Brain Intelligence and Artificial Intelligence

人脑智能与机器智能

Lecture 1 - Introduction

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SUSTech, BME department

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南方科技大学 Southern University of Science and Technology (SUSTech) is a young, public university in Shenzhen, China.
It was founded in 2010, and is working towards becoming a world-class university, ranked 8th in China by Times Higher Education & QS World University Rankings in 2021.
CENTE

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 p

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 neuros

2023年

01-Introduction.pptx
02-Visual System.pptx
03-Learning & GD.pptx
04-Auditory System.pptx
05-A brief intro to AI.pptx
07-Somatosensory System.pptx
08-Data and pretraining.pptx
09-motor system 1.pptx
10-motor system 2.pptx
11 - Intro2EEG.pptx
12 - Emotion.pptx
13 - Sleep&Dream.pptx
14-Language.pptx
15-AI for neuroscience.pptx
16-visual cognition.pptx
17-Interpretable concept space.pptx
18-Olfaction.pptx
19-Structure, function and behavior.pptx
20-Controlling the brain.pptx

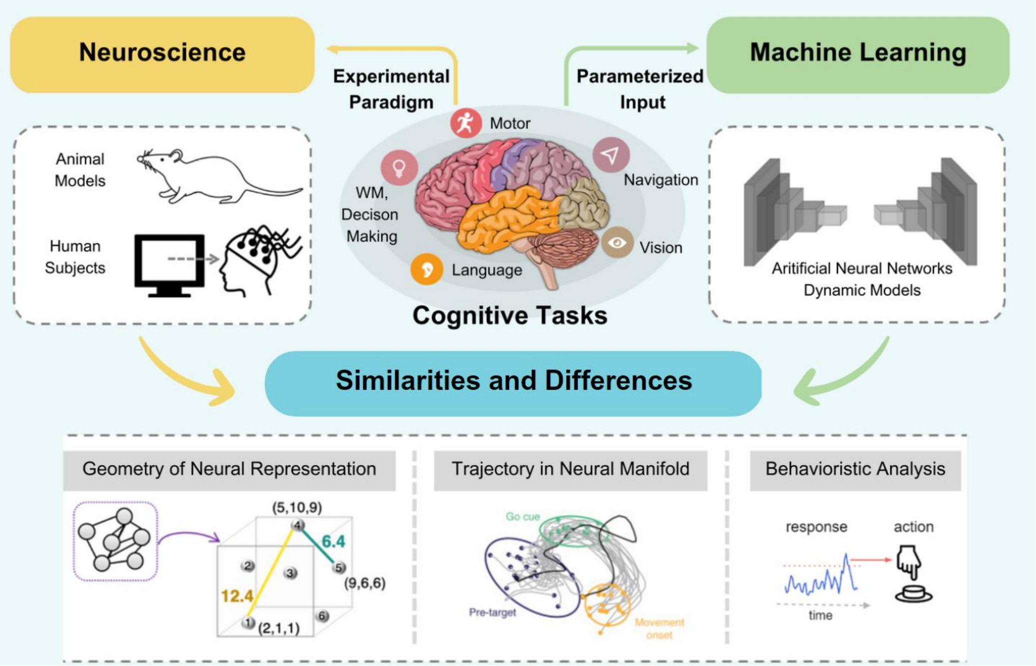
刘泉影

神经计算与控制实验室
Neural Computing & Control Lab

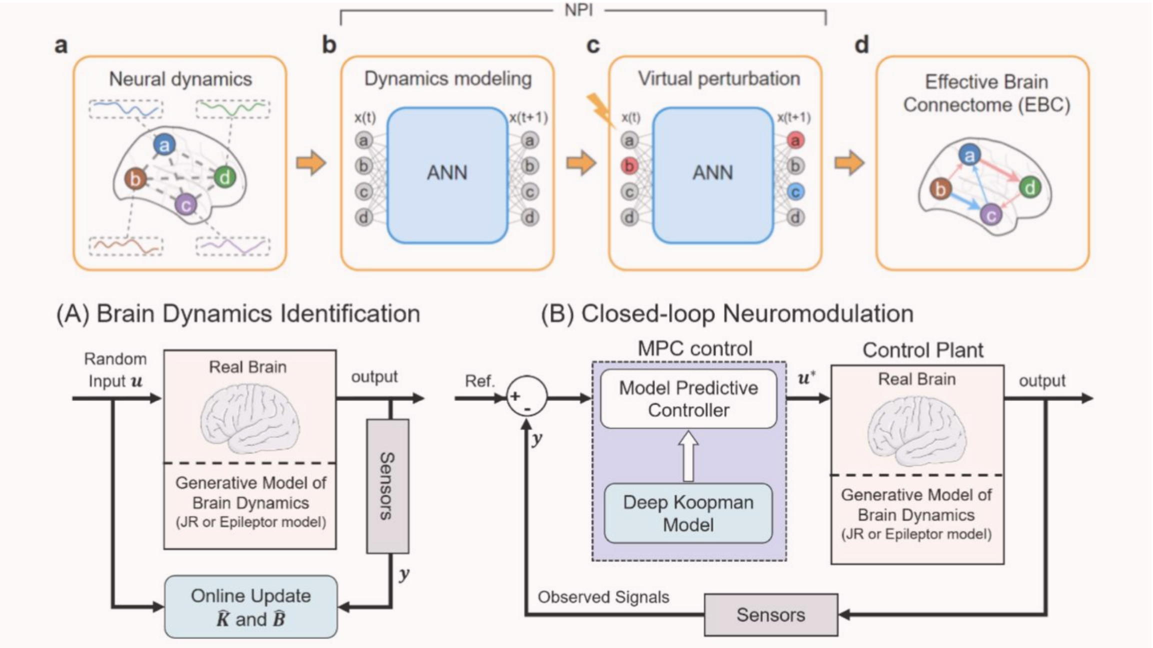
南方科技大学 生物医学工程系，助理教授、博导、PI

兰州大学本科/硕士，瑞士ETH博士，美国Caltech博士后

AI for Brain Science



Brain Network Control



- ❑ AI处理神经数据: hdEEG, SEEG, fMRI, DTI...
- ❑ AI与大脑对齐: Neural alignment across cognitive tasks

- ❑ 数据驱动：全脑神经动力学建模、全脑仿真与生成
- ❑ 模型驱动：精准神经调控、因果分析、脑疾病治疗

神经计算与控制实验室

神经计算与控制实验室
Neural Computing & Control Lab

Neural Computing & Control (NCC) lab

PI：刘泉影

科研人员：博后、博士、硕士、RA等二十余人

Bilibili视频号

微信公众号

研究方向：

1. **多模态神经数据处理算法** 基于数据融合模型，开发多模态脑影像(hdEEG、SEEG、fMRI、T1、DTI)的cutting-edge处理技术，并应用于临床诊断
2. **精准神经调控** 基于动力学模型及控制理论，学习大脑功能动态，设计神经调控优化函数，优化最佳的神经刺激(DBS、tES、TMS)，实现对大脑活动和行为的精准调控，应用于疾病治疗
3. **AI for neuroscience** 基于AI大模型，研究多种认知任务下的大脑神经表征及认知任务表现，开发大脑启发的AGI模型

Multi-modal neural data

- spikes
- EEG
- SEEG/ECoG
- fMRI
- T1/T2
- DTI

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
- Bayesian 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

B站账号：NCC_lab

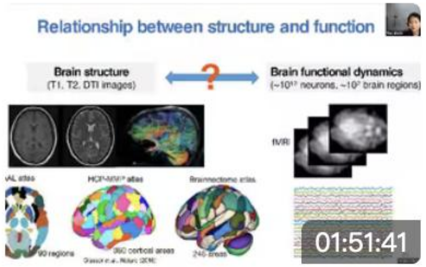
技术干货

如何研究三体星人和chatGPT的认知水平

506 3–2

大一学生能看懂的CNN模型

1064 2–20



【Tutorial:大脑结构–功能融合建模】刘泉影(主讲)\梁智超(代码)

1204 2022–12–18

三分钟学会用chatGPT写学术论文 ––NCC lab 罗文伟

10.6万 2022–12–11

BI & AI 合集

合集·南方科技大学BME5012《人脑智能与机器智能》课程全集–刘泉影 18 播放全部 更多

【BI&AI】Lecture 1 – Introduction

1567 2022–9–6

【BI&AI】Lecture 2 – Visual system

605 2022–9–7

【BI&AI】Lecture 3 – GD & BP & CNN & Hands–on

496 2022–9–21

【BI&AI】Lecture 4 – What do neurons in AI/brain

297 2022–9–23

本科生毕业答辩系列

南方科技大学–生物医学工程系–神经计算与控制实验室–2019级本科生

559 6–3

南方科技大学–生物医学工程系–神经计算与控制实验室–2019级本科生

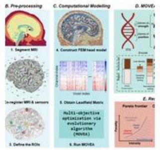
615 6–3

微信公众号：

神经计算与控制实验室

严肃科普系列

09月05日 已群发



NCC论文 | MOVEA：人脑高通道经颅电刺… 原创 已修改

1,702　6　15　¥ 10.00　0

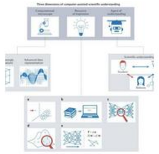
08月14日 已群发

神经计算与控制 Neural Computing &

招生 | 南科大刘泉影课题组NCC lab招收保研硕士生 原创

2,789　5　47　¥ 5.00　0

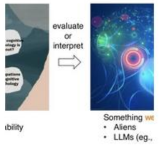
07月20日 已群发



文章分享 | 大语言模型时代的科学研究：迷思与… 原创

1,232　2　12　¥ 81.00　1

07月17日 已群发



文章分享 | 大语言模型的能力评估的第一步 原创

764　2　6　¥ 2.00　1

06月19日 已群发

NCC论文 | 基于图神经网络和fMRI的可解释大脑… 原创

1,255　1　14　¥ 39.00　0

老师胡说系列

03月21日 已群发

老师胡说 | 人类与AI之间，老师与学生之间 原创

1,584　15　71　¥ 25.00　0

03月13日 已群发

老师说 | 师生关系 原创 已修改

1,524　6　61　¥ 18.20　0

2022年12月16日 已群发

老师说 | 学习首先是自娱自乐，然后才众乐乐 原创

1,018　8　49　¥ 14.00　0

2022年05月24日 已群发

老师说 | 毕业赠语 原创

1,732　14　127　¥ 34.80　0

2022年04月26日 已群发

老师说 | 导师的责任与压力 原创

1,526　8　99　¥ 52.00　0

Logistics

- Class hours:
  - Monday, 19:00-20:50 (each week, 三教105)
  - Wednesday, 19:00-20:50 (odd weeks, 三教105)

- Lecturer: Quanying Liu (刘泉影)
  - My Office hours: Wendeaday, 13:00-14:00, Engineering building, South 535 (工学院南楼535)
  - Lunch hours: Please send an email to make an appointment for having lunch together.

- Some books (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.
- No textbook (We are drafting our own BI&AI textbook. Coming in 2024 winter...)

- 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

Hypothesis-driven
Fit model with data

Deep learning

Data-driven
Learn from data

All code in R are provided.

《认知和行为的计算建模》
Simon Farrell, Stephan Lewandowsky
伍海燕、刘泉影 主译
清华大学出版社

Survey on BI&AI 2024

yes (举手）　　no（不举手）

0、平均每天写代码超过**2小时**

1、用过 GPT

2、用过 文心一言、Kimi、通义千问

3、用大模型写作业

4、用大模型改论文

5、用大模型写代码

6、用大模型做PPT

【我有、你没有】说出一个你用过的大模型的最独特的用途

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*.

What is intelligence?

Sensing/Acting
Learning
Reasoning
Inferring
Decision making
…

Emotional
Social
Free will
Irrational
Instinctive
…

Intelligence

人工智能

计算机视觉

自然语言处理

优点：**性能好、功能多**

缺点：**数据量大、参数量大、能耗高**
芯片卡脖子、缺乏可解释性

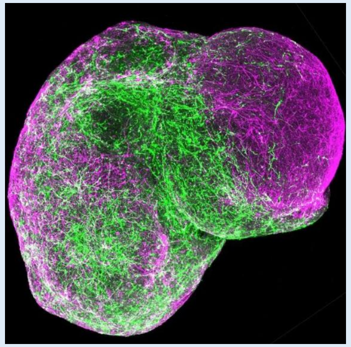
双向融合

优势互补

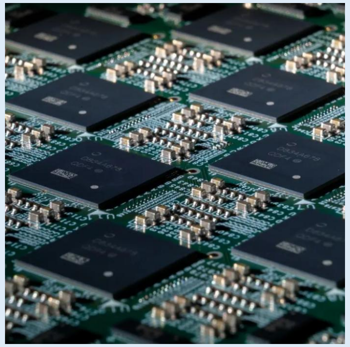
仿生智能

生物神经网络模型

类器官



神经芯片

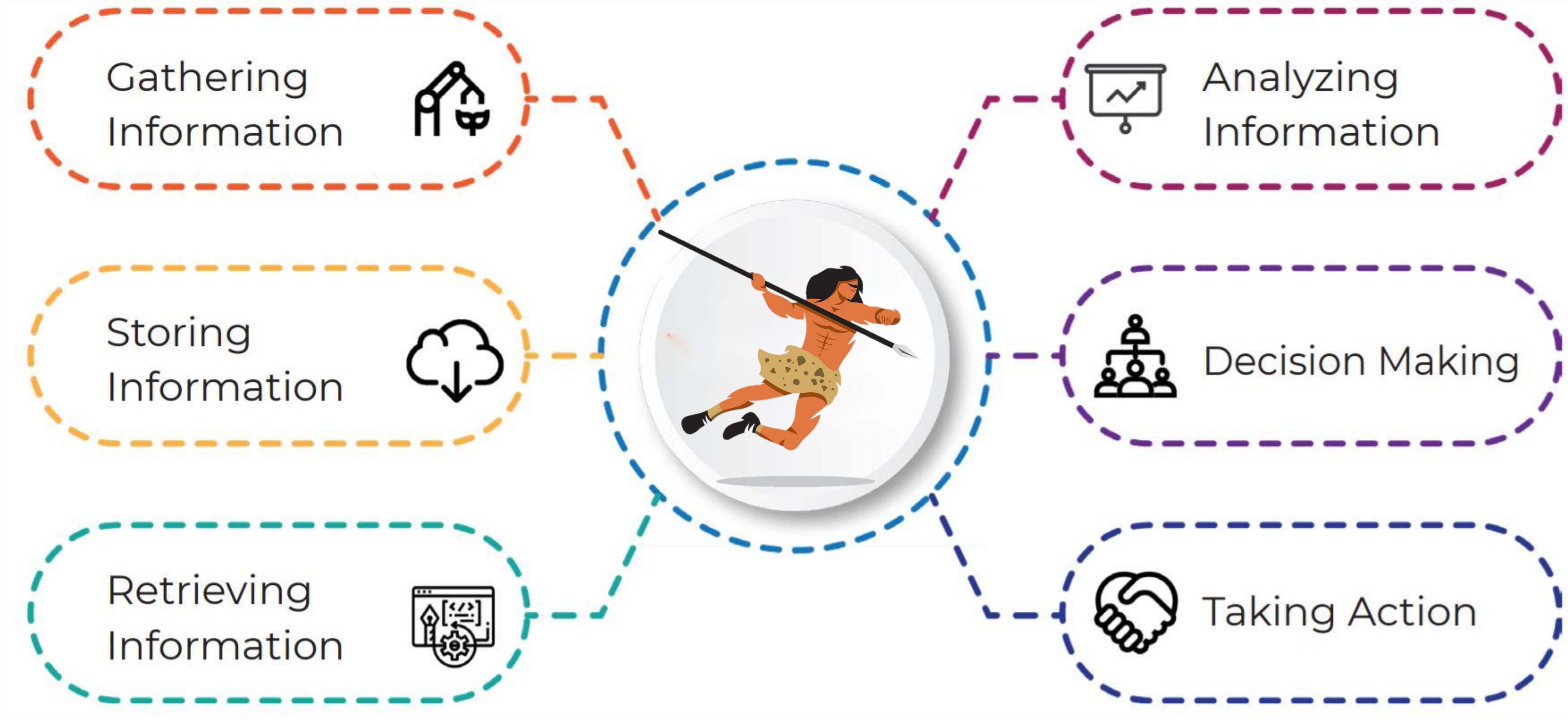


优点：**可解释性强、能耗低**

缺点：**仿生性不足、功能单一**
生物机制不清晰，发展刚刚起步

BI与AI的融合，实现 “强”仿生 多功能 通用智能

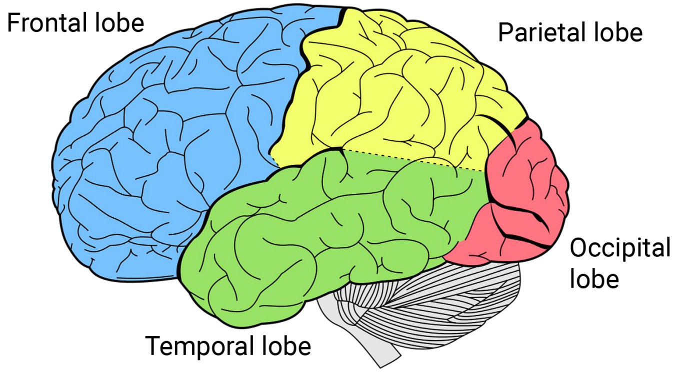
大脑智能 (Brain Intelligence)



大脑

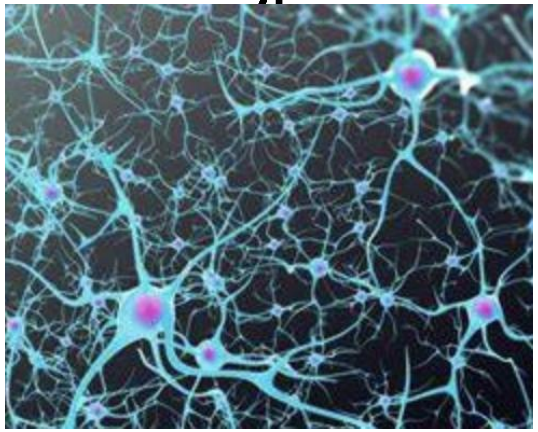
一个大脑

几个大的脑区



上百个精细脑区

860亿个神经元



一个**大脑**，能实现丰富多样的**功能**，能完成各种复杂的**任务**：

感知觉（色声香味触法）

语言（听说读写）

运动控制

决策推理

… …

判断题：是/否?

判断1　我们只使用了10%的大脑

判断2　人类是世界上大脑最大的动物

判断3　神经系统像血液循环系统一样是一个连通网络

判断4　大脑靠放电传递信息、实现计算、执行功能

判断5　从大脑到手的信息传递速度可达 100米/秒

判断题：是/否?

判断1(否) 我们只使用了10%的大脑

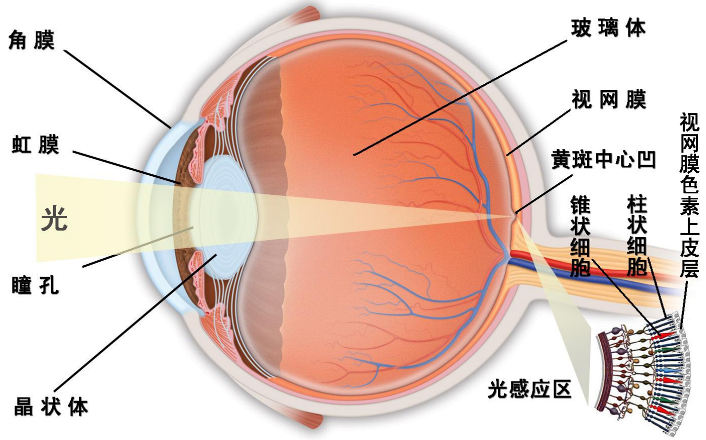
判断2(否) 人类是世界上大脑最大的动物

判断3(否) 神经系统像血液循环系统一样是一个连通网络

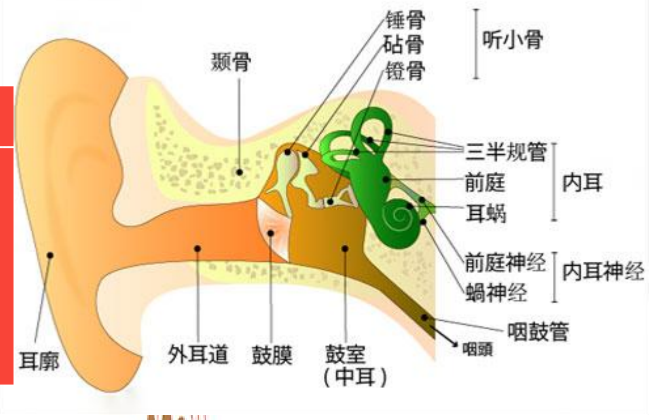
判断4(是) 大脑靠放电传递信息、实现计算、执行功能

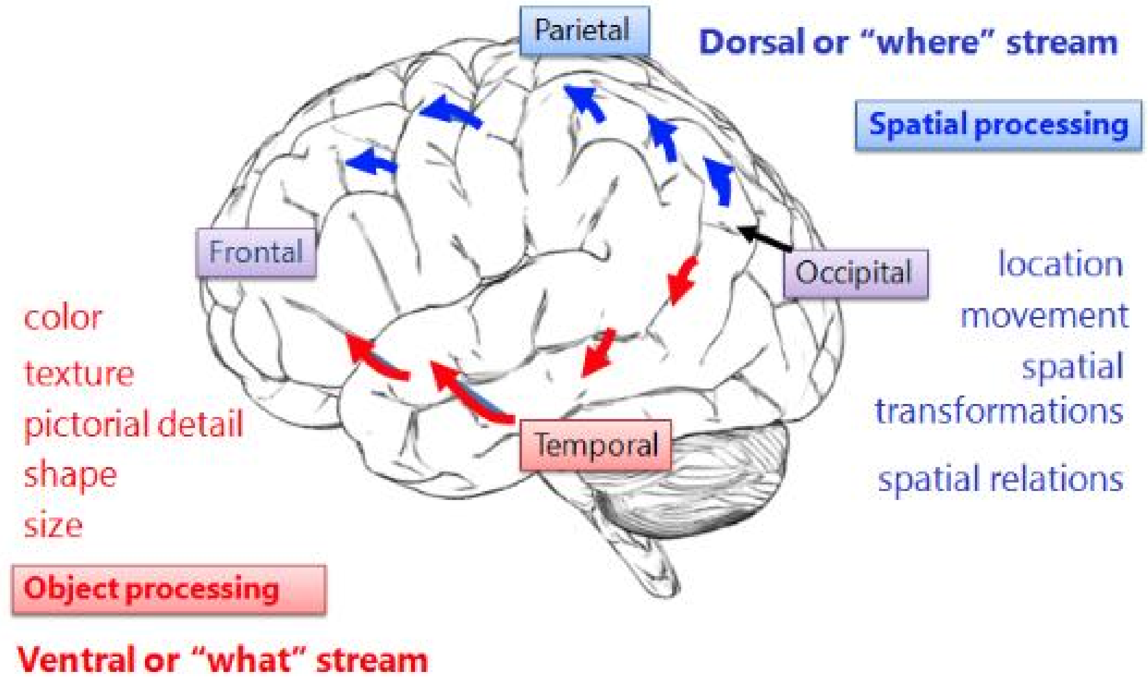
判断5(是) 从大脑到手的信息传递速度可达 100米/秒

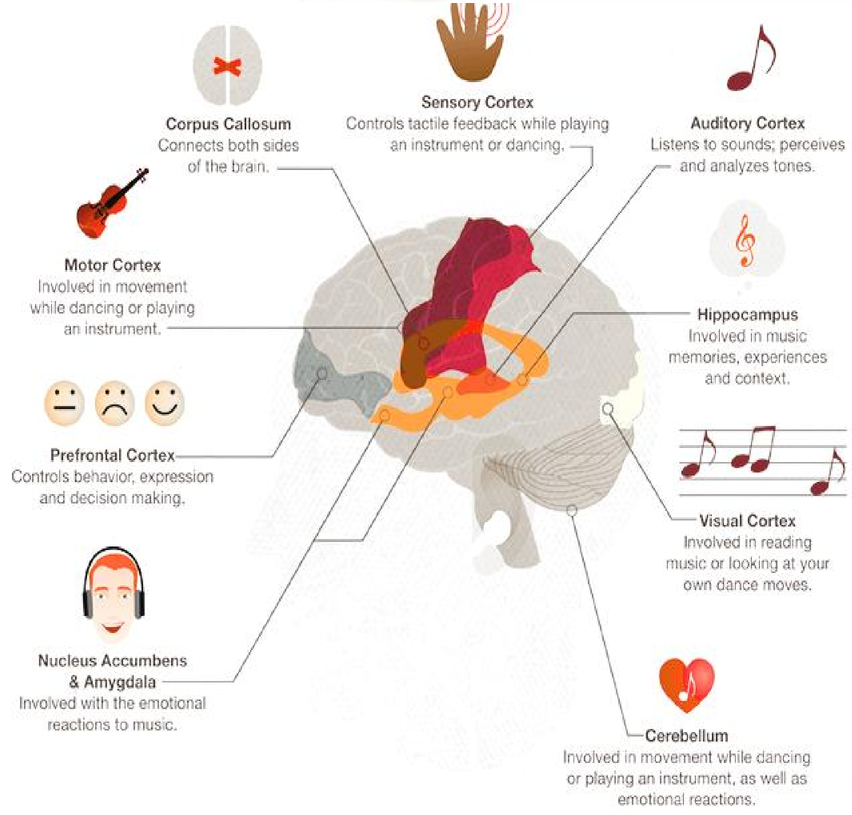
大脑的看与听



Vision	Audition
视网膜：光信号 --》电信号 大脑：电信号的处理	耳蜗：声音震动 --》电信号 大脑：电信号的处理







The Marr's three levels of explanation

top-down

Level 1: Computation theory

- 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: Algorithmic

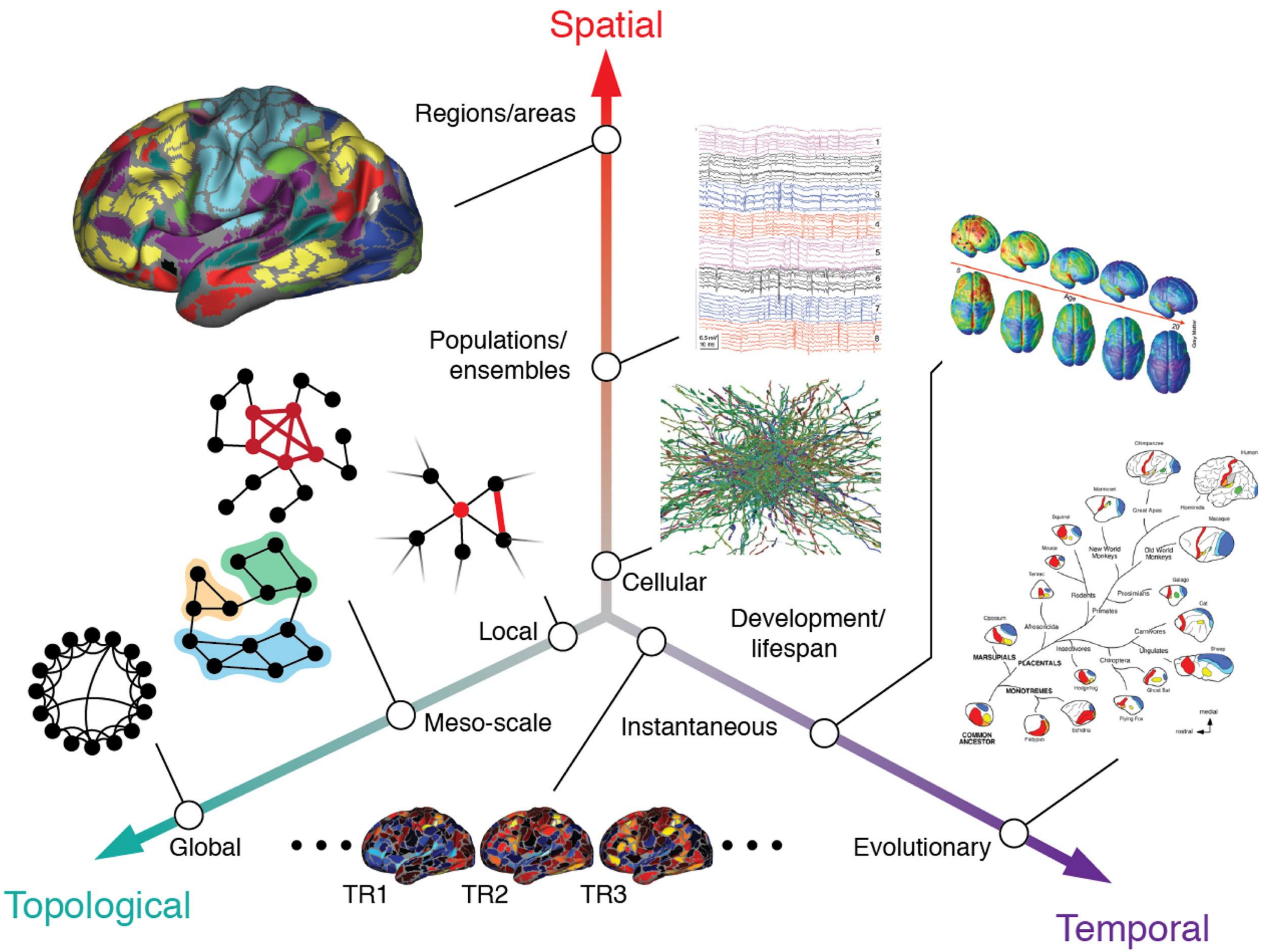
- How is the information represented and processed to achieve the computational goal?

Level 3: Implementation

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

Bottom-up

The brain is a complex, networked dynamic system.



Brain network modelling across scales

1. Spatial
cellular --> region

2. Topological
local --> global

3. Temporal:
instantaneous --> evolutionary

Modelling Brain Function

- Decisions: Reaction time, Accuracy
- Movement trajectory
- Rating

Behavioral recordings (cognitive, decision-making process)

Bottom-up
from observed neural data to cognitive process

Top-down
from observed behavior to cognitive process

Neural recordings (10^{12} neurons, 10^{2} brain regions)

- Neuronal spikes
- Local field potential
- iEEG (eg., ECoG/SEEG)
- EEG/MEG
- fMRI

Modelling Brain Function

- Decisions: Reaction time, Accuracy
- Movement trajectory
- Rating

Behavioral recordings (cognitive, decision-making process)

Bottom-up
from observed neural data to cognitive process

Top-down
from observed behavior to cognitive process

Neural recordings (10^{12} neurons, 10^{2} brain regions)

- Neuronal spikes
- Local field potential
- iEEG (eg., ECoG/SEEG)
- EEG/MEG
- fMRI

The cognitive process

External world (image, text, sound …)

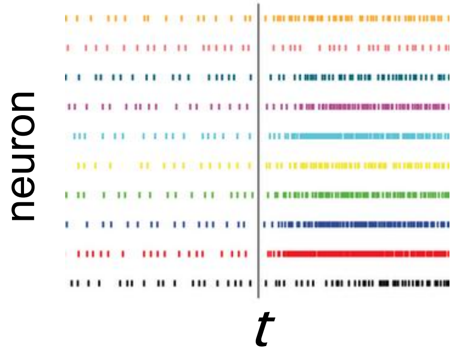
Neural data (10^{12} neurons, 10^{2} brain regions)

Cognitive process

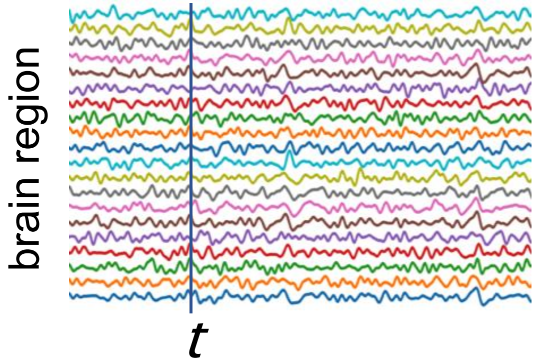
Senses (感觉)
Motion (运动)
Emotion (情绪)
Attention (注意力)
Cognition (认知)

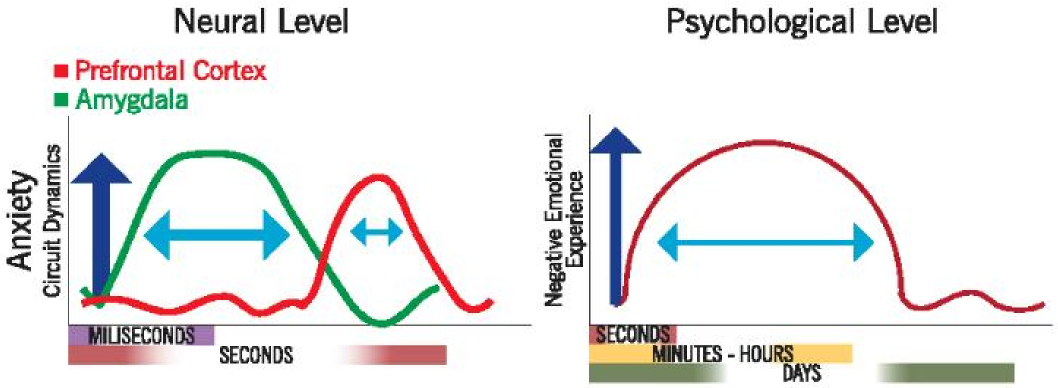
上善若水。水善利万物而不争，
处众人之所恶，故几于道。
居善地，心善渊，与善仁，
言善信，政善治，事善能，
动善时。夫唯不争故无尤。

neural spikes



fMRI data





Heller & Casey (2016) *Developmental science*

The encoding/decoding model

External world (image, sound … stimuli)

Neural data (10^{12} neurons, 10^2 brain regions)

Cognitive process

Senses (感觉)
Motion (运动)
Emotion (情绪)
Attention (注意力)
Cognition (认知)

Neural encoding model: dx/dt = f(x,u)

- Given the input u, and current neural data x(t), predict the future dynamics x(t+1)

Neural decoding model: s = g(x)

- Given neural data x, decode the cognitive state s
- **Brain-computer interfaces (BCI)** largely rely on the neural decoding model.
- There are various approaches for neural decoding, depending on the design of task, the brain areas involved, etc.

Any questions so far?

Artificial Intelligence

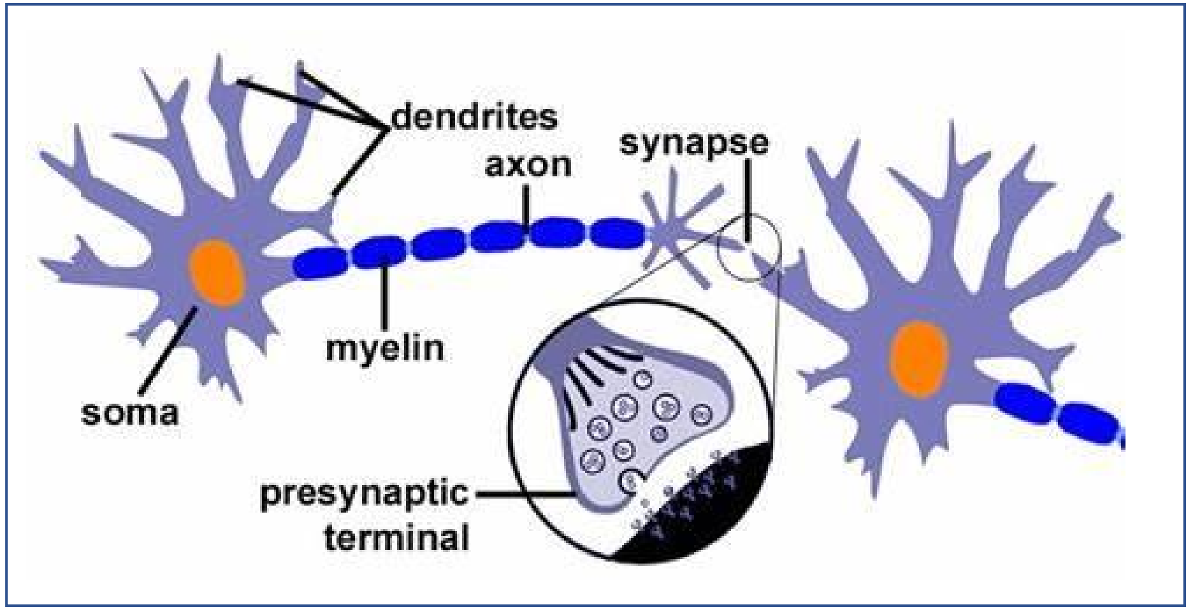
BI inspires AI.

AI helps understand BI.

Brain Intelligence

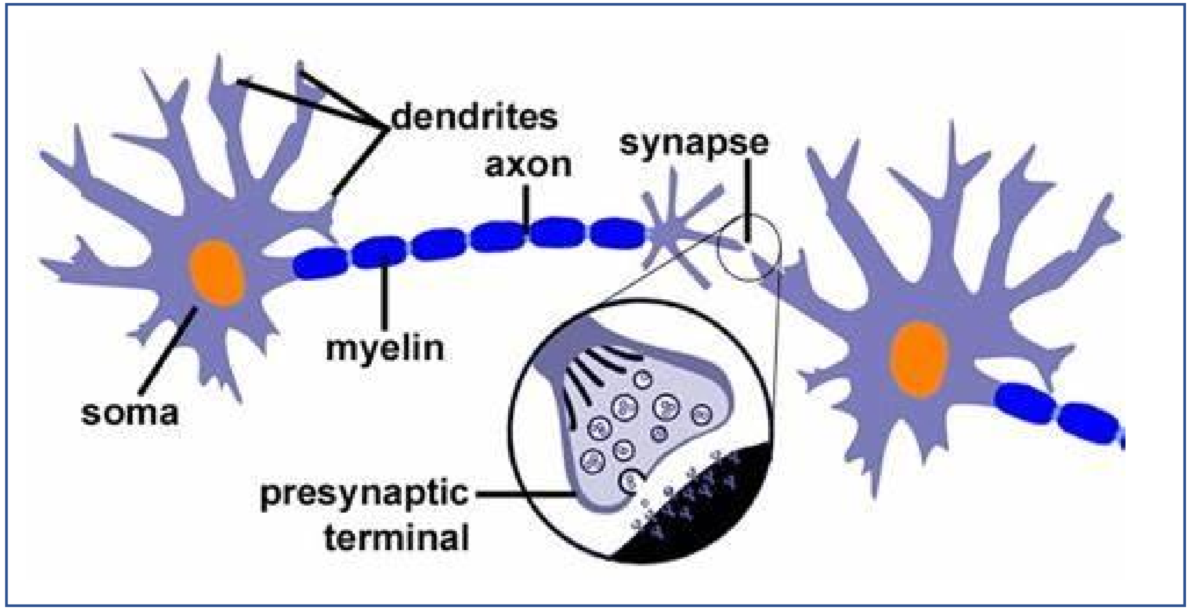
BI inspires AI

Biological Neuron

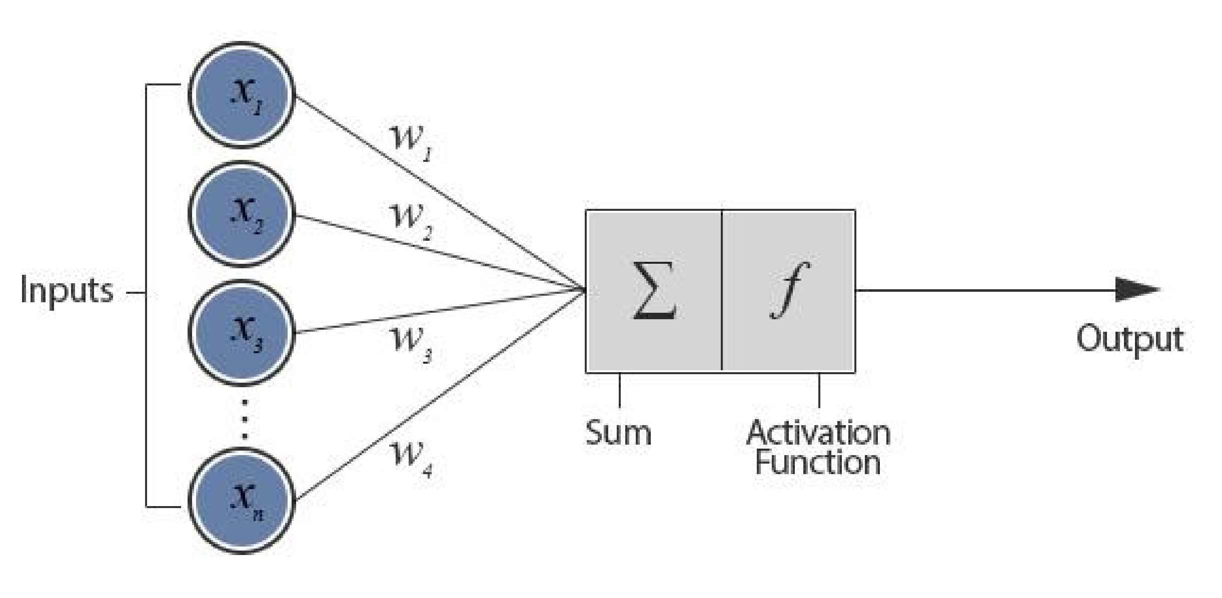


BI inspires AI

Biological Neuron

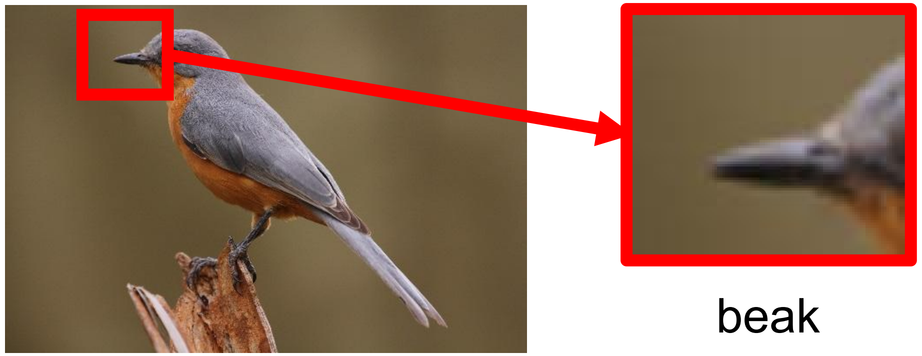


Artificial Neuron



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



beak

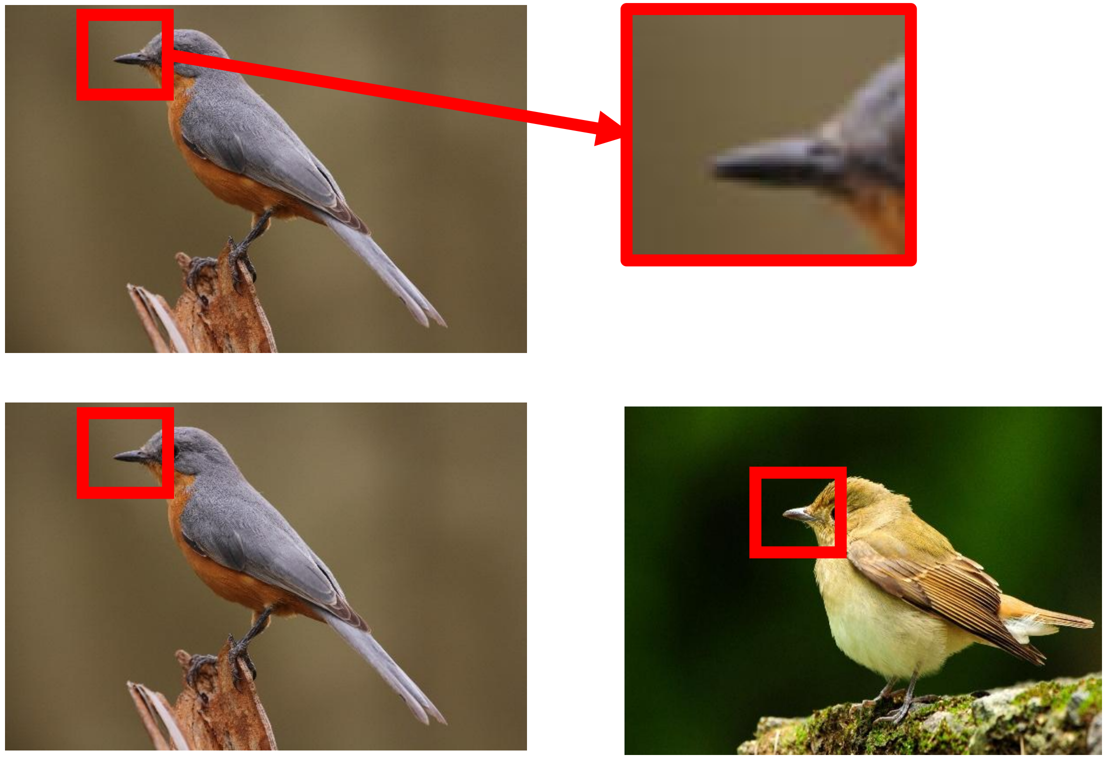
The way our brain process images

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



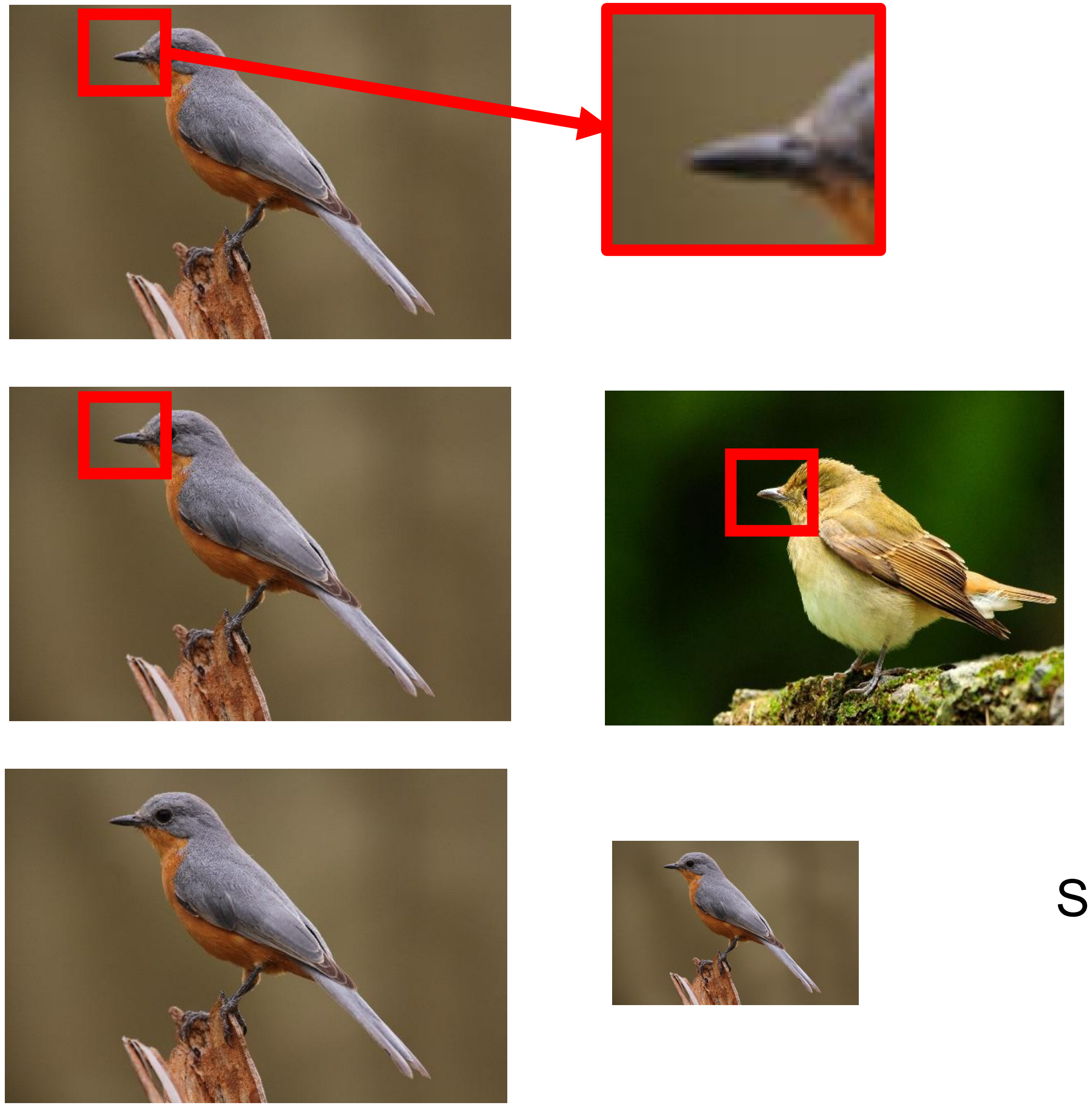
The same patterns appear in different regions.

They can use the same set of parameters.

The way our brain process images

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

BI inspires AI

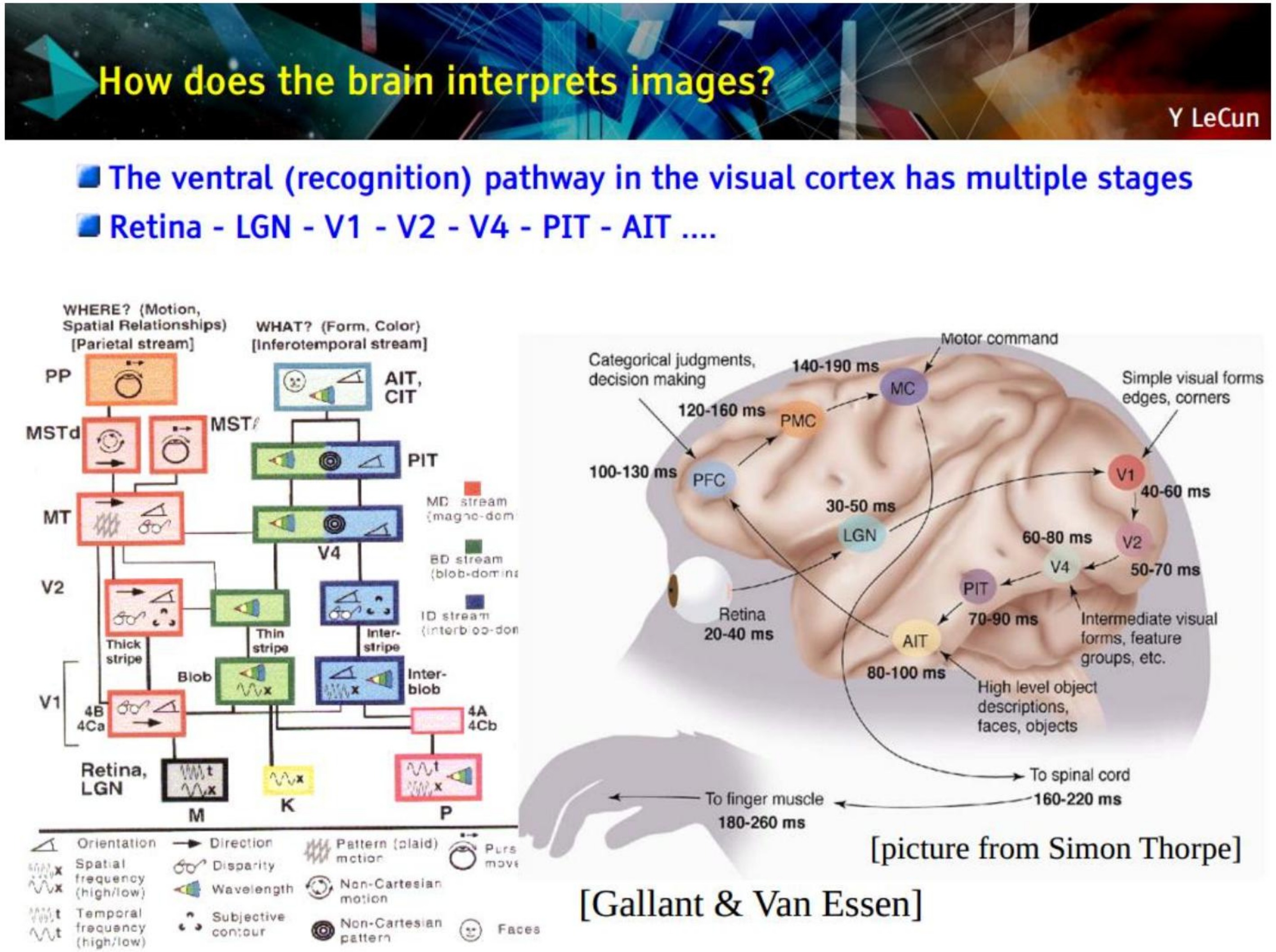


The way our brain process images

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)

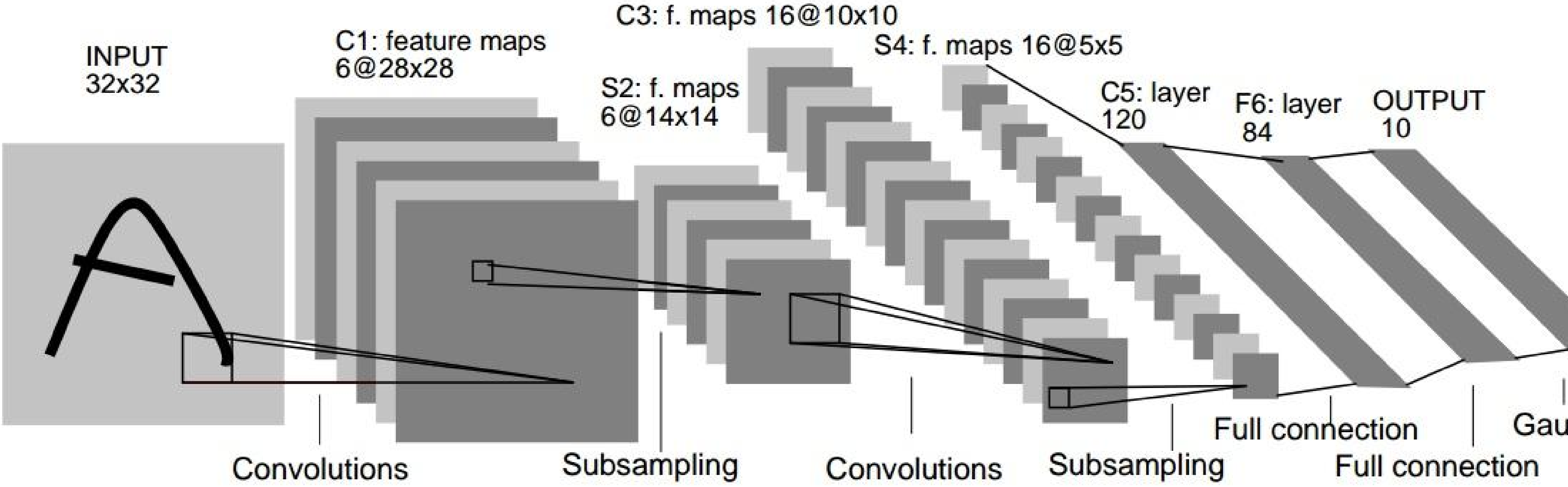
1. Local receptive fields
2. Shared weights
3. Sub-sampling
4. **Layered architecture**

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.

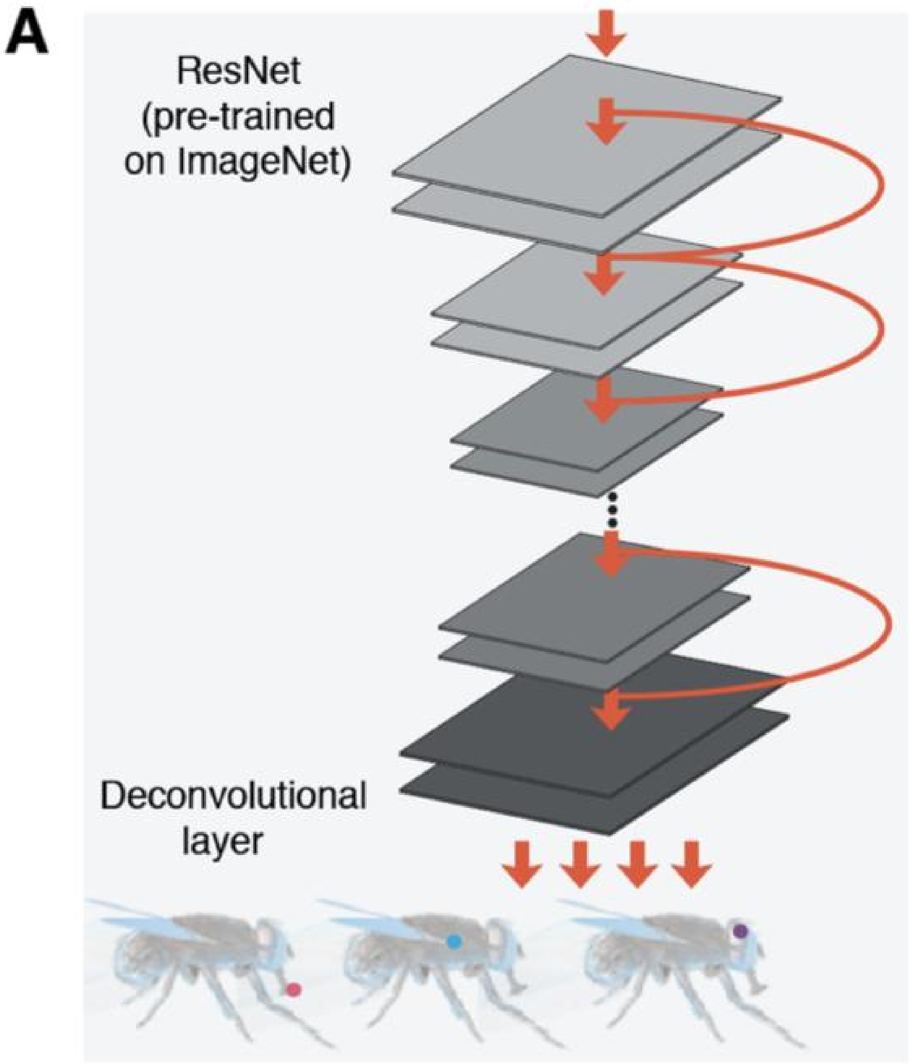
Artificial Intelligence

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.

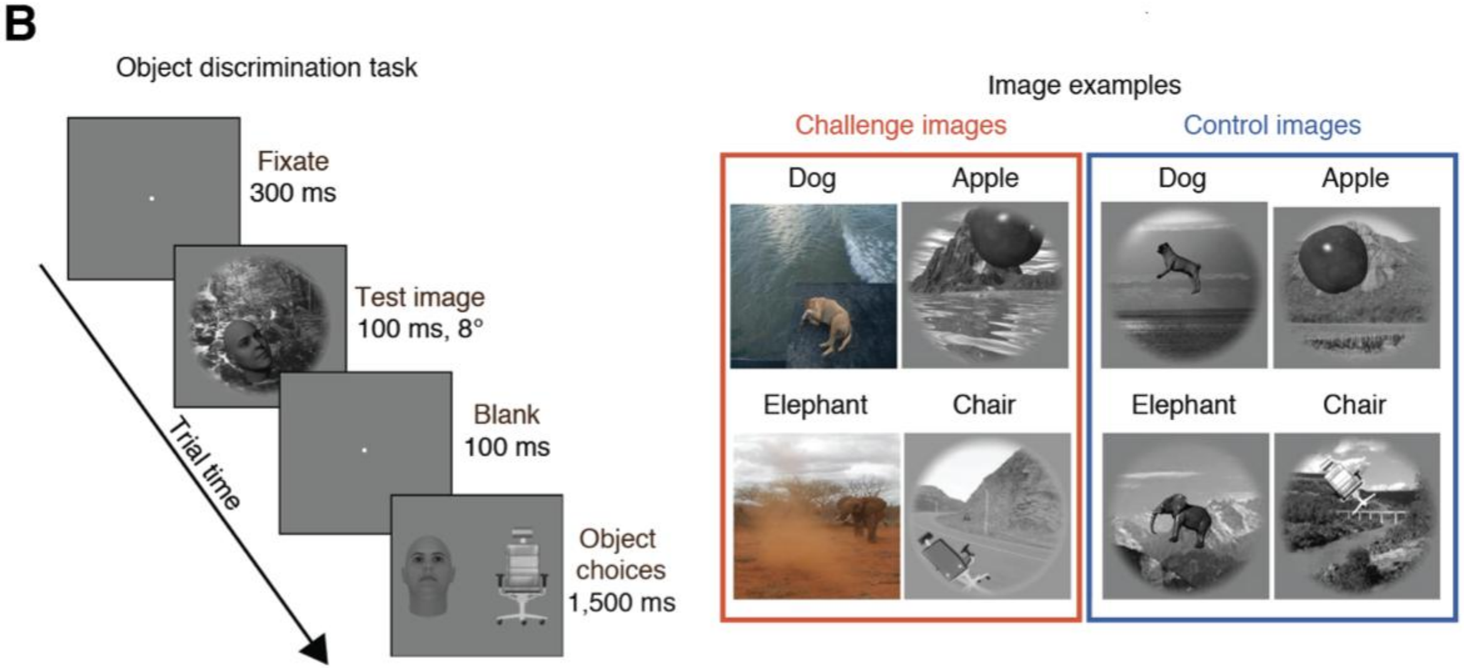
A good AI shall not only analyze the data, but also provide insights to **explain the underlying mechanisms** of how brain works.

AI helps understand BI

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

AI helps understand BI

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



Train both **monkey** and **ANNs** to perform <u>object discrimination tasks</u> 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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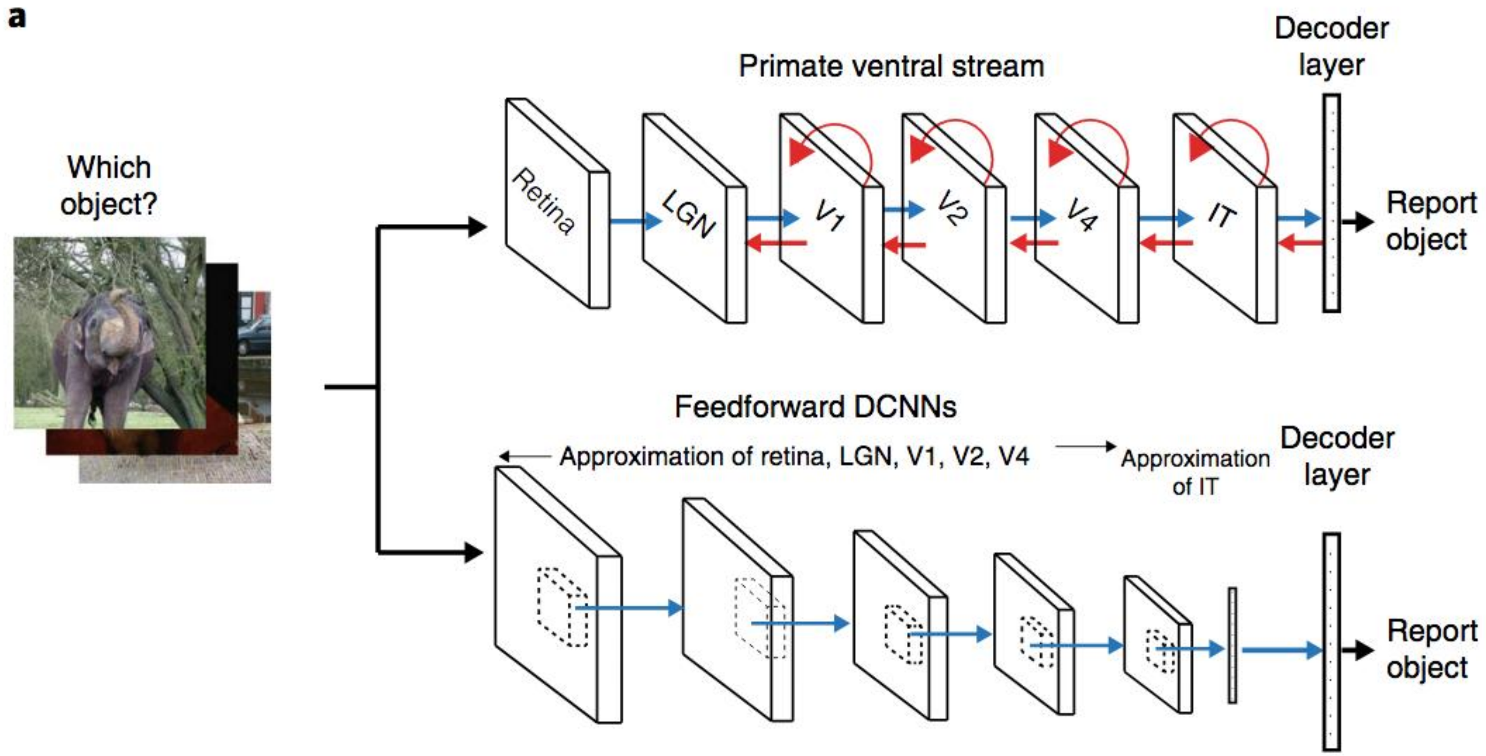

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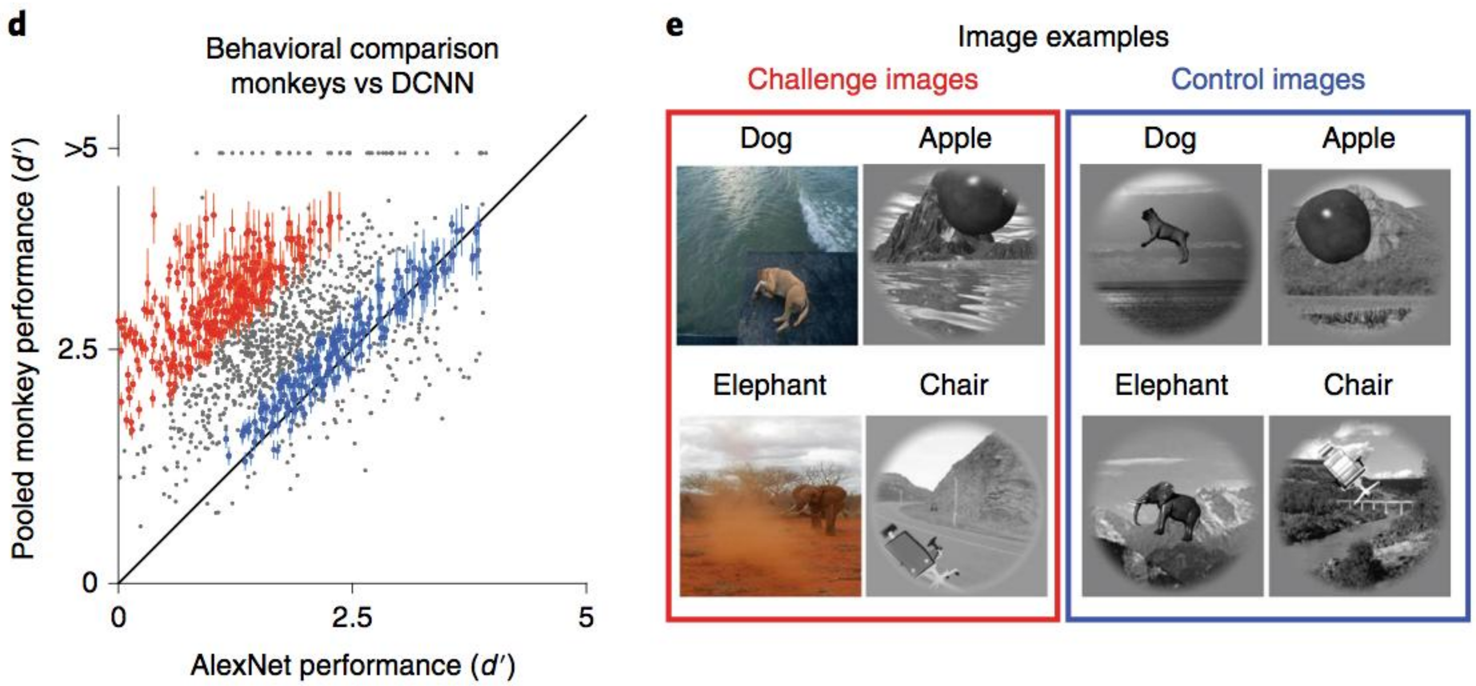


Train both **human** and **ANNs** to perform <u>object discrimination tasks</u> involving challenging naturalistic visual objects.

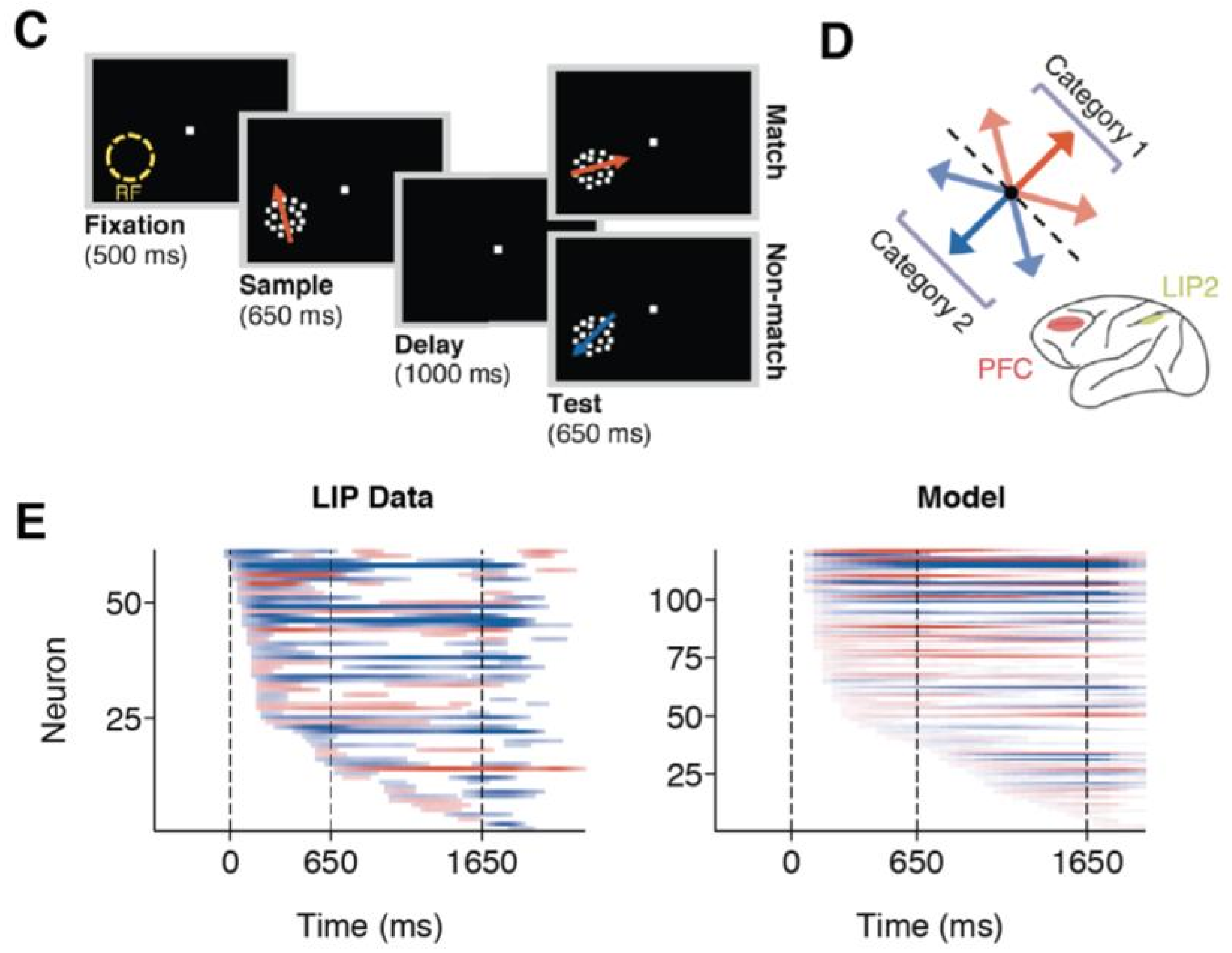
Results: Compared to purely feedforward networks, <u>recurrently-connected deep networks</u> are better at predicting responses of higher visual area neurons to behaviorally challenging images.

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

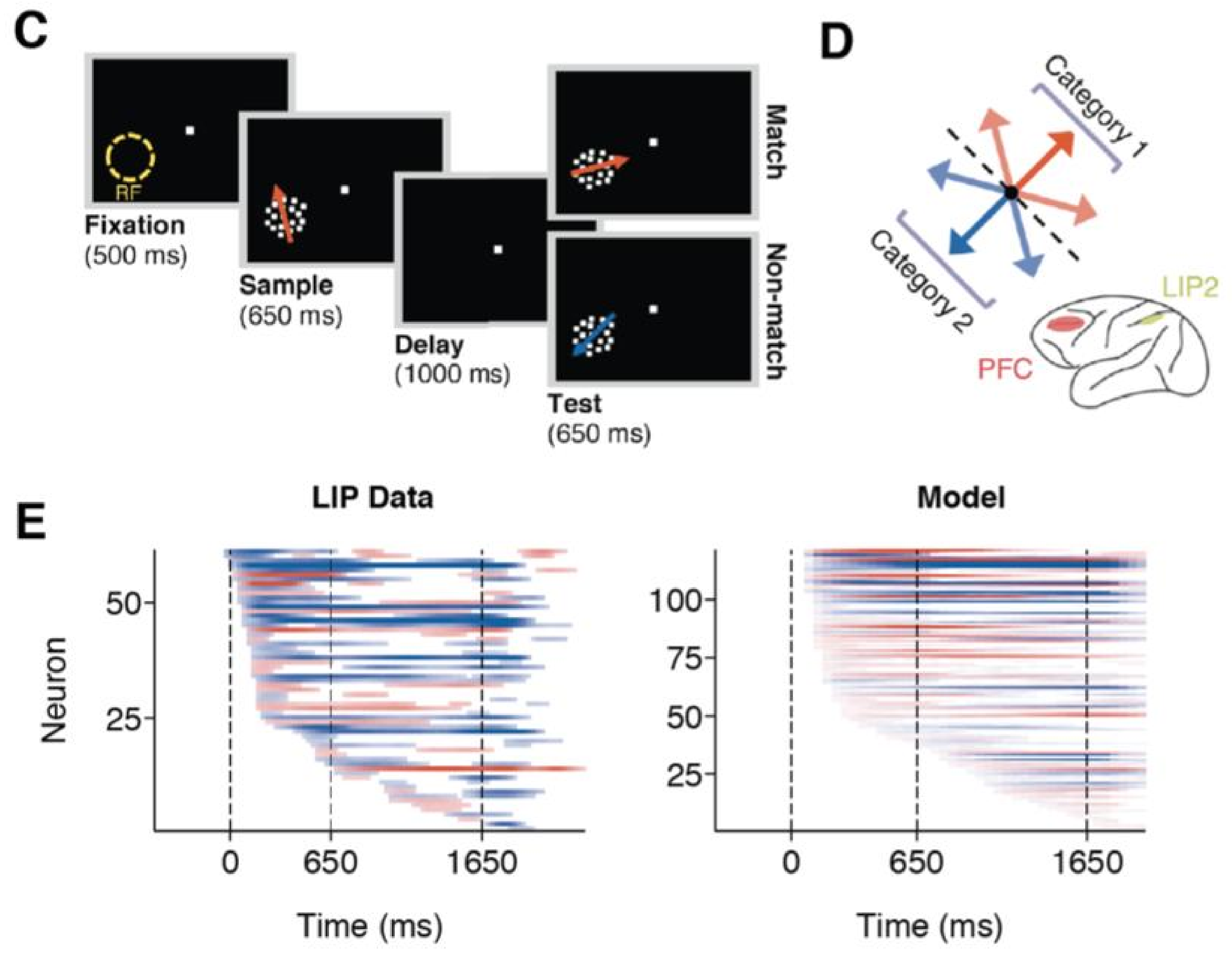


AI helps explain the wide diversity of activity patterns in neural populations.

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, to what extent 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）

大规模中文语料下中国人脑电数据集

与澳门大学伍海燕教授等十位海内外学者合作
受到陈天桥脑科学基金的资助

将大模型应用于中文语言认知加工中的脑信息解码，需要依托于中文语料刺激下脑电数据集进行模型的预训练与微调.

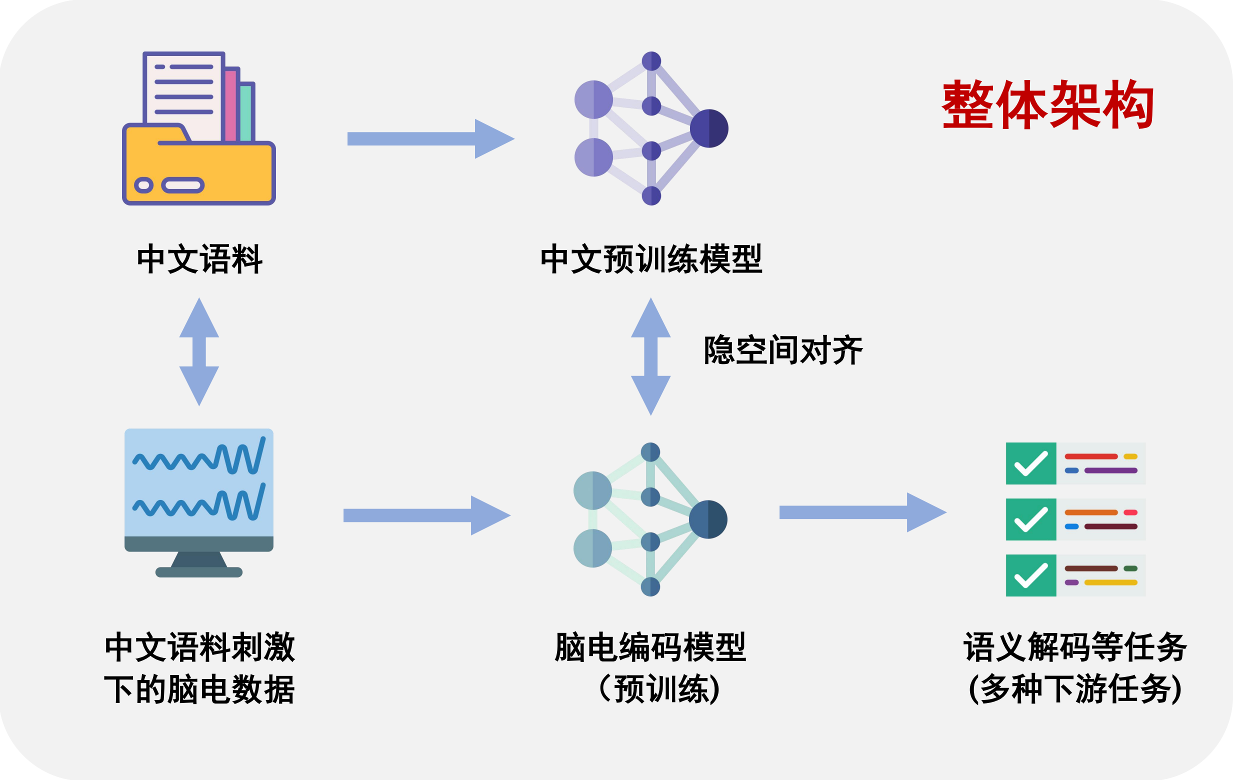
针对目前这类数据集缺失的现状,本项目将采集中文阅读时脑电数据，训练大规模脑电编码模型，推动脑电语义解码和无创BCI应用。

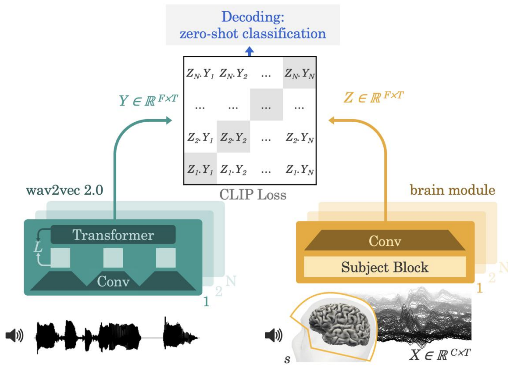
技术问题

- 和文本相比脑电差异性更大，如何减小差异性带来的影响
- 如何实现文本和脑电两种模态数据的对齐

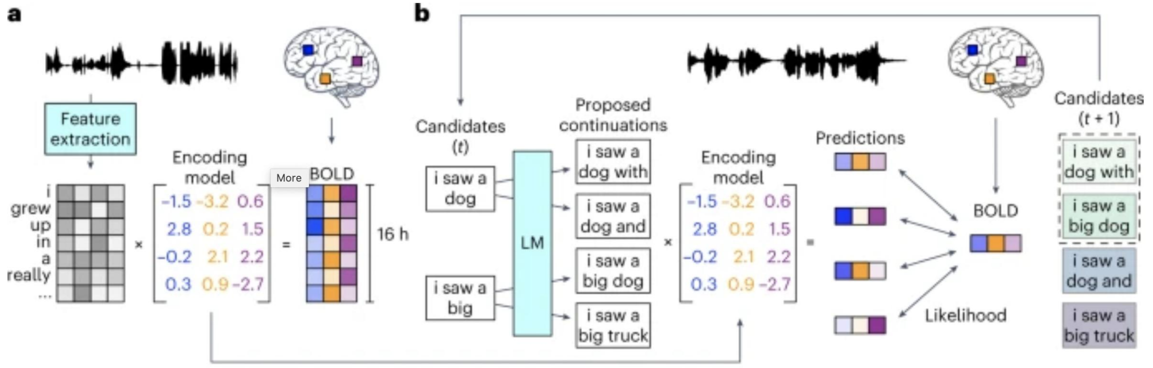
科学问题

- 大脑信息表征与预训练模型信息表征方式的异同及对于跨任务泛化的帮助

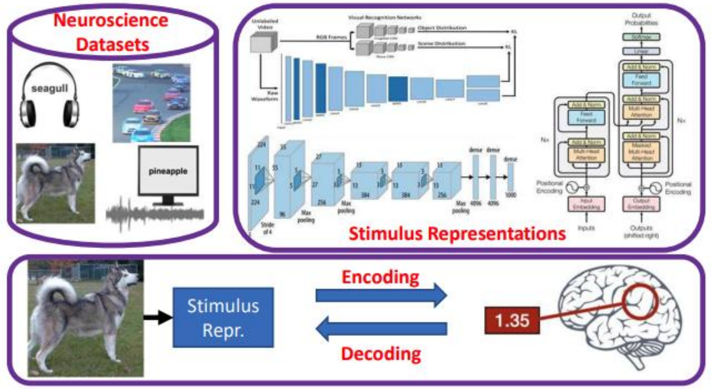




Défossez, Alexandre, et al. "Decoding speech from non-invasive brain recordings." arXiv:2208.12266 (2022).



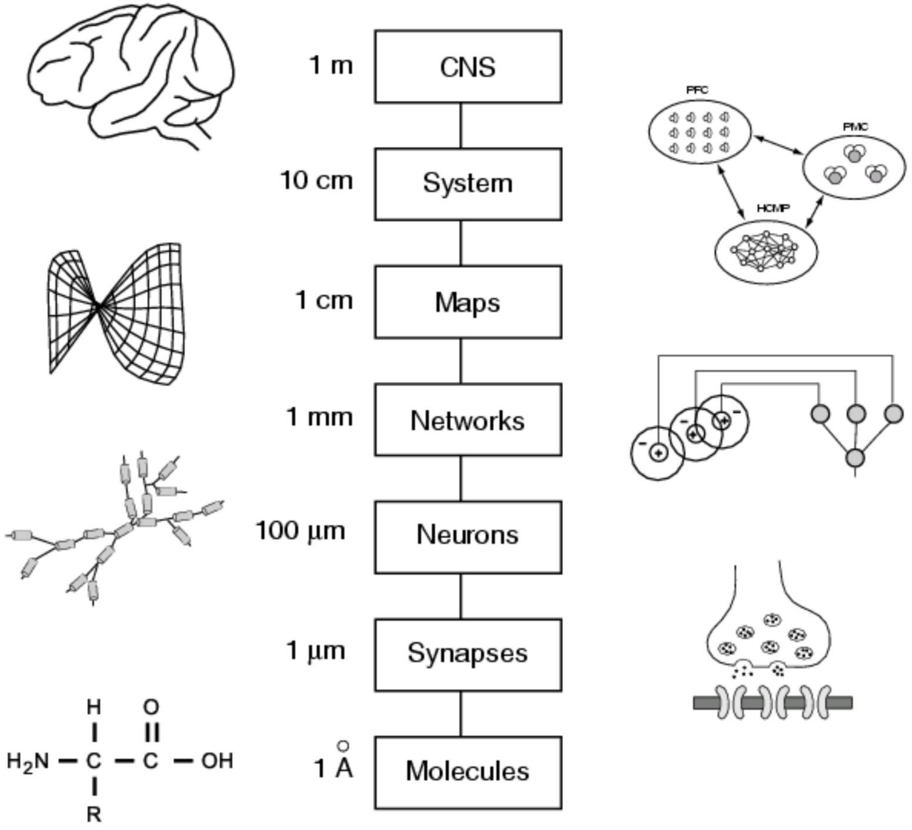
Tang, Jerry, et al. "Semantic reconstruction of continuous language from non-invasive brain recordings." Nature Neuroscience (2023): 1-9.



Oota, Subba Reddy, et al. "Deep Neural Networks and Brain Alignment: Brain Encoding and Decoding (Survey)." arXiv:2307.10246 (2023).

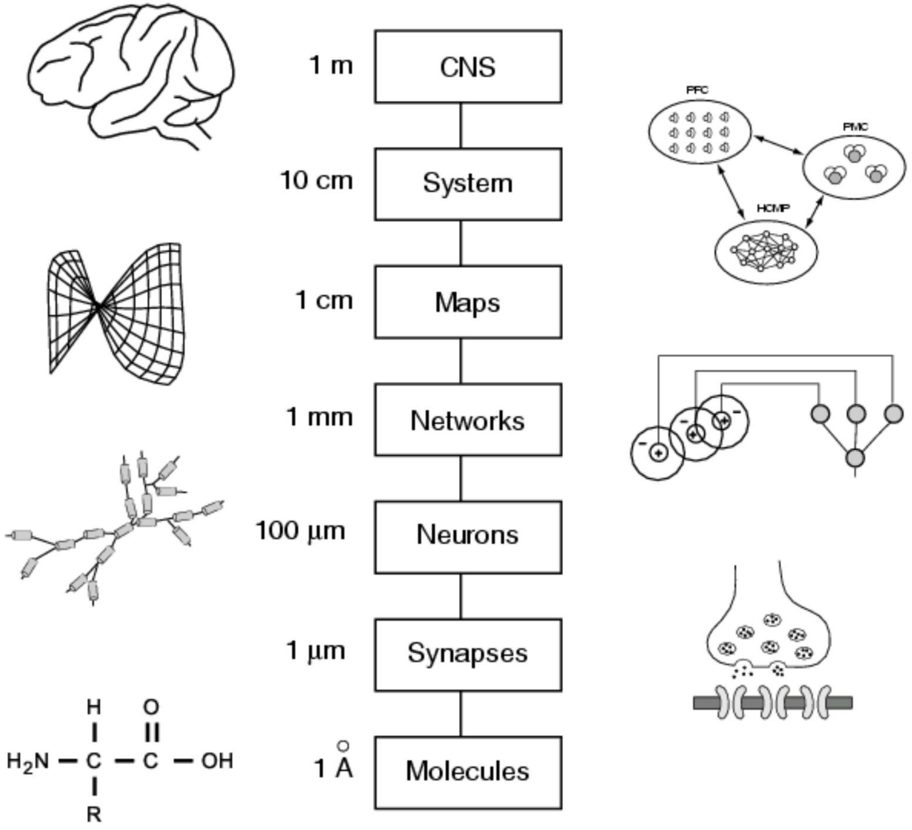
Multiple levels to investigate the brain

Different levels

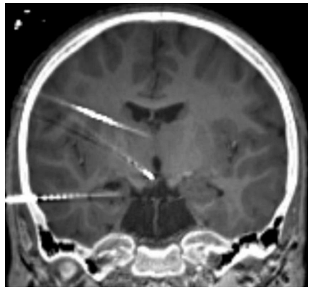


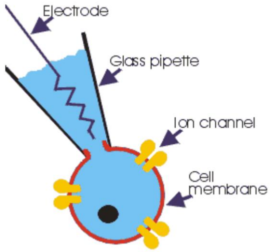
Techniques to see what is happening in the brain

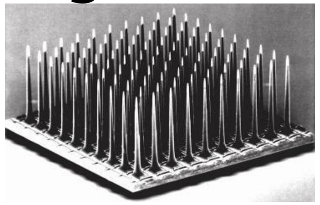
Different levels

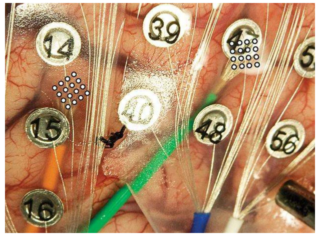


- MRI, fMRI
- EEG, MEG
- SEEG
- ECoG
- Local field potential (extracellular)
- Utah Array
- Patch clamp (intracellular ing)



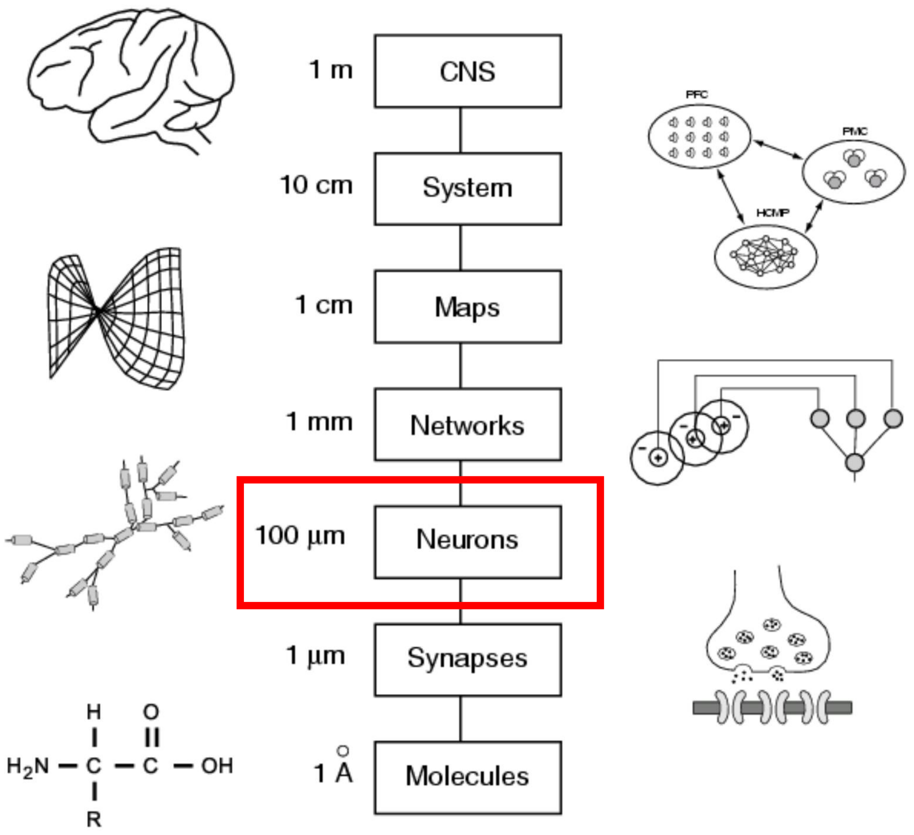


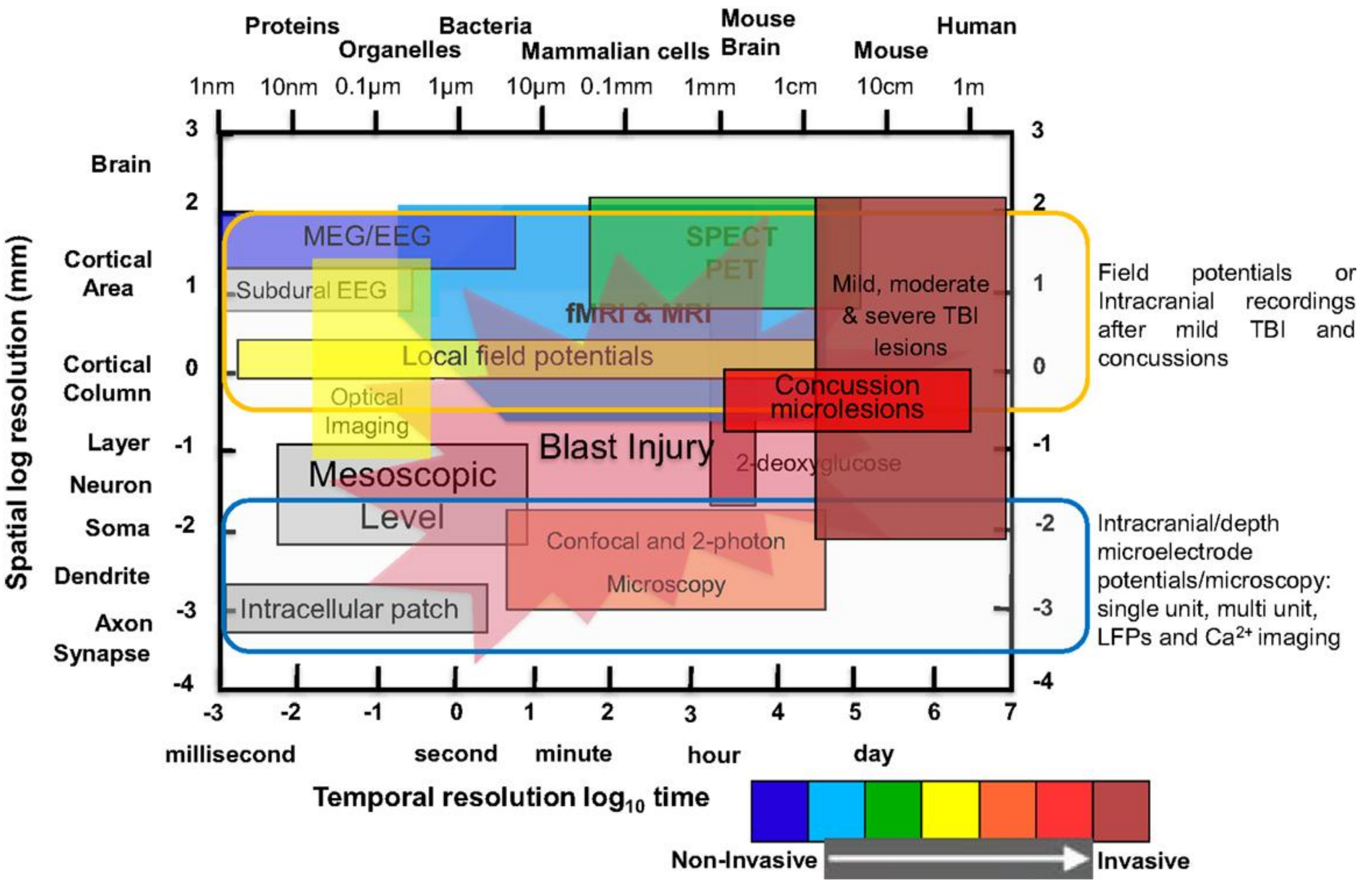




Techniques: Temporal resolution and Spatial resolution

Different levels

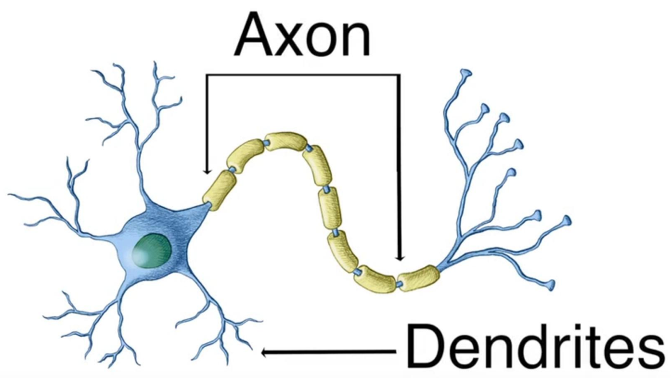




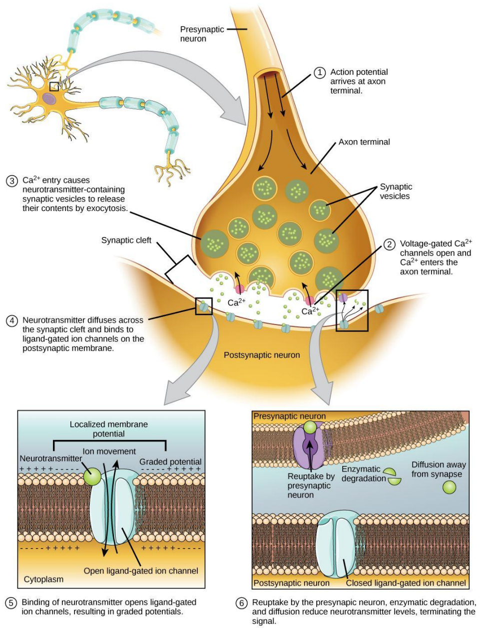
Manoj Kumar Jaiswal, Front Neurol 2015

Neuron and Action potential

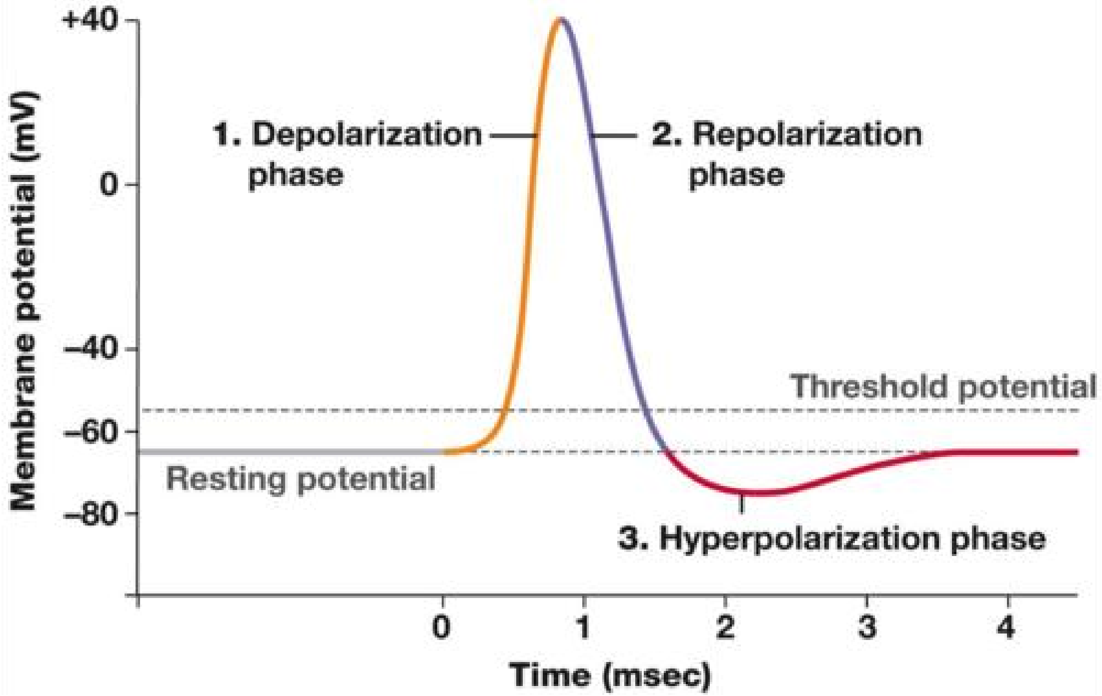
Neuron



Synapse



Action potential (spike)

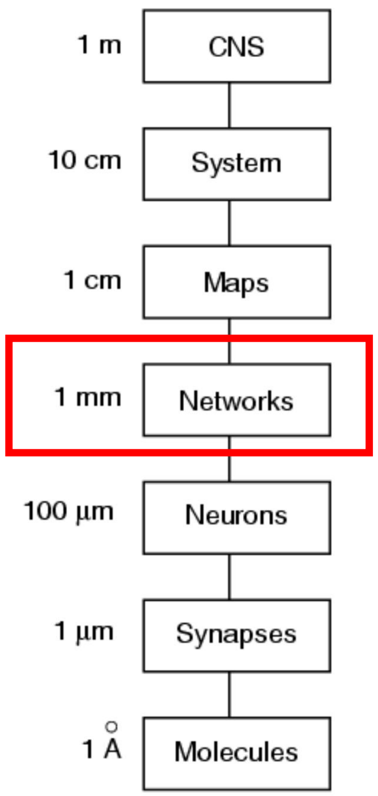


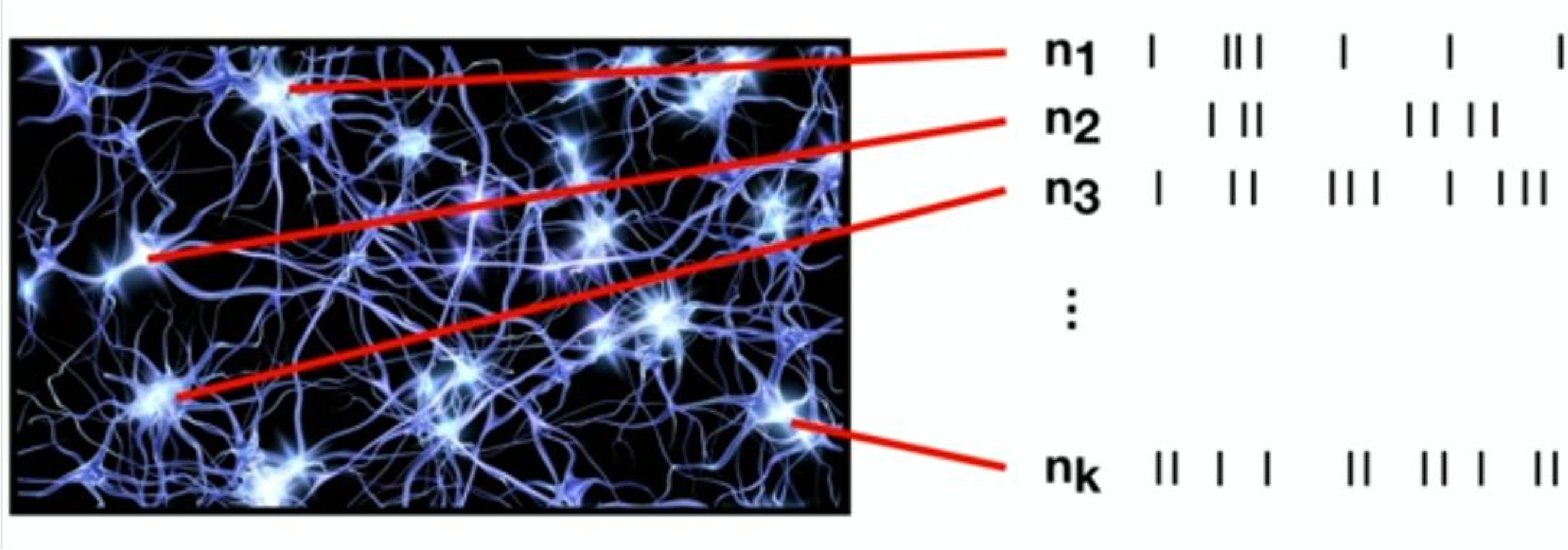
binary code: 0 1 0 0

Cell Membrane

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

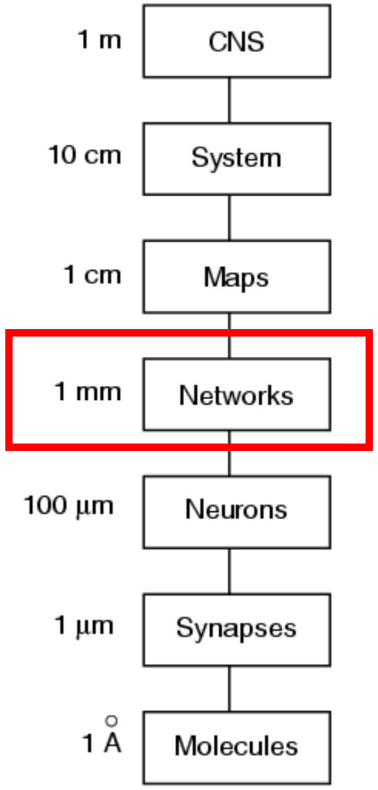
Biological neural network

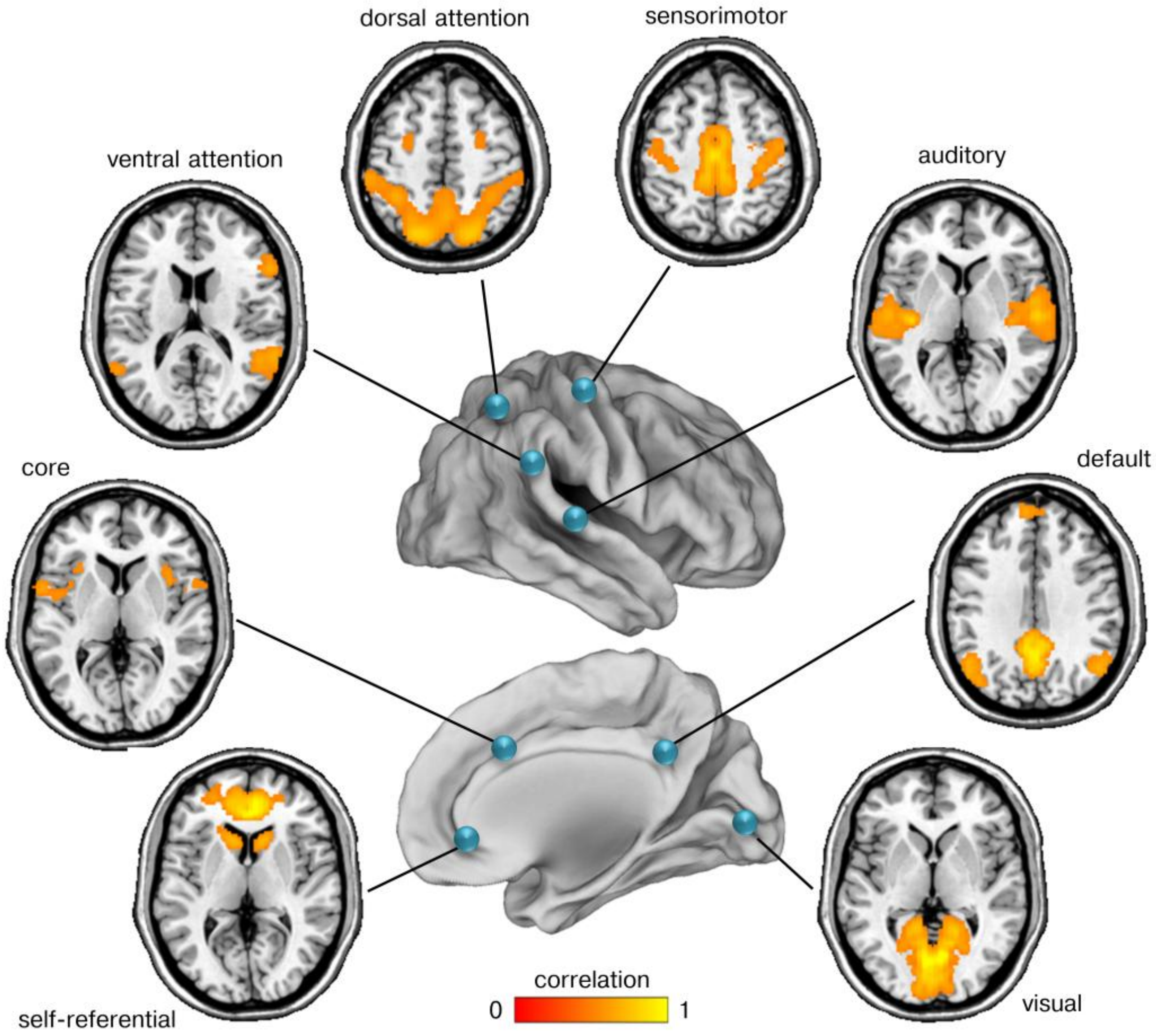




Biological neural network ⟷ Artificial neural network

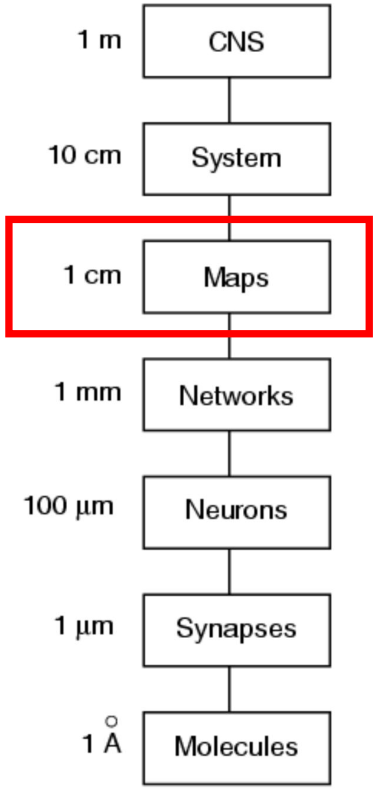
Brain functional networks



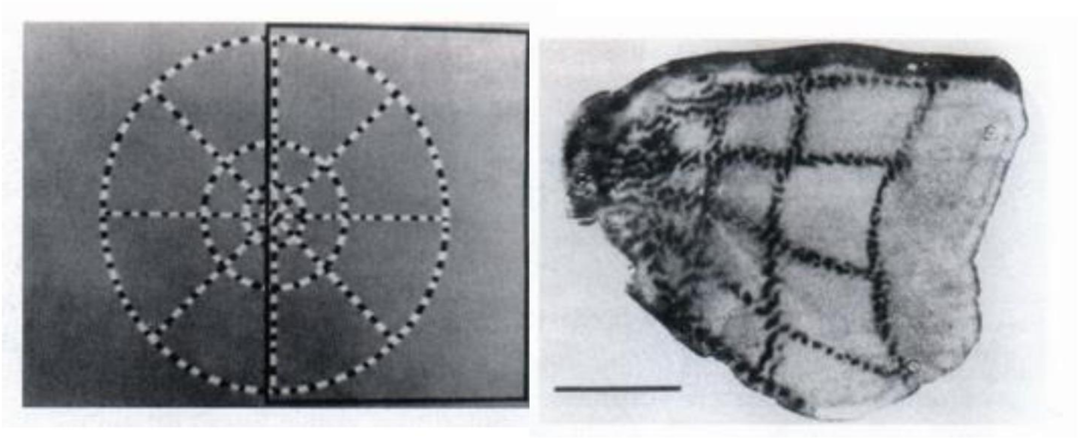


Gillebert and Mantini, *The Neuroscientist* 2013

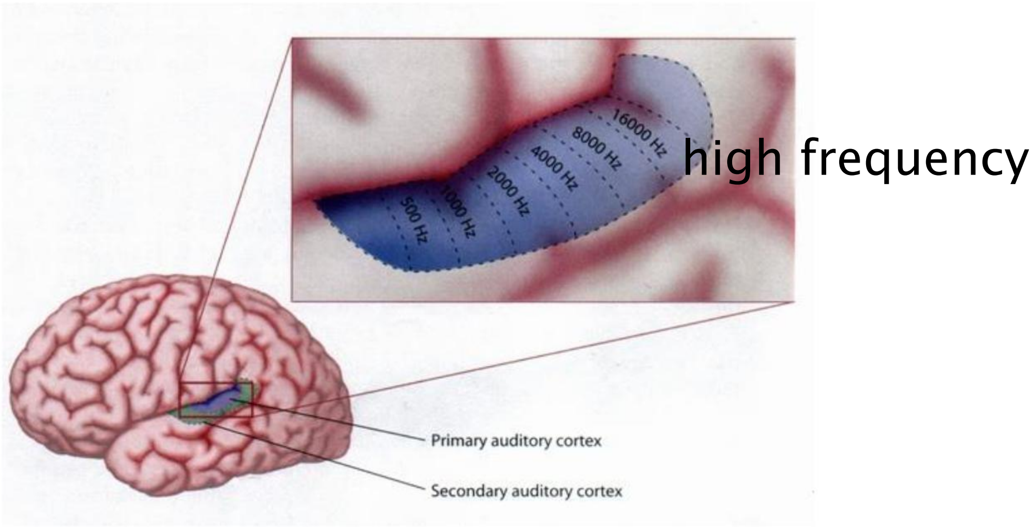
Topographic Maps



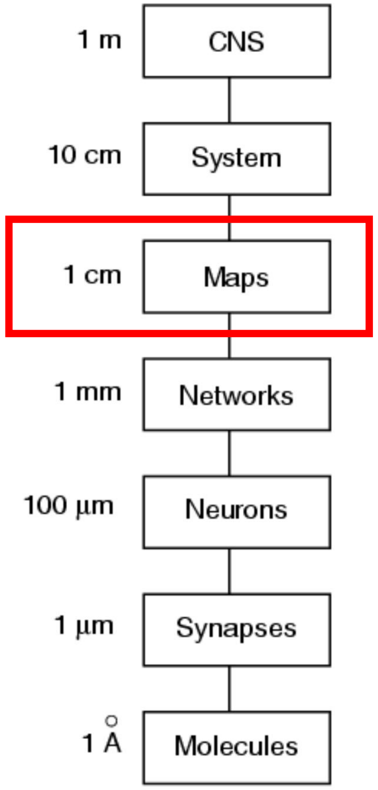
Retinotopic map

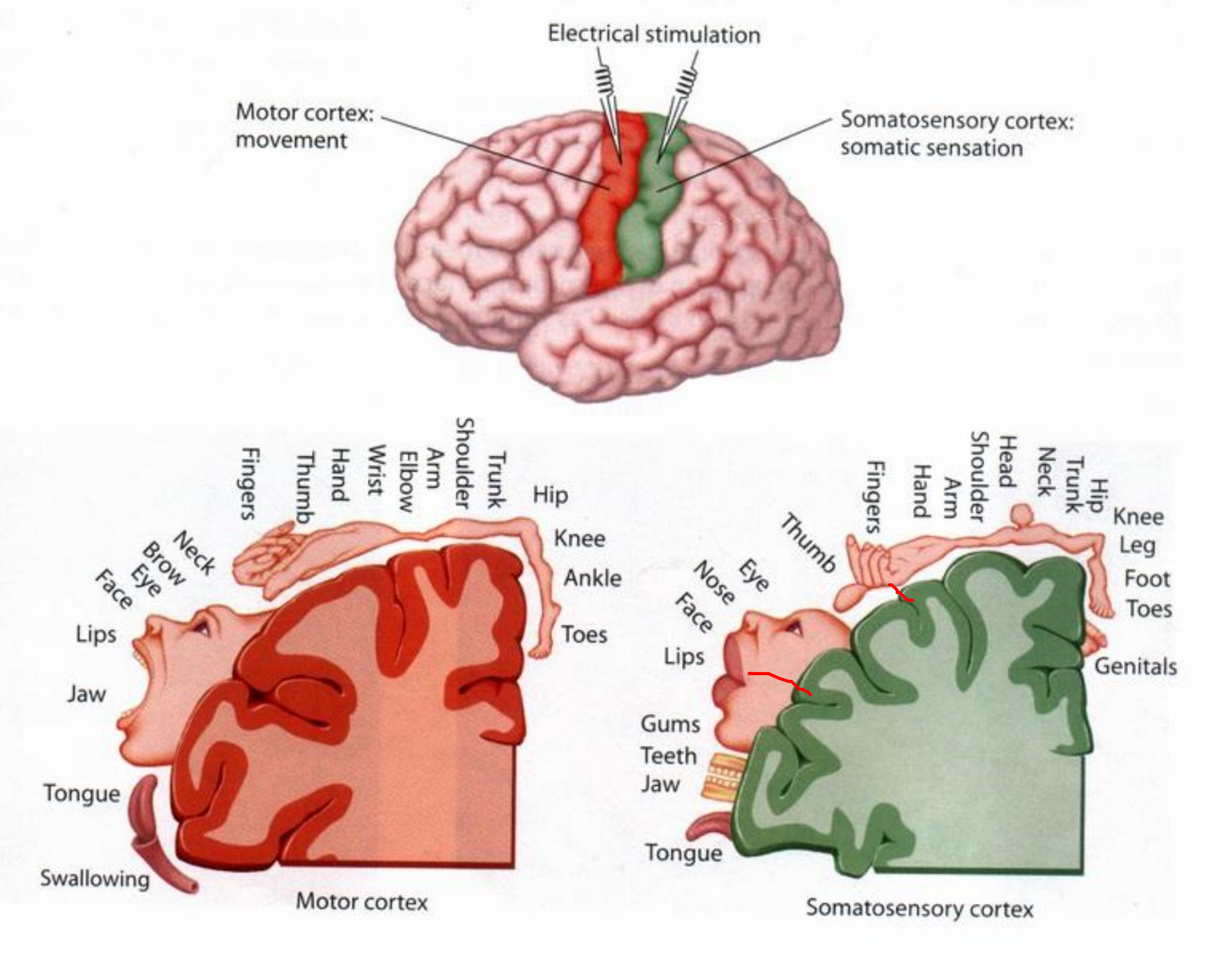


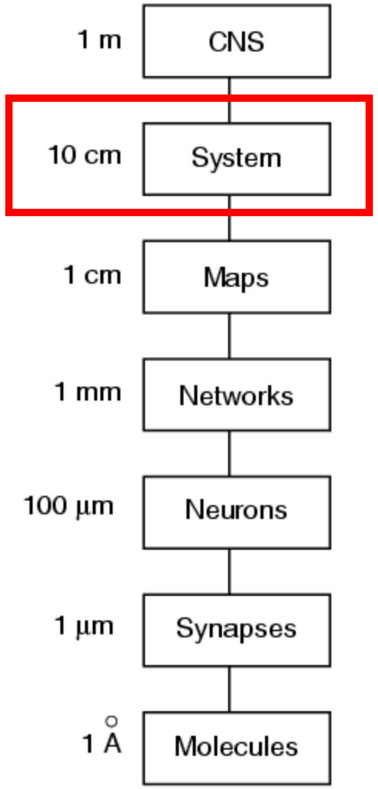
Tonotopic map



Topographic Maps at motor cortex & somatosensory cortex





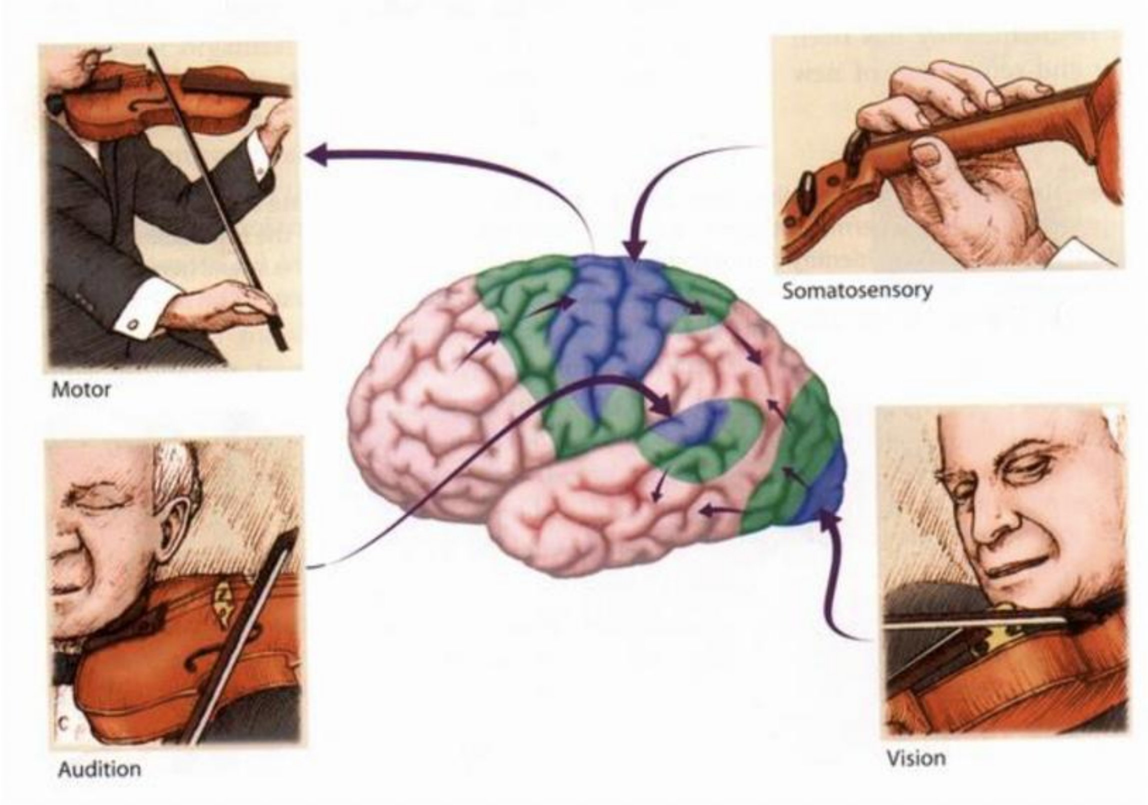


Visual system

Auditory system

Somatosensory system

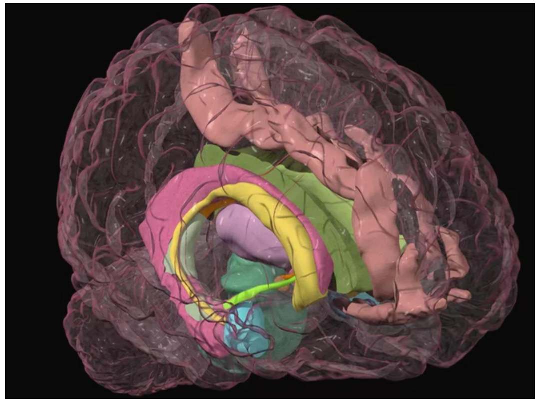
Motor system



Olfactory system (smell)

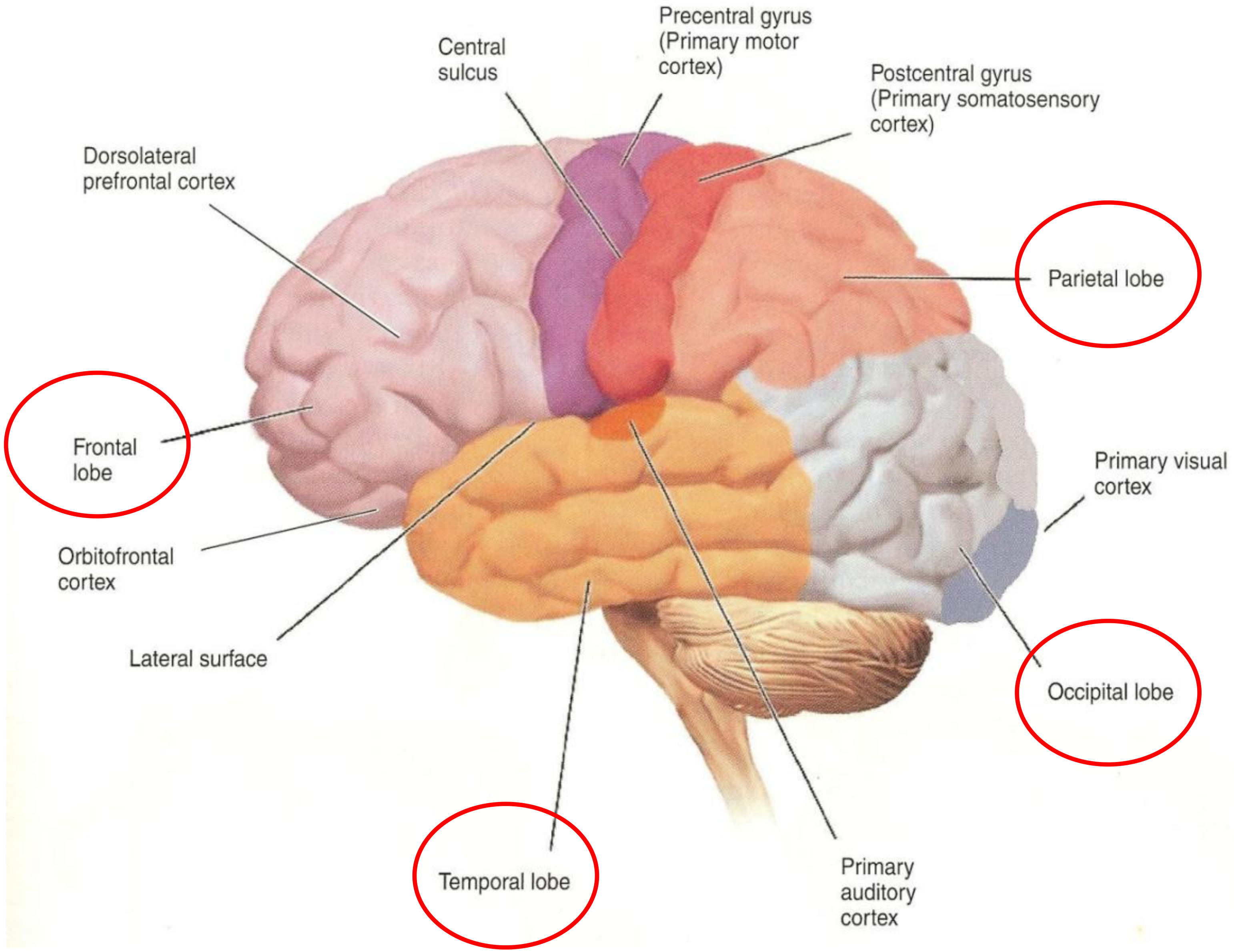
Limbic system (emotion & motivation)

Including amygdala and hippocampus

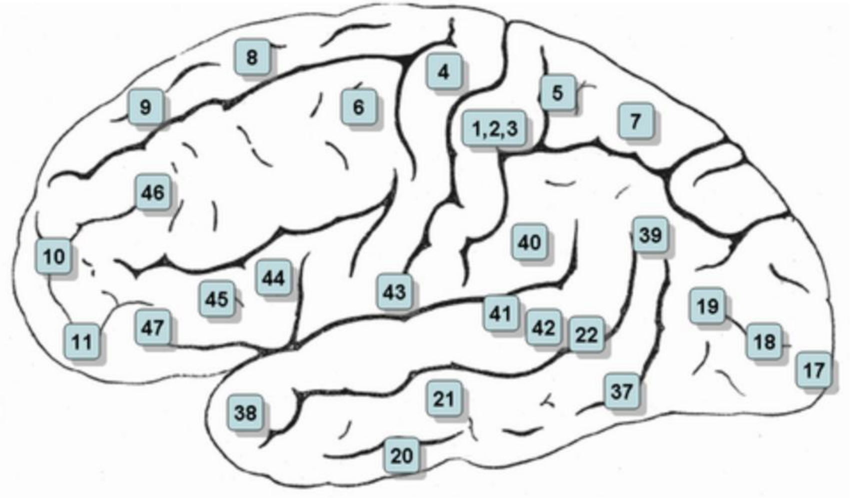


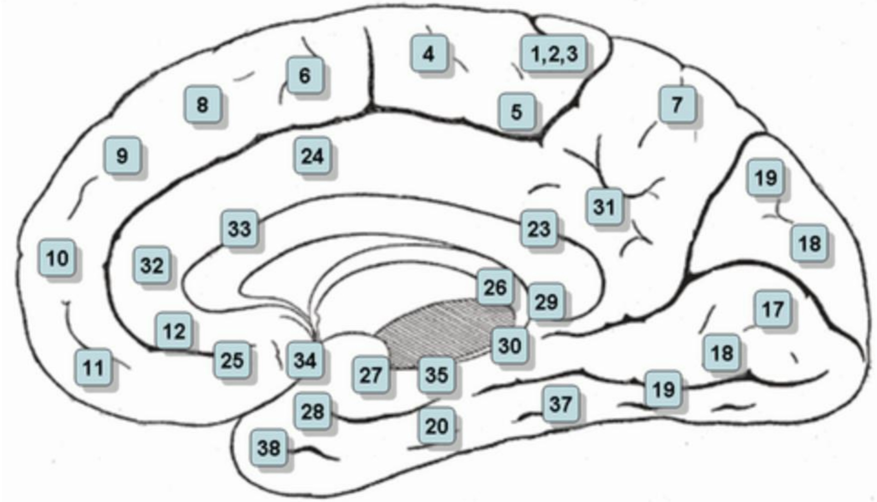
Other high-level cognition?
Such as consciousness, (free) will

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

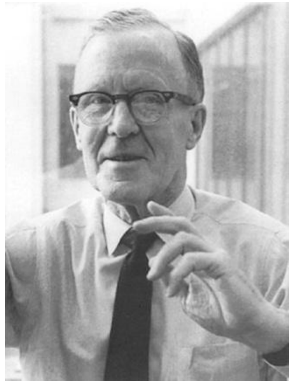
Area 27 – Piriform cortex
Area 28 – Ventral entorhinal cortex
Area 29 – Retrosplenial cingulate cortex
Area 30 – Part of cingulate cortex
Area 31 – Dorsal Posterior cingulate cortex
Area 32 – Dorsal anterior cingulate cortex
Area 33 – Part of anterior cingulate cortex
Area 34 – Dorsal entorhinal cortex)
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.

各种大脑分区的atlas

Atlas名称	年份	数据量	数据模态	方法
Brodmann	1909	–	组织切片	根据细胞结构的差异划分
AAL3	2002	152	T1	根据MNI152模板手动分割
Freesurfer DK	2006	40	解剖数据	解剖标记
Yeo	2011	500+500	rs-fMRI	Von Mises-Fisher distribution
Power ROIs	2011	300+40+106	rs-fMRI	Meta-analytic，FC-Mapping
Craddock	2012	41	rs-fMRI	Normalized cut spectral clustering (NCUT)
Shen	2013	79	rs-fMRI	Multigraph K-way clustering algorithm
Gordon	2016	120+108	rs-fMRI	RSFC-boundary mapping
Brainnetome	2016	40+40	rs-fMRI, T1, DTI	Spectral clustering
MMP	2016	210 +210	rs-fMRI, T1, DTI	Surface Gradients on Modality Spatial Maps
Schaefer	2018	744+745	rs-fMRI	Gradient-weighted Markov Random Field (gwMRF) model
Tian	2020	1113	3T rs-fMRI, 7T rs-fMRI, tfMRI	Gradientography

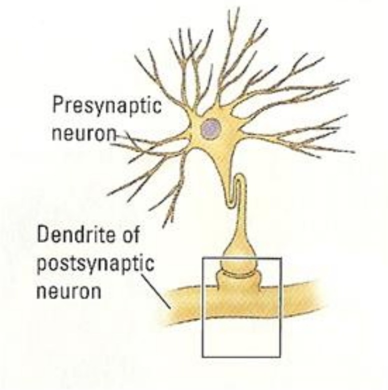
Learning in the brain (Hebbian learning)



D. O. Hebb

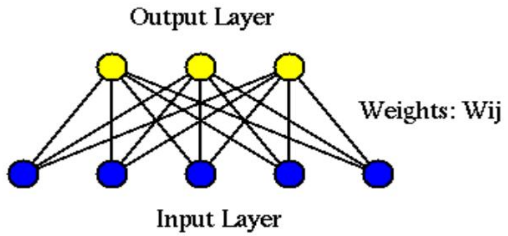
"When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased."

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



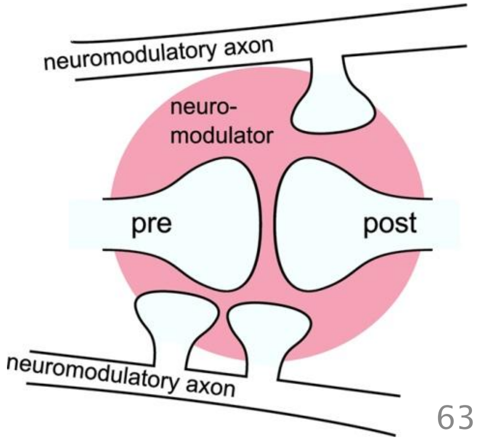
In other words: "**Cells that fire together wire together**."

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



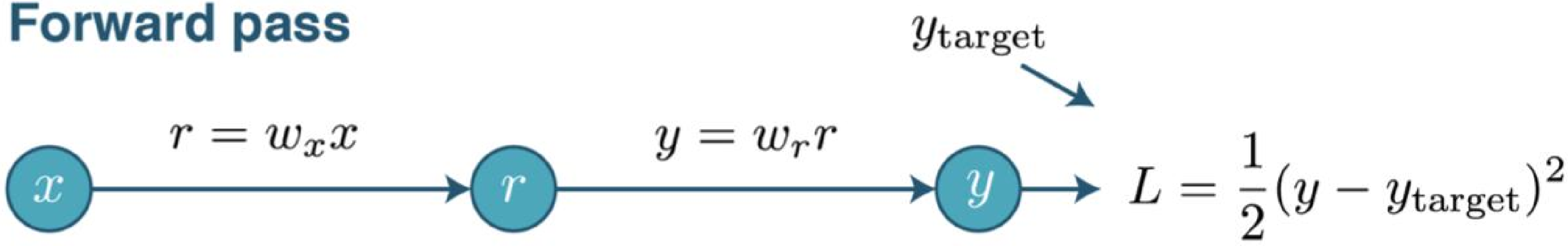
More complex and sophisticated ideas have been under continual exploration for over a half a century, including:

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



Learning in AI (Error backpropagation)

Forward pass



Backward pass

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

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

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

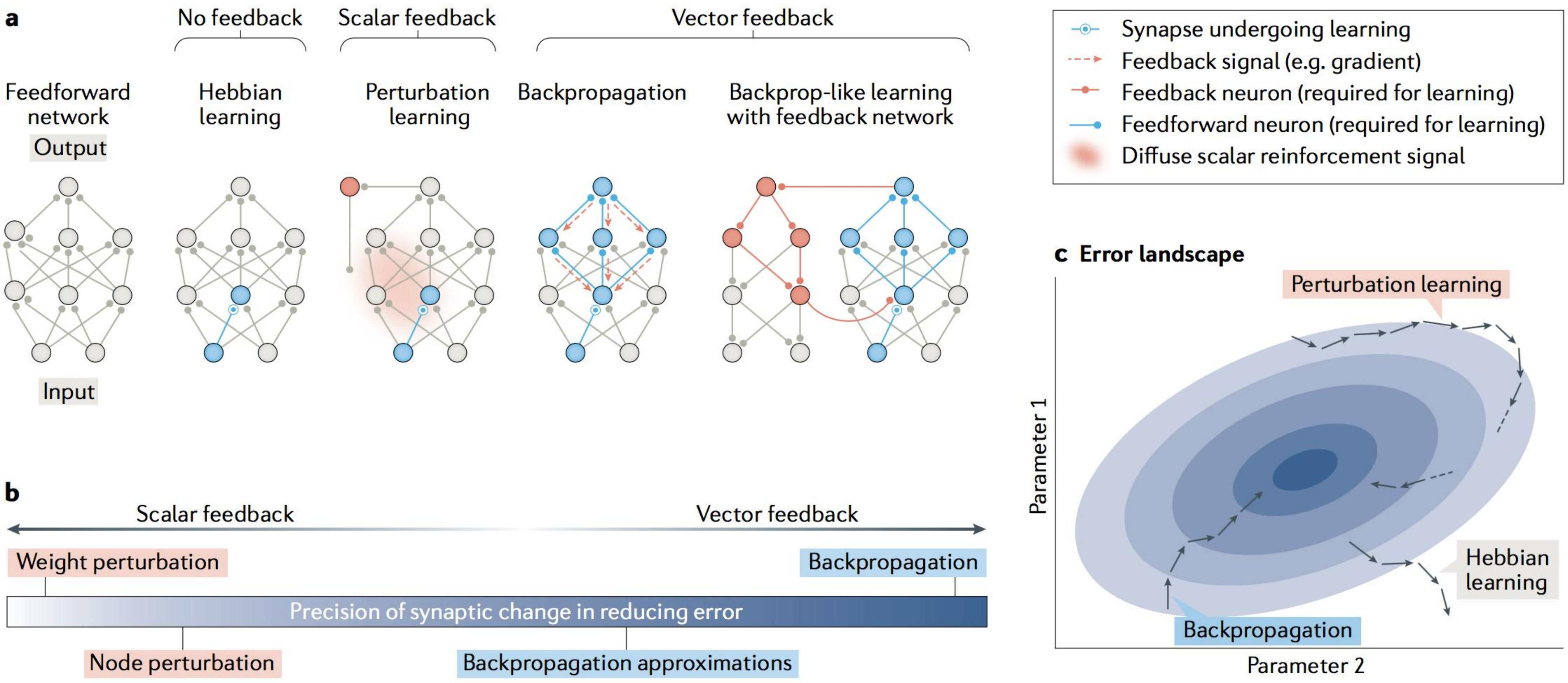
Non-local $\frac{\partial L}{\partial y} w_r$

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.

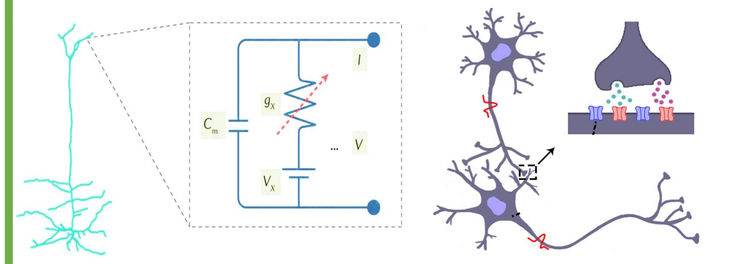
Hebbian learning vs BP vs other alternatives



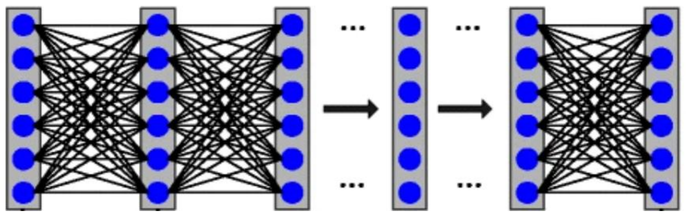
Timothy, Santoro, Marris, Akerman, Hinton (2020) Backpropagation and the brain, *Nature*

BI&AI 研究方向与关键问题

神经网络模型



树突计算模型　　单神经元模型

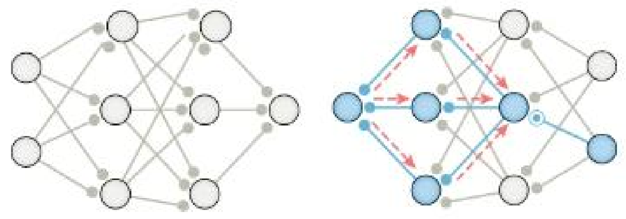


神经元网络模型

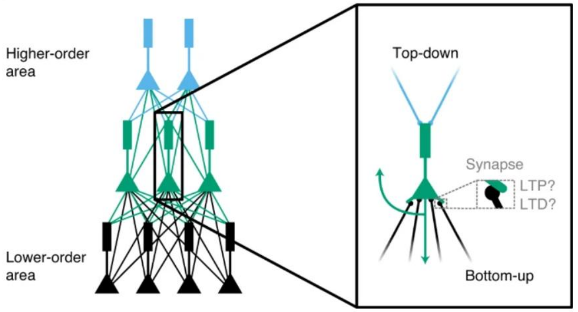
Poirazi et al. *Nat. Rev. Neurosci* 2020
Guo et al. *J COMPUT NEUROSCI* 2011

与生物大脑信息传递不匹配

网络学习算法



反向传播算法

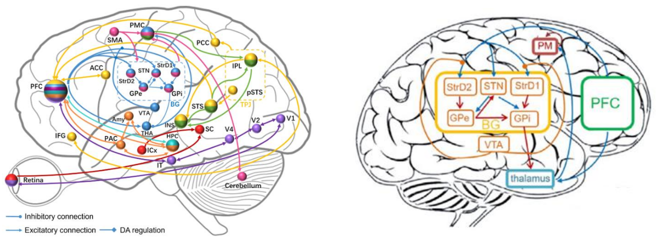


锥体神经元分层传播算法

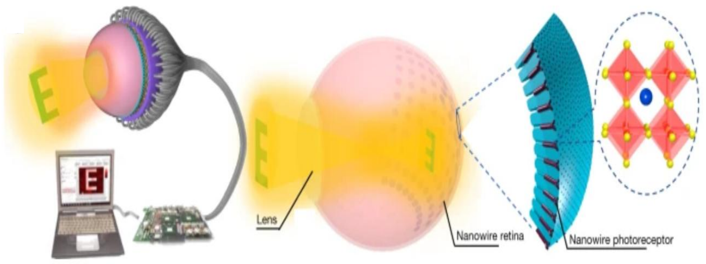
Lillicrap et al. *Nat. Rev. Neurosci* 2020
Payeur et al. *Nat Neurosci* 2021

与大脑前馈学习法则相矛盾

仿生智能系统



仿生智能模型



仿生神经形态设备

Zeng et al. ***Patterns*** 2023
Gu et al. ***Nature*** 2020

与智能生命功能实现有差距

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
- Neuron, Nature communications, Science Advances
- PNAS, Cell reports, 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?

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——《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?

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- Students (2020-now): All the students who took the BI&AI course.