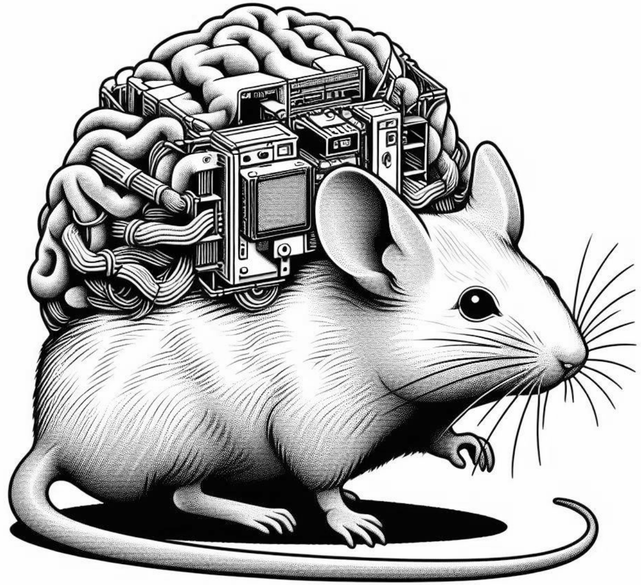
Foundation model of the mouse visual cortex

Bryan M. Li @bryalimy
Biomedical AI CDT, University of Edinburgh
Enrichment student, The Alan Turing Institute

Generated by Microsoft Image Creator



Journey

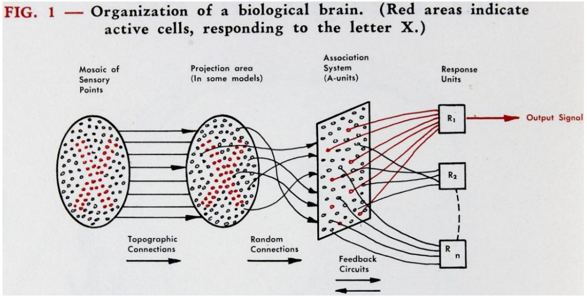
2023 - Present	Enrichment Scheme, The Alan Turing Institute
	- Contribute to the *autoemulate* digital twin project
2020 - Present	Biomedical AI PhD (CDT) at the University of Edinburgh
	- NeuroAI (machine learning and computational neuroscience)
	- Machine learning for healthcare
2019 - 2020	MSc by Research in AI at the University of Edinburgh
2018 - 2019	Research Engineer at Huawei Noah’s Ark Lab in Toronto
2017 - Present	FOR.ai (now Cohere For AI)
2016 - 2017	Software Engineer Intern at AMD (Embedded Team) in Toronto
2013 - 2018	BSc in Computer Science at the University of Toronto

Background

Machine learning and computational neuroscience

Neuroscience and machine learning

ML inspired by neuroscience



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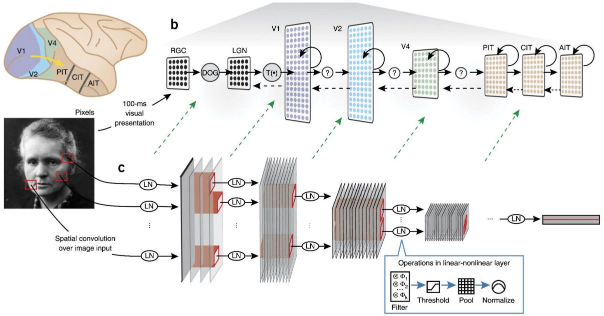

[2] CNN and the ventral stream

ML application in neuroscience

[3] decode behaviors from neural activities

[4] feature landscape of mouse visual cortex

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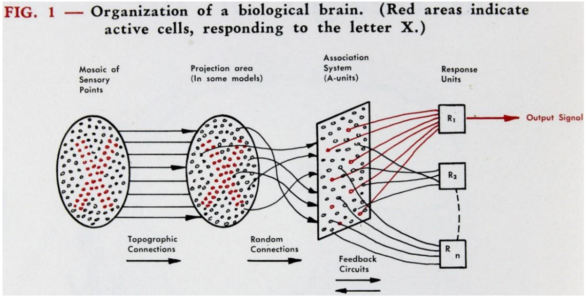

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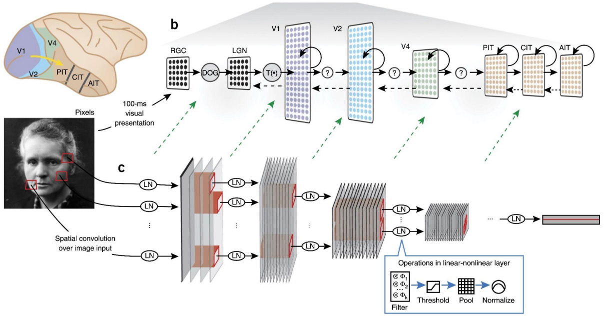

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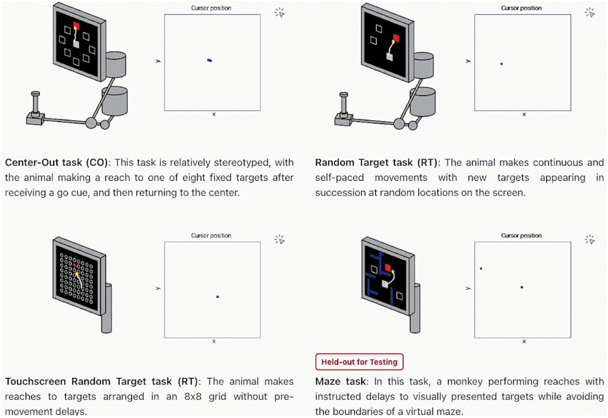

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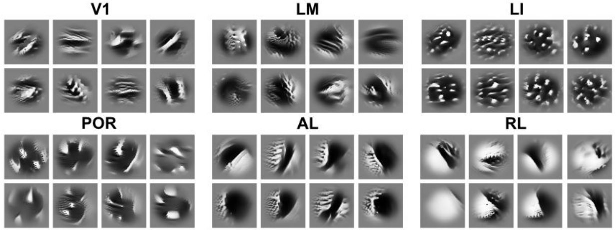

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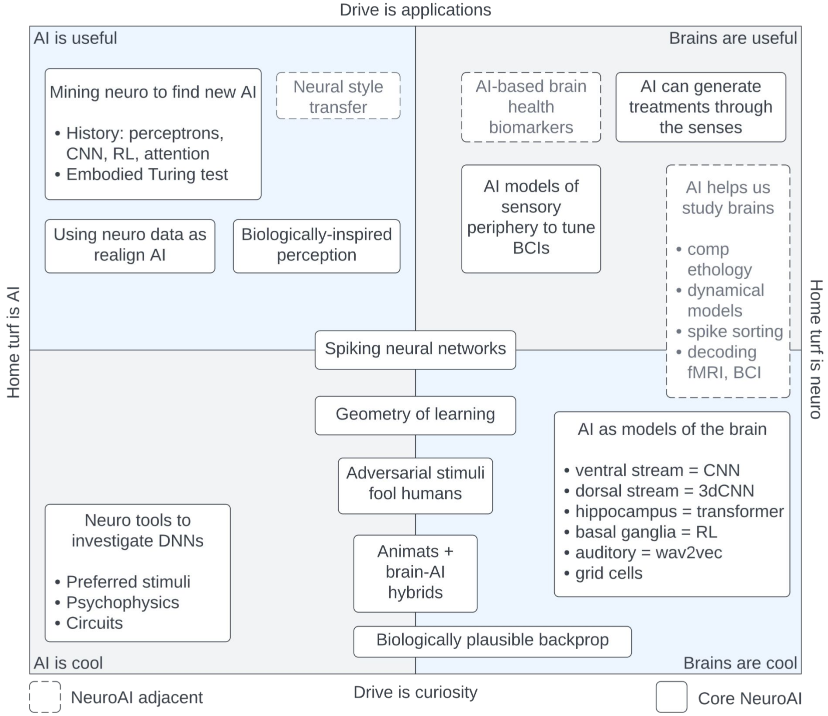
Emergence of NeuroAI

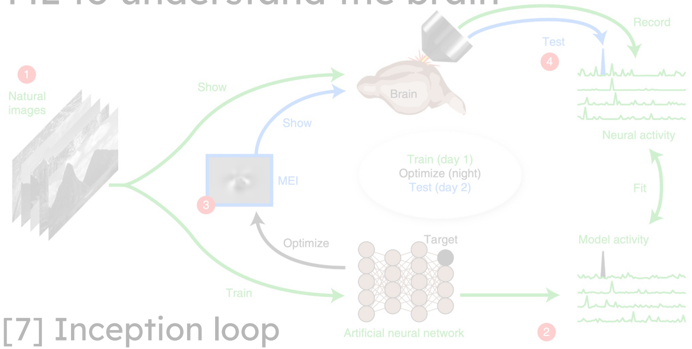
[5] Typology of NeuroAI



1. build better ML using knowledge of the brain

[6] Translate C. elegans locomotion circuits into swimming agent

2. use ML to understand the brain



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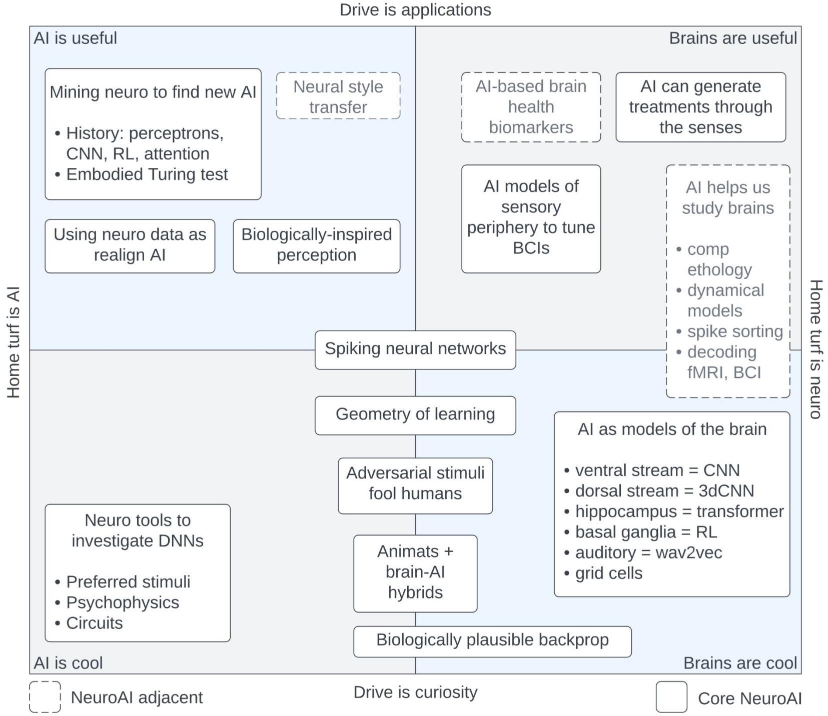

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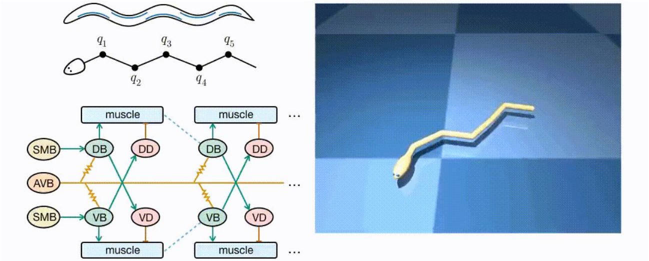

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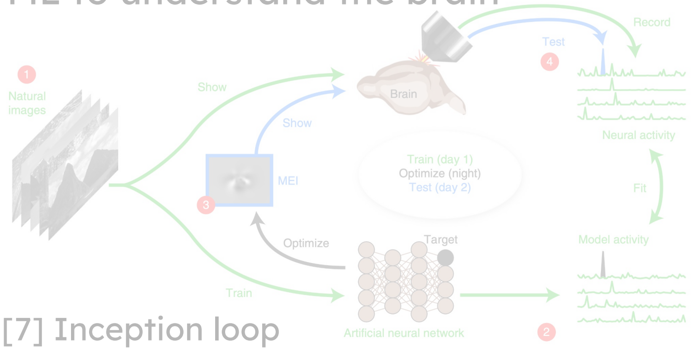

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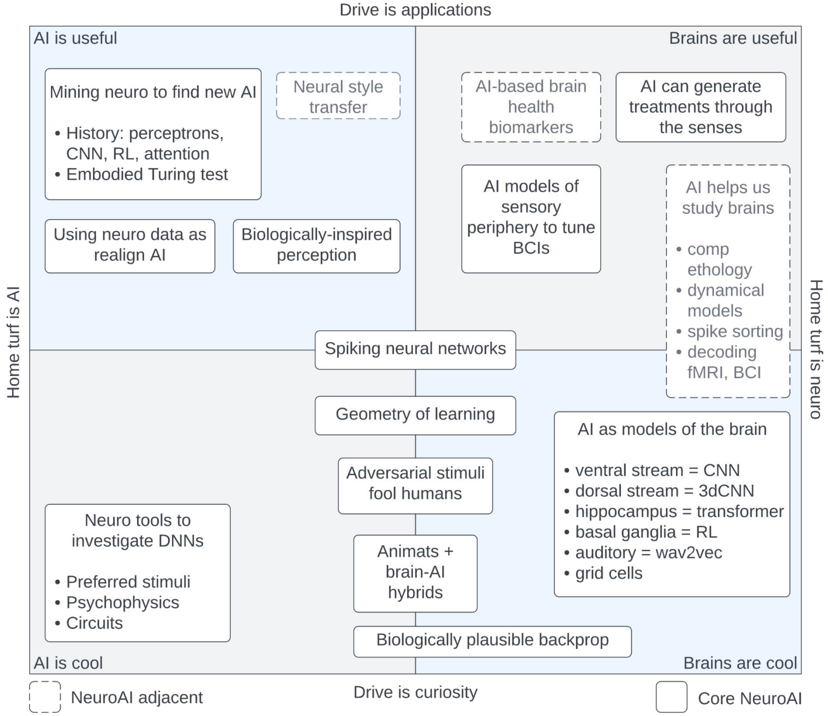

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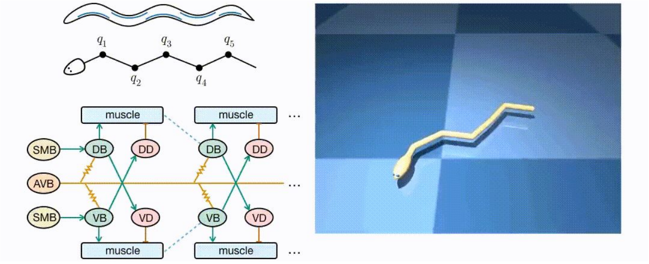

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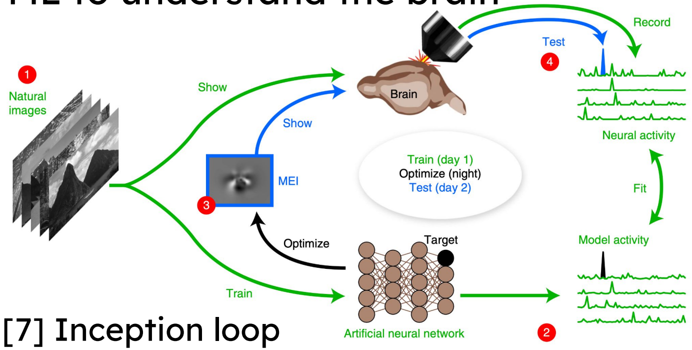

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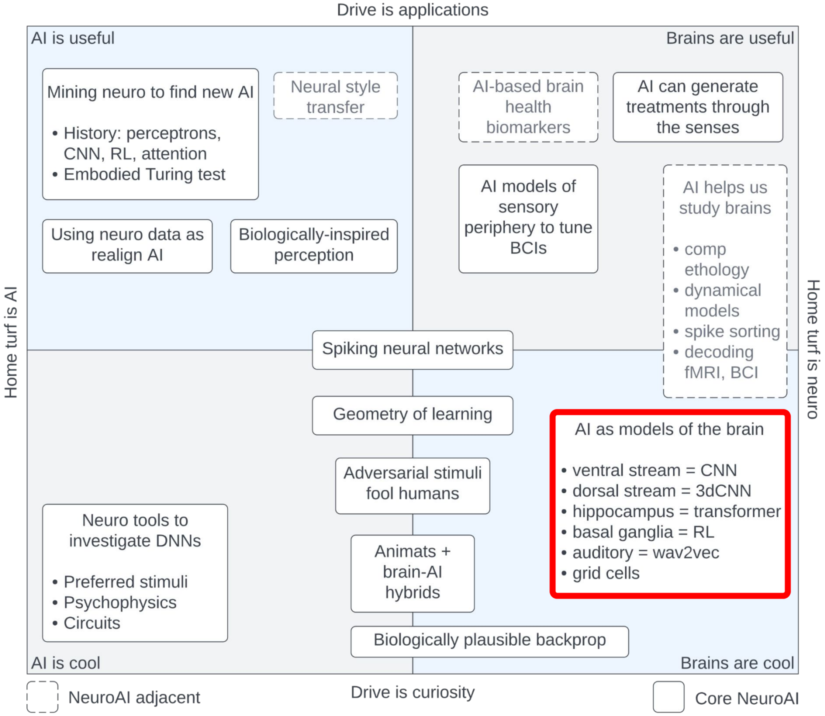

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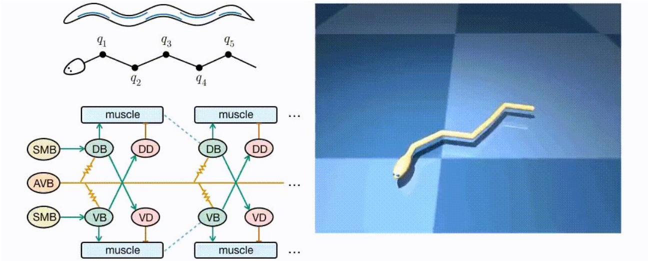

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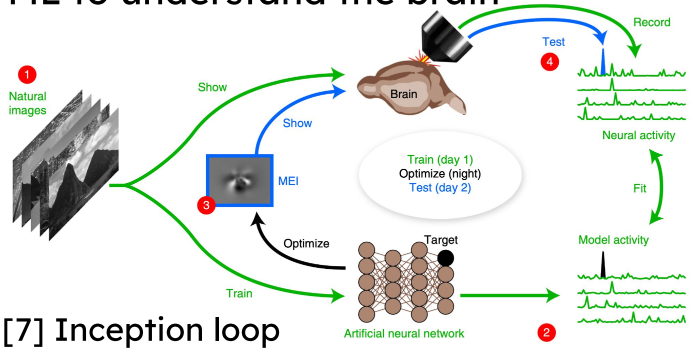

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ML as a model of the brain

Visual response prediction

Visual response prediction

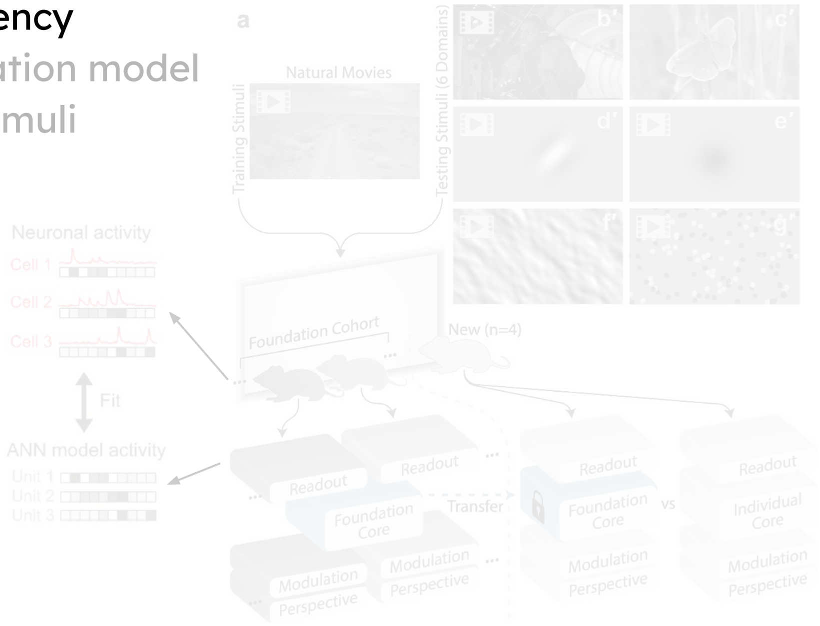
Understanding how the visual system processes information is a fundamental challenge

- Nonlinearity in neural activities w.r.t. visual stimuli
- Limited animal experiments in duration and frequency

Goal: build digital twin of the visual system, a foundation model

- accurately prediction visual response to natural stimuli
- generalize across animals and stimuli
- ML challenge: Brain score, Sensorium, ...

[8] foundation model of mouse V1



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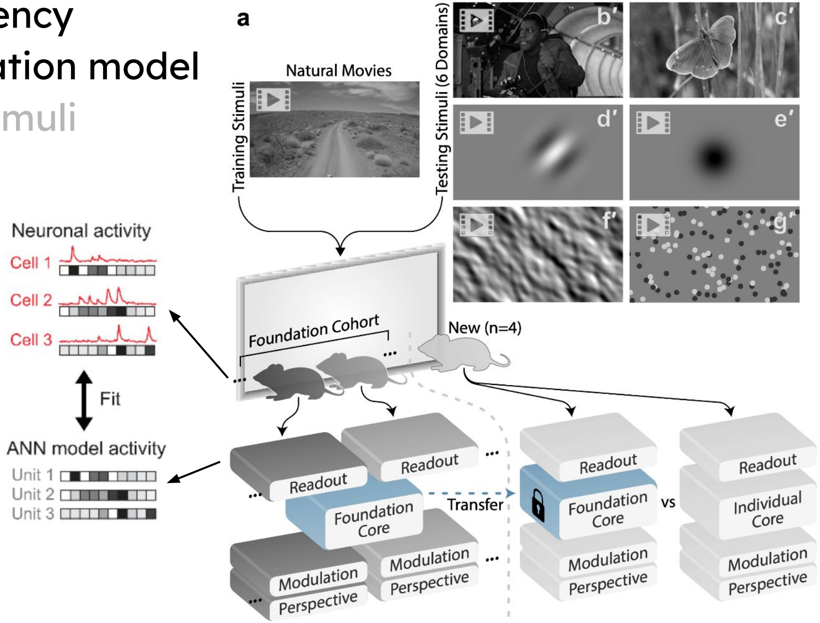

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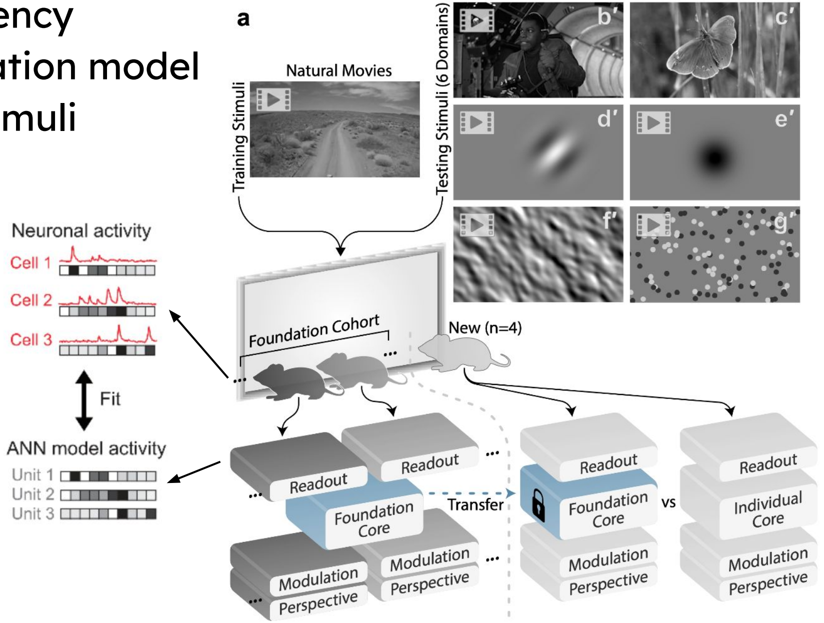

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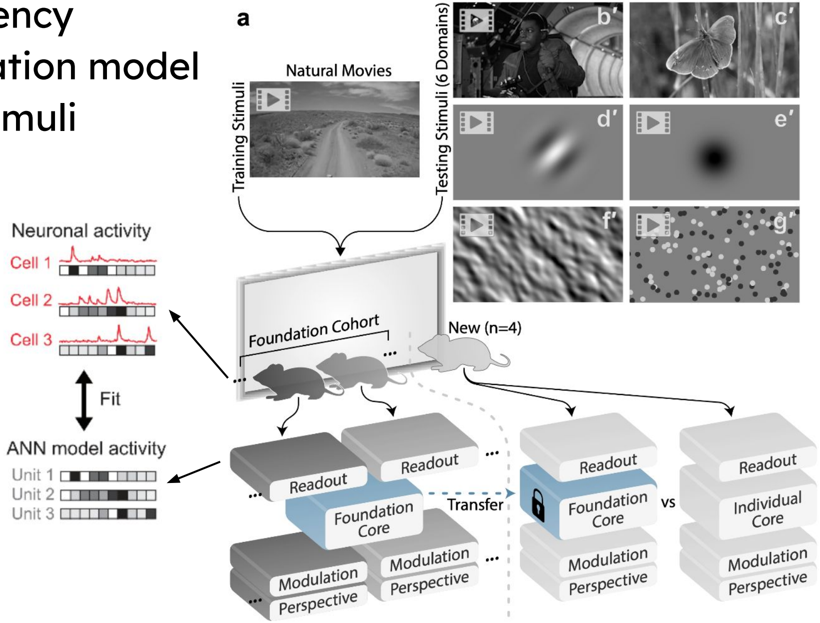

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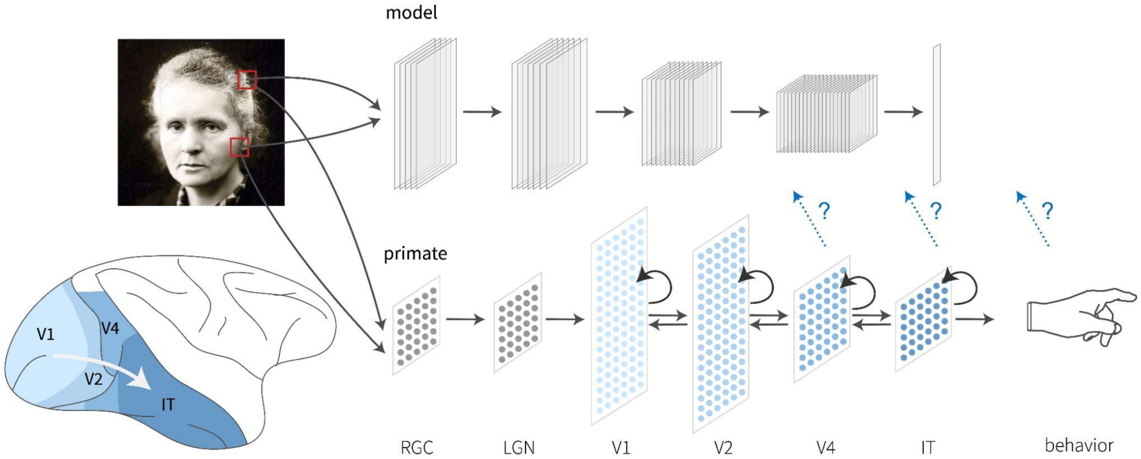
- ML challenge: Brain score



[9] align model response with macaque monkeys V4 and IT neurons.

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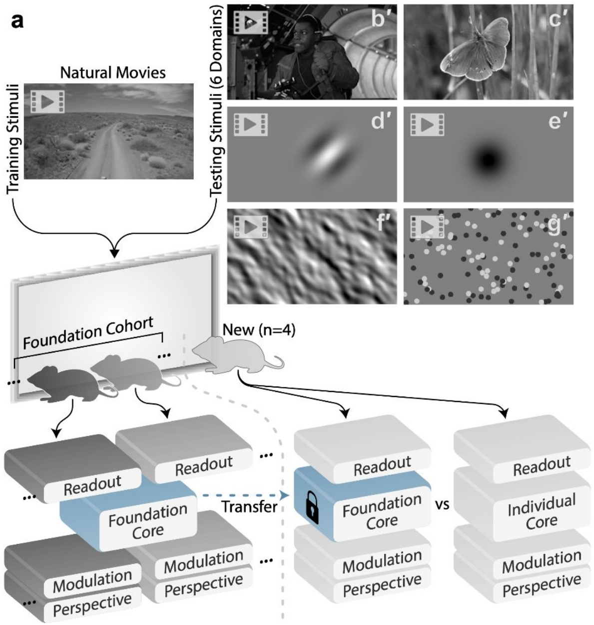

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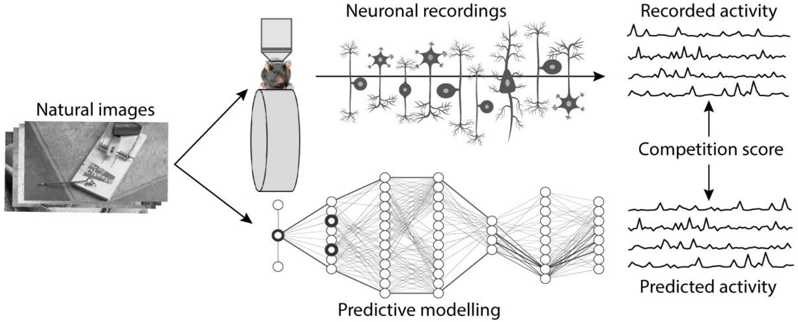
Goal: build digital twin of the visual system, a foundation model

- ML challenge: Sensorium (NeurIPS competition track)
  - Sensorium 2022: static stimuli
  - Sensorium 2023: dynamic stimuli



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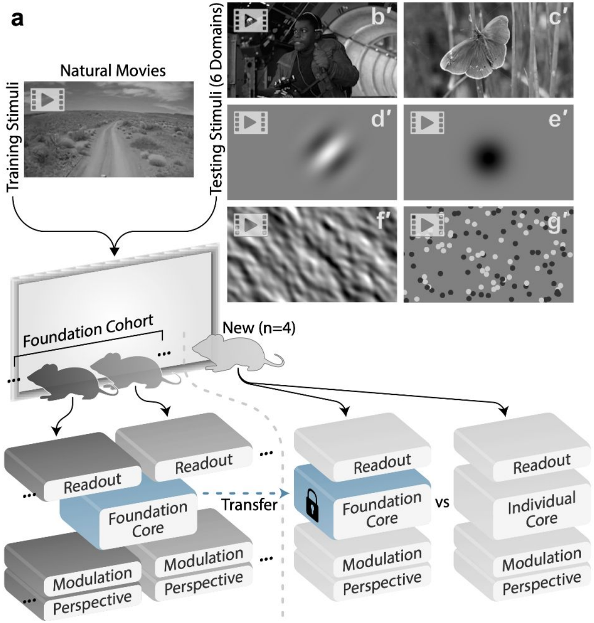

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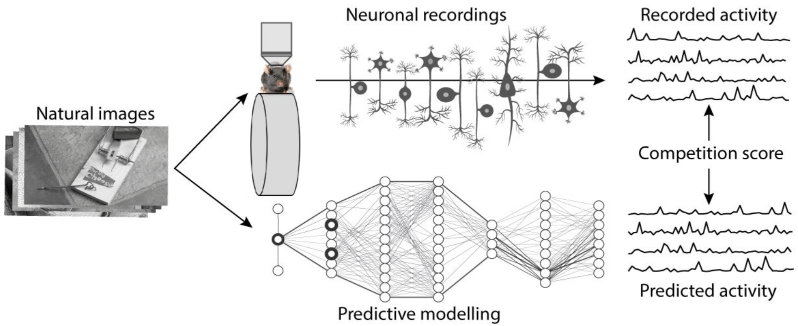

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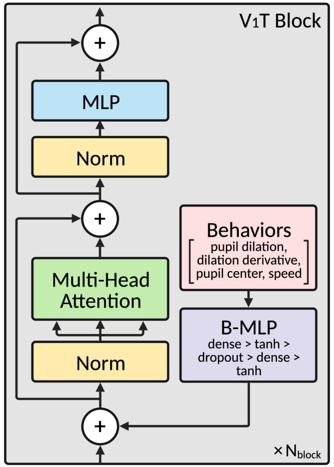

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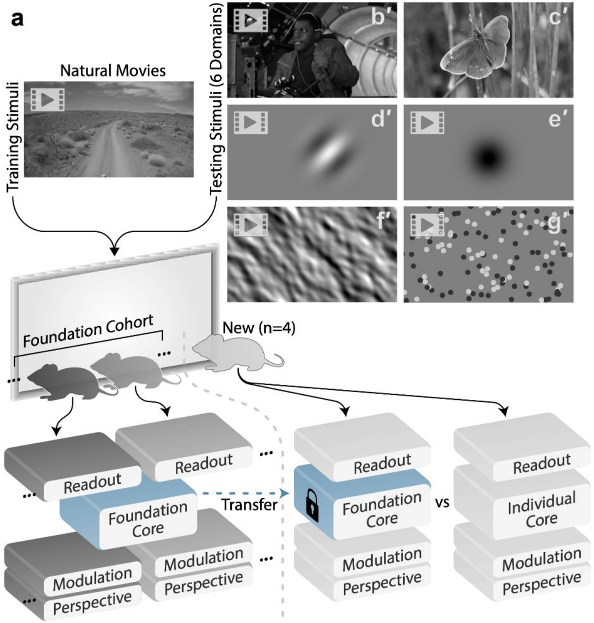

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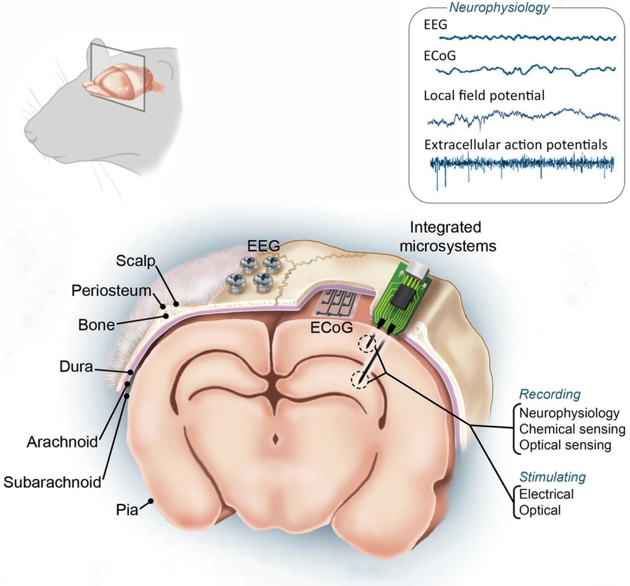
In vivo recordings from behaving mice

I am NOT an experimentalist

Neural recordings



Type of neural recordings [12]

Head fixed mouse in virtual maze navigation experiment [13]

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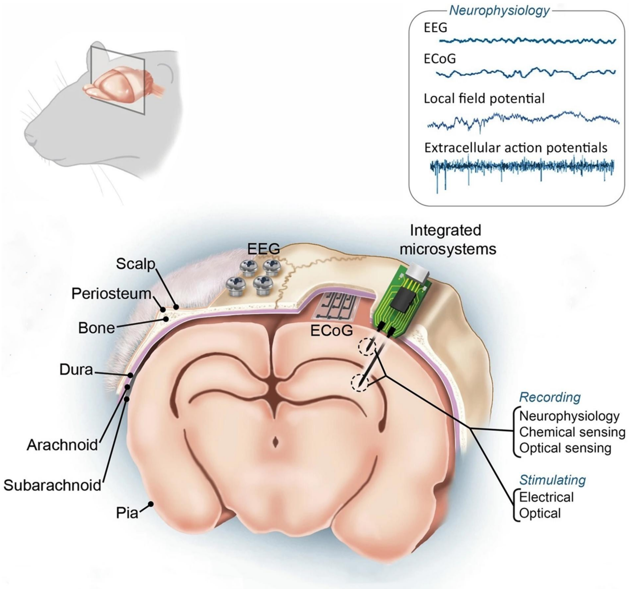

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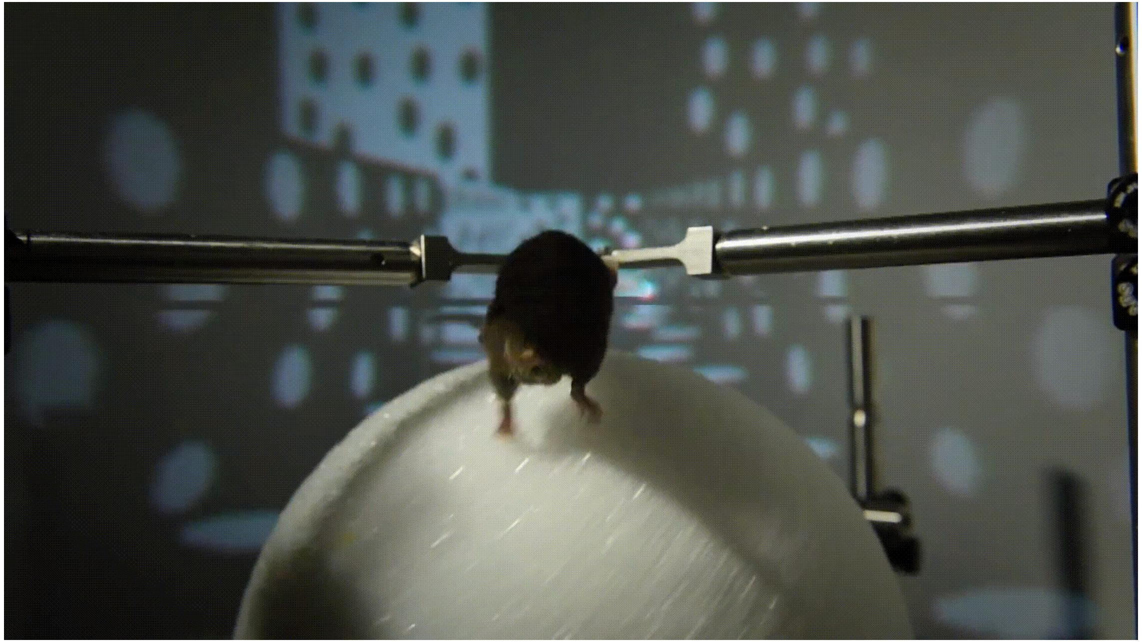

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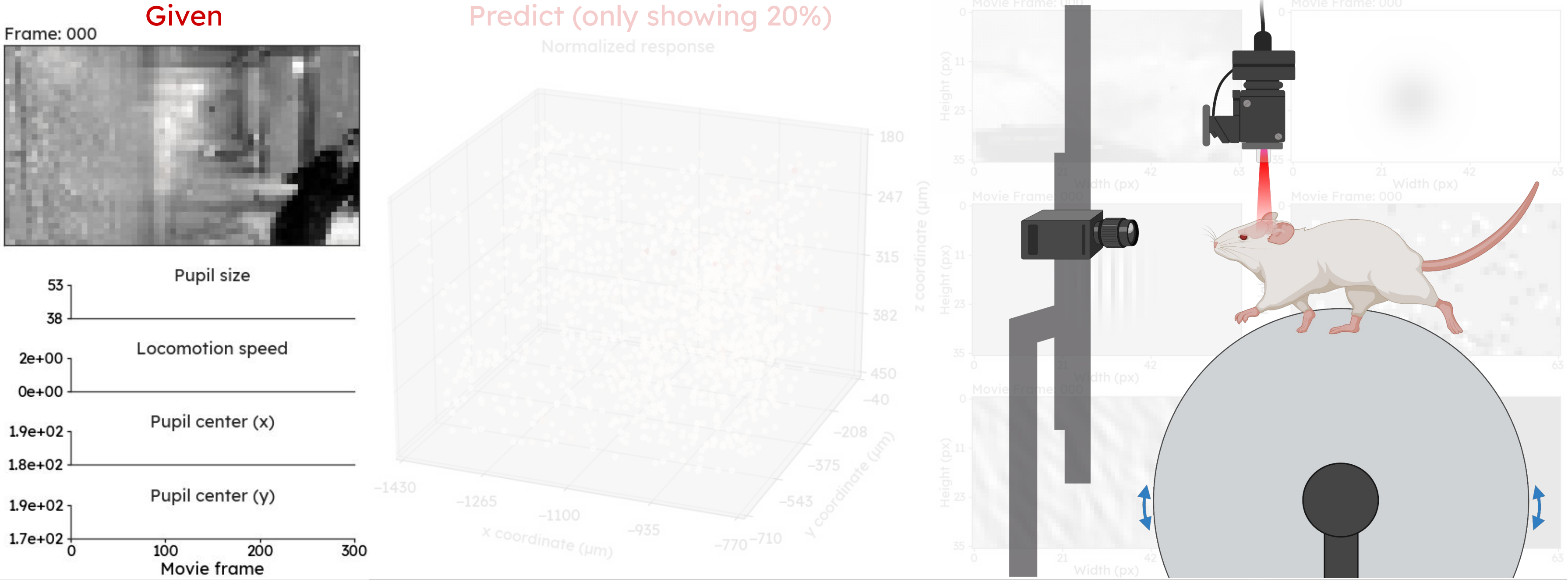
Sensorium 2023 [14] (NeurIPS competition track)

Predict mouse V1 response to dynamic stimuli
10 mice, ~8000 neurons per mouse.

Train on movie (10s clips, ~300 clips per mouse)
Test on unseen movies and artificial patterns



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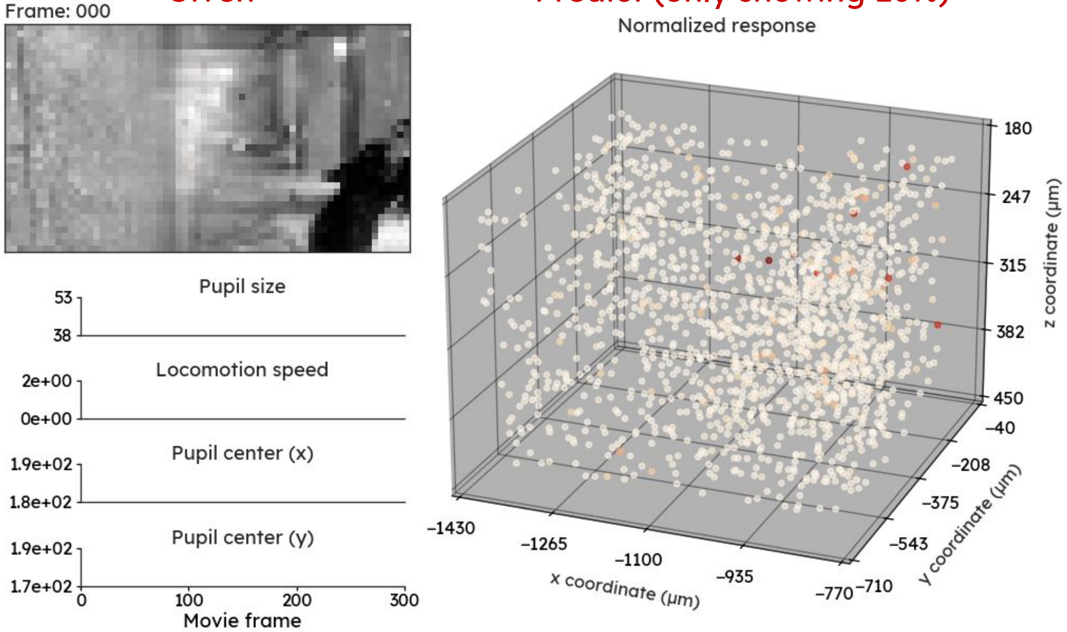

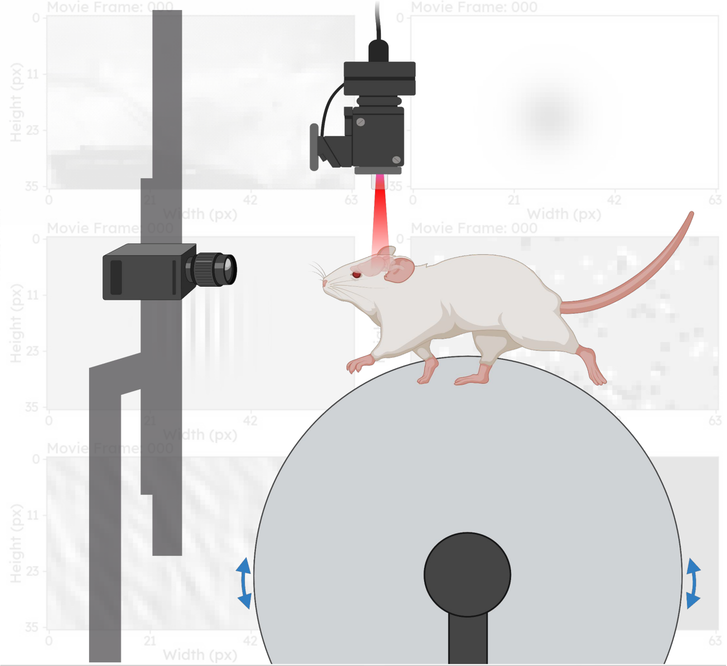

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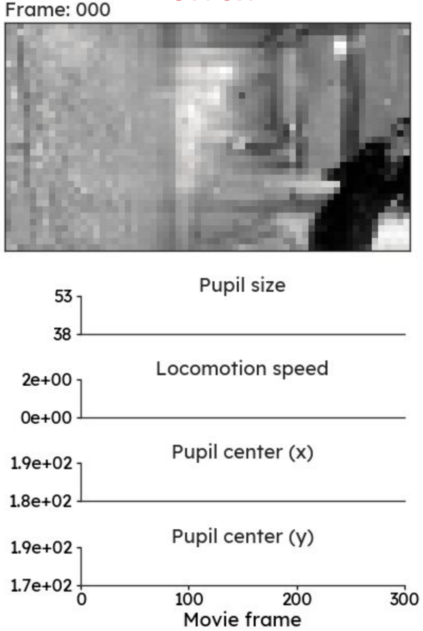

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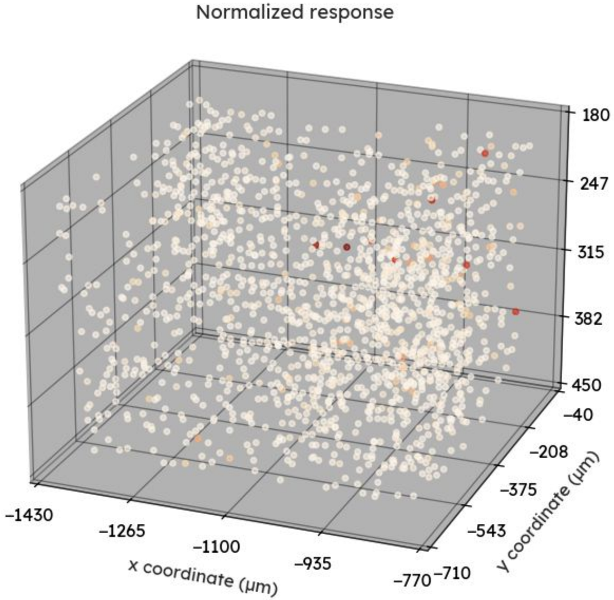

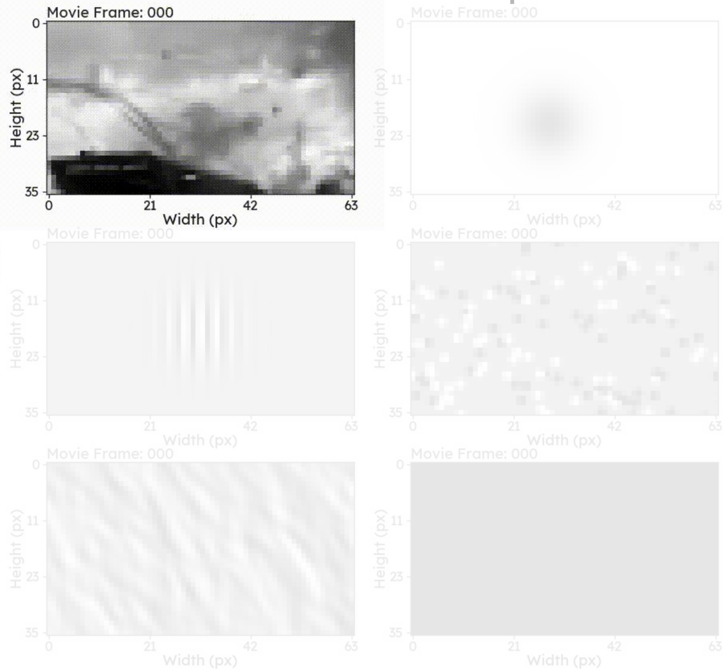

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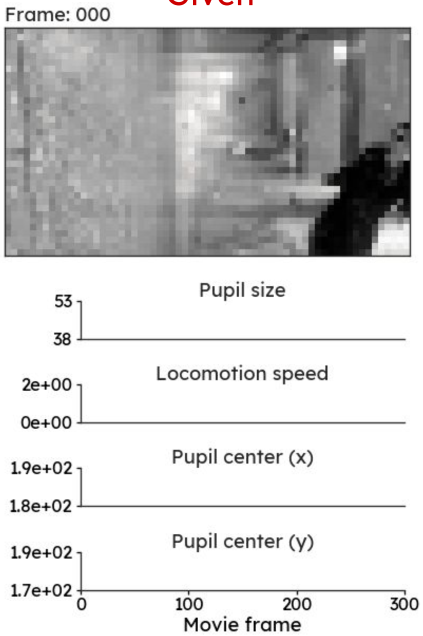

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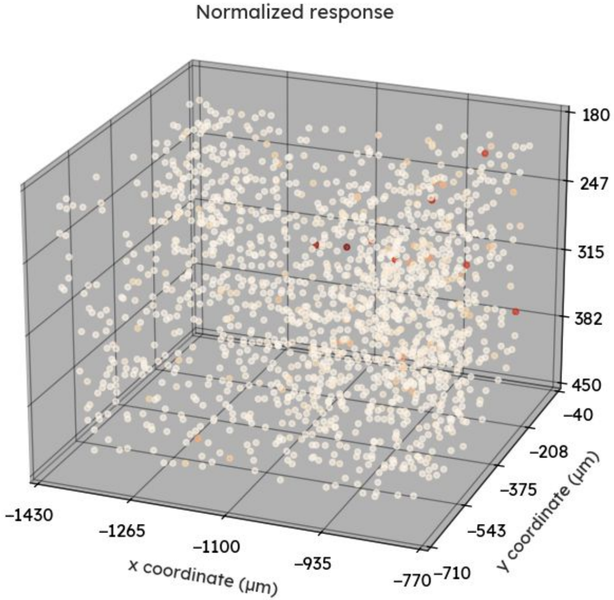

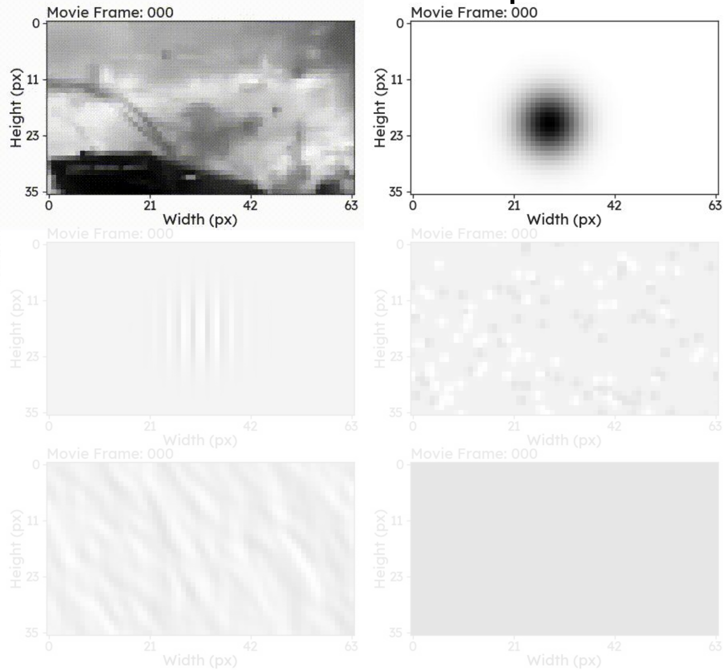

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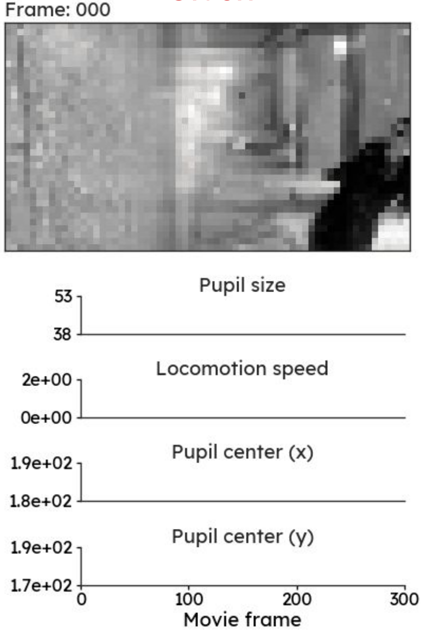

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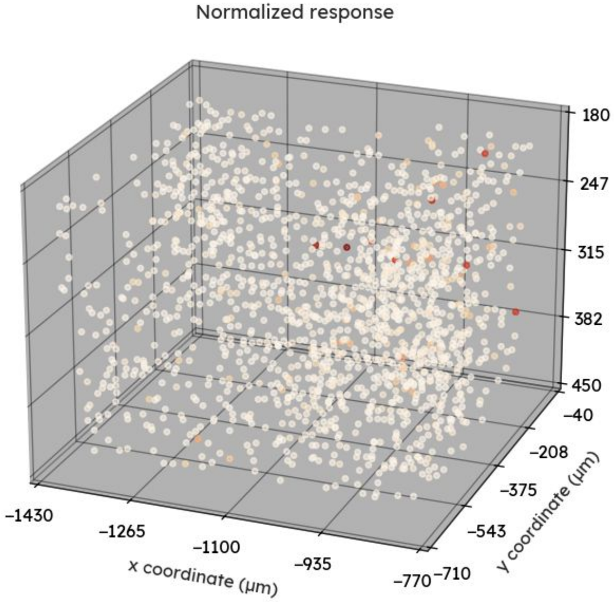

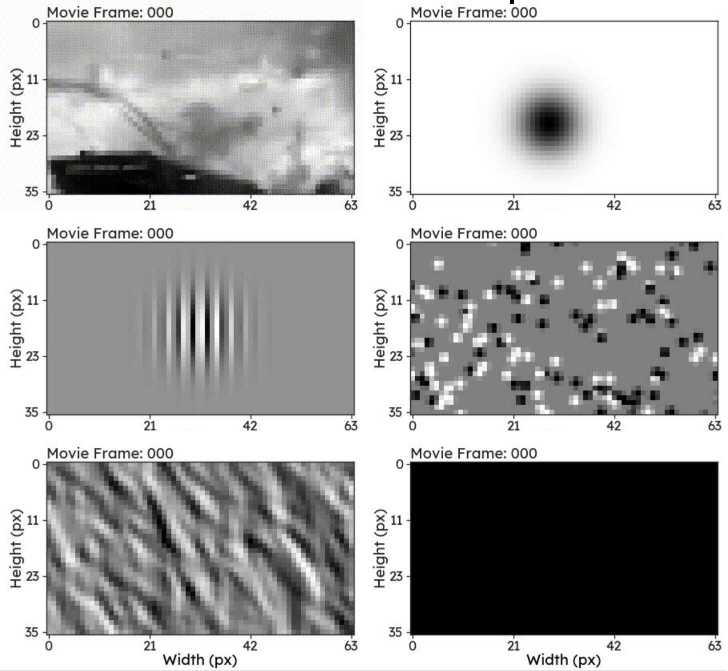

Video vision Transformer
for dynamic response prediction

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Best single model and 🥉 overall in the NeurIPS2023 challenge

movie test set

	Team	single trial correlation
1	lRomul	0.301
2	YuZhu	0.276
3	dunedin	0.254
4	gautam8387	0.231
5	dengkw	0.228
6	JBauer	0.210

OOD test set

	Team	single trial correlation
1	lRomul	0.217
2	YuZhu	0.180
3	dunedin	0.175
4	dengkw	0.147
5	gautam8387	0.141
6	BENCHMARK	0.128

Same training procedure as prev SOTA [20], +12% and +19% in movies and artificial patterns

🥉 in movie and artificial patterns in the competition overall (incl. ensembles)

🥇 in single model setting

[20] Höfling et al. bioRxiv 2022.

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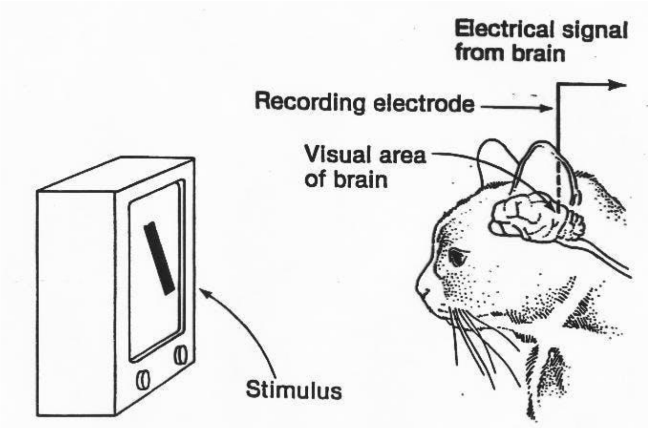
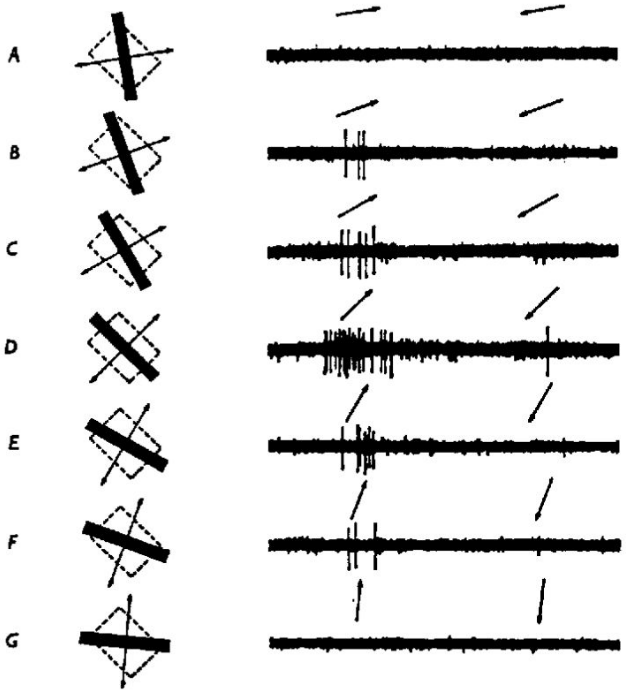
Functional twin of the mouse visual cortex

Model learns tuning properties of mouse V1 neurons



Specialized neurons that respond only to certain sensory information (e.g. orientation and direction of movement) [21]



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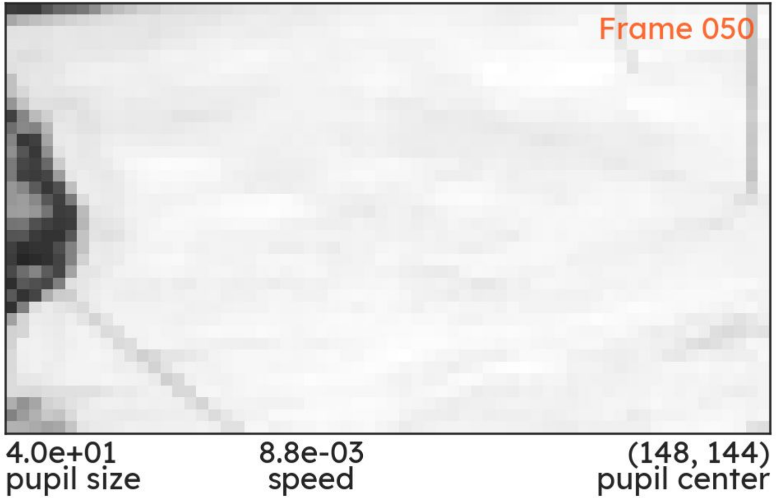
A platform to investigate the computation in the visual system *in silico*

What/where is the model looking at?



Visualize area(s) in the visual stimulus that drive response prediction via attention rollout [23]

“attention” **strictly** refers to the attention mechanism in Transformer [24]!

[23] Abnar and Zuidema, arXiv 2021. [24] Vaswani et al., NeurIPS 2017.

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Are Transformers better than CNNs in modelling the visual cortex?

IMO not necessarily

What is a good model of the visual cortex?

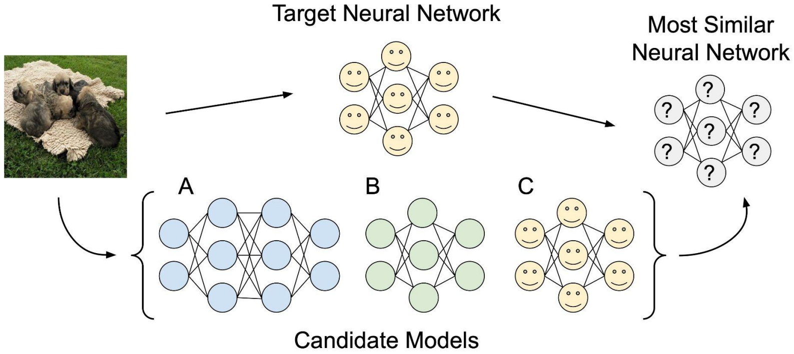
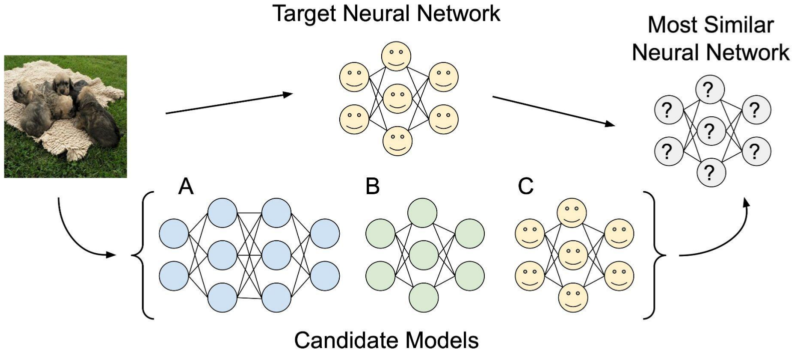


Figure 1. **Illustration of the research question:** If one of the candidate models matches the target neural network (brain) closely, can the current model evaluation methods accurately find that out?

“What I cannot create, I do not understand.” - Richard Feynman

What I can create, I do not necessarily understand?

What is a good model of the visual cortex?



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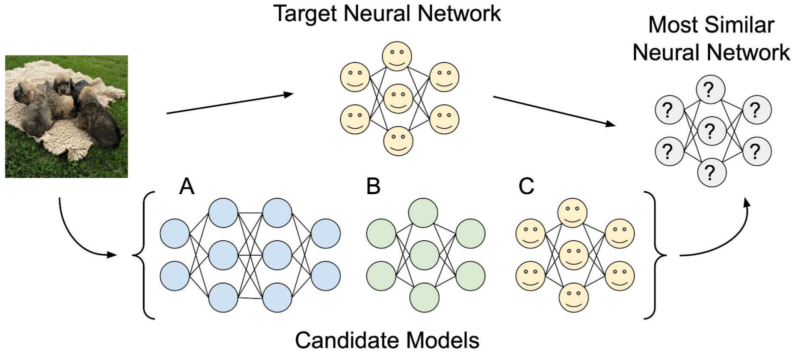
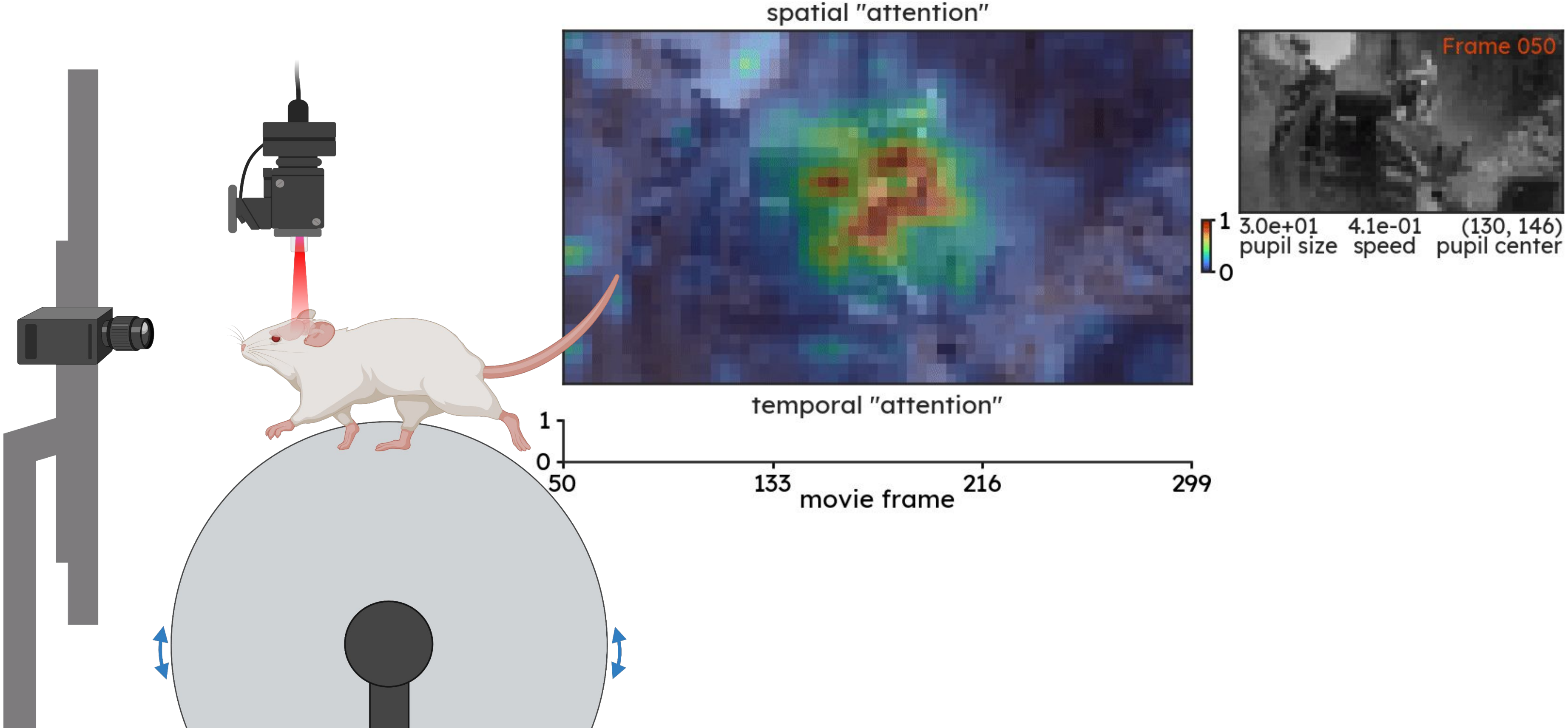


Figure 1. **Illustration of the research question:** If one of the candidate models matches the target neural network (brain) closely, can the current model evaluation methods accurately find that out?

"What I cannot create, I do not understand." - Richard Feynman

What I can create, I do not necessarily understand?

Find me @bryanlimy



slides removed

V1T

Backup

Cross-animal generalization

Cross-animal: pre-train on 4 animals, fine-tune readout on the left-out animal in Dataset S

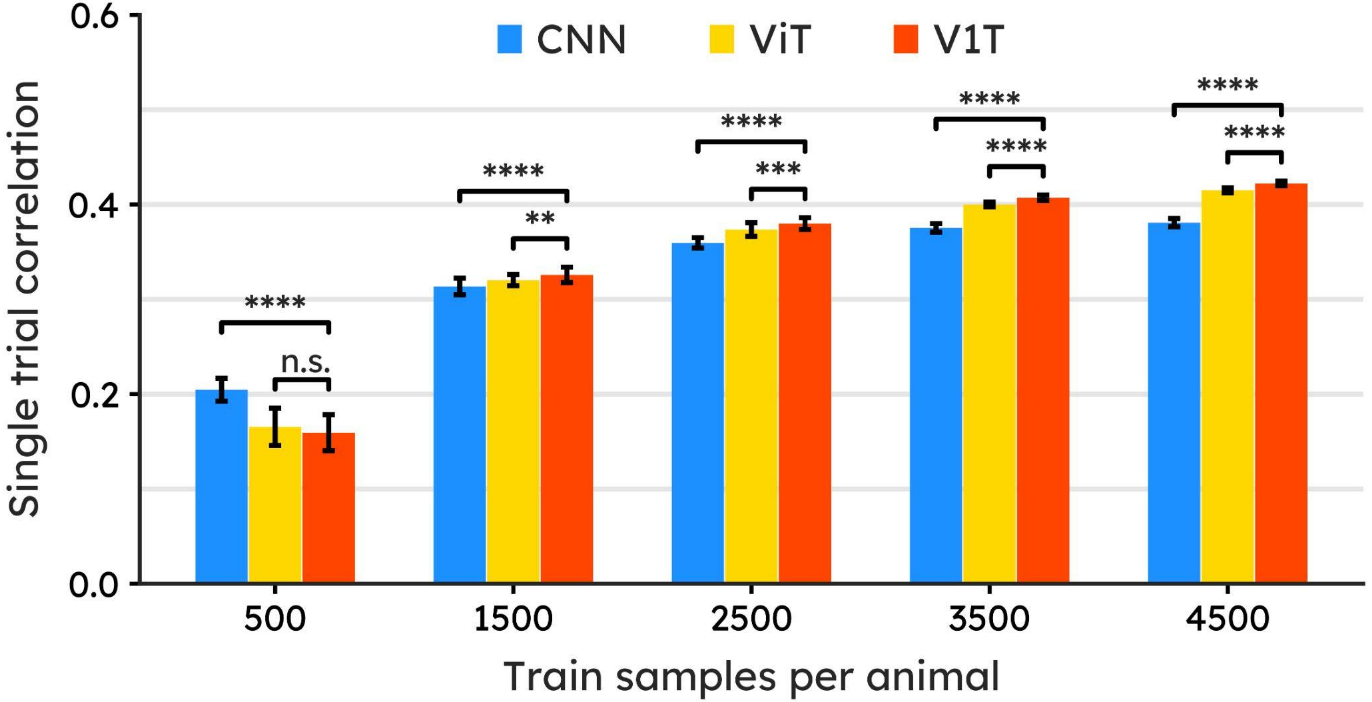
	A	B	C	D	E	mean	std
			CNN				
Original	0.350	0.424	0.385	0.371	0.360	0.378	0.029
1-out	0.353	0.394	0.373	0.365	0.333	**0.364**	0.023
% diff	0.920	-7.102	-3.101	-1.570	-7.479	**-3.666**	**3.609**
			V1T				
Original	0.401	0.464	0.430	0.436	0.401	0.426	0.027
1-out	0.388	0.450	0.415	0.417	0.384	**0.411**	0.027
% diff	-3.175	-2.885	-3.557	-4.381	-4.139	**-3.628**	**0.630**

Cross-dataset generalization

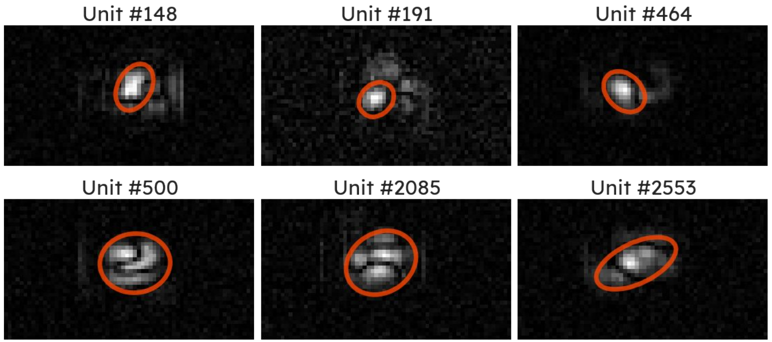
Cross-dataset: pre-train core on gray-scale Dataset F → fine-tune readouts on Dataset S

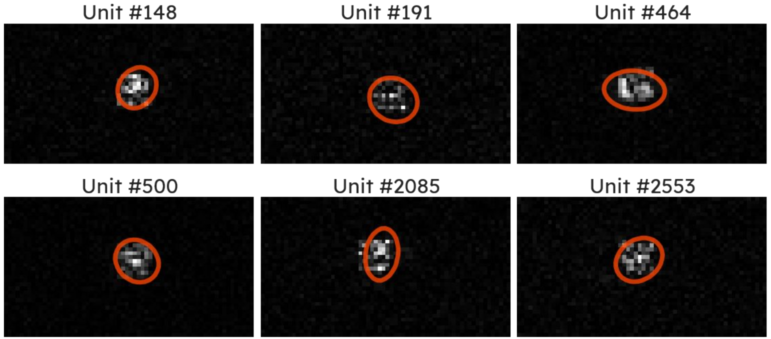
	A	B	C	D	E	mean	std
			CNN				
Original	0.350	0.424	0.385	0.371	0.360	0.378	0.029
Fine-tune	0.314	0.353	0.337	0.316	0.327	**0.329**	0.016
% diff	-10.182	-16.912	-12.373	-14.746	-9.363	**-12.715**	**3.143**
			V1T				
Original	0.401	0.464	0.430	0.436	0.401	0.426	0.027
Fine-tune	0.327	0.382	0.347	0.343	0.328	**0.345**	0.022
% diff	-18.291	-17.590	-19.310	-21.495	-18.114	**-18.960**	**1.548**

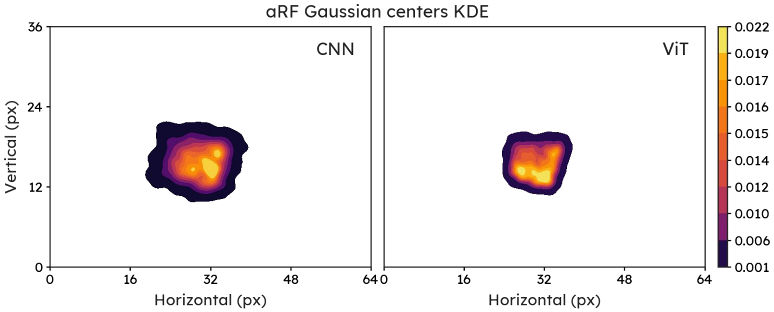
Sample efficiency

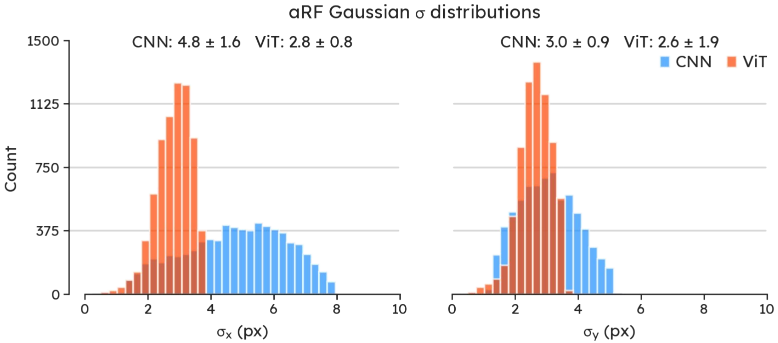


CNN vs ViT in visual response prediction

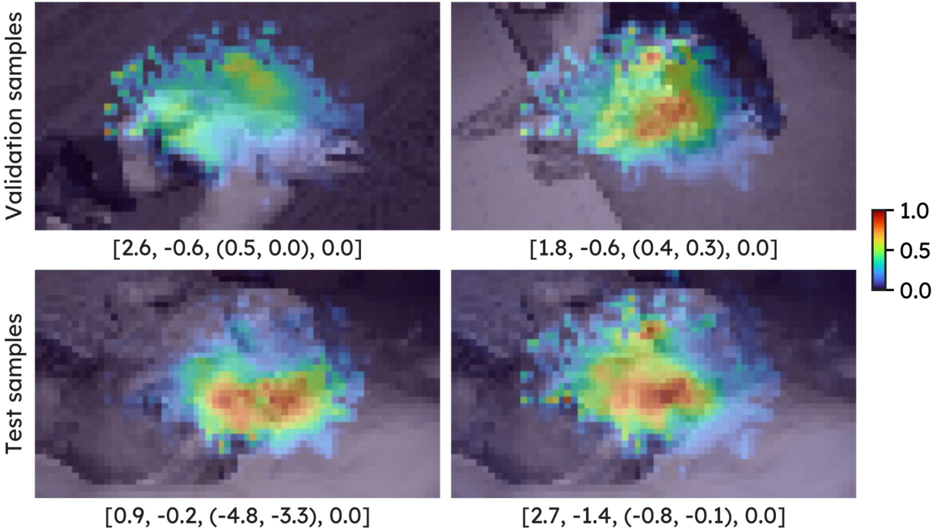








Attention rollout maps



Correlation between
pupil centers and attention map center of mass

Mouse	Horizontal	Vertical
A	0.682 (****)	0.568 (****)
B	0.489 (****)	0.493 (****)
C	0.505 (****)	0.370 (****)
D	0.484 (****)	0.310 (****)
E	0.464 (****)	0.302 (****)
Avg.	0.525	0.409

Application

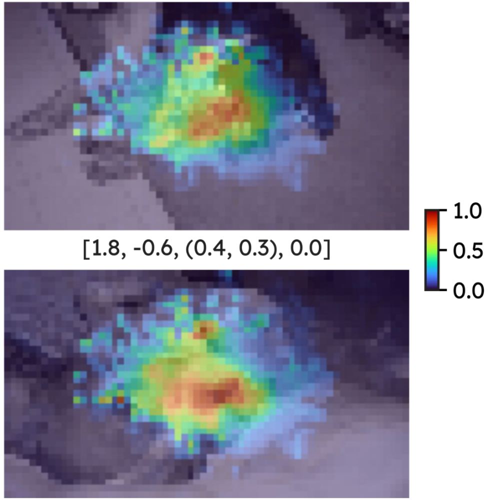
Investigate the coding of visual information across visual cortical areas

- e.g. larger receptive fields in higher visual areas

Determine which part of a visual scene was relevant when performing more specific tasks

- e.g. object recognition, decision-making, or spatial navigation

“Attention-guided” visual predictive models



[1.8, -0.6, (0.4, 0.3), 0.0]

[2.7, -1.4, (-0.8, -0.1), 0.0]