Southern University of Science and Technology

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

Brain Intelligence and Artificial Intelligence

人脑智能与机器智能

Lecture 14 – AI for brain science

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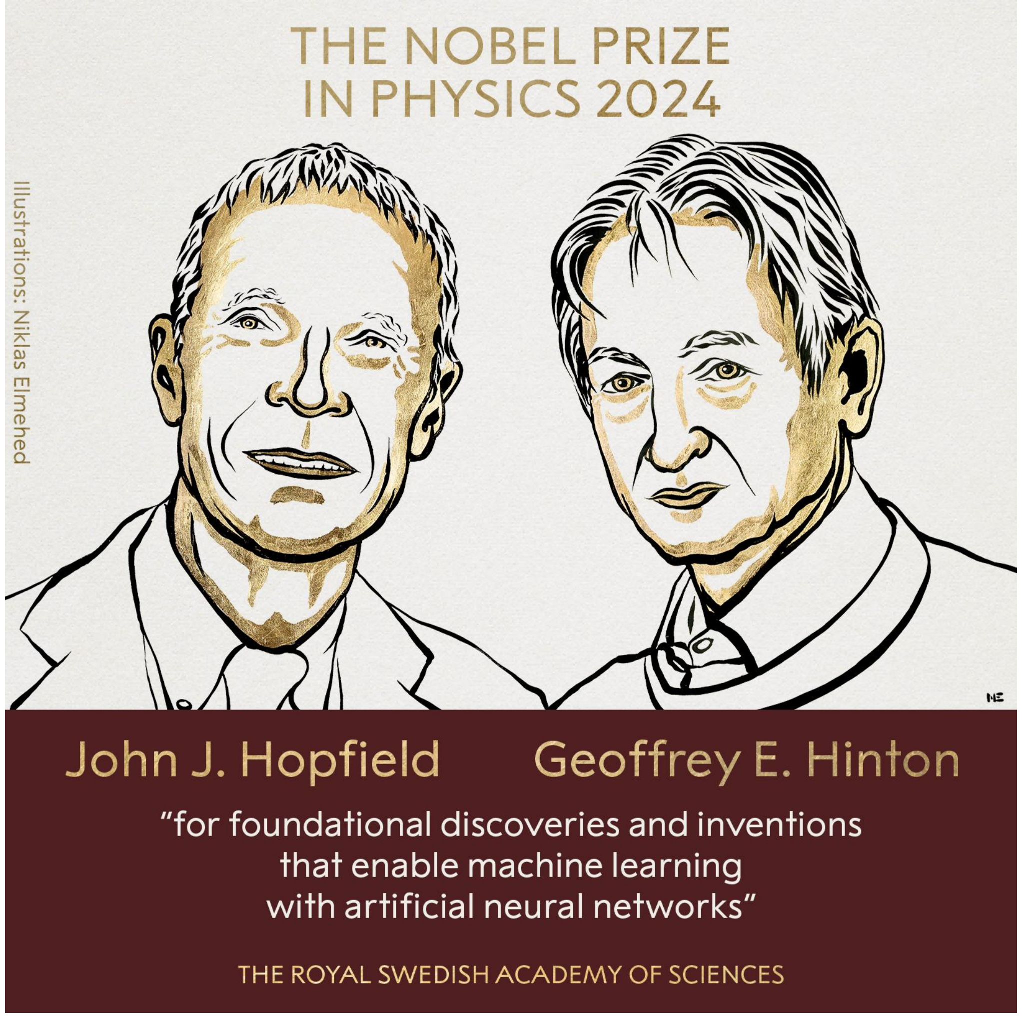
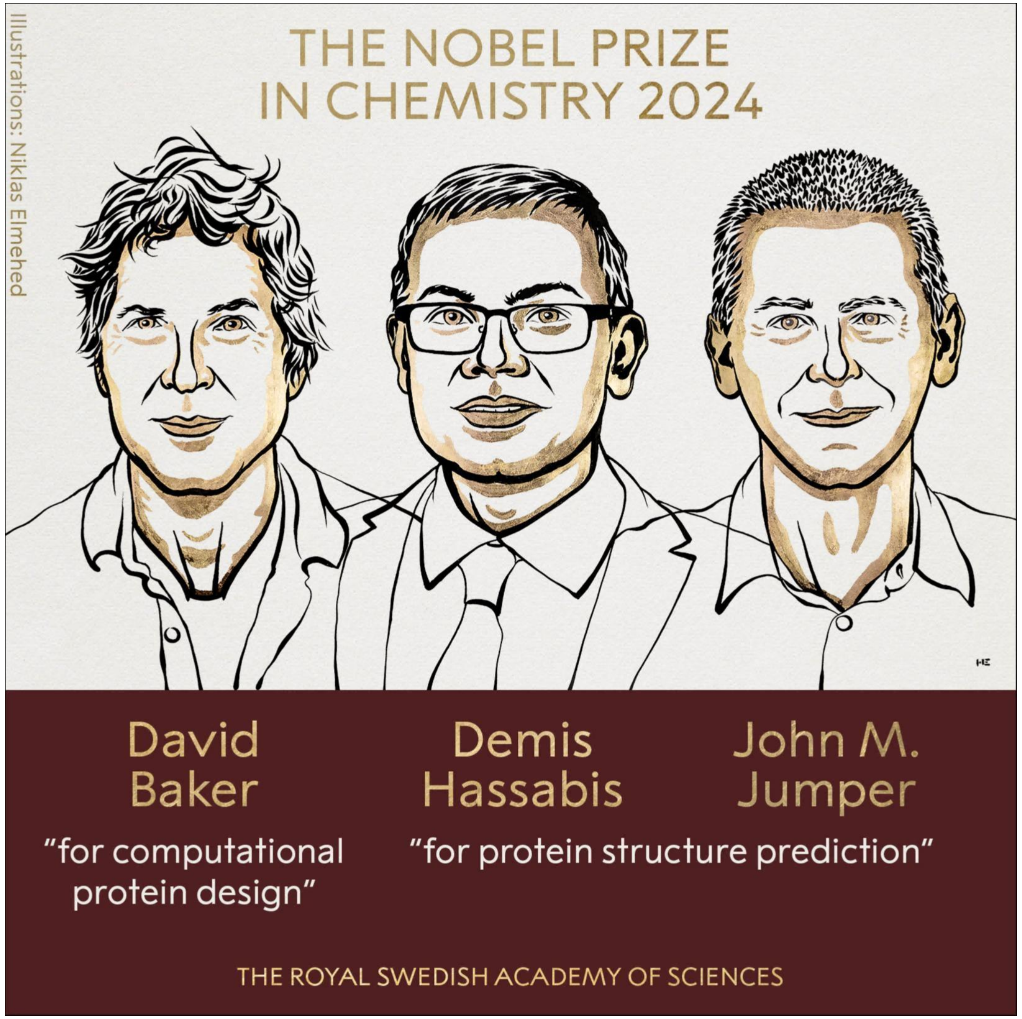
AI for Science





AI Revolution in Science Discovery

The old good days，学生充满学识。。。

一个年轻的研究生，

经过多年的学习

积累了深厚的领域内的知识

提出一个看着像是靠谱的hypothesis

设计实验

采集数据

统计分析

哇哈，结果显著，发表论文

Oh no!
结果不显著!!!

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哇哈，结果显著，发表论文

Oh no!
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Nowadays，学生无需学识。。。

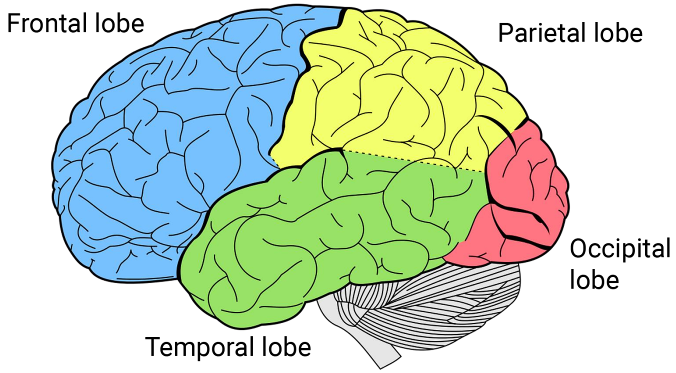
一个年轻的研究生，
经过几天AI的学习
从网上扒一些开放数据和模型
通过各种可耻的tricks魔改AI模型
在训练数据中训练模型
在测试数据中跑实验
计算metrics
哇哈，结果SOTA，发表论文

Oh no!
性能打不过!!!

The human brain

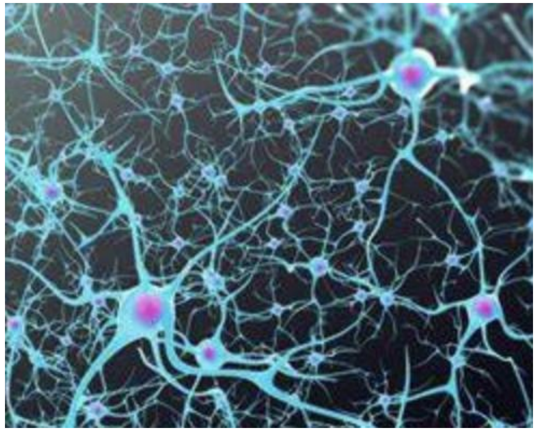
a brain

few lobes



hundreds of regions

100 billions of neurons



一个大脑，能实现各种各样的功能，做各种各样的任务。

而神经网络AI模型，往往只能做某种任务或某类任务，会面临灾难性遗忘的问题。

Brain inspires AI.

AI for brain research.

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 …)

A model to **encode** (predict) neural signals

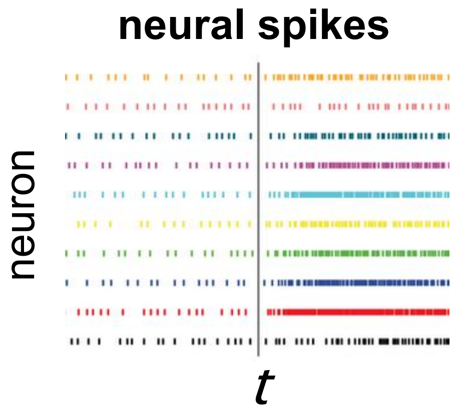
Neural data (10^{12} neurons, 10^{2} brain regions)

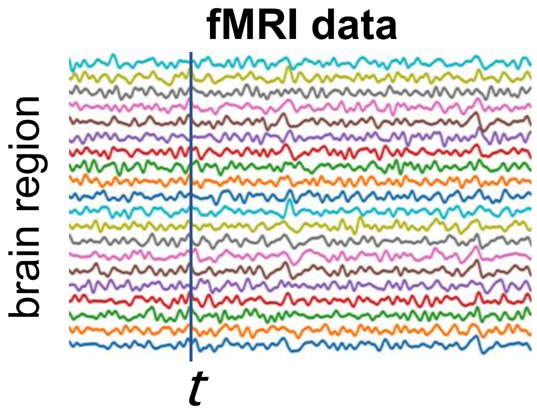
A model to **decode** (understand) neural signals

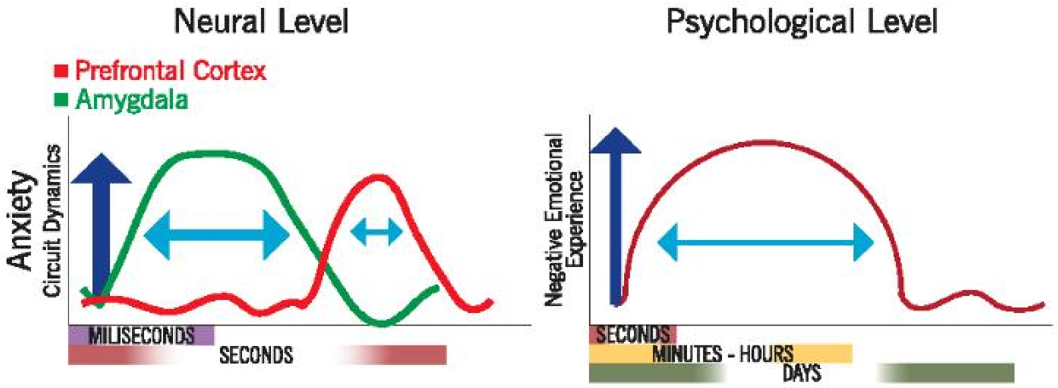
Cognitive process

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。







Heller & Casey (2016) *Developmental science*

The encoding/decoding model

External world (image, sound … stimuli)

A model to **encode** (predict) neural signals

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

A model to **decode** (understand) neural signals

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.

Motivations: Modelling the large-scale brain dynmaics

External world (image, sound … stimuli)

A model to **encode** (predict) neural signals

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

A model to **decode** (understand) neural signals

Cognitive process

Senses (感觉)
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Attention (注意力)
Cognition (认知)

Input-response modelling:

$$x(t+1) = f(x(t), u(t))$$

$x(t)$: the state of the brain
$u(t)$: the input to the brain
$f(\ )$: the dynamical model

Motivations:

- Synthesize neural data at multiple scales
- Bridge the input to the brain $u(t)$ and the neural response $x(t+1)$
- Predict the state-dependent response
- Do virtual experiments

Data: Modelling the large-scale brain dynmaics

External world (image, sound … stimuli)

A model to **encode** (predict) neural signals

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

A model to **decode** (understand) neural signals

Cognitive process

Senses (感觉)
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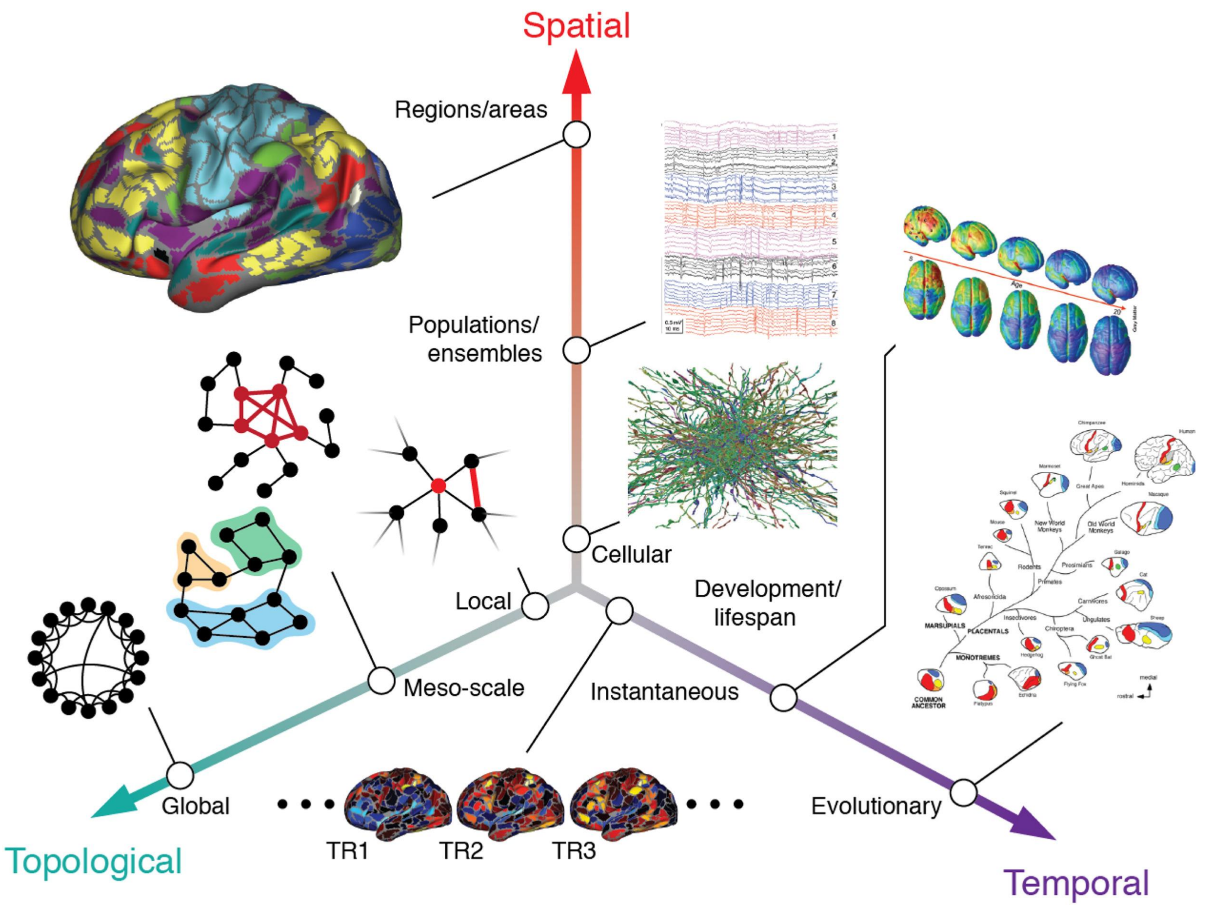
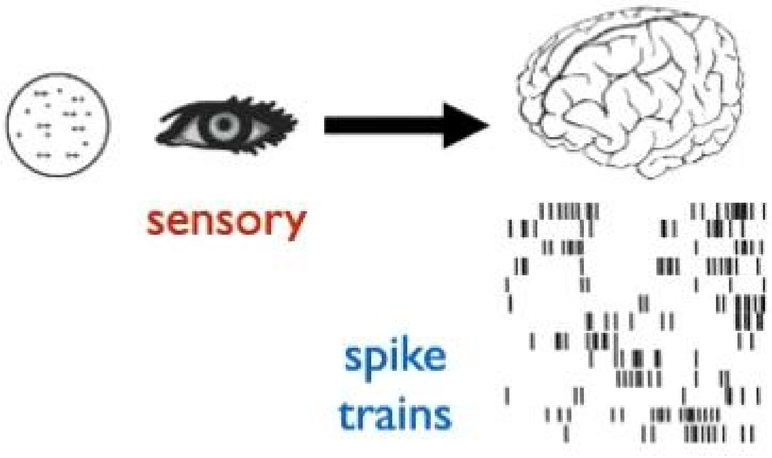


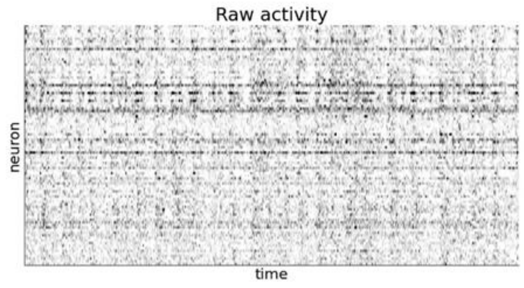
Betzel, Richard F., and Danielle S. Bassett. *Neuroimage* (2017)

Neural population coding



Y

High-D



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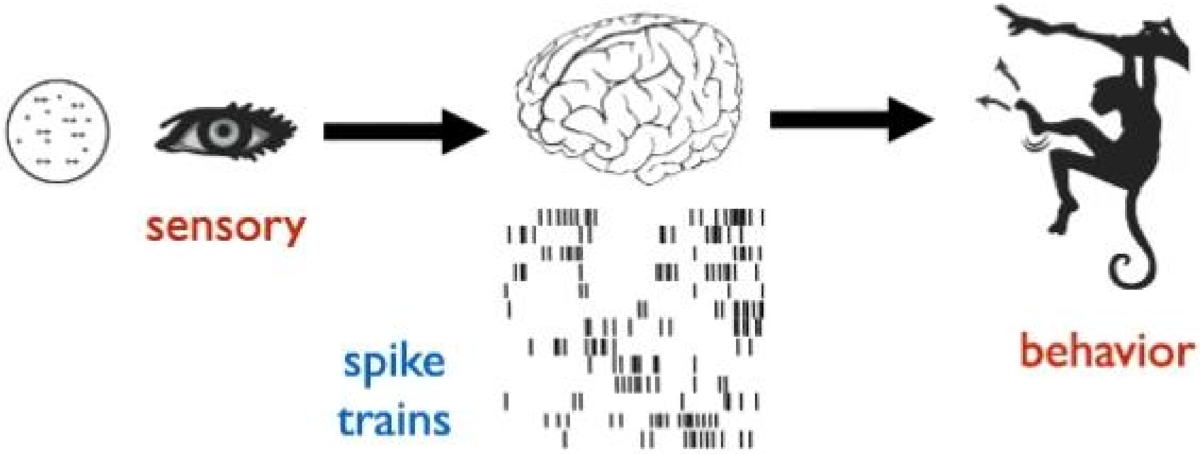
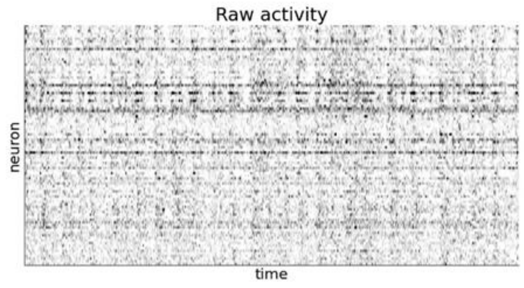


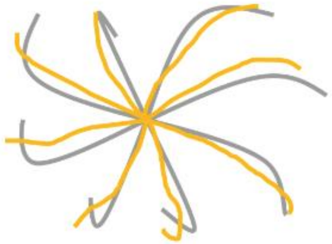
Y

High–D

Z

Low–D





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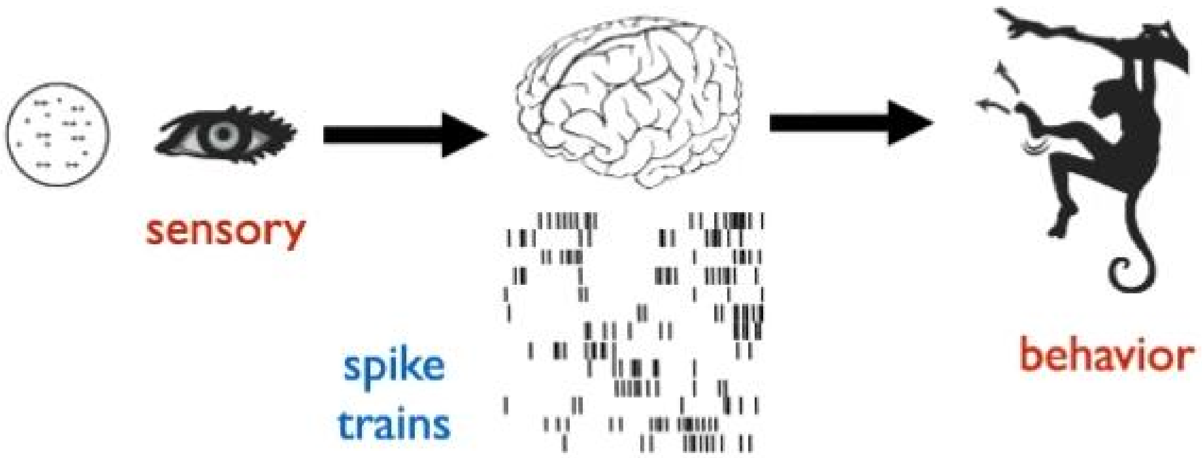
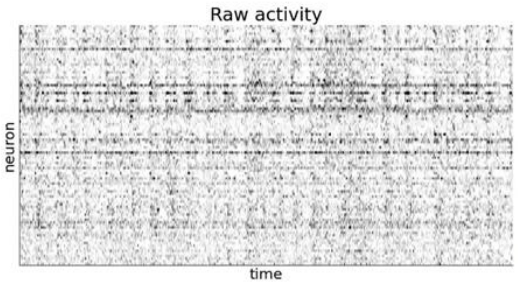
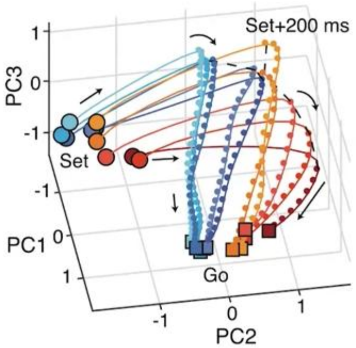
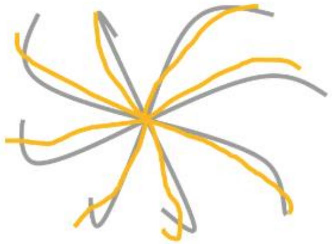


Y → X → Z

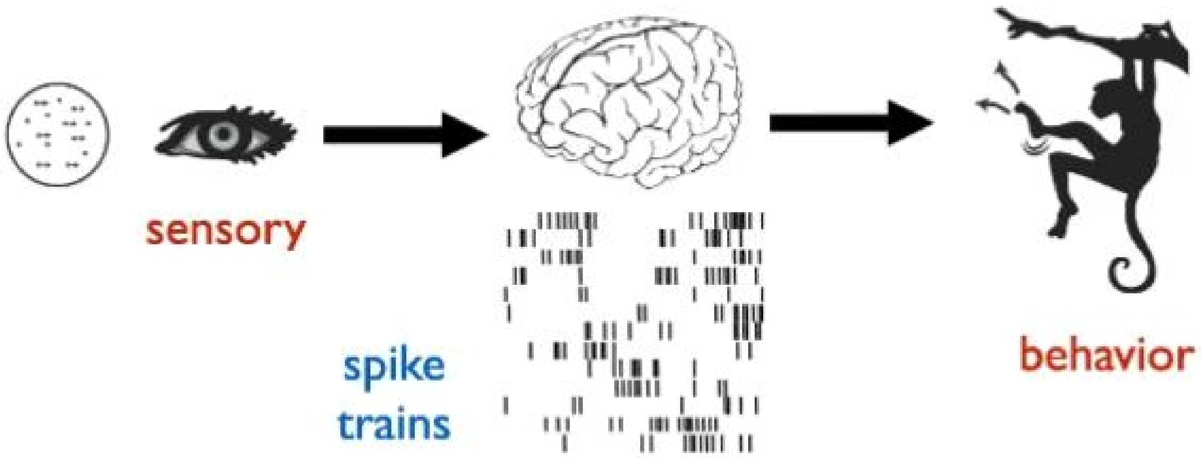
High–D   Low–D   Low–D







Neural population coding



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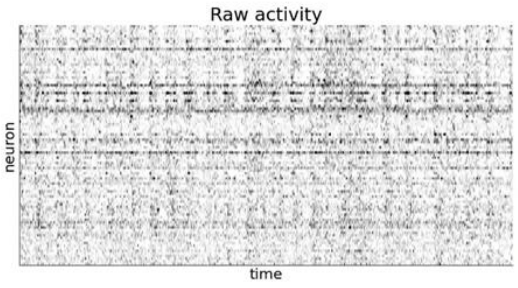
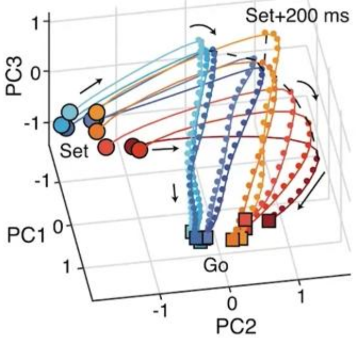
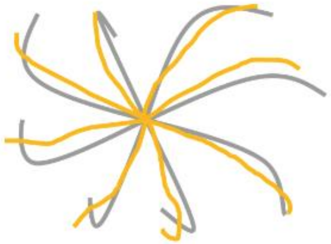
High–D   Low–D   Low–D







Dimensionality reduction in neuroscience

Non-parametric

- Principle component analysis (PCA)
- Gaussian process factor analysis (GPFA)
- Gaussian process latent variable model (GPLVM)

Dynamical systems

- PLDS
- PfLDS
- LFADS
- GPFADS
- CEBRA

Lawrence and Hyvärinen, (2005). JMLR
Wu et al. (2017) NeurIPS
Wu et al. (2018) NeurIPS
Gao et al. (2016) NeurIPS
Pandarinath et al. (2018) Nature Methods
Rutten et al. (2020) NeurIPS
Schneider et al (2023) Nature
Miller et al (2024) NeurIPS

AI for brain science

- ➢ **AI为脑科学提供数据分析工具**
  - 神经解码
  - 行为分析
- ➢ **AI为脑科学提供实验仿真工具**
  - 多认知任务下的神经表征
  - 神经动力学仿真
- ➢ **AI为脑科学提供有潜力的科学假设**
  - 大脑网络在进化中优化到near-optimal以支撑复杂的脑功能
  - 大脑的分布式并行计算支撑了大脑在多任务中的高性能

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Data in neuroscience

External stimulus：

(Visual, auditory, touch, smell, taste...)

Brain structure

(T1, T2, DTI image)

Neural data：

(electrophsiological recordings)

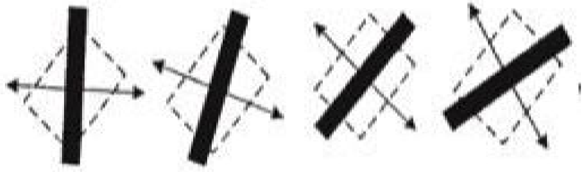
Behavioral data：

(Movement, decision making,....)

Data in neuroscience: low-dimensional

External stimulus： ~1D

(Visual, auditory, touch, smell, taste...)

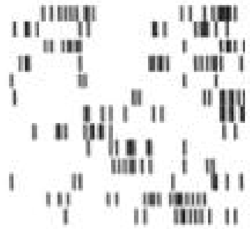


Brain structure

(T1, T2, DTI image)

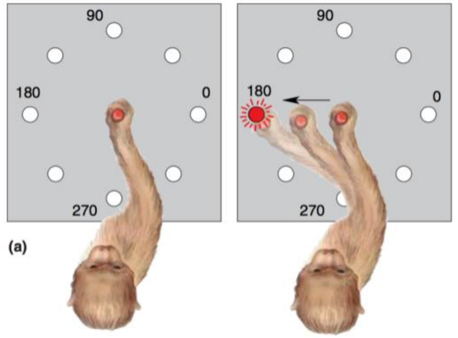
Neural data： ~10D

(electrophsiological recordings)



Behavioral data： ~2D

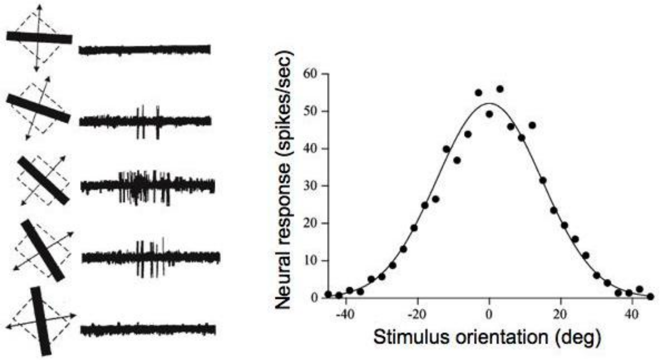
(Movement, decision making,....)



Neuroscience: hypothesis-driven studies

External stimulus： ~1D

(Visual, auditory, touch, smell, taste...)



Hubel, Wiesel (1968)

Correlation analysis

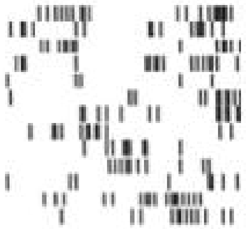
Computational models with few parameters

Brain structure

(T1, T2, DTI image)

Neural data： ~10D

(electrophsiological recordings)

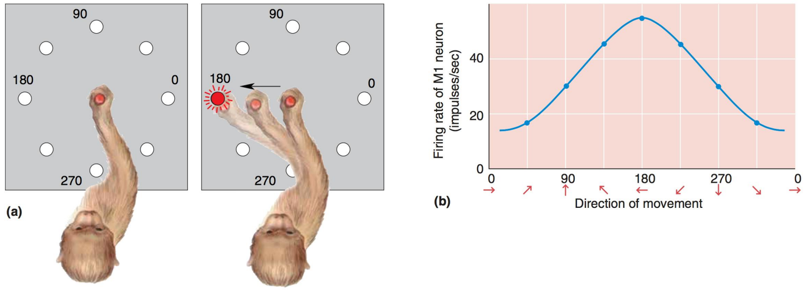


Correlation analysis

Computational models with few parameters

Behavioral data： ~2D

(Movement, decision making,....)



Churchland et al (2012)

Data in neuroscience: from low-D to high-D

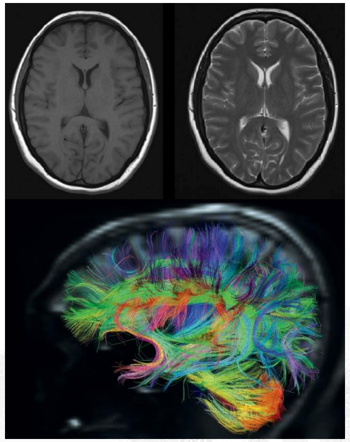
External stimulus：

(Visual, auditory, touch, smell, taste...)

上善若水。
水善利万物而不争，
处众人之所恶，
故几于道。

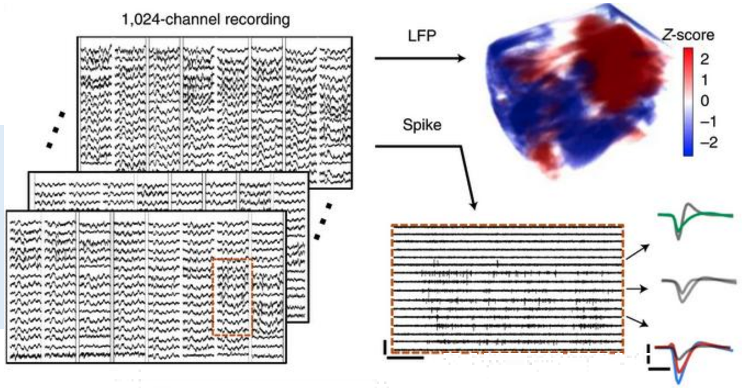
Brain structure

(T1, T2, DTI image)



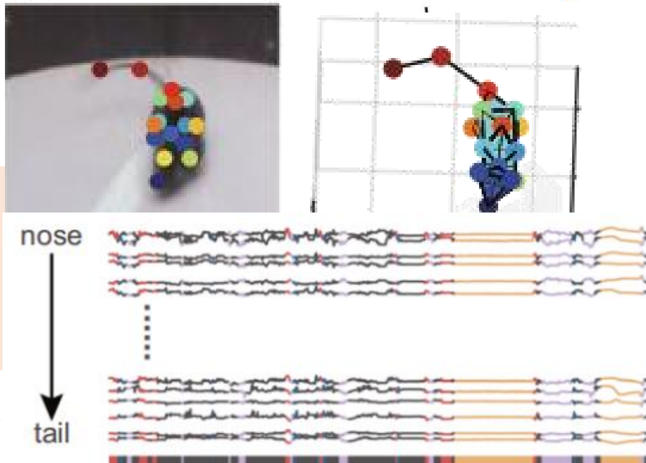
Neural data：

(86 billion neurons, 10^2 ~10^3 brain regions)



Behavior：

(Action, movement, decision making,....)

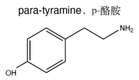


Data in neuroscience: from low-D to high-D

External stimulus： ~10^6D

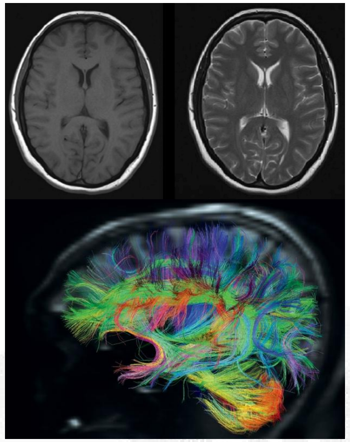
(Visual, auditory, touch, smell, taste...)

上善若水。
水善利万物而不争，
处众人之所恶，
故几于道。



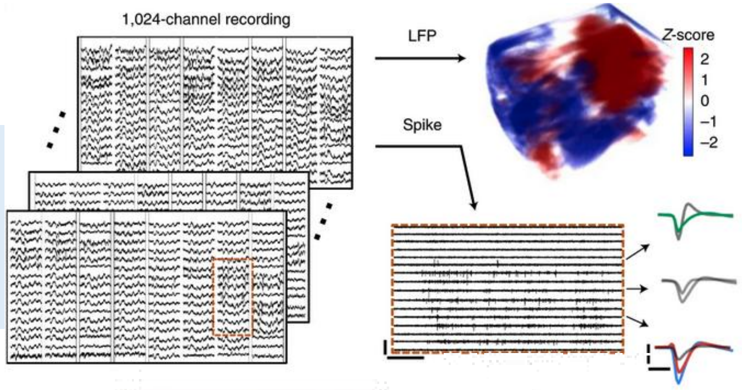
Brain structure

(T1, T2, DTI image)



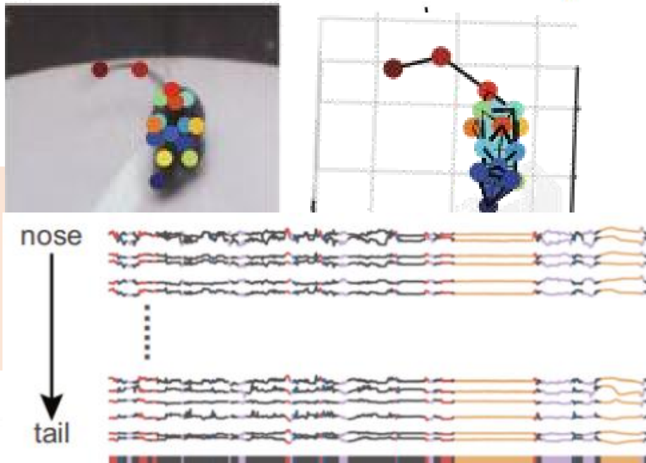
Neural data： ~10^3D

(86 billion neurons, 10^2 ~10^3 brain regions)



Behavior： ~10^2D

(Action, movement, decision making,....)



Neuroscience: Data-driven studies

External stimulus： ~10^6D

(Visual, auditory, touch, smell, taste...)

Decode: reconstruct external stimuli from neural data

Encode: predict neural dynamics from external input

Brain structure

(T1, T2, DTI image)

constraint

Neural data： ~10^3D

(86 billion neurons, 10^2 ~10^3 brain regions)

The world model in the brain

Encode: infer neural dynamics from behaviors

Decode: predict behaviors from neural data

Behavior： <10^2D

(Action, movement, decision making,....)

Data-driven models in neuroscience

External stimulus： ~10^6D

(Visual, auditory, touch, smell, taste...)

Decode: reconstruct external stimuli from neural data

Encode: predict neural dynamics from external input

Brain structure

(T1, T2, DTI image)

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(86 billion neurons, 10^2 ~10^3 brain regions)

The world model in the brain

Encode: infer neural dynamics from behaviors

Decode: predict behaviors from neural data

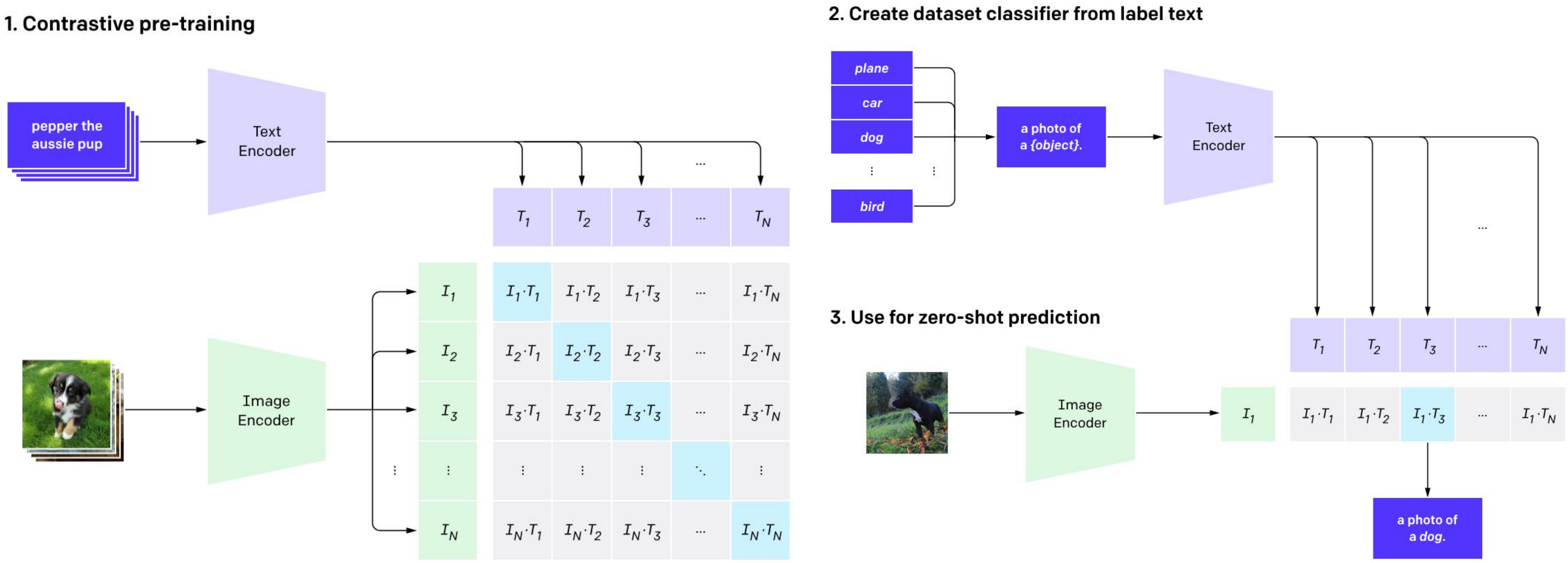
Behavior： <10^2D

(Action, movement, decision making,....)

CLIP: contrastive language-image pre-training

CLIP

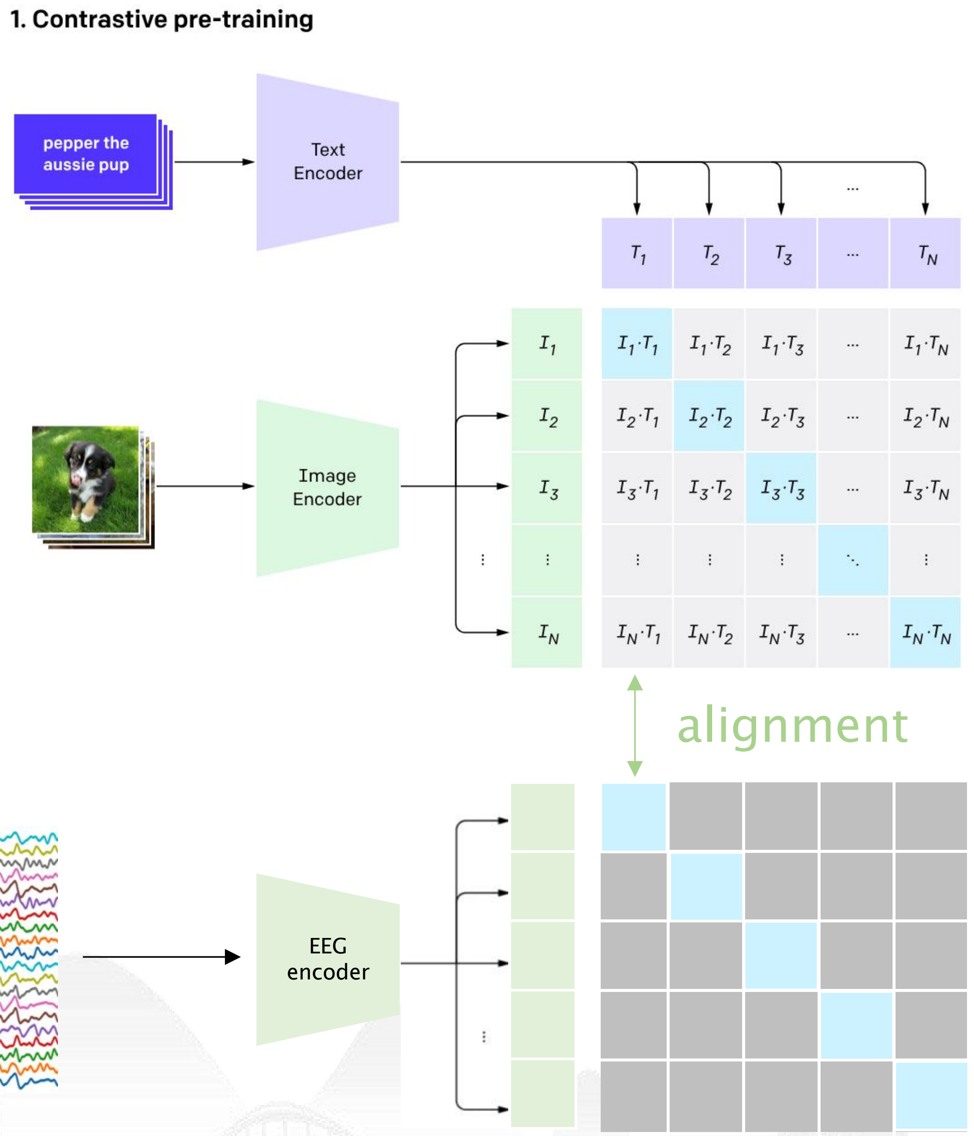
一只小猫咪



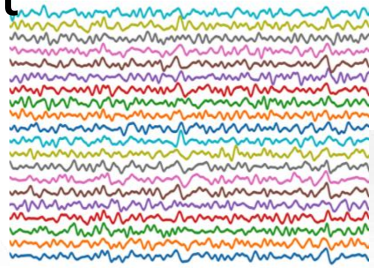
Brain-AI alignment: aligning representations of AI & brain

CLIP

一只小猫咪



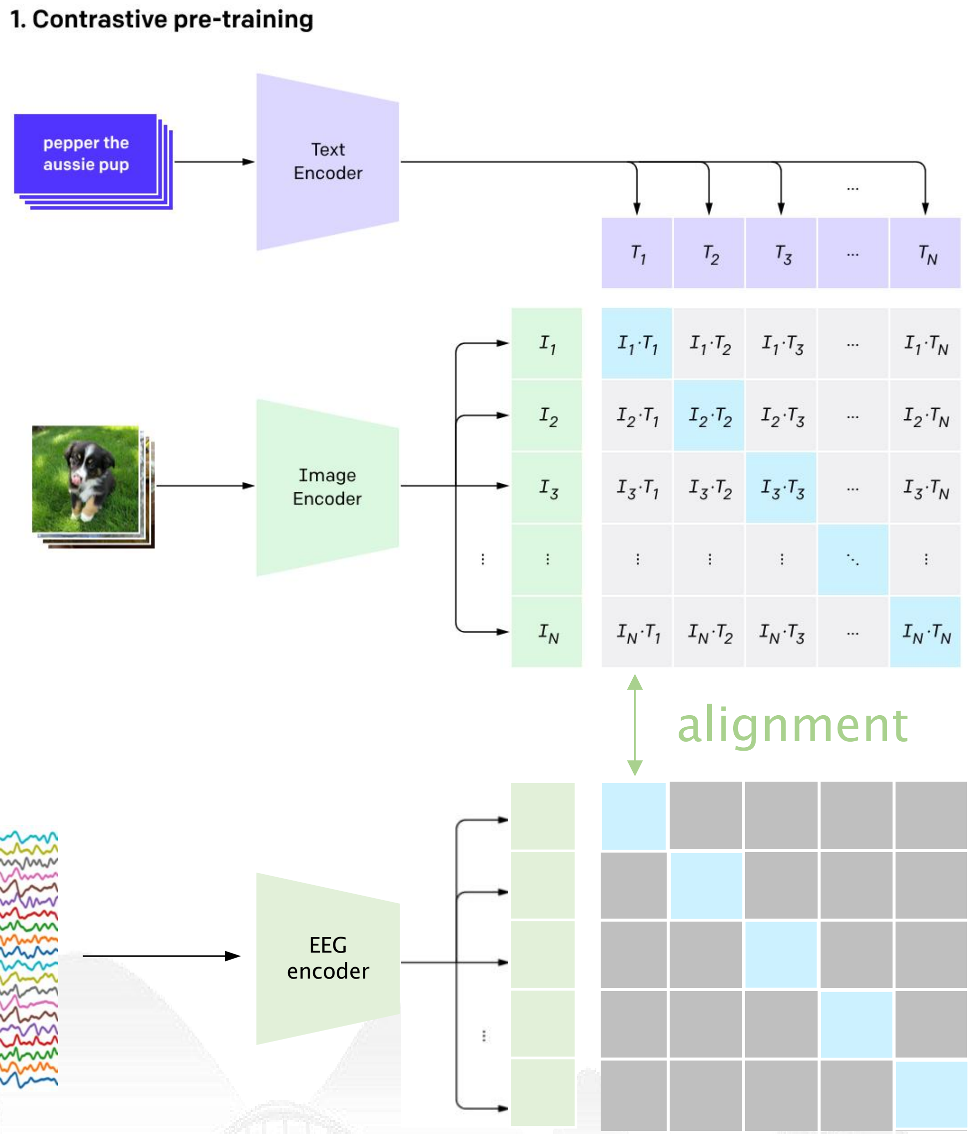
Brain-AI alignment



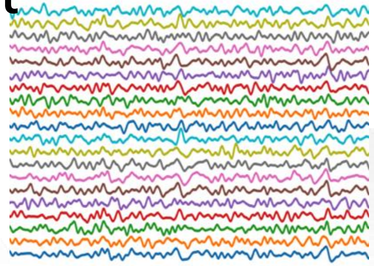
Brain-AI alignment: benefits

CLIP

一只小猫咪



Brain-AI alignment



Benefits for AI

1) better abstraction
2) better generalizability
3) Interpretability
4) AI safety

...

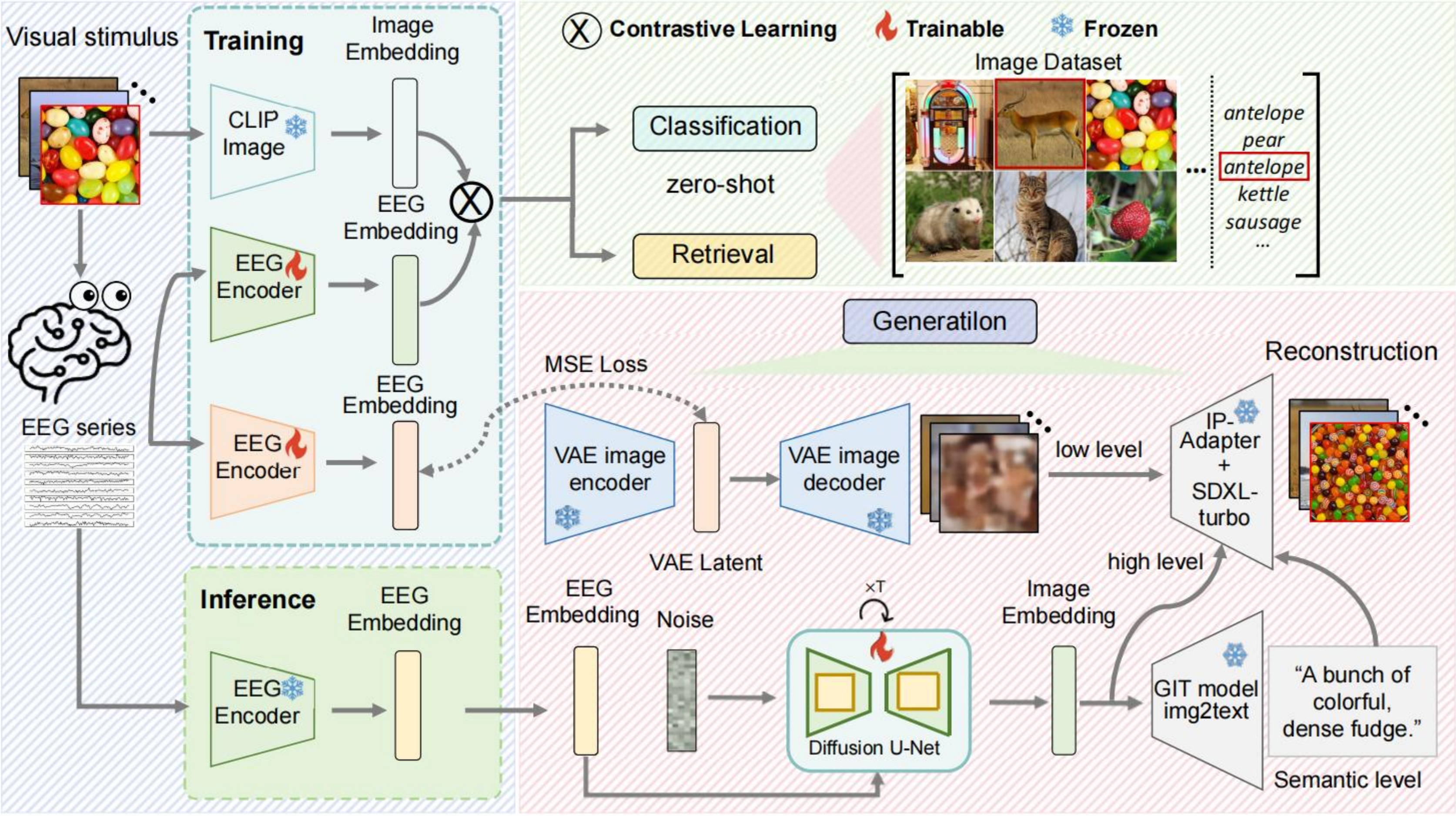
Benefits for neuroscience:

1) less neural data
2) multiple downstream tasks
3) zero-shot / few-shot capability
4) Virtual experimental platform
5) New science discovery

...

EEG/MEG-based visual decoding framework

The **EEG encoder** is designed as a flexible replacement component.
After aligning with CLIP features, the EEG features are used for zero-shot retrieval and classification tasks, and the reconstructed images.

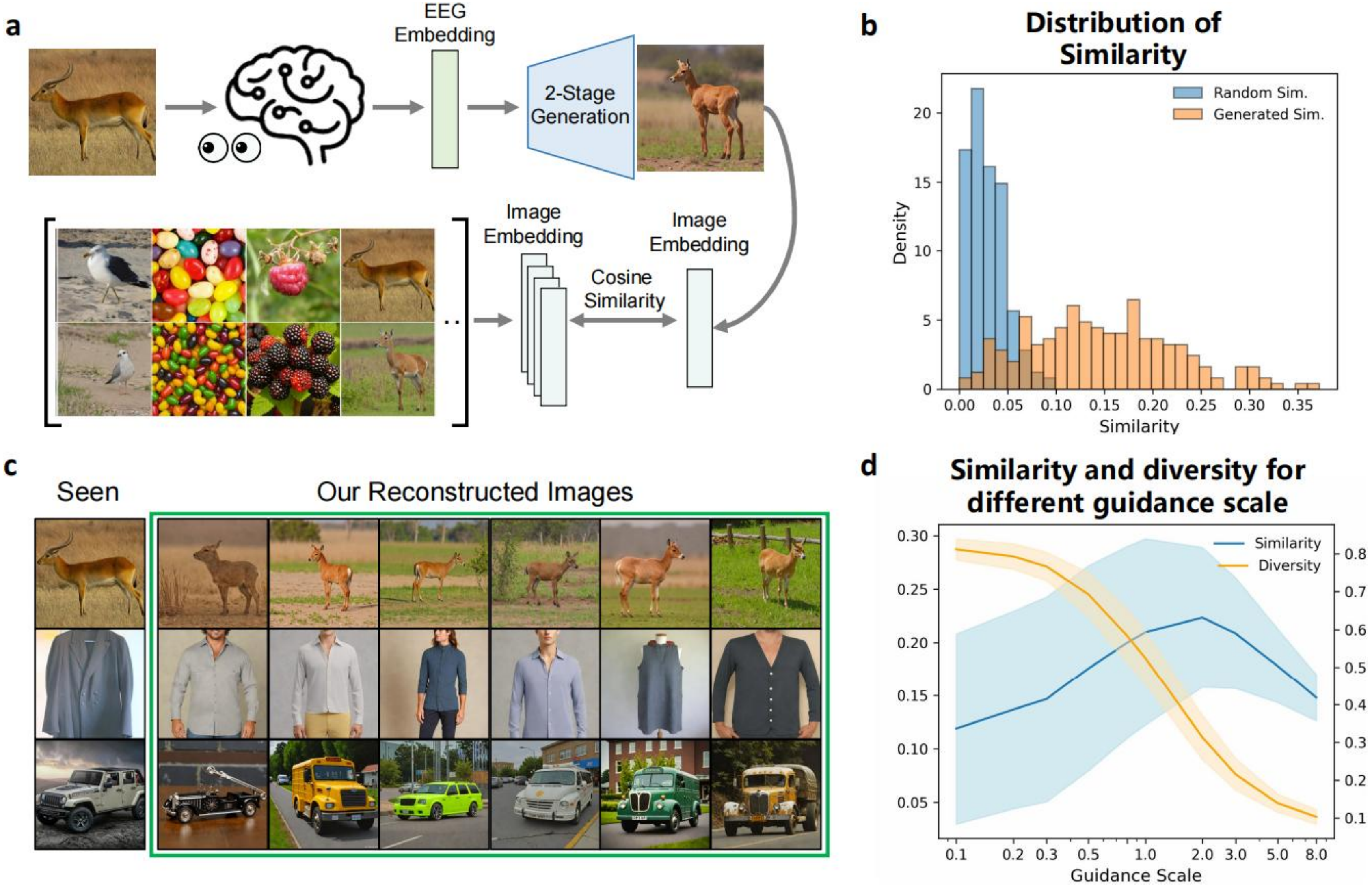


Dongyang Li, et al. (2024) NeurIPS

Paper link

Code link

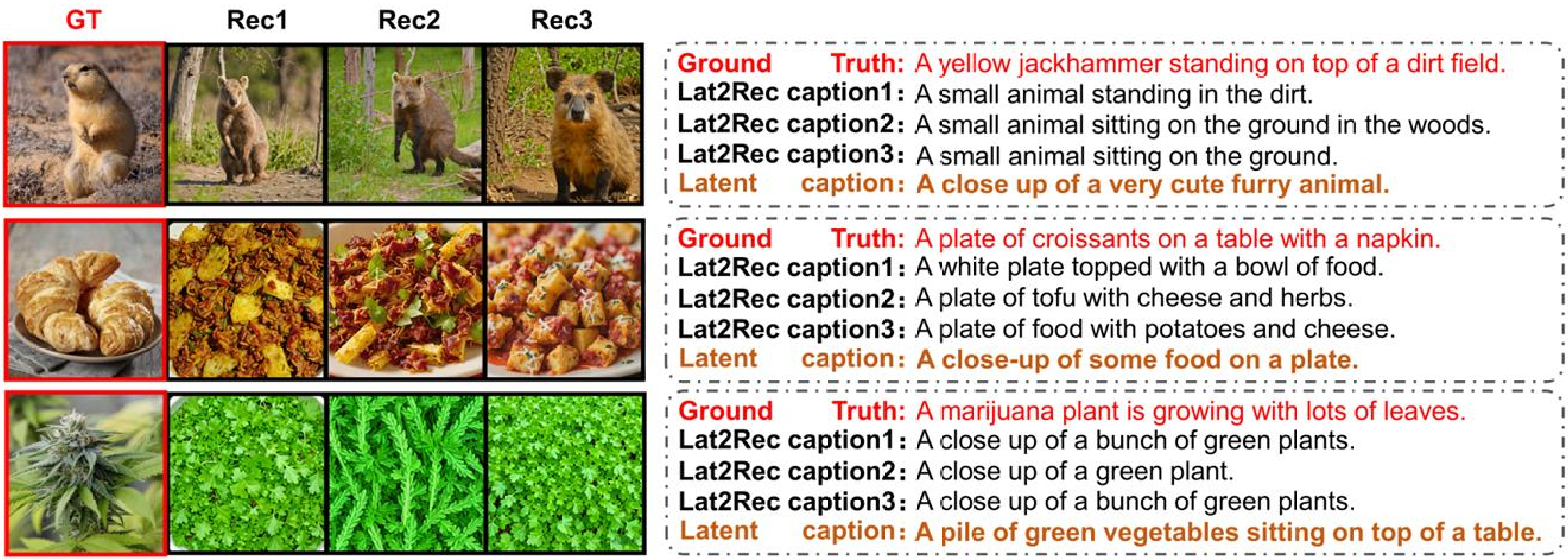
EEG embedding guided image generation



Dongyang Li, et al. (2024) NeurIPS

Zero-shot visual captioning from EEG data

We achieved EEG captioning for the first time.



Li, D., **Wu, M.**,et al (2024). *RealMind: Zero-shot EEG-based visual decoding and captioning using multi-modal models.* https://arxiv.org/abs/2410.23754

Evaluation of EEG-to-image captions

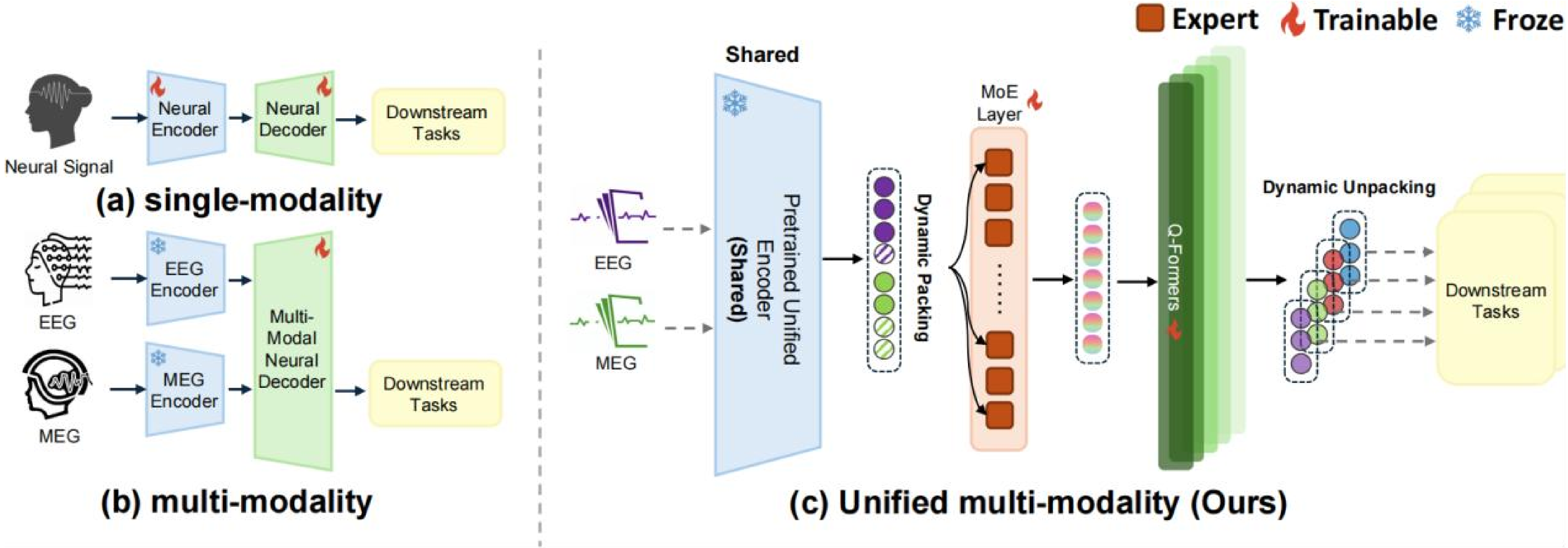
L2Cap: directly generating captions from EEG latent

I2Cap: reconstructing images and then generating captions

Metric	Shikra captions		GIT captions		BLIP2 captions	
	L2Cap	I2Cap	L2Cap	I2Cap	L2Cap	I2Cap
BLEU-1 ↑	**26.59**	23.09	15.43	18.28	18.31	25.97
BLEU-4 ↑	**4.31**	3.88	2.90	3.70	3.25	4.65
METEOR ↓	**17.79**	15.00	15.43	14.20	15.01	18.40
Sentence ↑	**17.76**	19.62	14.26	23.78	15.60	25.99
CLIP-ViT-L ↑	**55.78**	53.91	57.83	61.34	58.77	57.52

Li, D., **Wu, M.**,et al (2024). *RealMind: Zero-shot EEG-based visual decoding and captioning using multi-modal models*. https://arxiv.org/abs/2410.23754

A unified framework: fusing multi-modal neural data



Dongyang Li, Mingyang Wu, et al (in prep)

Zero-shot visual reconstruction

Zero-shot visual reconstruction from EEG/MEG data

	Low-level		High-level				
Dataset ↑	PixCorr ↑	SSIM ↑	AlexNet(2) ↑	AlexNet(5) ↑	Inception ↑	CLIP ↑	SwAV ↓
NSD-fMRI [4]	0.305	0.366	0.962	0.977	0.910	0.917	0.410
NSD-fMRI [33]	0.254	0.356	0.942	0.962	0.872	0.915	0.423
NSD-fMRI [41]	0.130	0.308	0.917	0.974	0.936	0.942	0.369
THINGS-MEG [4]	0.058	0.327	0.695	0.753	0.593	0.700	0.630
THINGS-MEG (averaged) [4]	0.076	0.336	0.736	0.826	0.671	0.767	0.584
THINGS-MEG (Ours)	0.104	0.340	0.613	0.672	0.619	0.603	0.651
THINGS-EEG (Ours)	0.160	**0.345**	**0.776**	**0.866**	**0.734**	**0.786**	**0.582**

Dongyang Li, Mingyang Wu, et al (in prep)

Data-driven models in neuroscience

External stimulus： ~10^6D

(Visual, auditory, touch, smell, taste...)

Decode: reconstruct external stimuli from neural data

Encode: predict neural dynamics from external input

Brain structure

(T1, T2, DTI image)

constraint

Neural data： ~10^3D

(86 billion neurons, 10^2 ~10^3 brain regions)

The world model in the brain

Encode: infer neural dynamics from behaviors

Decode: predict behaviors from neural data

Behavior： <10^2D

(Action, movement, decision making,....)

行为是大脑的输出

行为(behavior)：

行为是动物对外界环境和内在状态的改变所做出的整体、动态、组织性活动和反应。行为是神经活动在宏观层面的反映。

行为的分类:

按**产生途径**划分：本能行为、习得行为

按**功能**划分：摄食、领地、攻击、防御、生殖、节律、社会行为。

行为学（ethology）：

行为学在于理解行为是如何随着进化过程而发展，探究其生物学意义，关注行为的生物学基础。

根据特定科学问题，选择合适的模式生物(果蝇、啮齿类、非人灵长类等)，研究其**行为表型**(behavioral phenotype)。

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External world (image, text, sound …)

↓ A model to **encode** (predict) neural signals

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

↓ A model to **decode** (understand) neural signals

Cognitive process

↓

Behaviors

行为是大脑的输出

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行为学研究（behavioral studies）在多个领域中具有重要价值。其核心在于通过观察、分析和解释个体或群体的行为，揭示其背后的生理、心理和环境因素。这类研究不仅对学术界有意义，在应用层面上也广泛地影响着教育、医疗、商业、社会政策等多个领域。以下是行为学研究的几大价值：

1. 深入理解人类和动物行为

行为学研究为理解复杂行为提供了系统的方法，可以揭示影响人类和动物行为的多方面因素，包括遗传、环境、认知过程等。通过实验和观察，研究人员能够探索行为的演变机制及其适应性功能，这有助于完善有关大脑与行为关系的理论模型。

2. 促进心理健康与治疗方法的改进

行为学研究在心理健康领域有广泛的应用。例如，行为疗法（behavioral therapy）就是基于行为学研究发展出的干预手段，特别是对焦虑症、抑郁症、成瘾等问题有良好的疗效。研究可以帮助识别行为异常的早期预兆，并为个体化治疗方案提供科学依据。

3. 推动教育和学习方法的优化

行为学研究帮助揭示学习过程中的行为模式和影响因素，进而推动教育方法的改进。例如，通过分析儿童的学习行为，可以设计出更有利于理解和记忆的教学策略；同时，行为干预（behavioral intervention）方法可以帮助有学习障碍的儿童提高学习效果。

4. 提升人机交互与人工智能系统的设计

在人机交互（HCI）和人工智能（AI）设计中，理解人类行为模式可以使系统更符合用户需求。行为学研究为设计友好、直观的界面和人性化的人工智能系统提供了基础数据。特别是在社会机器人、智能助理等领域，行为学研究帮助开发出更具交互性的技术。

5. 有助于社会政策的制定与公共安全的提升

行为学研究可以为政策制定者提供数据支持。例如，交通行为研究可以帮助制定安全的道路规则和提高公共安全；消费行为研究可以为经济政策提供方向。理解群体行为和决策过程有助于政府和组织应对社会问题。

6. 动物行为学在保护和管理野生动物中的应用

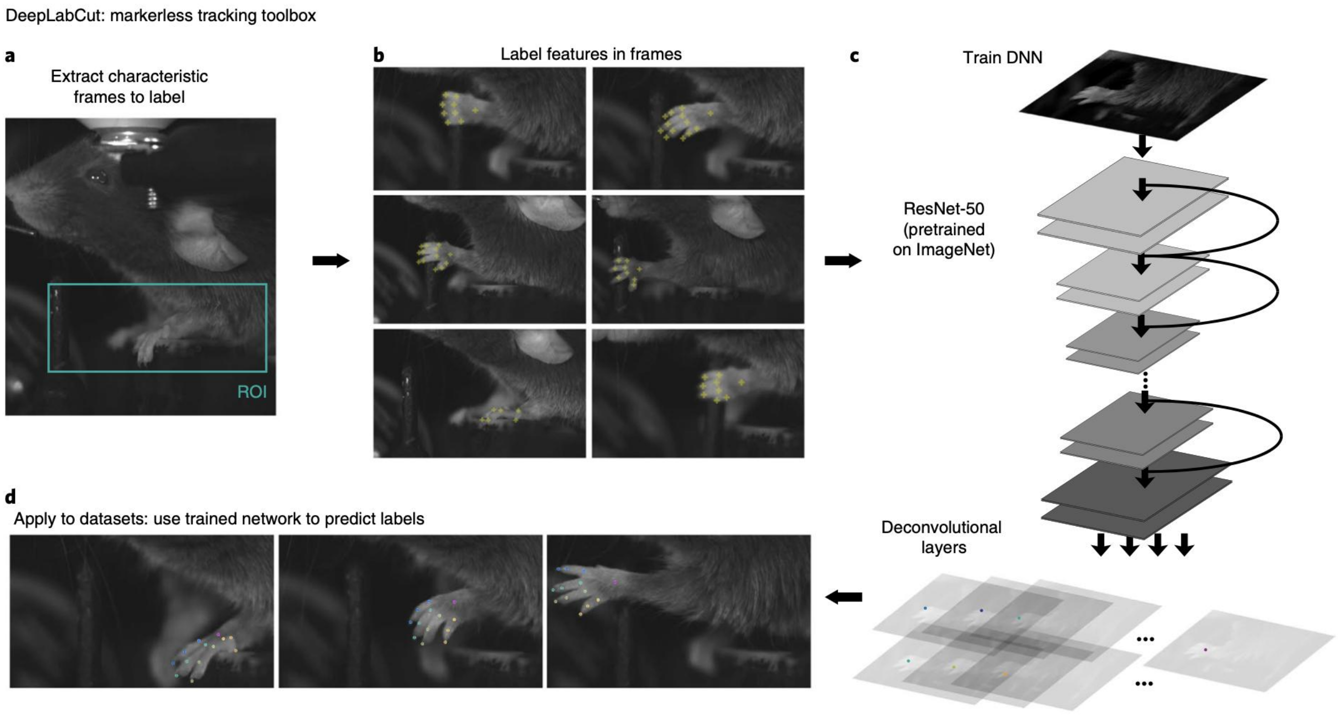
对动物行为的研究可以帮助了解它们的生存需求、迁徙模式等，促进濒危物种的保护和野生动物栖息地的管理。通过行为研究制定科学的保护策略，对于生态环境的可持续发展具有重要作用。

总之，行为学研究通过系统的观察和实验，为揭示行为背后的驱动因素提供了宝贵的见解。这不仅丰富了人类对行为科学的理论认知，同时也对社会实际应用产生深远影响。

AI for low-level behavioral analysis

nature neuroscience
TECHNICAL REPORT
https://doi.org/10.1038/s41593-018-0209-y

DeepLabCut: markerless pose estimation of user-defined body parts with deep learning

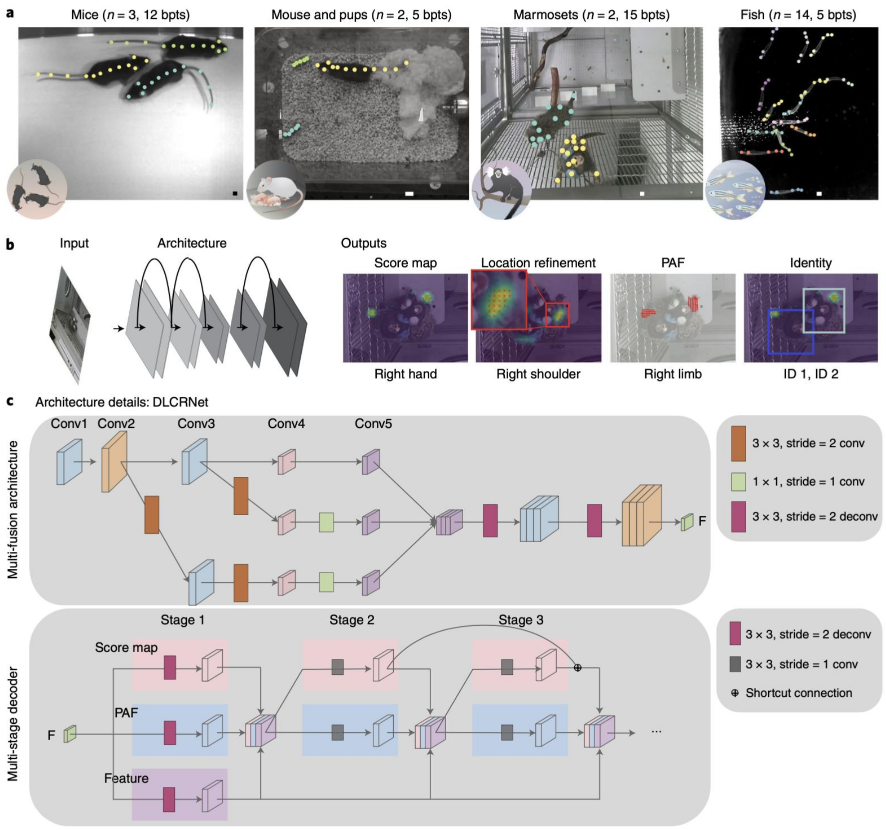


Mathis et al., Nature Neuroscience (2018)

ARTICLES
https://doi.org/10.1038/s41592-022-01443-0
nature methods
Check for updates

OPEN

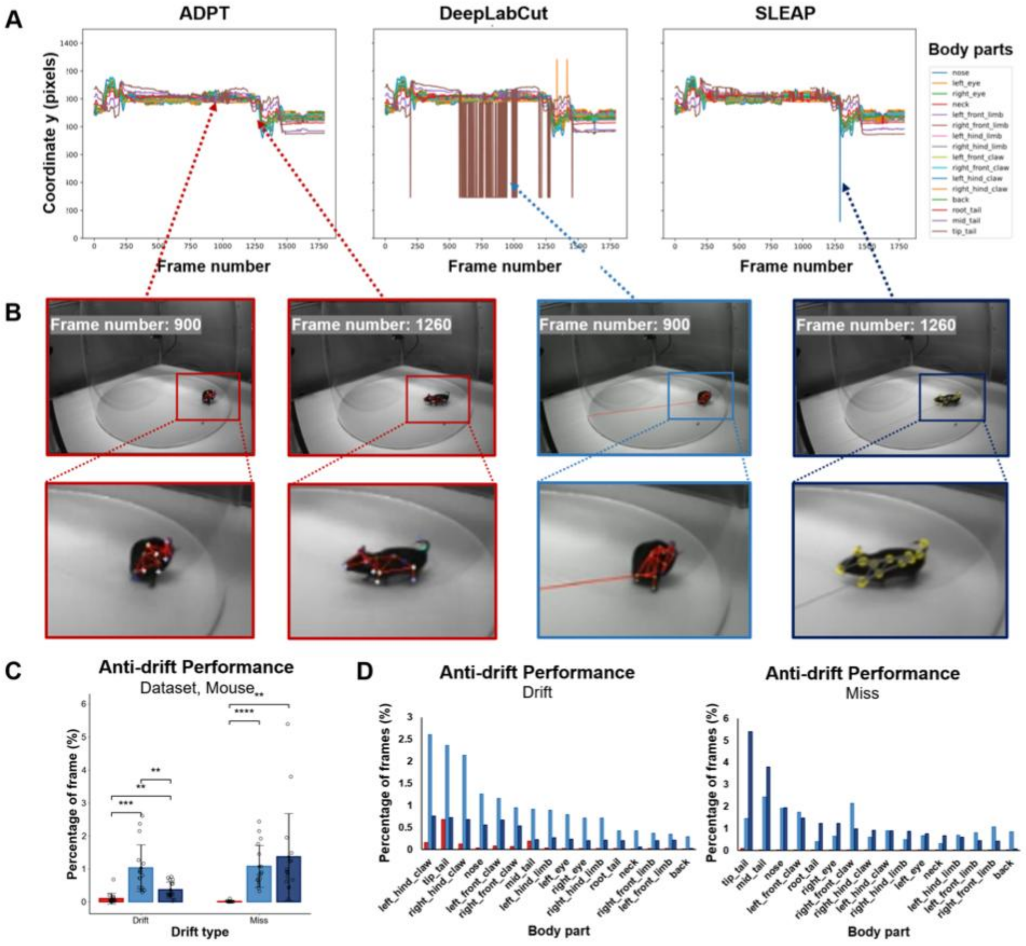
Multi-animal pose estimation, identification and tracking with DeepLabCut



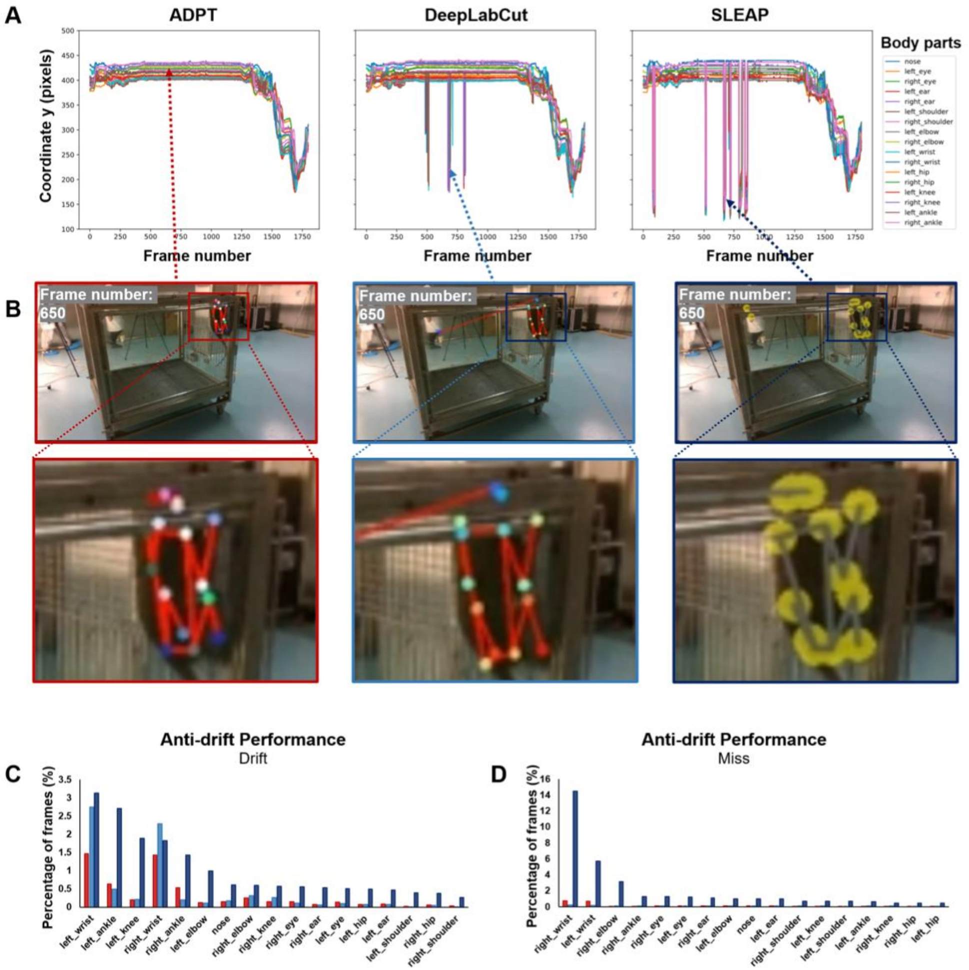
Lauer et al., Nature Methods (2022)

Anti-drift pose tracker (ADPT)

老鼠的躯体关键点追踪



非人灵长类的躯体关键点追踪

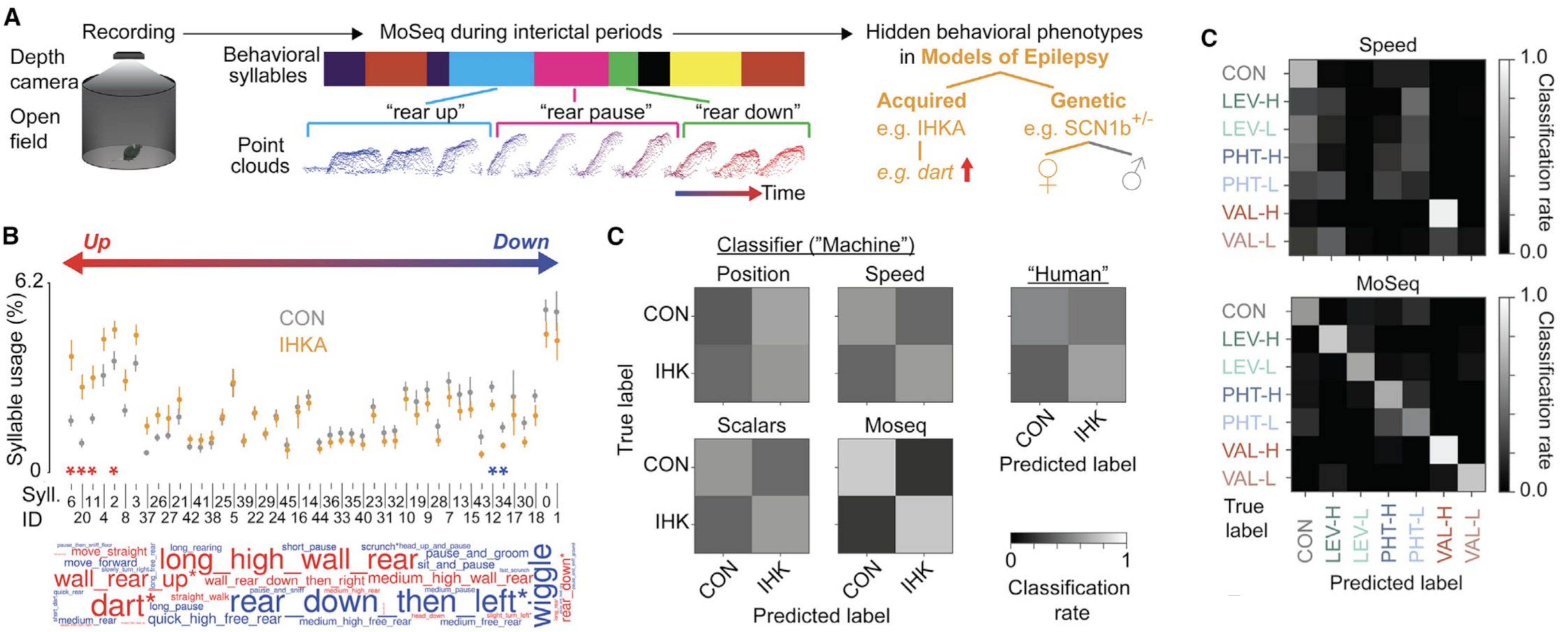


Guoling Tang#, Yaning Han#, et al., eLife (accepted)

先进院蔚鹏飞老师团队合作

The code of ADPT is available at https://github.com/tangguoling/ADPT

AI for high-level behavioral analysis



Gschwind et al., Neuron (2023)

AI for disease symptom analysis

症状学知识

Table 1 Semiology descriptions and frequencies

Semiology category	Descriptions and examples	Percentage of non-topological data
Tonic	Stiff posturing of one or more limbs or torso	9.8%
Oral and manual automatisms	Upper limb automatisms, automotor (stereotyped distal limb movements), fiddling, pedal automatisms (excluding hypermotor or cycling), lip smacking, chewing, oro-alimentary, orofacial automatisms, ictal drinking, ictal swallowing	9.7%
Dialeptic-LOA-LOC	Blank stare, loss of awareness, unaware, loss of contact, psychomotor arrest, distant gaze, dreamy state, loss of consciousness (excluding generalized seizures) or dyscognitive states. Does not distinguish between partial or complete loss of consciousness.	8.3%
Epigastric	Abdominal rising sensation; e.g. butterfly sensation	6.1%
Vocalization—unintelligible noises	Grunting, mumbling, humming. Cf with ictal speech and dysphasia categories in Supplementary Materials (Supplementary Table 1)	5.5%
Autonomic	Autonomic symptoms or signs relating to any system, including respiratory, cardiovascular, genitourinary and gastrointestinal; e.g. hypopnoea, urinary urge, pilomotor or laryngeal constriction	4.7%
Olfactory	Any kind of ictal smell e.g. of burning	4.6%
Head version	Forced head deviation over the shoulder, extreme head turn	4.3%
Dystonic	Twisted posture or reported dystonia	3.4%
Other automatisms	Blinking, ictal cough, gelastic, dacrystic, ictal nose wiping and ictal face rubbing	3.1%
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Somatosensory	Tingling or touch sensation	2.9%
All 23 other semiology categories	See Supplementary Table 1 for full list	34.5%

Twelve semiologies from the Semio2Brain database with their descriptions. Only those semiologies are shown where, after querying the database, the number of patients with localizing data for both the non-topological and topological subsets exceeded 100. The list is sorted in descending order of the number of patients with the semiology from the non-topological subset.

Alim-Marvasti, Ali, et al. "Probabilistic landscape of seizure semiology localizing values." Brain Comm. (2022)

AI for disease symptom analysis

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大语言模型

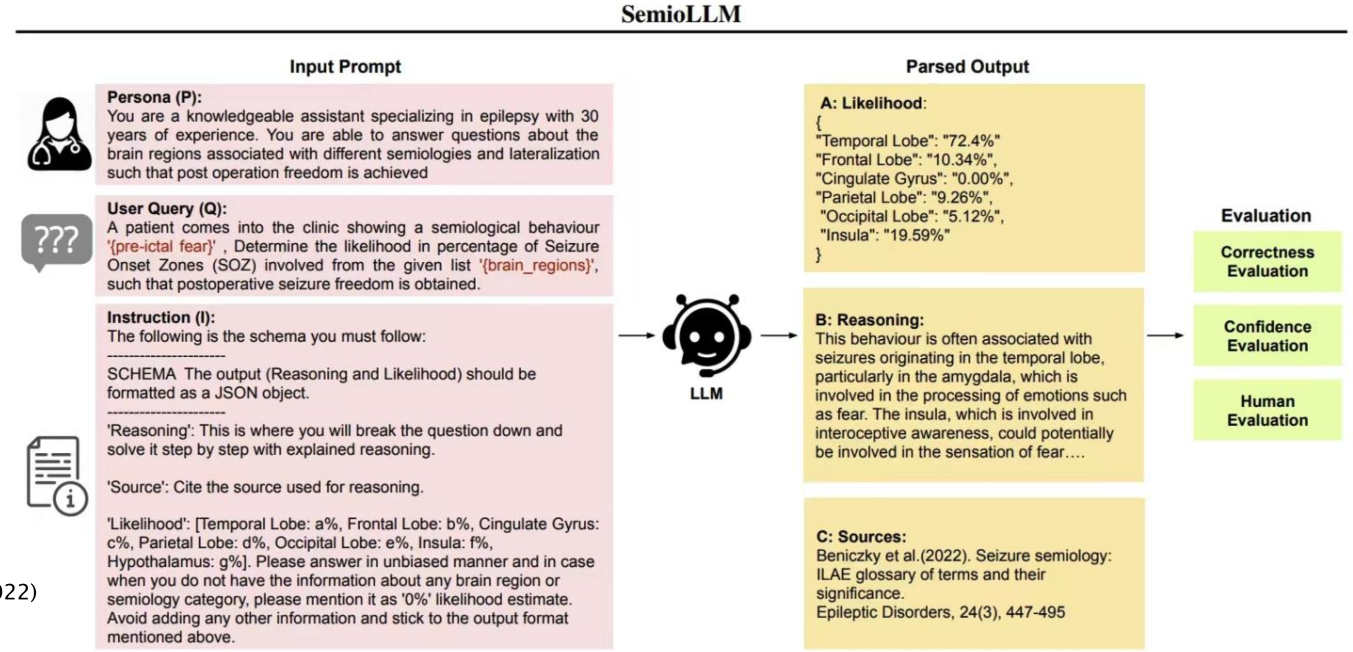

Table 1. Comparison results for four state-of-the-art LLMs with different prompting techniques: zero-shot (ZS), few-shot, chain-of-thought (CoT), few-shot CoT and Self-Consistency(SC) prompting techniques. The table reports standard weighted F1 scores, where higher values indicate better performance. The last row presents the evaluation of clinician responses for comparison.

LLM	Prompt Strategy				
	Zero-Shot	Few-Shot	CoT	FewShot-CoT	SC
GPT-3.5	38.13	48.36	49.32	51.65	51.84
GPT-4.0	**52.33**	**50.96**	**52.64**	52.11	**53.78**
Mixtral8x7B	23.07	42.26	48.97	**52.72**	52.29
Qwen-72B	39.23	44.64	45.47	48.17	45.75
Clinician	49.07				

Dani, Meghal, et al. "SemioLLM: Assessing Large Language Models for Semiological Analysis in Epilepsy Research." (2024) arXiv

AI for disease symptom analysis

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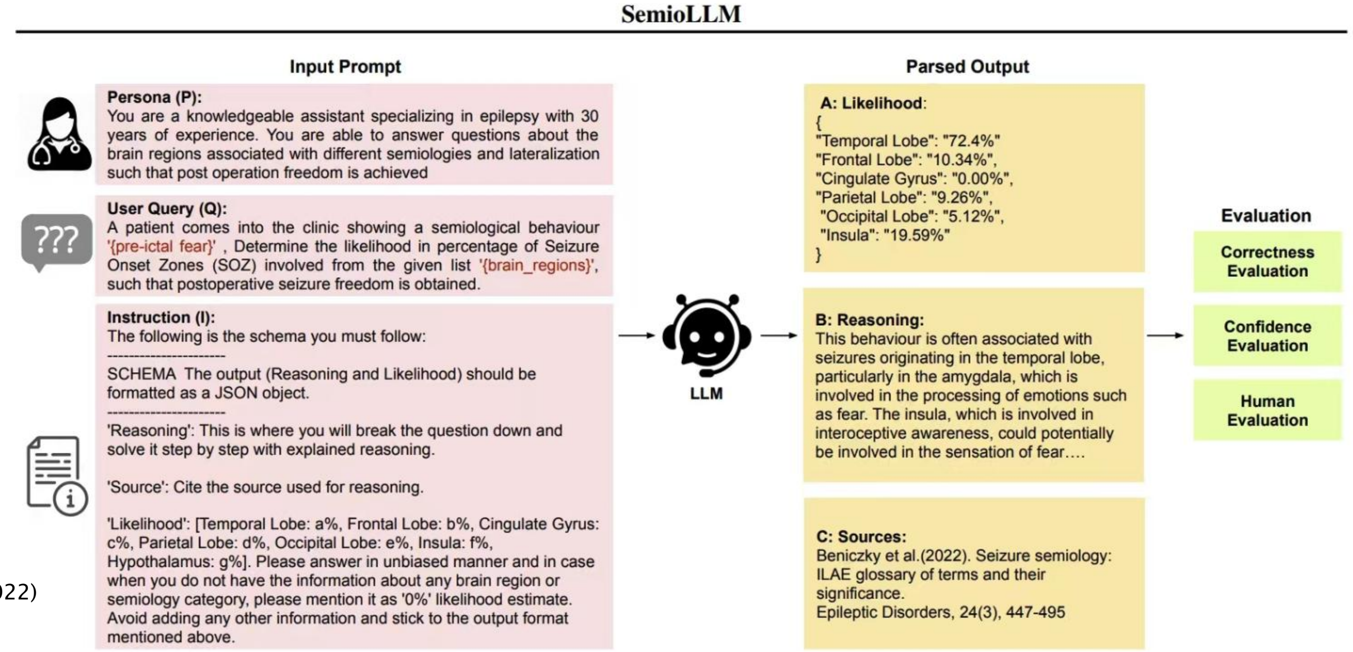
大语言模型



基于AI的视频分析

视频-语言多模态大模型

AI for brain science

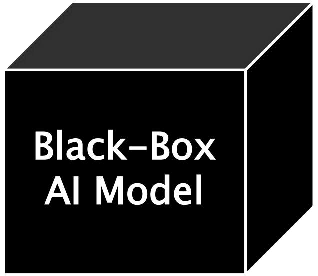
- AI为脑科学提供数据分析工具
  - 神经解码
  - 行为分析
- AI为脑科学提供实验仿真工具
  - 多认知任务下的神经表征
  - 神经动力学仿真
- AI为脑科学提供有潜力的科学假设
  - 大脑网络在进化中优化到near-optimal以支撑复杂的脑功能
  - 大脑的分布式并行计算支撑了大脑在多任务中的高性能

大脑智能与人工智能有何相似之处？

- **组成单元相似：**都有神经元（生物神经元或人工神经元）
- **结构相似：**都有层级结构（信息逐层进行计算和传播）
- **功能相似：**都能进行物体识别（识别人脸、花花草草等）
- … …

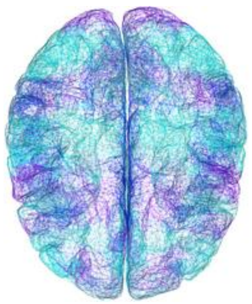
AI model as a surrogate brain

The surrogate brain



无限逼近

The real brain



灵活的AI模型结构：

MLP
CNN
RNN
Neural ODE
transformer
…

脑结构影像： T1/T2-MRI，DTI

脑功能影像： （新陈代谢水平）PET
（血氧水平）fMRI

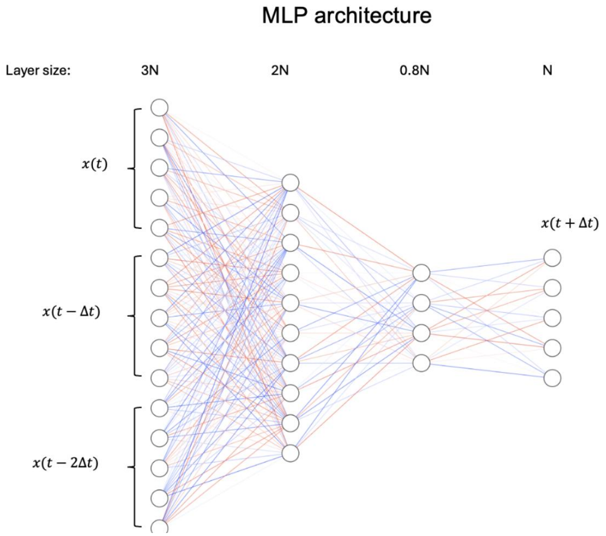
神经电生理记录： （微观）细胞层面：neuronal spikes
（介观）局部场：LFP
（宏观）脑区：ECoG/SEEG，EEG

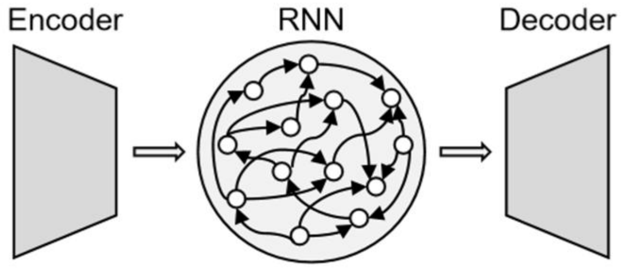
大脑状态记录： （自评）情绪状态、运动意图
（从神经数据中解码）注意力、睡眠状态

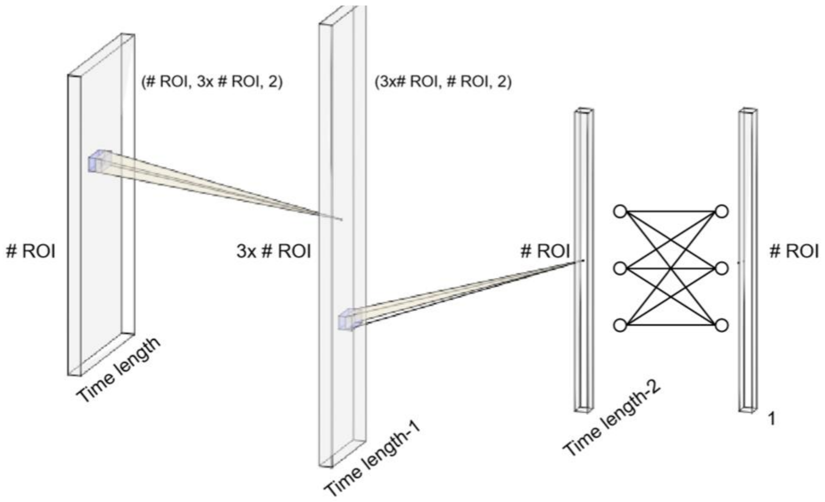
行为观测记录 （任务中的行为）决策反应
（自由行为）视频记录

AI surrogate human brain

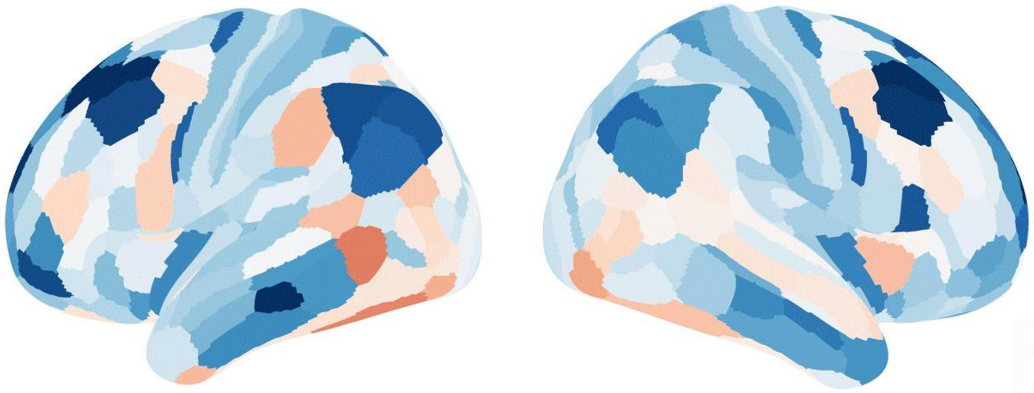
AI孪生脑
网络结构



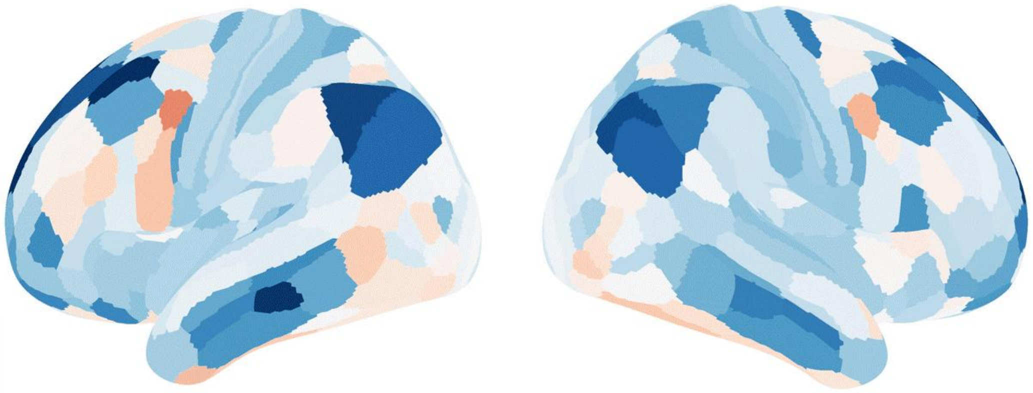




Ground-truth dynamics

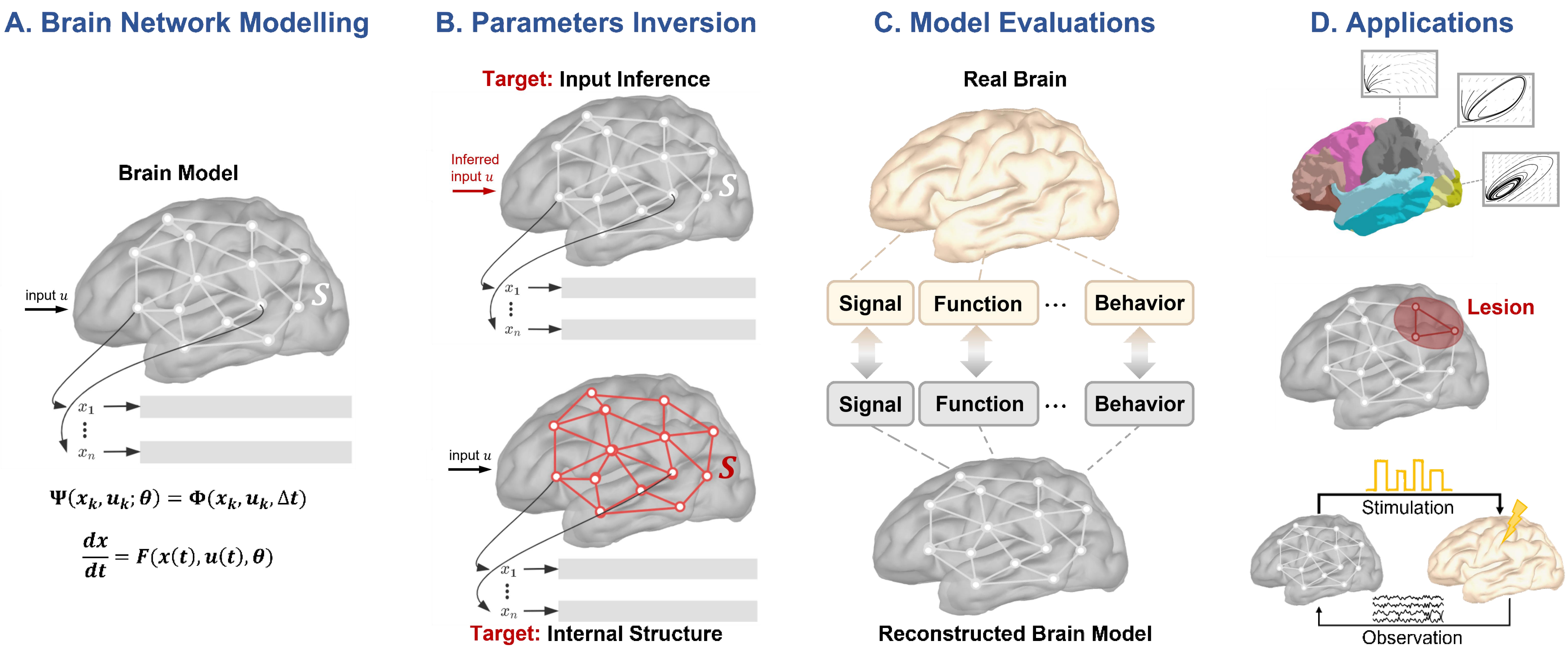


ANN-predicted dynamics



t = 0.00 s

Recipes for AI surrogate brain



1. Construct the model (e.g., neural mass model, AI model)

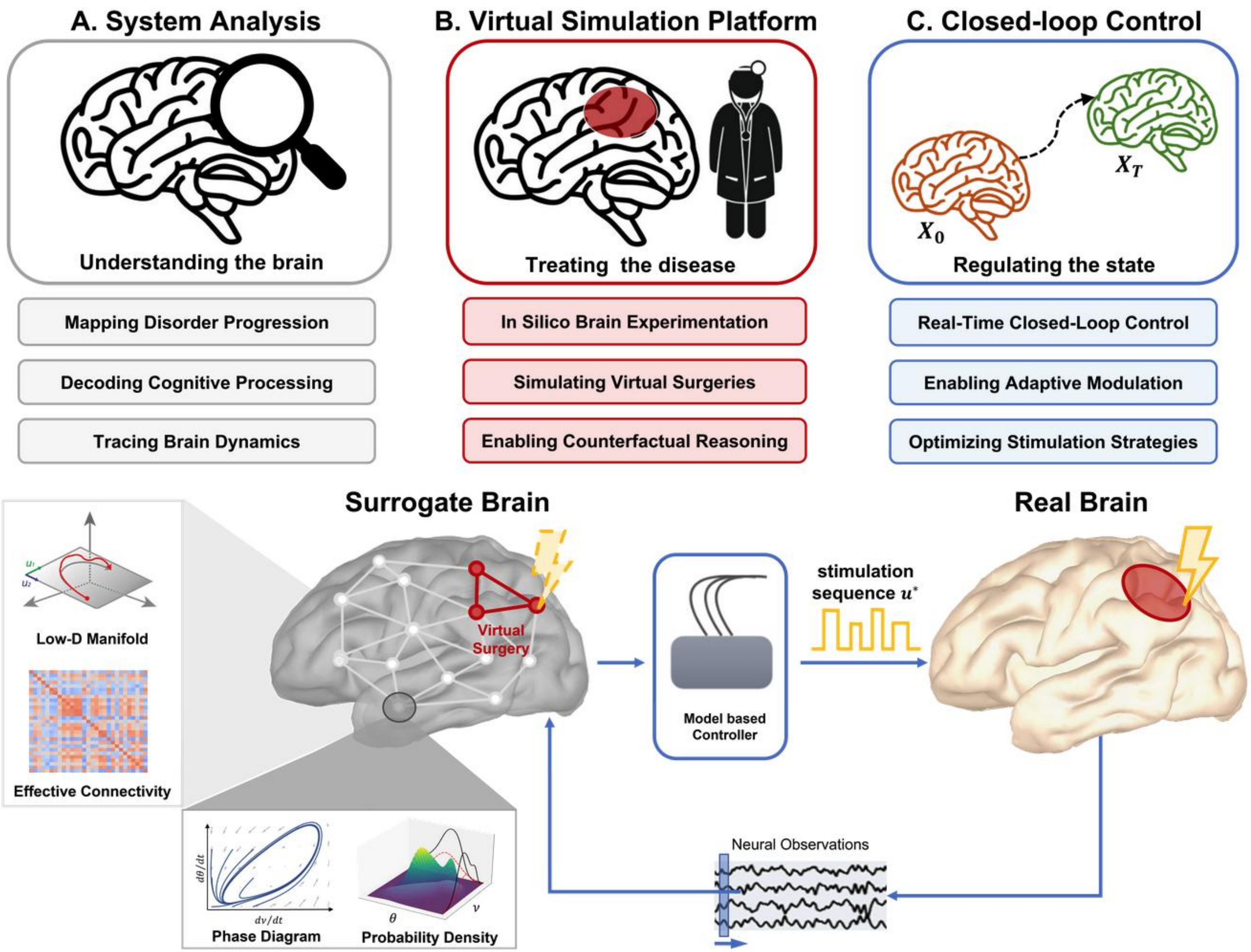
2. Learn the model parameters by minimizing loss function

3. Compare the real brain and the learned model

4. Apply the learned model

Zhang, Chen, Liang, Lou, Gao*, Liu*. Data-driven Approaches for Inverse Problems of Neural Dynamical System (in prep)

Potential applications



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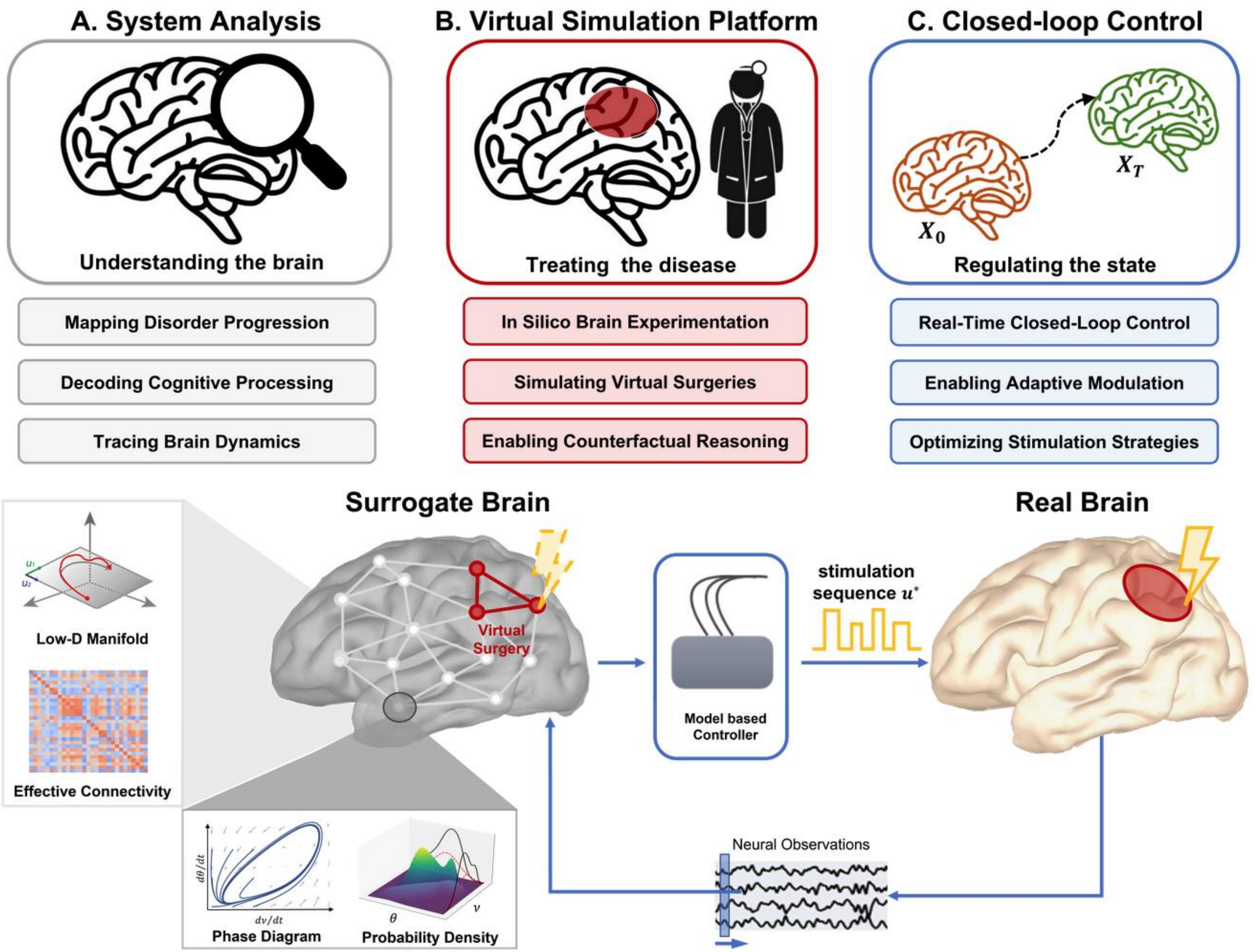
Potential applications



1. 个性化神经科学研究

数字孪生脑能够以特定个体的神经特征为基础进行训练，使得个性化的脑动力学建模成为可能。这可以帮助研究大脑如何在健康与疾病状态之间转变，并使临床医生能够为特定个体设计精准的治疗策略。例如，通过模拟不同的刺激或治疗方法，观察大脑对这些干预的反应，从而优化个性化治疗方案。

2. 脑疾病机制研究与药物开发

数字孪生脑可以被用于研究各种神经疾病的发病机制。通过改变模拟中的特定参数（例如神经网络连接强度、突触可塑性等），研究人员可以探索癫痫、帕金森病、阿尔茨海默病等脑疾病的动力学特征和进程。此外，数字孪生脑可以用于药物和治疗方法的虚拟测试，减少早期临床试验的需求，从而加速药物开发进程。

3. 脑-机接口与神经调控技术的优化

数字孪生脑为脑-机接口（BCI）和神经调控技术提供了一个虚拟测试平台。研究人员可以在该平台上模拟大脑对神经调控的反应，从而优化刺激参数和算法，以提高BCI的解码精度和神经调控的有效性。例如，在虚拟环境中测试闭环刺激系统的响应效果，可以减少实验中的潜在风险并加速研发进度。

4. 认知过程与感知机制的探索

数字孪生脑能够重现注意力、记忆、决策等认知过程的动力学机制，为认知神经科学提供了一个精细的模拟工具。通过调整数字孪生脑的参数，研究人员可以探索不同的认知负荷、任务需求对大脑动态的影响，深入理解这些过程的神经机制。

5. 心理与情感计算

数字孪生脑可以模拟大脑在不同情感状态下的动力学变化，为情感计算提供数据支持。通过研究情绪状态在脑网络中的传播模式，研究人员可以开发出更精准的情绪识别算法和心理状态检测系统，应用于精神健康评估、情绪调节干预等领域。

6. 多尺度大脑网络动力学研究

通过数字孪生脑，可以在宏观（如脑区）、中观（如脑网络）、微观（如神经元群）等不同尺度上探索大脑动力学特征，帮助揭示多尺度大脑活动之间的联系。这对于理解大脑整体功能和各区域之间的协作关系非常有帮助，有助于发展新的大脑功能理论模型。

7. 虚拟试验和“假设-检验”实验平台

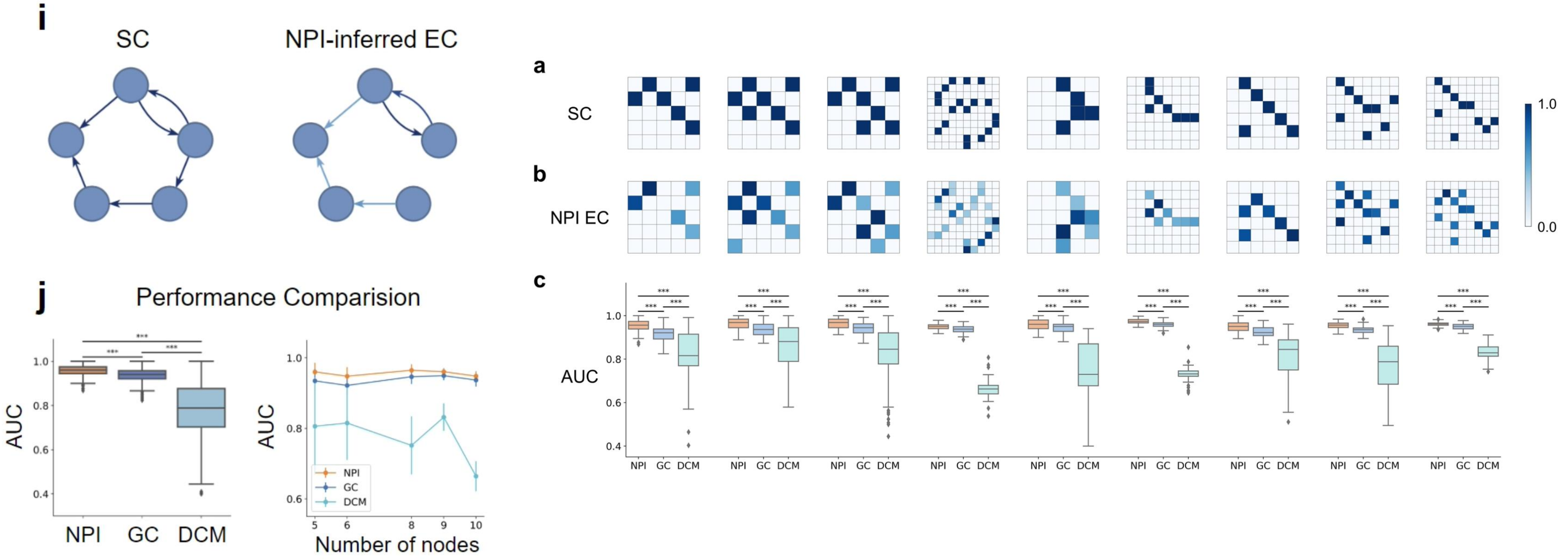
数字孪生脑可以作为虚拟实验平台，用于测试新的理论假设和数据驱动的假设。例如，在尝试设计新的脑刺激模式、假设特定脑区对某类任务的贡献或模拟某类学习过程时，数字孪生脑可以提供一种低成本、低风险的虚拟环境来进行“假设-检验”。

8. 预测神经系统对新任务或环境的适应

通过训练一个数字孪生脑来模拟神经系统在新[illegible]、新环境下的适应过程，可以用于研究神经可塑性和学习机制。例如，可以观察数字孪生脑在模拟的学习任务中的神经变化过程，以研究不同学习阶段

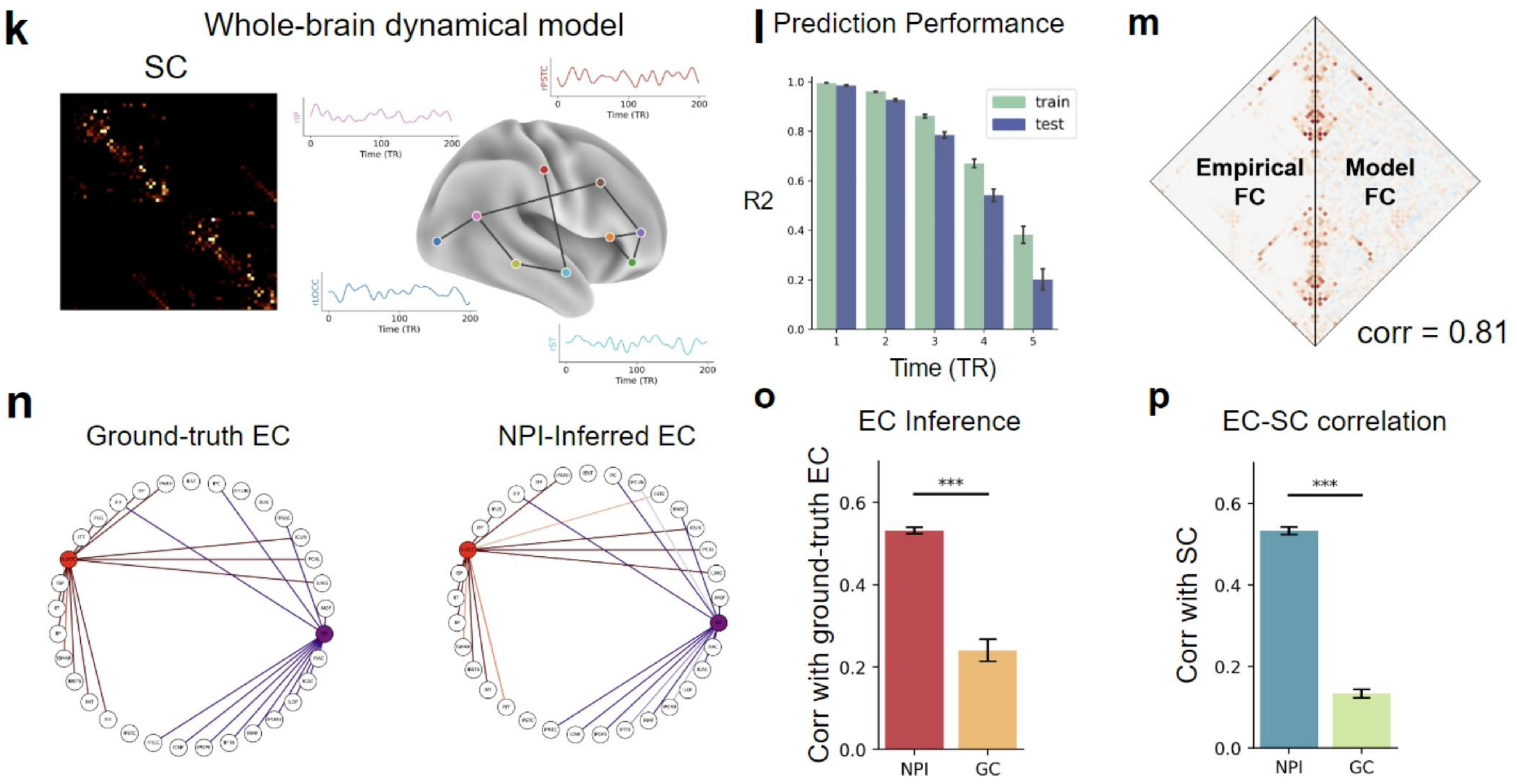
Zhang, Chen, Liang, Lou, Gao*, Liu*. Data-driven Approaches for Inverse Problems of Neural Dynamical System (in prep)

验证NPI：已知连接的Jansen-Rit模型生成数据



Luo, Zixiang, et al. "Mapping effective connectivity by virtually perturbing a surrogate brain." arXiv preprint arXiv:2301.00148 (2023).

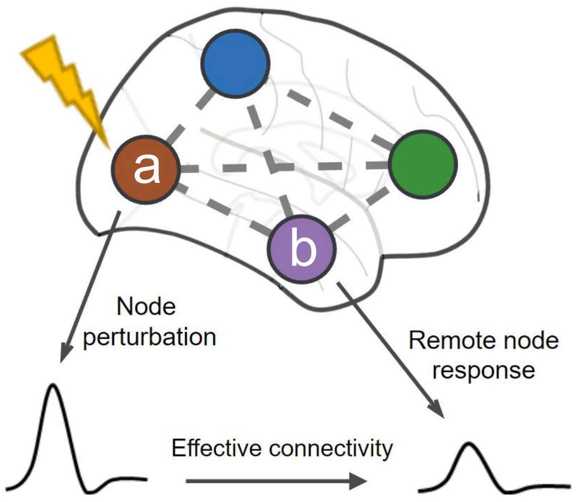
验证NPI：全脑Jansen-Rit模型生成数据



Luo, Zixiang, et al. "Mapping effective connectivity by virtually perturbing a surrogate brain." arXiv preprint arXiv:2301.00148 (2023).

Invasive experiments the in real brain

Perturbational Inference

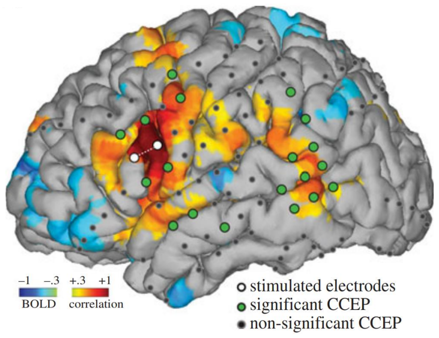


Experiment Pipeline:

① Inject perturbation (stimulation)

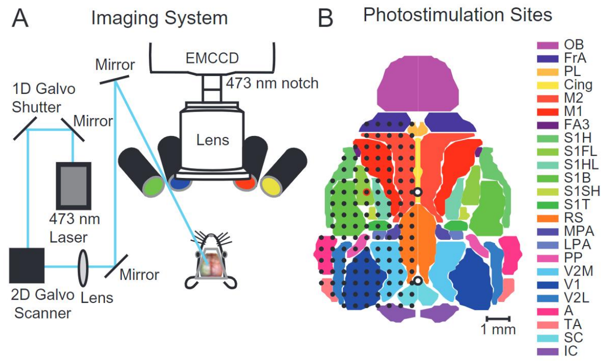
② Record neural response

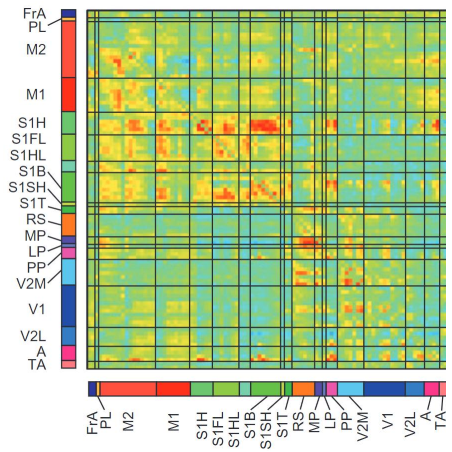
1. Cortical-cortical evoked potential in **human**



Keller et al., (2014)
Phil. Trans. R. Soc. B

2. Optogenetic stimulation in **mouse**

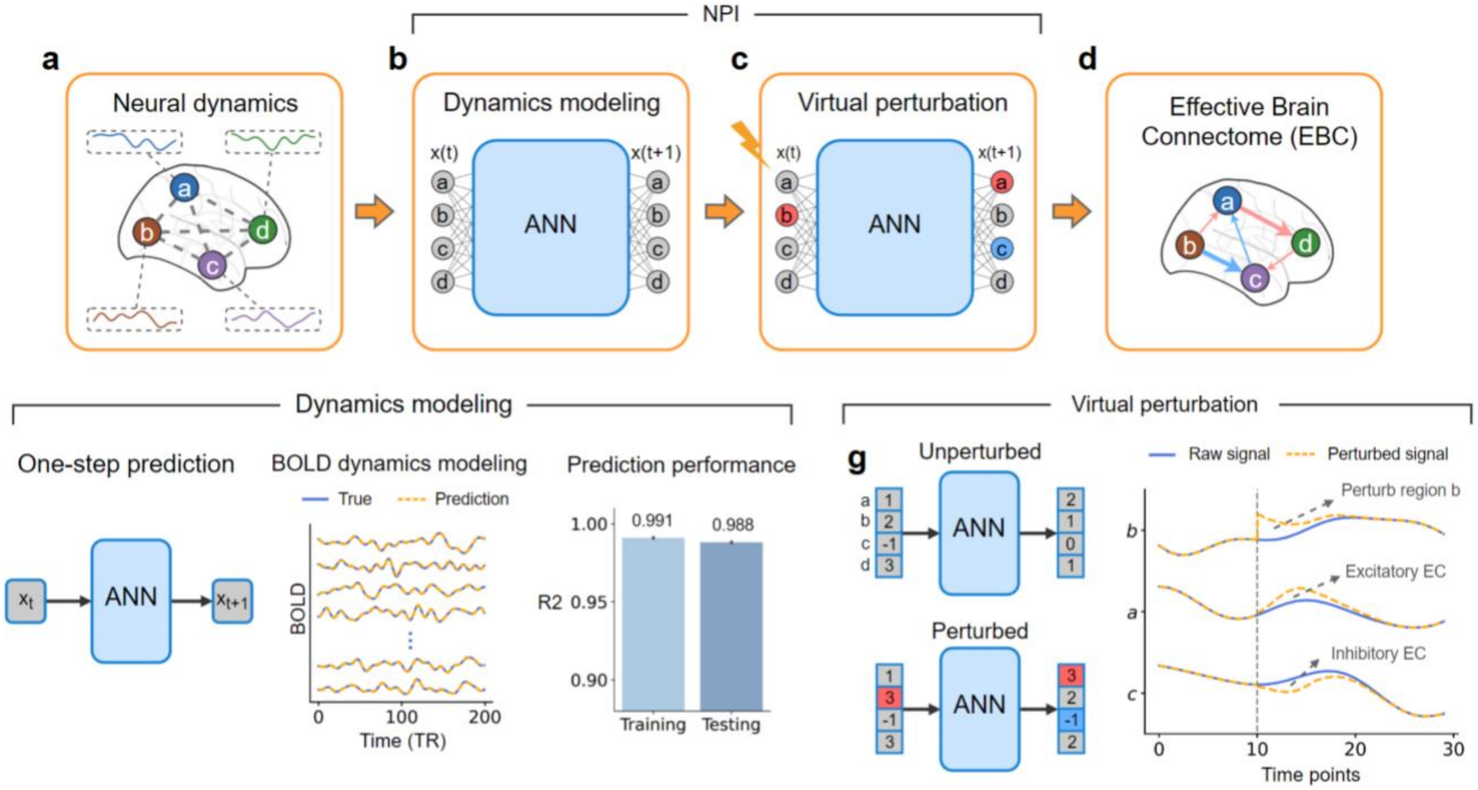


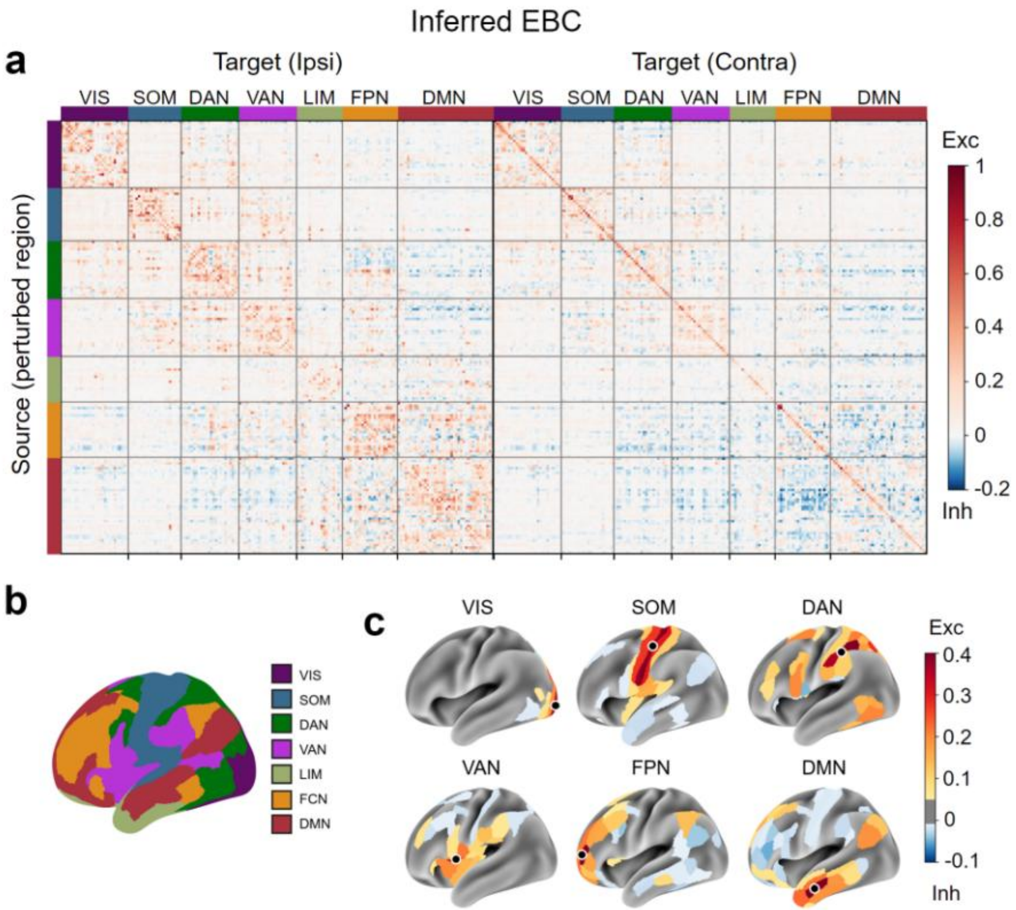


Bauer et al., (2018) Cereb Cortex

Virtual experiments on AI surrogate brain

- Use a **neural network** as a brain substitute to be perturbed
- Obtain the **whole-brain EC** with strength, direction, and sign of information flow

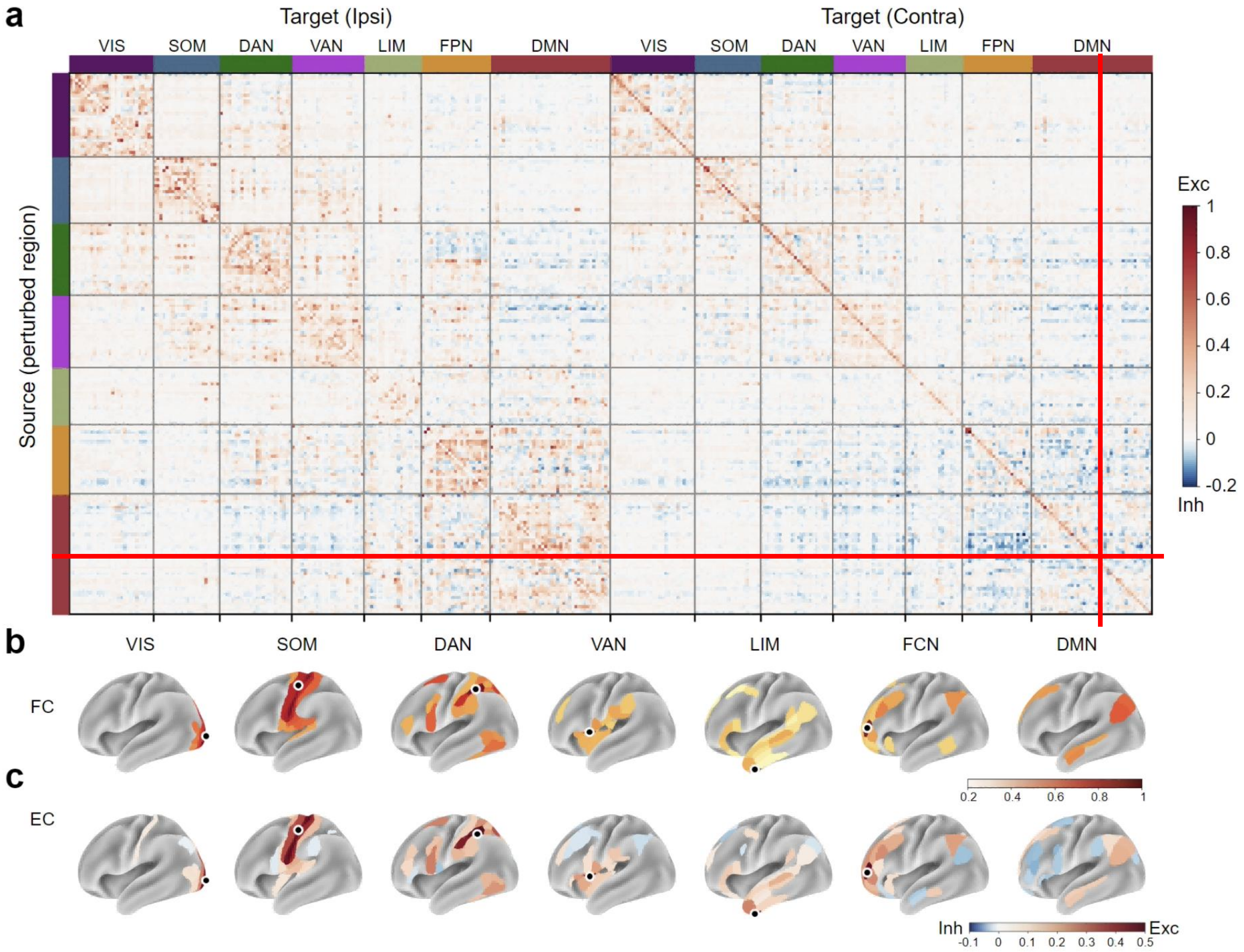




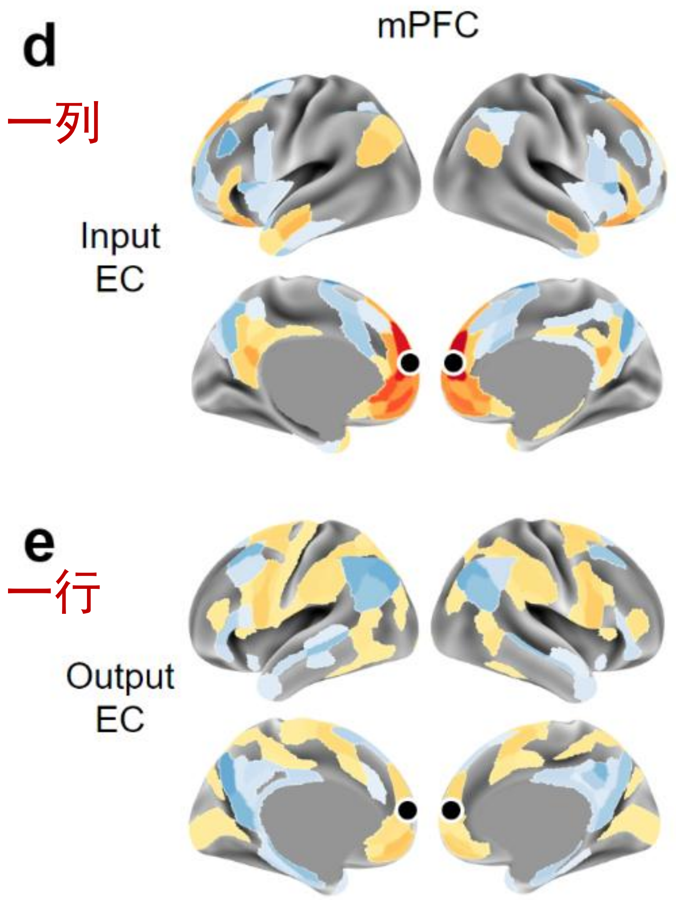
Luo, Zixiang, et al. "Mapping effective connectivity by virtually perturbing a surrogate brain." arXiv preprint arXiv:2301.00148 (2023).

人类全脑有效连接组

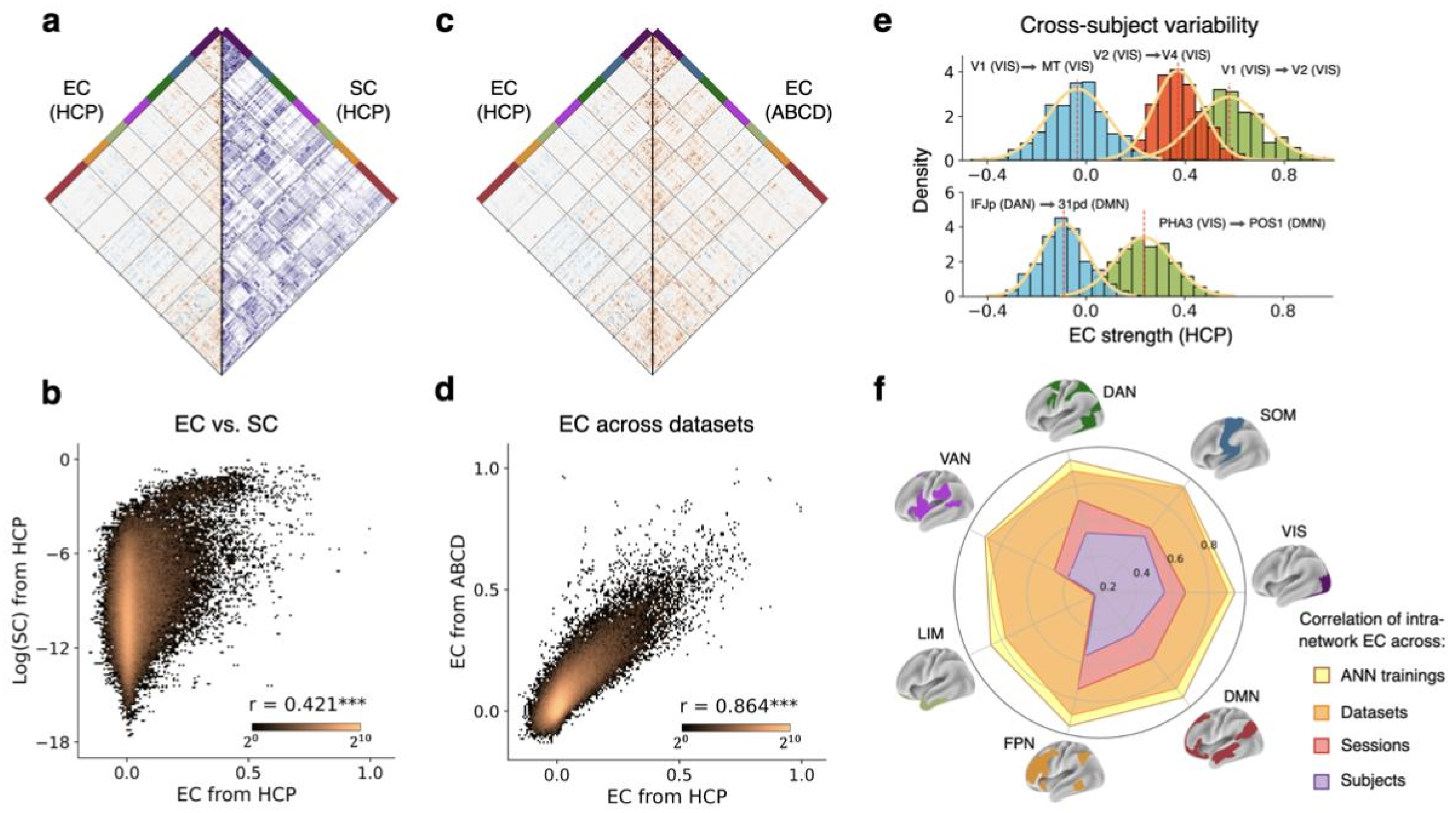
人类全脑有效连接图谱 (EBC)



EBC矩阵的一行和一列指导神经调控

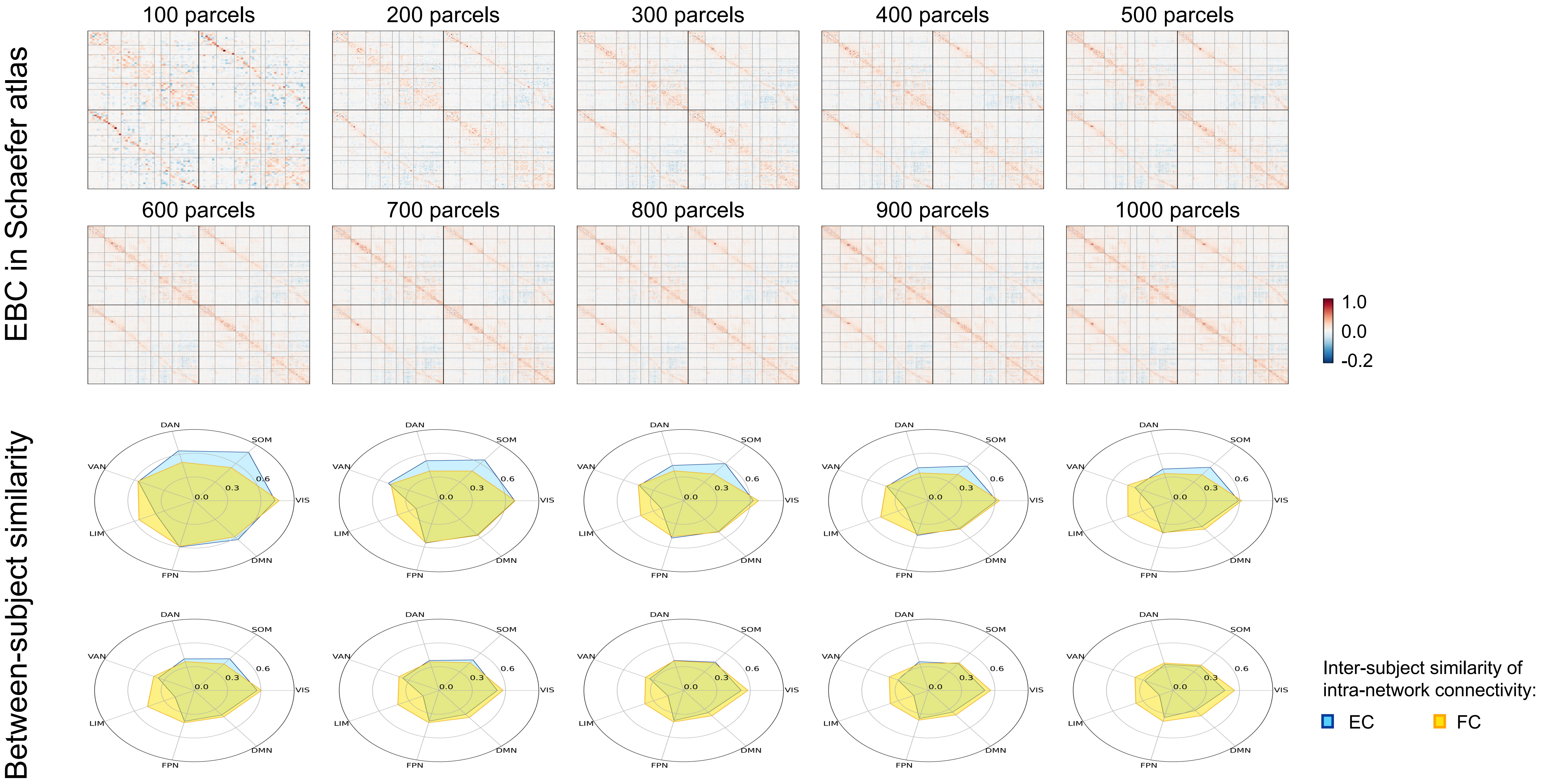


可重复性测试

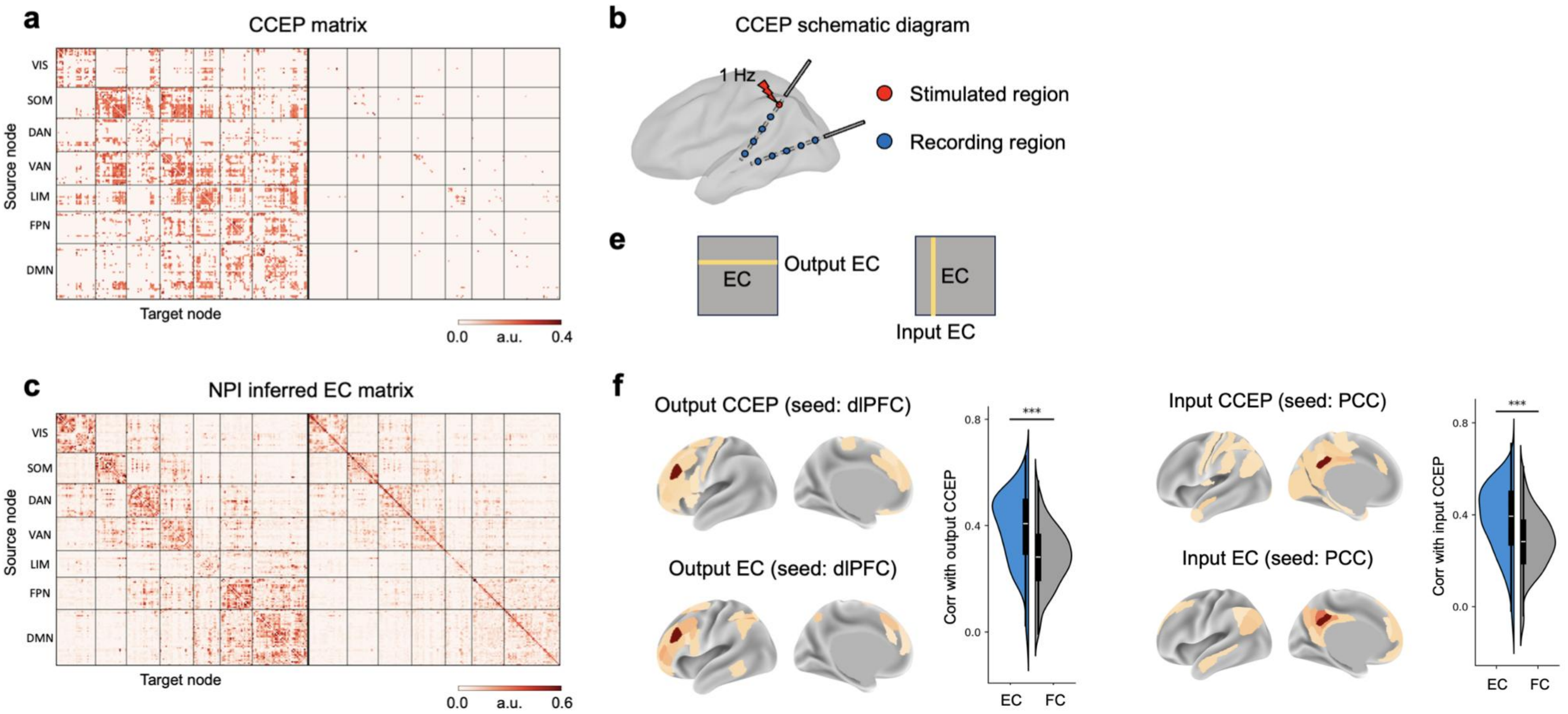


Luo, Liu* et al., *arXiv:2301.00148* (under review)

不同空间尺度下的EBC



预测神经电刺激的响应



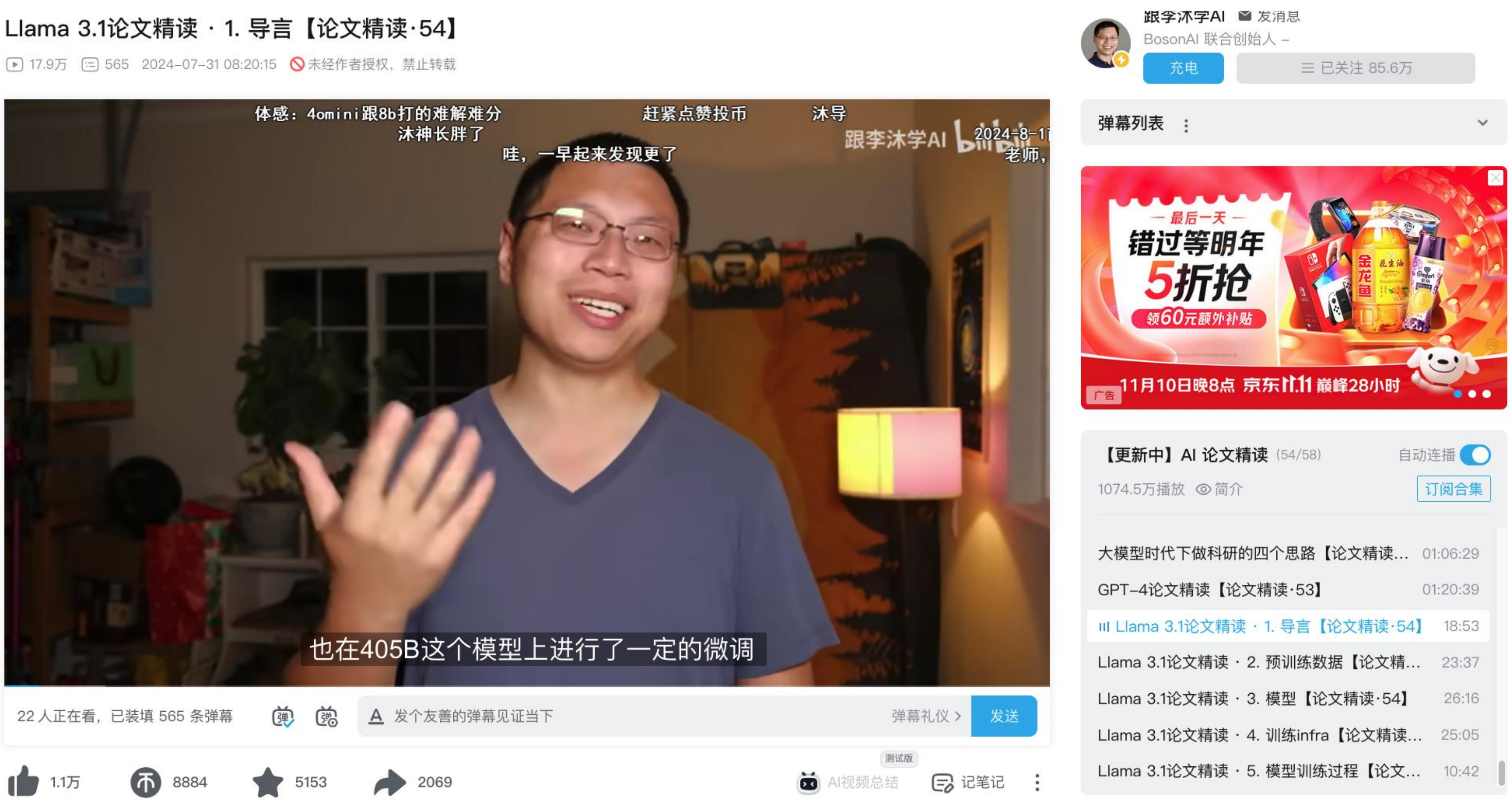
Luo, Liu* et al., *arXiv:2301.00148* (under review)

Quiz 4

1. GPT-4, GPT-o1, Claude-3, Llama, 文心一言, Kimi这些用RLHF来跟人类价值align过的不同大模型，它们的智能水平、价值观、道德观是统一的吗？该如何evaluate呢？
2. 跟AI大模型相比，大脑智能的核心的优势在哪里？最根本的劣势在哪里？
3. 对于进化缓慢、寿命有限的人类，人类智能的前景在哪里？

强烈推荐【李沐】的B站视频！！！

https://www.bilibili.com/video/BV1WM4m1y7Uh/



AI for brain science

- AI为脑科学提供数据分析工具
  - 神经解码
  - 行为分析
- AI为脑科学提供实验仿真工具
  - 多认知任务下的神经表征
  - 神经动力学仿真
- AI为脑科学提供有潜力的科学假设
  - 大脑网络在进化中优化到near-optimal以支撑复杂的脑功能
  - 大脑的分布式并行计算支撑了大脑在多任务中的高性能