南方科技大学
SOUTHERN UNIVERSITY OF SCIENCE AND TECHNOLOGY

Brain Intelligence and Artificial Intelligence

人脑智能与机器智能

Lecture 1 - Introduction

Quanying Liu （刘泉影）

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NEURAL COMPUTING CONTROL

NCC Lab

Neural Computing & Control lab

神经计算与控制实验室（Neural Computing & Control Lab, NCC lab)

实验室负责人：刘泉影（现为 南方科技大学 生物医学工程系 助理教授)

团队成员：常驻科研人员20人，包括博士后(1)、博士生(6)、硕士生(8)、研究助理(5)

研究方向：

- 神经计算：用数学建模的方法，研究大脑神经信号表征与脑功能和行为的关系，理解大脑计算的方式
- 人工智能与人脑智能的融合：基于深度学习算法，对神经信号进行解码、推理、反馈；利用神经科学的理论，为AI算法提供新方向和生物可行性的支撑
- 脑影像处理：研发各种高通道脑电、立体脑电、脑影像处理技术，广泛应用于临床医学诊断
- 神经反馈控制：基于控制理论，优化神经反馈刺激的方式，对大脑进行刺激和调控，及其临床应用

神经计算与控制实验室(NCC lab)

Multi-modal neural data
- EEG
- SEEG
- fMRI
- sMRI

技术问题
Technology

科学问题
Science

Neural representation
- Vision / motor / language
- Decision making
- Multiple tasks
- Learning

Machine Learning
- Deep learning
- Probabilistic models
- Parameter estimation
- Matrix/tensor decomposition

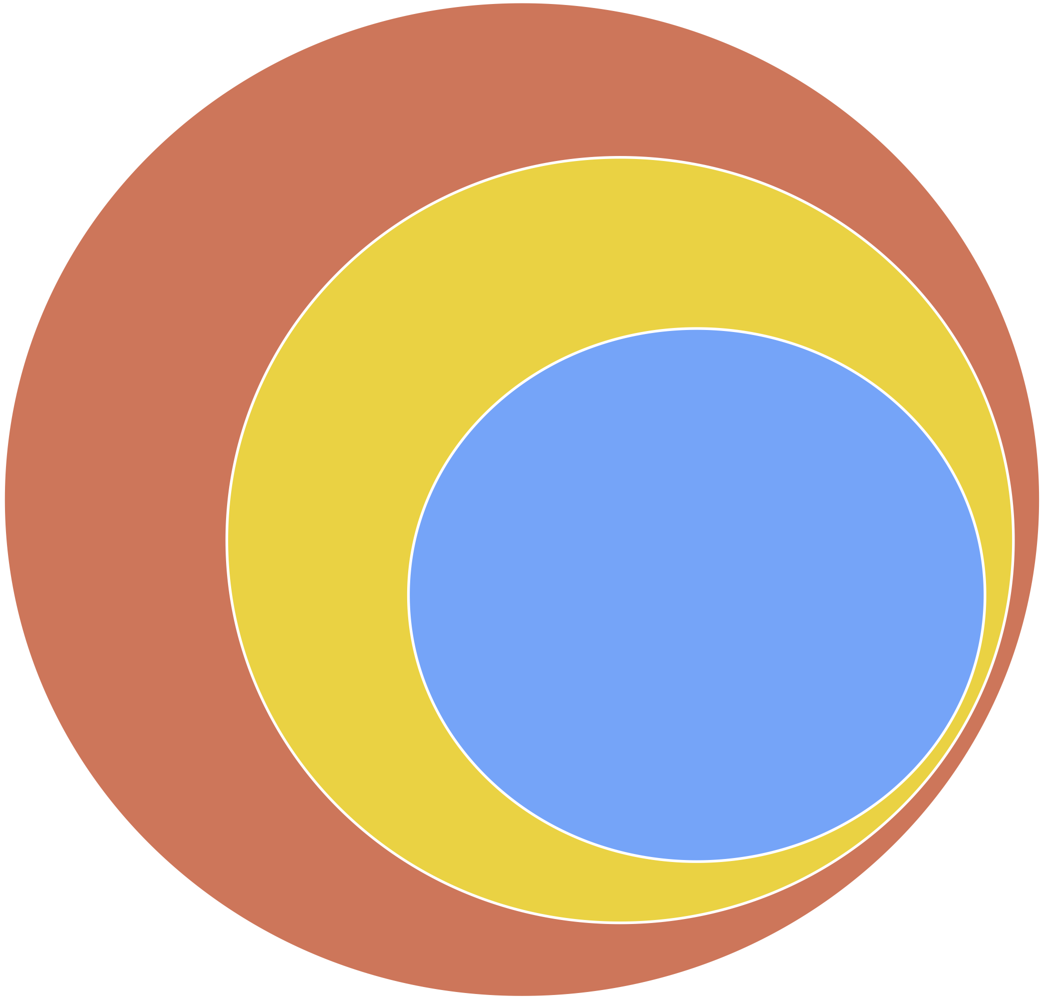
Control Theory
- Dynamical models
- State-space models
- Network control
- Optimal control

Structure / Function / Behavior
- Visual system
- Motor system
- Language system
- Normal vs Diseased

What is intelligence?

Sensing/Acting
Learning
Reasoning
Inferring
Decision making
…

Emotional
Social
Free will
Irrational
…



Artificial Intelligence
projects to build non-human intelligence

Machine Learning
machines that learn to be smarter

Deep Learning
particular kinds of machine learning

Goals of this course

- Learn the neural basis of brain intelligence (how brain generates intelligence)
    - visual system
    - auditory system
    - motor system
    - decision making
    - …
- Learn basic algorithms for artificial intelligence (how machine generates intelligence)
    - CNN
    - RNN
    - GAN
    - …
- Do a course project (to bridge BI and AI)
    - propose a project to solve a scientific/technical question
    - use some AI methods on your data
    - make a course presentation
    - **Poster Day** (present your posters in front of the 工学院南楼5楼)

Make friends.
Expand your knowledge.

Logistics

神经计算与控制实验室
NCC lab

- Class hours:
  - Monday, 19:00-20:50 (each week, 三教305)
  - Wendesday, 16:20-18:10 (odd weeks, 三教305)

NCC lab
微信公众号

- Lecturer: Quanying Liu (刘泉影)
  - My Office hours: Monday, 13:00-14:00, Engineering building South (工学院南楼) 541
  - Lunch hours: Please send an email to make an appointment for having lunch together.

- No textbook
- Extra reading (not necessary):
  - Computational Modelling of Cognition and Behavior, by Simon Farrell & Stephan Lewandowsky
  - Cognitive Neuroscience, by Michael S. Gazzaniga, Richard B. Ivry and George R. Mangun
  - Pattern Recognition and Machine Learning, by Christopher M. Bishop
  - Machine Learning: A Probabilistic Perspective, by Kevin P. Murphy
- Some reading materials will be recommended at the class.

Logistics

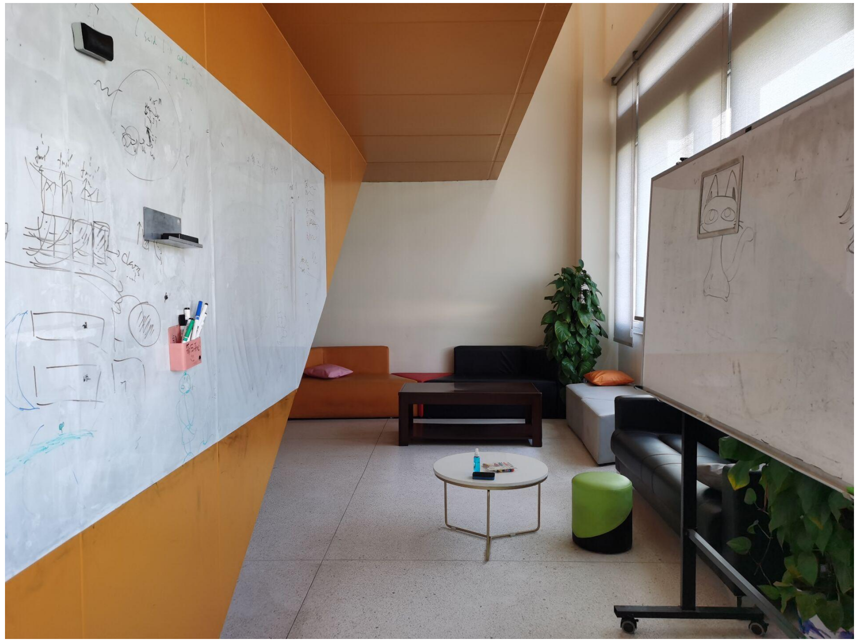
- TAs:
  - Jingwei Qiu (仇竞纬)
  - Junjie Yu (余俊杰)

- Scoring:
  - No exams!!!

  - **30%** Quiz + Discussions at the class
    - Please attend the class!
  - **30%** Paper reading and presentation (~8 weeks)
  - **40%** Course project (~10 weeks)
    - 10% proposal, 10% presentation, 10% poster

两位TAs答疑的地点

工学院南楼541外面的讨论区



提供咖啡，请自带杯子

You have coffee.

Do you have a mug?

Machine Learning & NeuroEngineering (ML&NE)

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

Deep learning

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

2021年

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

2022年

1 - Introduction to BI & AI
2 - Visual system
3 - Auditory system
4 - CNN hands-on
5 - GD & error backpropagation
6 - What does AI/brain learn
7 - Brain Network and Control
8 - NODE & fMRI hands-on
9 - EEG data analysis
10 - somatosensory system
11 - motor system 1
12 - motor system 2
13 - emotion
14 - language
15 - sleep & dreaming
16 - Data for deep learning
17 - RNN & hands-on
18 - Generative models for neuroscience

What does BI&AI BME5012 provide?

For those who have attended ML&NE,
BI&AI will be *less technical* and *more scientific*, as it is a graduate-level course.

For those who have neuroscience/biology background,
BI&AI will offer you *new tools* to analyze your data, and sharpen your research questions.

For those who have pure ML/AI background,
BI&AI will guide you to **the history & the future of** *AI in lights of BI*.

Any questions so far?

Artificial Intelligence

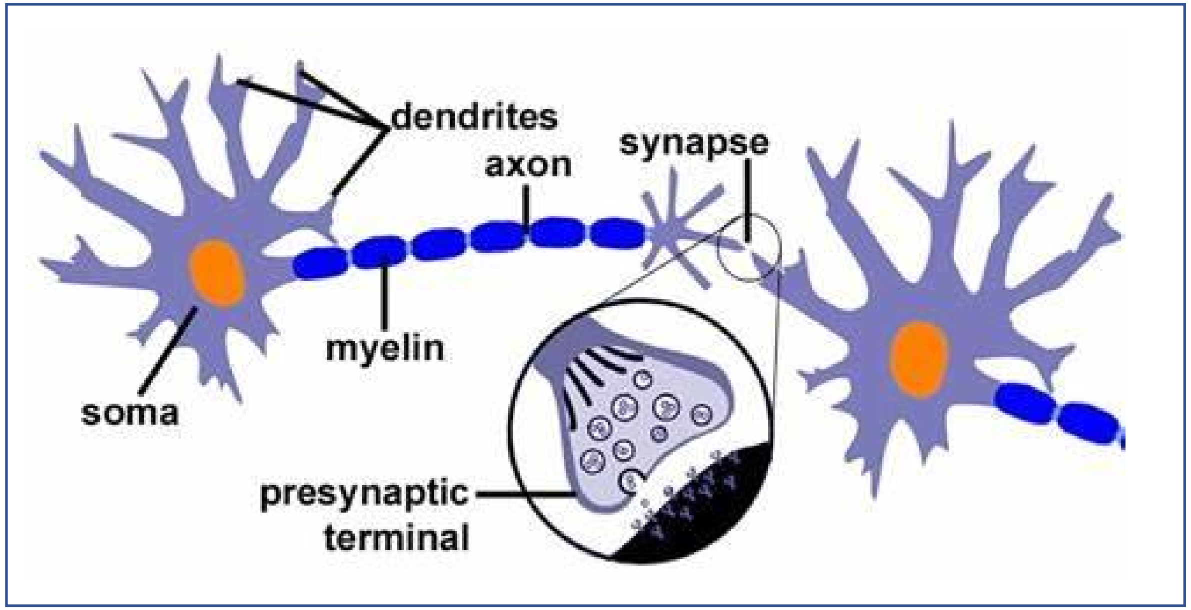
BI inspires AI.

AI helps understand BI.

Brain Intelligence

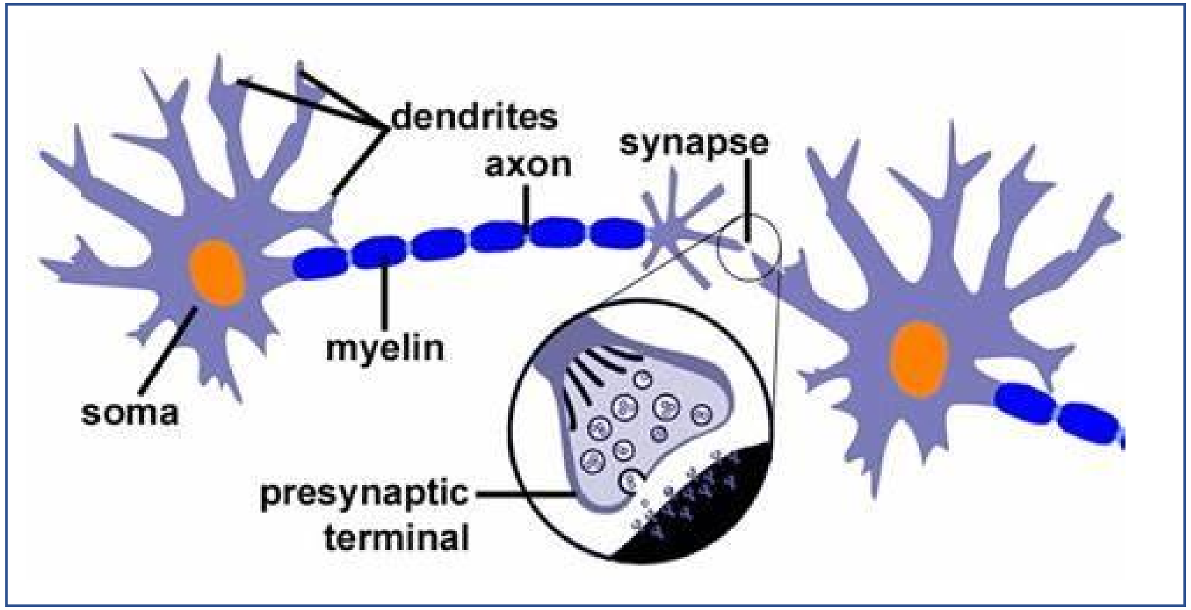
BI inspires AI

Biological Neuron

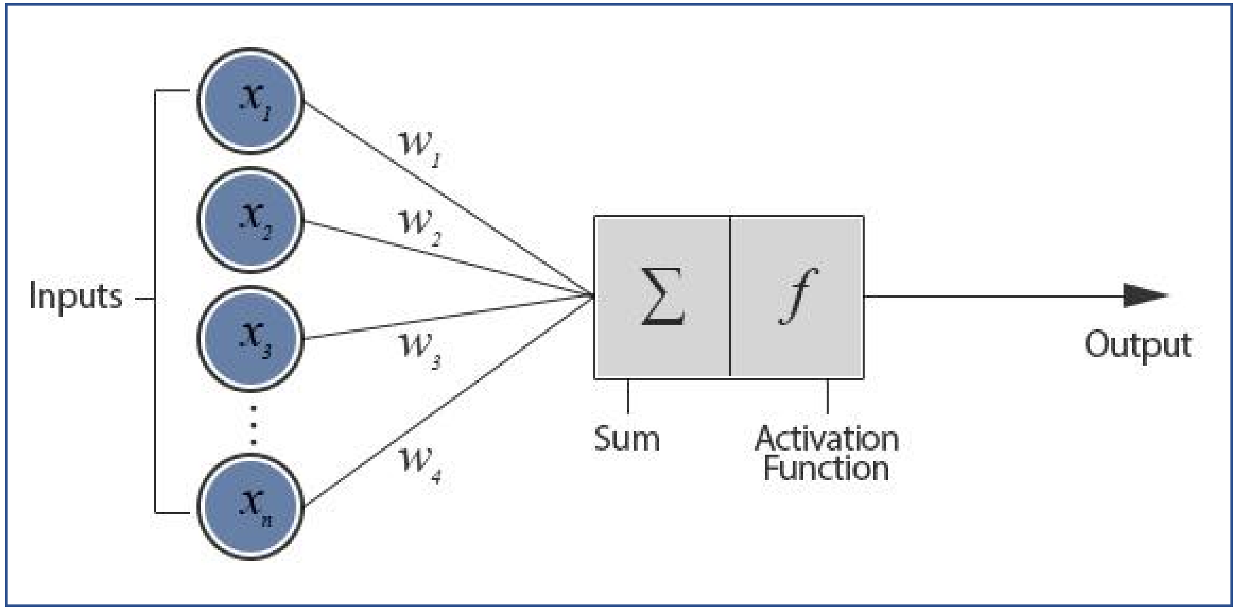


BI inspires AI

Biological Neuron

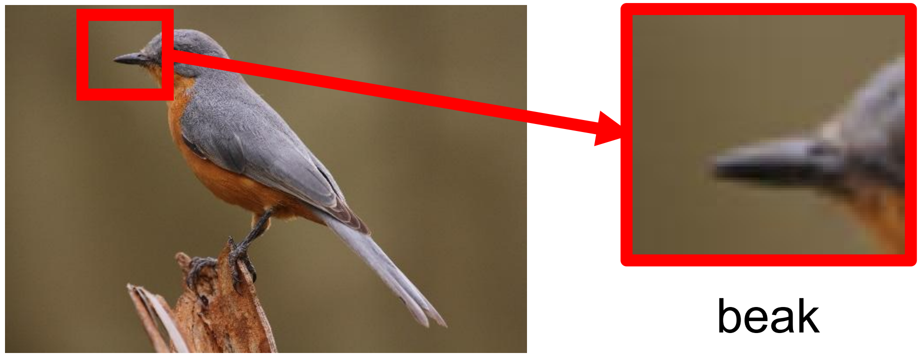


Artificial Neuron



Warren S. McCulloch and Walter Pitts (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*

BI inspires AI



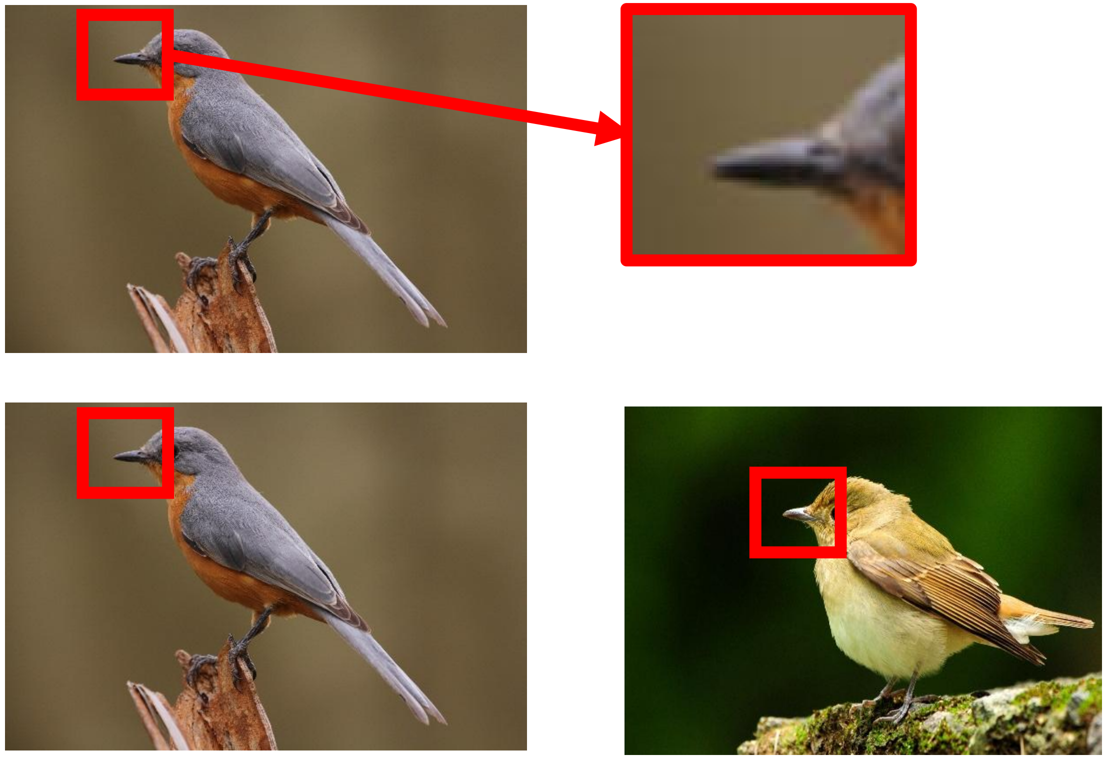
The way our brain process images

1. **Local receptive fields**

Some patterns are much smaller than the whole image.

A neuron does not have to see the whole image to discover the pattern.

BI inspires AI



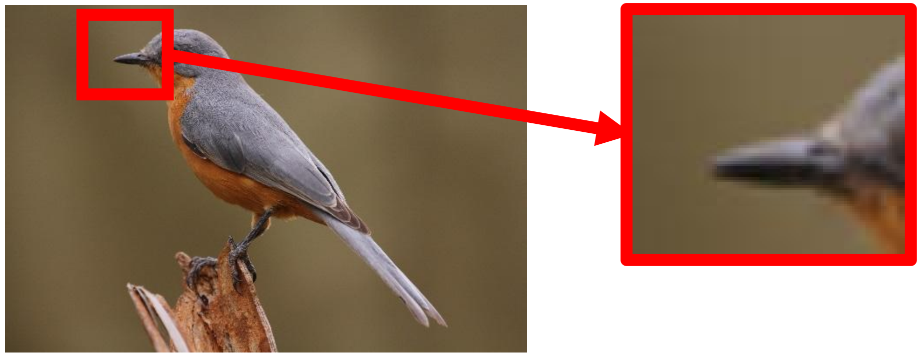
The same patterns appear in different regions.

They can use the same set of parameters.

The way our brain process images

1. Local receptive fields
2. **Shared weights**

BI inspires AI

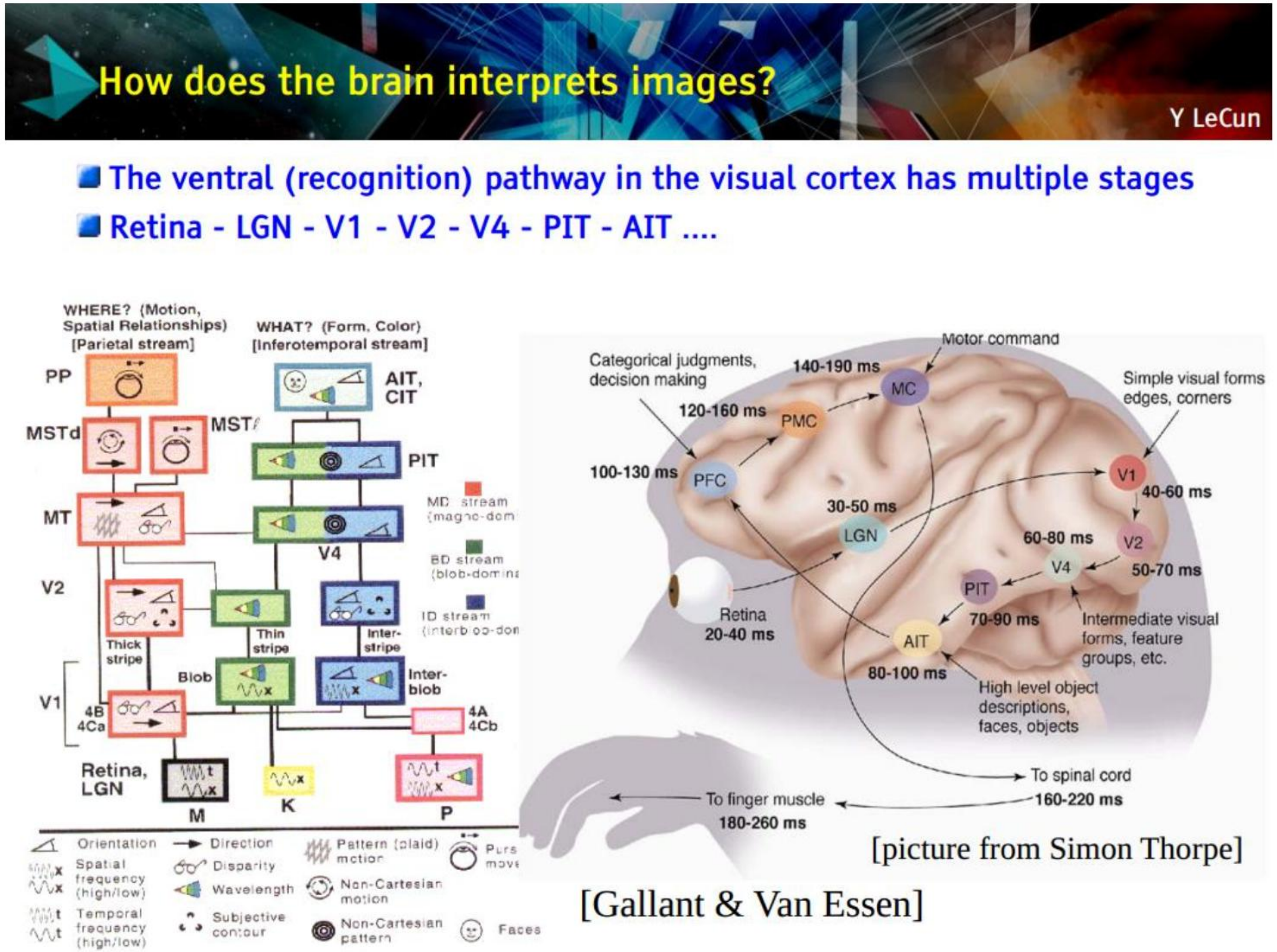


The way our brain process images

1. Local receptive fields
2. Shared weights
3. **Sub-sampling**

Subsampling the pixels will not change the object.

BI inspires AI



The way our brain process images inspire convolutional neural network (CNN)

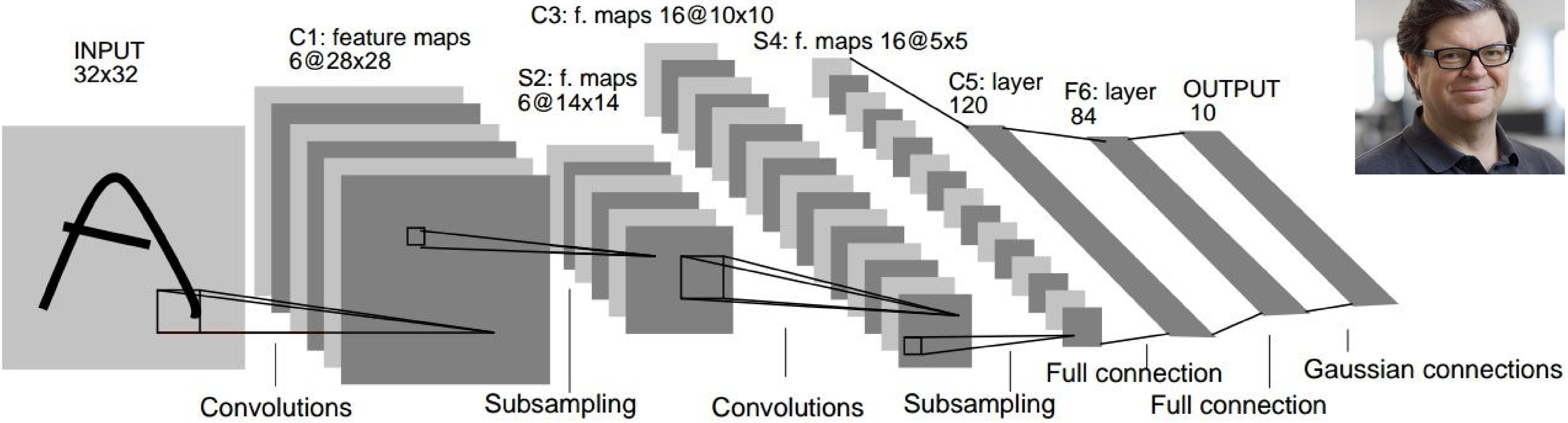
1. Local receptive fields
2. Shared weights
3. Sub-sampling
4. **Layered architecture**

BI inspires AI

The way our brain process images inspire convolutional neural network (CNN)

1. Local receptive fields
2. Shared weights
3. Sub-sampling
4. Layered architecture

LeNet-5



Lecun Y, Bottou L, Bengio Y, et al. (1998) Gradient-based learning applied to document recognition.

READ the CODE of LeNet-5

https://github.com/ganyc717/LeNet

Implement the LeNet using tensorflow to recognize handwritten number. Training with MNIST.

Some modifications here:

- Training with MNIST set with image size 28 * 28. To match the size of LeNet, the first convolution layer applied padding.
- Using Relu instead of Sigmod as activation function.
- Applied dropout in the FC layer.
- This net can get 99.1% correct rate on MNIST test set.

Lecun Y, Bottou L, Bengio Y, et al. (1998) Gradient-based learning applied to document recognition.

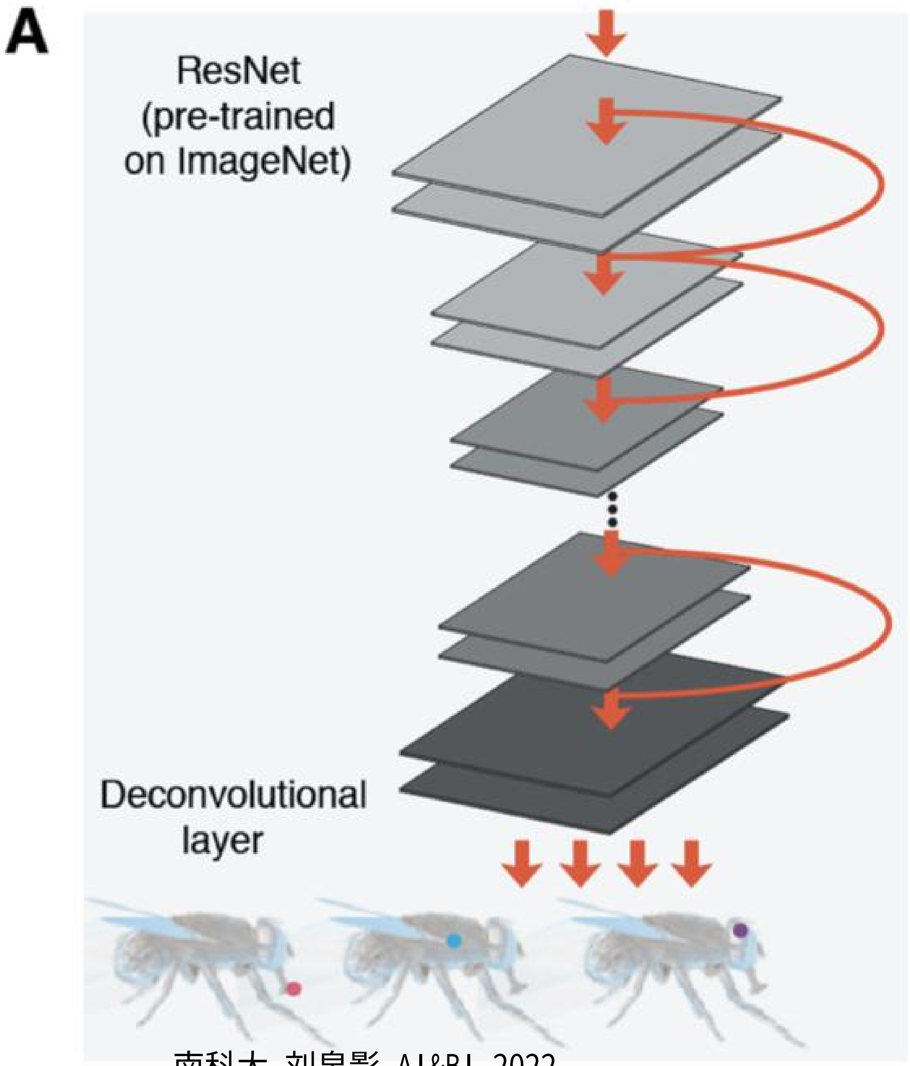
Artificial Intelligence

BI inspires AI.

AI helps understand BI.

Brain Intelligence

AI helps understand BI



AI as a tool to analyze neural / behavioral data.

ANNs can serve as image processing tools for efficient pose estimation.

A. Mathis, P. Mamidanna, K. M. Cury, T. Abe, V. N. Murthy, M. W. Mathis, and M. Bethge (2018). **Deeplabcut**: markerless pose estimation of user-defined body parts with deep learning. Technical report

T. Nath, A. Mathis, A. C. Chen, A. Patel, M. Bethge, and M. W. Mathis. (2019). Using **deeplabcut** for 3d markerless pose estimation across species and behaviors. *Nature protocols*

AI as a tool to analyze neural / behavioral data

External World (stimuli)

An AI to encode (simulate) neural signals?

80 billions of neurons in human brain

Another AI to decode neural signals?

Senses
Action (behavior)
Emotion
Cognition

What is the problem of AI 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 AI shall not only analyze the data, but also provide insights to **explain the underlying mechanisms** of how brain works.

AI helps understand BI

AI helps explain the computational benefit or necessity of observed brain structures or functions.

AI helps understand BI

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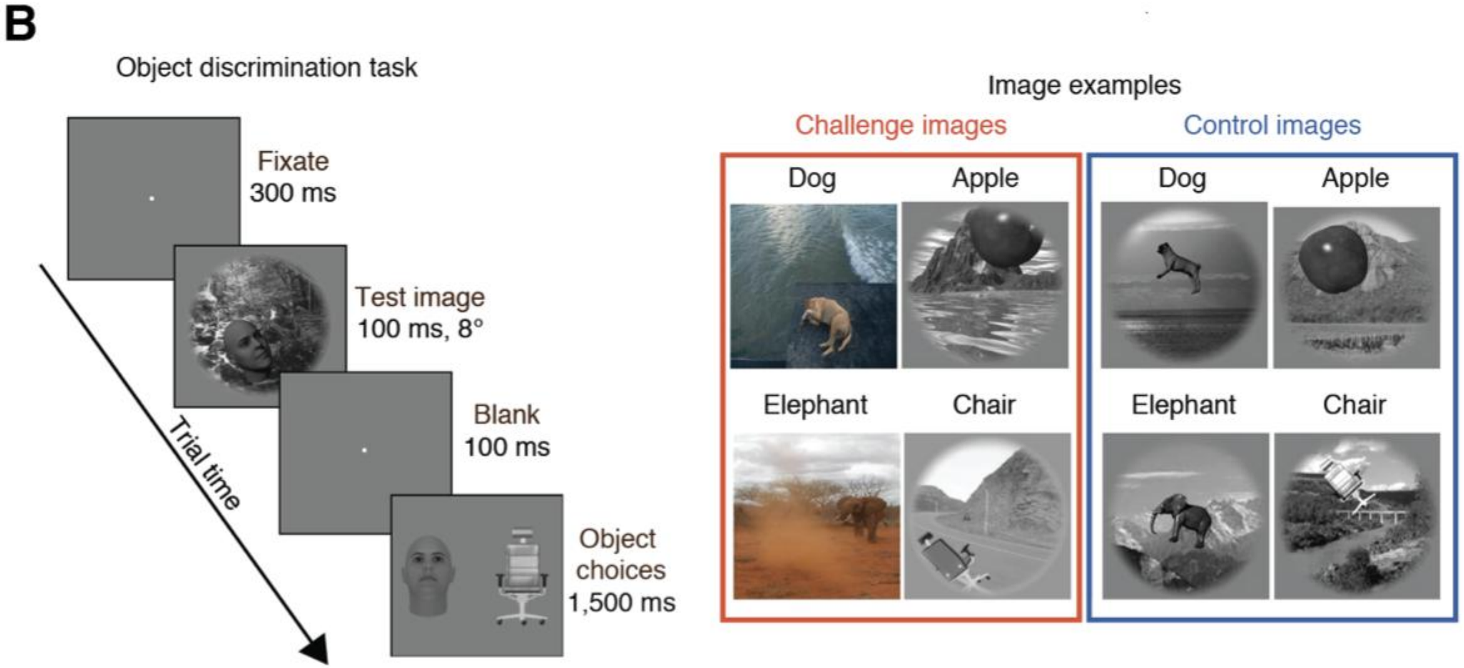

Train both **monkey** and **ANNs** to perform object discrimination tasks involving challenging naturalistic visual objects.

K. Kar, J. Kubilius, K. Schmidt, E. B. Issa, and J. J. DiCarlo. (2019) Evidence that recurrent circuits are critical to the ventral stream's execution of core object recognition behavior. *Nature neuroscience*

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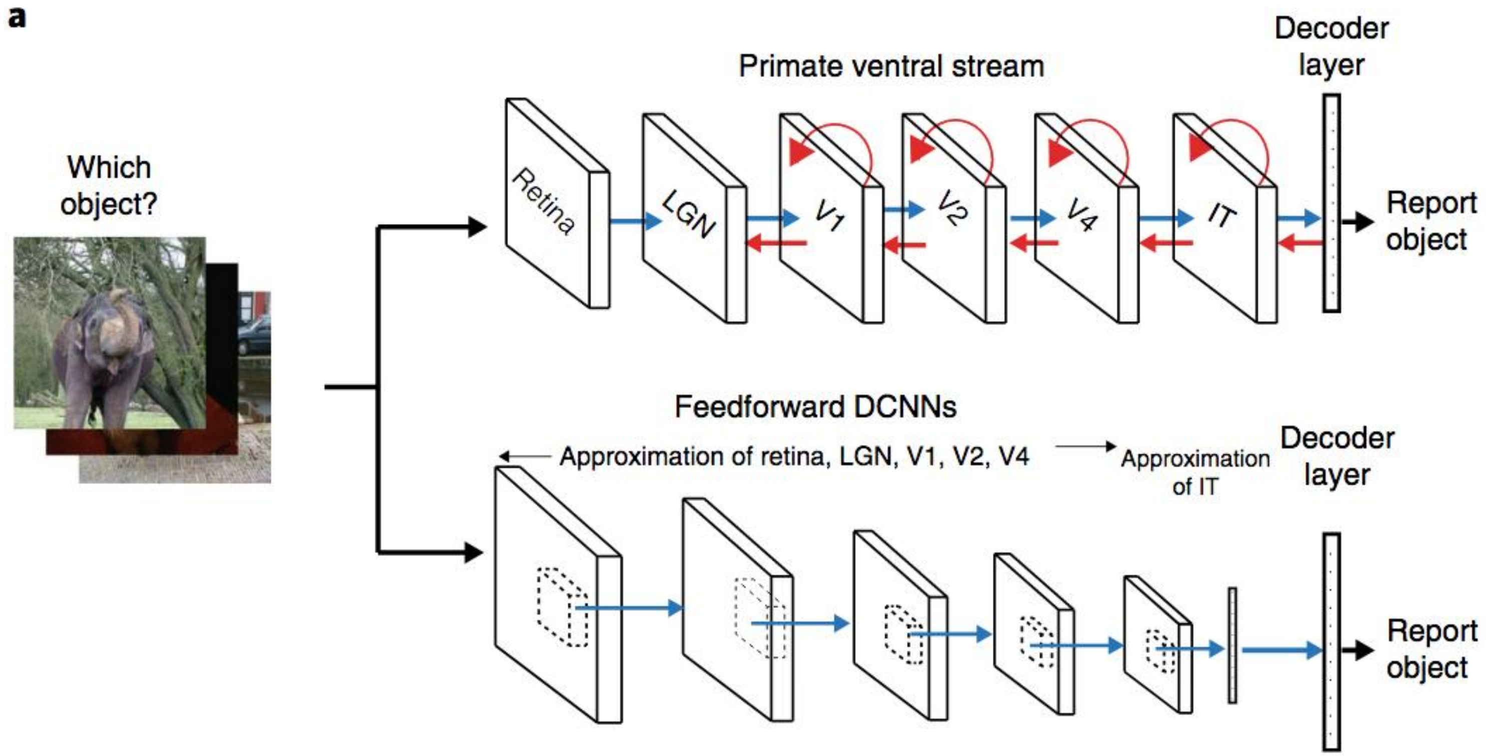

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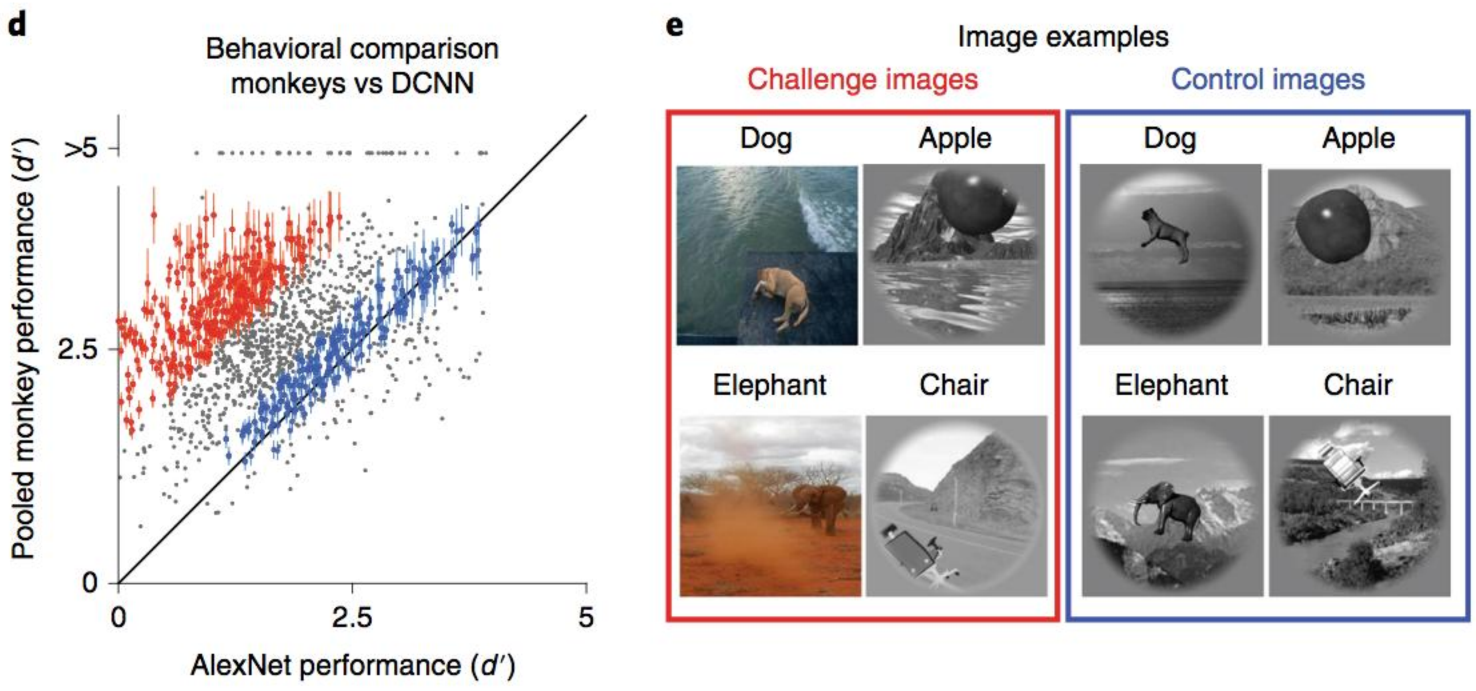


Train both **human** and **ANNs** to perform <u>object discrimination tasks</u> involving challenging naturalistic visual objects.

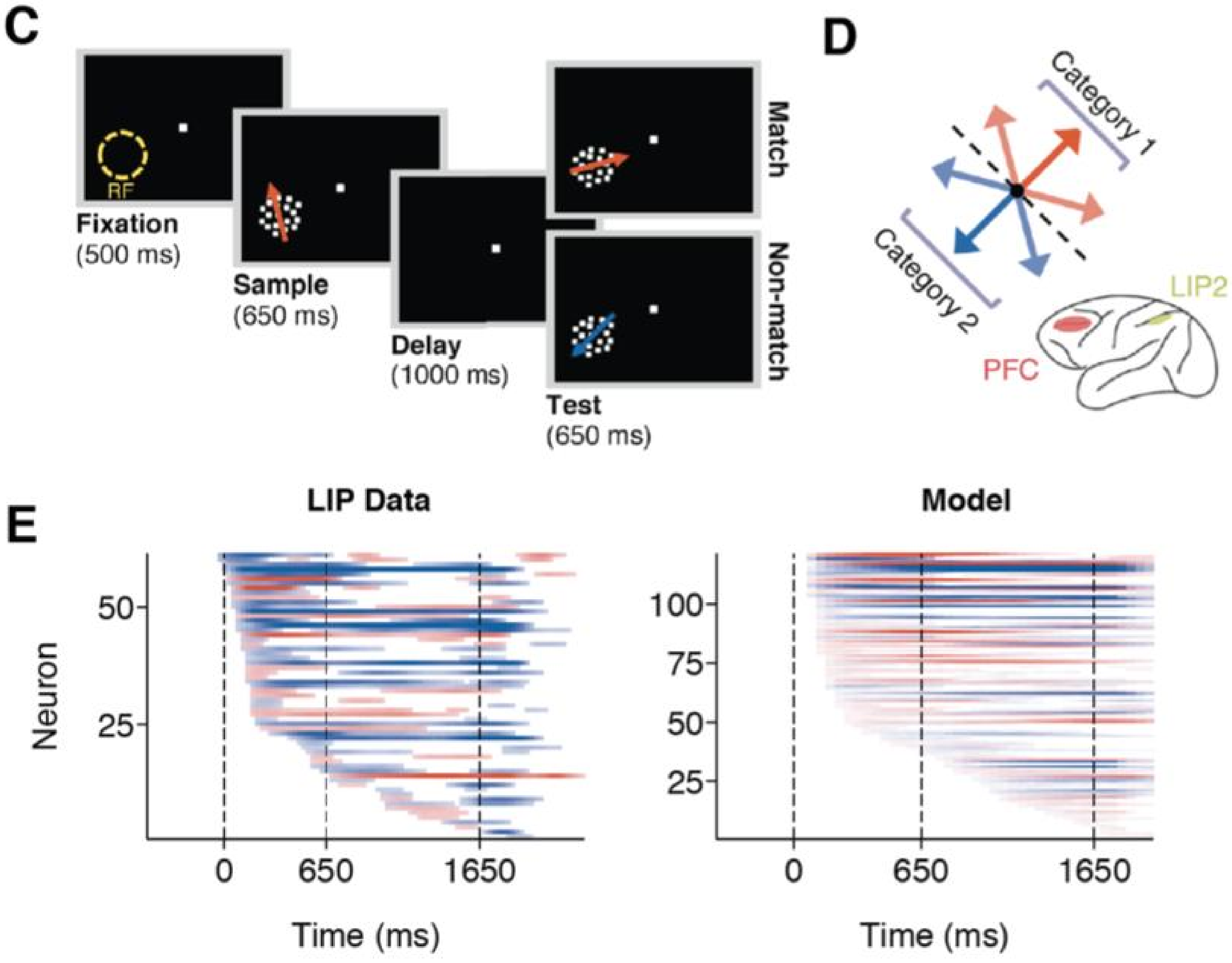
Results: Compared to purely feedforward networks, <u>recurrently-connected deep networks</u> are better at predicting responses of higher visual area neurons to behaviorally challenging images.

K. Kar, J. Kubilius, K. Schmidt, E. B. Issa, and J. J. DiCarlo. (2019) Evidence that recurrent circuits are critical to the ventral stream's execution of core object recognition behavior. *Nature neuroscience*

AI helps understand BI

AI helps explain the wide diversity of activity patterns in neural populations.

AI helps understand BI

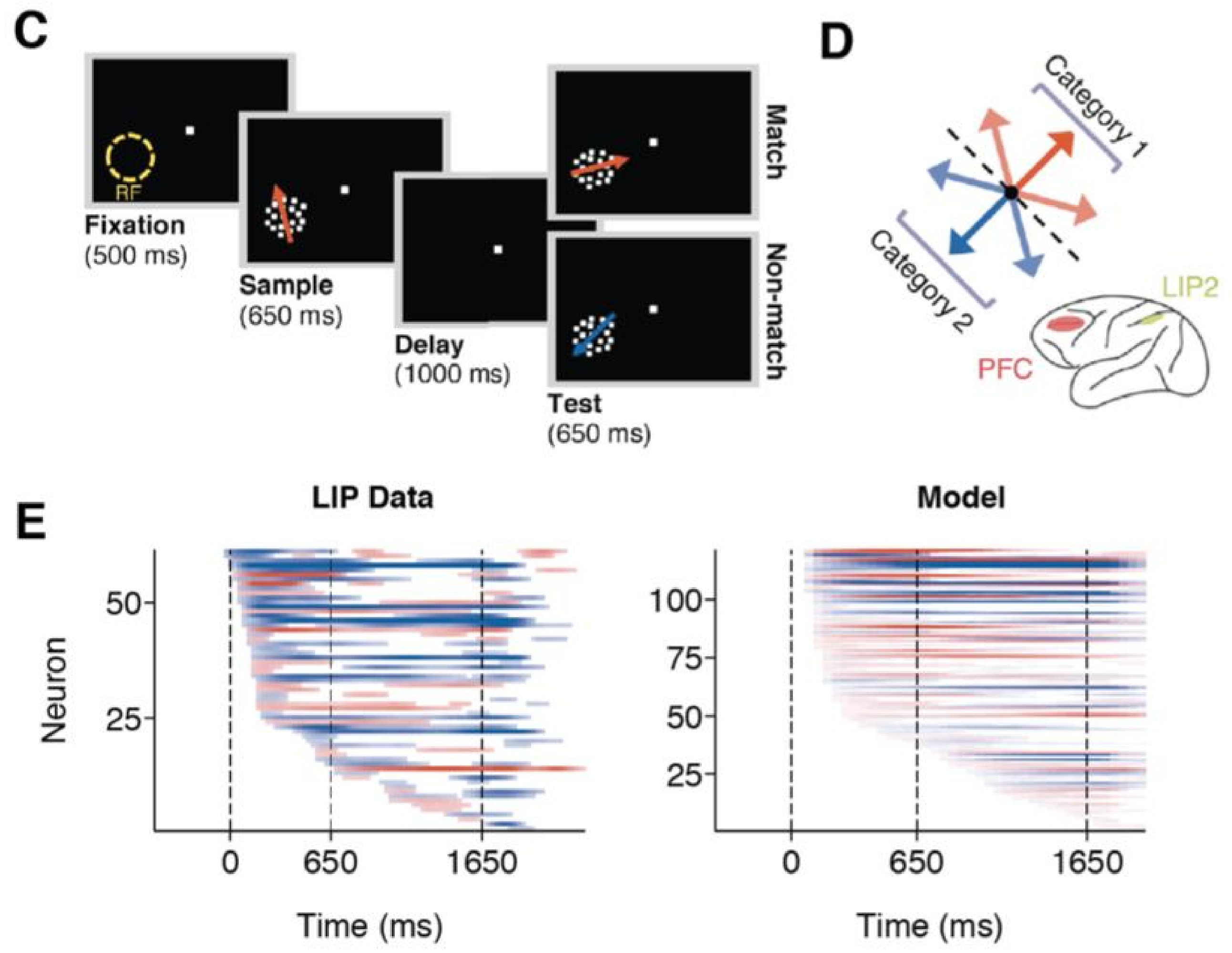


AI helps explain the wide diversity of activity patterns in neural populations.

Train both **monkey** and **RNN** to perform a delayed-match-to-category task.

D. J. Freedman and J. A. Assad (2006). Experience-dependent representation of visual categories in parietal cortex. *Nature*

AI helps understand BI



AI helps explain the wide diversity of activity patterns in neural populations.

Train both **monkey** and **RNN** to perform a delayed-match-to-category task.

Results: The onset time of biological neurons in Lateral IntraParietal (LIP) area are **similarly** to the artificial neurons of the RNN model.

D. J. Freedman and J. A. Assad (2006). Experience-dependent representation of visual categories in parietal cortex. *Nature*

Questions:

Are there resemblance between BI and AI?

If so, <u>to what extent</u> they are resemble?

The Marr's three levels of explanation:

top

Level 1: *Computation theory* (objective)

- What is the problem to be solved?
- What are the inputs and outputs to the computation?
- What is the goal, and what is the logic by which it is carried out?

Level 2: Algorithmics (software)

- How is the information represented and processed to achieve the computational goal?

Level 3: Implementation (hardware)

- How is the computation realized in physical or biological hardware?

bottom

Q：To what extent they are resemble?

采用Bottom-up 思维

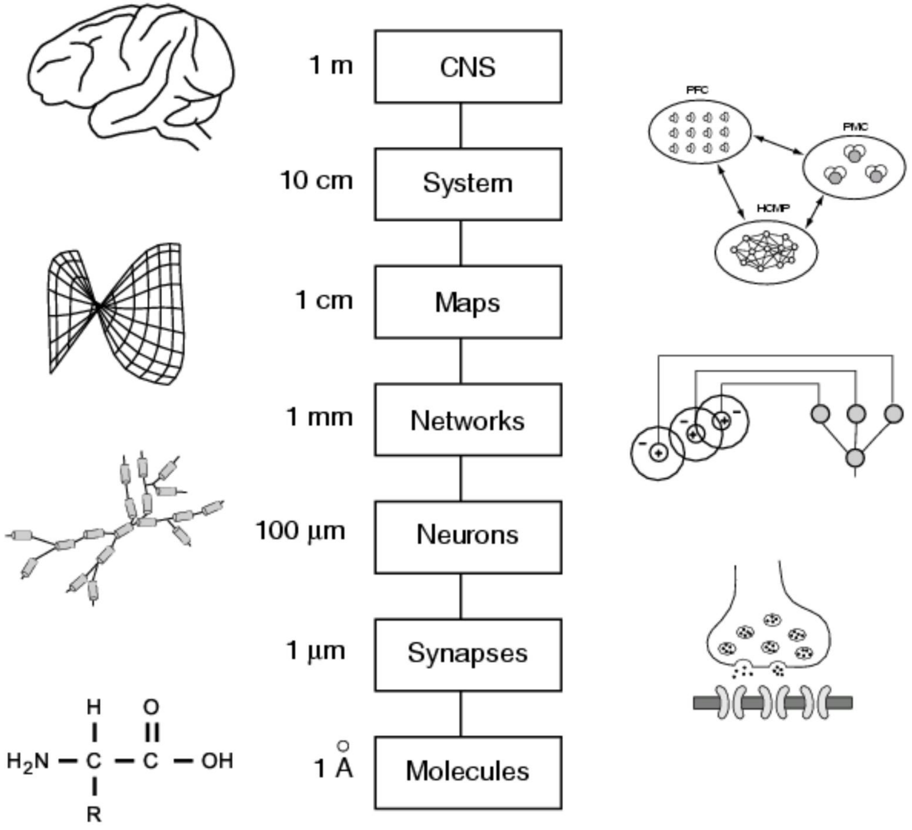
(hardware) 组成单元相似：都有神经元（生物神经元或人工神经元）

(algorithm) 信息表征相似：都有层级结构（信息逐层表征、计算和传播）

(objective) 功能相似：都能做同样的任务（例如，目标检测、物体识别）

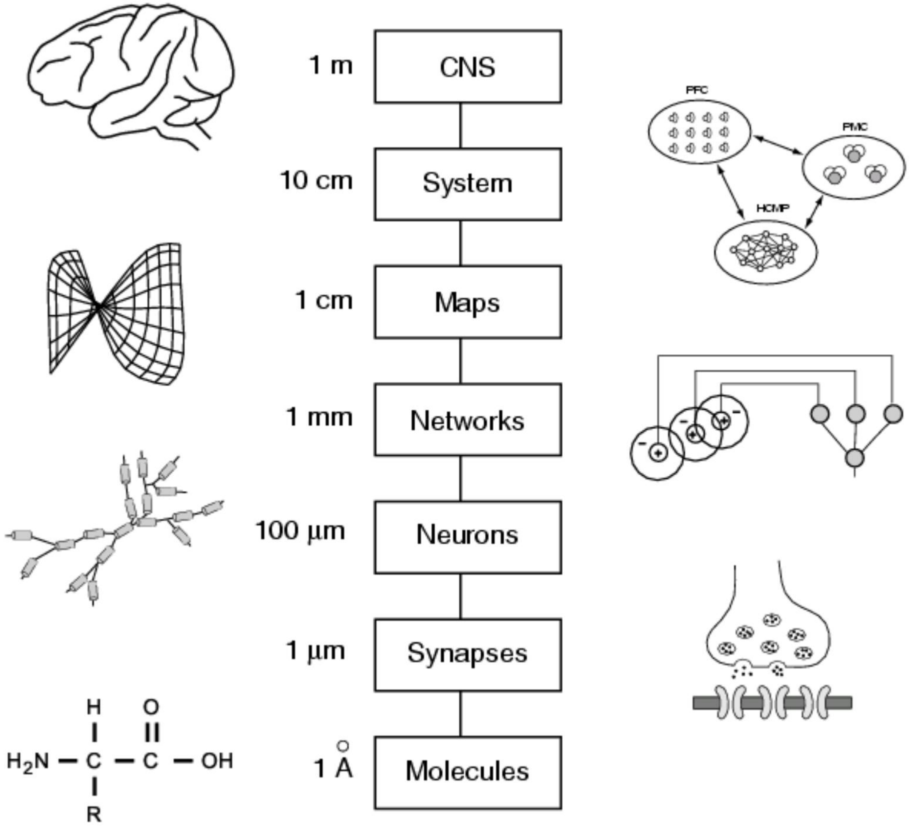
Multiple levels to investigate the brain

Different levels

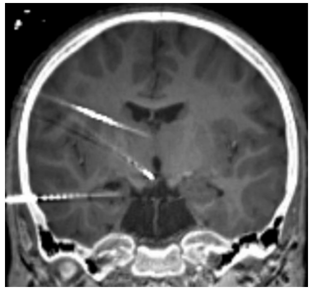


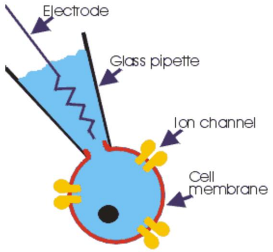
Techniques to see what is happening in the brain

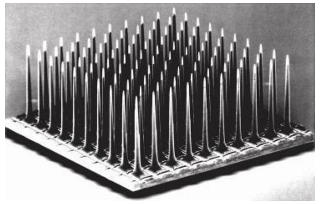
Different levels

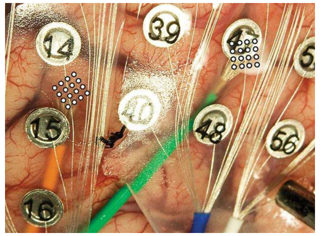


- MRI, fMRI
- EEG, MEG
- SEEG
- ECoG
- Local field potential (extracellular)
- Utah Array
- Patch clamp (intracellular recording)

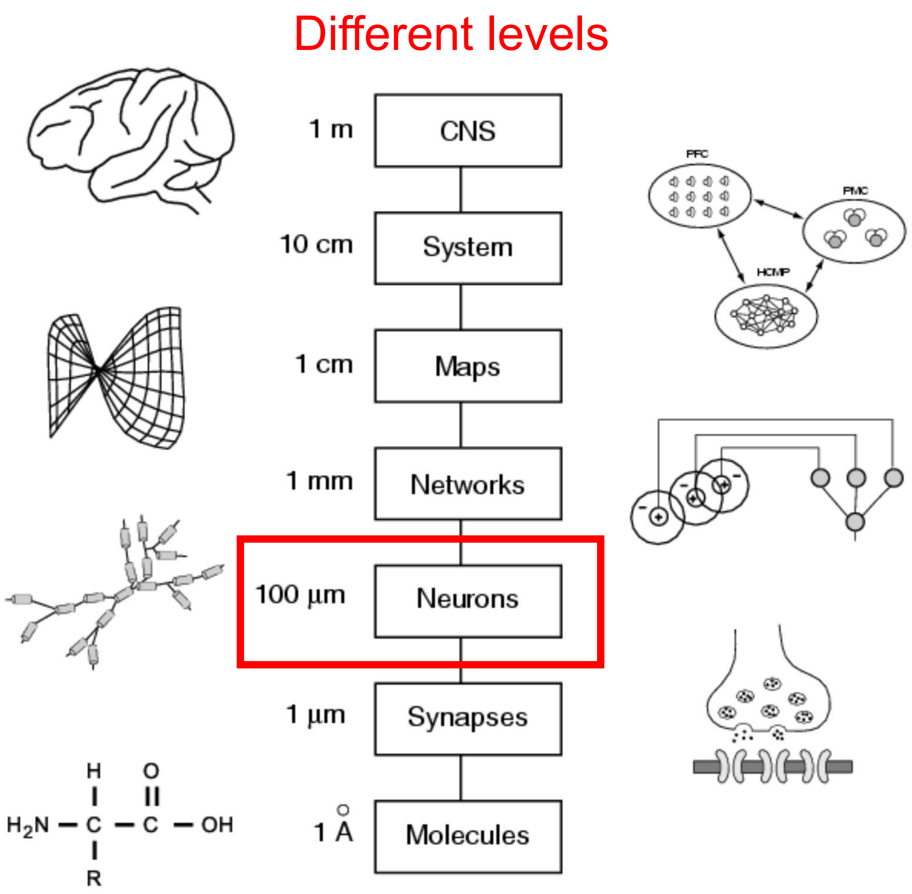


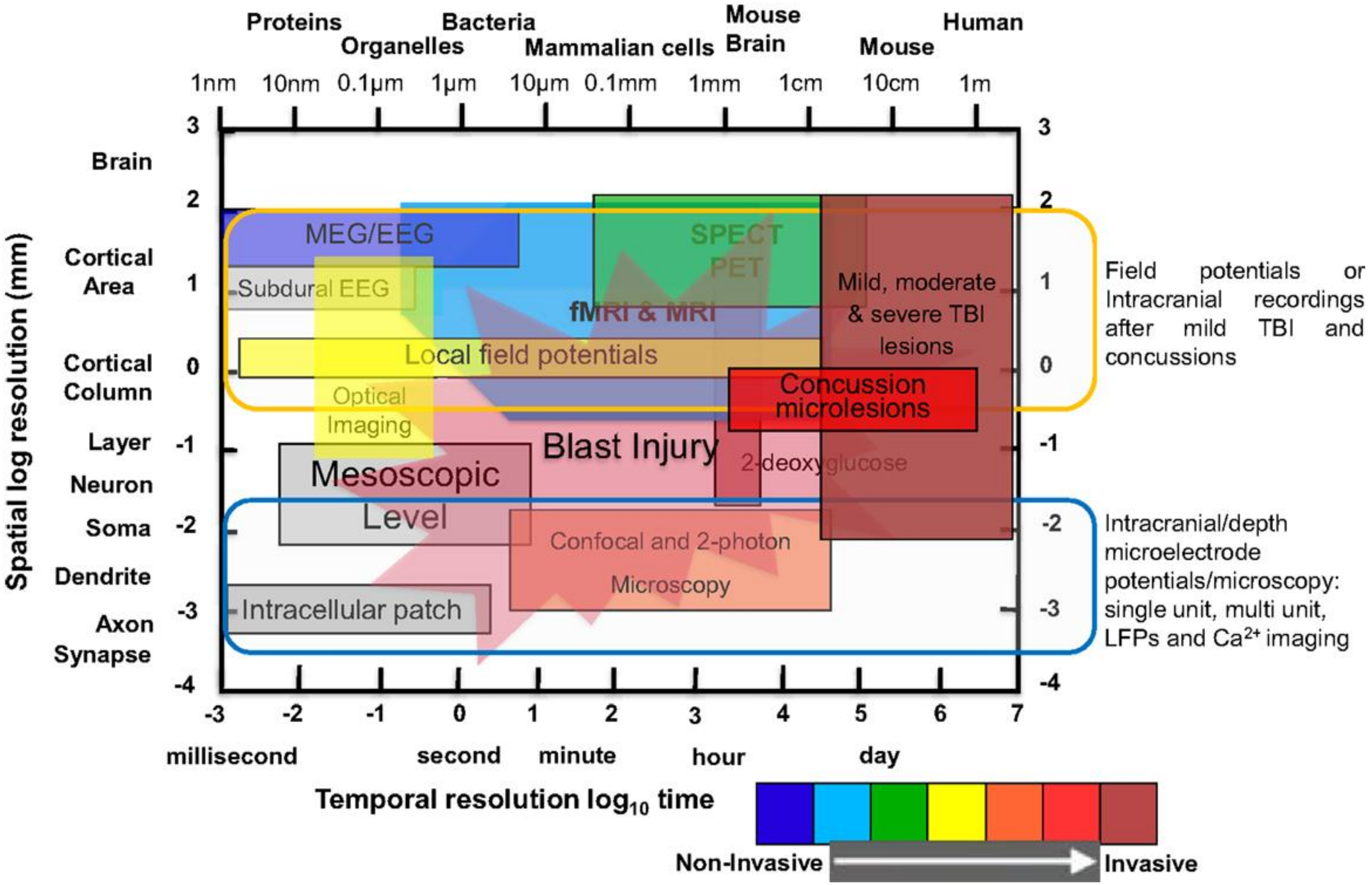






Techniques: Temporal resolution and Spatial resolution



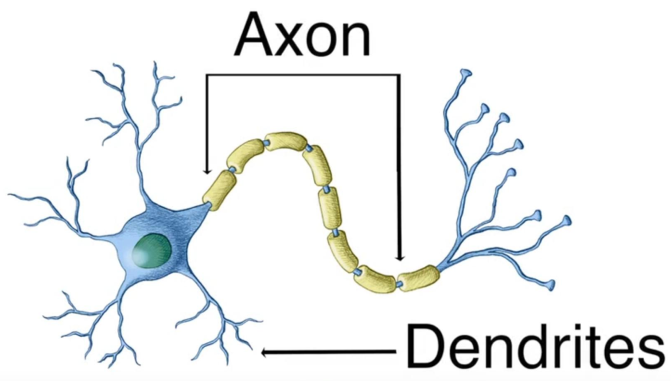


南科大-刘泉影-AI&BI 2022

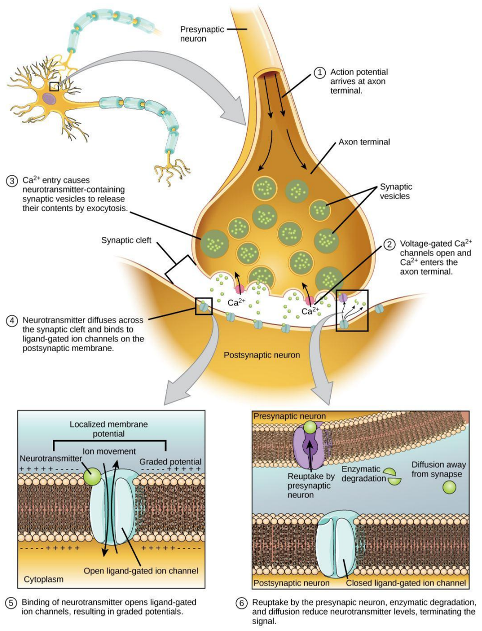
Manoj Kumar Jaiswal, Front Neurol 2015

Neuron and Action potential

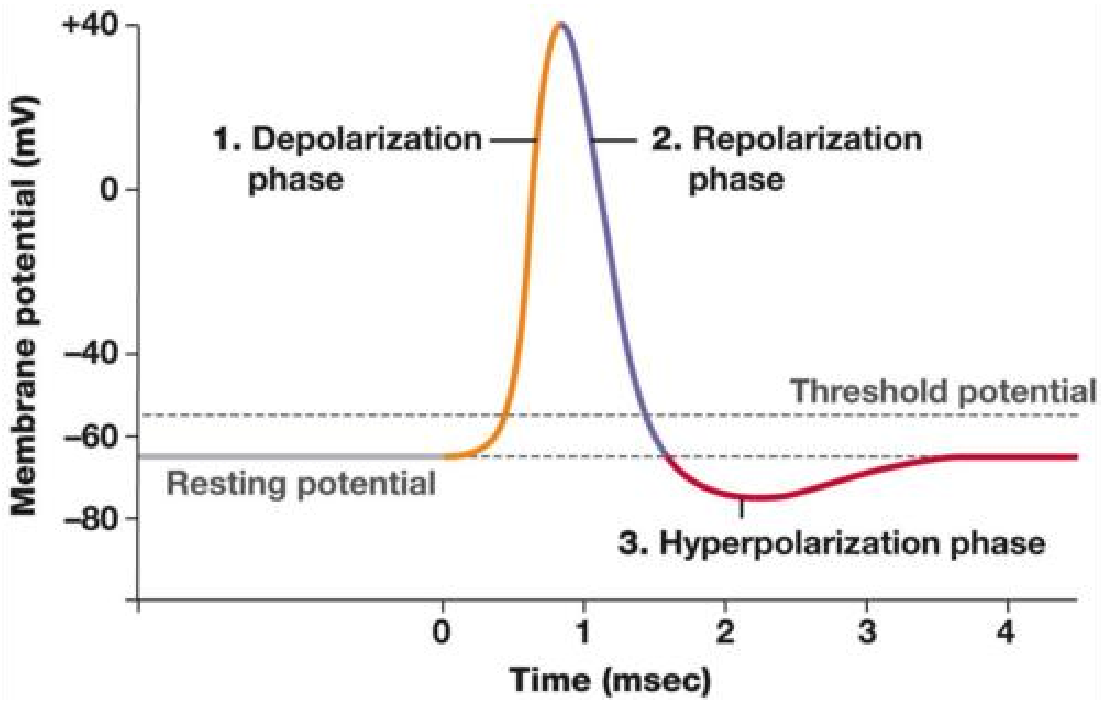
Neuron



Synapse



Action potential (spike)

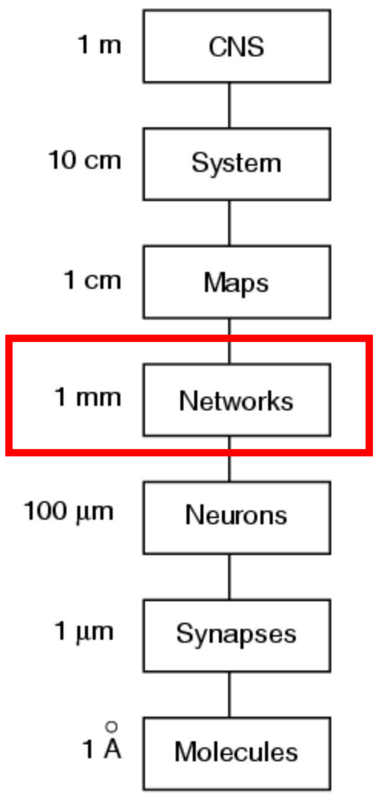


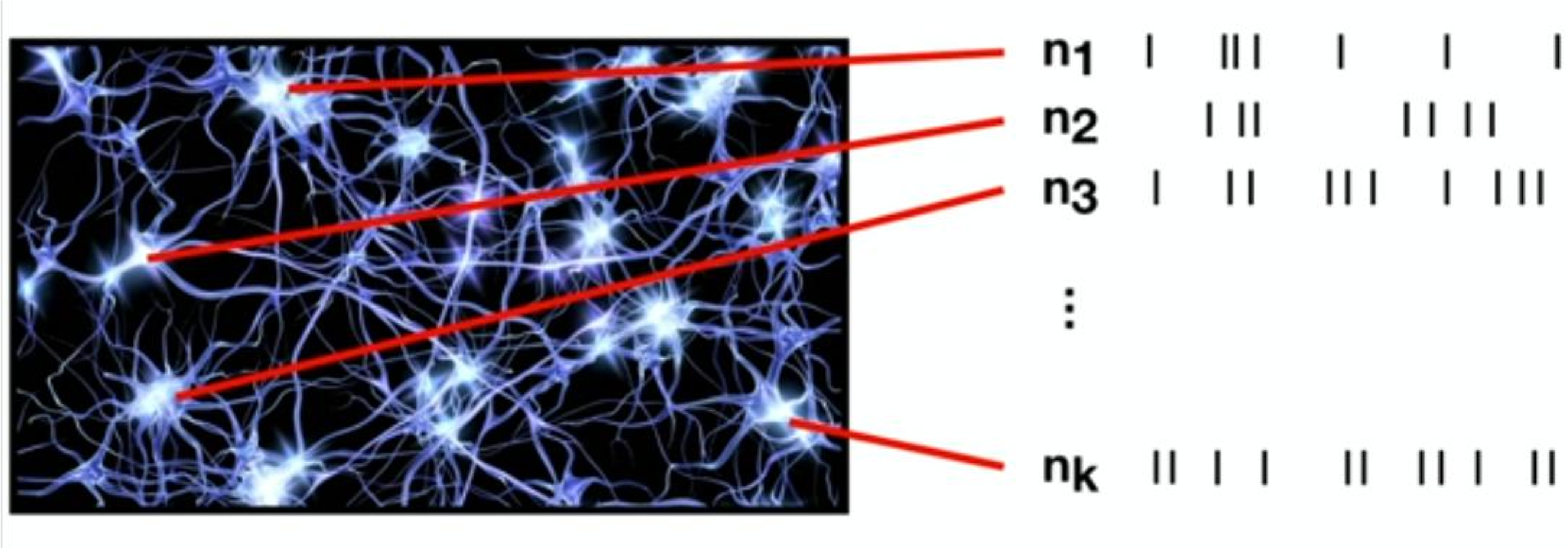
binary code: 0 1 0 0 0

Cell Membrane

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

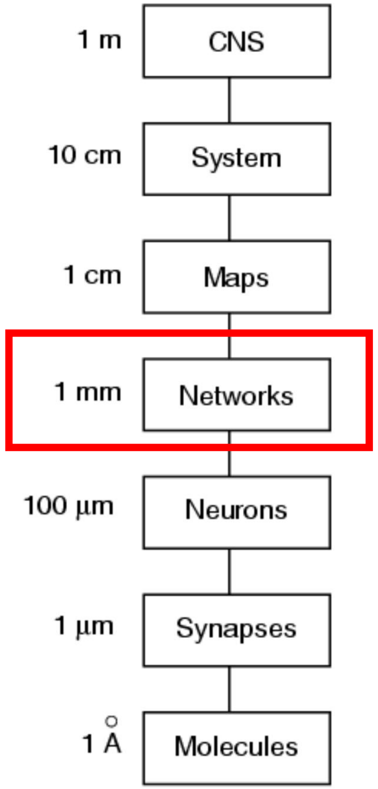
Biological neural network

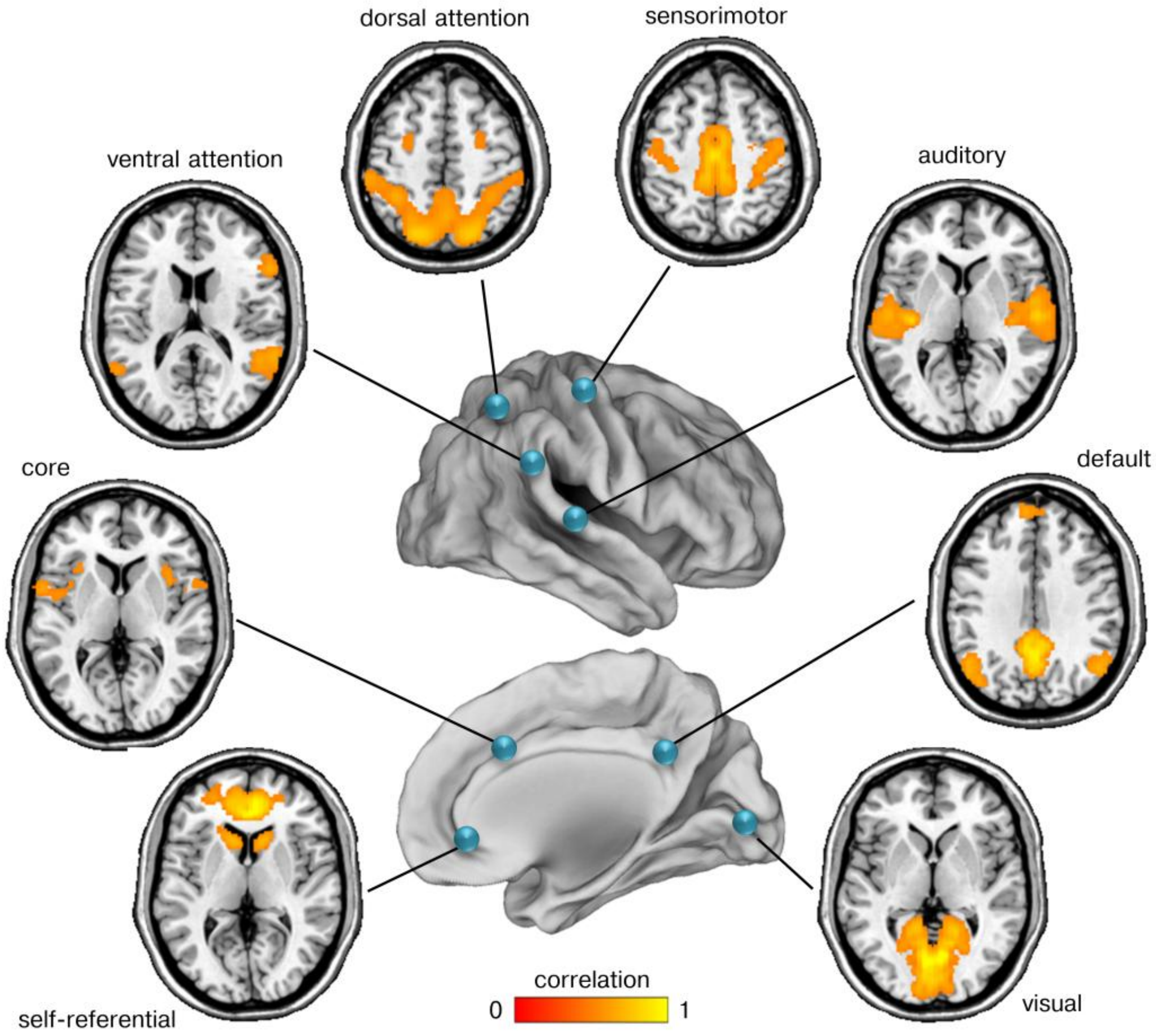




Biological neural network ⟺ Artificial neural network

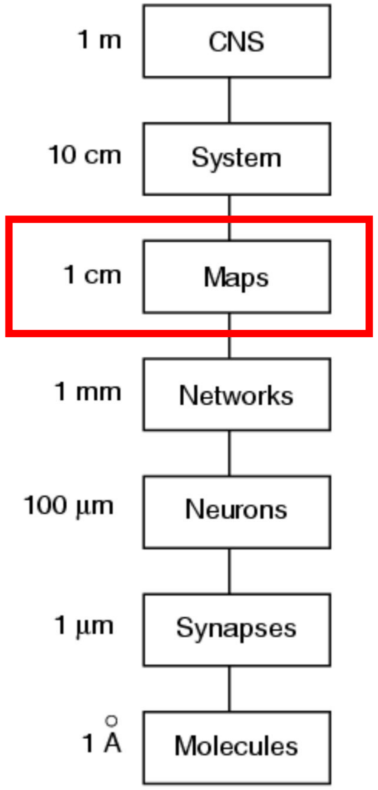
Brain functional networks



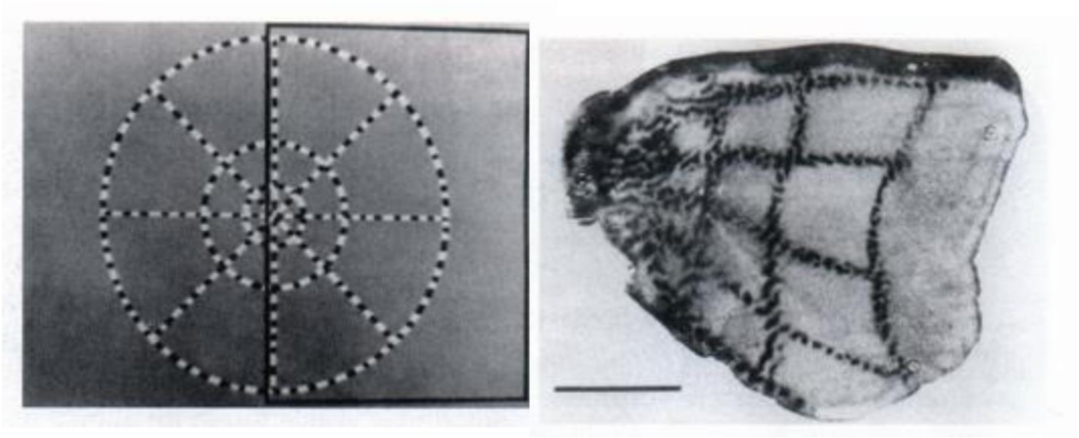


Gillebert and Mantini, *The Neuroscientist* 2013

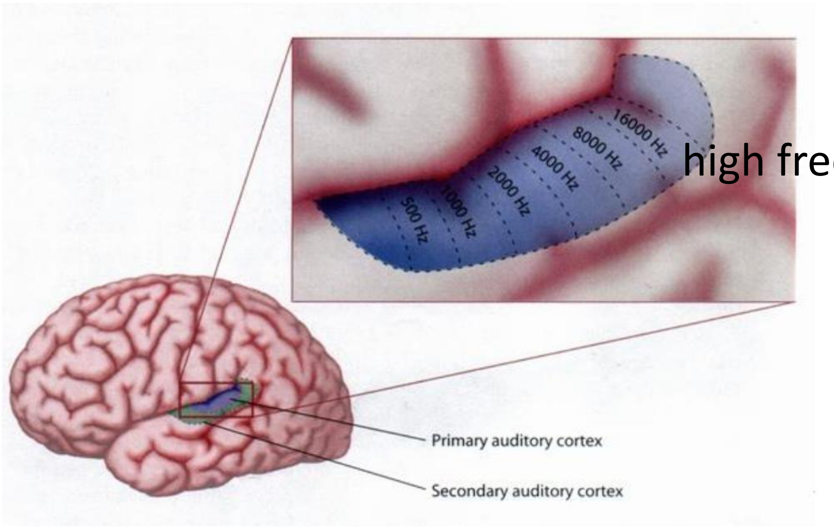
Topographic Maps



Retinotopic map

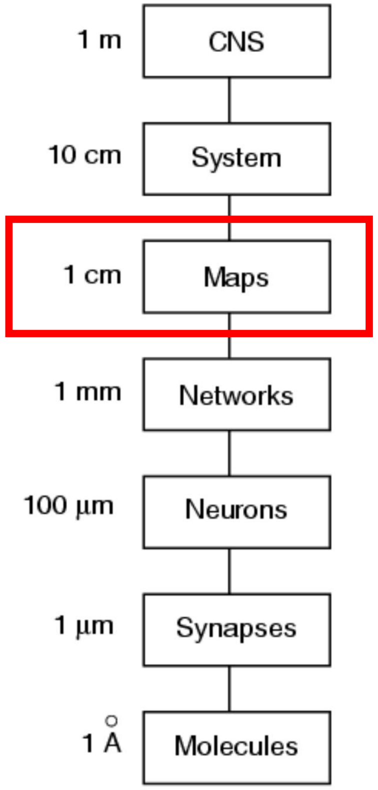


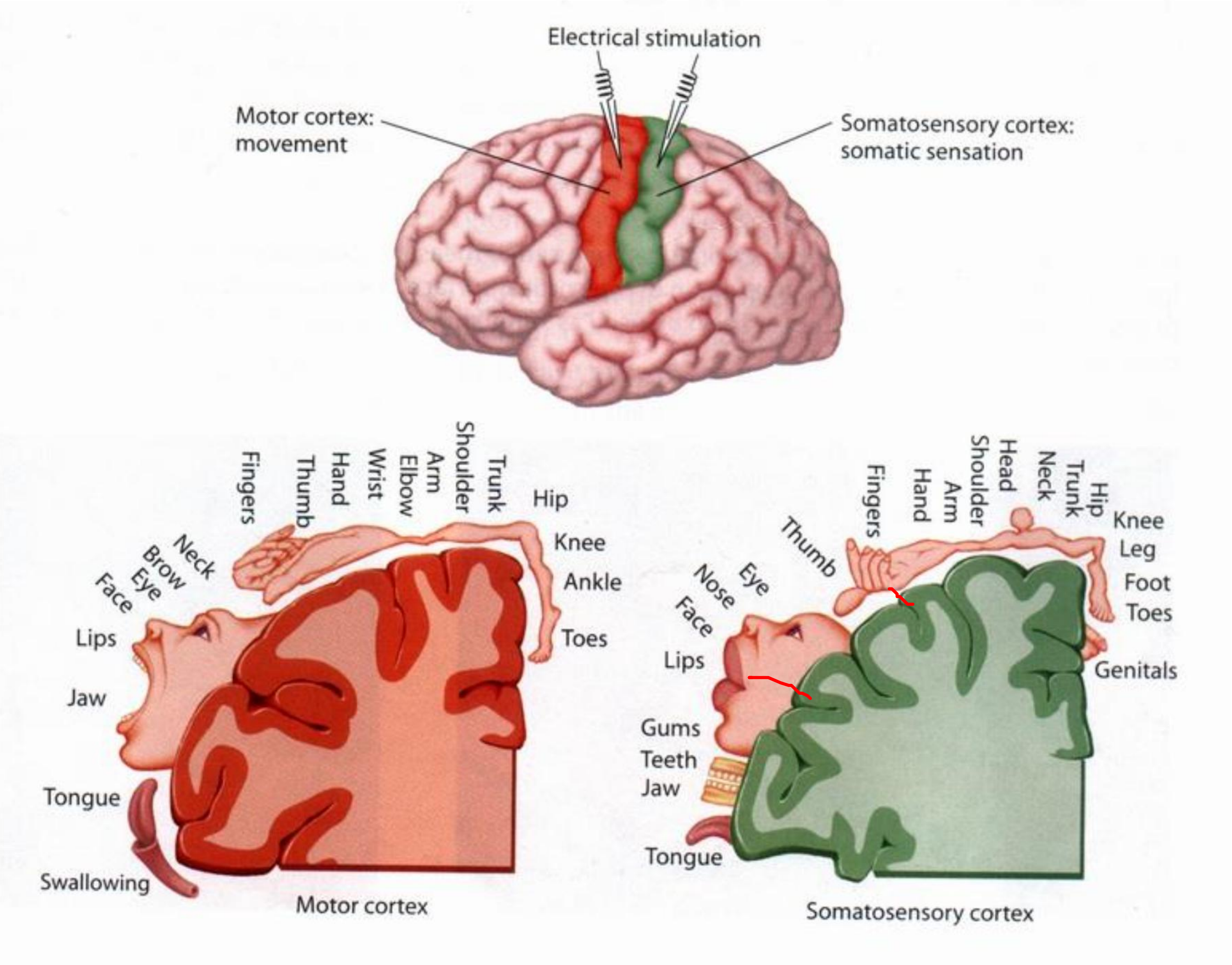
Tonotopic map

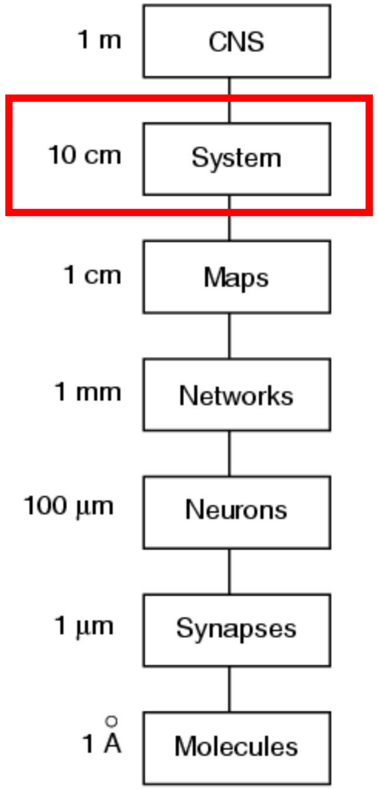


high frequency

Topographic Maps at motor cortex & somatosensory cortex





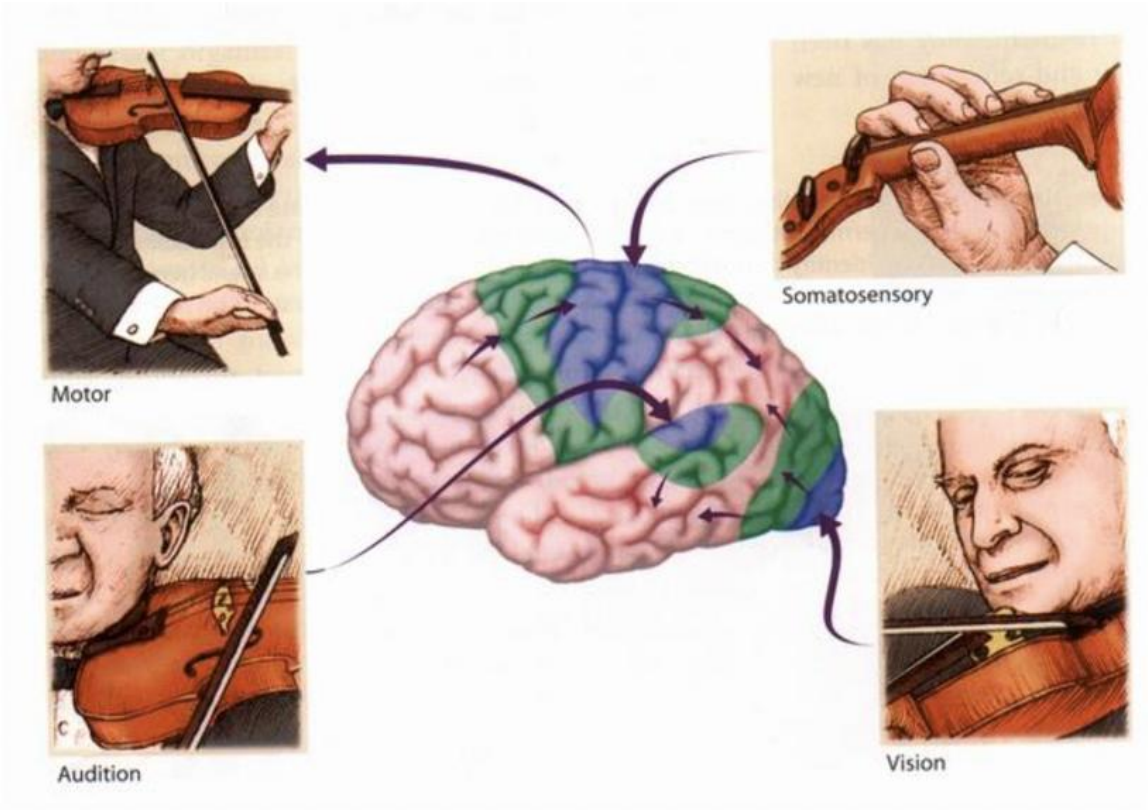


Visual system

Auditory system

Somatosensory system

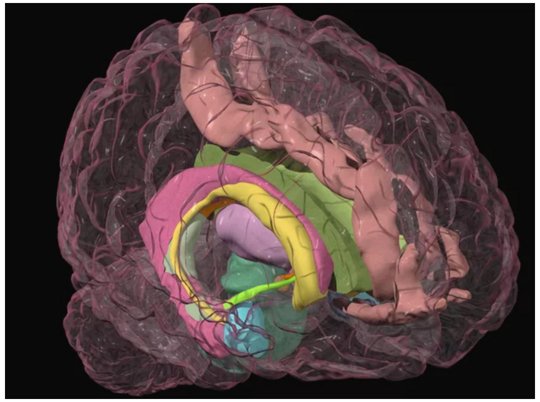
Motor system



Olfactory system (smell)

Limbic system (emotion & motivation)

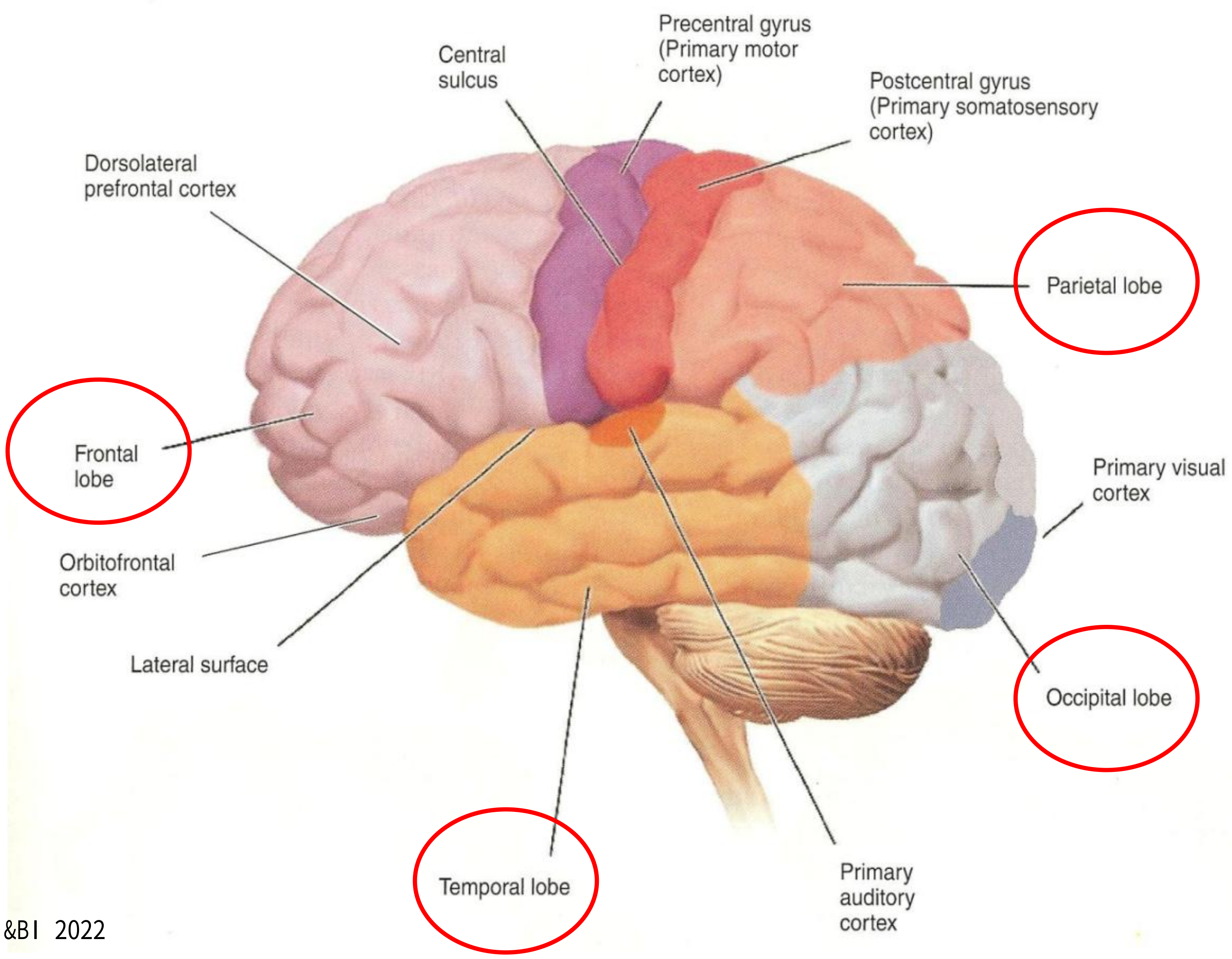
Including amygdala and hippocampus



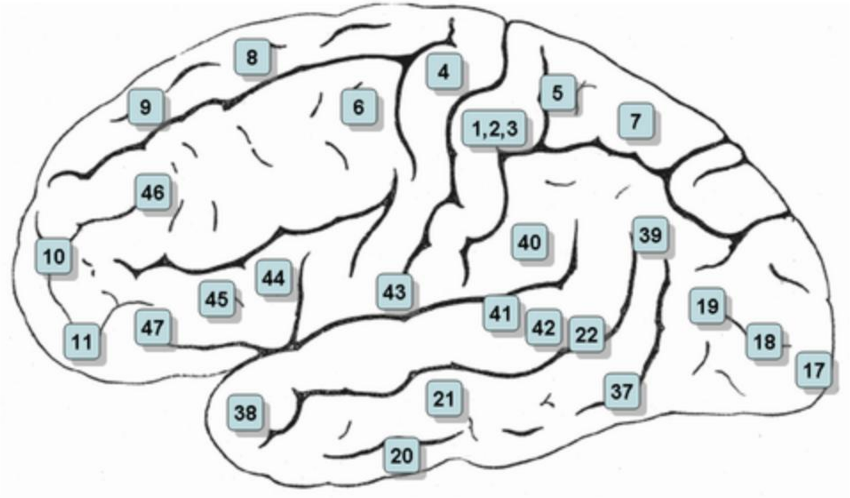
Other high-level cognition?

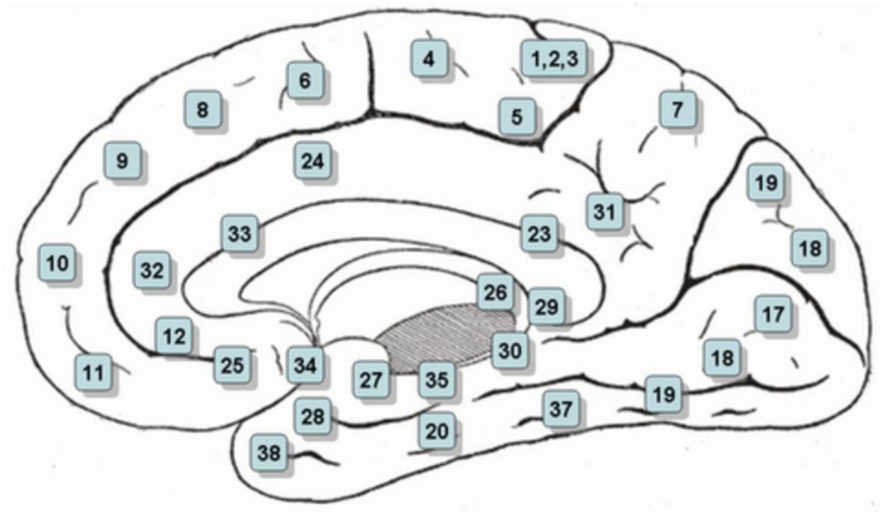
Such as consciousness, (free) will

Marco organization of human brain



Broadmann area (52 BAs)



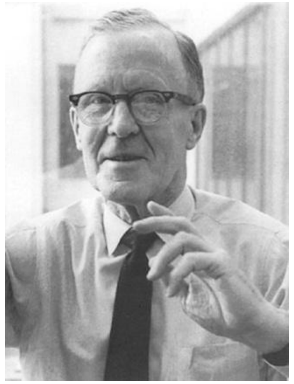


Areas 3, 1 & 2 – Primary Somatosensory Cortex
Area 4 – Primary Motor Cortex (M1)
Area 5 – Somatosensory Association Cortex
Area 6 – Premotor cortex (M2)
Area 7 – Somatosensory Association Cortex
Area 8 – Includes Frontal eye fields
Area 9 – Dorsolateral prefrontal cortex
Area 10 – Anterior prefrontal 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.

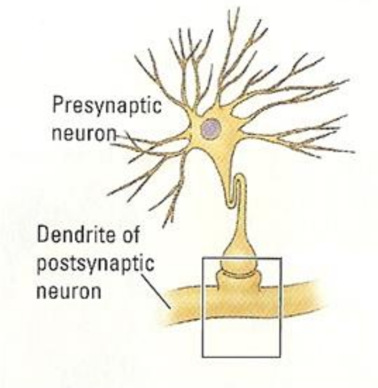
Learning in the brain (Hebbian learning)



D. O. Hebb

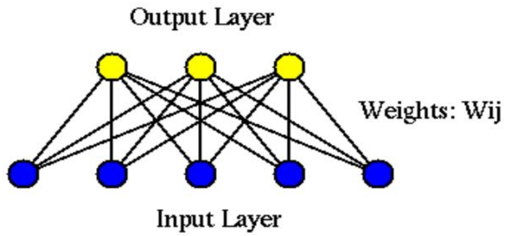
"When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased."

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



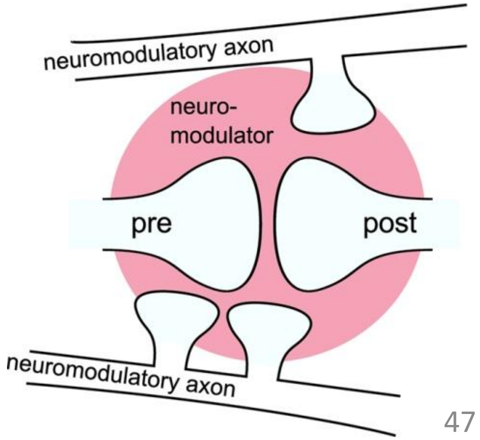
In other words: "**Cells that fire together wire together**."

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



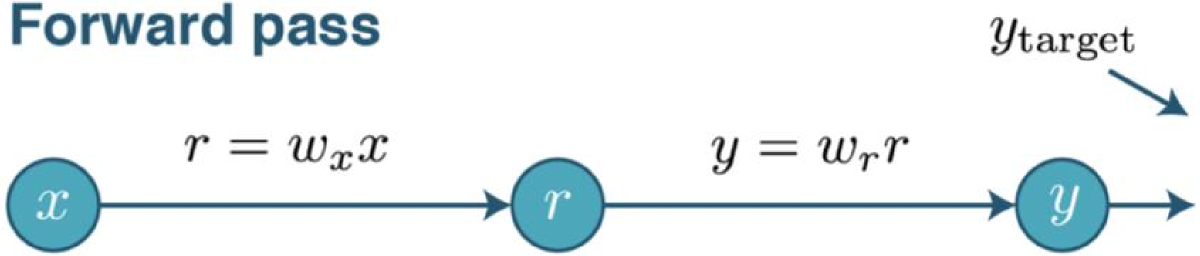
More complex and sophisticated ideas have been under continual exploration for over a half a century, including:

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



Learning in AI (Error backpropagation)

Forward pass



$$L = \frac{1}{2}(y - y_{\mathrm{target}})^2$$

Backward pass

$$\frac{\partial L}{\partial r} \longleftarrow \frac{\partial L}{\partial y}$$

$$\frac{\partial L}{\partial w_x} = \frac{\partial L}{\partial r}\frac{\partial r}{\partial w_x}$$

$$\frac{\partial L}{\partial r} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial r} = \frac{\partial L}{\partial y} w_r$$

Non-local $\frac{\partial L}{\partial y} w_r$

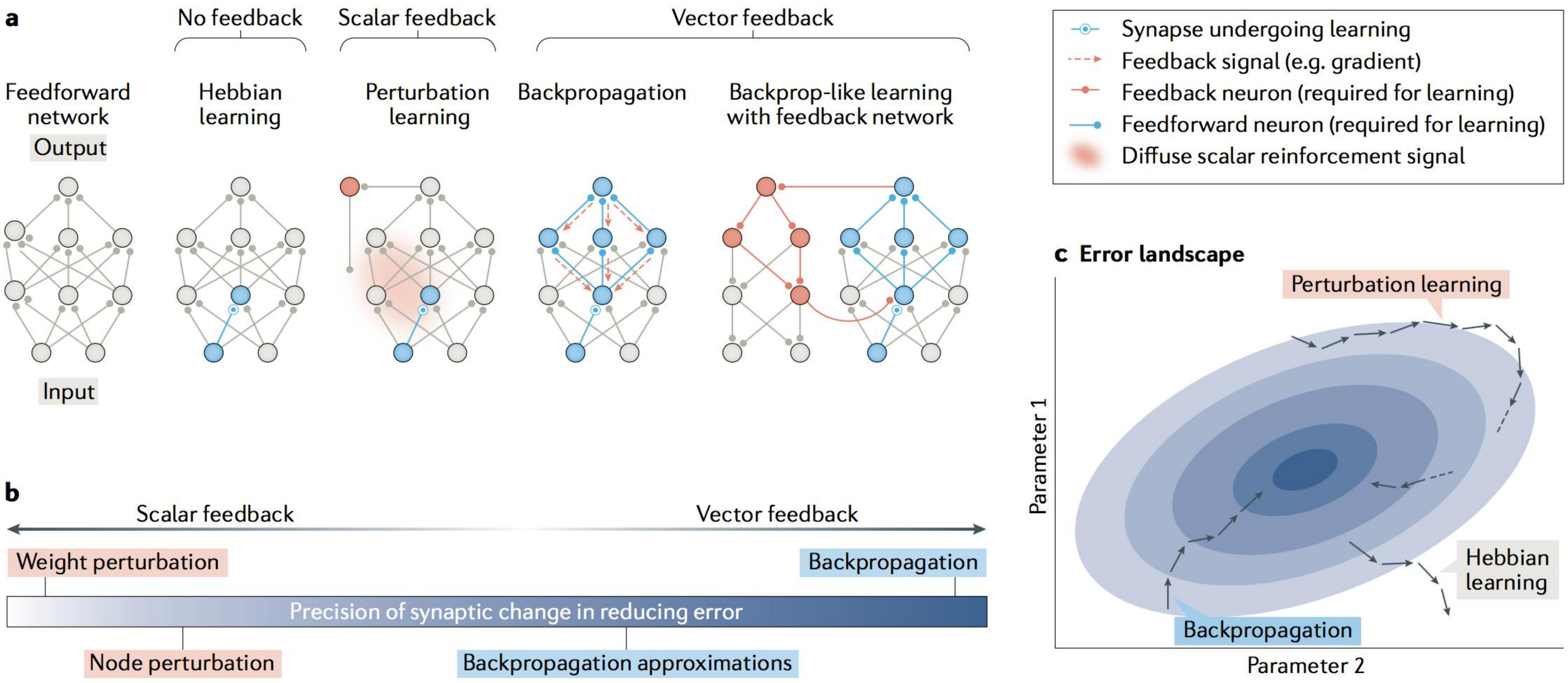
x Local

Backpropagation (BP) in the Brain?

- There is no direct evidence that the brain uses a backprop-like algorithm for learning. → Most of researchers think BP in brain is biologically implausible.
- **Difficulties** in implementing BP in the Brain:

1. Backprop demands synaptic symmetry (the same weights) in the forward and backward paths → how to design synaptic connections in forward and backward neural circuits?
2. Error signals are signed and potentially extreme-valued. → how to convey signed and extreme-valued errors in real neuron spikes?
3. Feedback in brains alters neural activity. → In NNs, feedback delivers error signals that do not influence the activity states of neurons produced by feedforward propagation. But it does change neural activity in the brain.

Hebbian learning vs BP vs other alternatives



Timothy, Santoro, Marris, Akerman, Hinton (2020) Backpropagation and the brain, *Nature*

Summary of Lecture 1

1. Some examples that BI inspires AI.
2. Some examples that AI helps understand BI.
3. Marr's three levels of explanation
4. Levels: molecular, synapse, neurons, networks, maps, system, CNS
5. Learning in the brain vs Learning in AI

Recommended materials

Papers

- Yang GR, Wang X-J (2020). Artificial neural networks for neuroscientists: A primer, Neuron
- Timothy, Santoro, Marris, Akerman, Hinton (2020) Backpropagation and the brain, *Nature*

Journals & Conferences

BI journals

- CNS (cell, nature, science)
- Nature neuroscience/bme/biotechnology/machine intelligence
- Nature communications, Science Advances
- Neuron, eLife
- Neuroimage, Human Brain Mapping

AI conferences

- ICML, NeurIPS, ICLR, AAAI, IJCAI
- CVPR, ICCV, ECCV
- MICCAI

Any questions?

2021年4月10日下午，上海交通大学携手《Science》杂志发布“新125个科学问题”

——《125个科学问题：探索与发现》

Neuroscience

1. What are the coding principles embedded in neuronal spike trains?

2. Where does consciousness lie?

3. Can human memory be stored, manipulated, and transplanted digitally?

4. Why do we need sleep?

5. What is addiction and how does it work?

6. Why do we fall in love?

7. How did speech evolve and what parts of the brain control it?

8. How smart are nonhuman animals?

9. Why are most people right-handed?

10. Can we cure neurodegenerative diseases?

11. Is it possible to predict the future?

12. Can we more effectively diagnose and treat complex mental disorders?

2021年4月10日下午，上海交通大学携手《Science》杂志发布“新125个科学问题”

——《125个科学问题：探索与发现》

Artificial Intelligence

1. Will injectable, disease-fighting nanobots ever be a reality?

2. Will it be possible to create sentient robots?

3. Is there a limit to human intelligence?

4. Will artificial intelligence replace humans?

5. How does group intelligence emerge?

6. Can robots or AIs have human creativity?

7. Can quantum artificial intelligence imitate the human brain?

8. Could we integrate with computers to form a human-machine hybrid species?