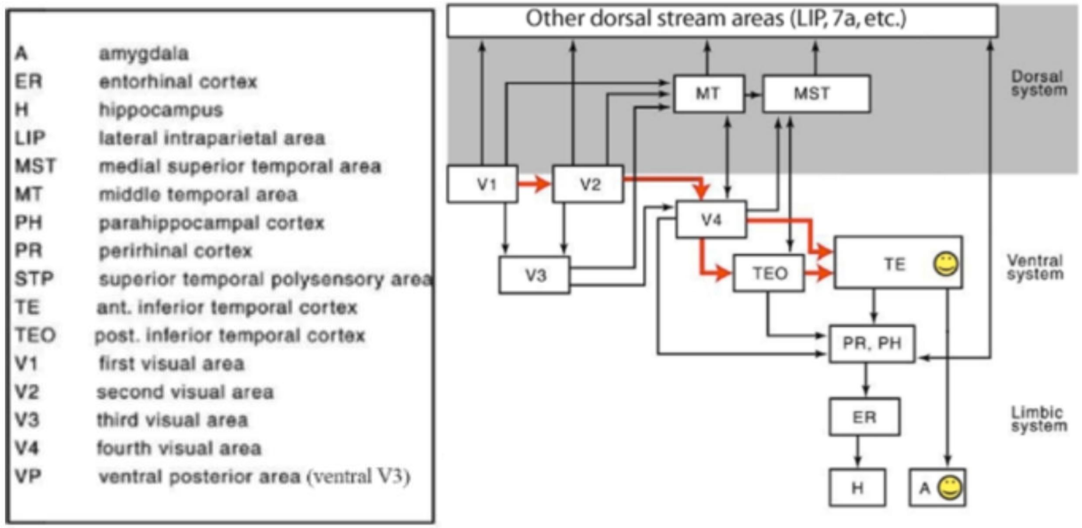
(V1, V2, V4 and inferior temporal areas)

‘What’: object recognition

the detailed features, form, and object identity

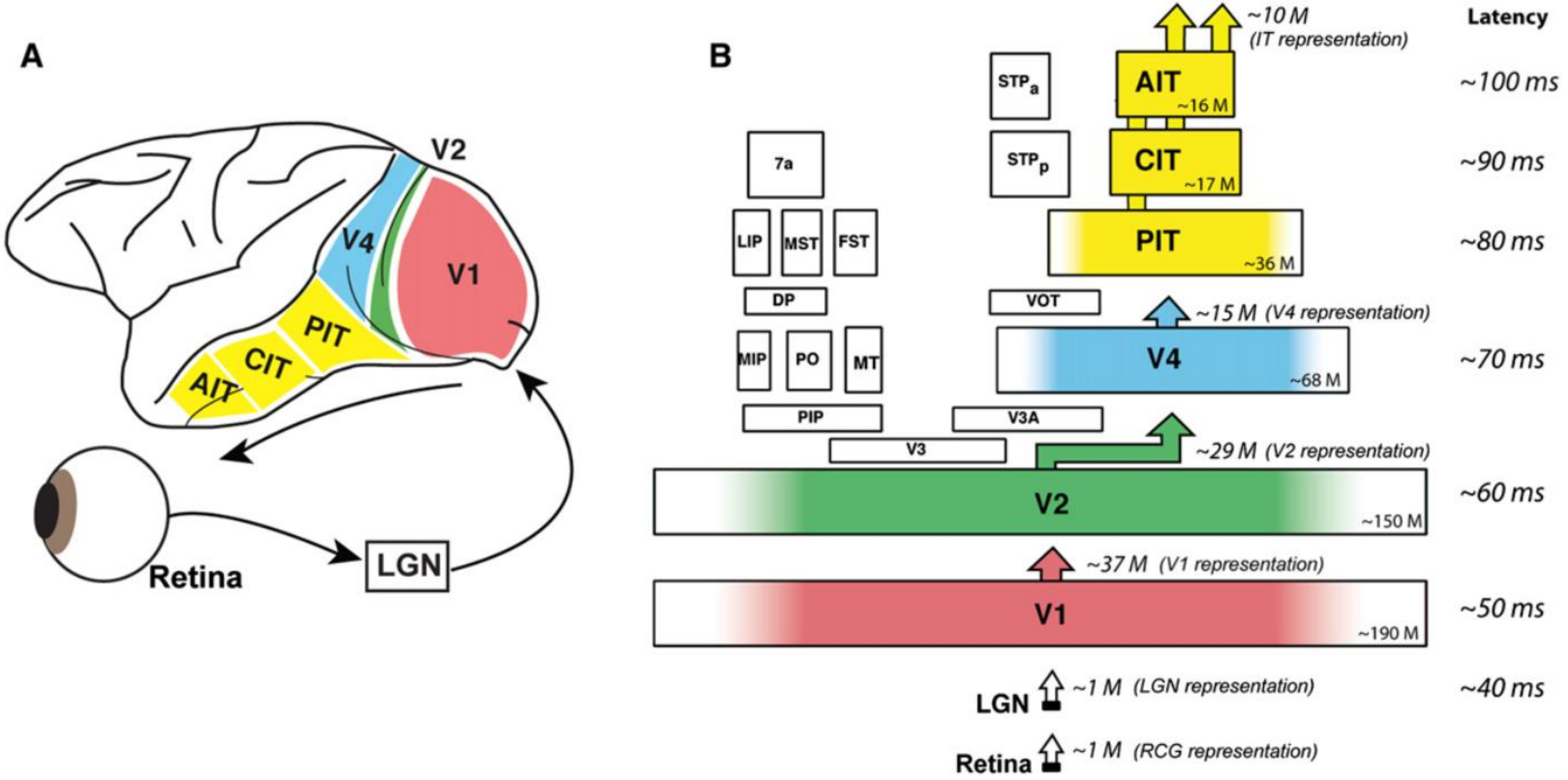
(V1, V2, V3, MT (V5), MST and inferior parietal cortex)

Each functional area contains a full retinotopic map.



Goodale MA, Milner AD (1992). “Separate visual pathways for perception and action”. Trends Neurosci. ***15*** *(1): 20–5.*

The Ventral Visual Pathway: for object recognition

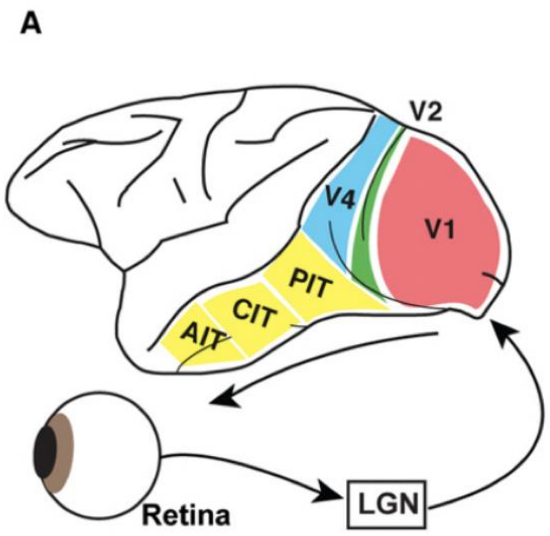


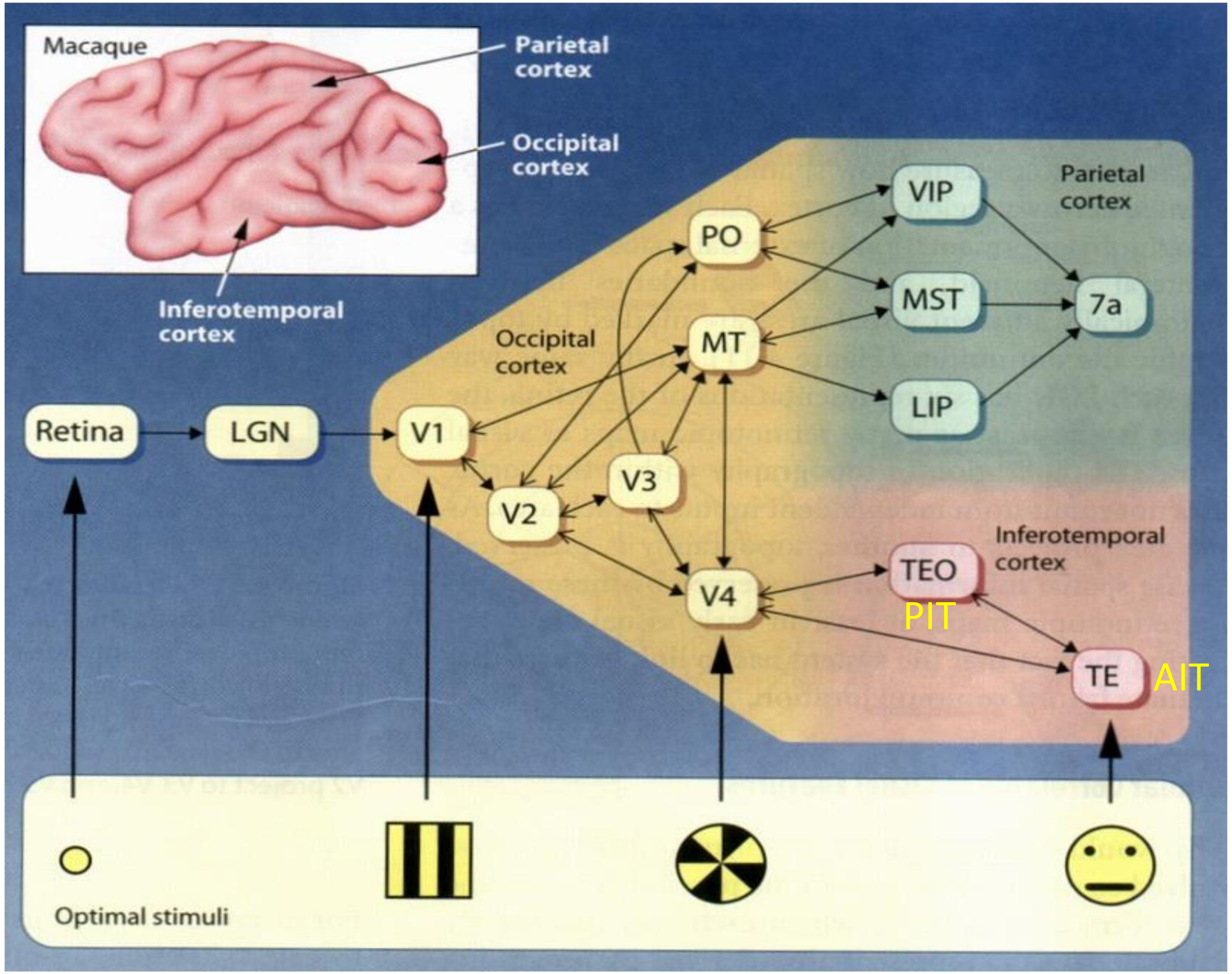
Anterior Inferior Temporal

Lateral Geniculate Nucleus

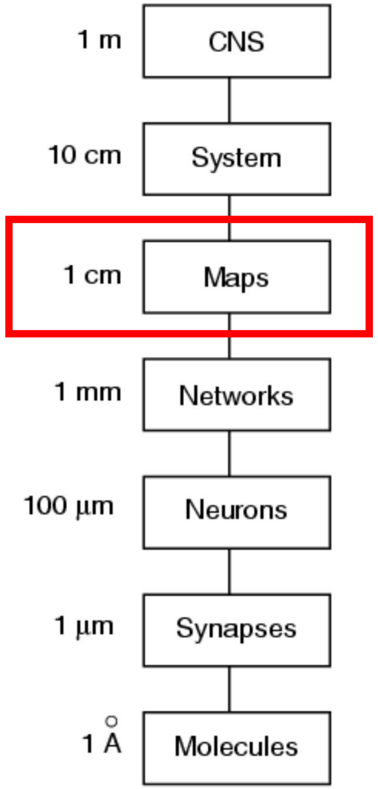
(A) Ventral stream cortical area locations in the macaque monkey brain, and flow of visual information from the retina.
(B) Each area is plotted so that its size is proportional to its cortical surface area (Felleman and Van Essen, 1991). Approximate total number of neurons (both hemispheres) is shown in the corner of each area (M = million). The approximate dimensionality of each representation (number of projection neurons) is shown above each area, based on neuronal densities (Collins et al., 2010), layer 2/3 neuronal fraction (O'Kusky and Colonnier, 1982), and portion (color) dedicated to processing the central 10 deg of the visual field (Brewer et al., 2002). Approximate median response latency is listed on the right (Nowak and Bullier, 1997; Schmolesky et al., 1998).

Along the Ventral Visual Pathway, feature extraction from simple to complex.

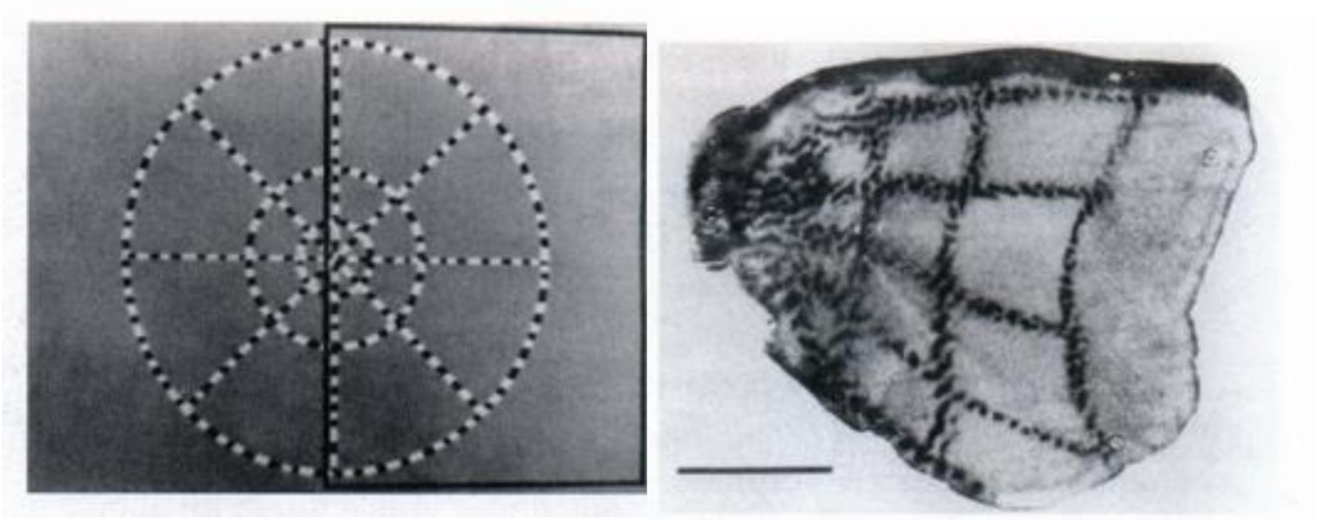




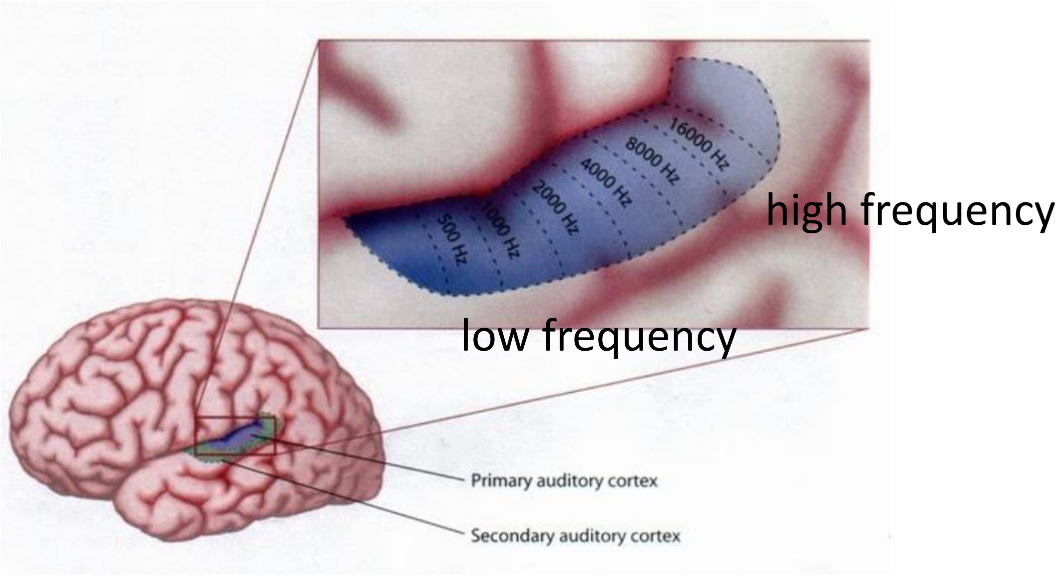
Topographic Maps at cortex



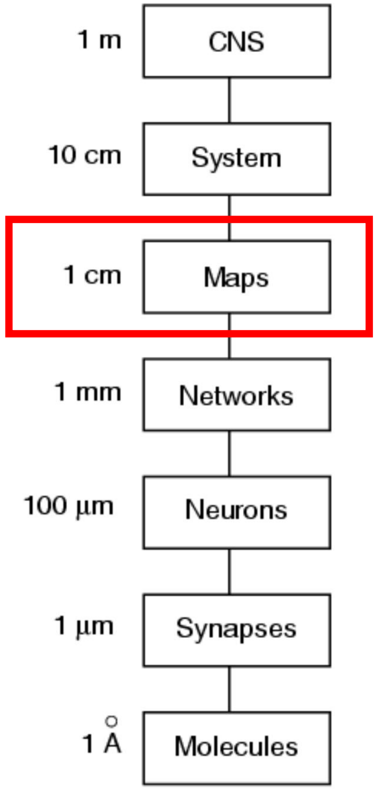
Retinotopic map

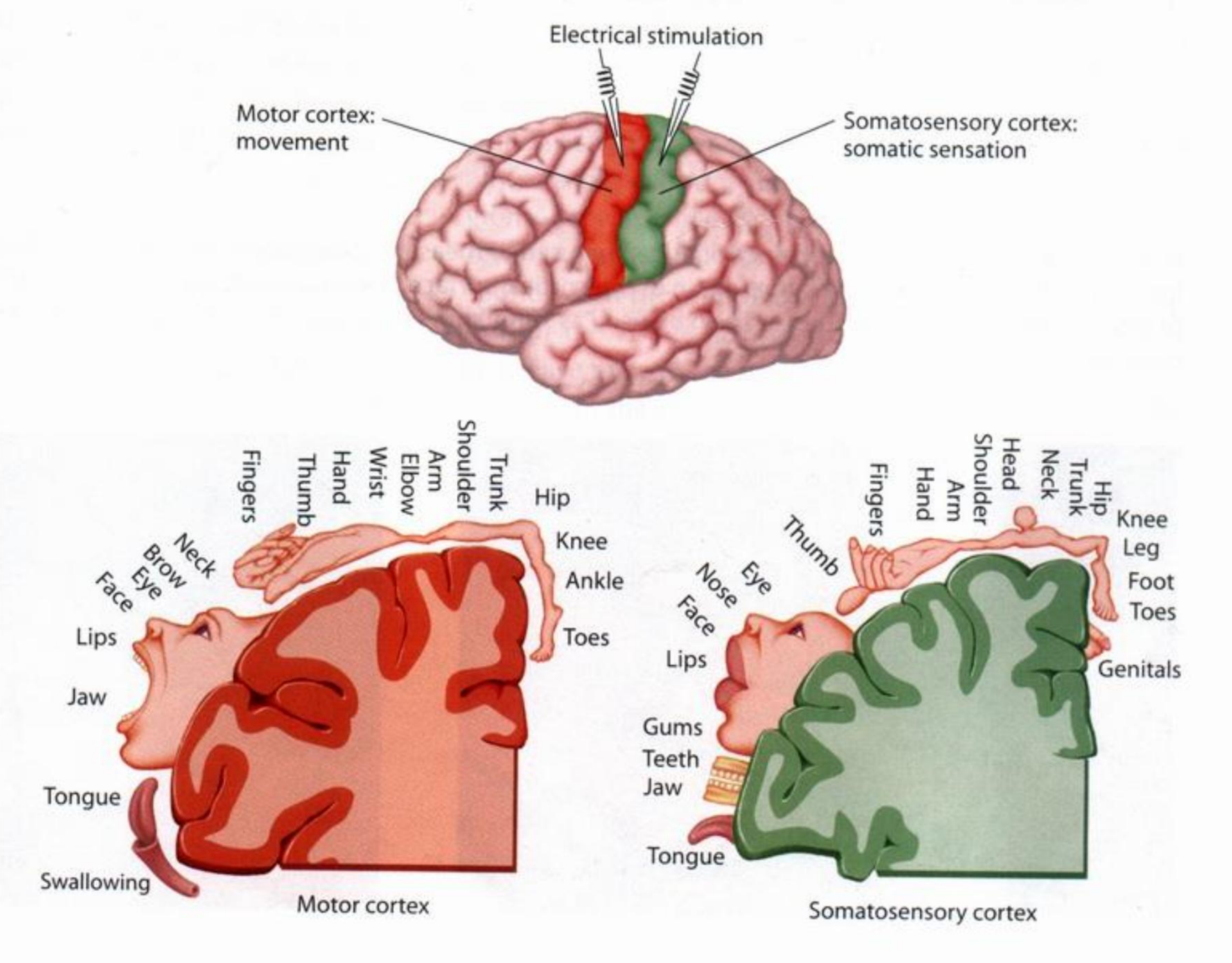


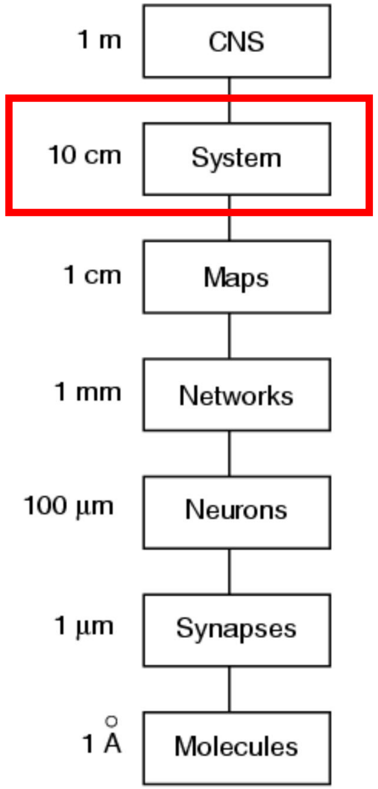
Tonotopic map



Topographic Maps at motor cortex & somatosensory cortex





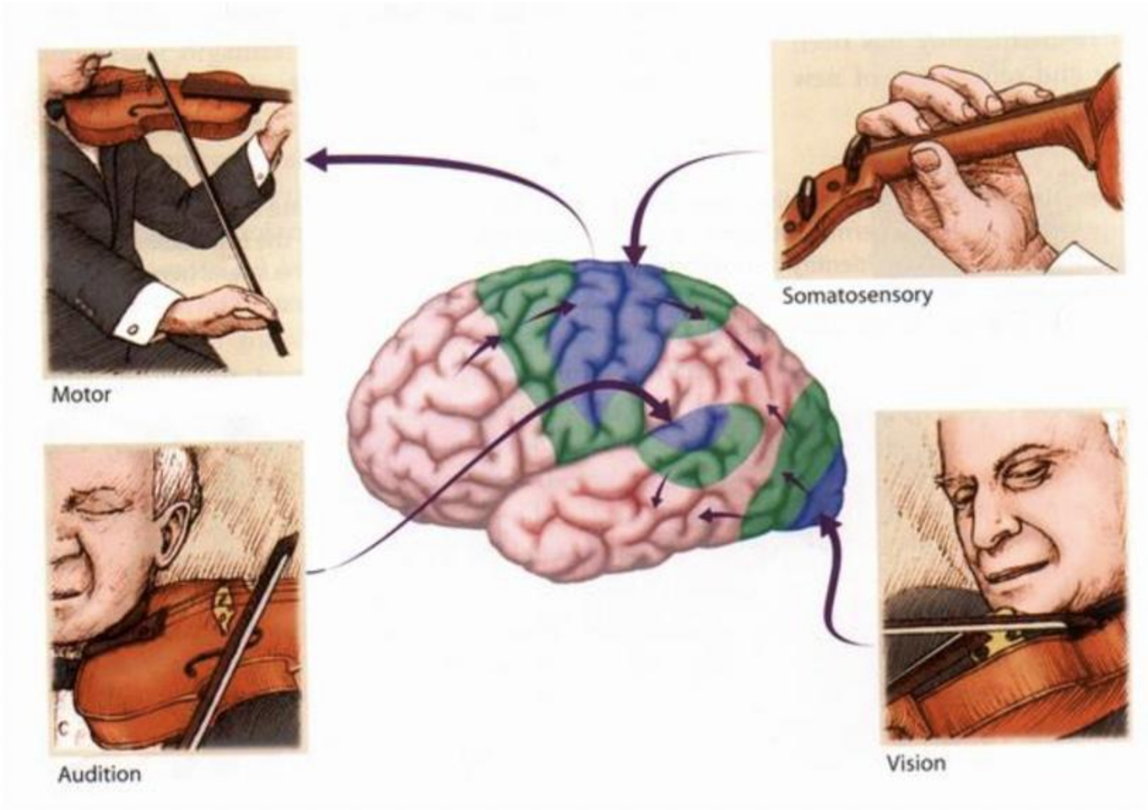


Visual system

Auditory system

Somatosensory system

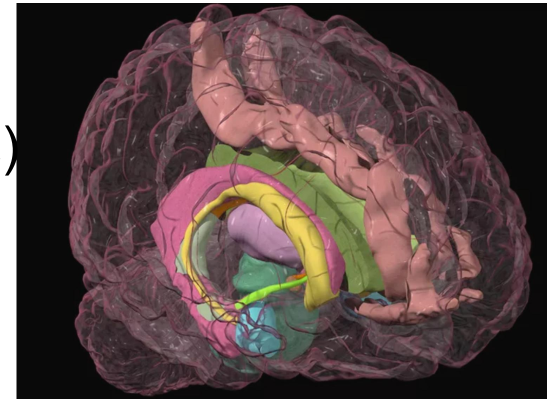
Motor system



Olfactory system (smell)

Limbic system (emotion & motivation)

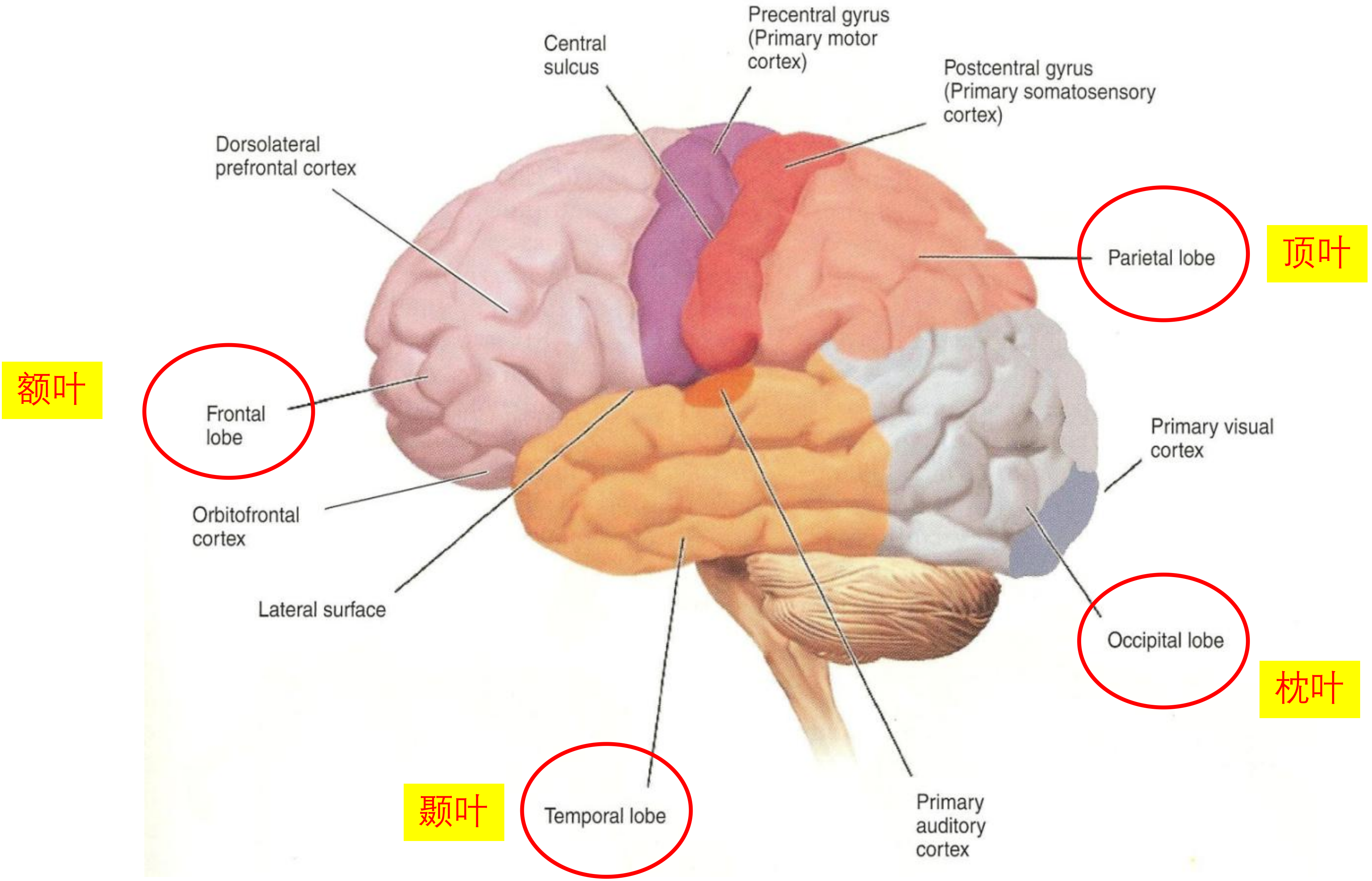
Including amygdala (杏仁核) and hippocampus (海马体)



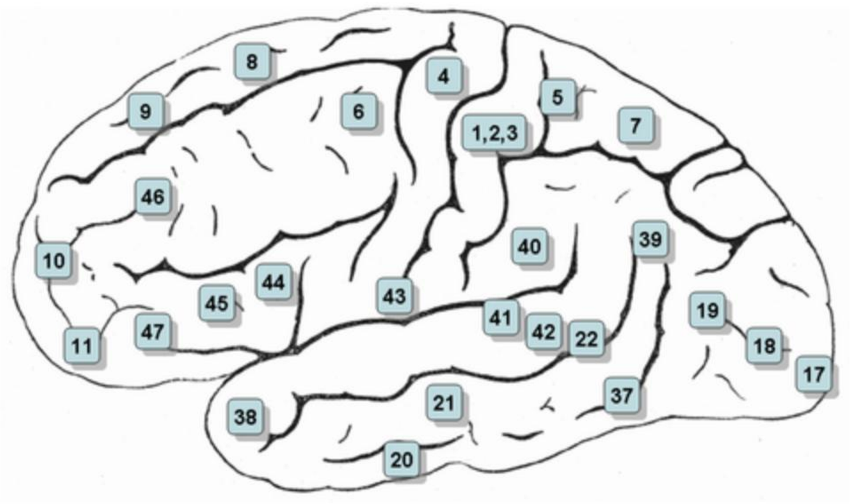
Other high-level cognition?

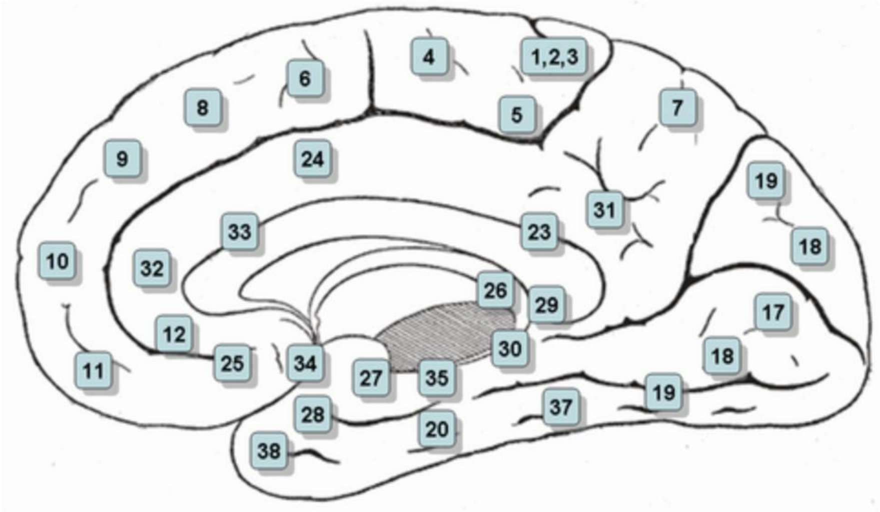
Such as consciousness, (free) will

Marco organization of human brain



Broadmann area (52 BAs)





Areas 3, 1 & 2 – Primary Somatosensory Cortex
Area 4 – Primary Motor Cortex (M1)
Area 5 – Somatosensory Association Cortex
Area 6 – Premotor cortex (M2)
Area 7 – Somatosensory Association Cortex
Area 8 – Includes Frontal eye fields
Area 9 – Dorsolateral prefrontal cortex
Area 10 – Anterior prefrontal cortex
Area 11 – Orbitofrontal area
Area 12 – Orbitofrontal area
Area 13 and Area 14* – Insular cortex
Area 15* – Anterior Temporal lobe
Area 16 – Insular cortex
Area 17 – Primary visual cortex (V1)
Area 18 – Secondary visual cortex (V2)
Area 19 – Associative visual cortex (V3,V4,V5)
Area 20 – Inferior temporal gyrus
Area 21 – Middle temporal gyrus
Area 22 – Superior temporal gyrus (Wernicke's area)
Area 23 – Ventral posterior cingulate cortex
Area 24 – Ventral anterior cingulate cortex.
Area 25 – Subgenual area
Area 26 – Ectosplenial portion of retrosplenial region

Area 27 – Piriform cortex
Area 28 – Ventral entorhinal cortex
Area 29 – Retrosplenial cingulate cortex
Area 30 – Part of cingulate cortex
Area 31 – Dorsal Posterior cingulate cortex
Area 32 – Dorsal anterior cingulate cortex
Area 33 – Part of anterior cingulate cortex
Area 34 – Dorsal entorhinal cortex)
Area 35 – Perirhinal cortex (in the rhinal sulcus)
Area 36 – Ectorhinal area
Area 37 – Fusiform gyrus
Area 38 – Temporopolar area
Area 39 – Angular gyrus, (Wernicke's area)
Area 40 – Supramarginal gyrus (Wernicke's area)
Areas 41 and 42 – Auditory cortex
Area 43 – Primary gustatory cortex
Area 44 – Pars opercularis, (Broca's area)
Area 45 – Pars triangularis, (Broca's area)
Area 46 – Dorsolateral prefrontal cortex
Area 47 – Pars orbitalis
Area 48 – Retrosubicular area
Area 49 – Parasubicular area in a rodent
Area 52 – Parainsular area

Wernicke's area is closely associated with the comprehension of both written language and speech
Broca's area is associated with speech production, as well as controlling facial neurons.

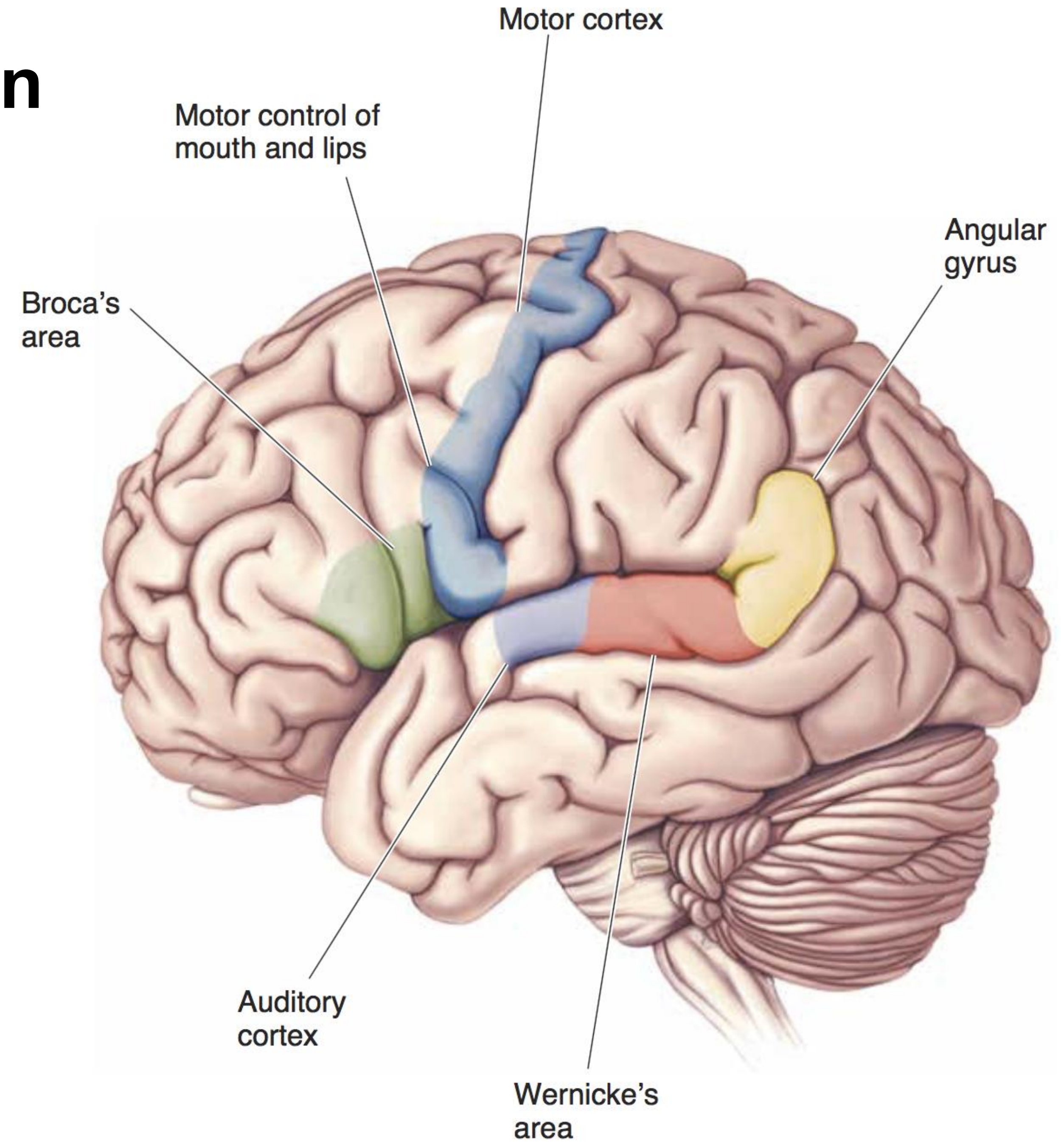
The language system in brain

In the frontal lobe, **Broca's area** lies next to the area that controls the mouth and lips in the motor cortex.

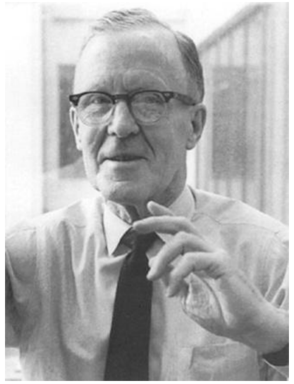
→ In Broca's Aphasia, patients have difficulty speaking, even though he or she can understand language heard or read.

Wernicke's area, on the superior surface of the temporal lobe, is situated between the auditory cortex and the angular gyrus.

→ In Wernicke's aphasia, speech is fluent, but **comprehension** is poor.



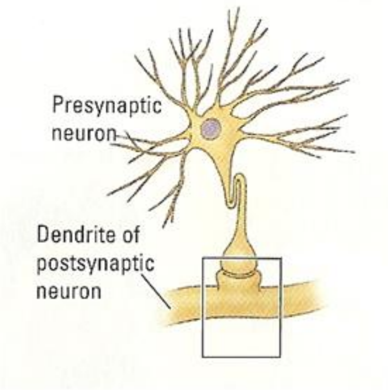
How does brain learn?
Hebbian learning & Other Learning Rules



D. O. Hebb

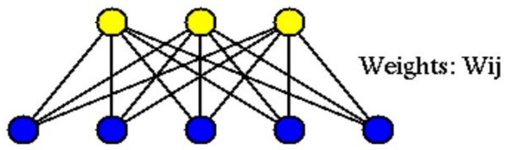
"When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased."

D. O. Hebb, *Organization of Behavior*, 1949



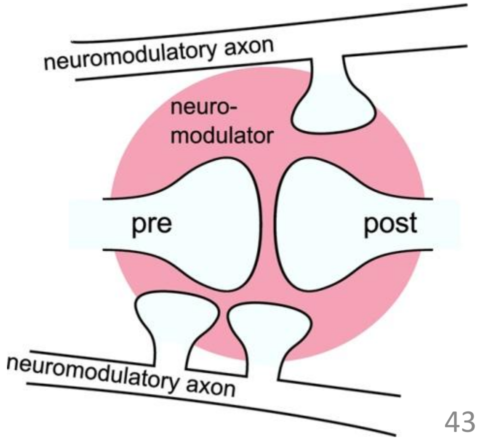
In other words: "**Cells that fire together wire together.**"

Mathematically, this is often written as: $\Delta w_{ij} = \varepsilon x_i x_j$



<u>More complex and sophisticated ideas</u> have been under continual exploration for over a half a century, including:

- Reward-modulated learning (reinforcement learning)
- Competitive learning
- Error correcting learning
- Spike-time dependent plasticity



Summary of Lecture 1

1. The purpose of models is not to fit the data but to sharpen the questions.
2. Some basic neuroimaging techniques
3. Levels: molecular, synapse, neurons, networks, maps, system, CNS
4. Neuron, action potential, Hodgkin-Huxley model
5. Dorsal ‘where’ pathway and ventral ‘what’ pathway
6. Topographic Maps at cortex
7. Marco organization of human brain (brain regions and their function)
8. Hebbian learning rule in brain

Please think about two Questions.

What we know about brain?

What we don’t know about brain?

Recommended materials

Reading materials

- From Neuron to Brain, ed5. Chapter 23 (Constructing Perception) Must read.

Online courses

Not obliged. Only for fun and curiosity.

- **Fundamentals of Neuroscience,** Harvard University, **Part 3: The Brain**
  https://www.bilibili.com/video/av41830186/?p=1
- **Human Mind and Brain**, MIT, by Prof Nancy Kanwisher
  https://www.bilibili.com/video/av24615914/?p=2