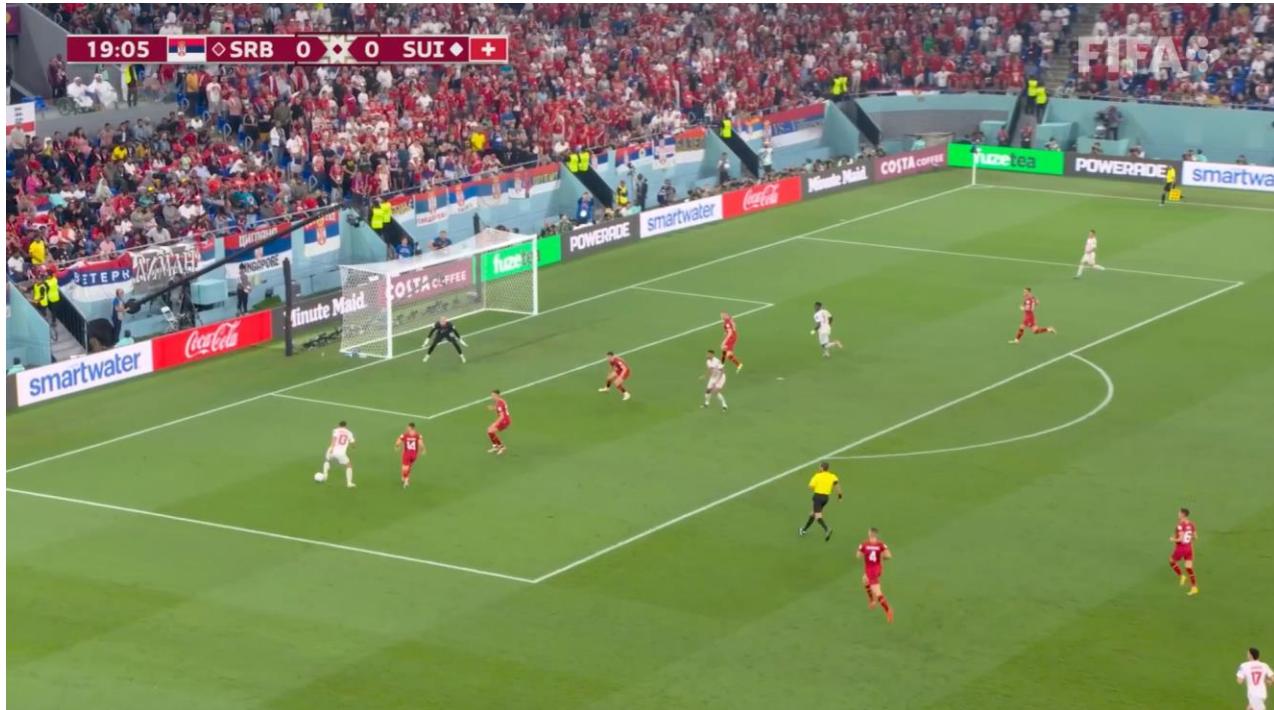


NX-435

NeuroAI

Prof. Mackenzie Mathis, PhD
Spring 2025

Biological Intelligence ← → Artificial Intelligence



World Cup 2022 CH



DeepMind 2023

This is still a large gap in our ability to build adaptive embodied AI

Of course, artificial Intelligence has made huge leaps with LLMs...



tell me a joke about Swiss soccer players vs. DeepMind robots playing soccer

Dogs or Muffins?



Karen Zack (art director)



Slide courtesy of Prof. Andreas Tolias



please tell me what is in each cell in a tabular format aligned with this picture grid.

Here's the content of each cell in the provided image, organized in a tabular format:

	1	2	3	4	5	6
1	Muffin	Dog	Muffin	Muffin	Dog	Muffin
2	Dog	Dog	Muffin	Dog	Dog	Muffin
3	Muffin	Dog	Muffin	Muffin	Dog	Muffin
4	Dog	Dog	Dog	Muffin	Dog	Dog
5	Muffin	Dog	Muffin	Dog	Dog	Muffin
6	Dog	Dog	Muffin	Dog	Dog	Muffin

This table identifies each cell as either a muffin or a dog, corresponding to the grid in the image.



A please tell me what is in each cell in a tabular format aligned with this picture grid.



Show drafts ▾
◆ Certainly! Here's a tabular representation of the image content, aligned with the grid:

Row	Column 1	Column 2	Column 3	Column 4	Column 5
1	Muffin	Chihuahua	Muffin	Chihuahua	Muffin
2	Chihuahua	Muffin	Chihuahua	Muffin	Chihuahua
3	Chihuahua	Muffin	Chihuahua	Muffin	Chihuahua
4	Chihuahua	Muffin	Chihuahua	Muffin	Chihuahua



ANTHROPIC

A please tell me what is in each cell in a tabular format aligned with this picture grid.

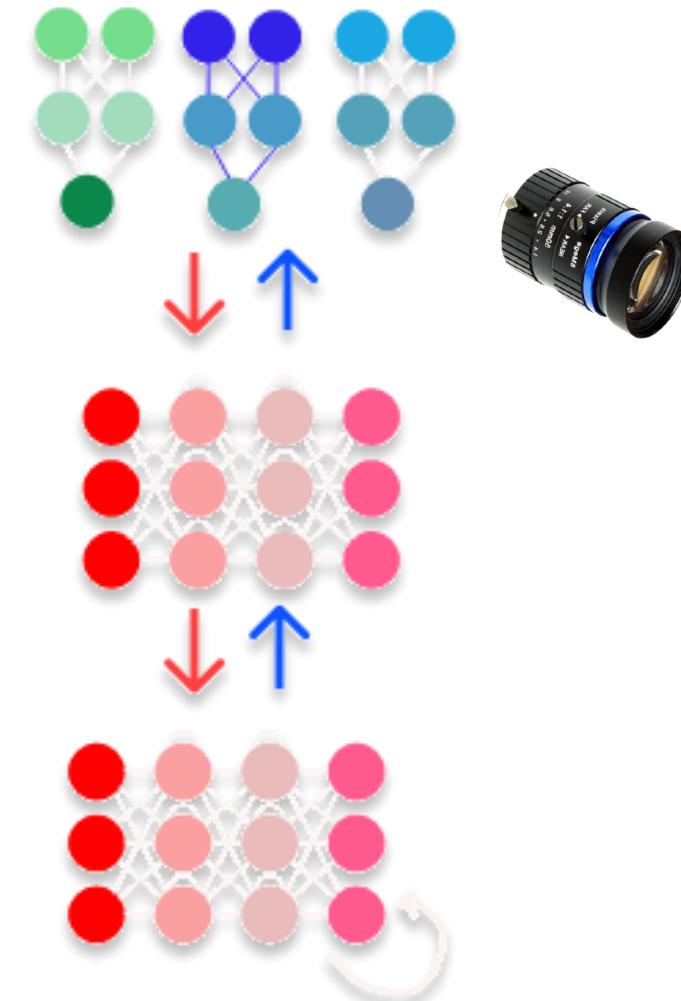
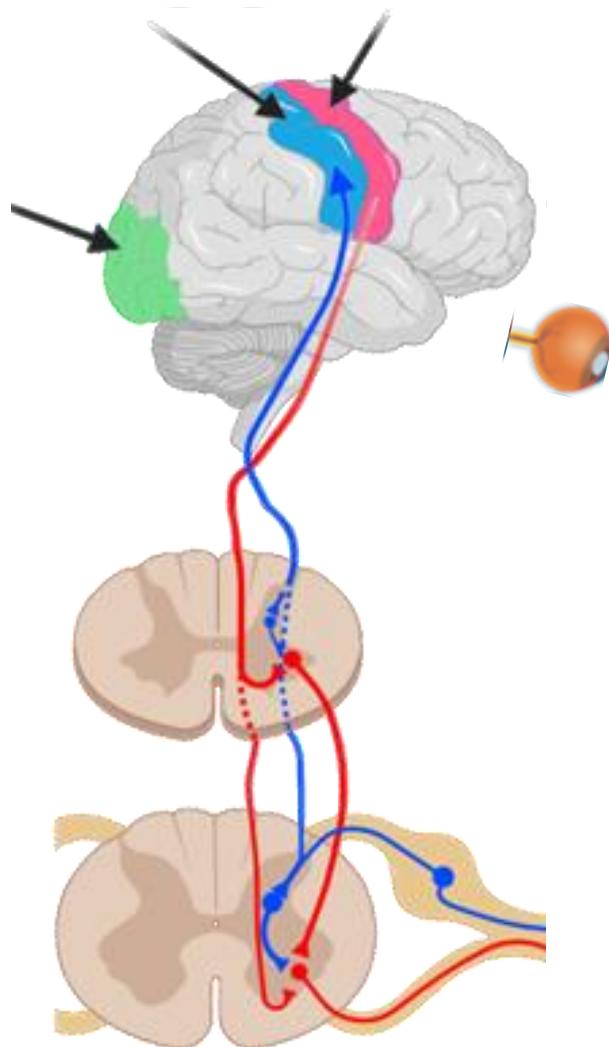
I'll describe the contents of each cell in a tabular format that aligns with the 4x8 grid shown in the image:

Muffin	Dog	Dog	Dog	Muffin	Dog	Dog	Dog
Dog	Muffin	Dog	Muffin	Dog	Dog	Muffin	Dog
Dog	Dog	Dog	Dog	Dog	Dog	Dog	Dog
Dog	Muffin	Dog	Muffin	Dog	Muffin	Dog	Muffin

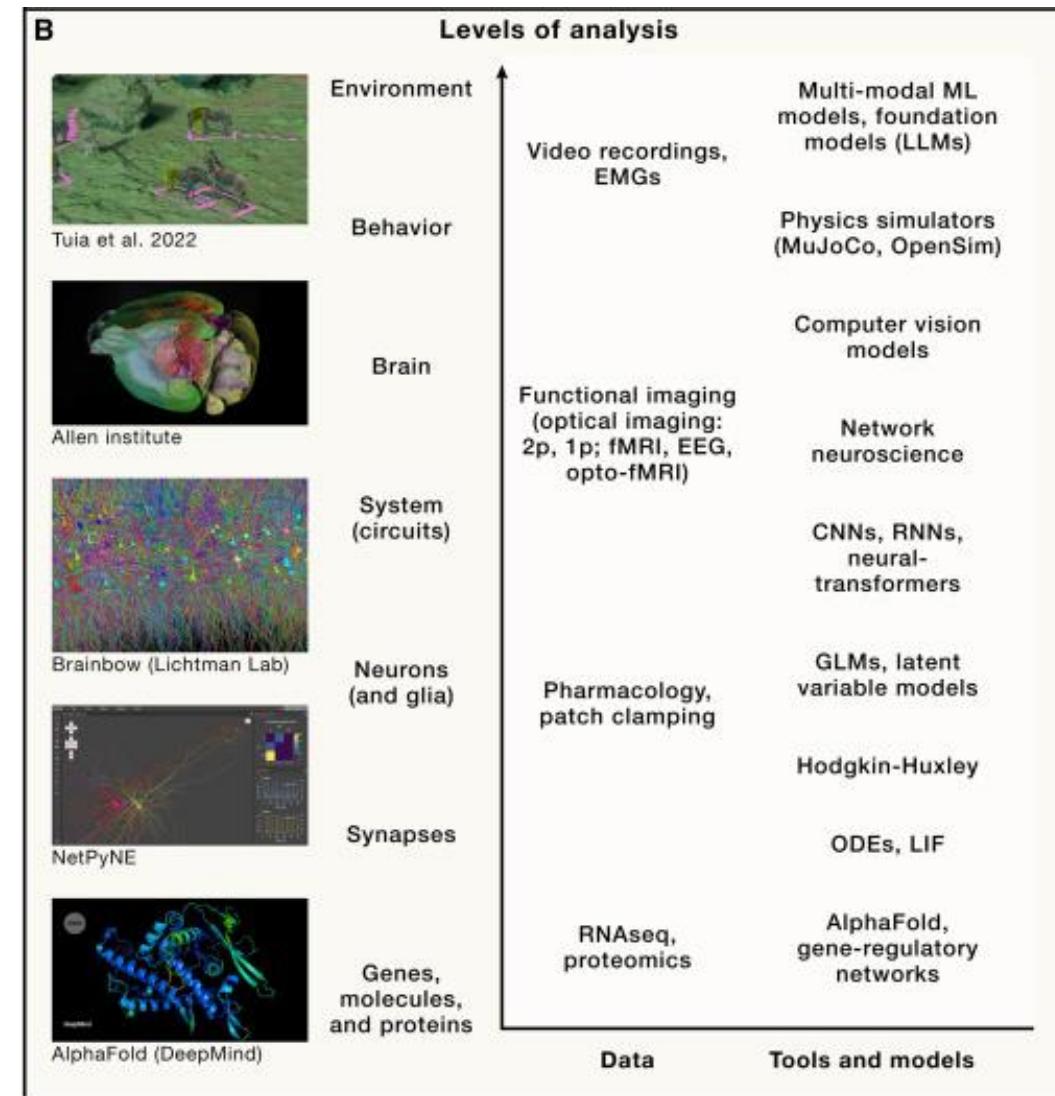
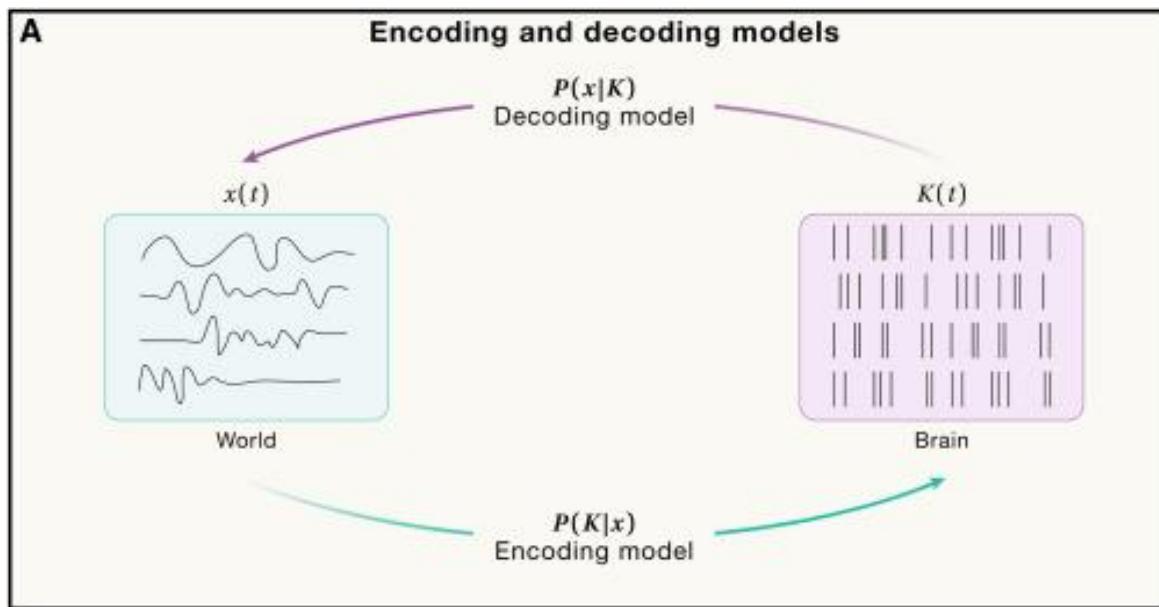


Slide courtesy of Prof. Andreas Tolias

Biological Intelligence ← → Artificial Intelligence

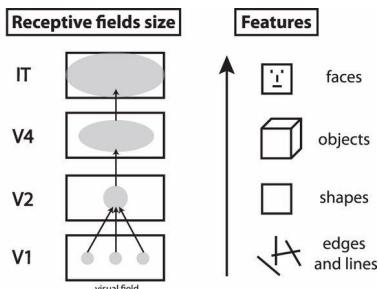
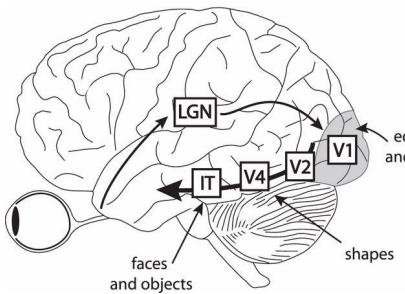


Biological Intelligence \longleftrightarrow Artificial Intelligence



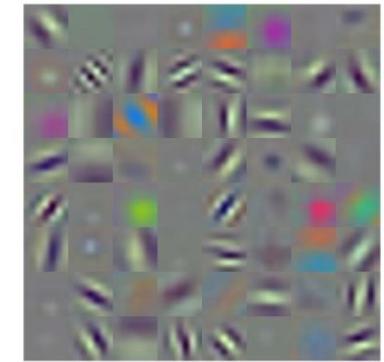
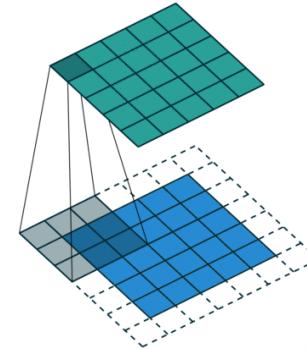
What is neuroAI?

Neuroscience



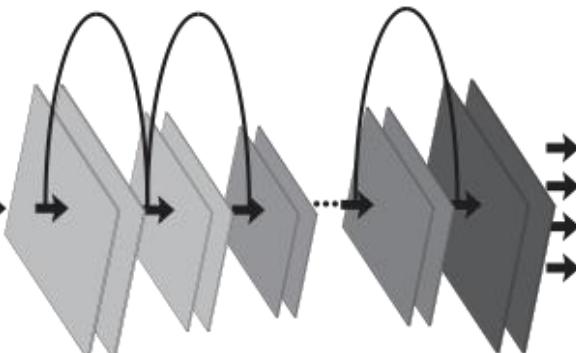
Hubel & Wiesel discoveries in cat V1 inspired convolutional neural networks

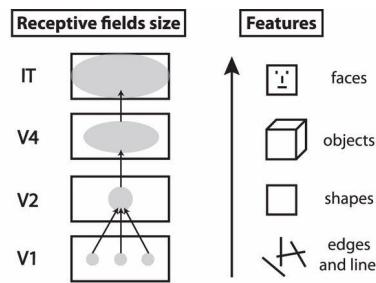
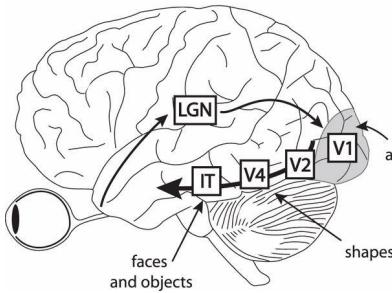
Artificial Intelligence (AI)



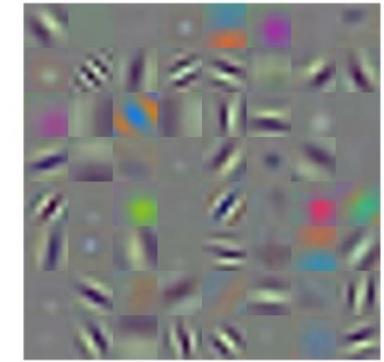
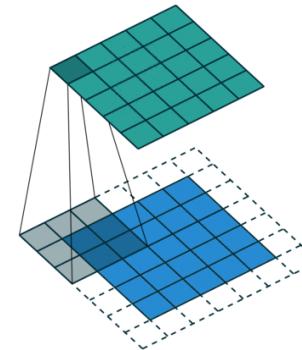
Convolutions (CNN)

Representations in ImageNet trained (CNN)





Hubel & Wiesel discoveries in cat
V1 inspired convolutional neural
networks



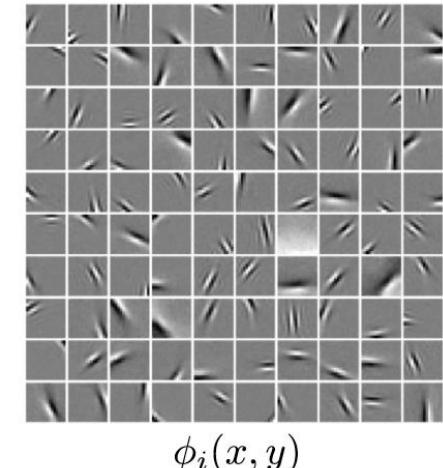
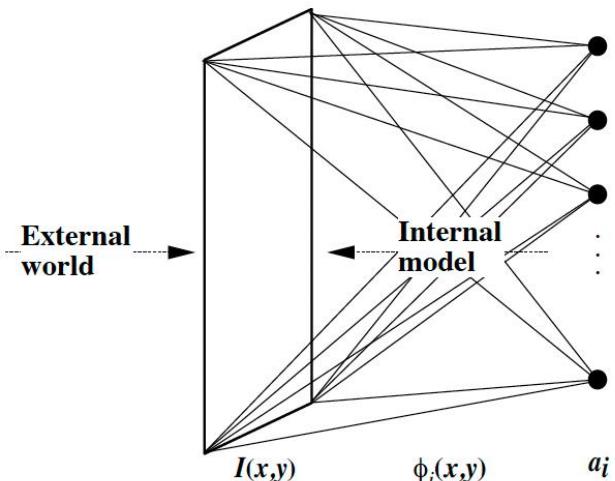
Convolutions
(CNN)

Representations
in ImageNet
trained (CNN)

edge detector neurons
can be explained with
sparse autoencoding

$$I(x, y) = \sum_i a_i \phi_i(x, y) + \epsilon(x, y)$$

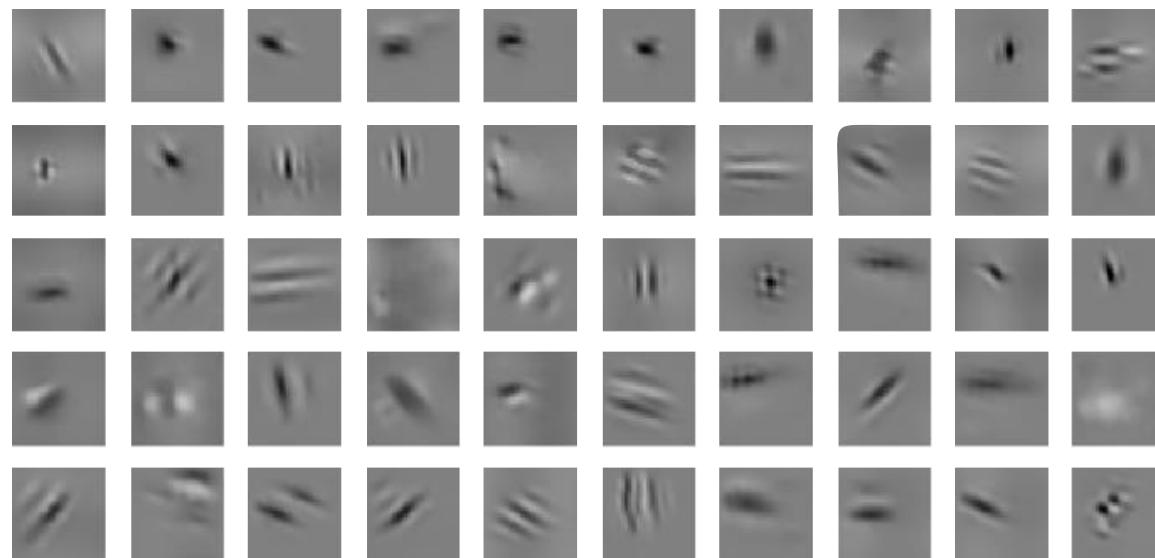
Adapted from A. Mathis



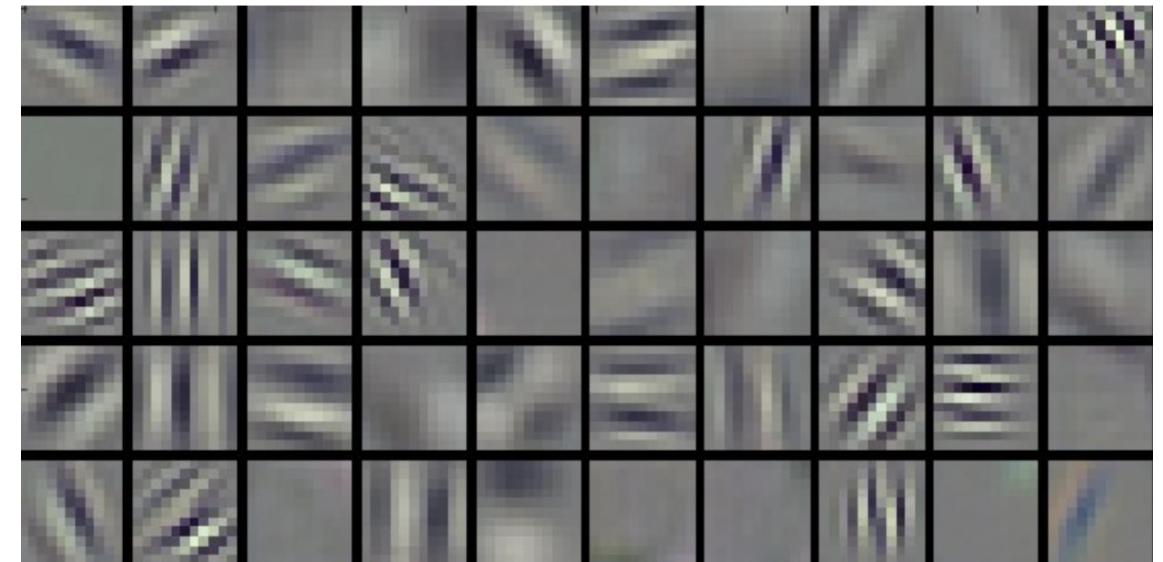
Olshausen & Field, 1996 Nature

Universality of Representations

feature detectors in macaque V1



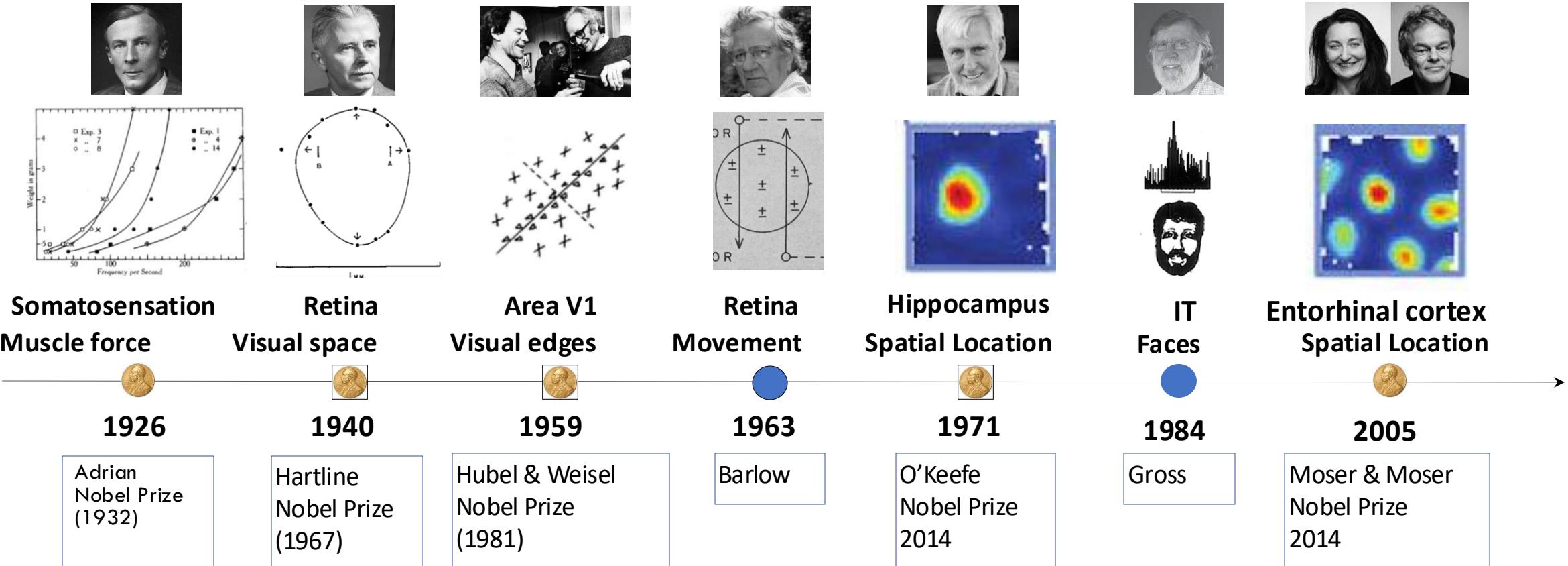
feature detectors in CNNs



Slide courtesy of Prof. Andreas Tolias

The representational level

Equivalences between neural activity and sensory input & behavior



What is neuroAI?

Neuroscience

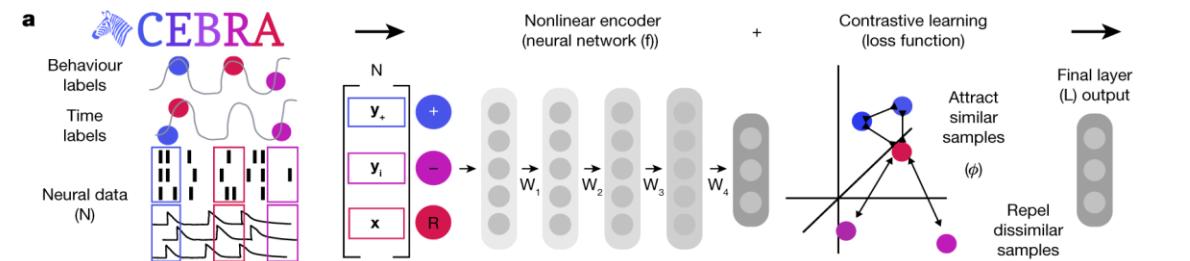


Data:Chowdhury
et al 2020 eLife



Which lead to better neural dynamical models of sensorimotor cortex (important for fundamental understanding and BCIs)

Artificial Intelligence (AI)

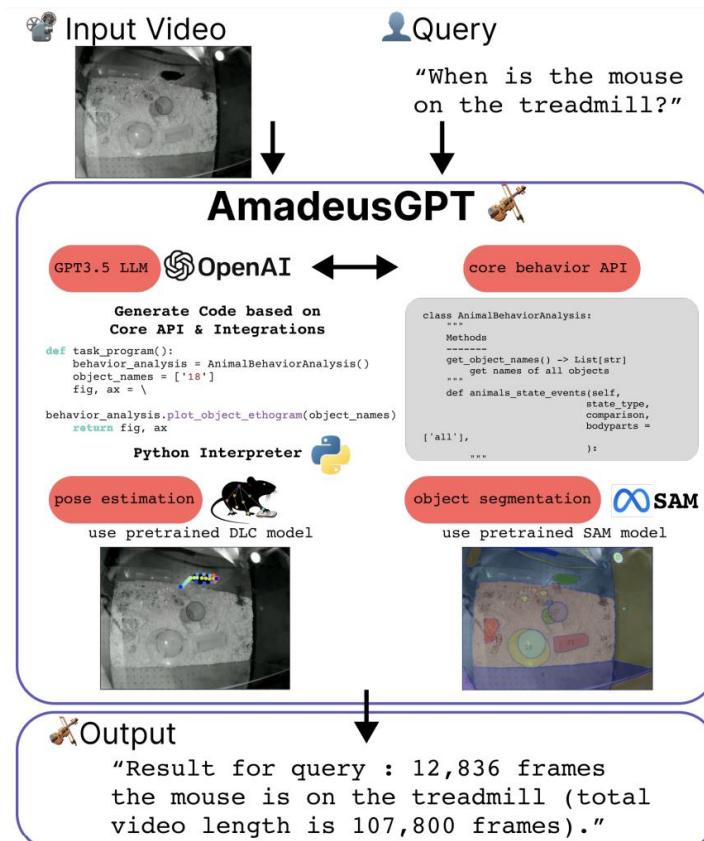


Schneider, Lee,
Mathis 2023 Nature

Advances in AI, such as **contrastive learning** in image processing could be expanded to neuro-specific domains

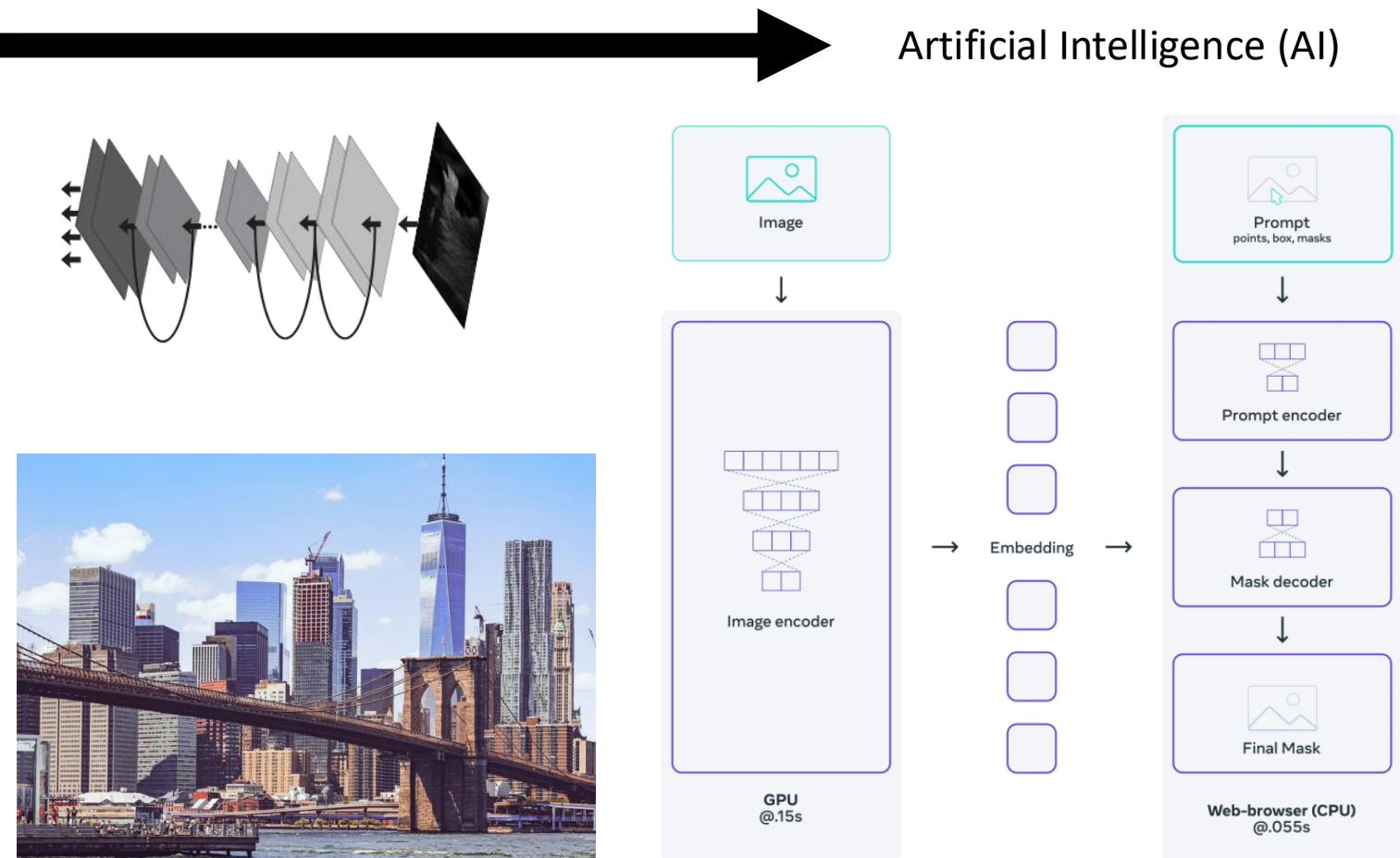
What is neuroAI?

Neuroscience



AmadeusGPT Ye et al. 2023

Artificial Intelligence (AI)



Segment Anything (Meta AI)

What is neuroAI:

- Many definitions, but widely accepted that it is the **new inter-disciplinary field of merging neuroscience and AI research (←→)**
- Others define it more narrowly as using neuroscience (→) to shape research in AI

nature neuroscience

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nature > nature neuroscience > perspectives > article

Perspective | Published: 28 October 2019

A deep learning framework for neuroscience

Blake A. Richards , Timothy P. Lillicrap, Philippe Beaudoin, Yoshua Bengio, Rafal Bogacz, Amelia Christensen, Claudia Clopath, Rui Ponte Costa, Archy de Berker, Surya Ganguli, Colleen J. Gillon, Danijar Hafner, Adam Kepcs, Nikolaus Kriegeskorte, Richard Naud, Christopher C. Pack, Pana Saxe, Benjamin Scellier, ... Konrad P. Kording

neuron
Review

Neuroscience-Inspired Artificial Intelligence

Demis Hassabis, ^{1,2,*} Dharshan Kumaran, ^{1,3} Christopher Summerfield, ^{1,4} and Matthew Botvinick^{1,2}

¹DeepMind, 5 New Street Square, London, UK
²Gatsby Computational Neuroscience Unit, 25 Howland Street, London, UK
³Institute of Cognitive Neuroscience, University College London, 17 Queen Square, London, UK
⁴Department of Experimental Psychology, University of Oxford, Oxford, UK
^{*Correspondence: dhcontact@google.com}

nature communications

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nature > nature communications > perspectives > article

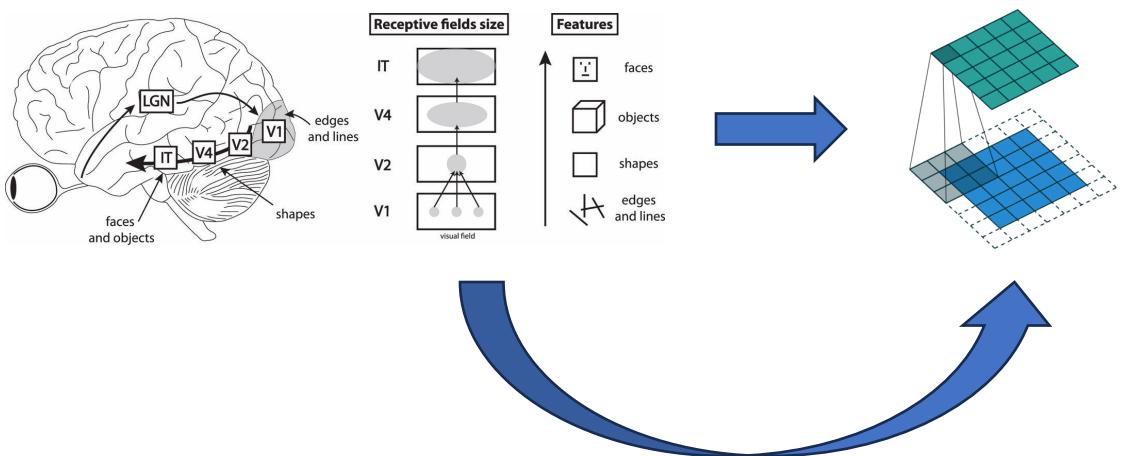
Perspective | **Open access** | Published: 22 March 2023

Catalyzing next-generation Artificial Intelligence through NeuroAI

Anthony Zador , Sean Escola, Blake Richards, Bence Ölveczky, Yoshua Bengio, Kwabena Boahen, Matthew Botvinick, Dmitri Chklovskii, Anne Churchland, Claudia Clopath, James DiCarlo, Surya Ganguli, Jeff Hawkins, Konrad Kording, Alexei Koulakov, Yann LeCun, Timothy Lillicrap, Adam Marblestone, Bruno Olshausen, Alexandre Pouget, Cristina Savin, Terrence Sejnowski, Eero Simoncelli, Sara Solla, David Sussillo, Andreas S. Tolias & Doris Tsao

— Show fewer authors

One rapidly growing area is trying to build better AI by better understanding Biological Intelligence (BI) / Natural Intelligence (NI)



How can we build better models of neural systems, and what is the role of systems neuroscience?

<https://ellis.eu/programs/natural-intelligence>

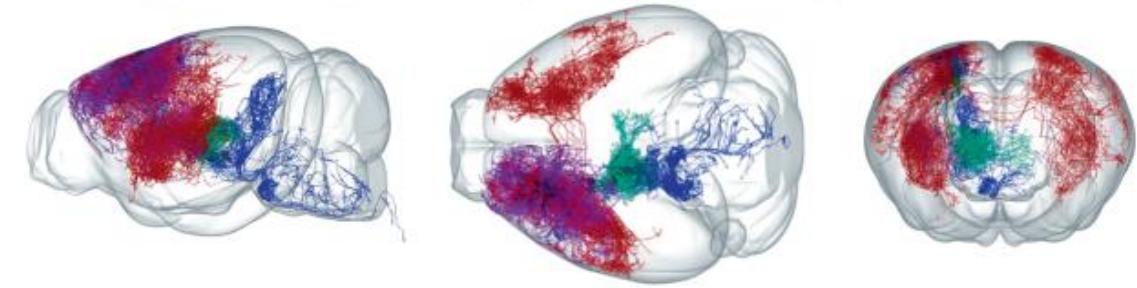
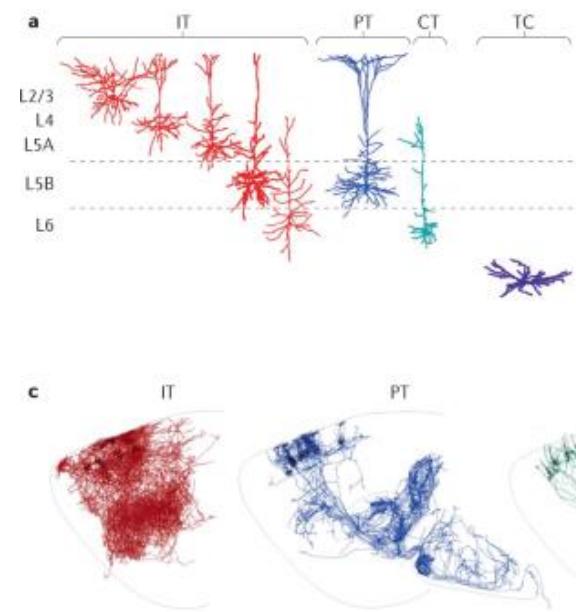
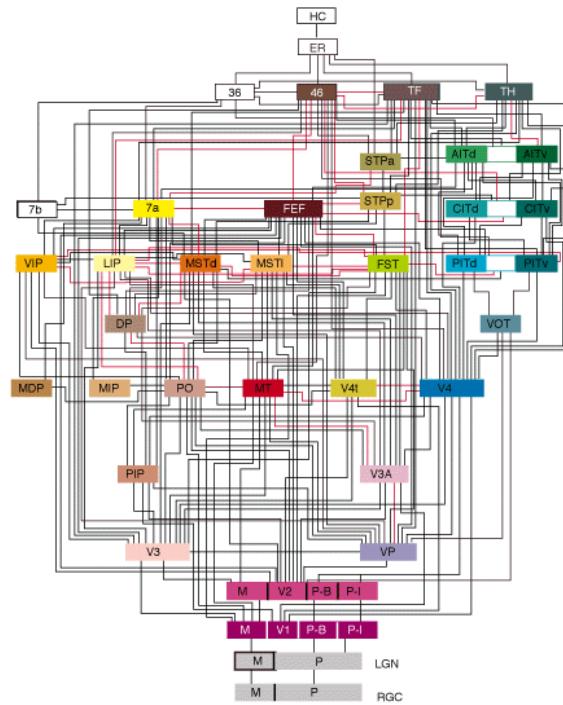
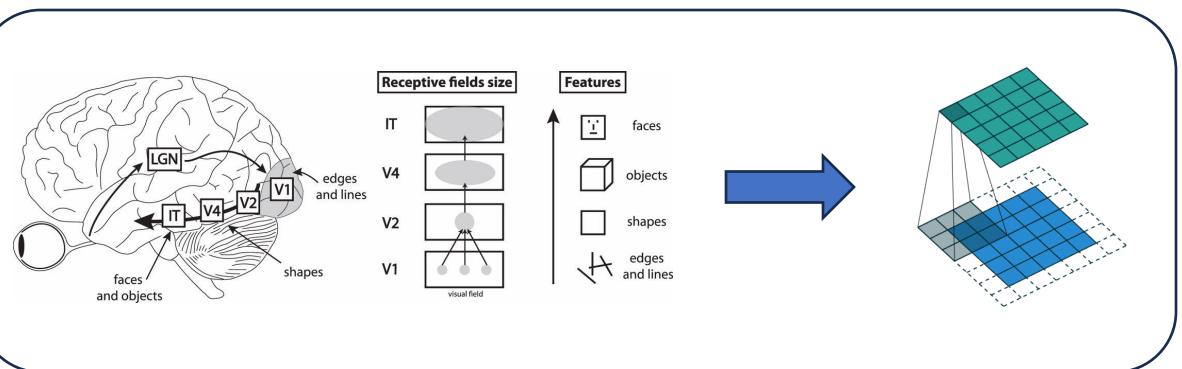
*note, ELLIS also has the top umbrella PhD program in Europe for ML/AI research

- “If a new facet of biological computation found to be critical to supporting a cognitive function, then we would consider it an excellent candidate for incorporation into artificial systems”



“neuroscience can provide validation of AI techniques that already exist. If a known algorithm is subsequently found to be implemented in the brain, then that is strong support for its plausibility as an integral component of an overall general intelligence system”

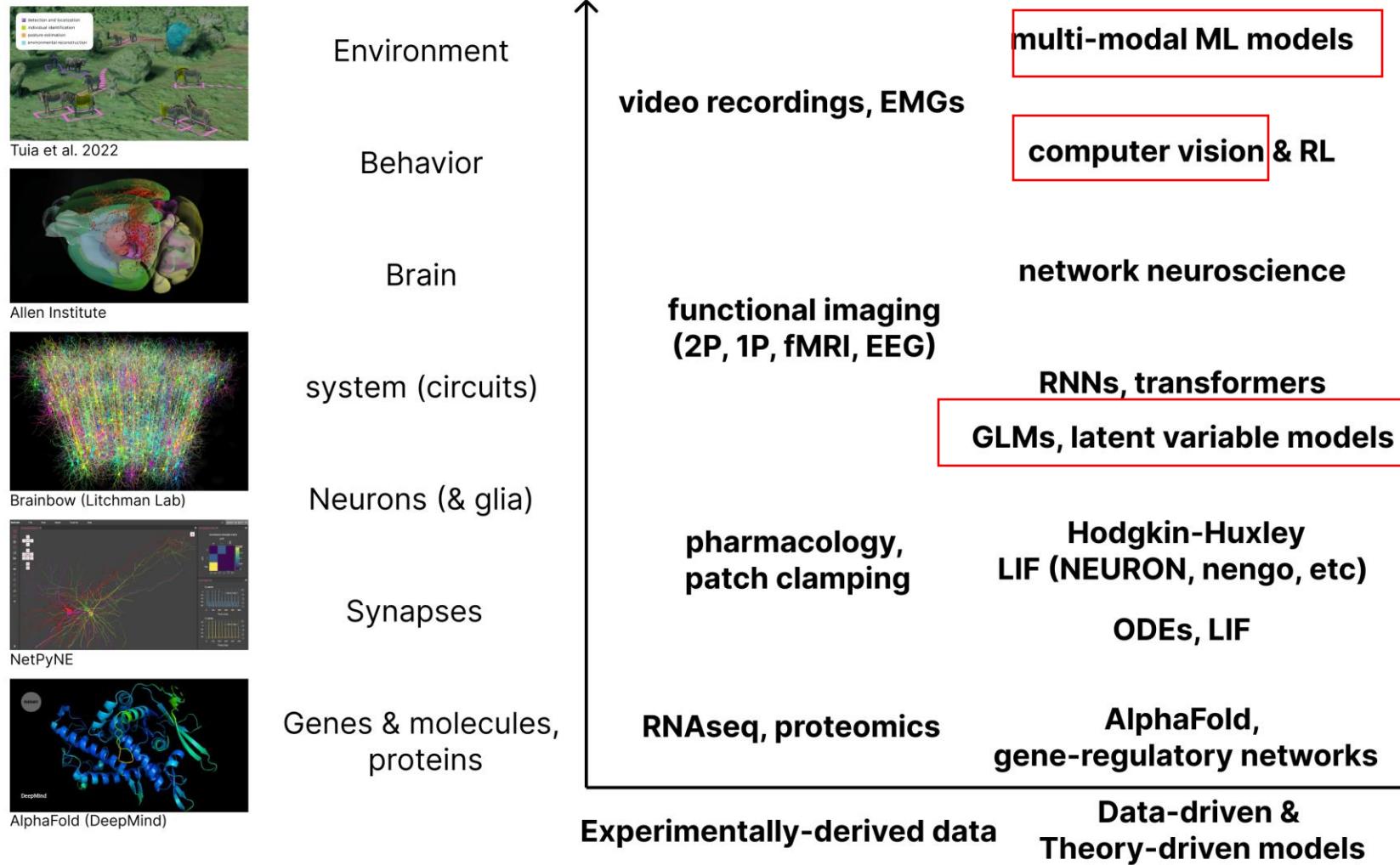
Neural circuits are much more complex than modern AI systems ...



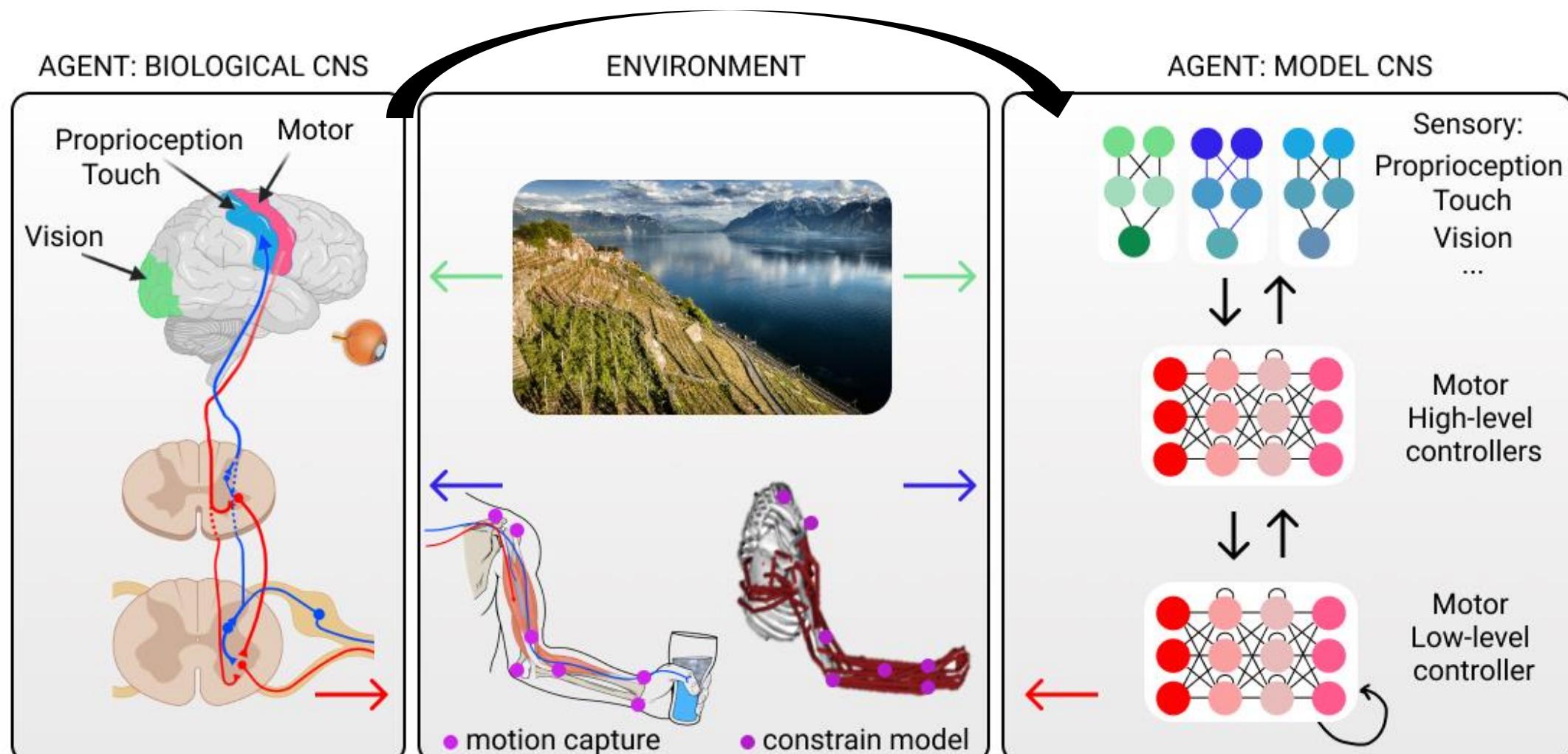
Felleman and Van Essen *Cerebral Cortex* 1991

Shepherd and Yamawaki *Nature review neuroscience* 2021

Previously we covered (some) tools for measuring and modeling behavioral and neural data with data-driven approaches ...

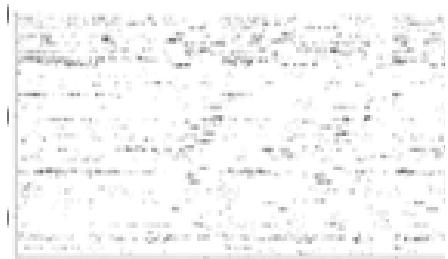


Data-driven and Task-driven modeling for understanding BI

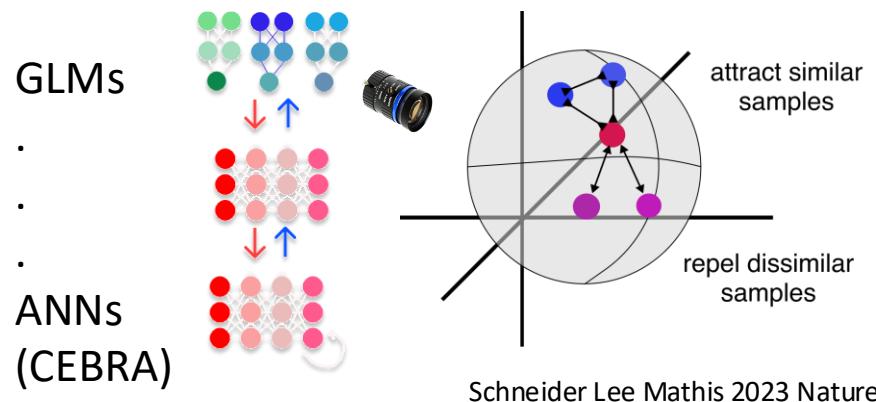


Data-driven modeling

GLMs, PCA, Sussillo et al. 2015 Nat Neuro
State-space models, ...



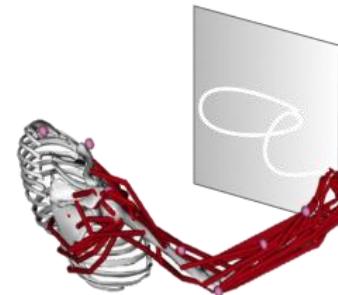
Record from neural data
during a behavioral task



Joint models that describe
neural variance & representations

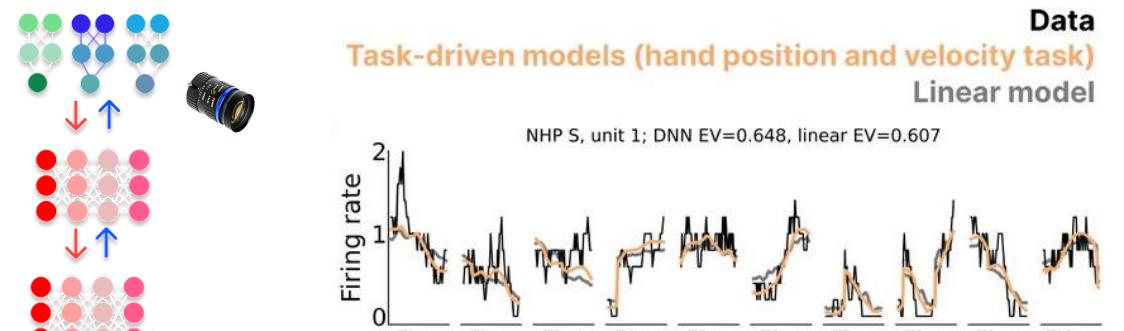
Task-driven modelling

Yamins et al. PNAS 2014, Kell et al. 2018 Neuron,
Banino et al. 2018 Nature



Constrain ANN based on
behavioral task to test
hypotheses about a system

Sandbrink et al. 2023 eLife



Marin Vargas et al. 2024 Cell

NN models that describe
neural variance & computationally
constrain system

Data-driven modeling

“If a new facet of biological computation found to be critical to supporting a cognitive function, then we would consider it an excellent candidate for incorporation into artificial systems”

Task-driven modelling

“neuroscience can provide validation of AI techniques that already exist. If a known algorithm is subsequently found to be implemented in the brain, then that is strong support for its plausibility as an integral component of an overall general intelligence system”

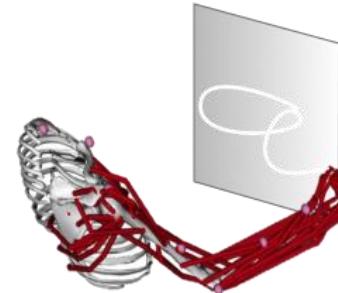


how task-driven models can inform us about the computational goals of the brain

(which can lead to validations and/or new ideas for AI)

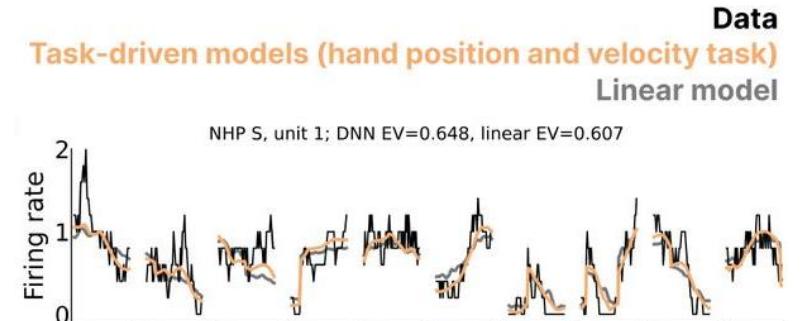
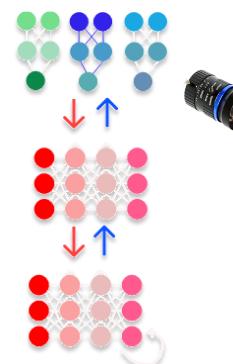
Task-driven modelling

Yamins et al. PNAS 2014, Sussillo et al. 2015 Nat Neuro, Kell et al. 2018 Neuron, Banino et al. 2018 Nature



Constrain ANN based on behavioral task to test hypotheses about a system

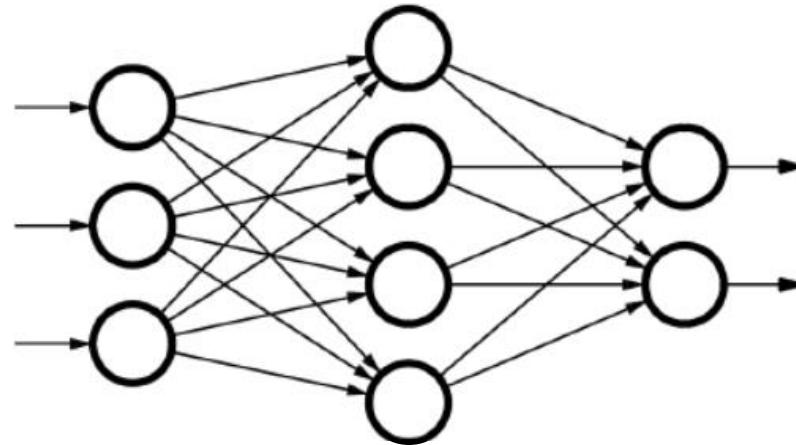
Sandbrink et al. 2023 eLife



Marin Vargas et al. 2024 Cell

NN models that describe neural variance & computationally constrain system

Using deep neural networks as task-driven models of a system



Vision: Yamins et al. (2014) .. Wang et al. (2025)



Audition: Kell et al. (2018)- speech recognition, speaker identification, natural sound identification



Barrel Cortex: Zhuang et al. (2017)

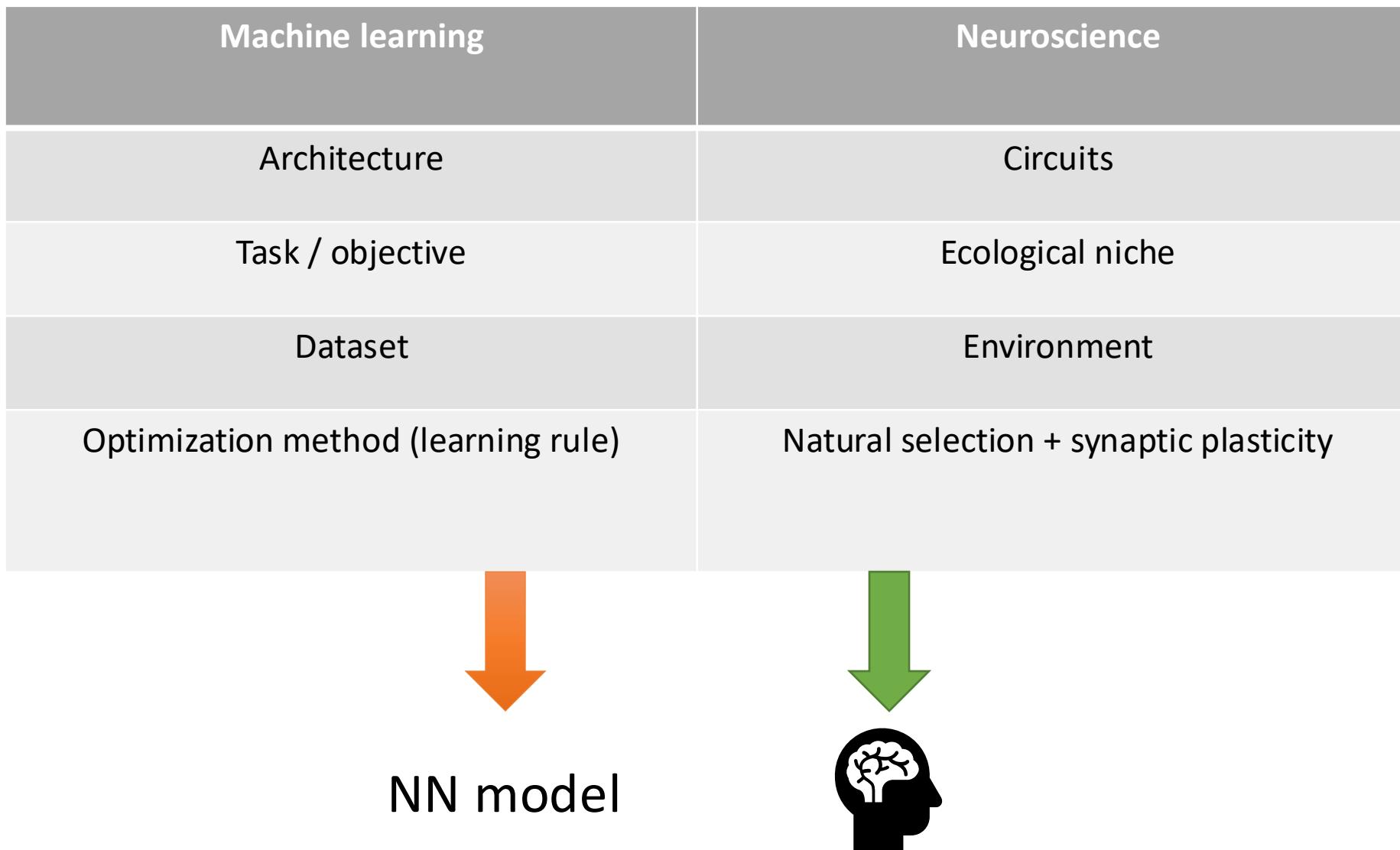


Cognition: Mante et al. (2013)

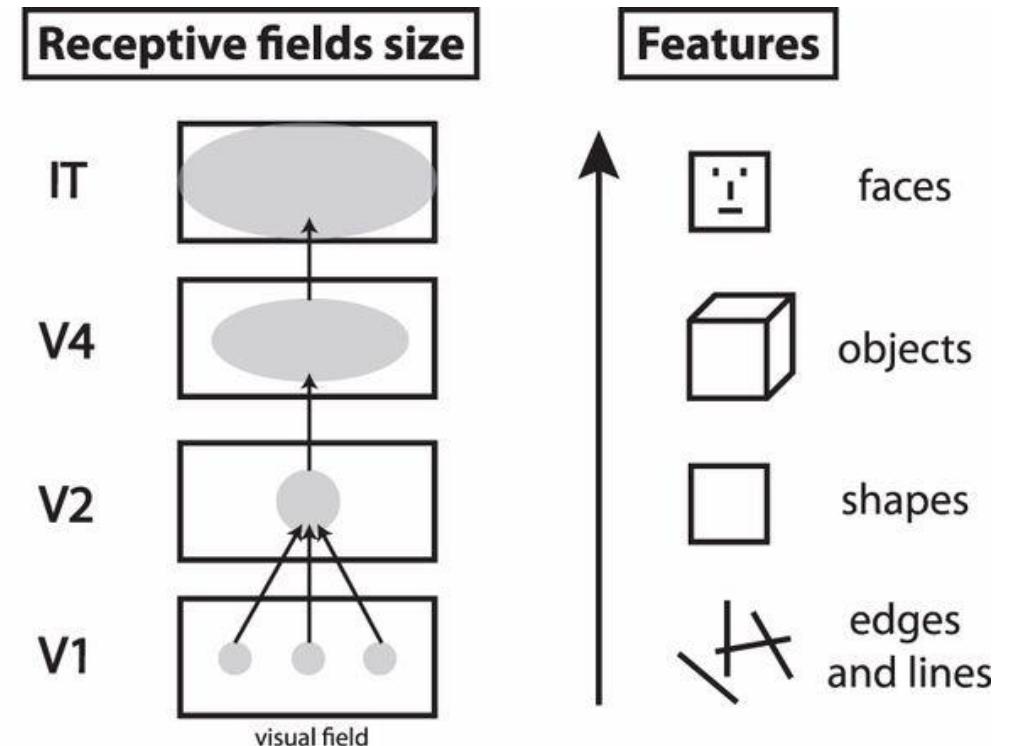
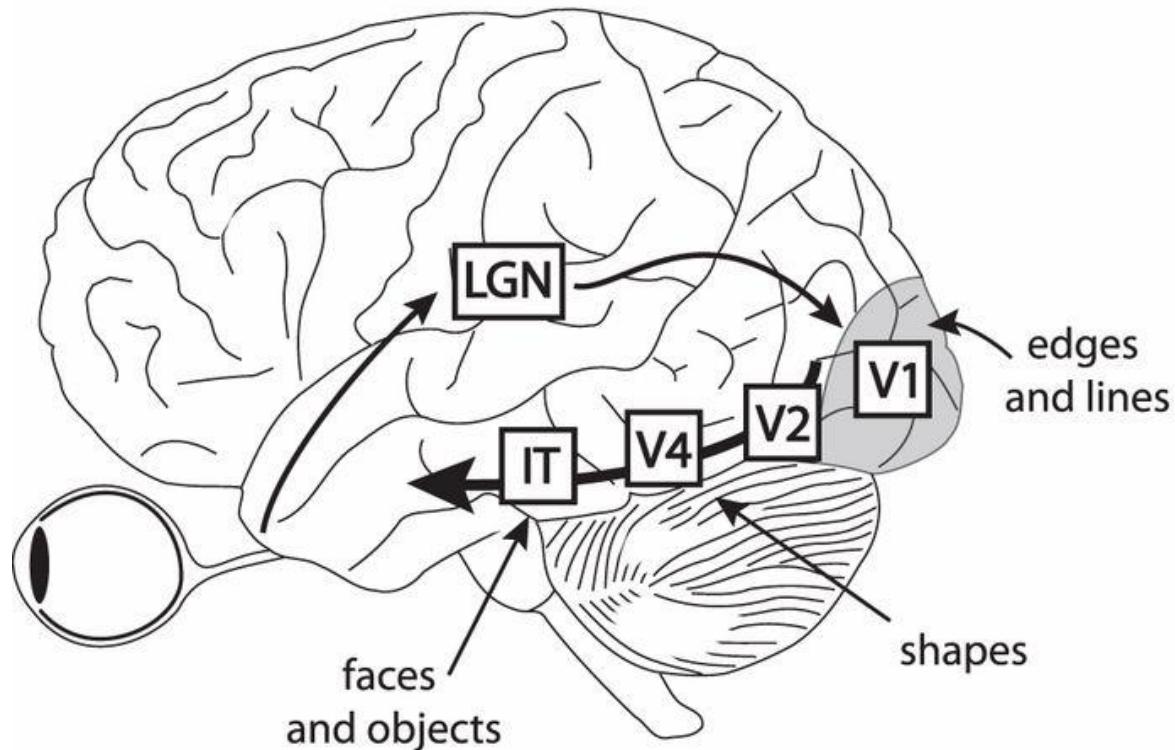


Proprioception: Sandbrink et al. (2023), Marin Vargas*, Bisi* et al. (2024)

The goal: to build NN models that are constrained to goals of a neural system



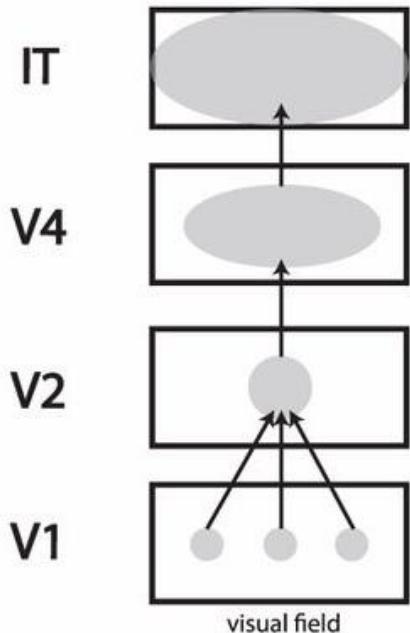
Hierarchical visual processing



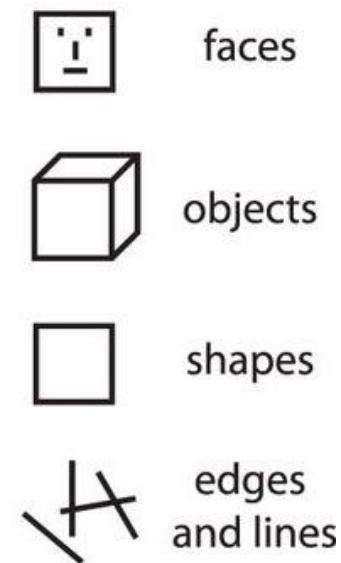
- V1 neurons are most sensitive to low-level features, such as edges and lines.
- In higher visual areas, like V4 and IT, receptive fields are larger, and neurons are sensitive to complex features, such as shapes and objects.
- Responses of high-level neurons are fully determined by the neural firing of lower-level neurons. For example, the neural firing to a square is determined by the neural firing for two vertical and two horizontal lines.

IT neurons are nonlinear

Receptive fields size



Features



From: When crowding of crowding leads to uncrowding
Journal of Vision. 2013;13(13):10. doi:10.1167/13.13.10

The Code for Facial Identity in the Primate Brain

Le Chang^{1,*} and Doris Y. Tsao^{1,2,3,*}

¹Division of Biology and Biological Engineering, Computation and Neural Systems, Caltech, Pasadena, CA 91125, USA

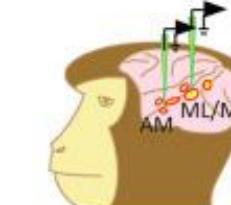
²Howard Hughes Medical Institute, Pasadena, CA 91125, USA

³Lead Contact

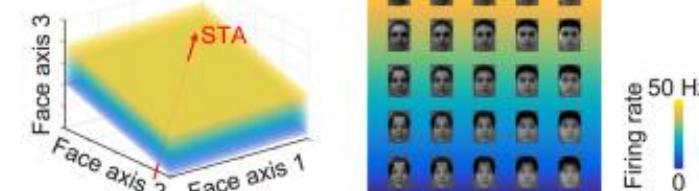
*Correspondence: lechang@caltech.edu (L.C.), dortsao@caltech.edu (D.Y.T.)

<http://dx.doi.org/10.1016/j.cell.2017.05.011>

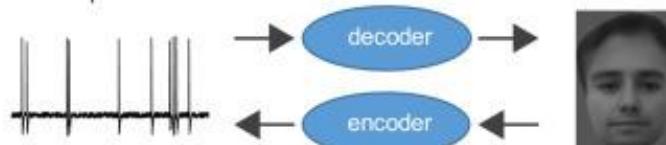
1. We recorded responses to parameterized faces from macaque face patches



2. We found that single cells are tuned to single face axes, and are blind to changes orthogonal to this axis

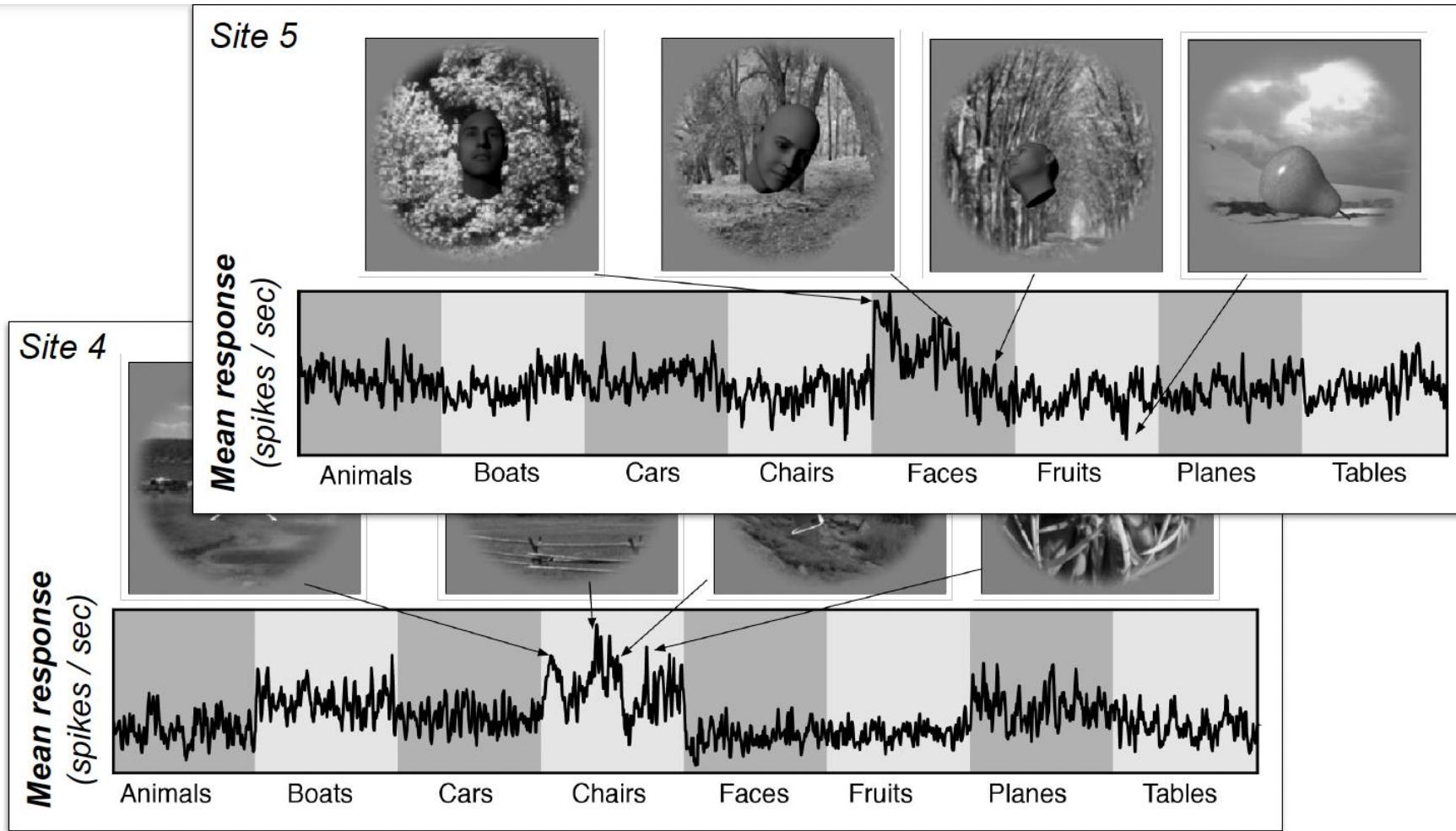


3. We found that an axis model allows precise encoding and decoding of neural responses

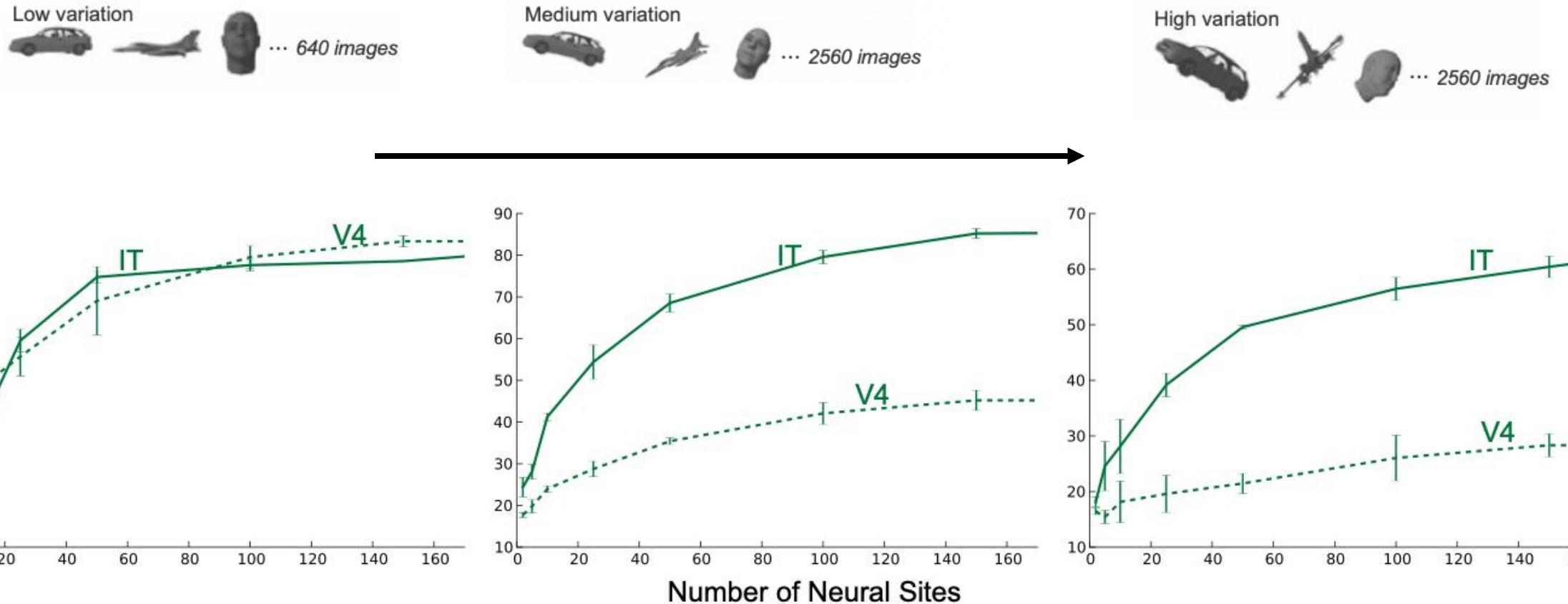


Example higher-order visual cortex responses

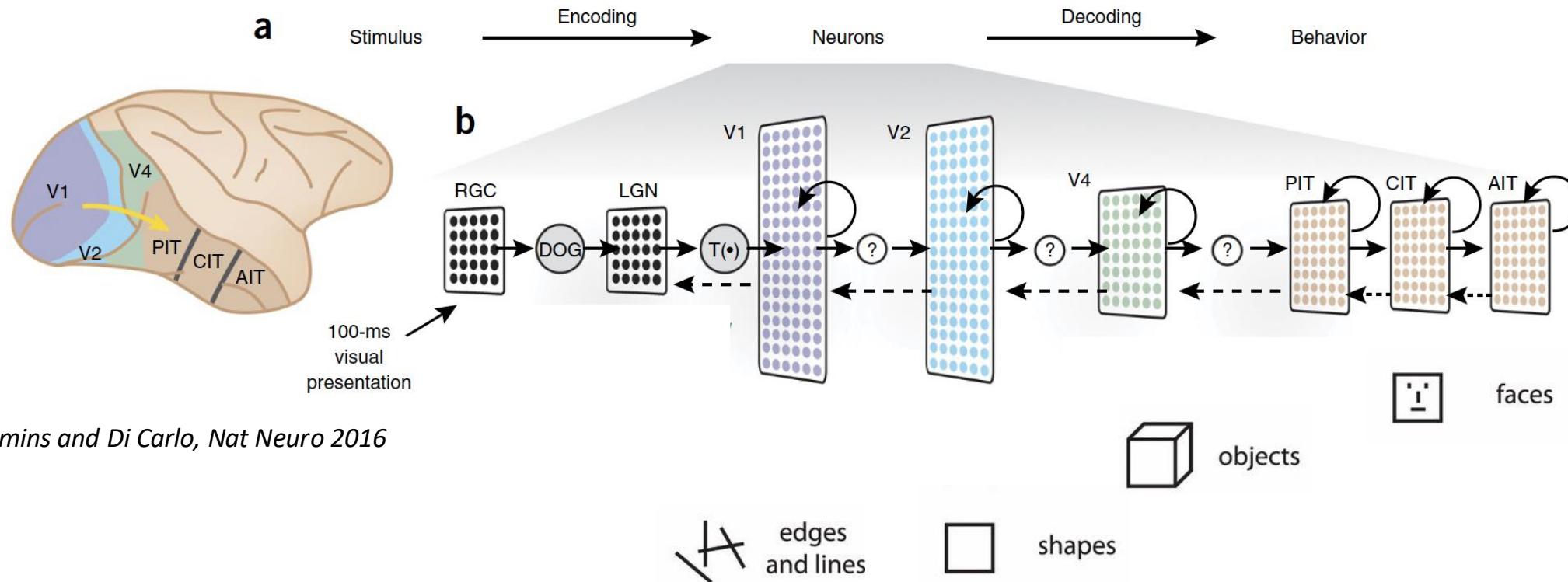
Examples of IT neuronal spiking responses



Decoding object identity from neural data



Core-object recognition and the visual pathway



Building models of visual pathway: what is the computational goal?

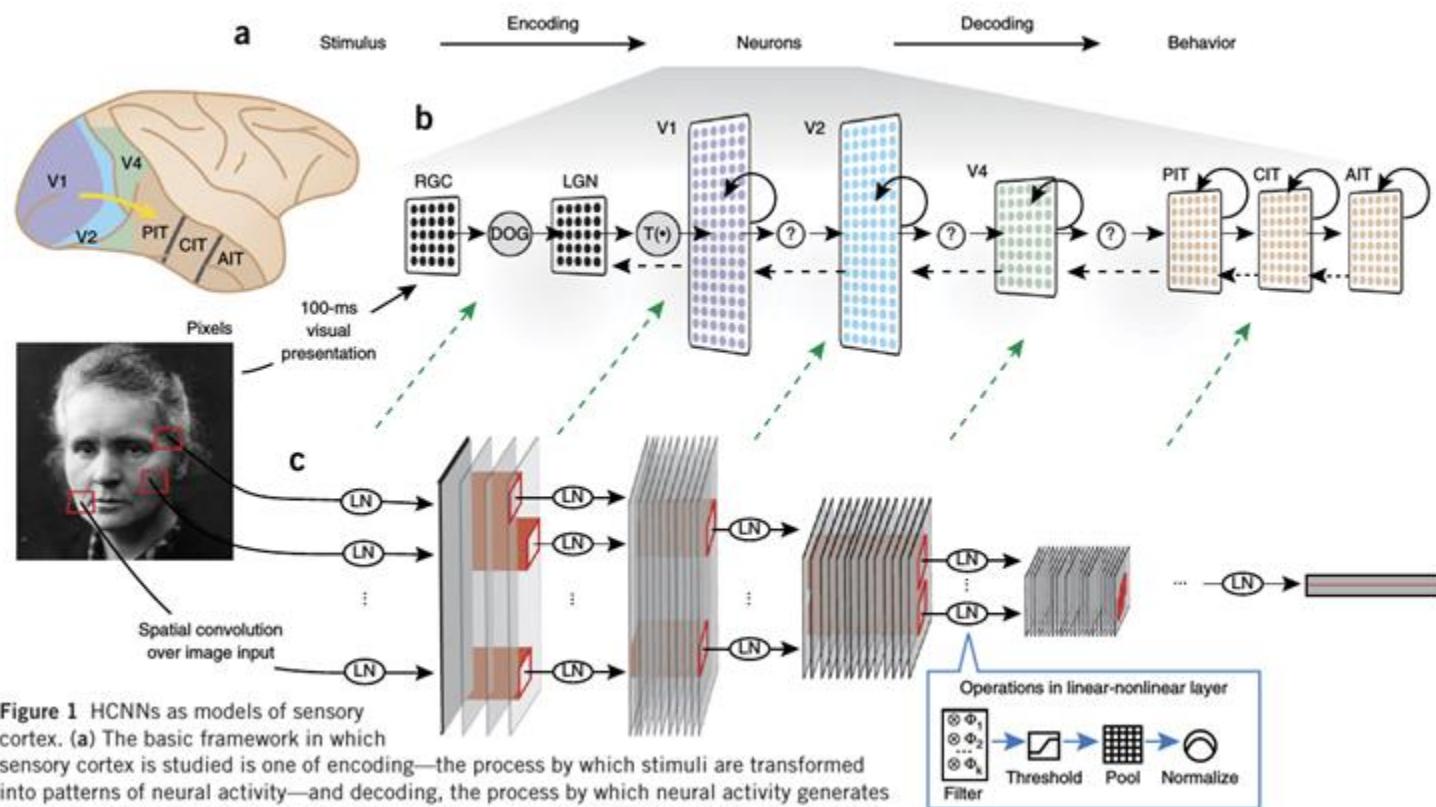


Figure 1 HCNNs as models of sensory cortex. (a) The basic framework in which sensory cortex is studied is one of encoding—the process by which stimuli are transformed into patterns of neural activity—and decoding, the process by which neural activity generates behavior. HCNNs have been used to make models of the encoding step; that is, they describe

Task information consistency

Single-unit response predictivity

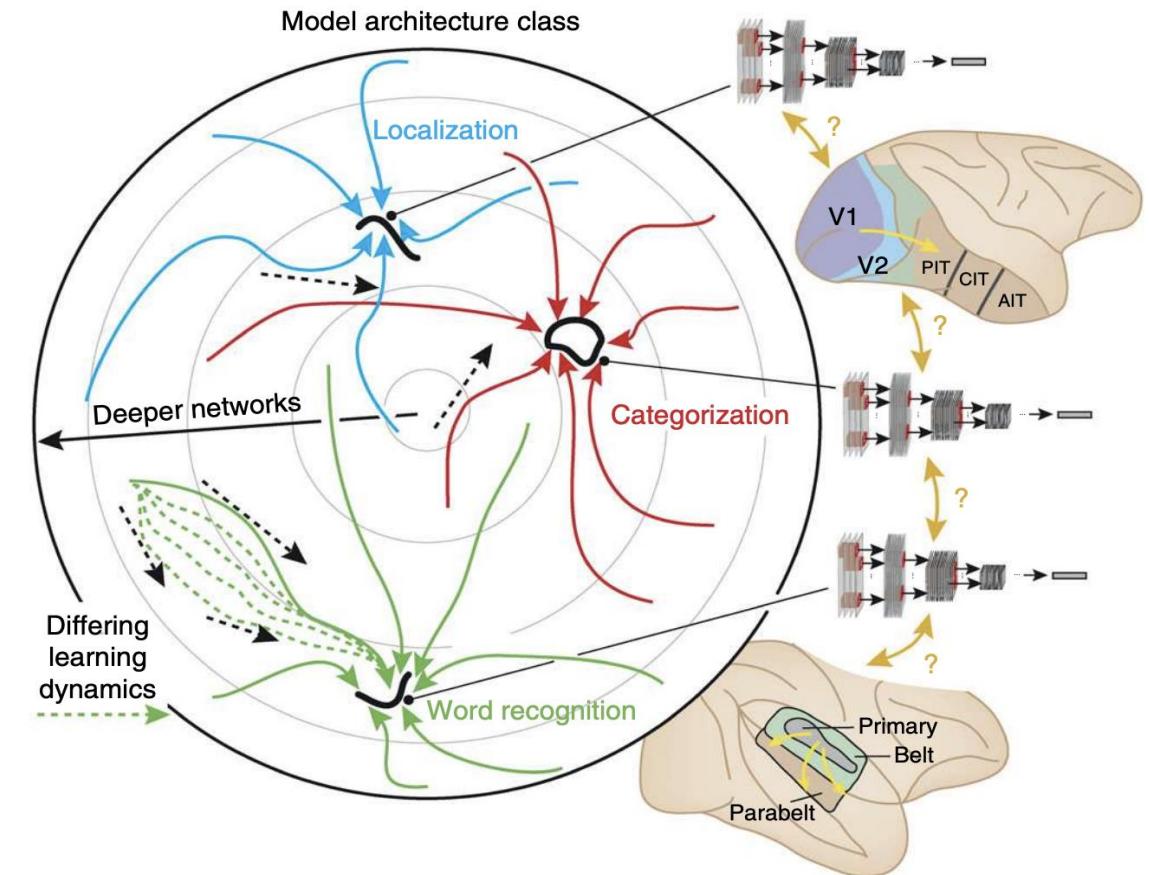
Population representational similarity

Yamins & DiCarlo Nature Neuroscience 2016

Building models of visual pathway: the ingredients

Task-driven deep neural network models are built from three basic components:

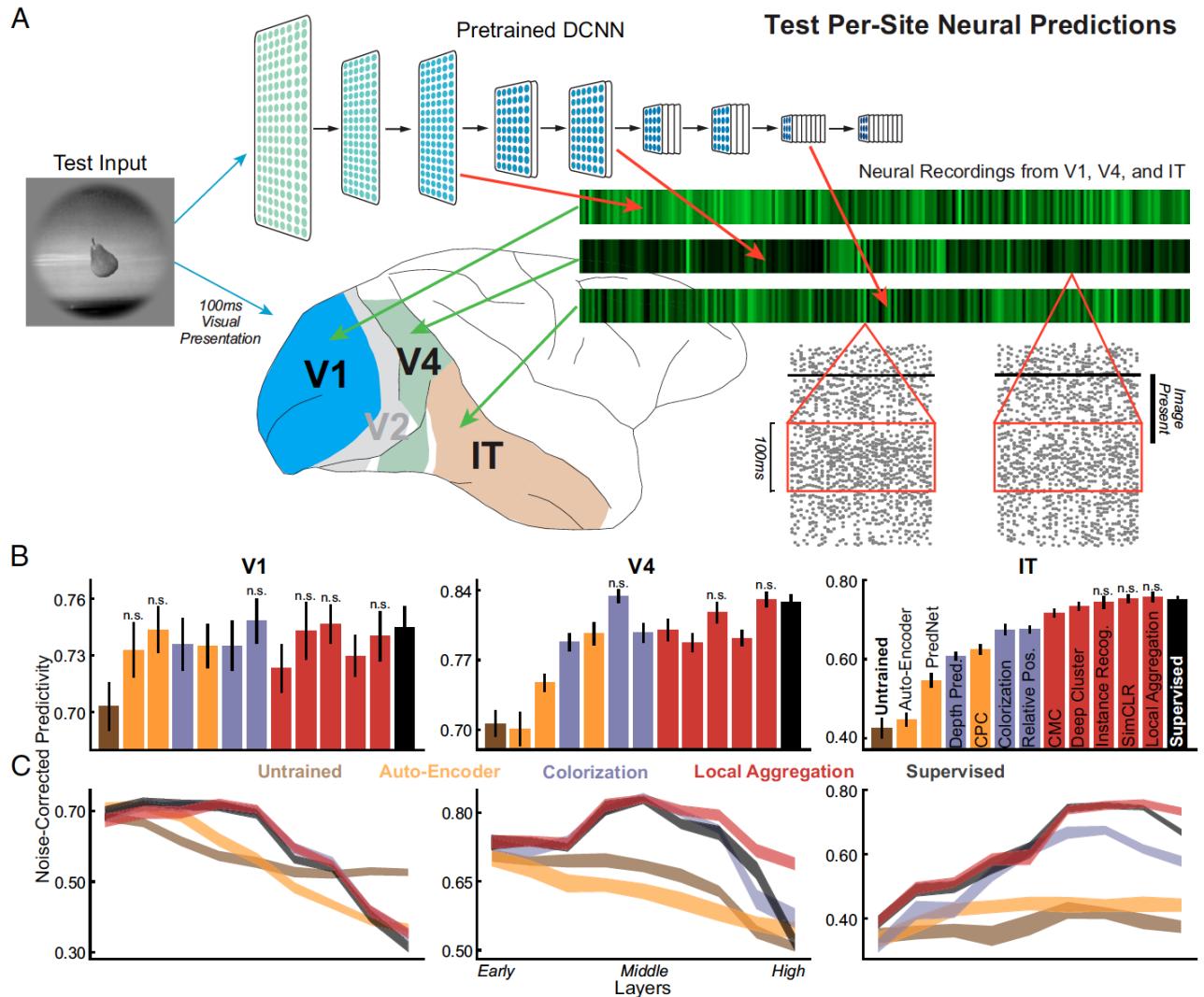
1. **model architecture class** from which the system is built, formalizing knowledge about the brain's anatomical and functional connectivity;
2. a **behavioral goal** that the system must accomplish, such as object categorization; and
3. a **learning rule** that optimizes parameters within the model class to achieve the behavioral goal.



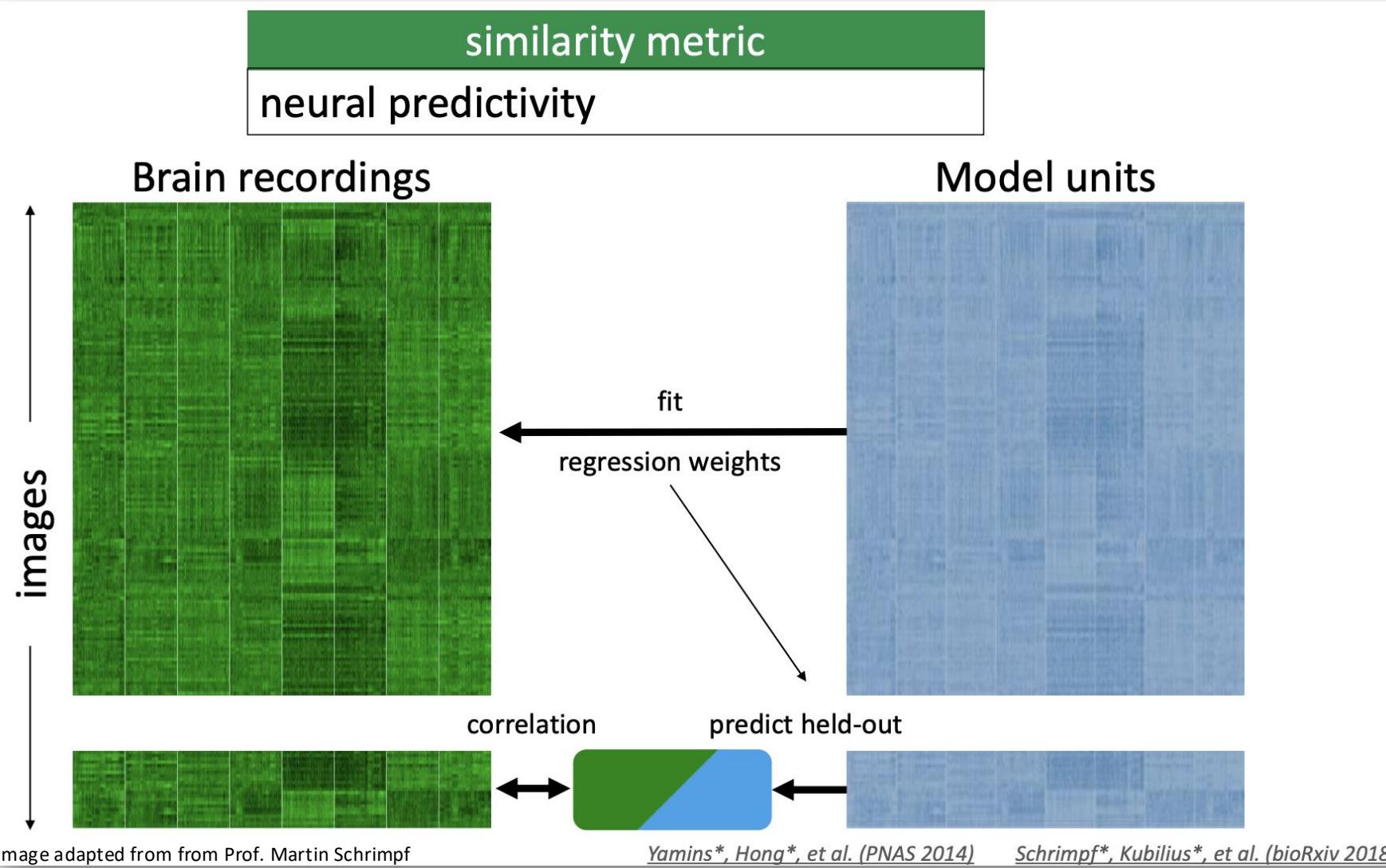
Yamins & DiCarlo (2016)

Learning, architecture search, and model comparison across visual areas

- Recordings from across the visual hierarchy
- Trained models outperform untrained models
- Supervised ImageNet models do very well, and so do unsupervised models...
- Early-Middle layers best predict V1, middle layer predict V4 and High layers best predict IT



Representational similarity analysis



- Representational Similarity Analysis (RSA) is a method to compare neural or model representations by **computing pairwise dissimilarities between activity patterns** (e.g., fMRI, neural data, or model activations) and comparing the resulting *representational dissimilarity matrices* (RDMs) across conditions

- Given n conditions with neural (or model) responses $\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_n \in \mathbb{R}^d$, RSA computes a Representational Dissimilarity Matrix (RDM) $D \in \mathbb{R}^{n \times n}$ where:

$$D_{ij} = 1 - \text{corr}(\mathbf{r}_i, \mathbf{r}_j)$$

Commonly, $\text{corr}(\cdot, \cdot)$ is Pearson or cosine correlation.

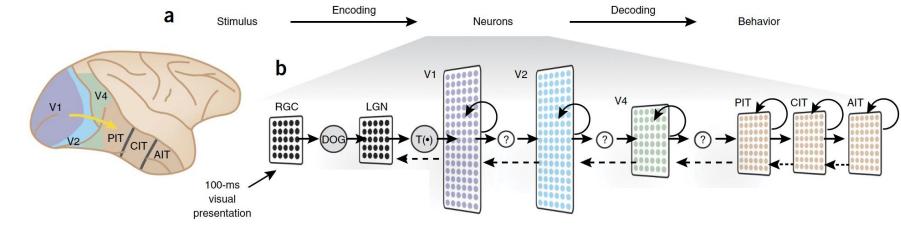
Intermediate Take Homes:

- NN models can be trained on different visual tasks to make hypotheses about the goal of the visual system
- Better NN models at the categorization task predicted IT neurons better
- Task mattered more than architecture or depth of networks
- Three points to consider when comparing:

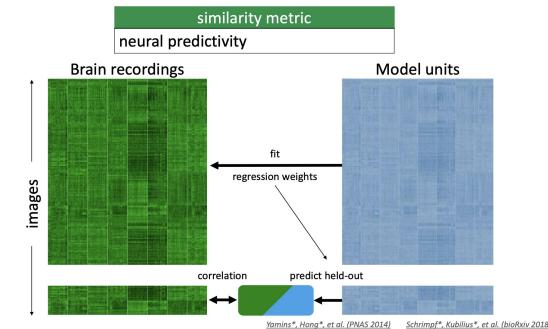
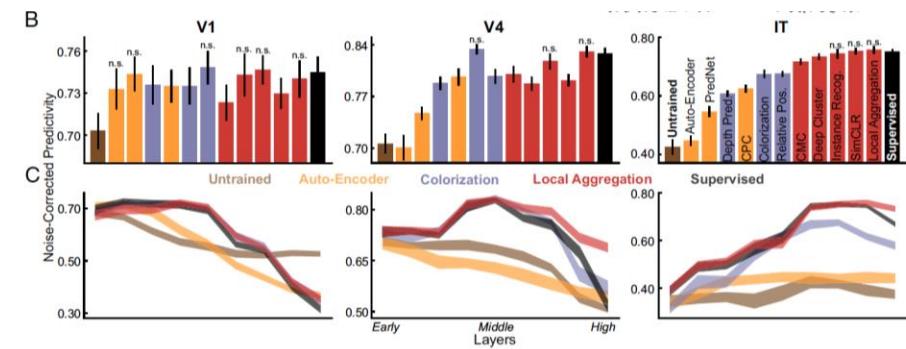
Task information consistency

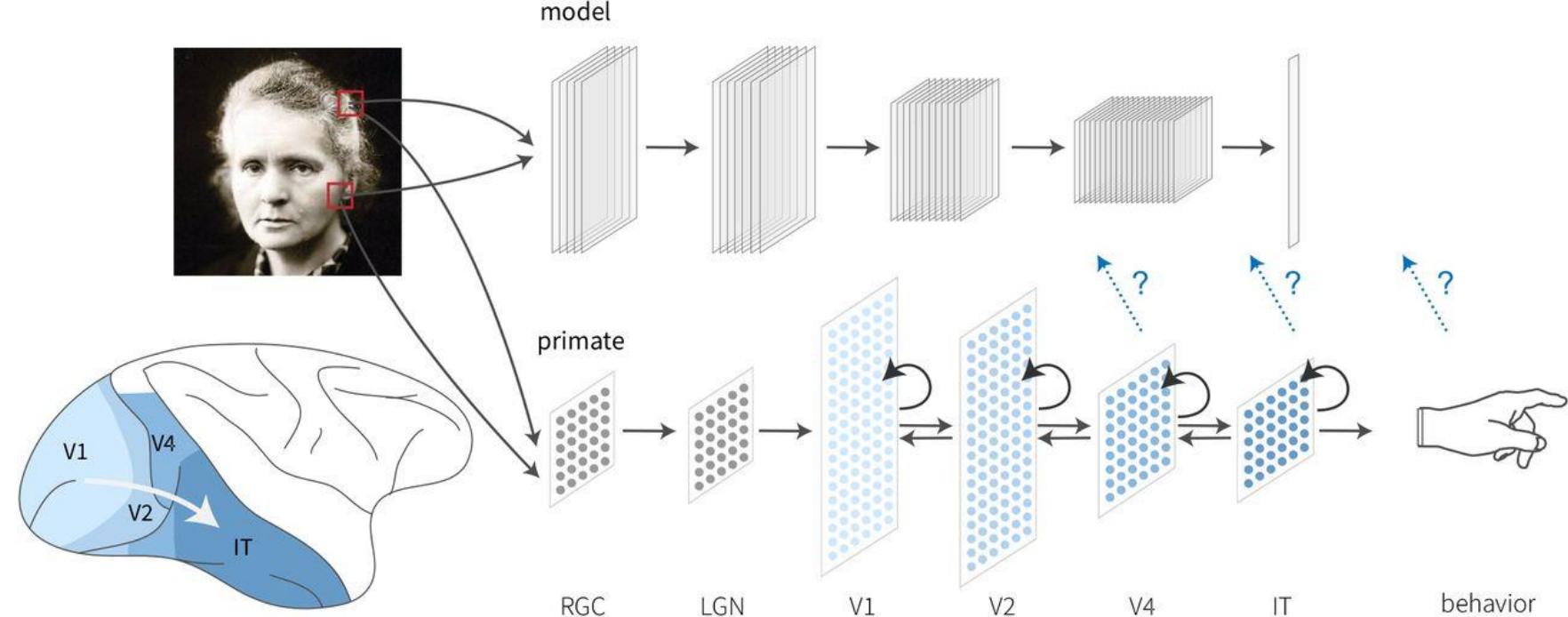
Single-unit response predictivity

Population representational similarity

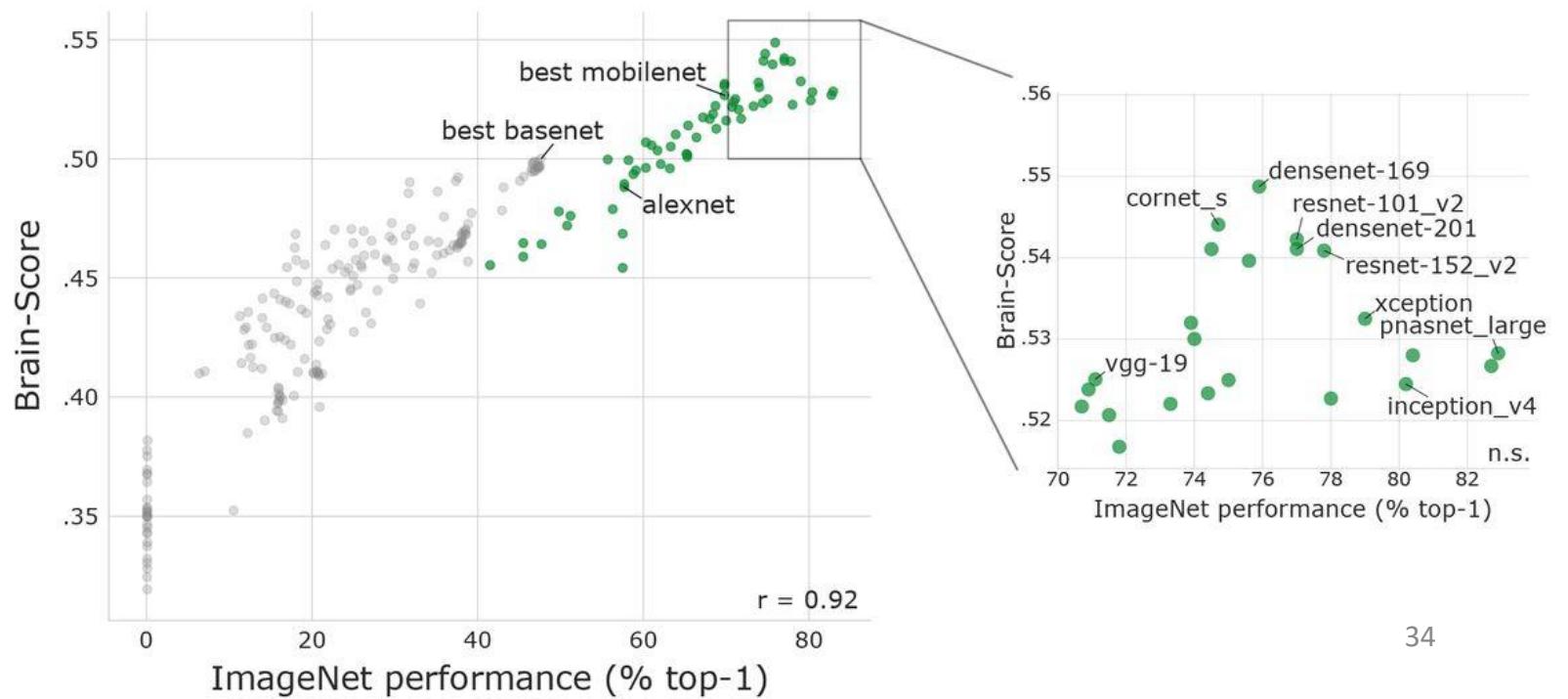


Yamins and Di Carlo, *Nat Neuro* 2016

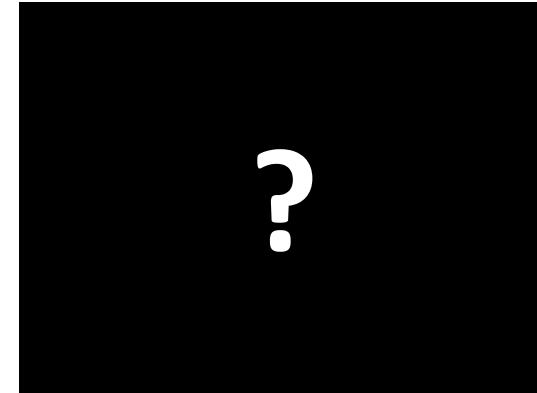
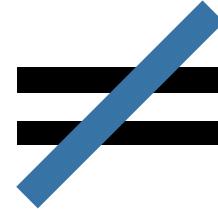
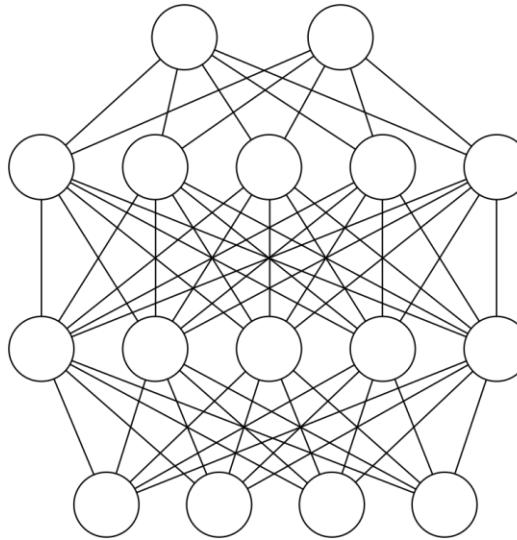




The hunt continues ...



Deep Neural networks are not entirely a black box!



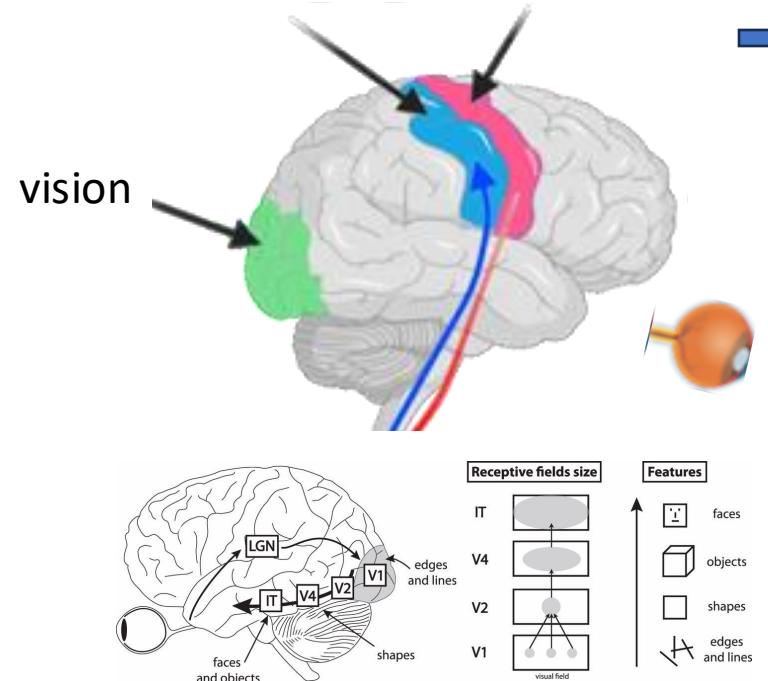
- can perform millions of *in silico* experiments
- derive experimentally testable predictions



Slide courtesy of Prof. Andreas Tolias

What other tasks? What other stimuli is the brain (visual) encoding?

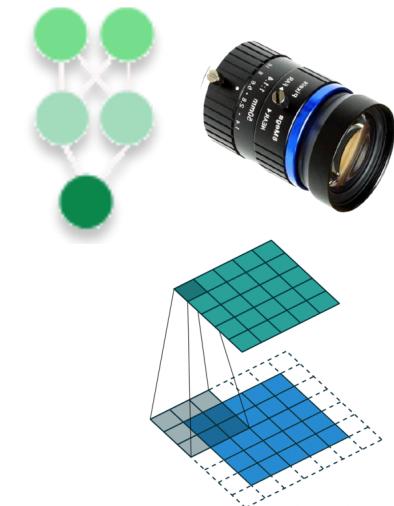
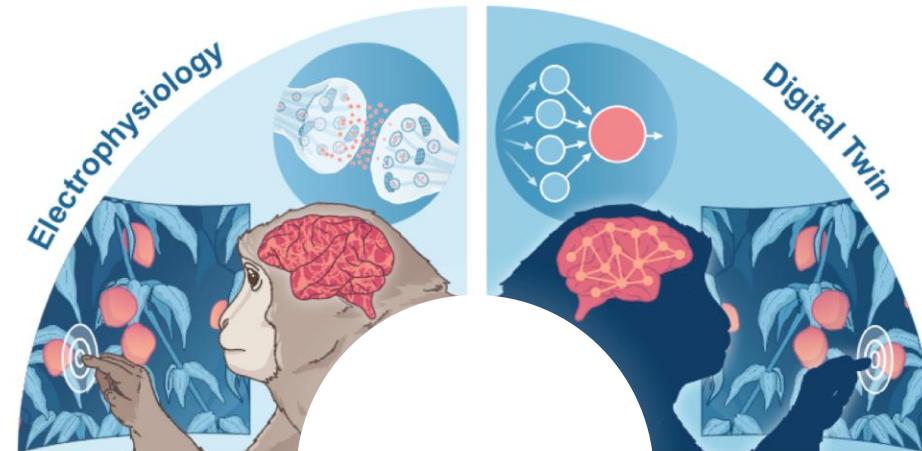
Biological: recordings in visual system



Hubel & Wiesel discoveries in cat V1
inspired convolutional neural networks

We now know a lot more (faces, motion, value coding) but we never can give enough stimuli
What would the ideal stimulus be for a given neuron?

Building “digital twins”, NN models of the system



Can we use our NN to produce predictions of optimal stimuli?

Can this help reveal anew computational principle, or validate a discovered rule?

Paper reading: developing deep predictive models for causal testing!

nature neuroscience

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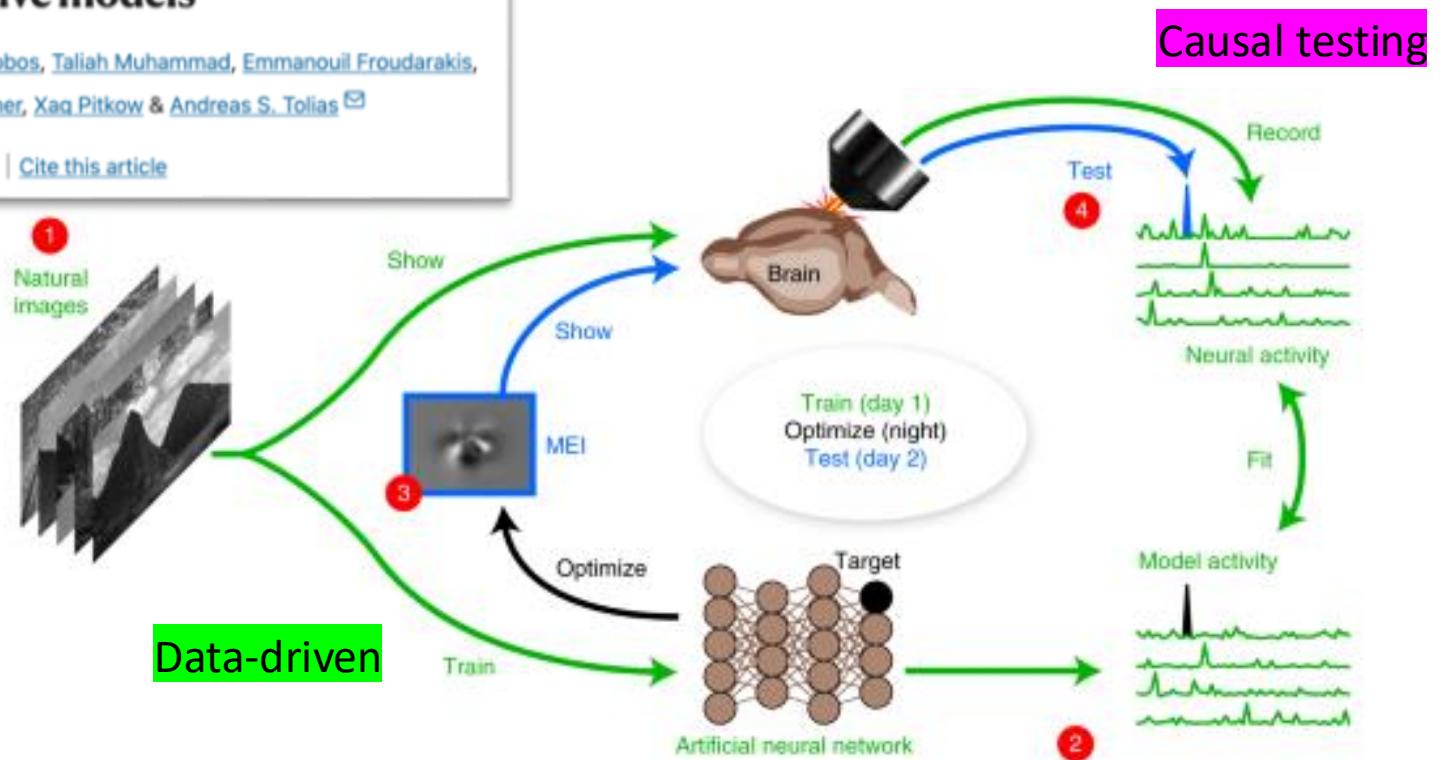
nature > nature neuroscience > articles > article

Article | Published: 04 November 2019

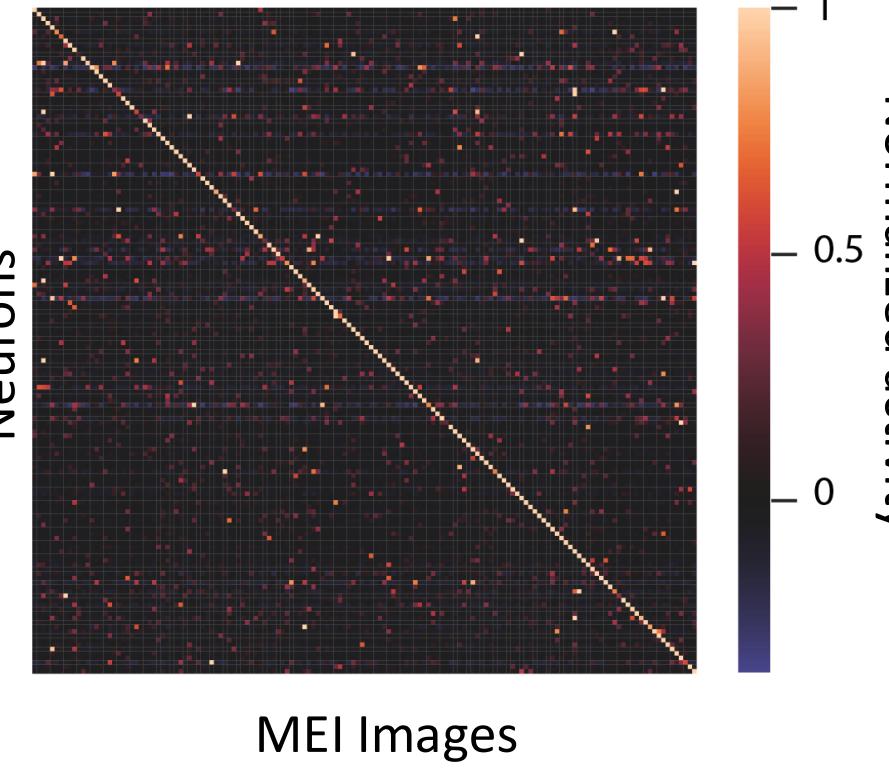
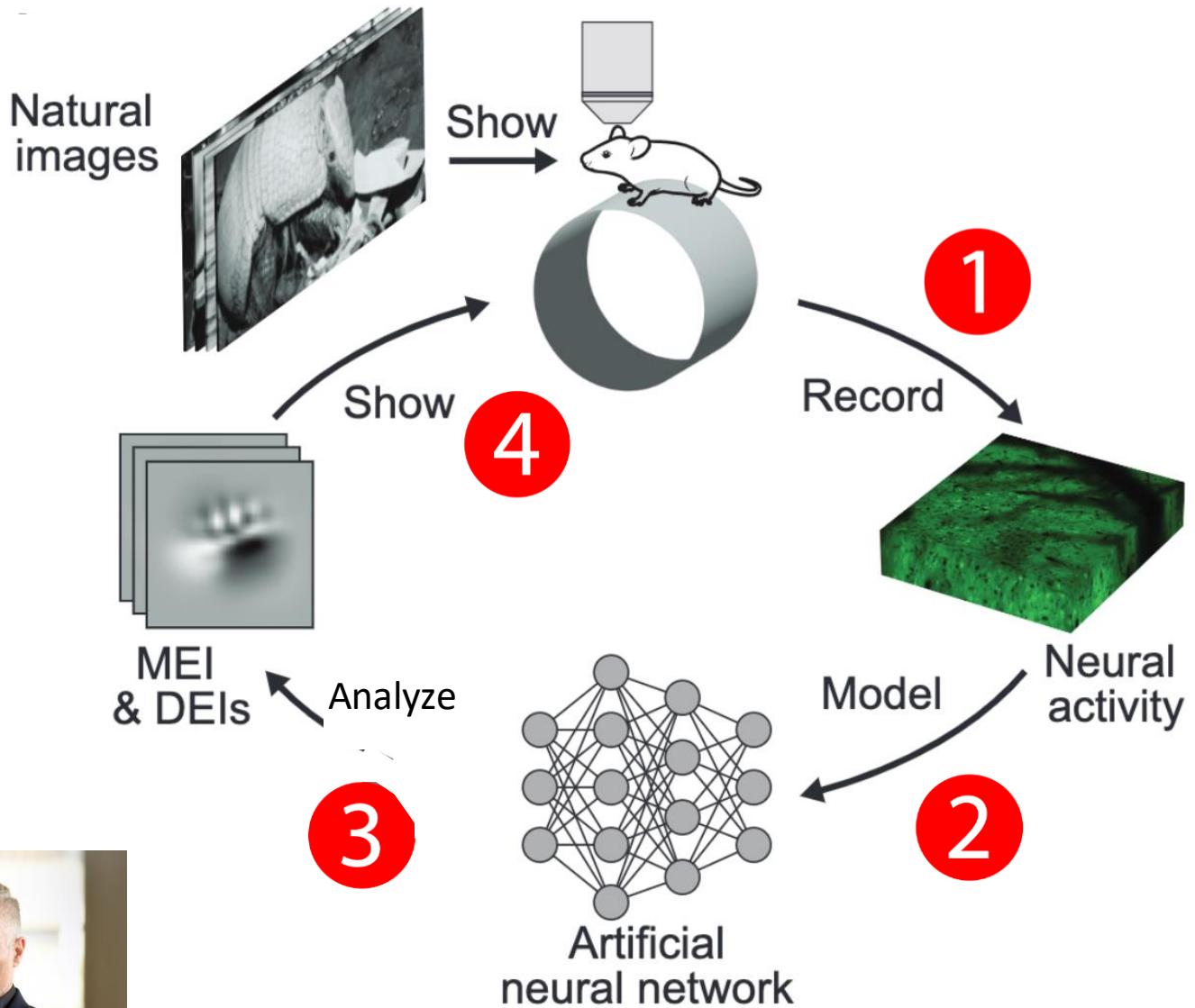
Inception loops discover what excites neurons most using deep predictive models

Edgar Y. Walker , Fabian H. Sinz , Erick Cobos, Taliah Muhammad, Emmanouil Froudarakis, Paul G. Fahey, Alexander S. Ecker, Jacob Reimer, Xaq Pitkow & Andreas S. Tolias 

Nature Neuroscience 22, 2060–2065 (2019) | Cite this article



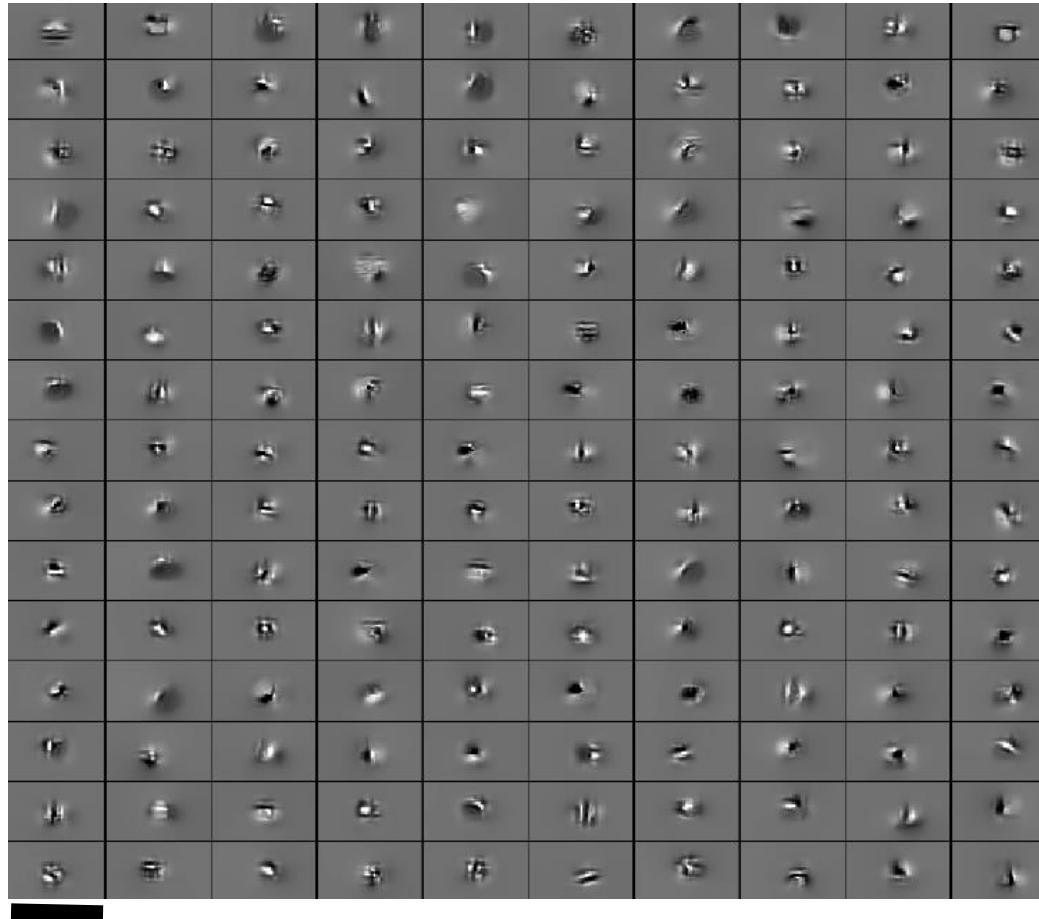
In vivo verification



Slide courtesy of Prof. Andreas Tolias

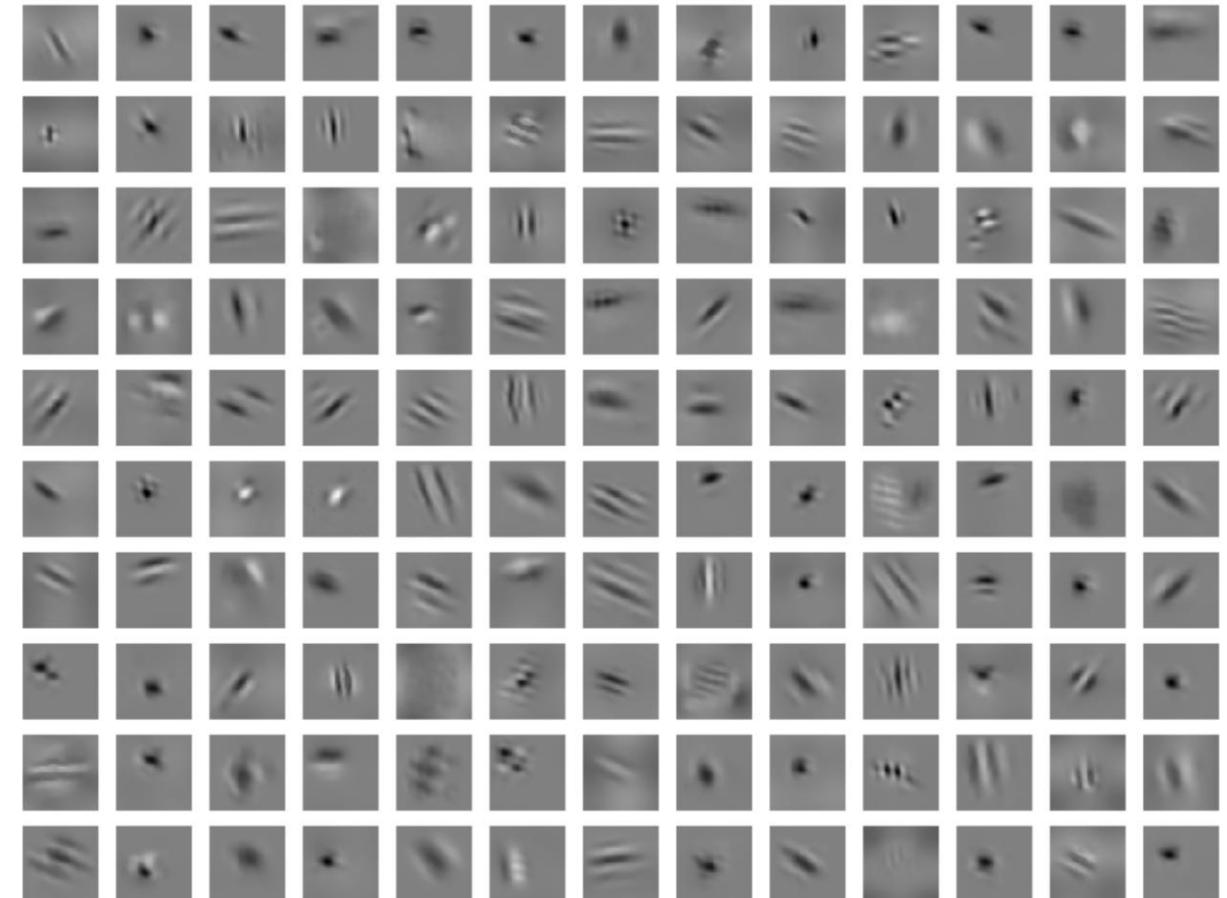
What about MEIs in macaque V1?

Mouse primary visual cortex



30 deg

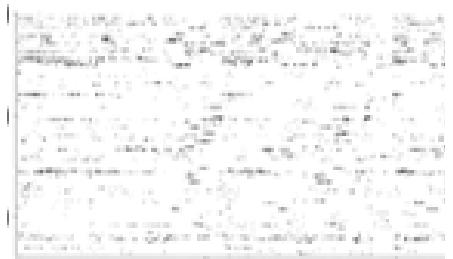
Macaque primary visual cortex



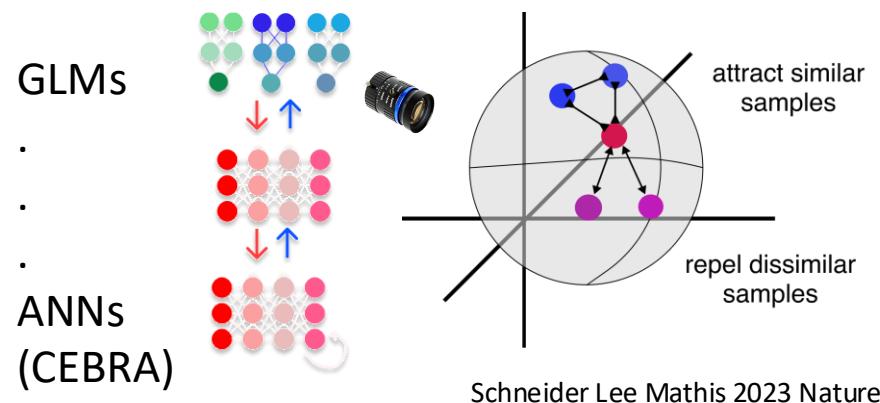
2 deg

Data-driven modeling

GLMs, PCA, Sussillo et al. 2015 Nat Neuro
State-space models, ...



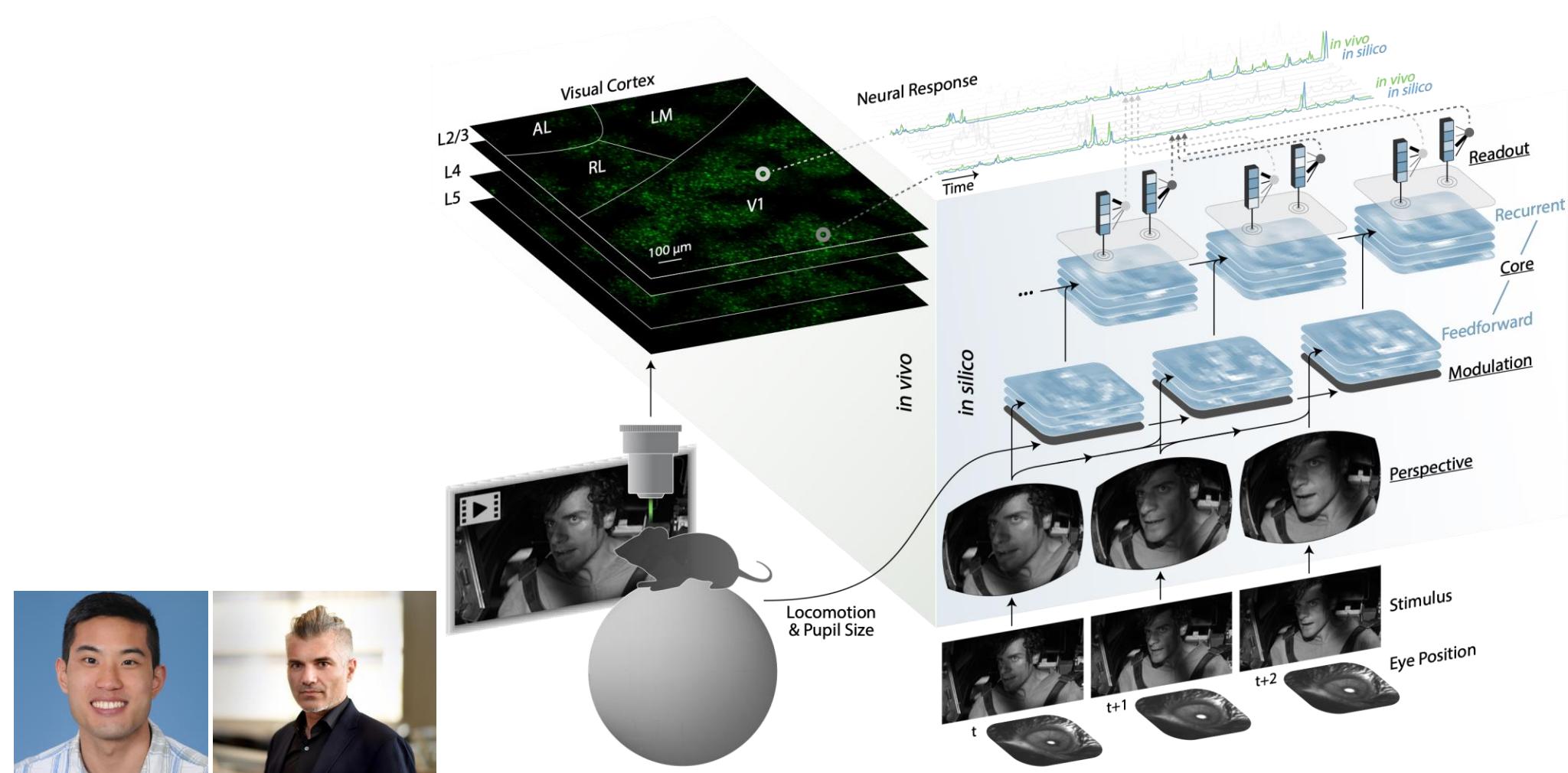
Record from neural data
during a behavioral task



Schneider Lee Mathis 2023 Nature

Joint models that describe
neural variance & representations

Generalization to new neurons, mice, stimulus domains and morphological cell types

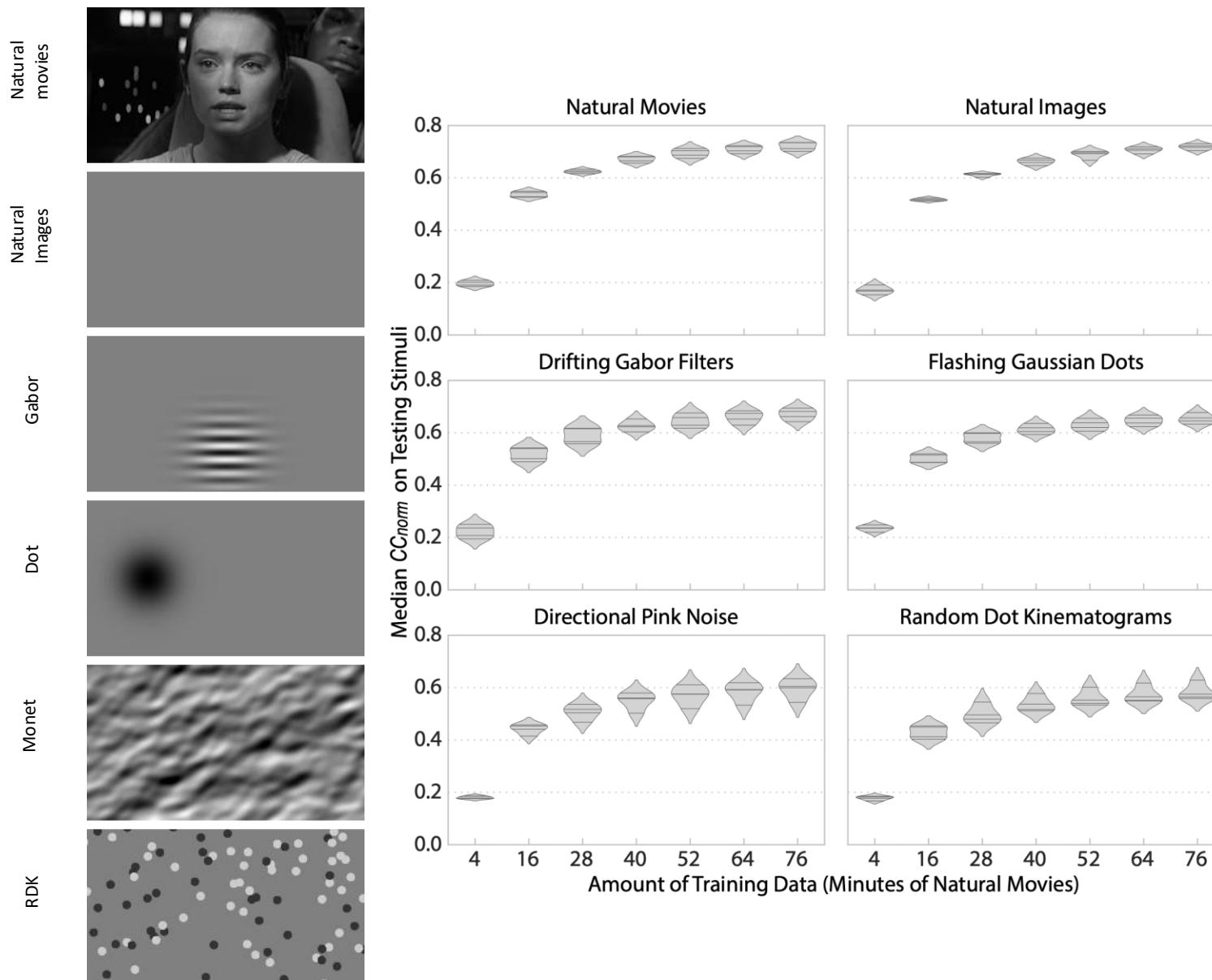


Eric Wang

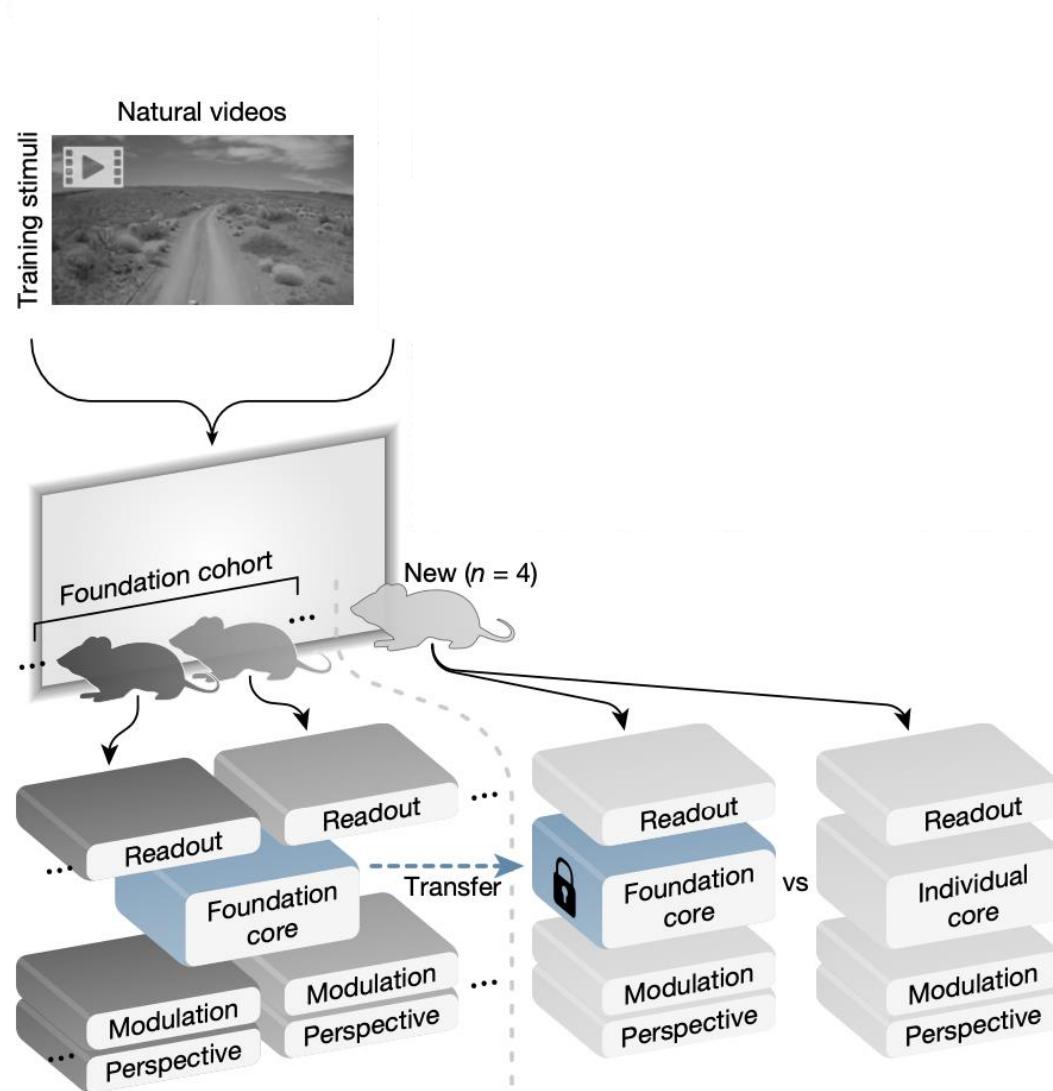
Slide courtesy of Prof. Andreas Tolias

41
Wang et al., Nature 2025

Generalization to out-of-distribution stimuli



Generalization to new neurons and mice

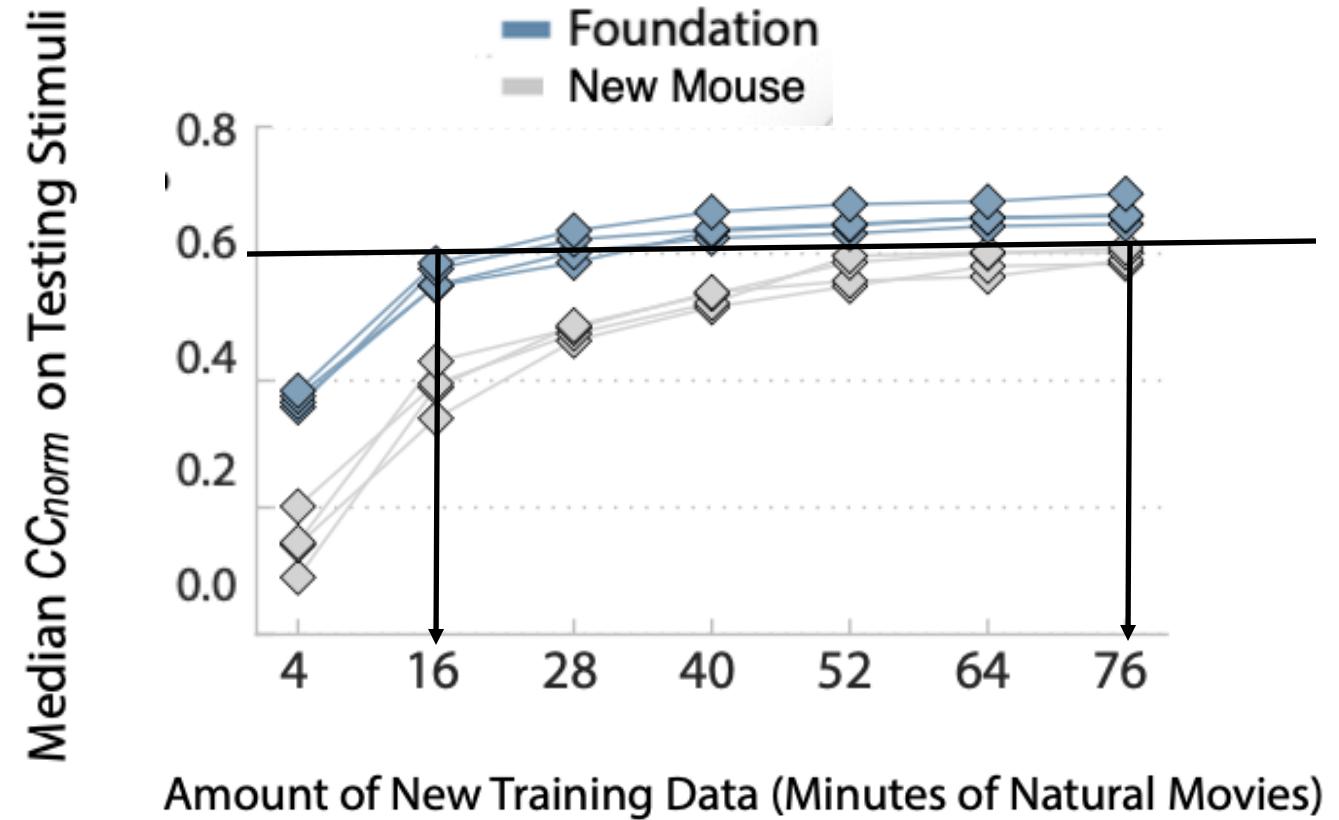
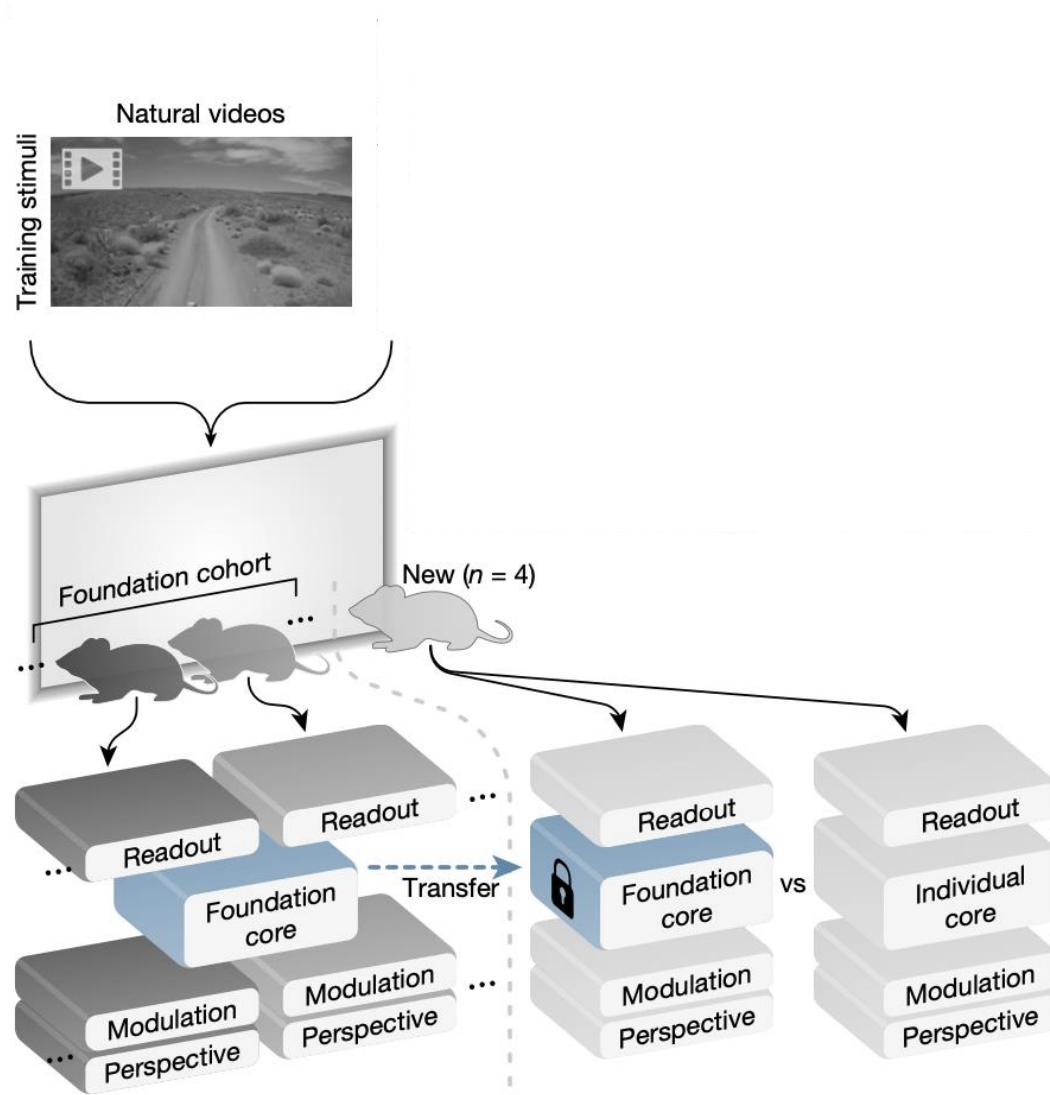


Wang et al., Nature 2025

43

Lurz et al., ICLR 2021 (with Sinz lab)

Generalization to new neurons and mice



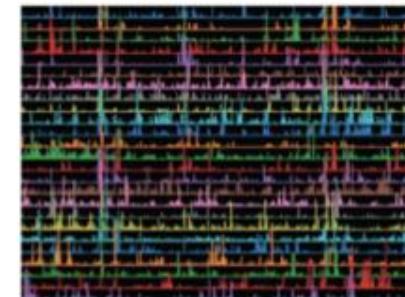
A functional connectome containing 200,000 cells, 75,000 neurons with physiology, and 523 million synapses.

This resource provides interactive visualizations of anatomical and functional data that span all 6 layers of mouse primary visual cortex and 3 higher visual areas (LM, AL, RL) within a cubic millimeter volume.

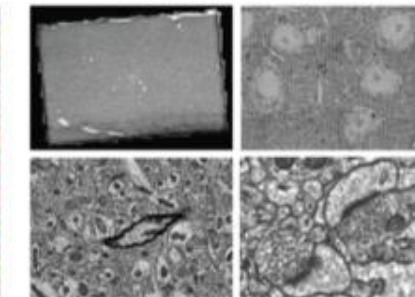
EXPLORE

Data Types

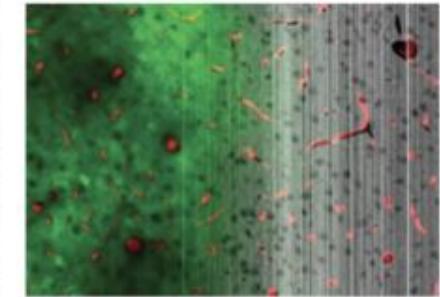
Available as a resource



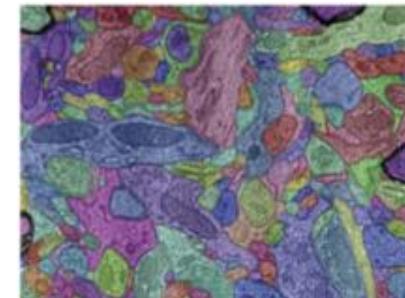
FUNCTIONAL DATA



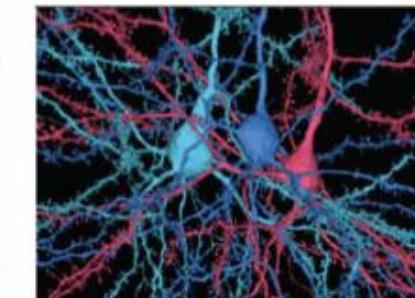
ELECTRON MICROSCOPY
IMAGERY



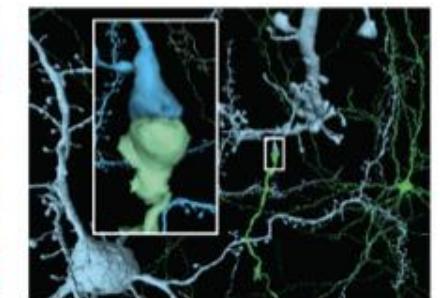
FUNCTIONAL -STRUCTURAL
CO-REGISTRATION



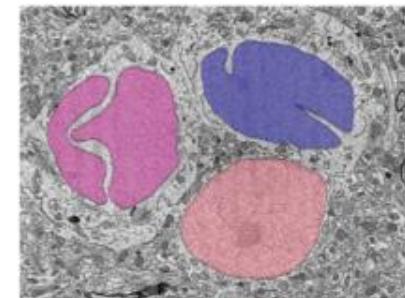
CELL SEGMENTATION



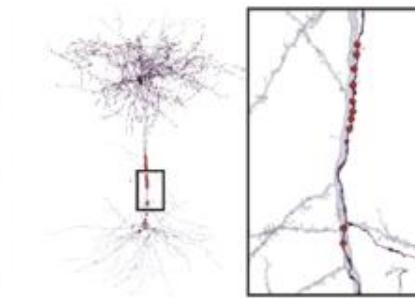
CELL MESHES



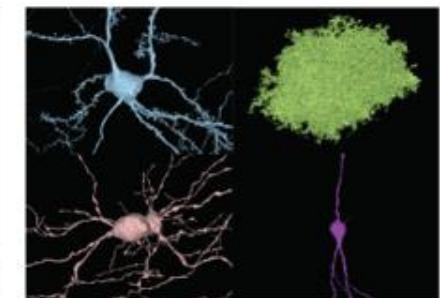
SYNAPSE CONNECTIVITY



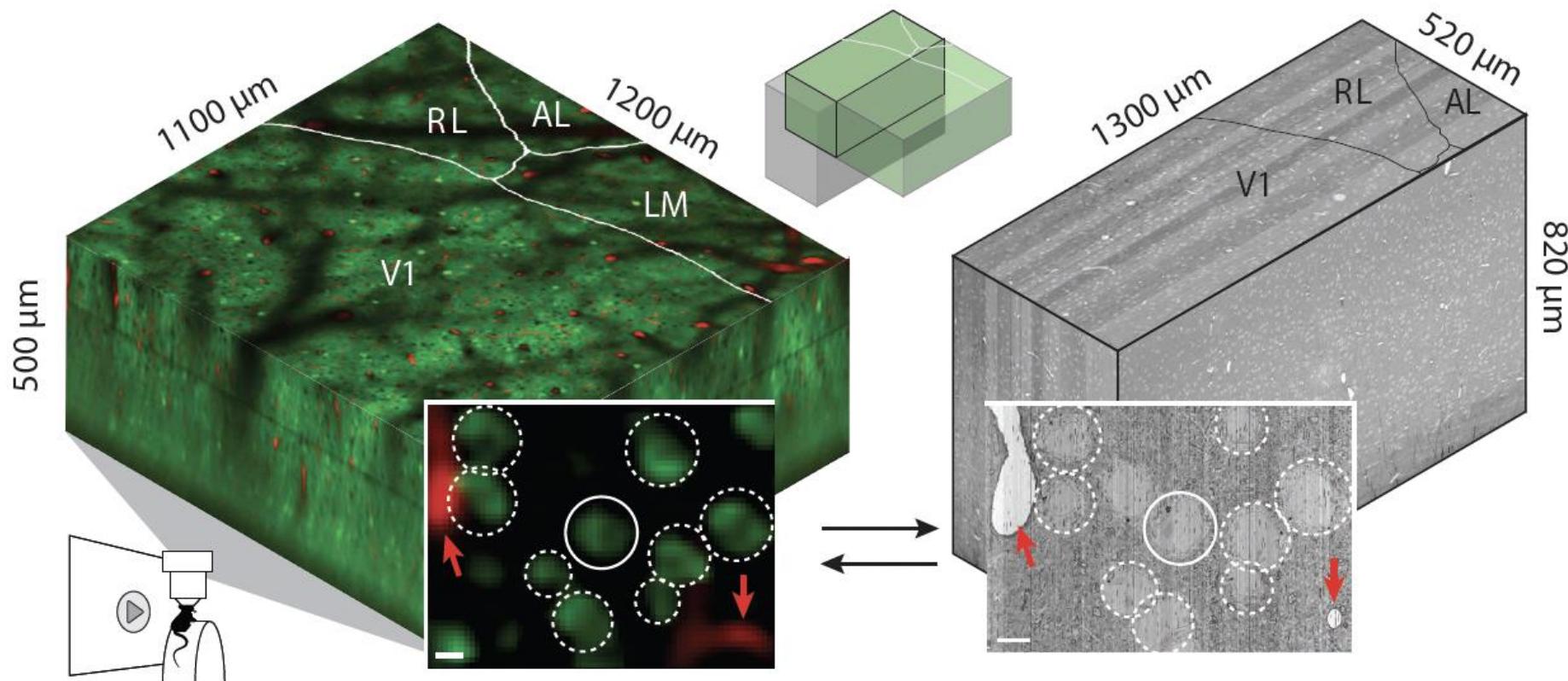
NUCLEUS
SEGMENTATION



PROOFREADING
STATUS



CELL TYPES



- mesoscopic 2-photon calcium imaging



Zhuokun
Ding



Paul
Fahey



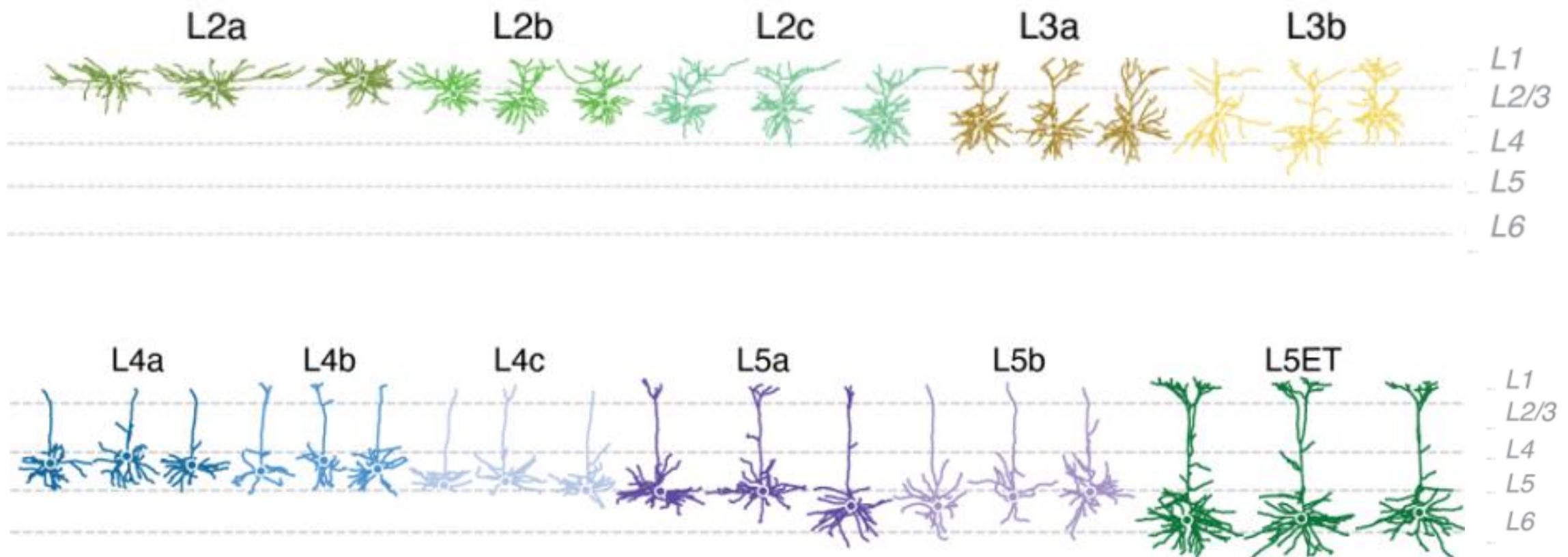
Stelios
Papadopoulos



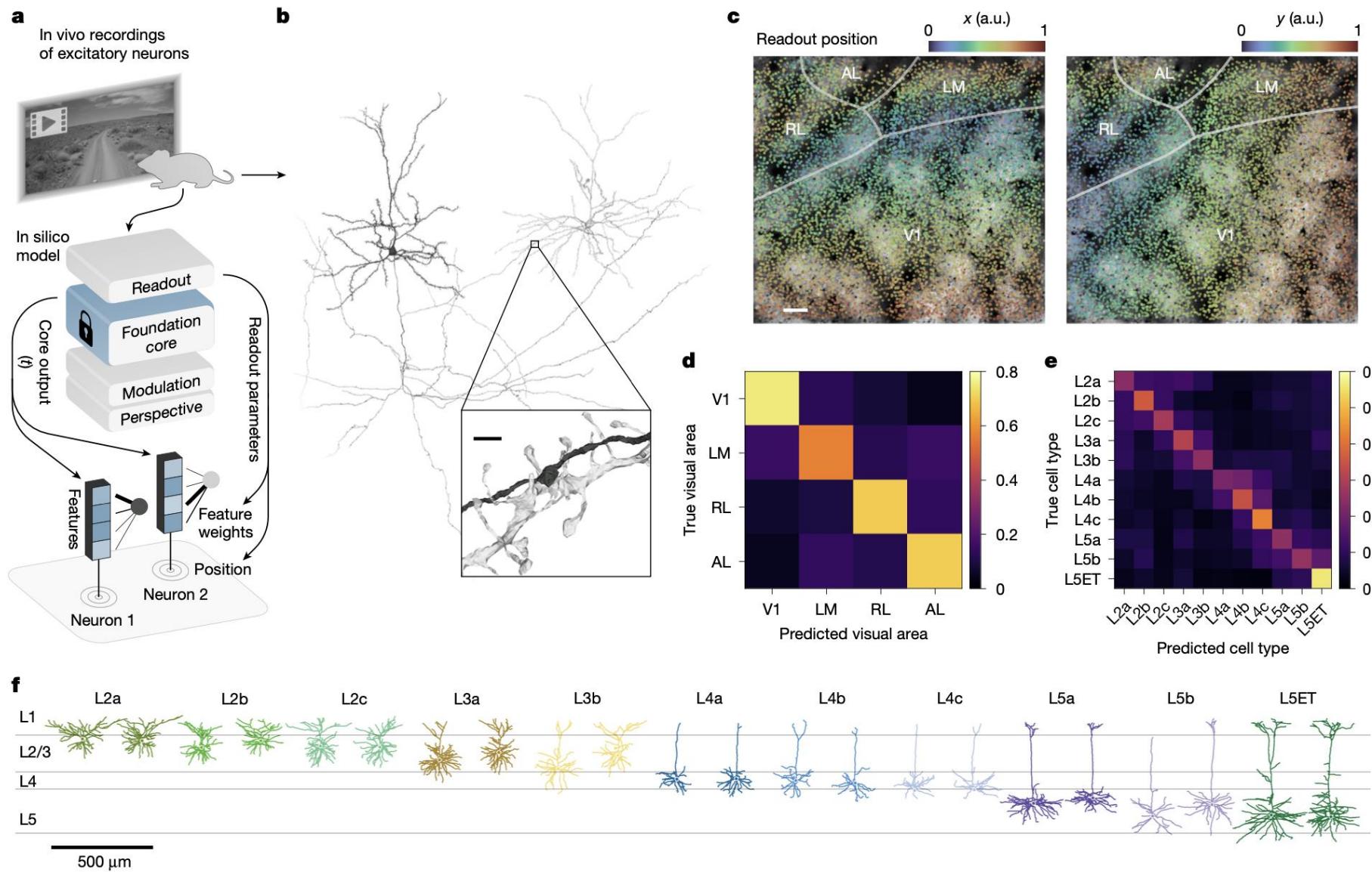
Ding, Fahey, Papadopoulos et al., Nature 2025

- large scale high resolution
electron microscopy

Predict morphological cell types in MiCrONS data



Predict morphological cell types in MiCrONS data



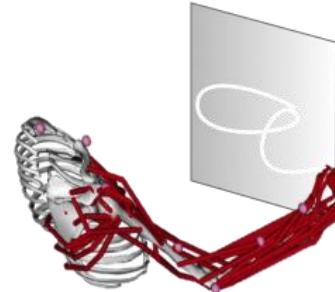
- They could recover the retinotopic map! (c)
- **AREA PREDICTION:** readout weights could predict visual areas with a balanced accuracy of 68%, exceeding the chance level of 25% (d)
- **CELL TYPE:** Using logistic regression they achieved a balanced accuracy of 32% for cell-type prediction, outperforming the chance baseline of 9% (e)

how task-driven models can inform us about the computational goals of the brain

(which can lead to validations and/or new ideas for AI)

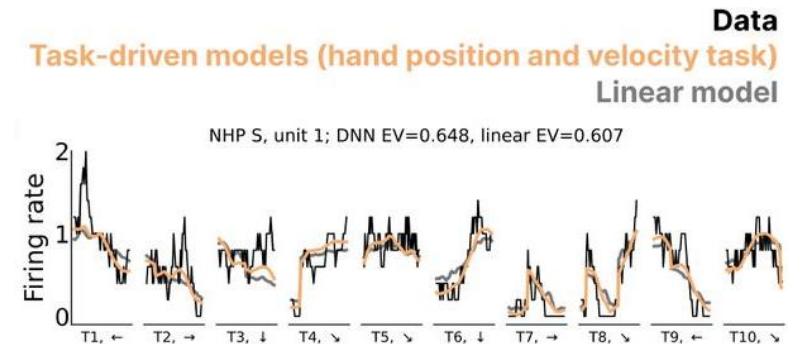
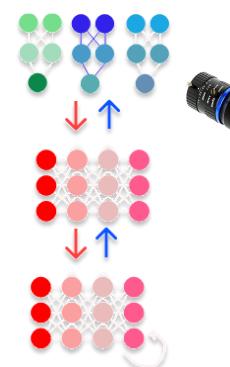
Task-driven modelling

Yamins et al. PNAS 2014, Sussillo et al. 2015 Nat Neuro, Kell et al. 2018 Neuron, Banino et al. 2018 Nature



Constrain ANN based on behavioral task to test hypotheses about a system

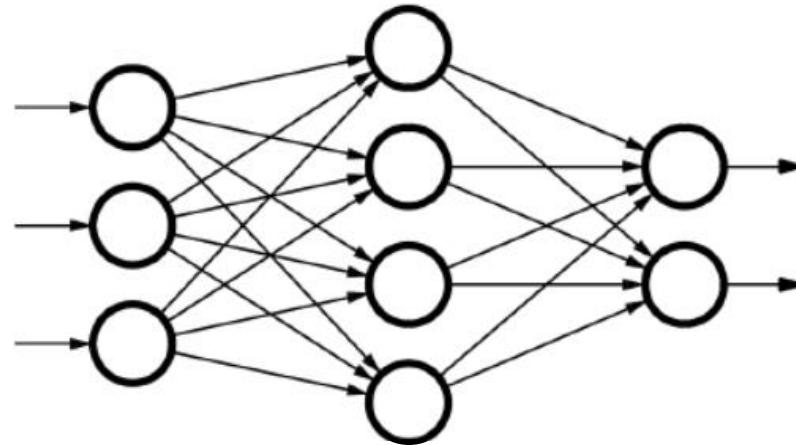
Sandbrink et al. 2023 eLife



Marin Vargas et al. 2024 Cell

NN models that describe neural variance & computationally constrain system

Using deep neural networks as task-driven models of a system



Vision: Yamins et al. (2014) .. Wang et al. (2025)



Audition: Kell et al. (2018)- speech recognition, speaker identification, natural sound identification



Barrel Cortex: Zhuang et al. (2017)



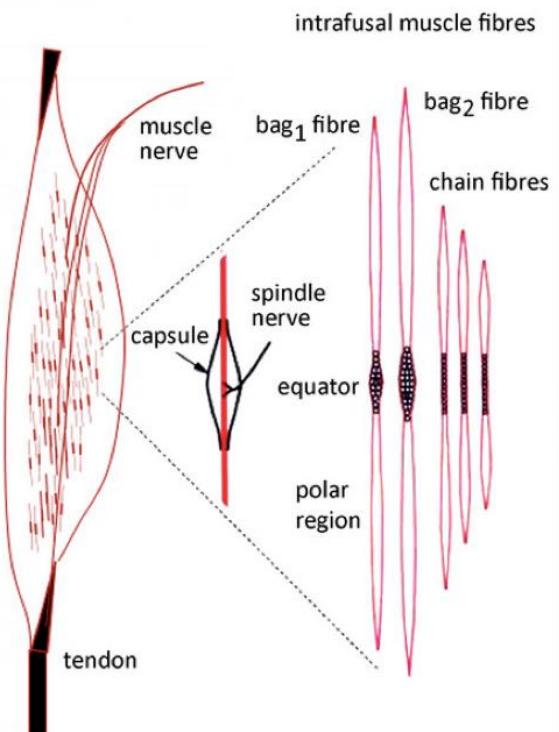
Cognition: Mante et al. (2013)



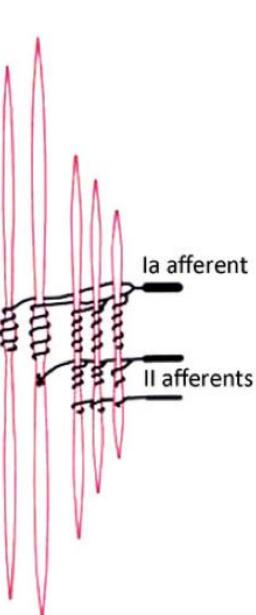
Proprioception: Sandbrink et al. (2023), Marin Vargas*, Bisi* et al. (2024)

Proprioception (the sense of posture)

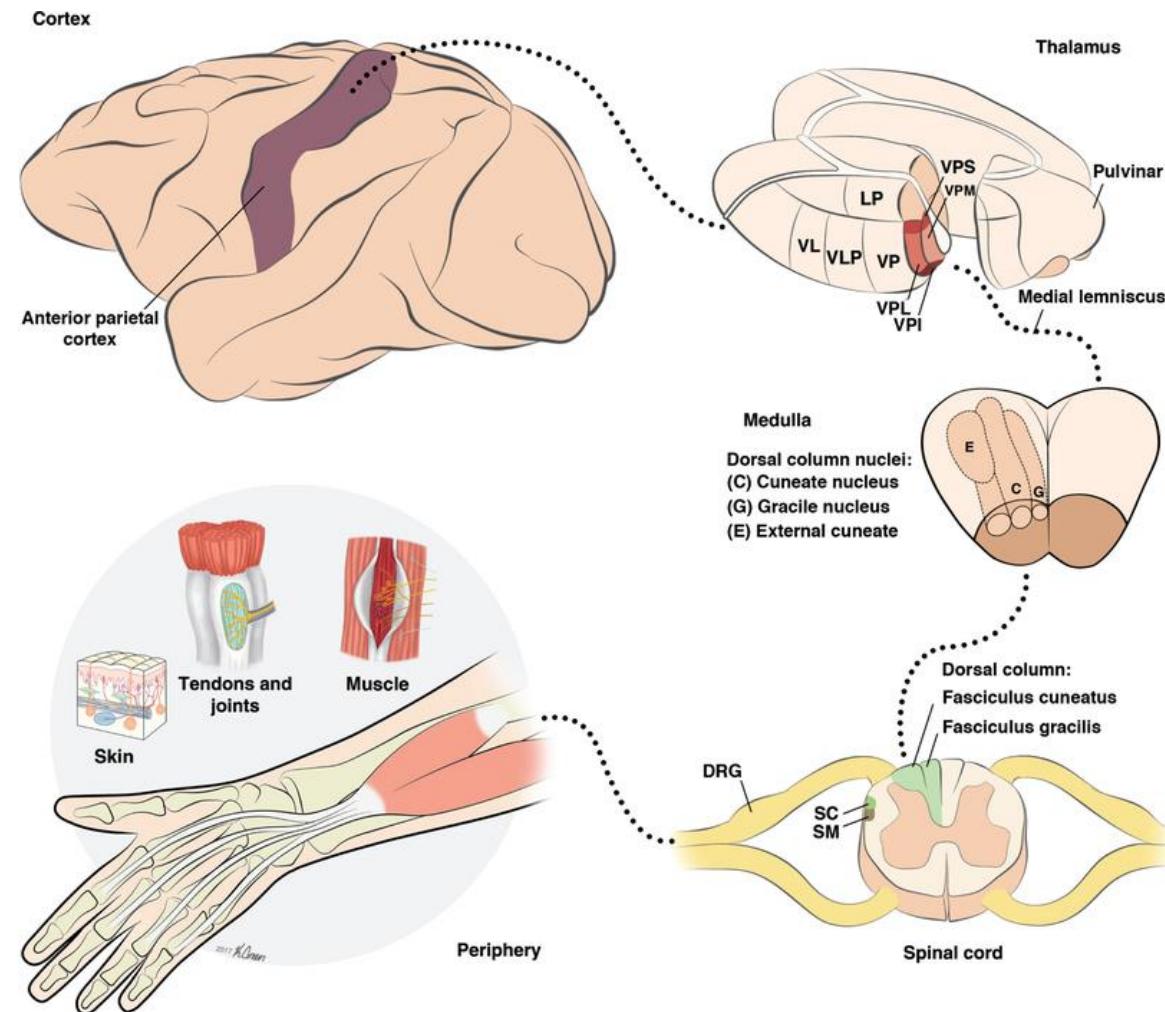
Muscle spindle



sensory innervation

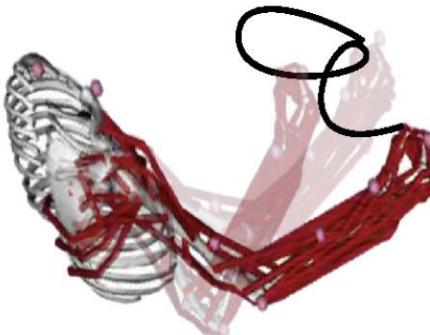


Banks 2020

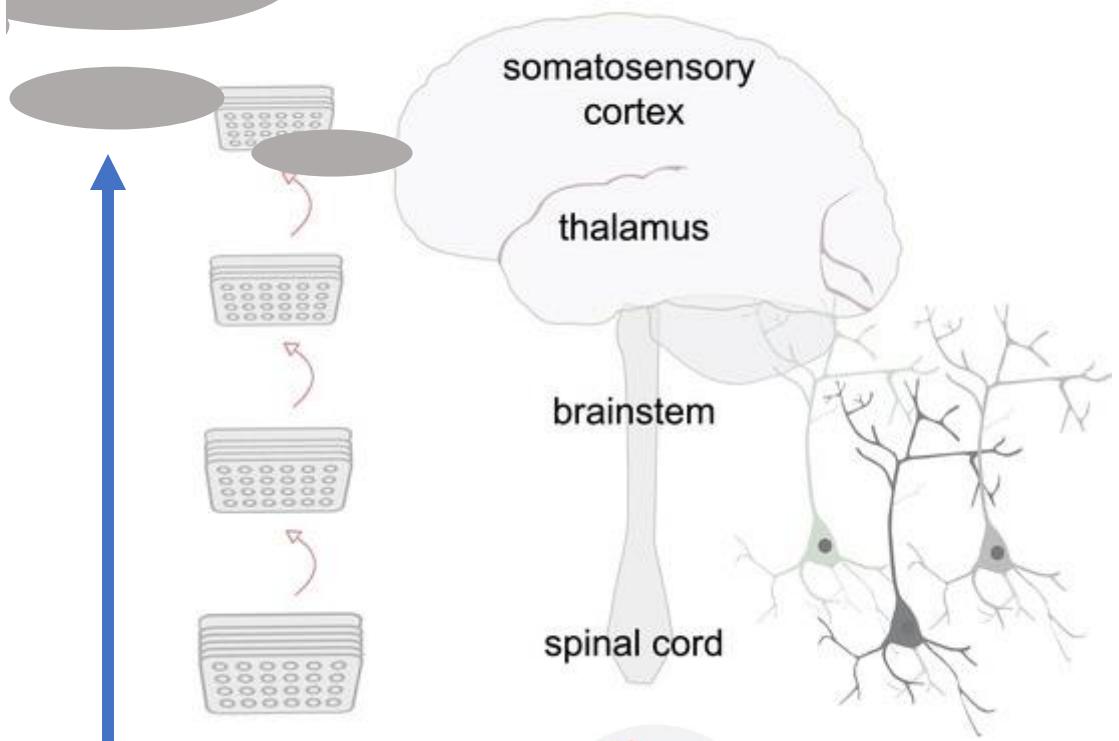
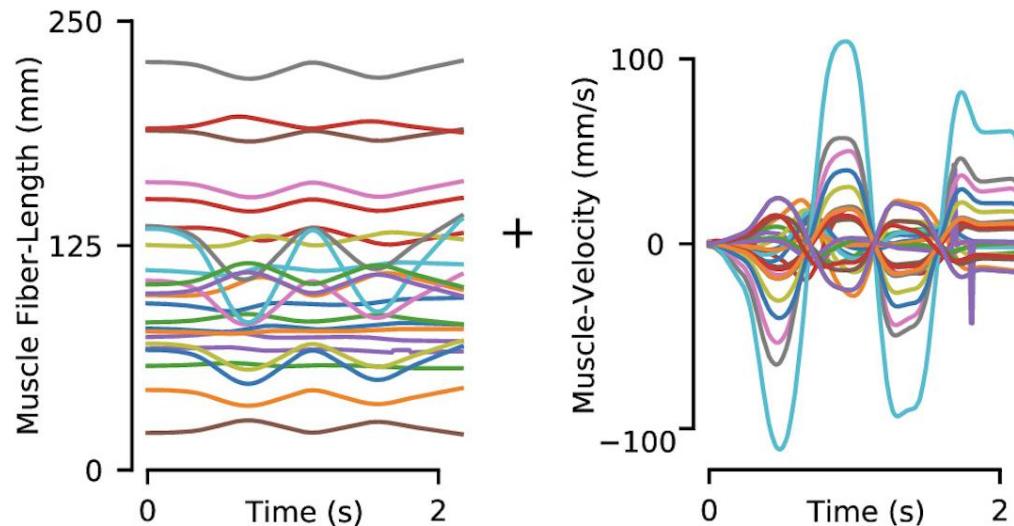


Delhaye et al., 2018

What's the trajectory of my limbs?



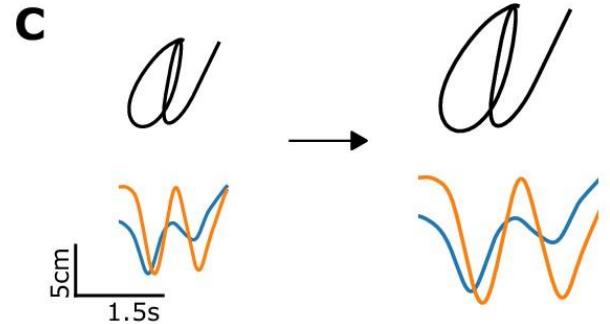
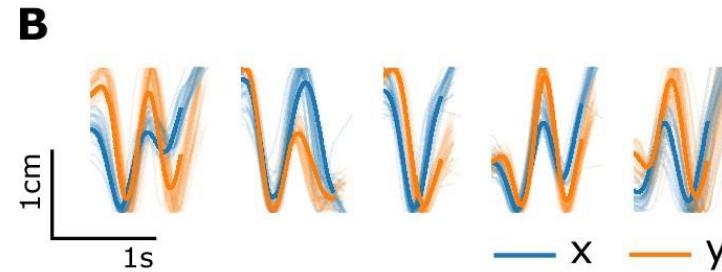
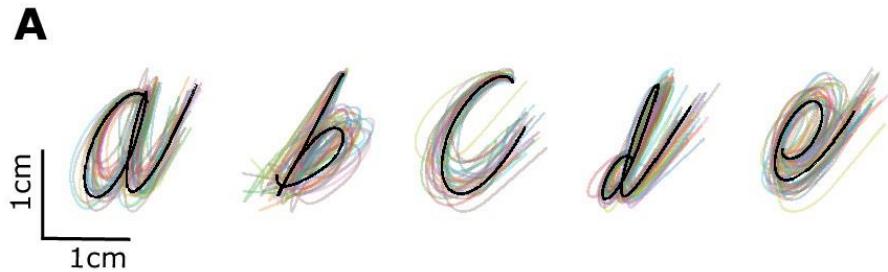
**What is the integrative logic
of proprioception?**



Sandbrink et al. 2023

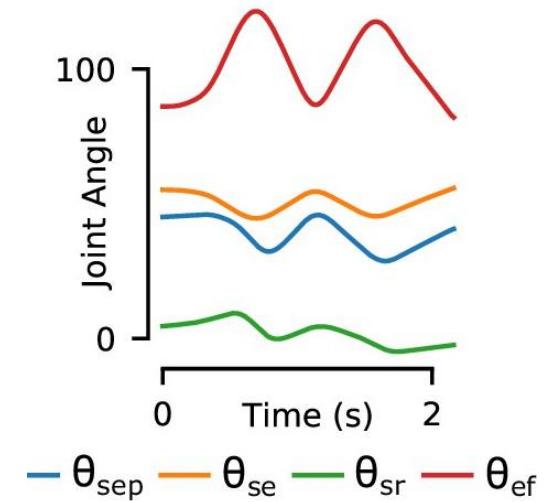
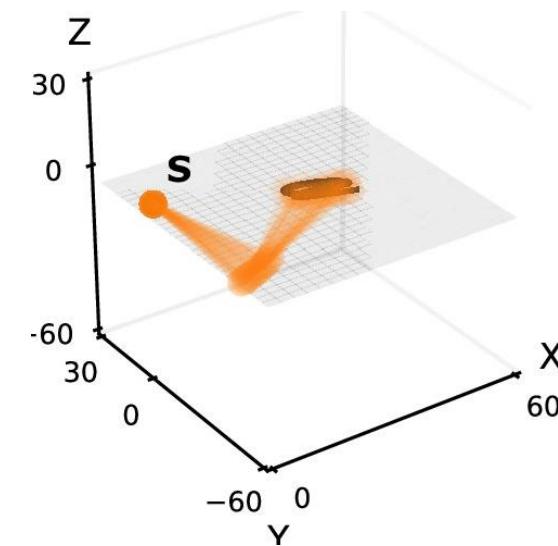
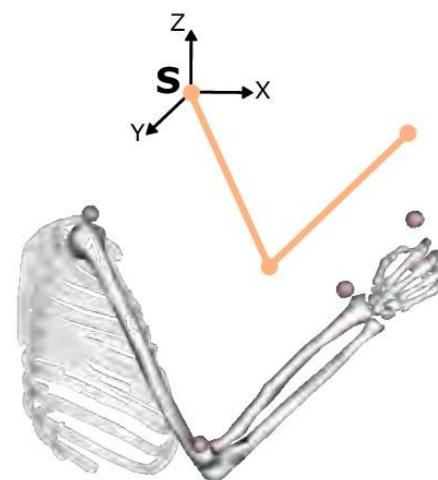
Delhaye et al., 2018

Task development: arm movements in 3D space

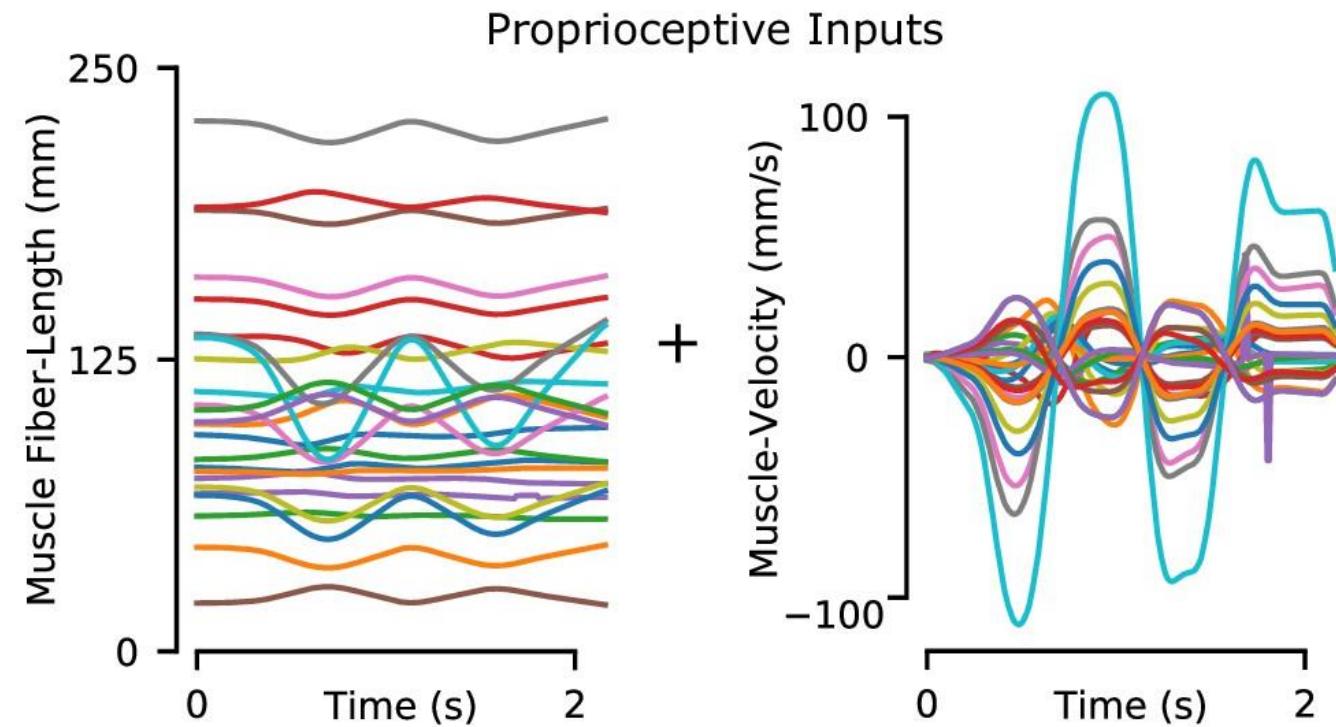
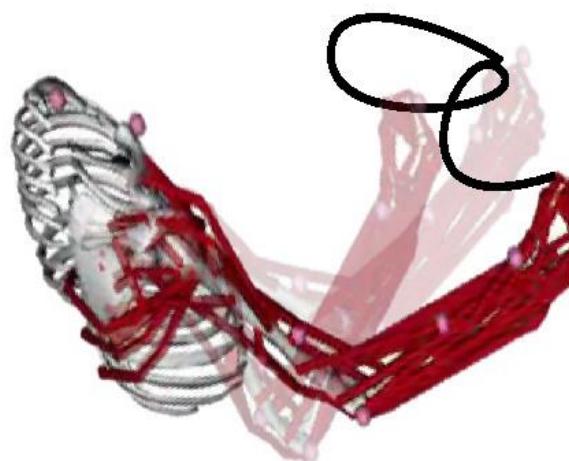


Human pen-tip
movements writing
Latin alphabet

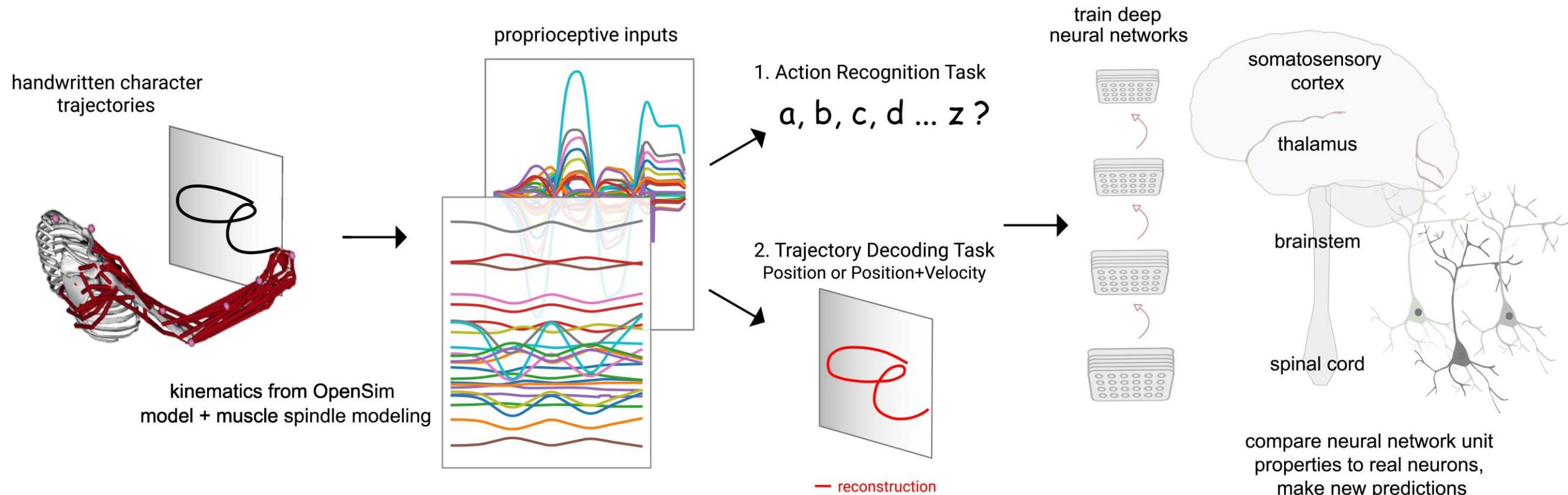
Generate synthetic arm
trajectories to re-create
movement in 3D space



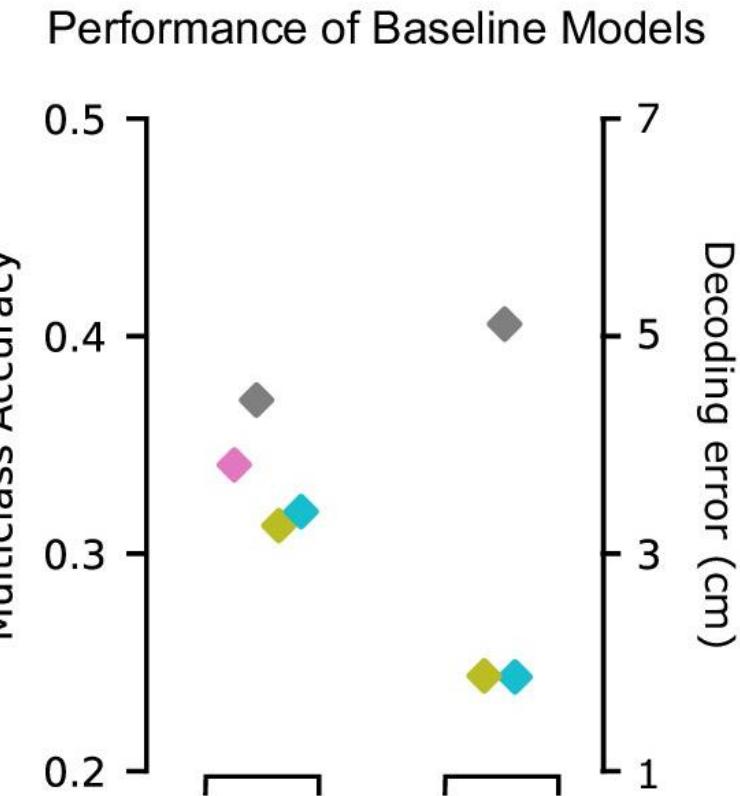
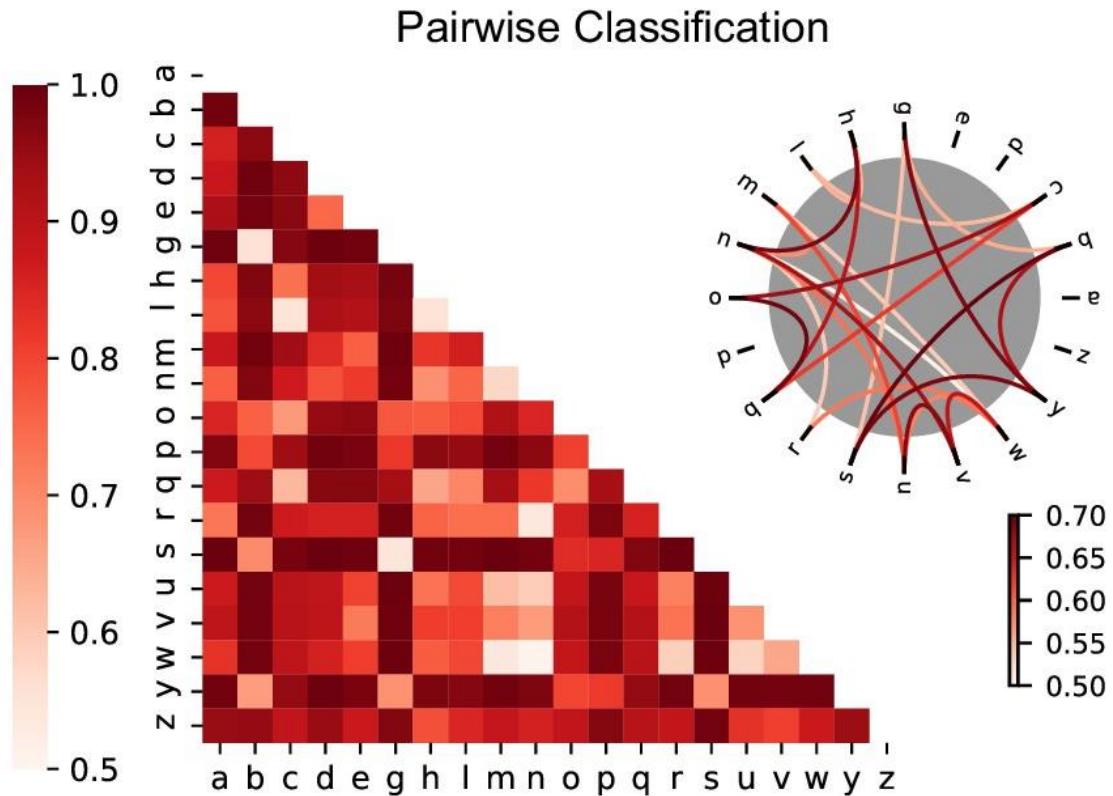
Derive muscle spindle activity for 1M trajectories



Task-driven modelling for the sensori(motor) system

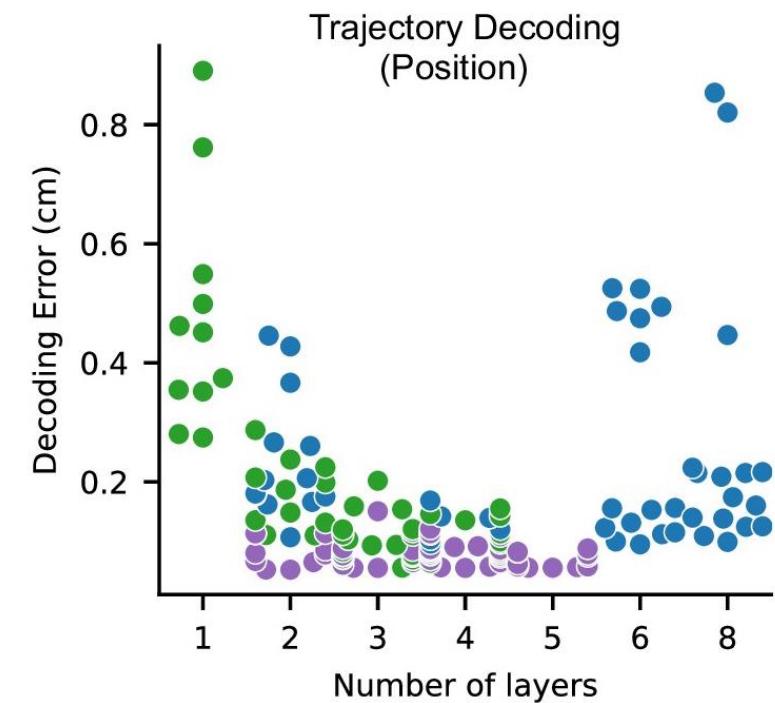
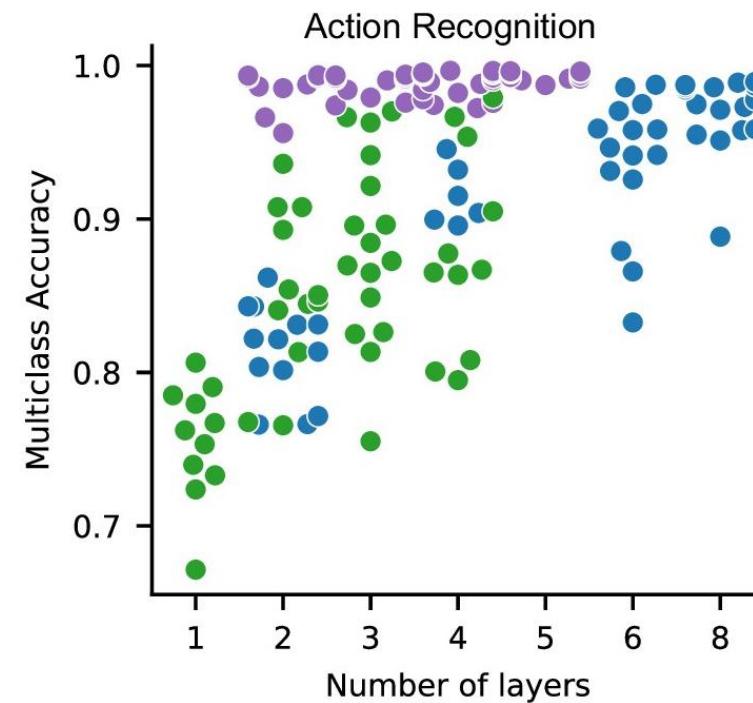
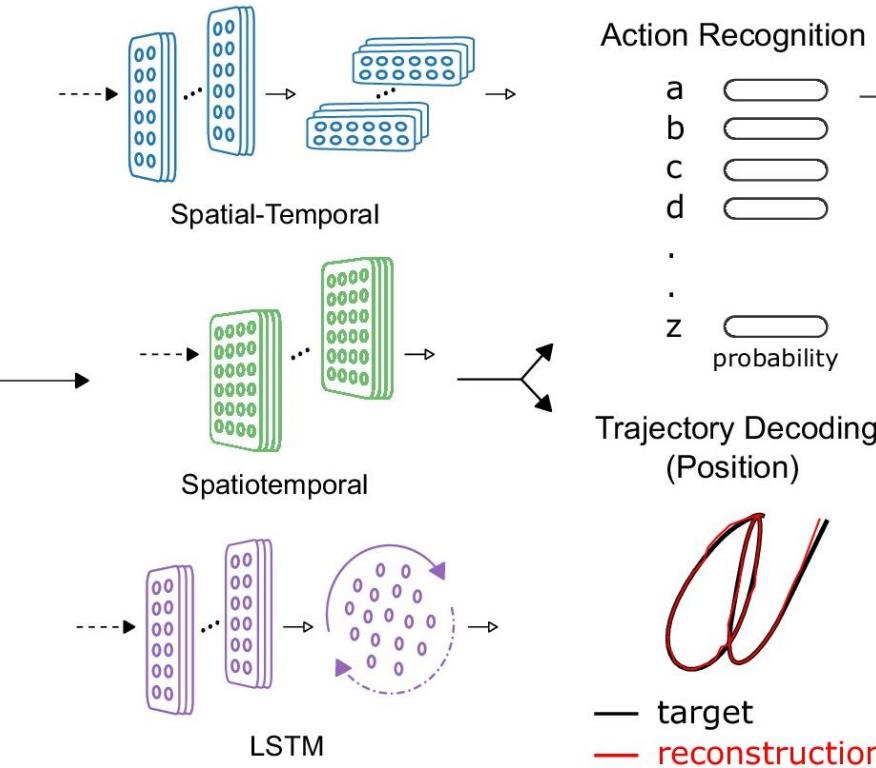


multi-class SVMs trained on proprioceptive inputs show action recognition is a hard task

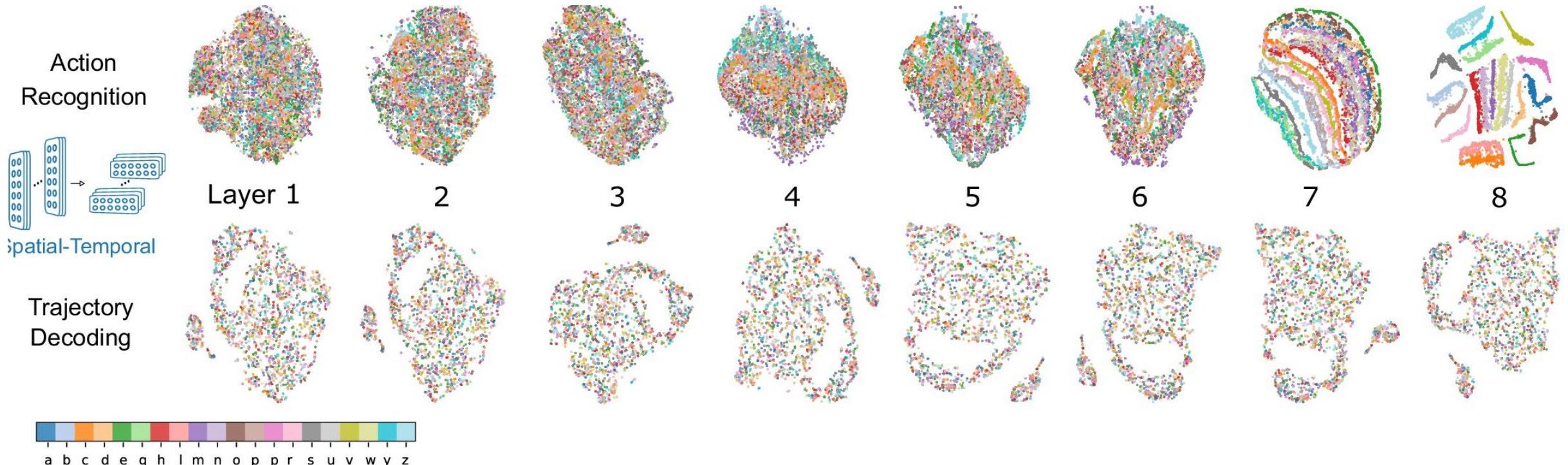


- ◆ End-effector Coords
- ◆ Proprioceptive Input
- ◆ Joint angles
- ◆ Muscle Lengths

Neural networks can readily solve both action recognition and trajectory decoding

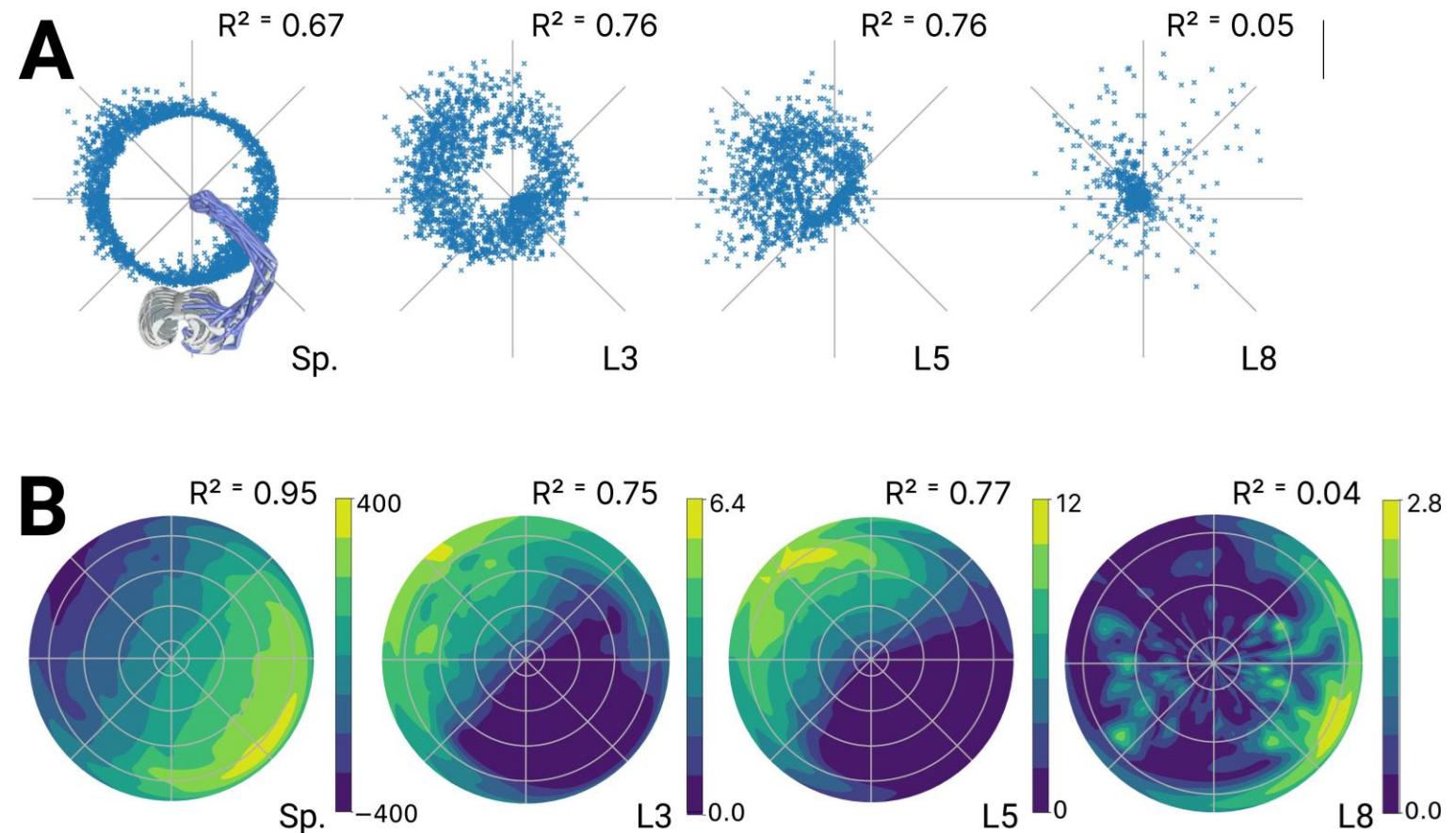
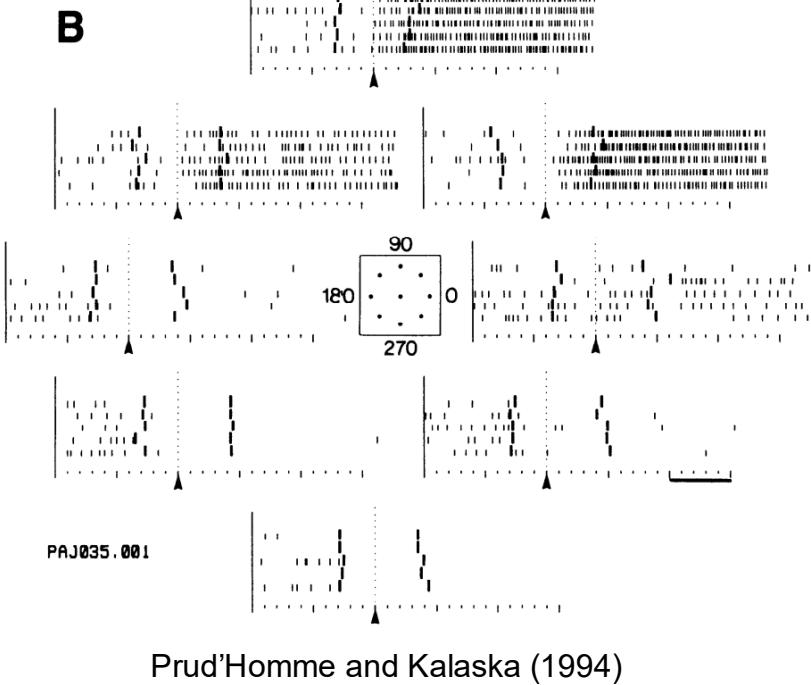


Different representations “emerge” in NNs trained on action recognition or trajectory decoding



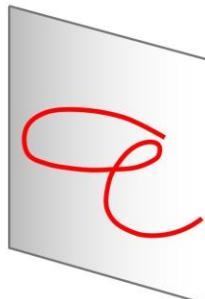
- Here, we used tSNE (nonlinear method) to look at changes in Label clustering across NN layers

Tuning curve analysis of NN units show canonical S1-like tuning



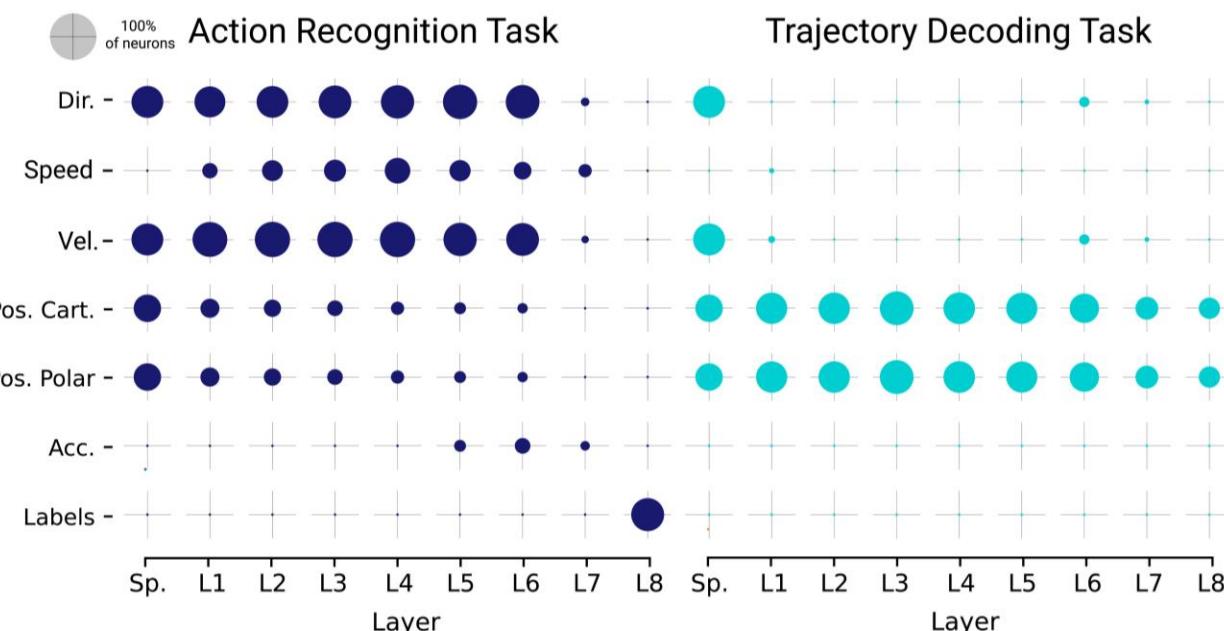
ART-trained models contain direction selective units, but TDT-trained do not ...

1. Action Recognition Task
a, b, c, d ... z ?



2. Trajectory Decoding Task
Position or Position+Velocity

— reconstruction

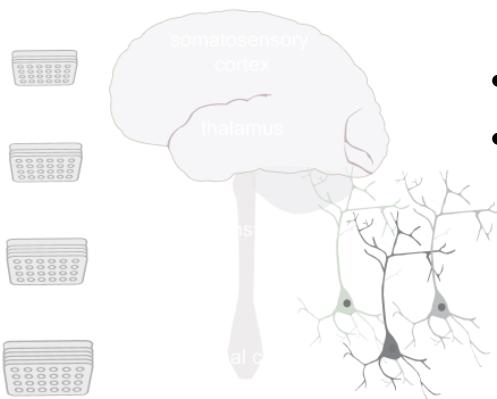
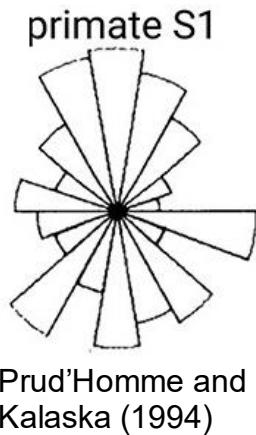


Textbooks tells us:

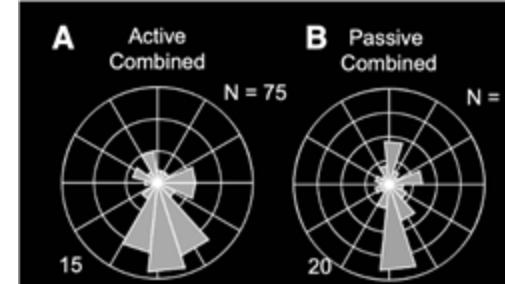
- proprioception is there to tell us where our body is in space
- We should see direction selectivity & positional information ...
- **If we train only on ART we see direction, less position; traj → position and no dir .. independent of ref. framework**

Population vector analysis of NN units show canonical S1-like tuning, in trained models

Action Recognition Task
a, b, c, d ... z ?

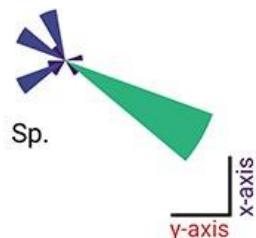


- ART Layer 4-5 most S1 like
- Hypothesized that:
 - cuneate nucleus closer to layer 1-2
 - S2 deepest layers (6+)

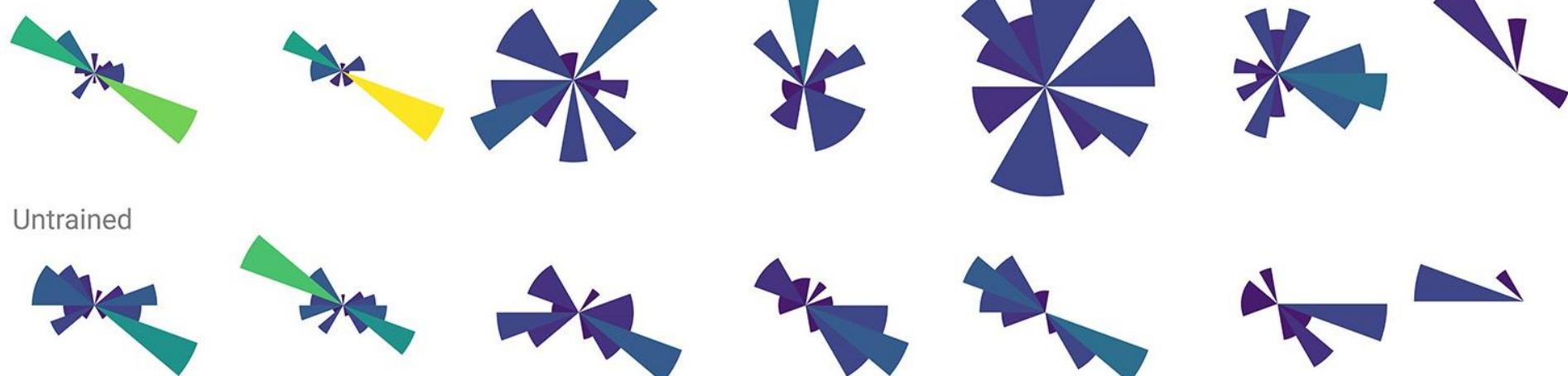


Versteeg et al.,
Journal of Neurophysiology (2021)

Spindles



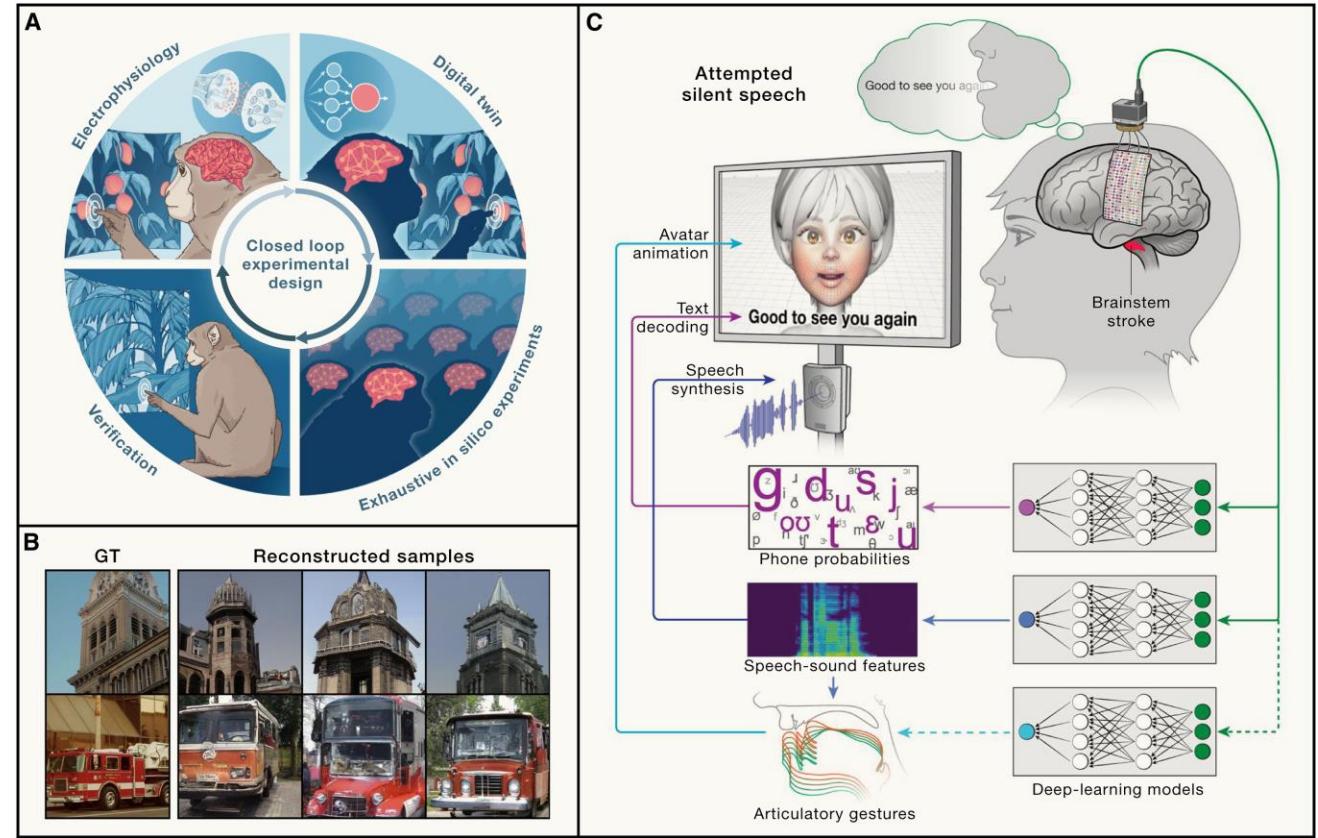
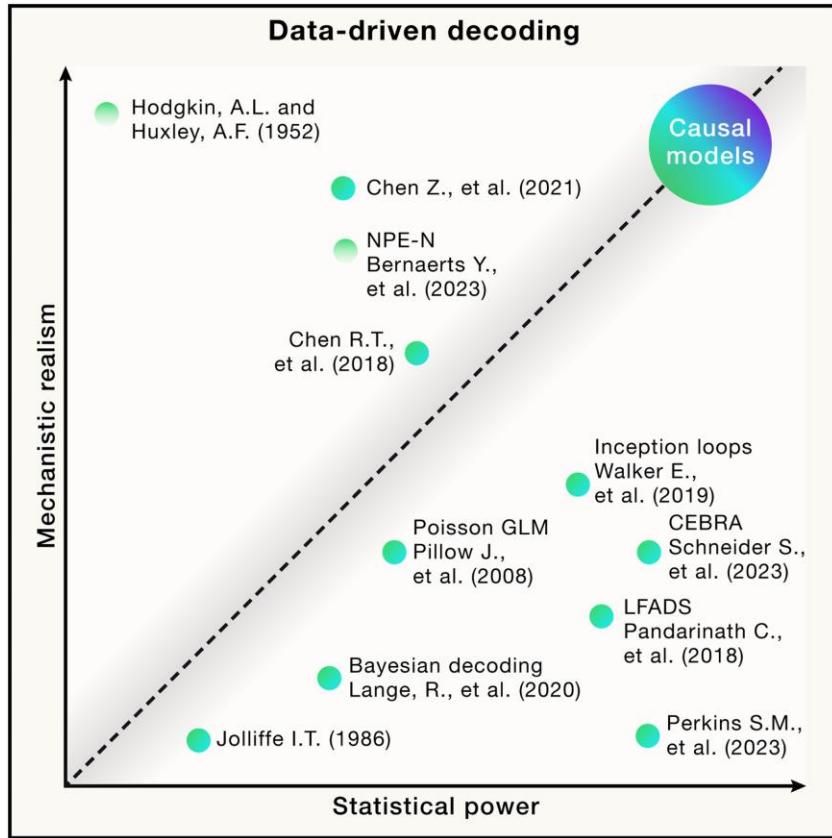
ART-trained



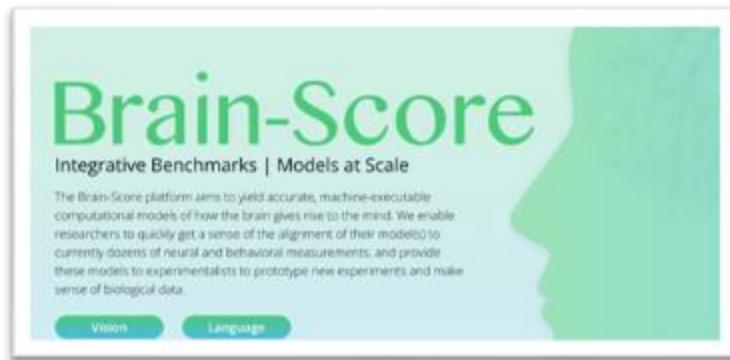
“Biomechanics only”
show direction
tuning...



Decoding the brain: towards more causal models ...



neuroAI in labs at EPFL:



Brain-Score
Integrative Benchmarks | Models at Scale

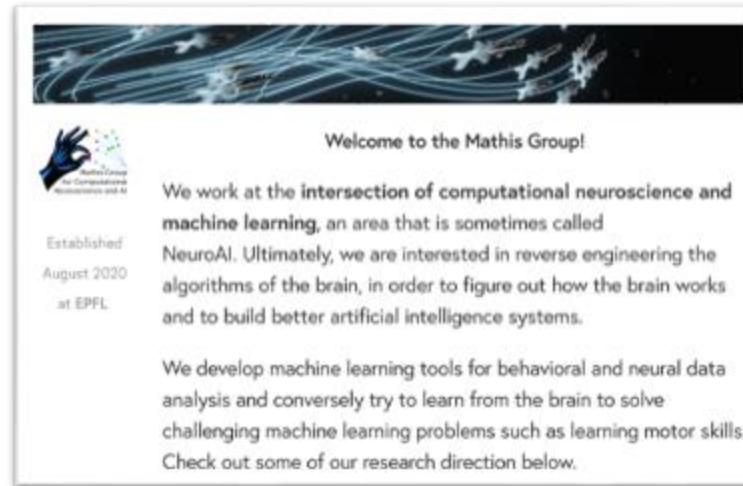
The Brain-Score platform aims to yield accurate, machine-executable computational models of how the brain gives rise to the mind. We enable researchers to quickly get a sense of the alignment of their models to currently dozens of neural and behavioral measurements, and provide these models to experimentalists to prototype new experiments and make sense of biological data.

Vision Language



<https://www.epfl.ch/labs/schrimpflab/>

Prof. Dr. Martin Schrimpf



Welcome to the Mathis Group!

Established August 2020 at EPFL

We work at the intersection of computational neuroscience and machine learning, an area that is sometimes called NeuroAI. Ultimately, we are interested in reverse engineering the algorithms of the brain, in order to figure out how the brain works and to build better artificial intelligence systems.

We develop machine learning tools for behavioral and neural data analysis and conversely try to learn from the brain to solve challenging machine learning problems such as learning motor skills. Check out some of our research direction below.



<https://www.mathislab.org/>

Prof. Dr. Alexander Mathis



EPFL Our world is always changing: how do our brains adapt? We aim to understand the mechanisms underlying adaptive behavior in intelligence systems, aka "adaptive intelligence", and develop new machine learning methods that enable us to do so.

Merging machine learning & neuroscience

The lab revolves around **two interactive areas**: developing open source machine learning tools & uncovering neural dynamics during adaptive behaviors. Specifically, we design behavioral assays for mice, perform large-scale neural recordings, and build tools to aid in our quest of finding internal models in the brain.



<https://www.mackenziemathislab.org/>

Prof. Dr. Mackenzie Mathis

Summary

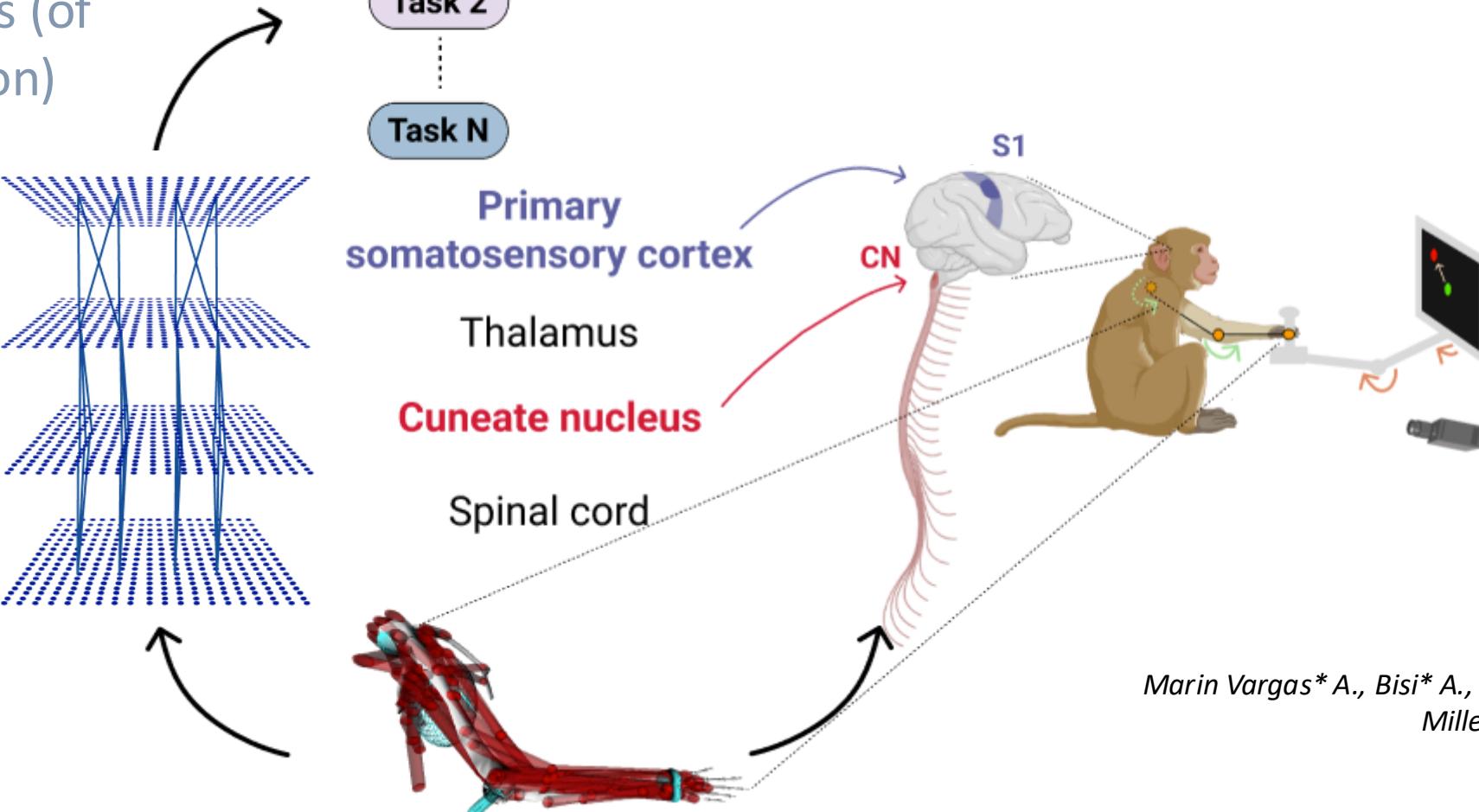
- NeuroAI is an emerging discipline that crosses across systems neuroscience and computer science
- Its goal is broadly to use neuro insights to build AI, and to develop AI for understanding the brain (neuro)
- It is needed as it is still VERY hard to develop embodied AI, human-like movement into robotics, and we still lack generally intelligent systems (although LLMs for language are impressive ...)
- Key example in Neuroscience inspiring AI: convolutional neural networks (likely transformers too “attention”): this is a hot area in industry – using cognitive neuro approaches to study NN btw!
 - Interestingly, CNNs developed representations similar to the brain
- Key examples of AI influencing neuro: better behavioral analysis tools, better neural analysis tools (see also BCI week soon!)
- What is missing? NNs are very simple “neurons,” that lack the complexity of what we find in the real brain: an opportunity awaits!
- Yet, there is a universality of the representations ...
- Data-driven and task-driven modeling: key approaches in neuroAI
- How do we model sensory systems: examples in vision and proprioception
 - What to consider: both how close they are at single cell, task performance, and population level similarity
 - Ongoing efforts: Brain-Score, **Inception Loops** ... **Foundation Models** to predict function < > structure

Creating *even more* task-driven models of proprioception

Ingredient 1:
Putative goals (of
proprioception)

HYPOTHESES TESTING

- Task 1
- Task 2
- Task N

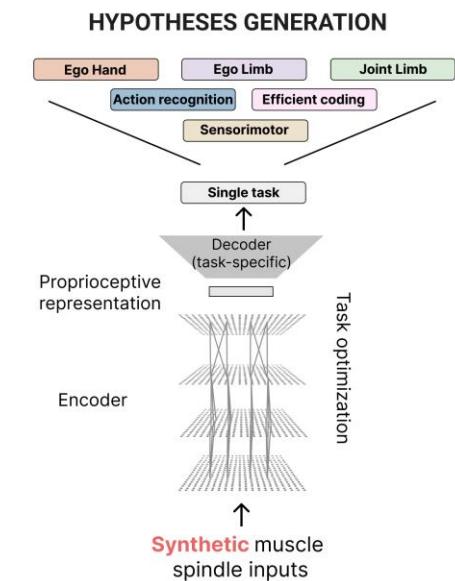
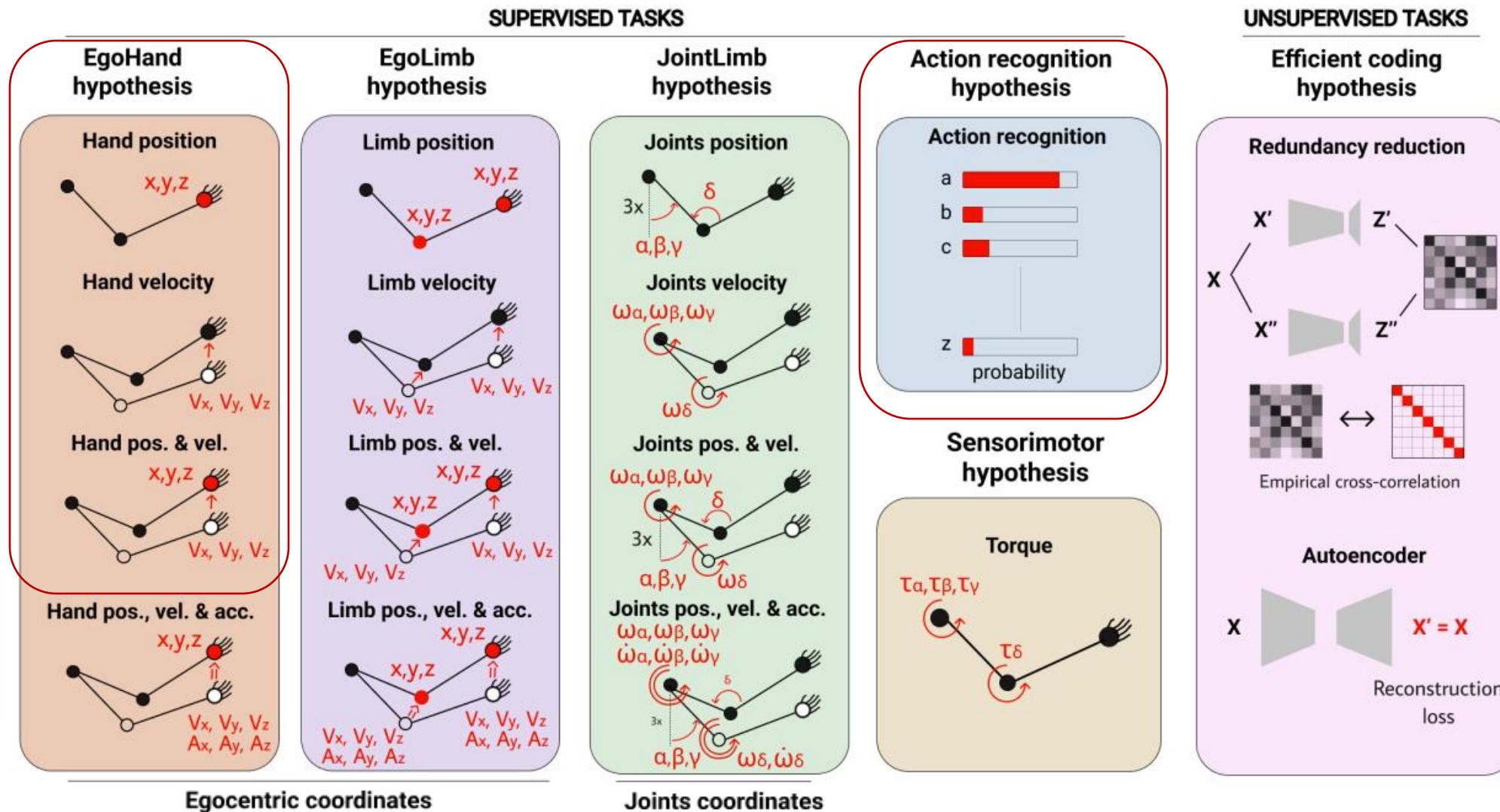


Ingredient 3: simulating spindle dynamics at scale

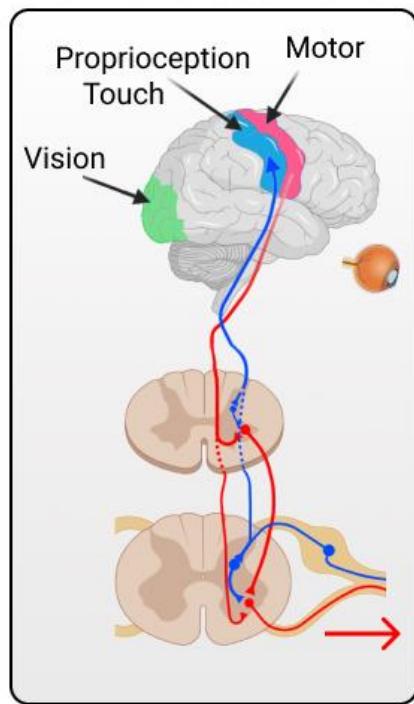
Marin Vargas* A., Bisi* A., Chiappa A., Versteeg C.,
Miller L., Mathis A. *Cell* 2024

Slide courtesy of A. Mathis

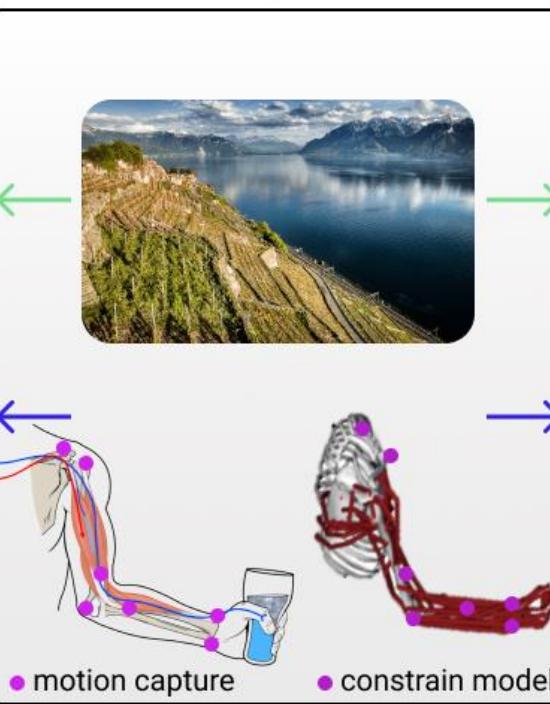
16 computational tasks to create candidate models



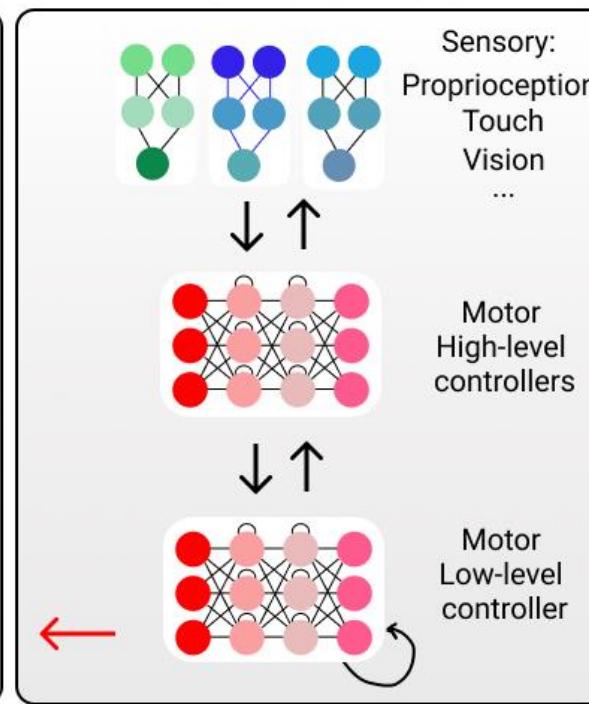
AGENT: BIOLOGICAL CNS



ENVIRONMENT

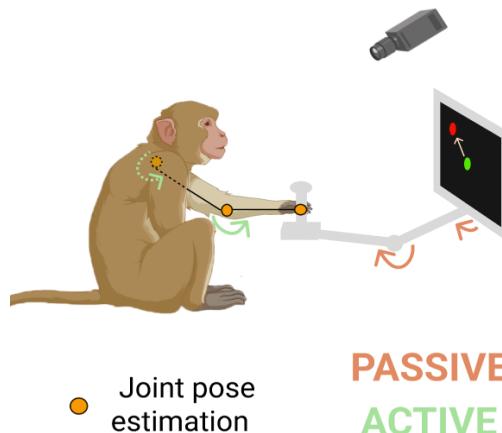


AGENT: MODEL CNS

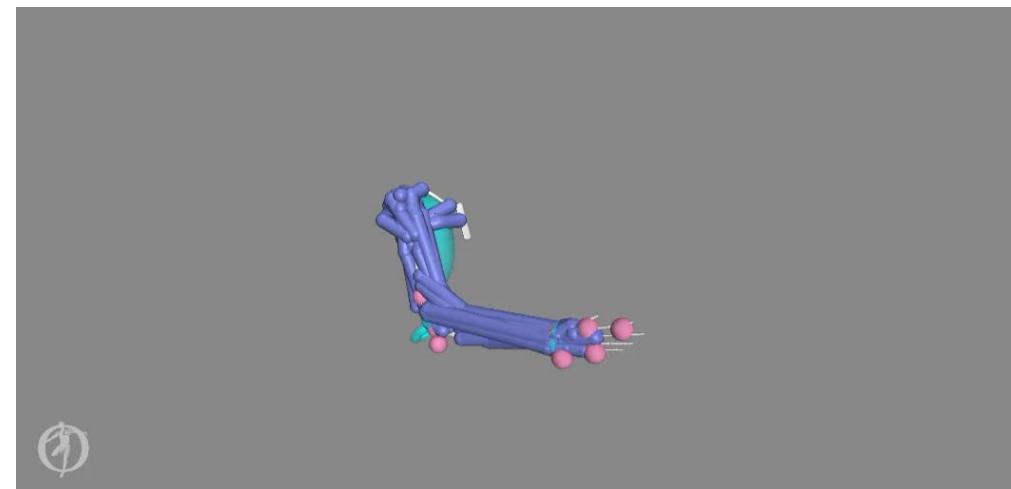


BEHAVIORAL EXPERIMENT

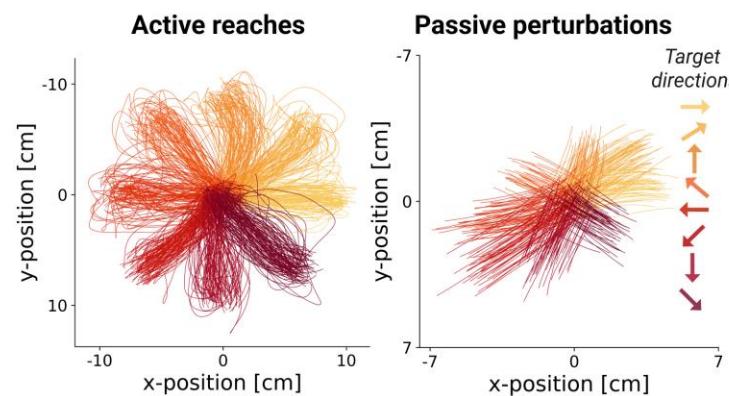
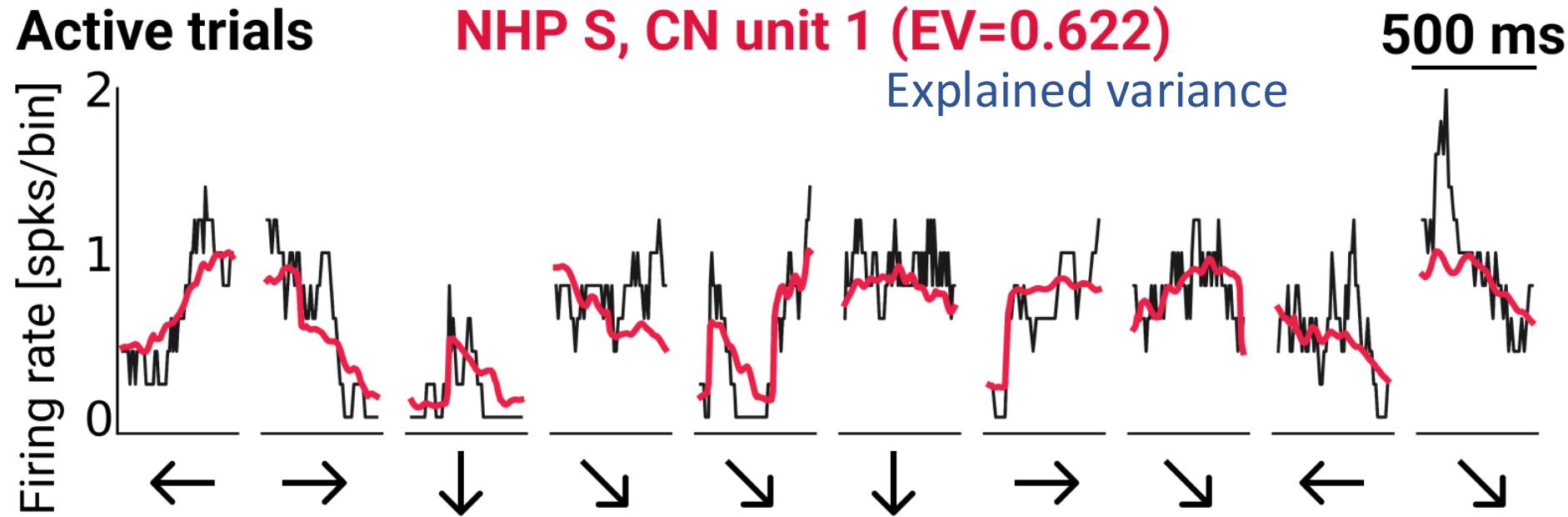
DeepLabCut



PASSIVE
ACTIVE

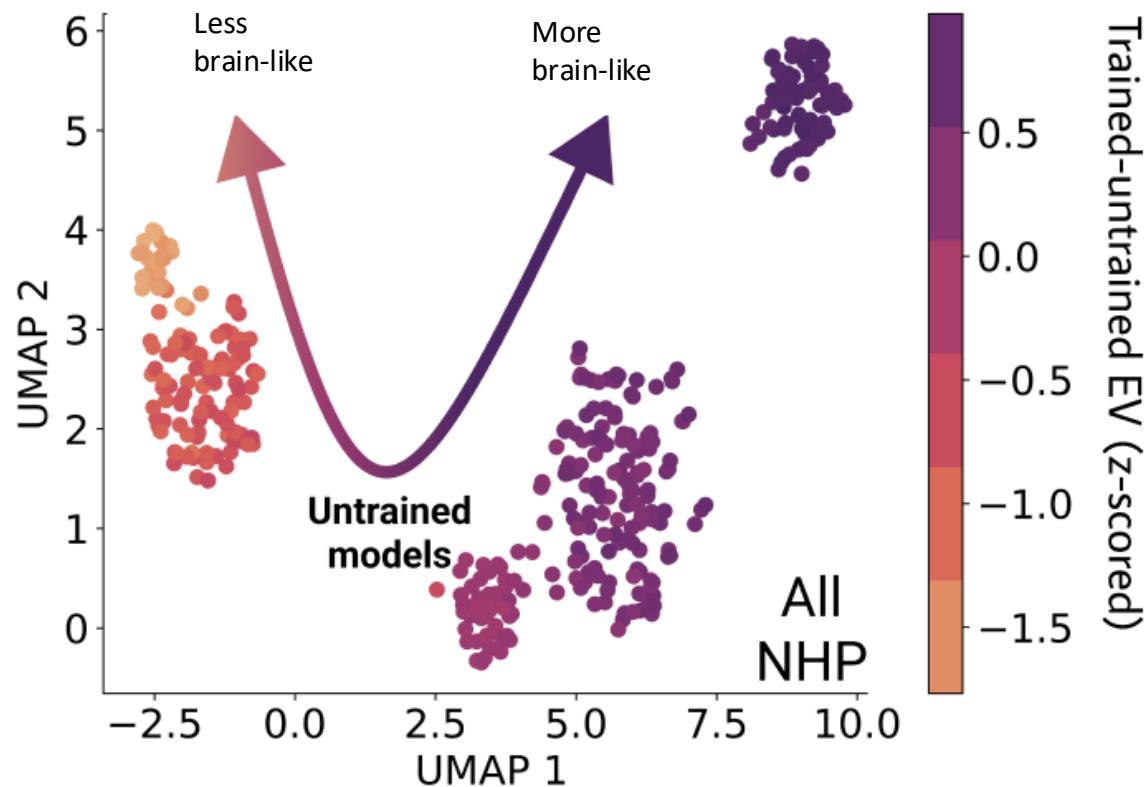


Task-trained models predict single neuron dynamics!



Comparing network representations with unsupervised UMAP clustering

ACTIVE



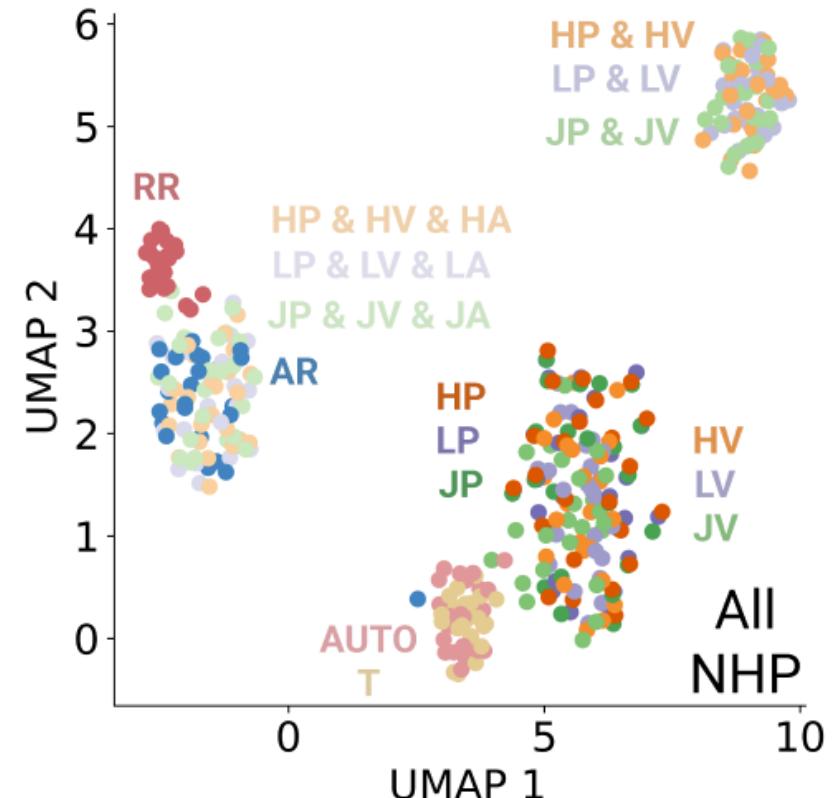
HP = Hand position
HV = Hand velocity
HA = Hand acceleration

LP = Limb position
LV = Limb velocity
LA = Limb acceleration

JP = Joint position
JM = Joint velocity
JA = Joint acceleration

RR = Redundancy Reduction
AUTO = Autoencoder

AR = Action Recognition
T = Torque



Task-trained models predict neuron dynamics!

- For all 16 hypotheses, if a *computation* is better learned on synthetic, passive spindle data, then the model also generalizes better to neural data
- Neural data (*in the active case*) is best explained by the **hypothesis that proprioception is optimized to encode the location and velocity of the body** (irrespective of coordinate framework (hand or limb))
- Lack of evidence for hierarchical processing; this suggests that proprioception even in the brain stem is dominated by efference copies ...

