Why NeuroAI Needs **Neuro*Agents***

Aran Nayebi
Carnegie Mellon University
Machine Learning Department
Neuroscience Institute (core faculty), Robotics Institute (courtesy)

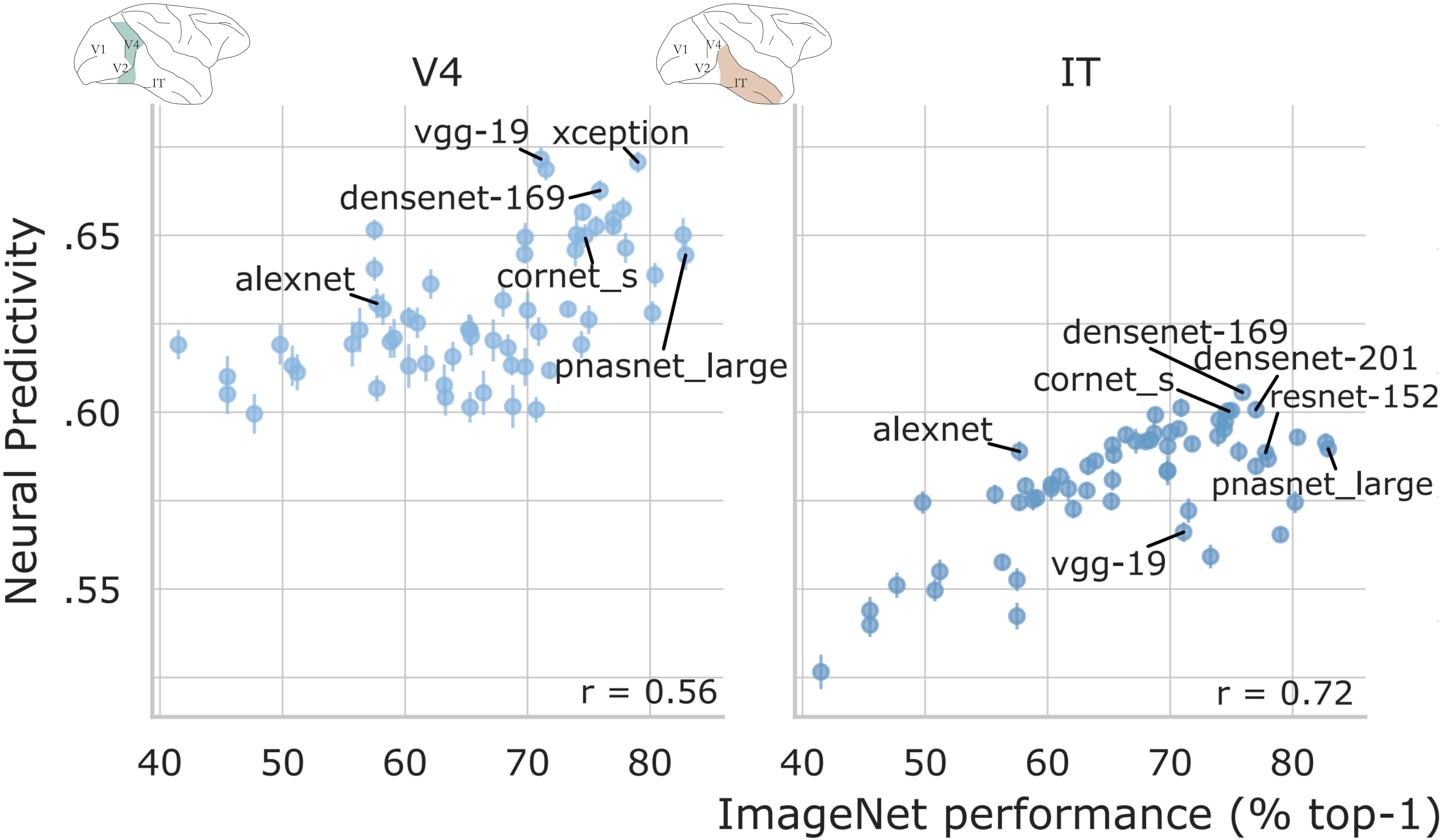
Cosyne 2025 Agents Workshop
2025.03.31

ML MACHINE LEARNING DEPARTMENT

Carnegie Mellon University Neuroscience Institute

THE ROBOTICS INSTITUTE

Similar predictivities among very different CNN architectures



Schrimpf, Kubilius* et al. 2018*

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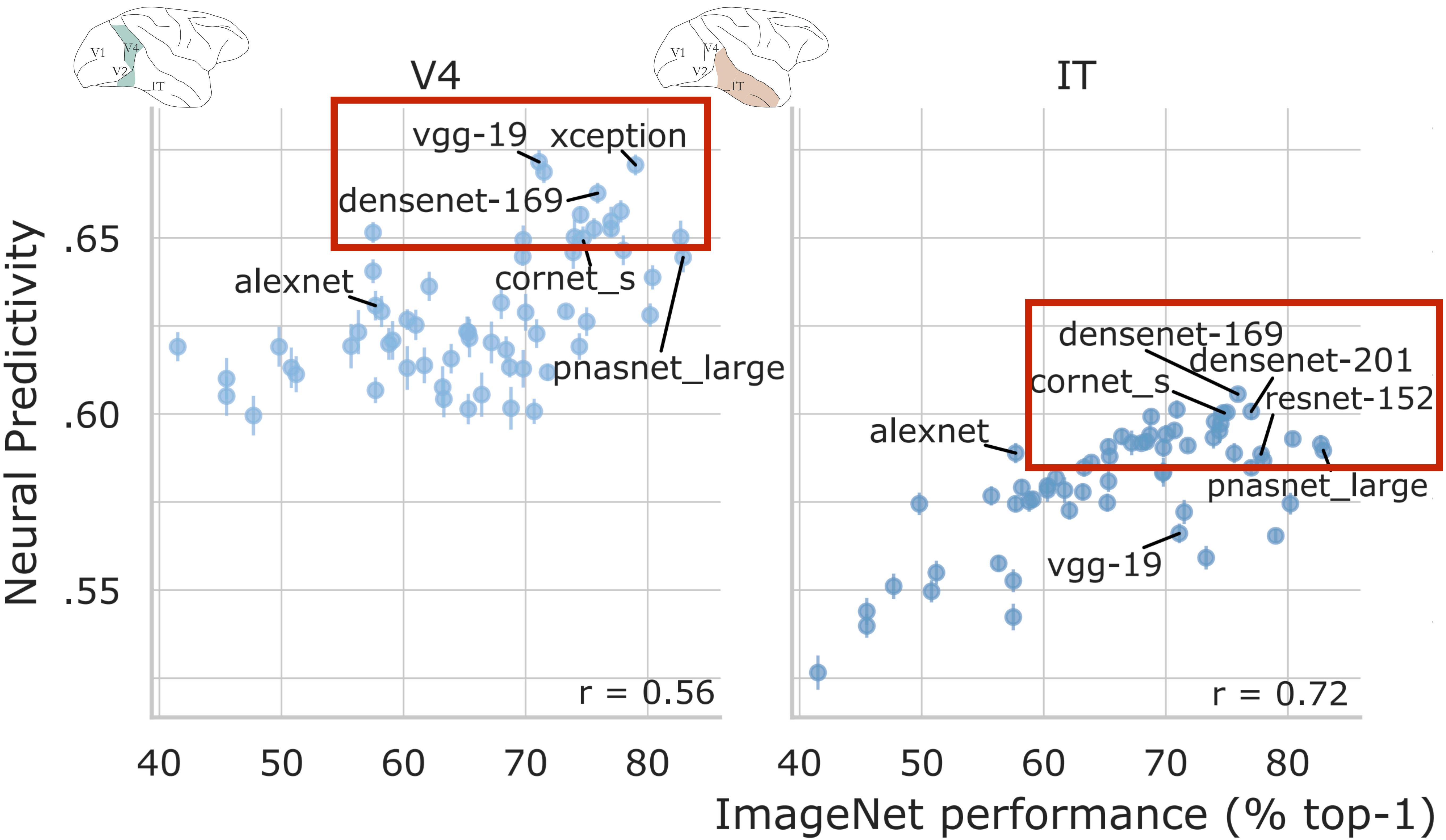

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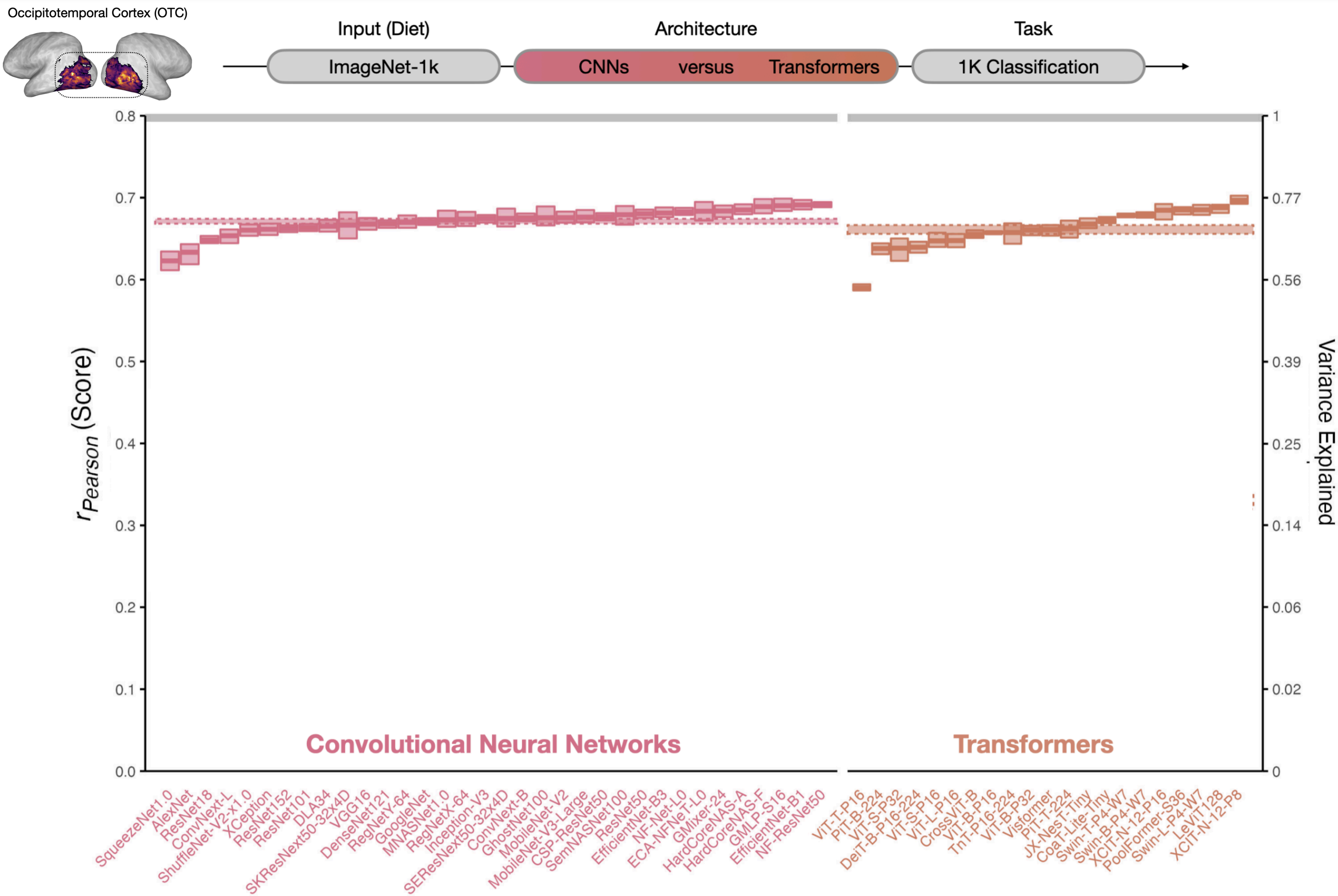

Conwell et al. 2023

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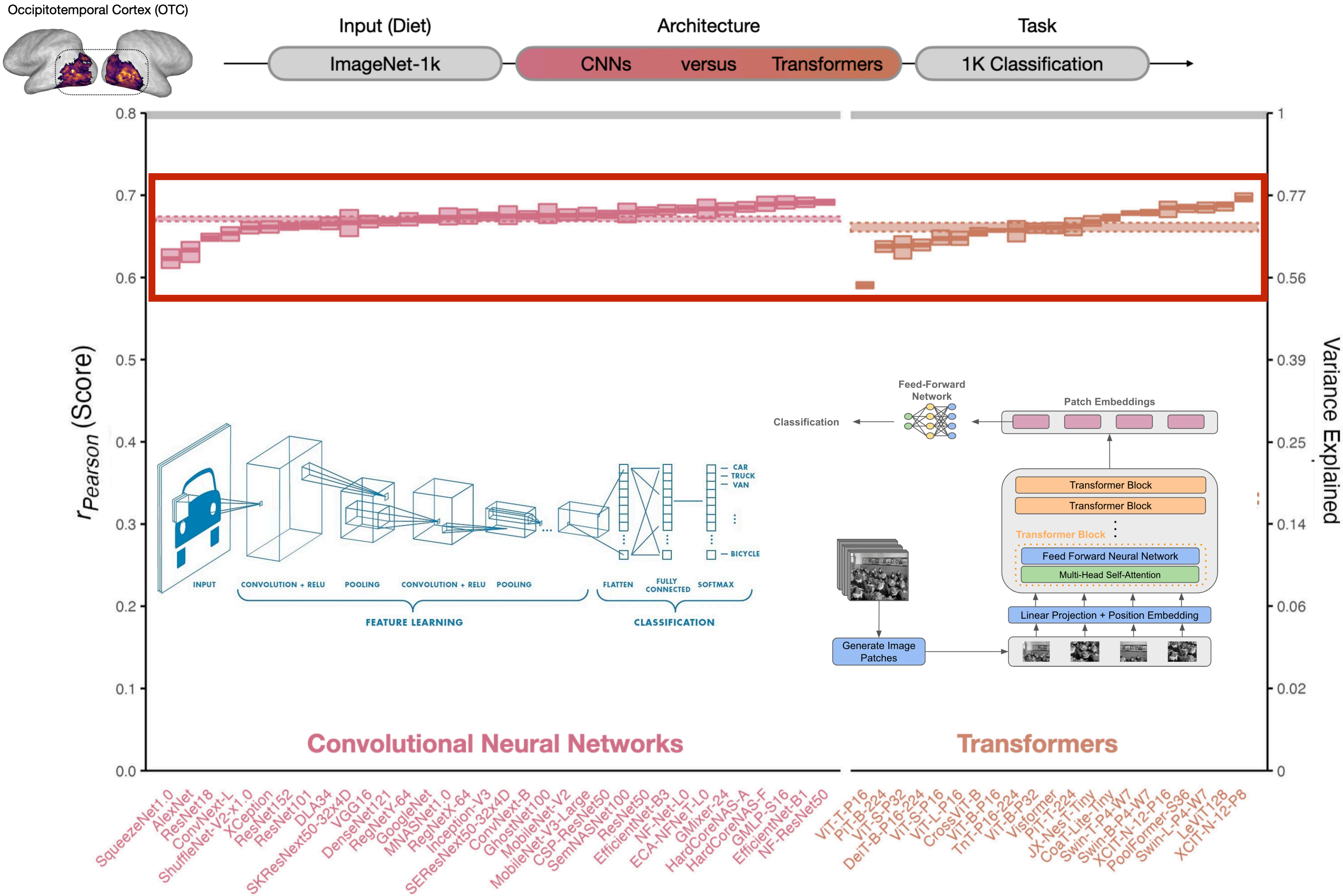

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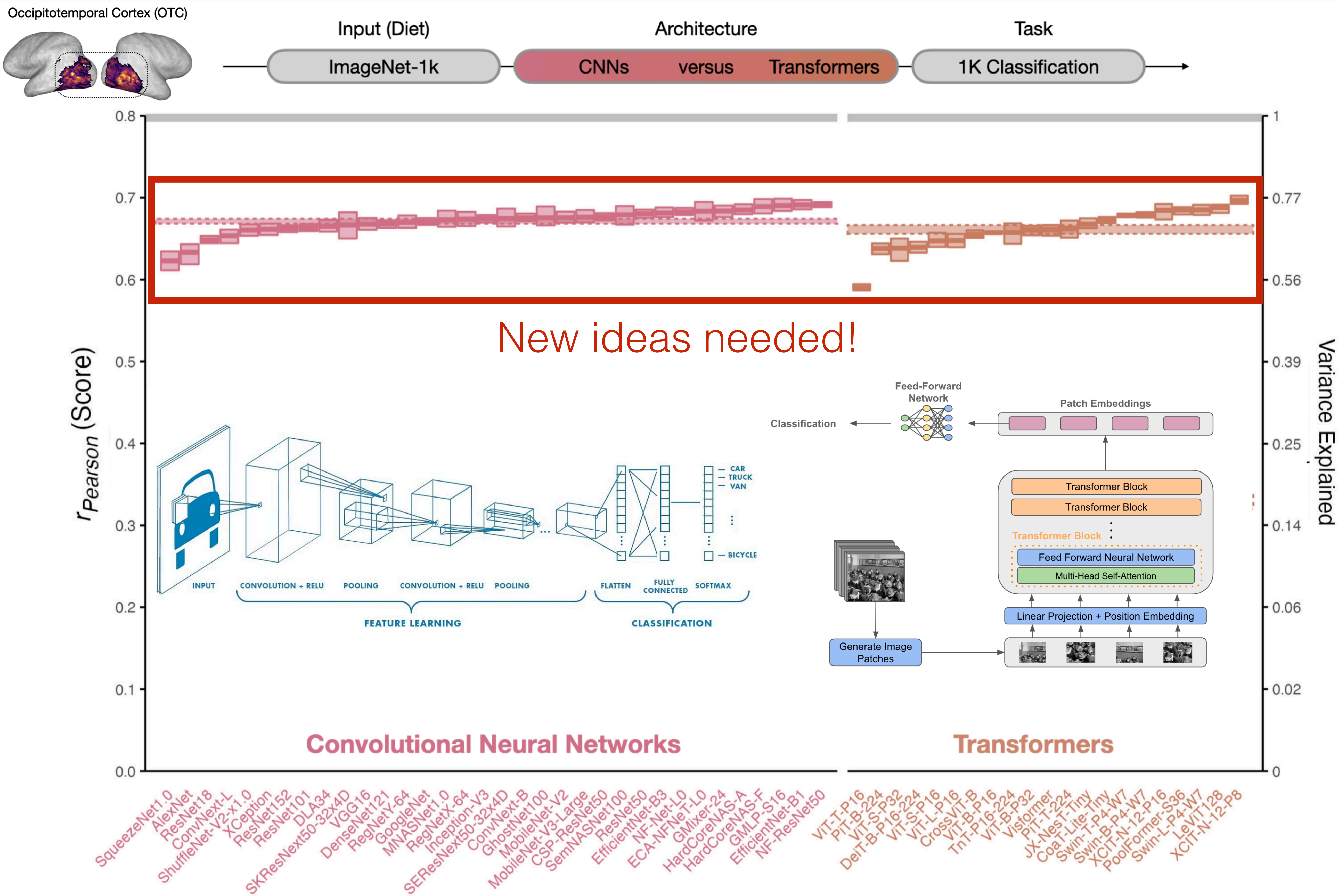

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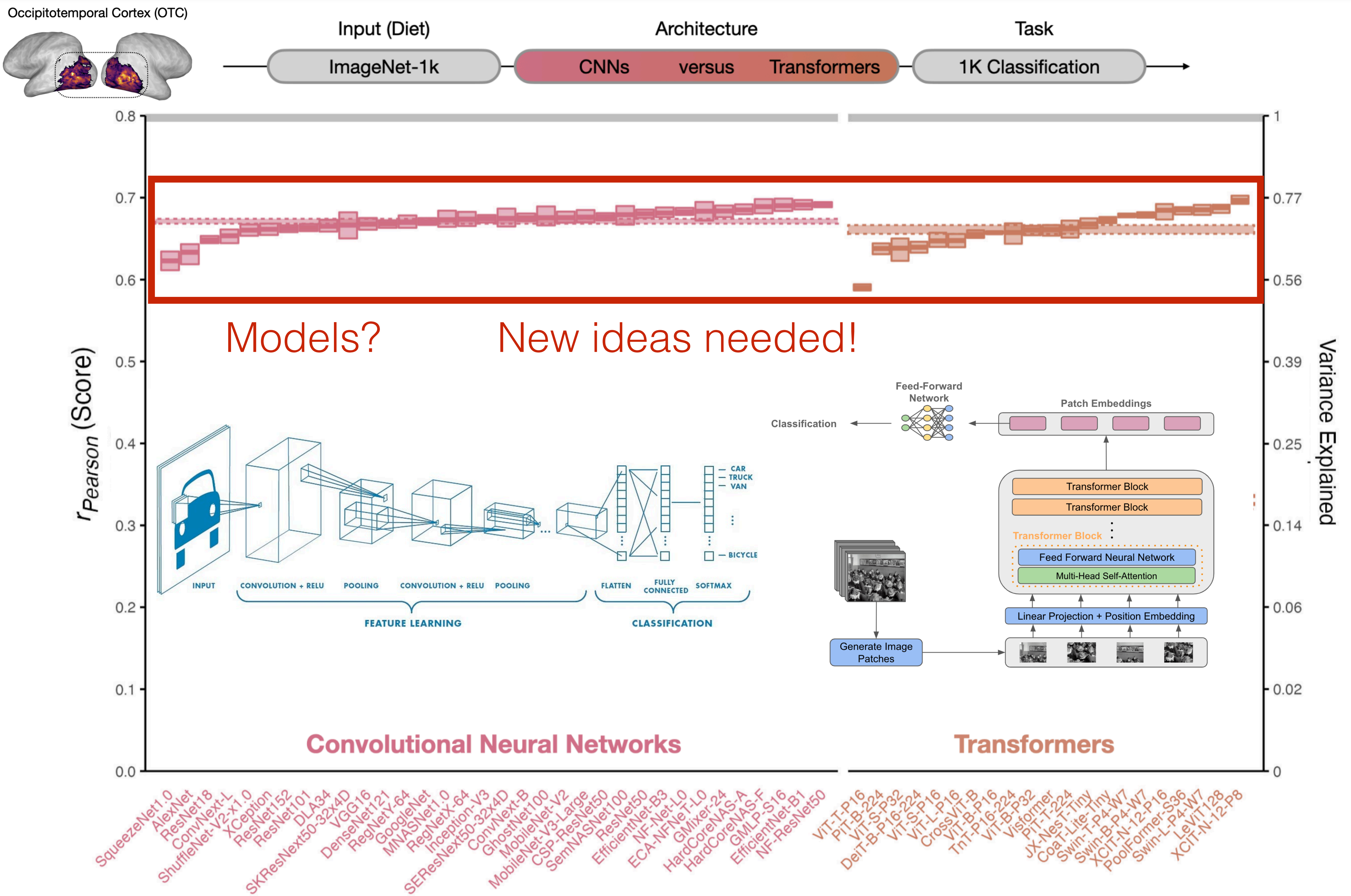

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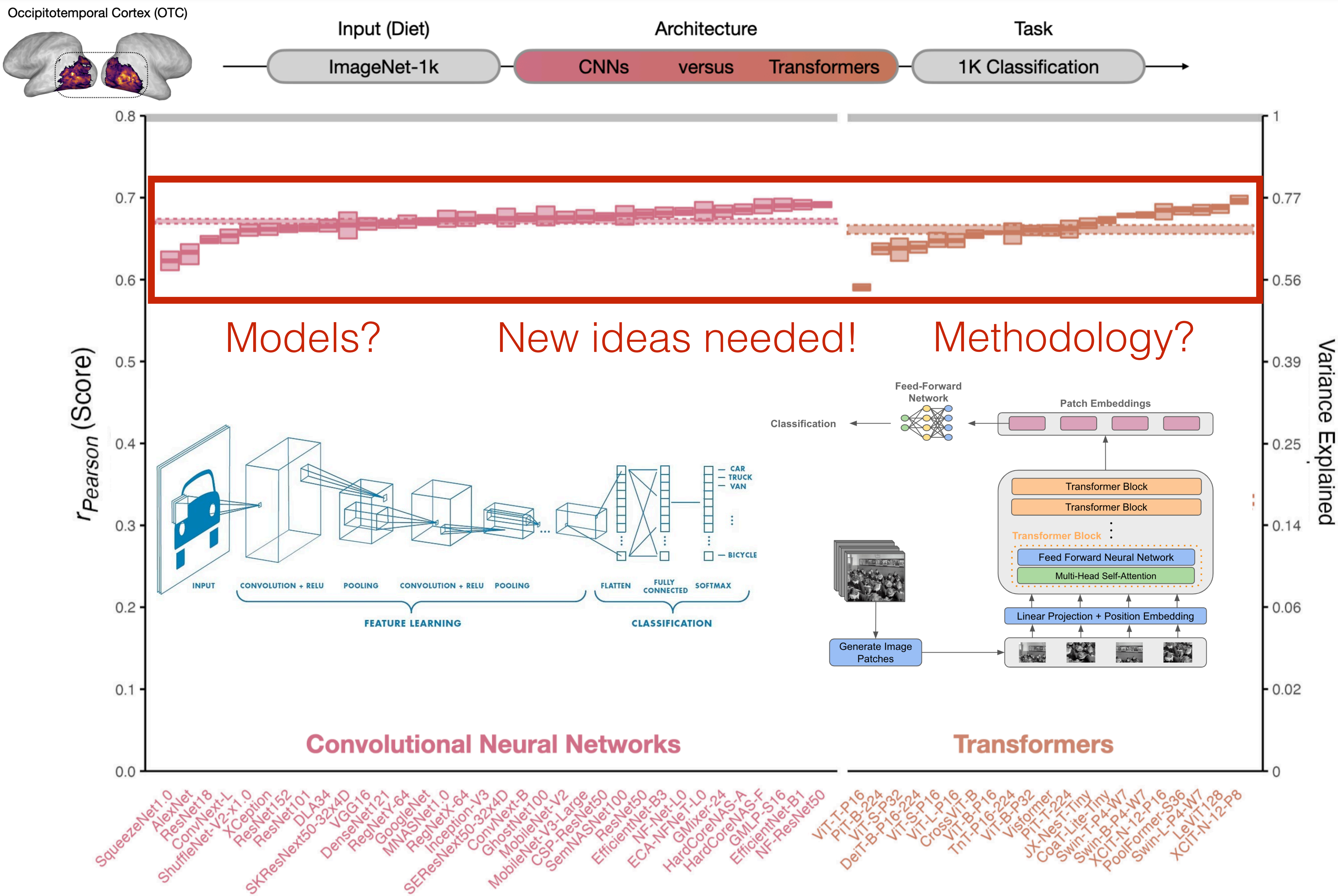

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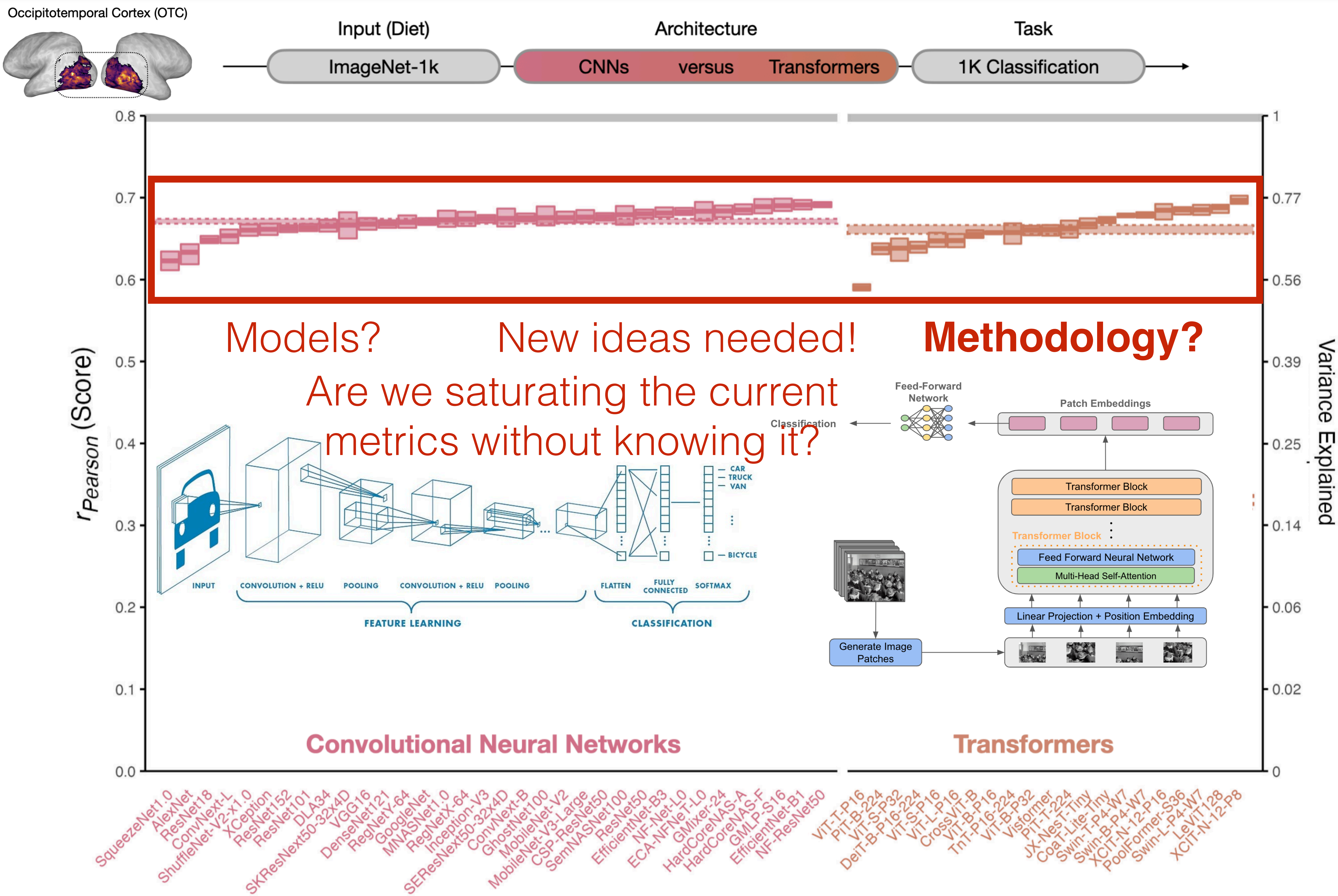

Conwell et al. 2023

Determining the Methodology

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Brain-Model Evaluations Need the NeuroAI Turing Test

Jenelle Feather[*1] **Meenakshi Khosla**[*2] **N. Apurva Ratan Murty**[*3] **Aran Nayebi**[*4]

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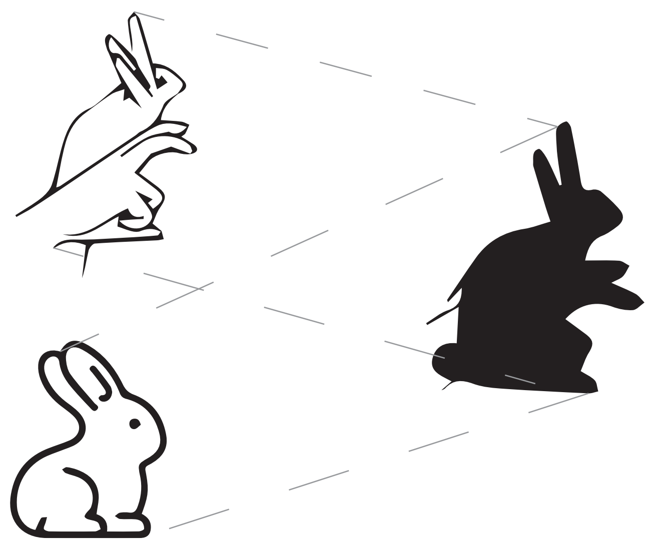
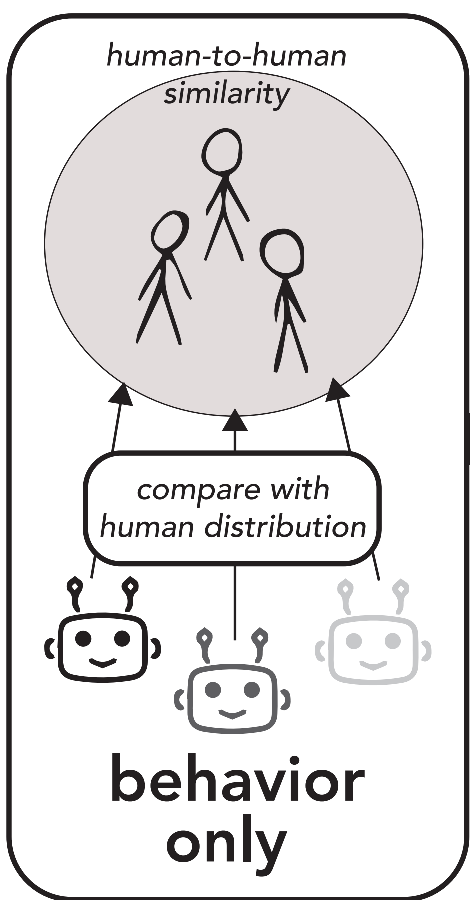
But, we do know that animals/subjects contain those desired properties (even if we can’t describe them), so we instead take a *relative* perspective

NeuroAI Turing Test

Just as distinct objects can cast the same shadow…



Turing Test



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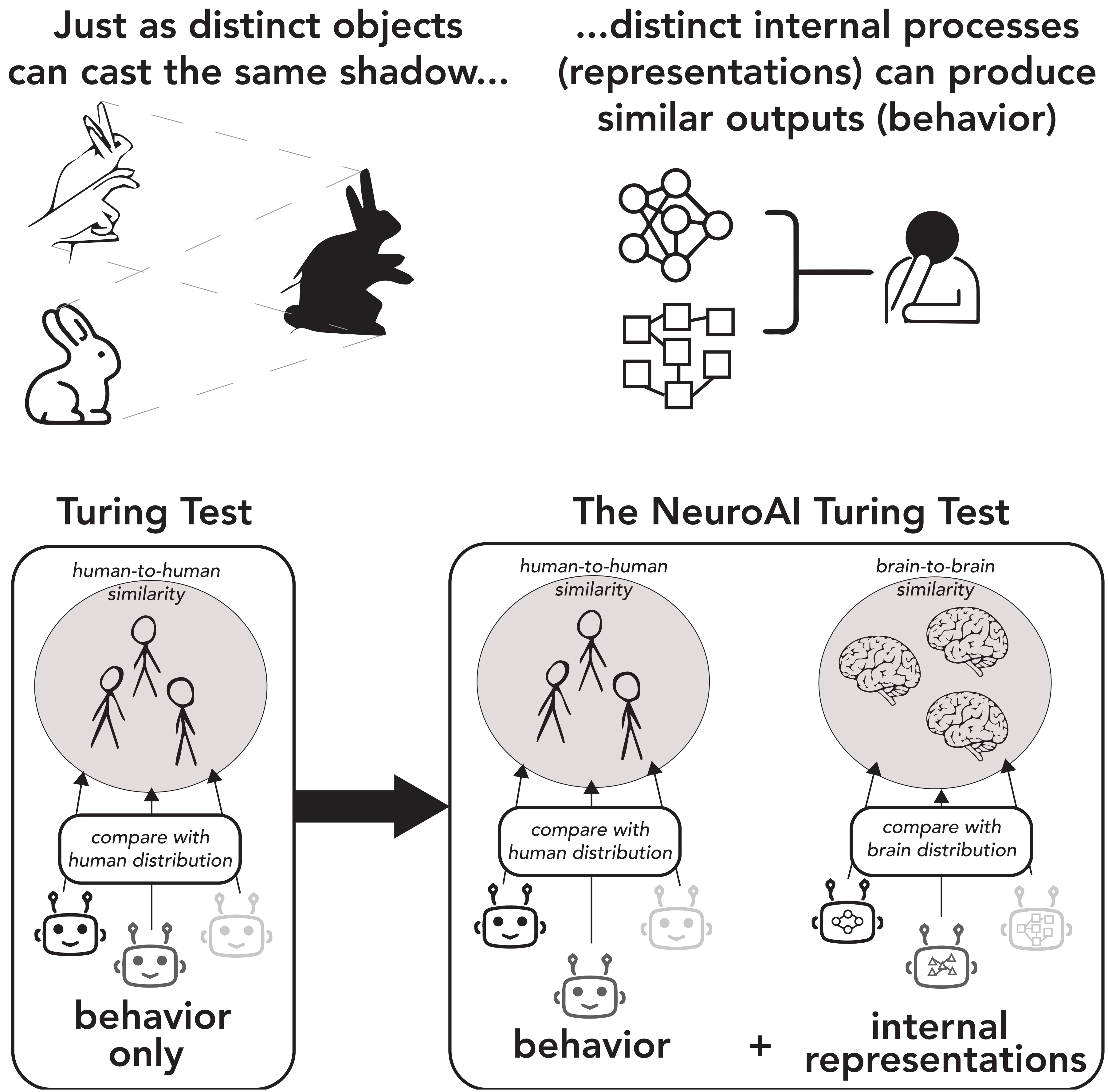

NeuroAI Turing Test: Possible Scenarios

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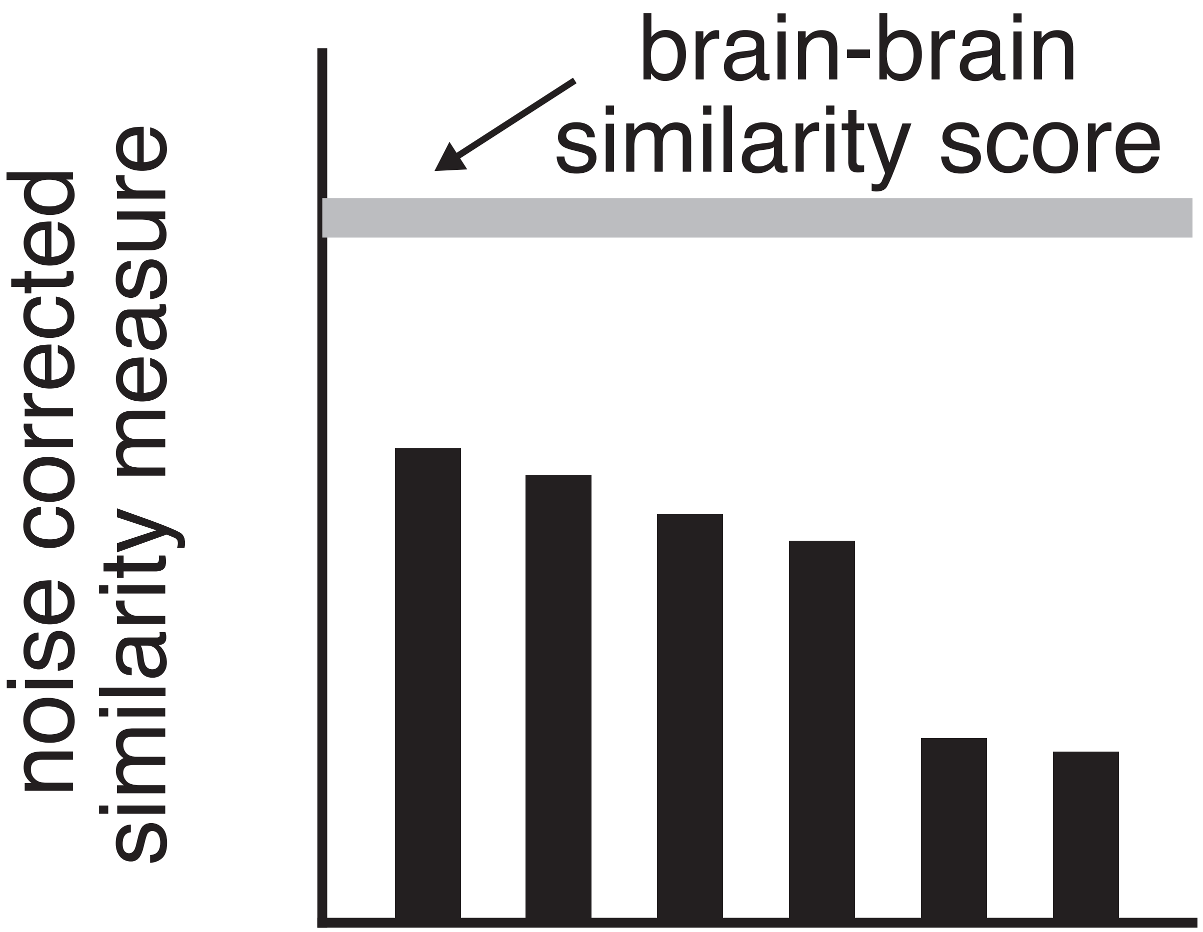

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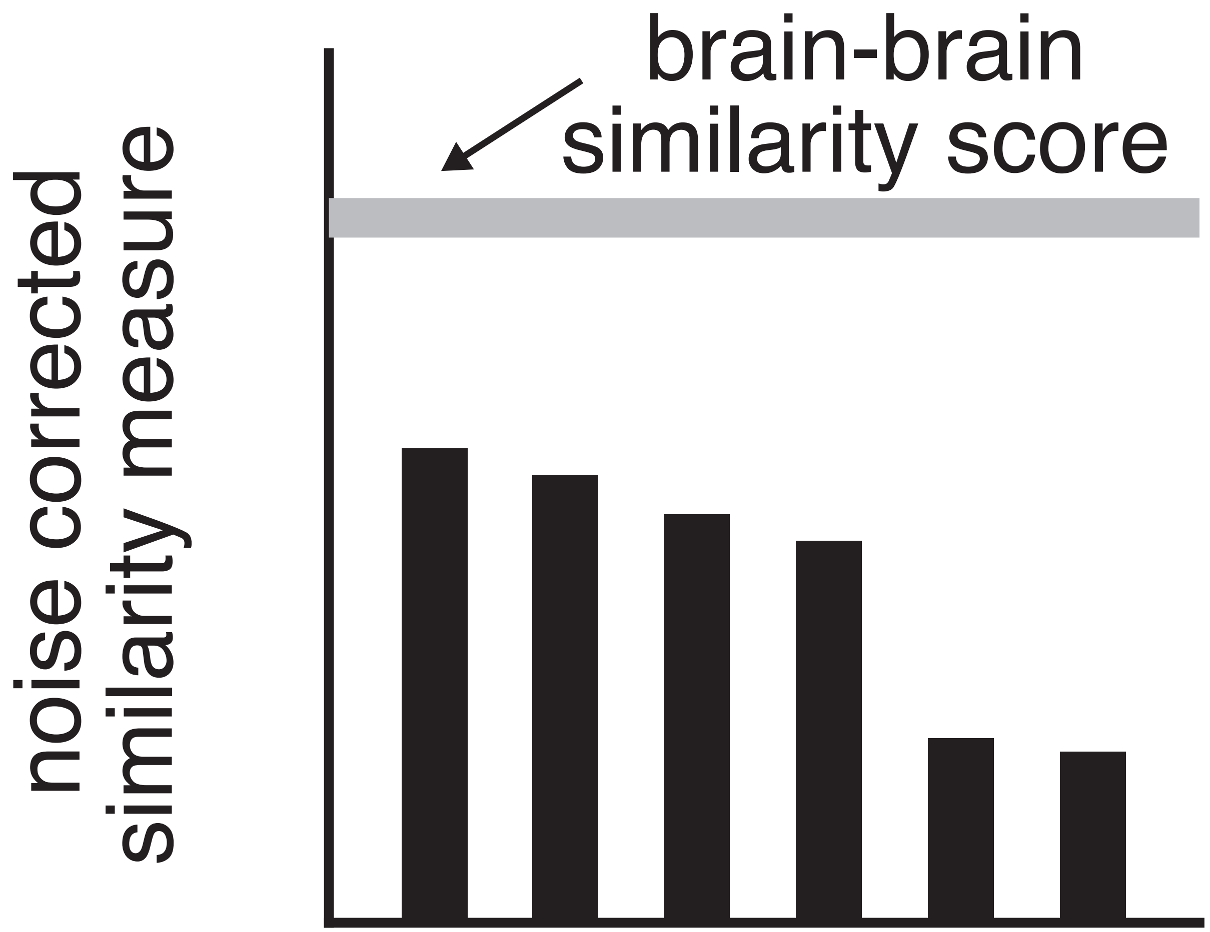

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Continue to refine models to improve on the benchmark

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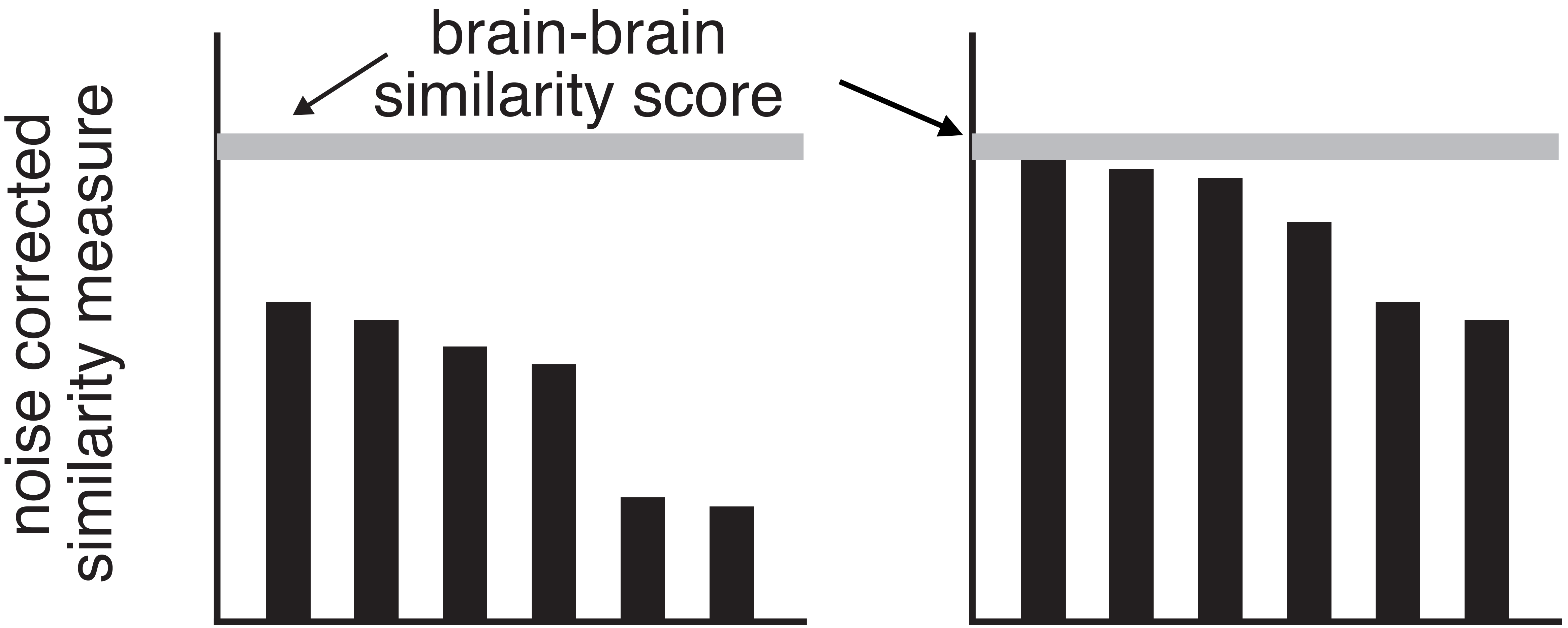

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Models reach brain-brain similarity, brain-brain similarity close to noise ceilng

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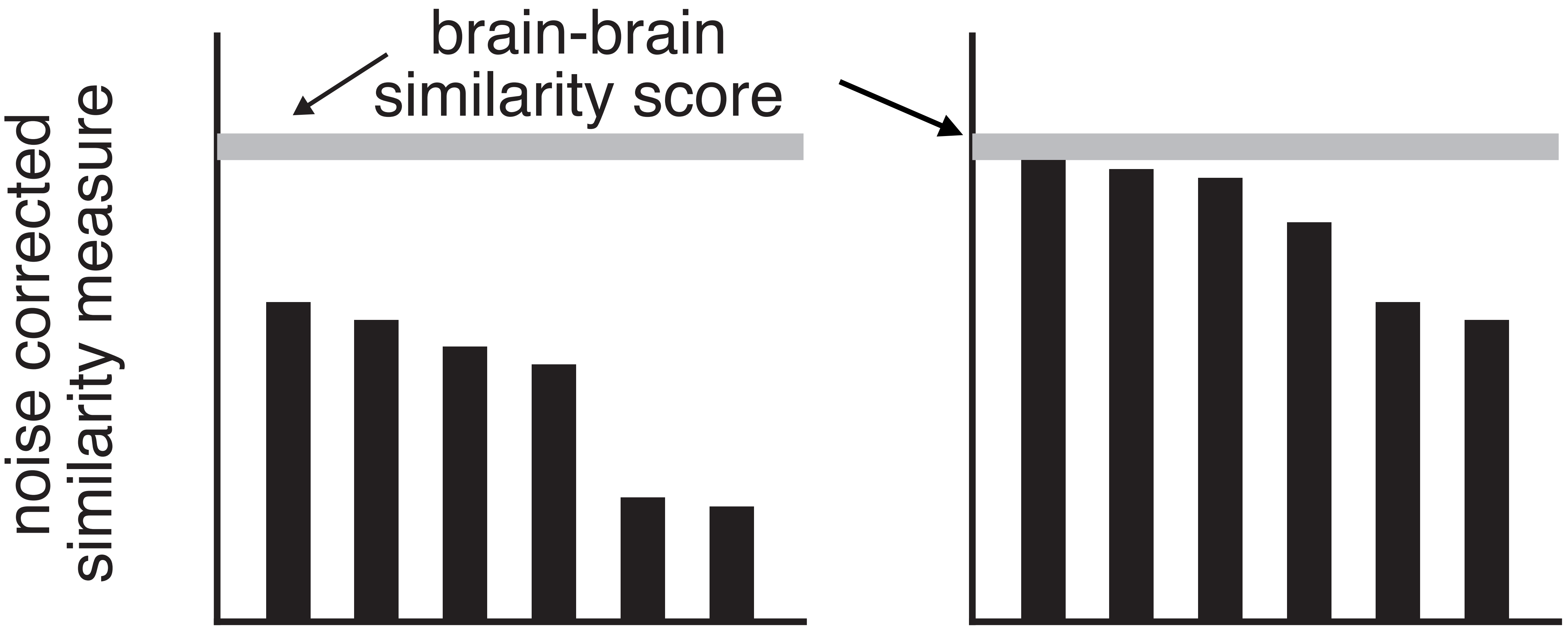


No models reach brain-brain similarity

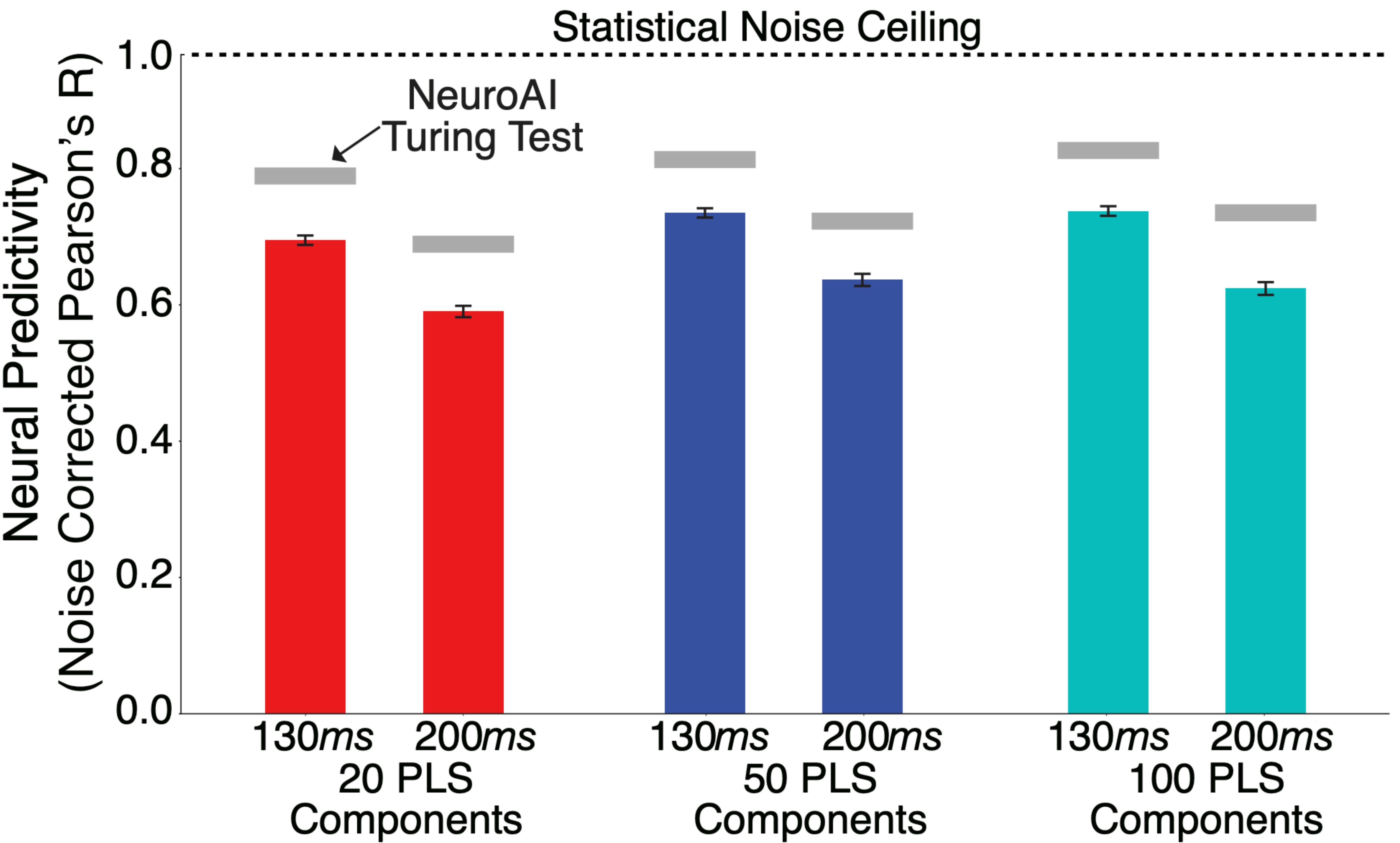
Models reach brain-brain similarity, brain-brain similarity close to noise ceilng

Continue to refine models to improve on the benchmark

Benchmark is saturated, move on to other benchmarks.

NeuroAI Turing Test: An Example in Primate Object Recognition

adapted from Nayebi et al. 2022, Fig S7B



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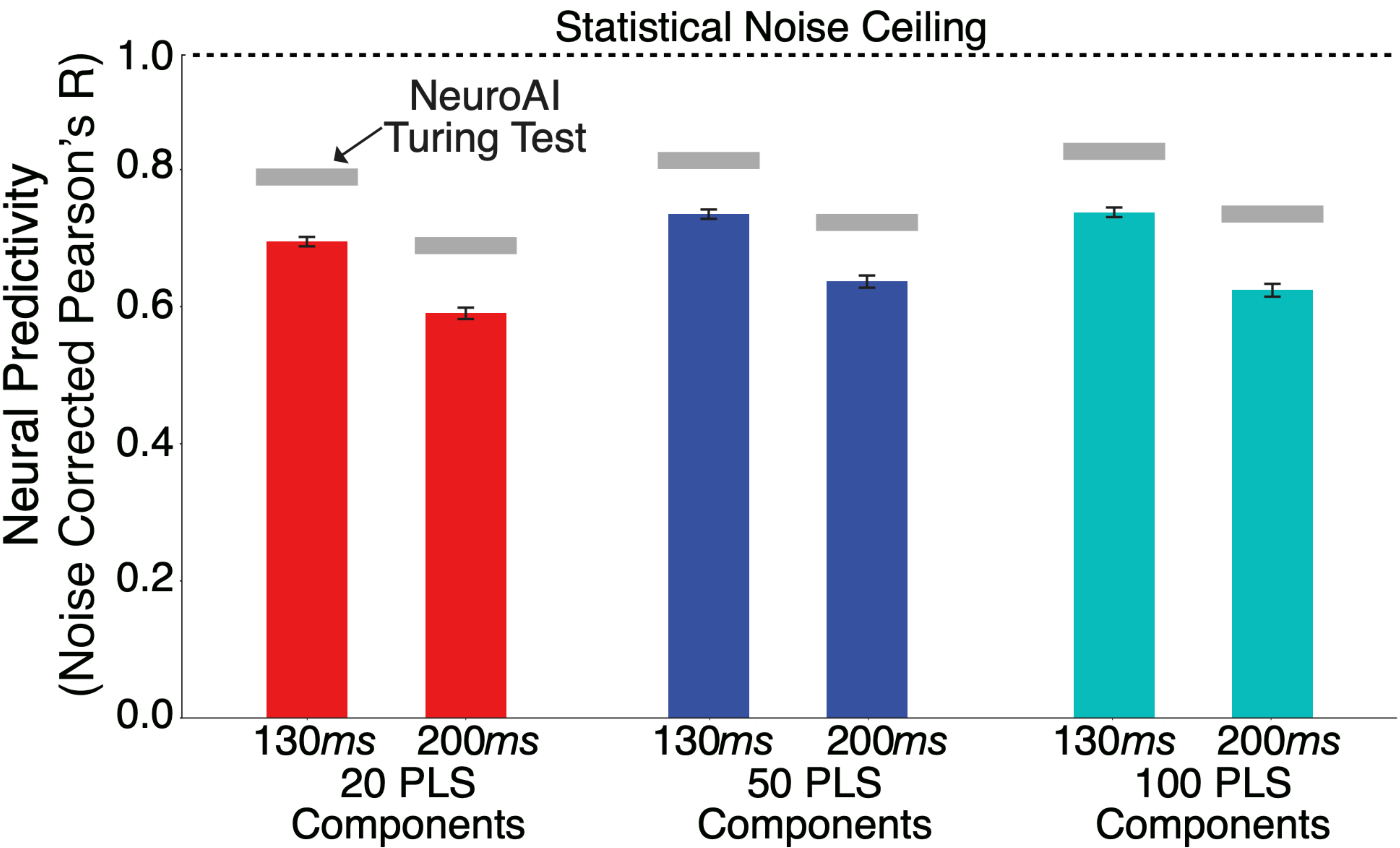

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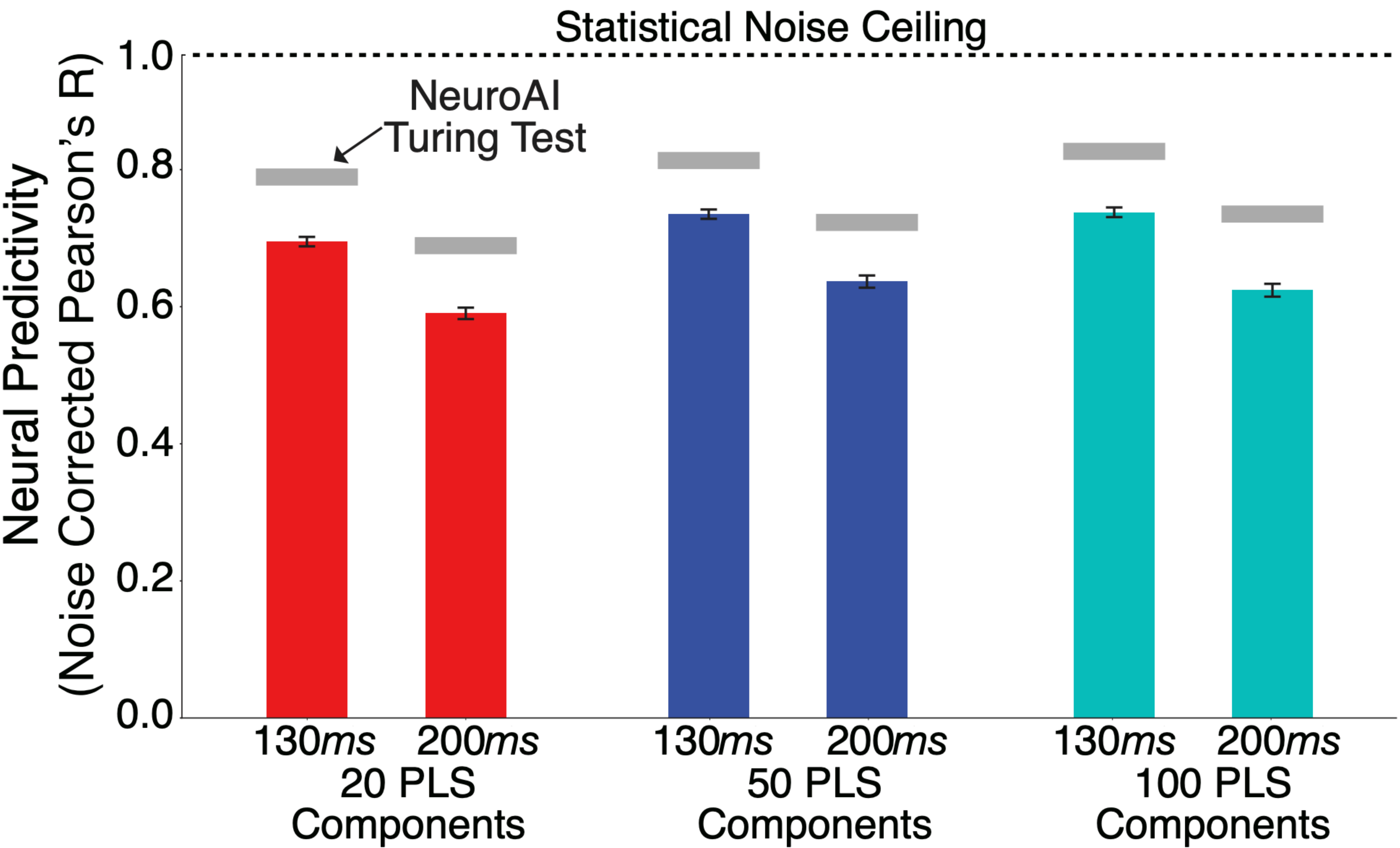

NeuroAI Turing Test: An Example in Primate Object Recognition

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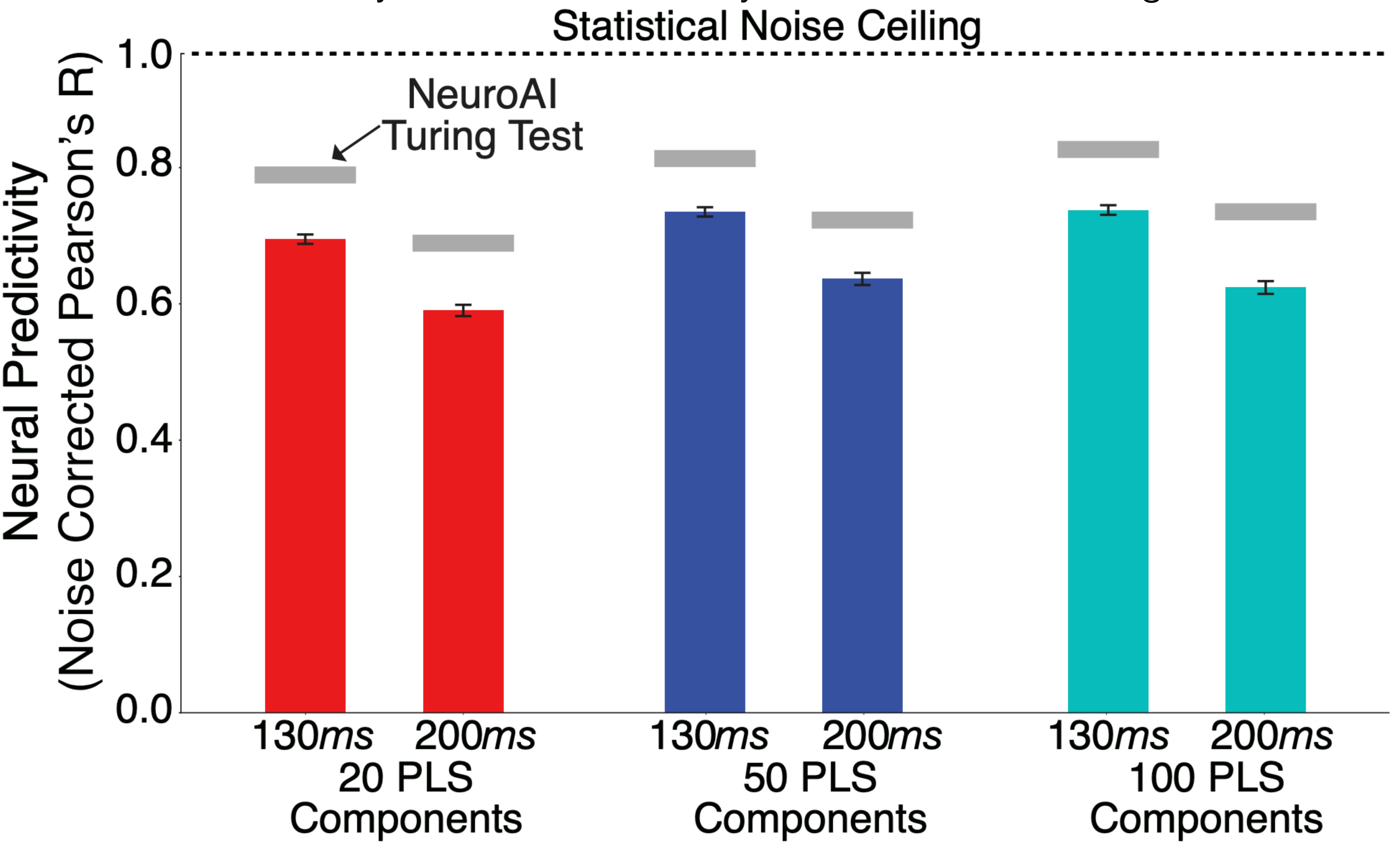
But I will show you that we haven’t yet in embodied intelligence…



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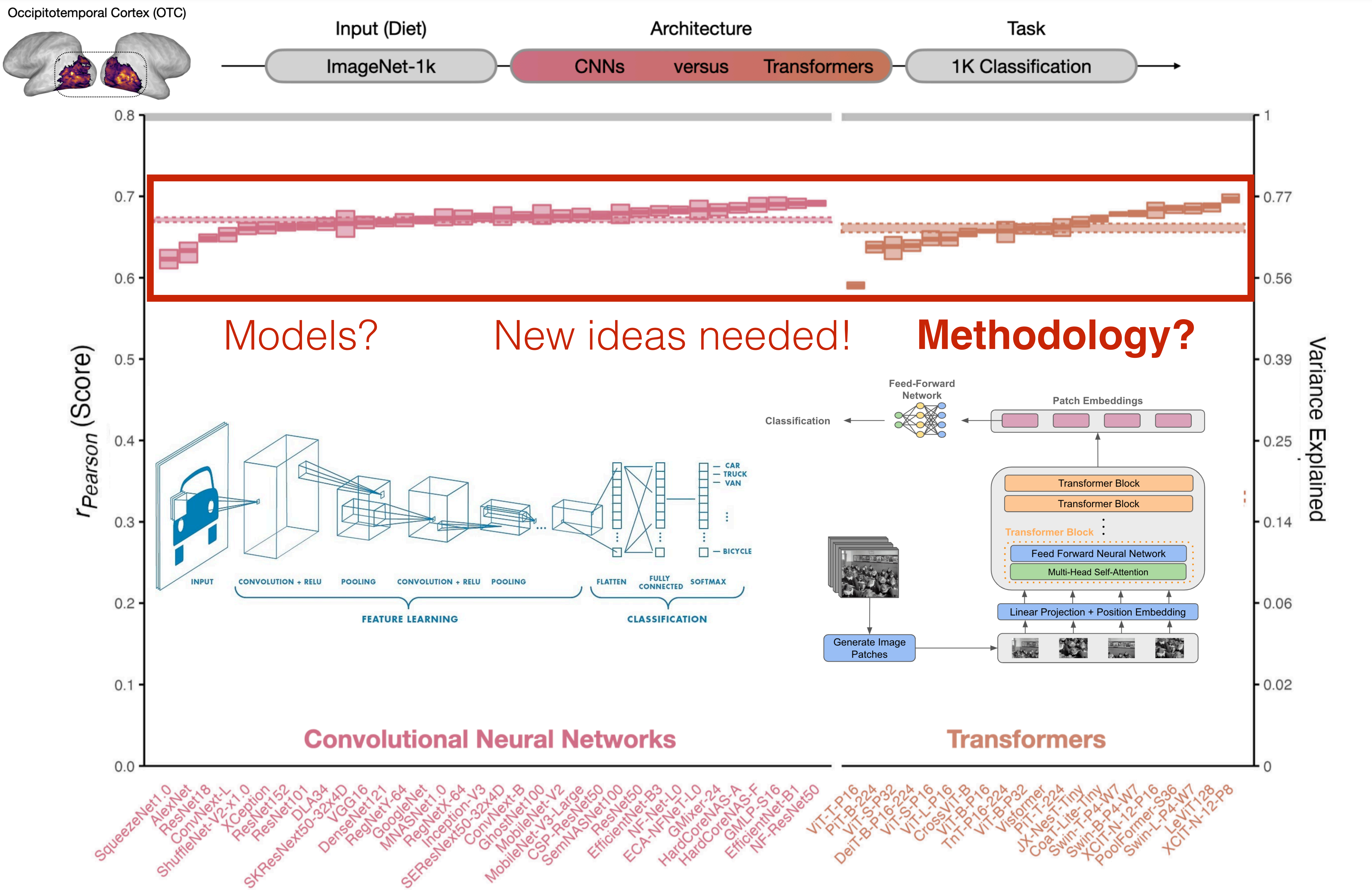

Conwell et al. 2023

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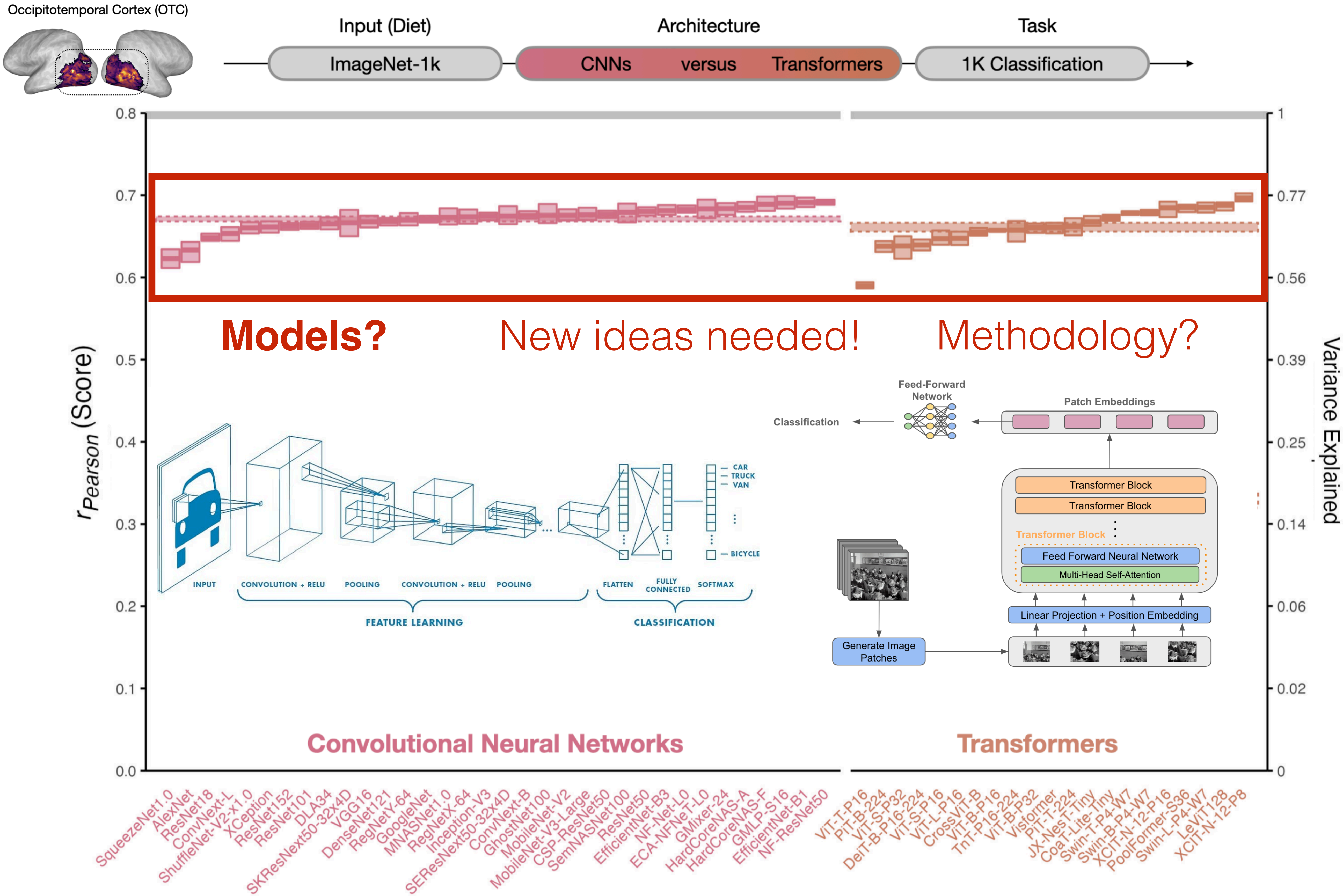
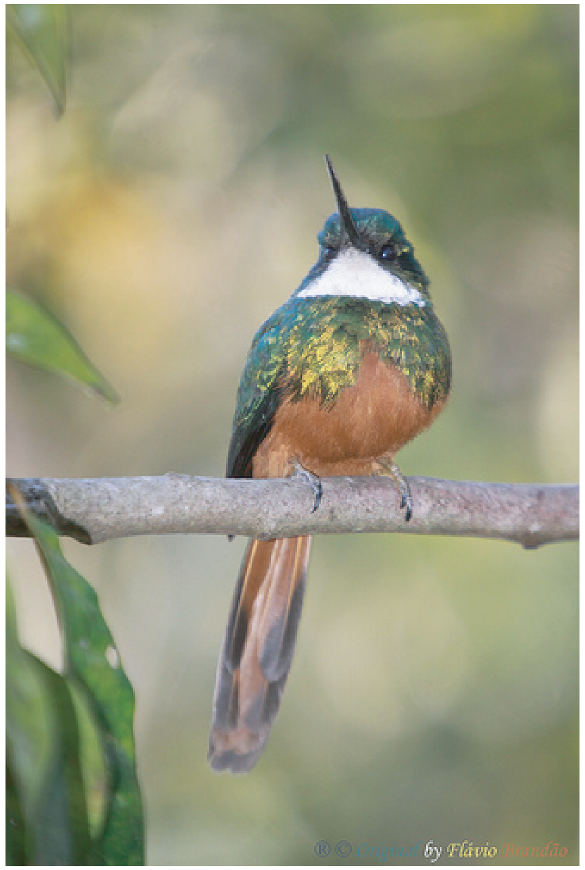


Conwell et al. 2023

We do a lot more than passive viewing…



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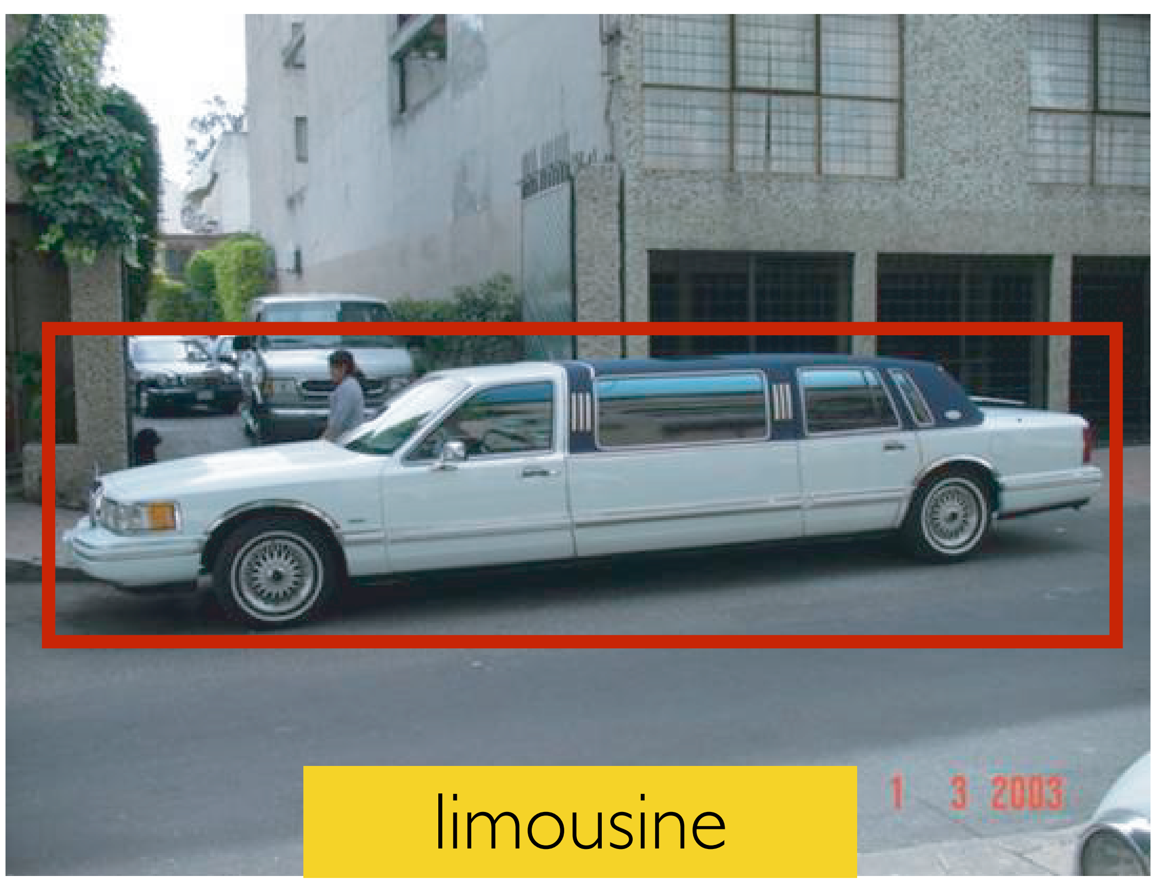

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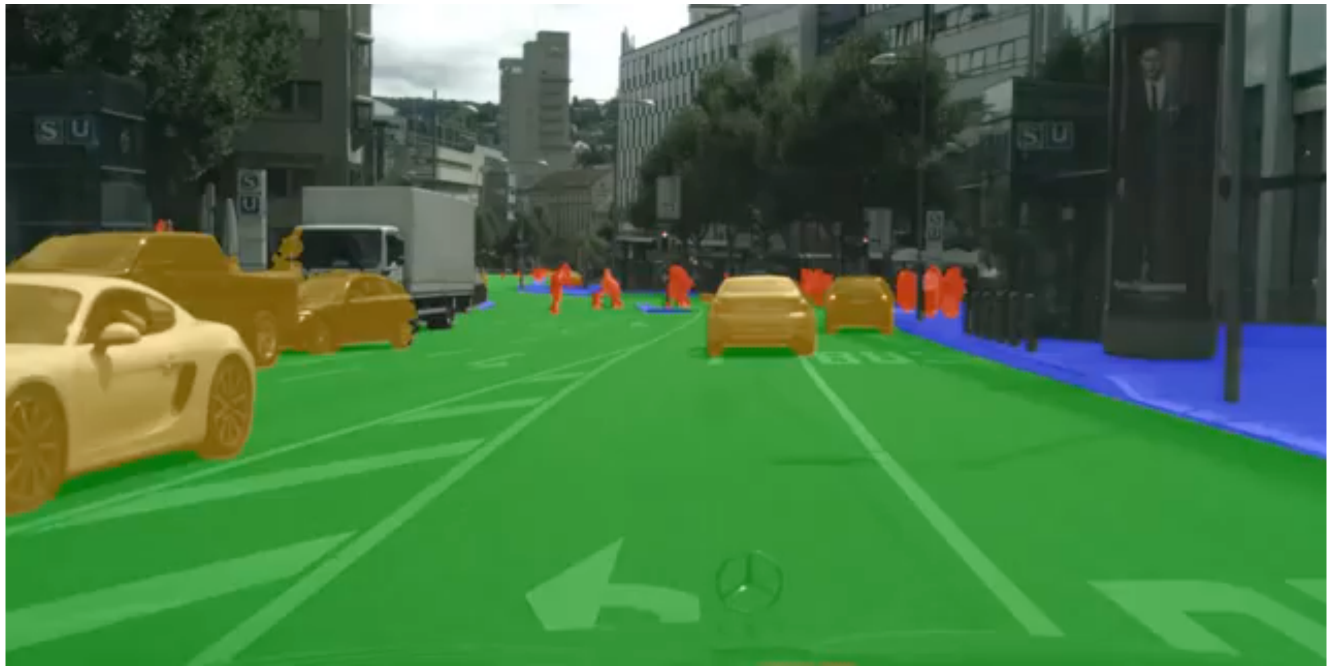

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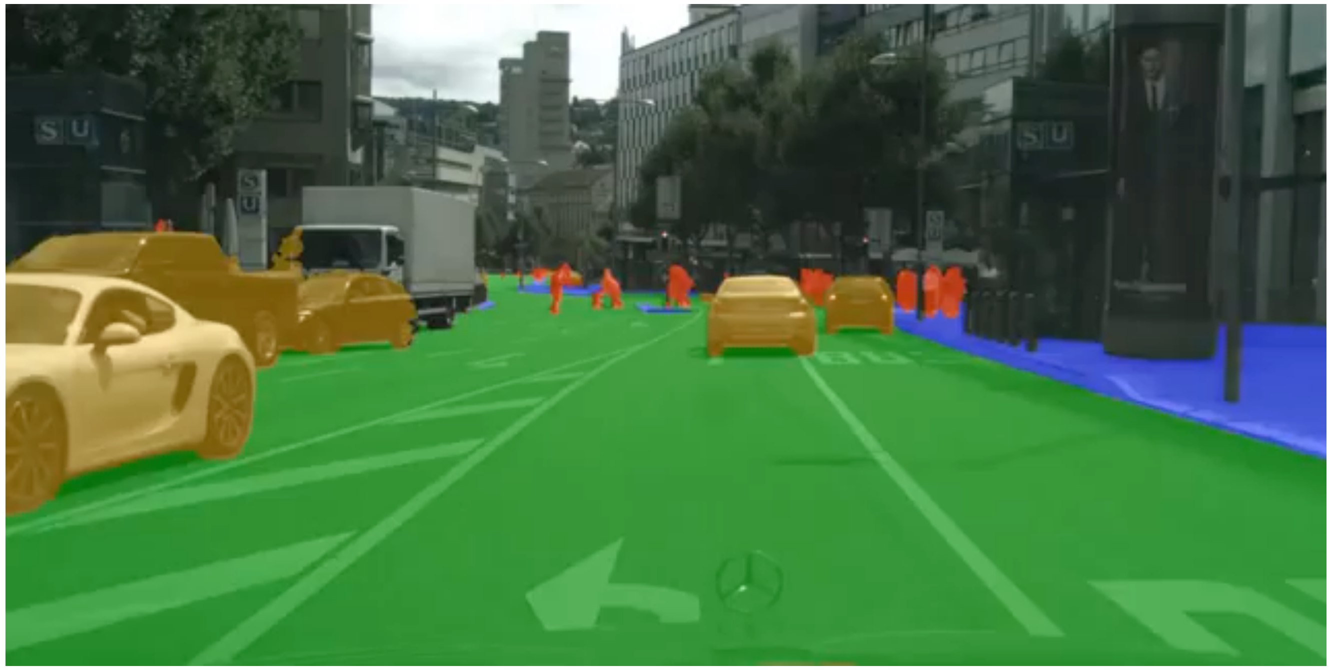

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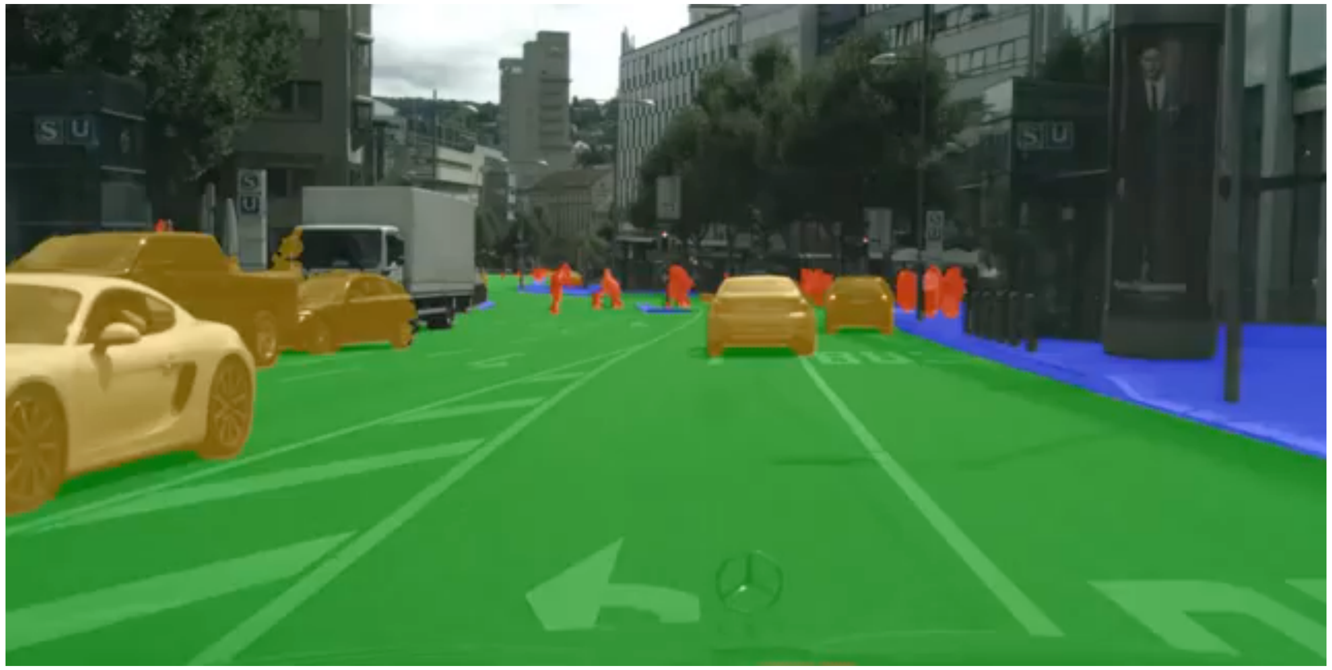

Multi-Step Planning

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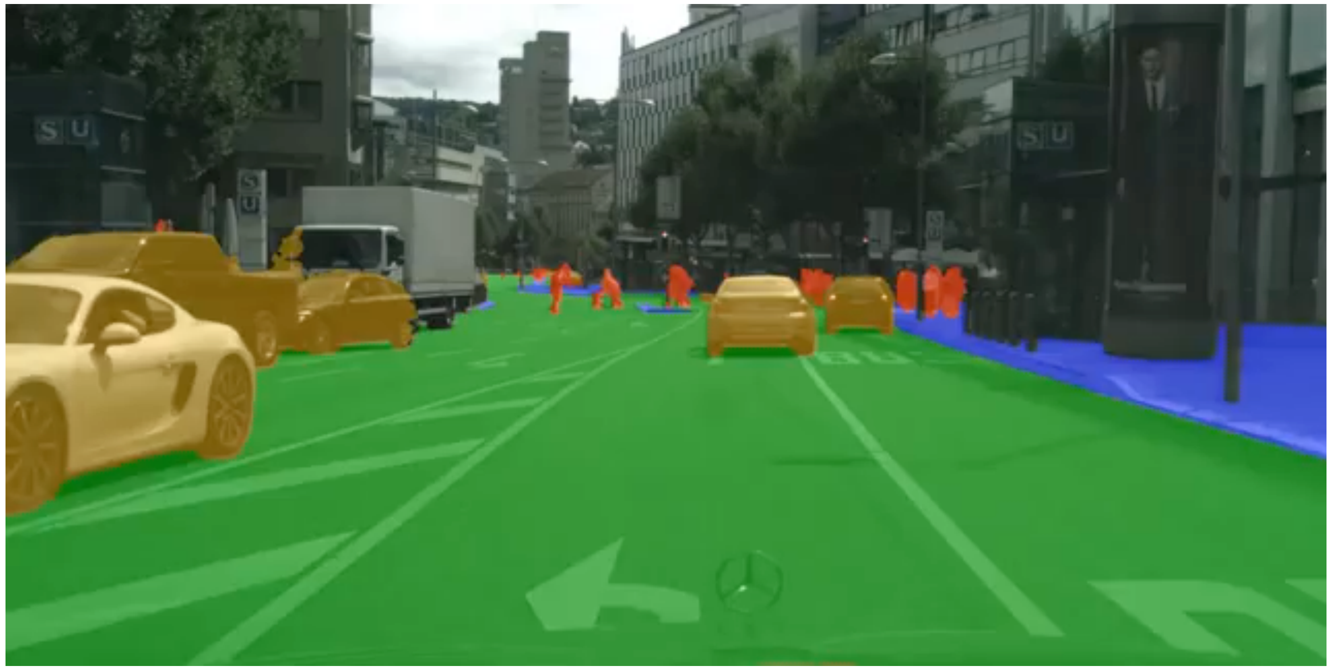

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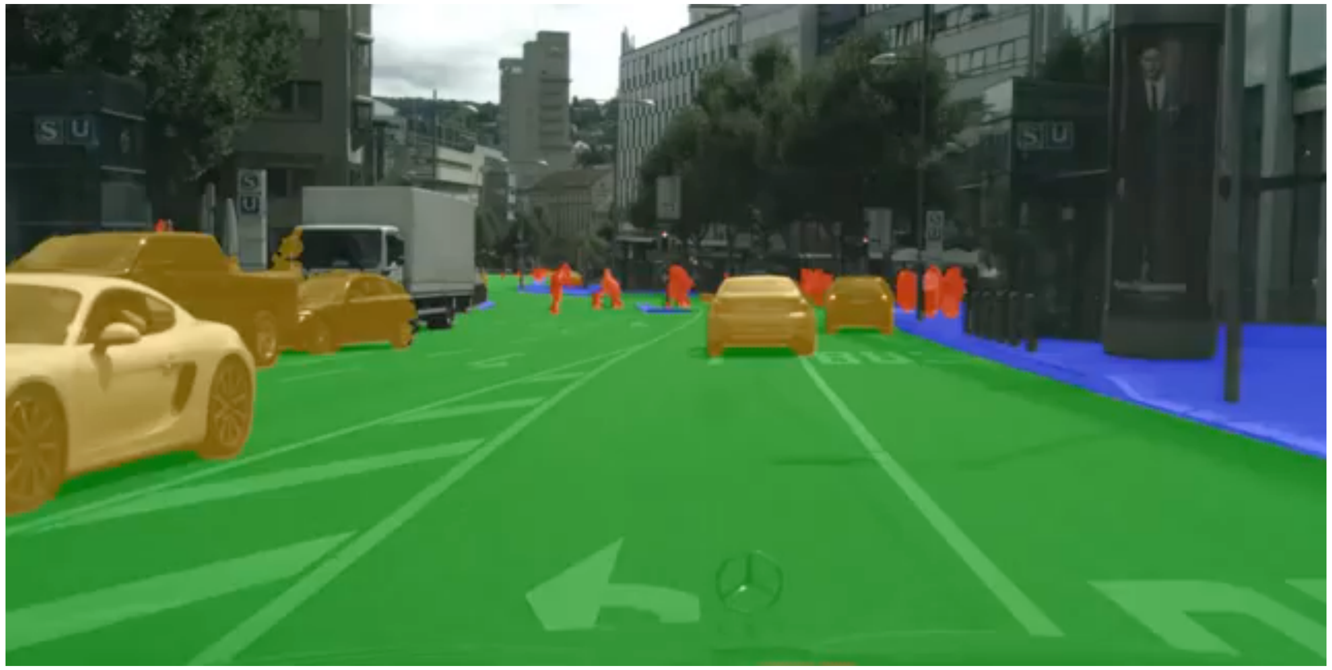

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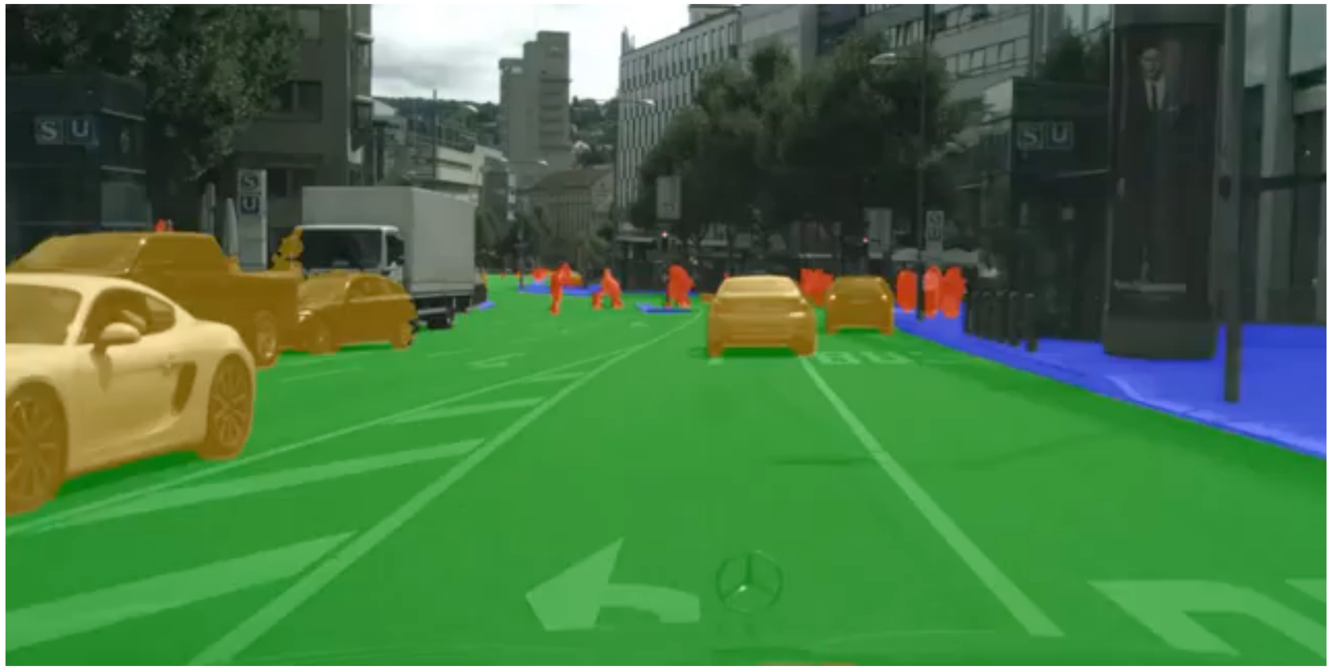

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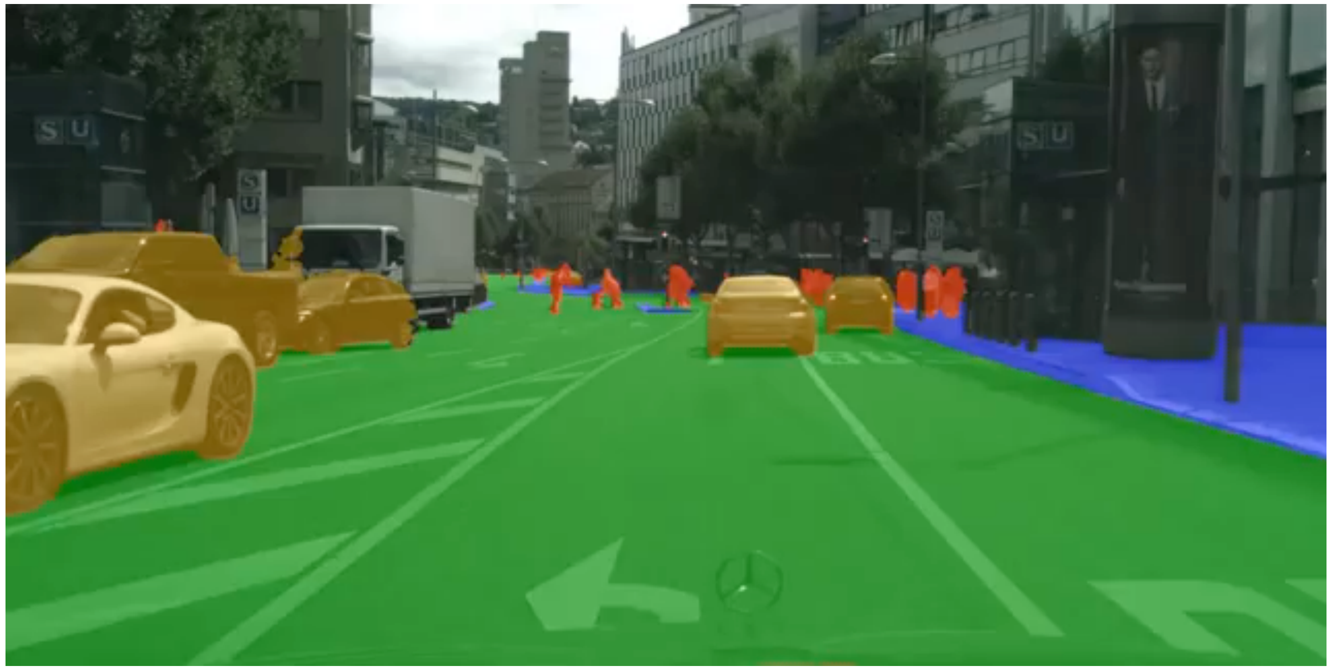

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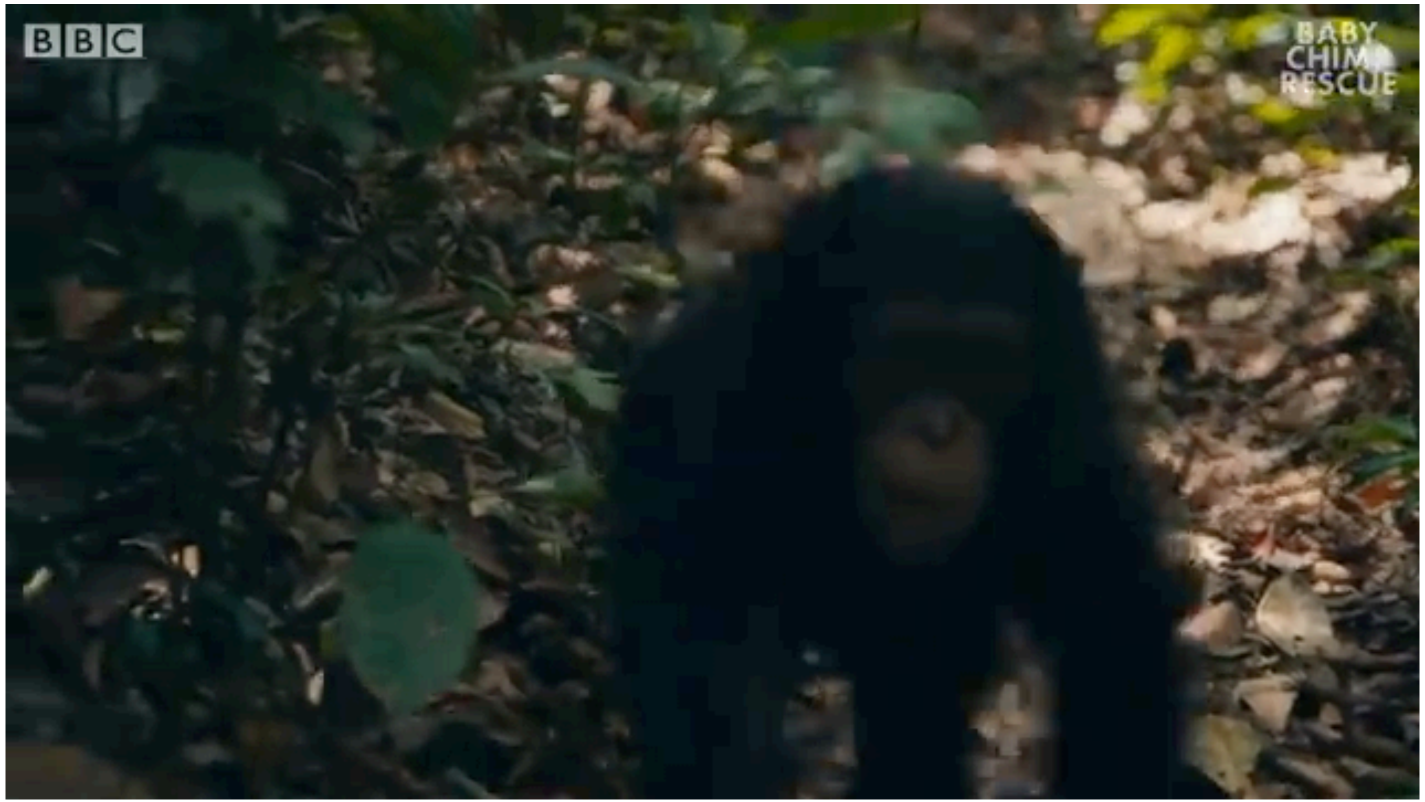

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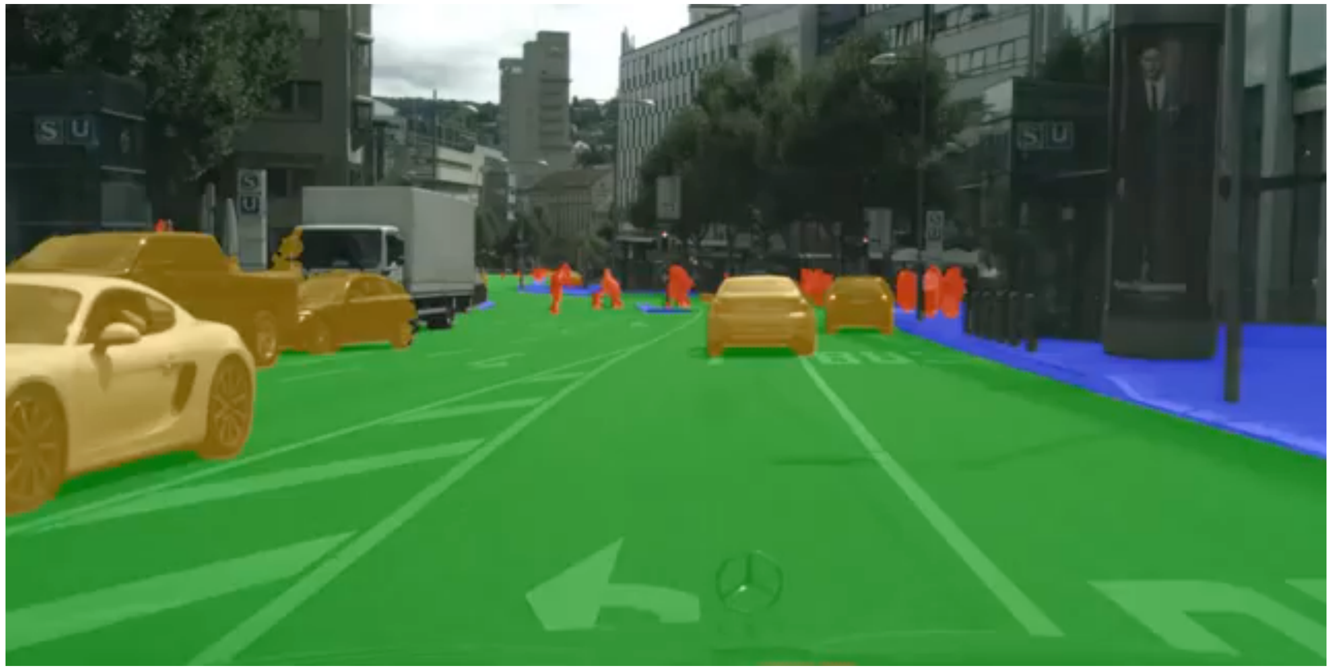

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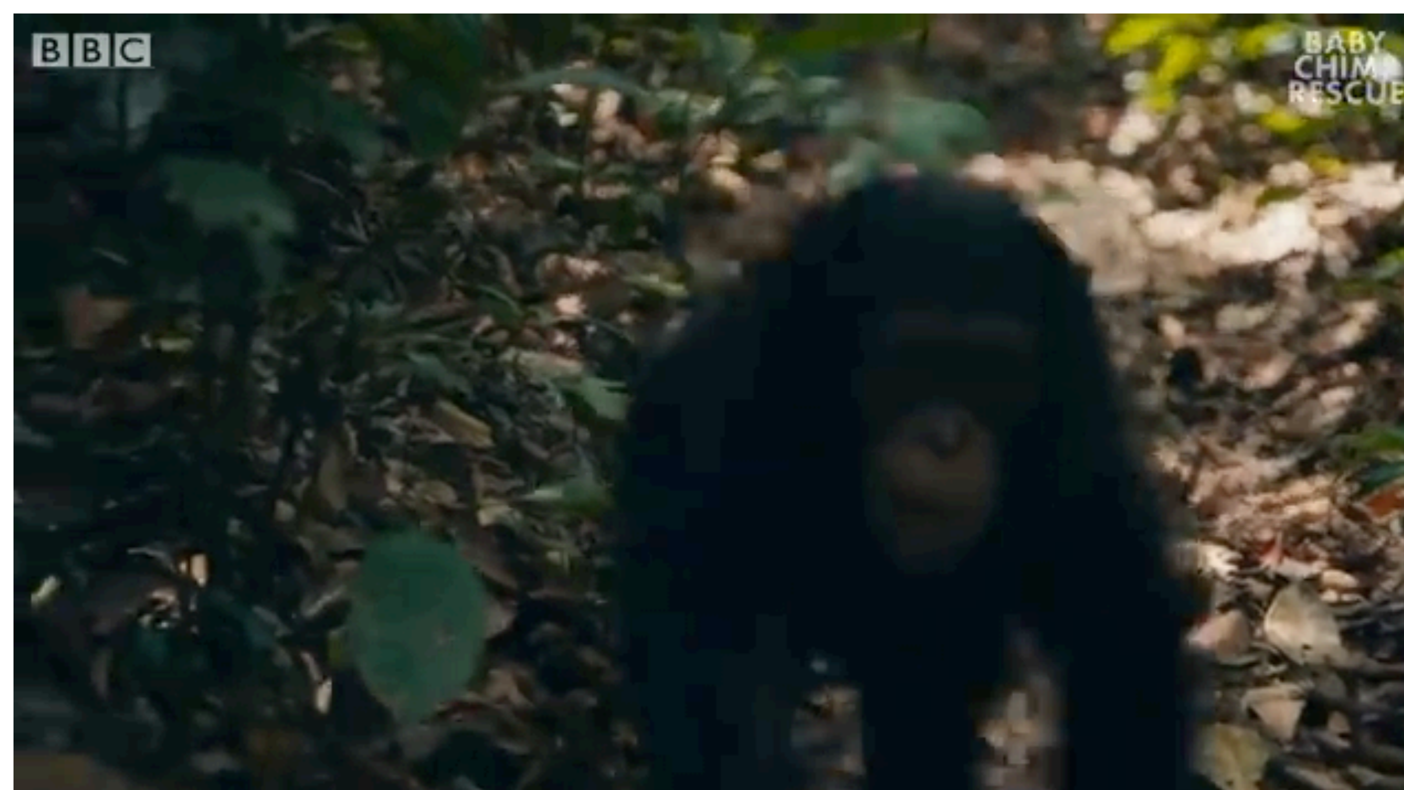

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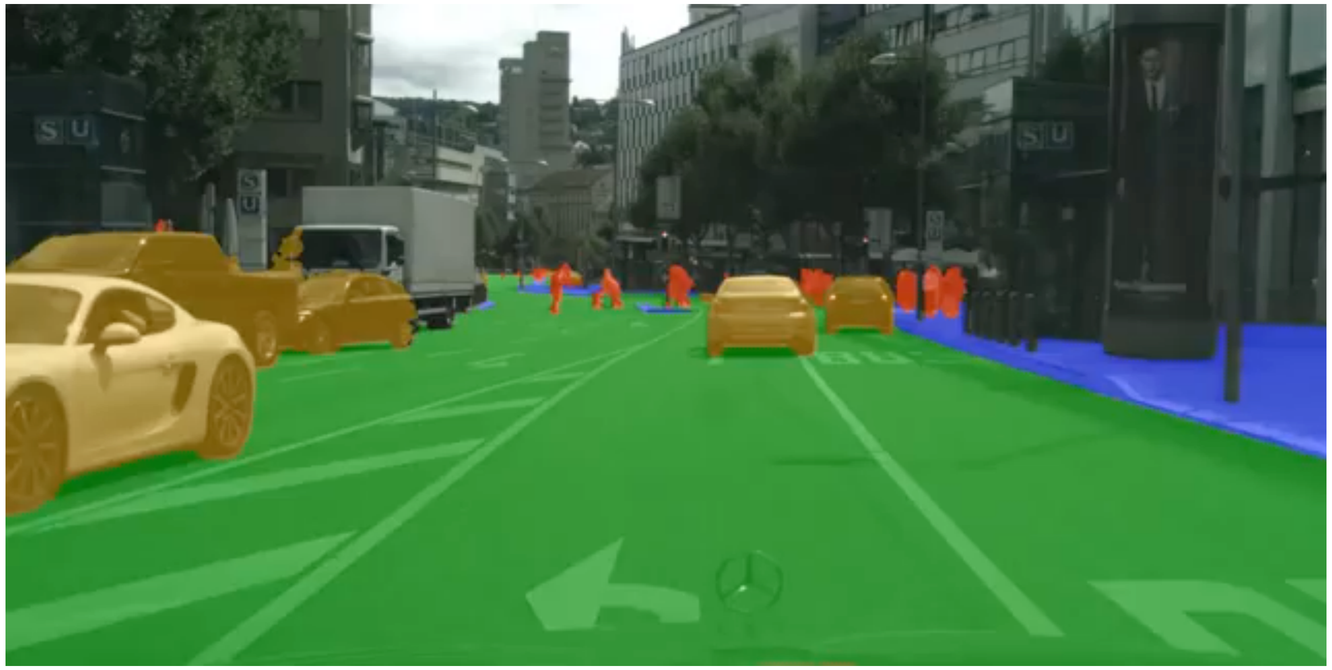

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All of these behaviors are done in a body!

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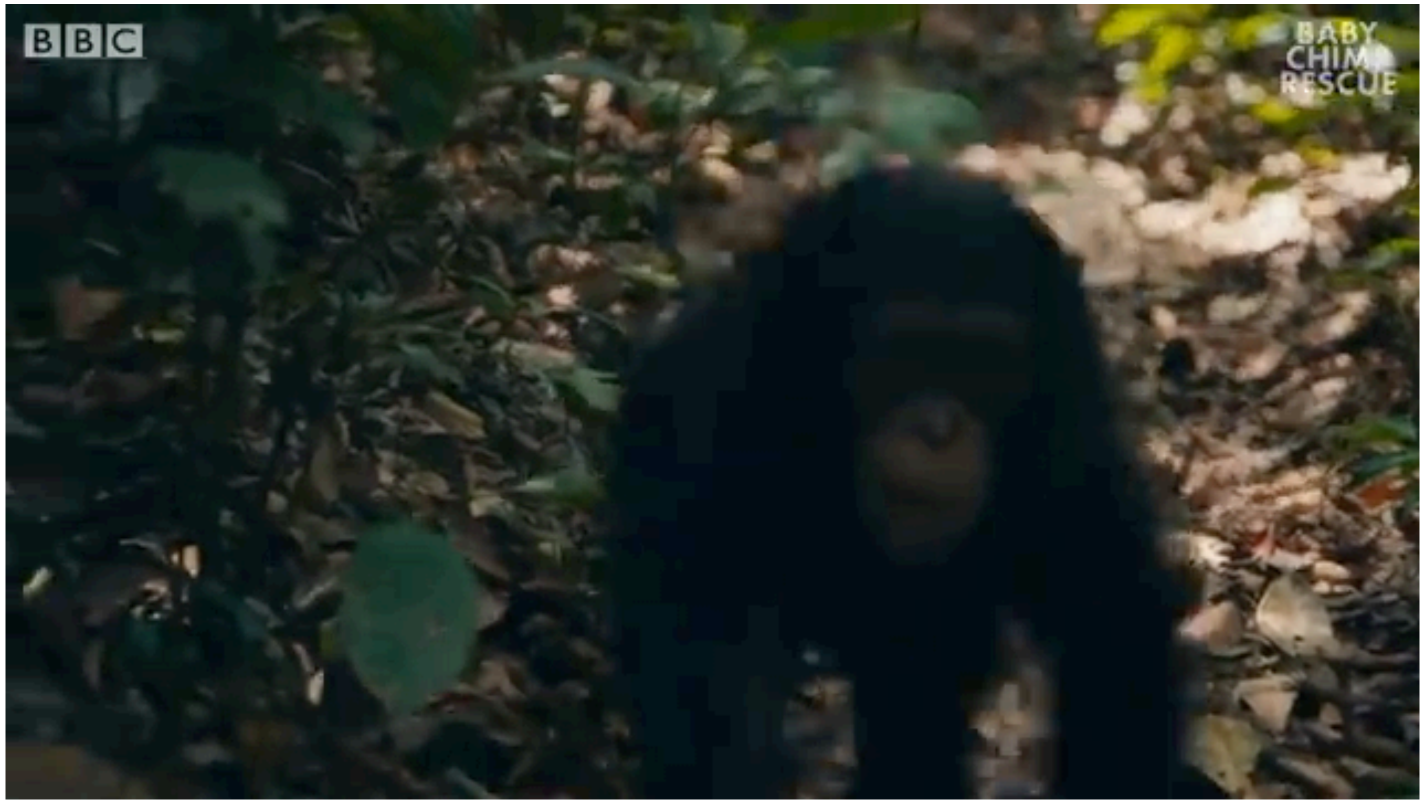

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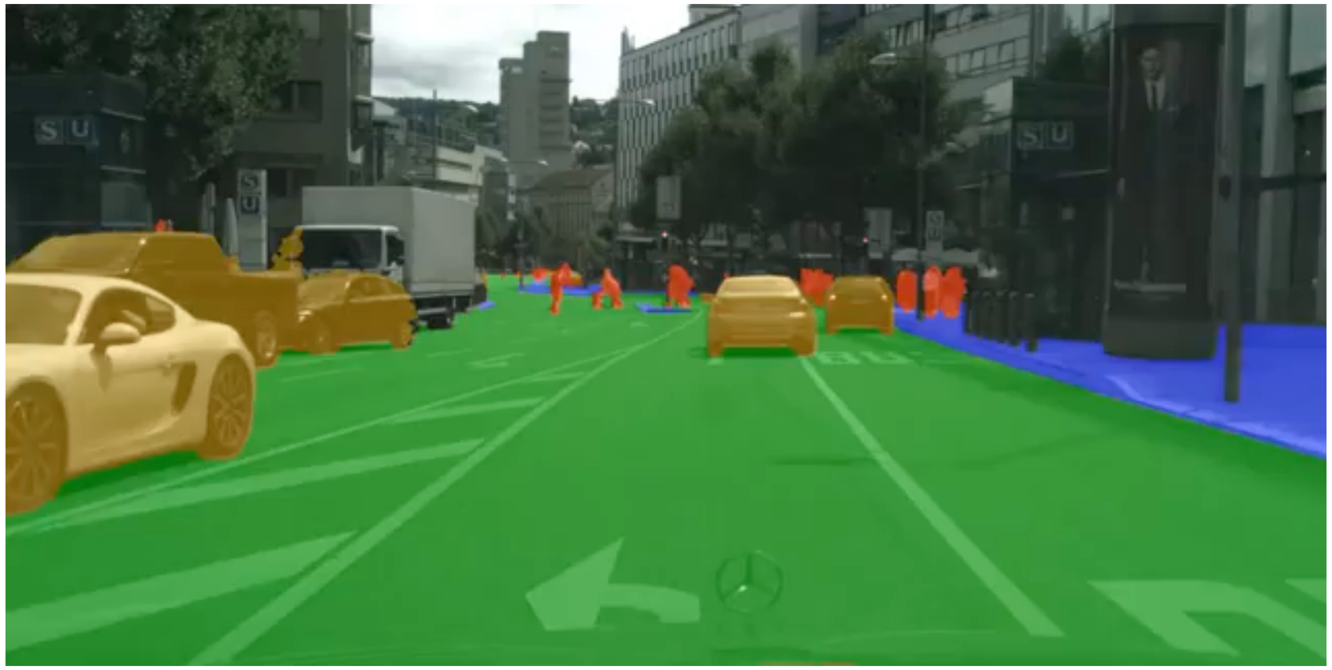

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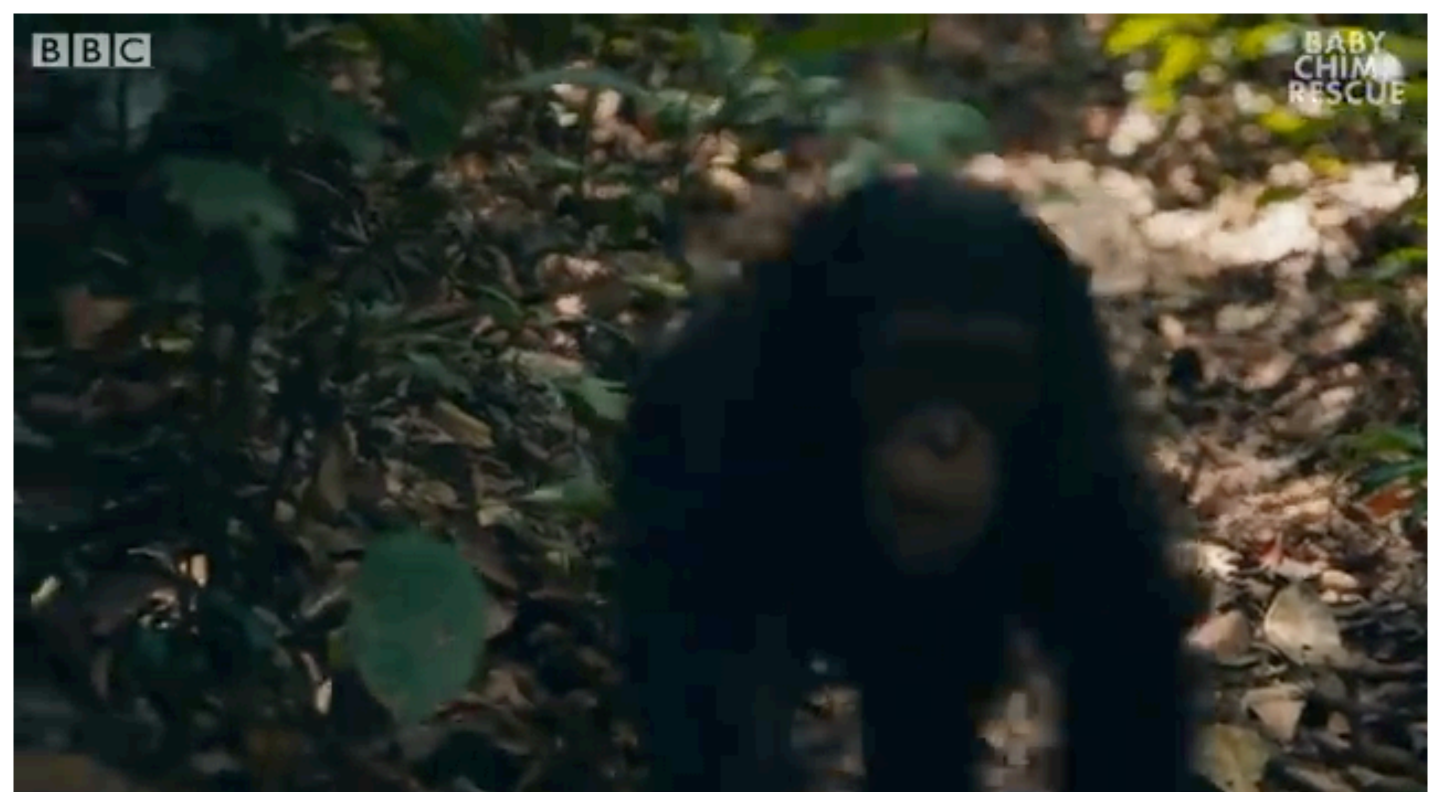

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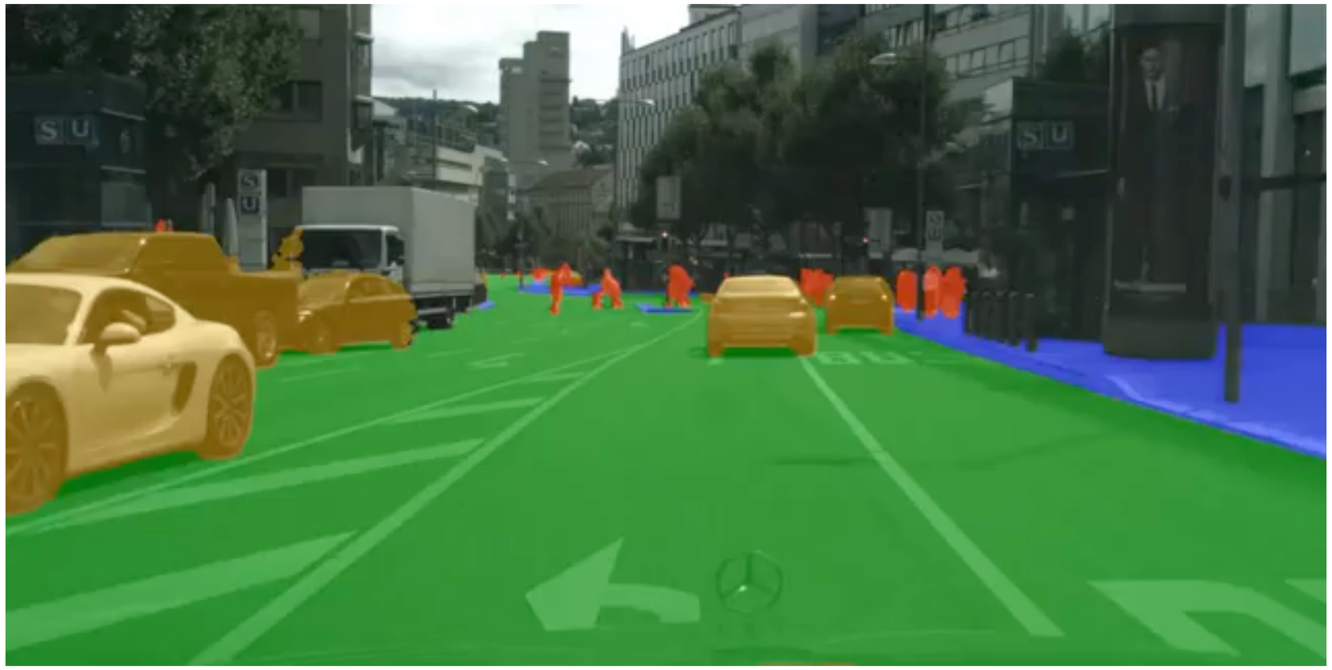

Multi-Step Planning

What are the core design principles that give rise to these abilities?

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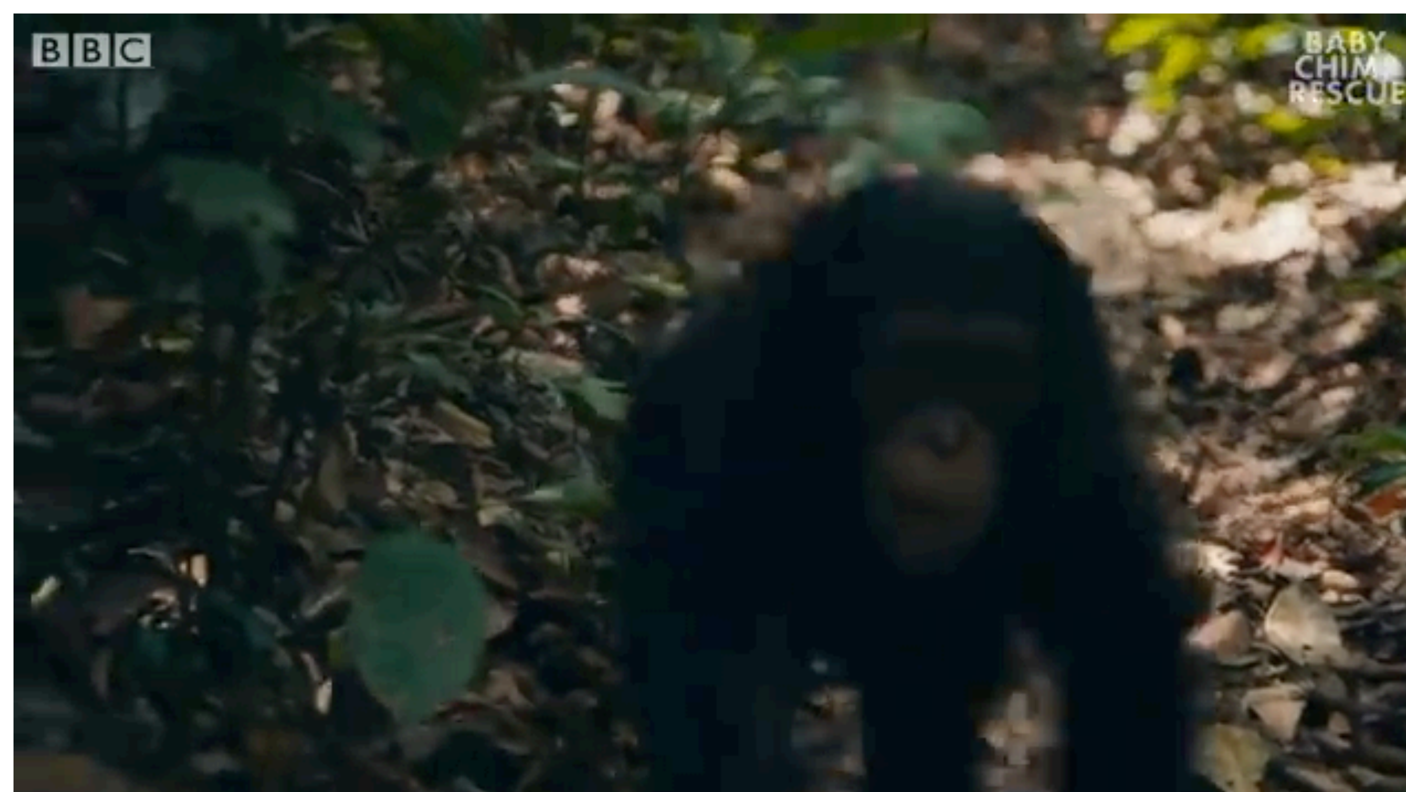

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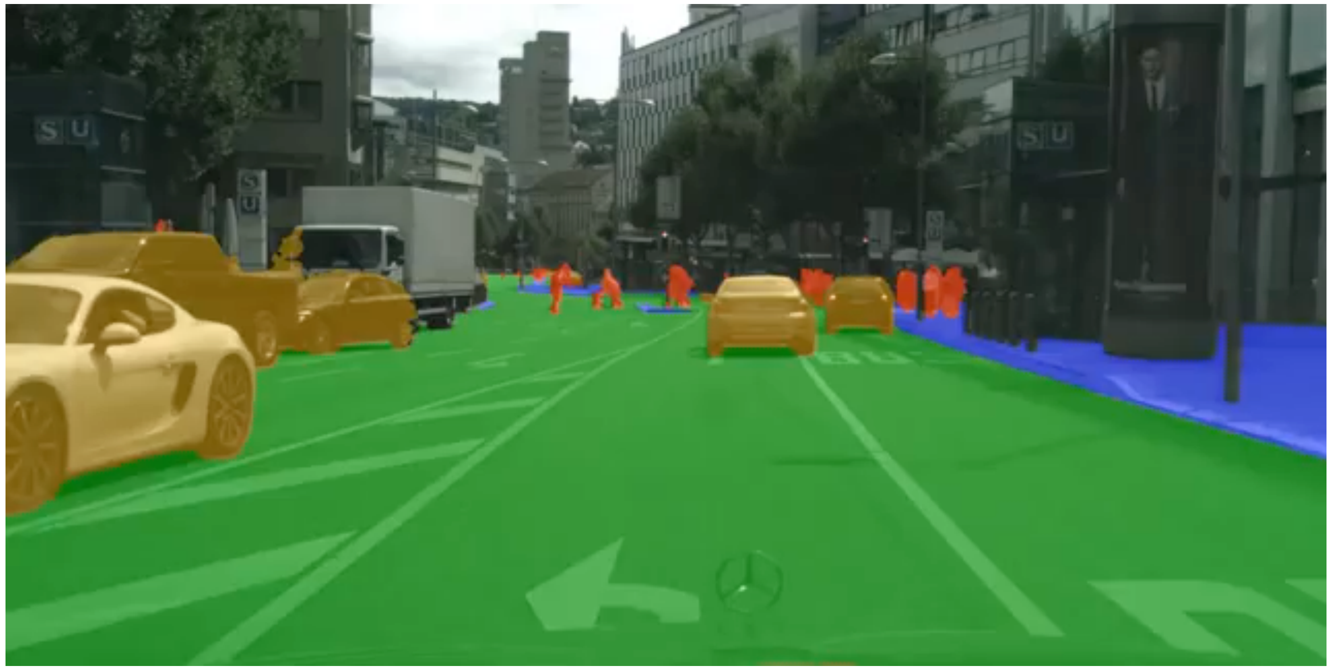

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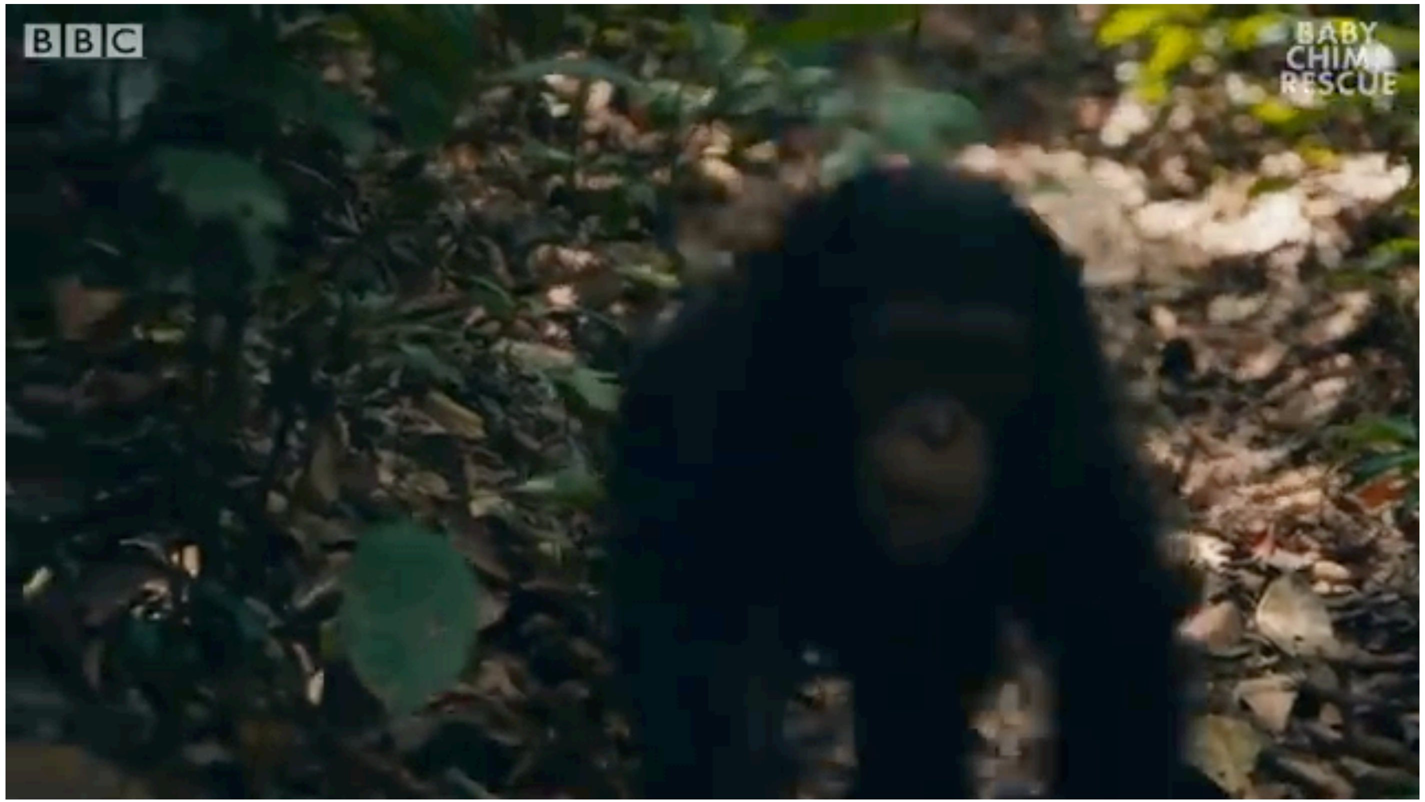

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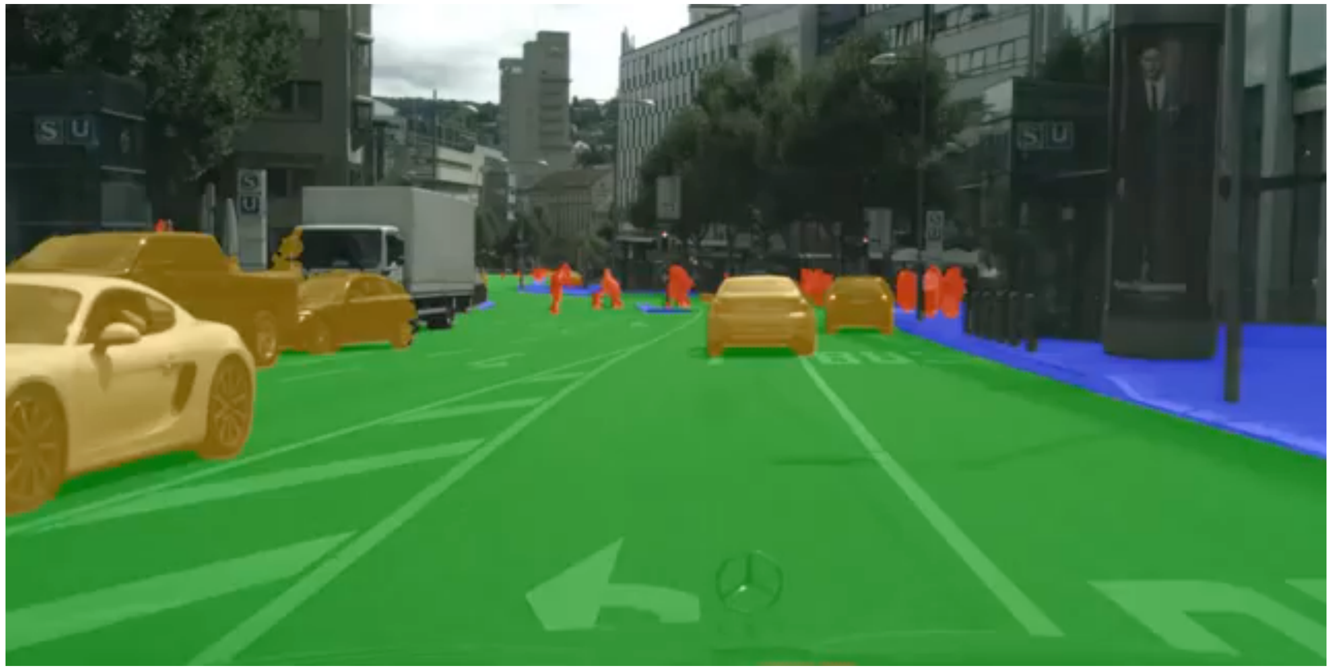

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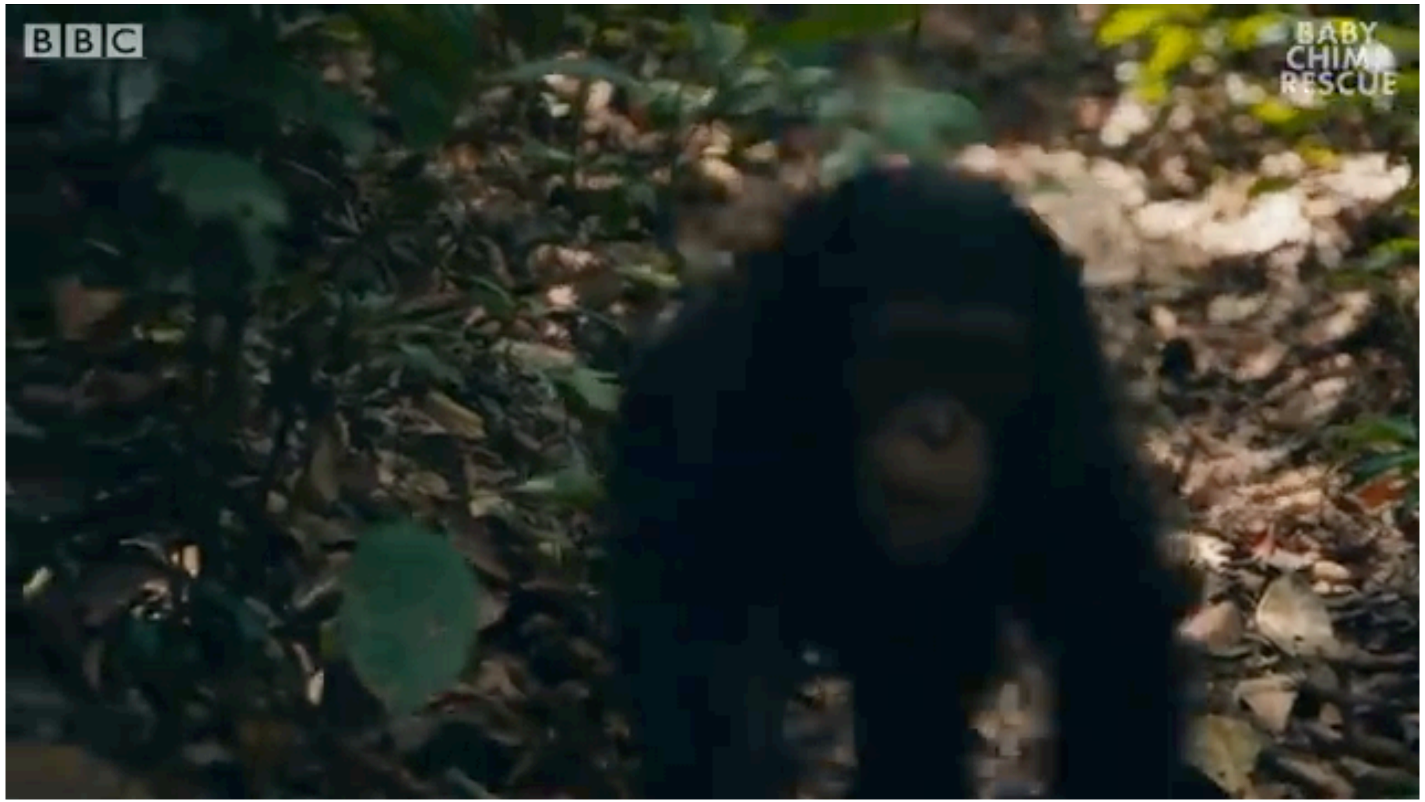

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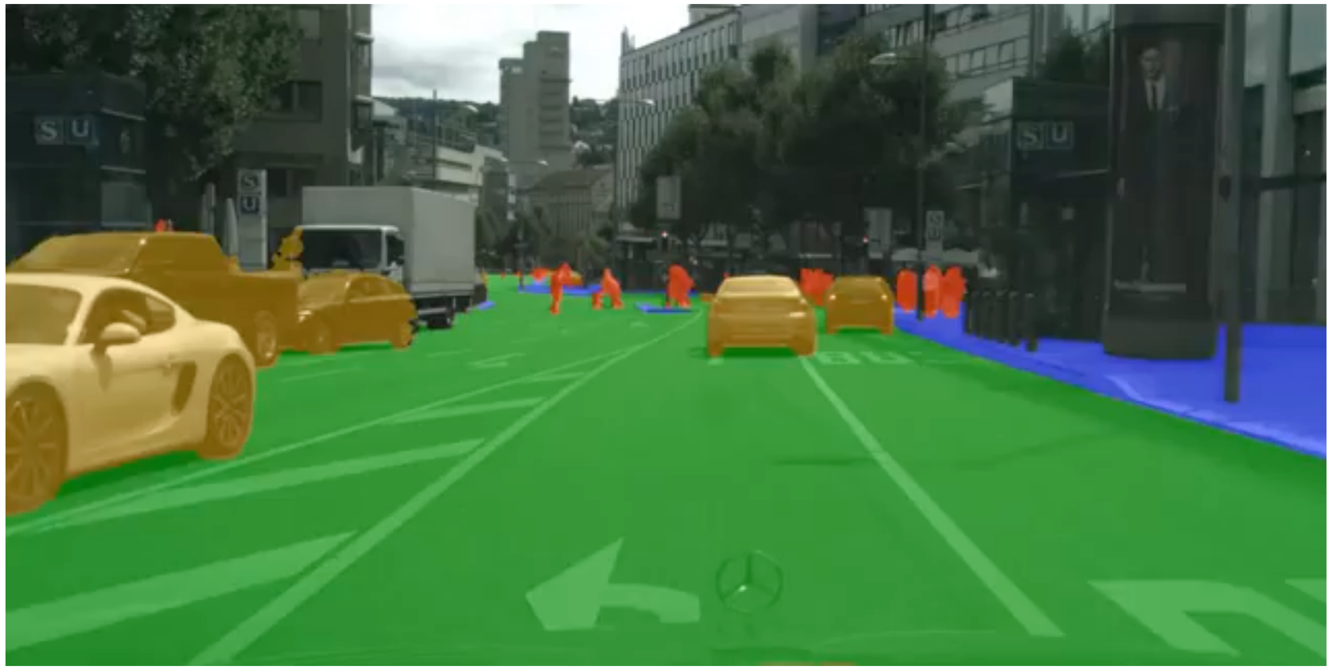

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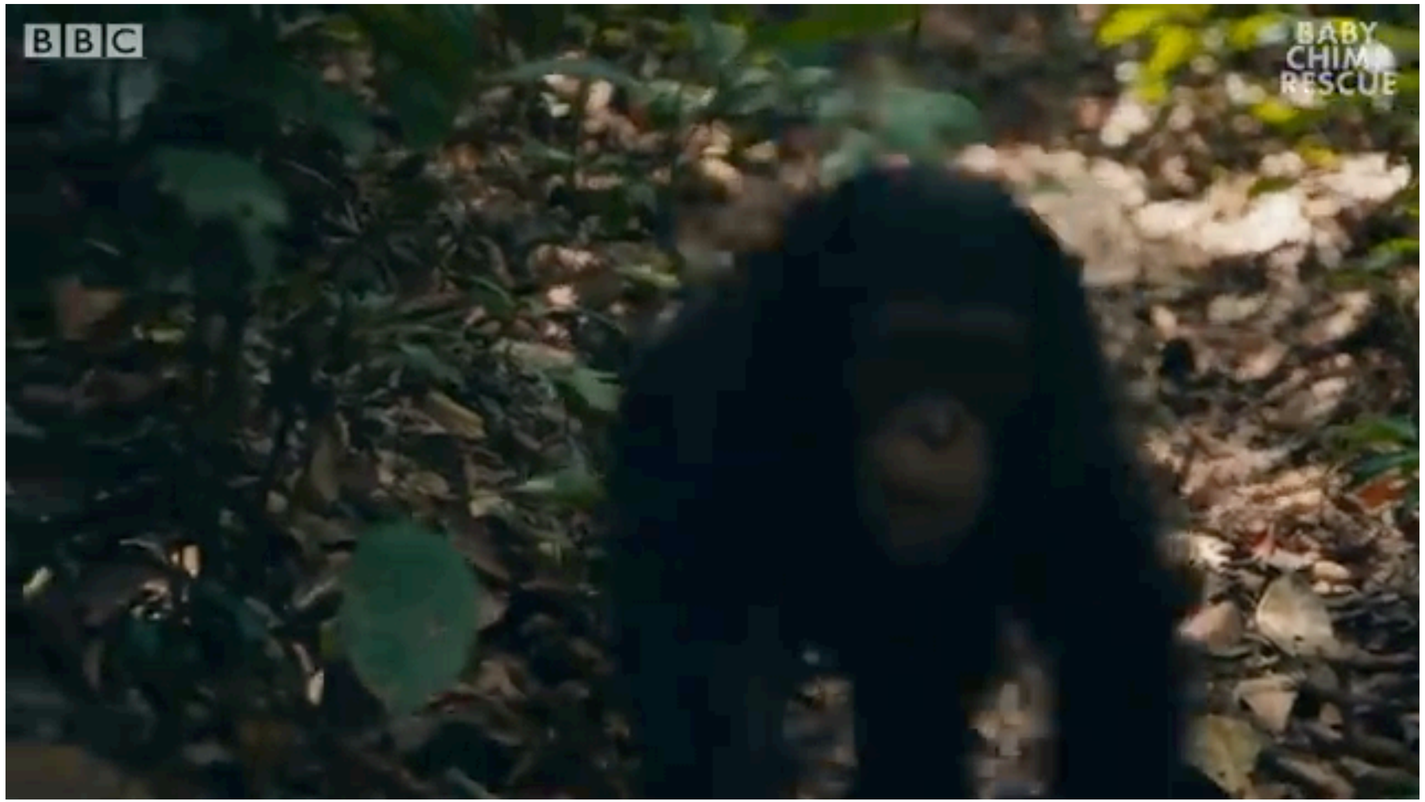

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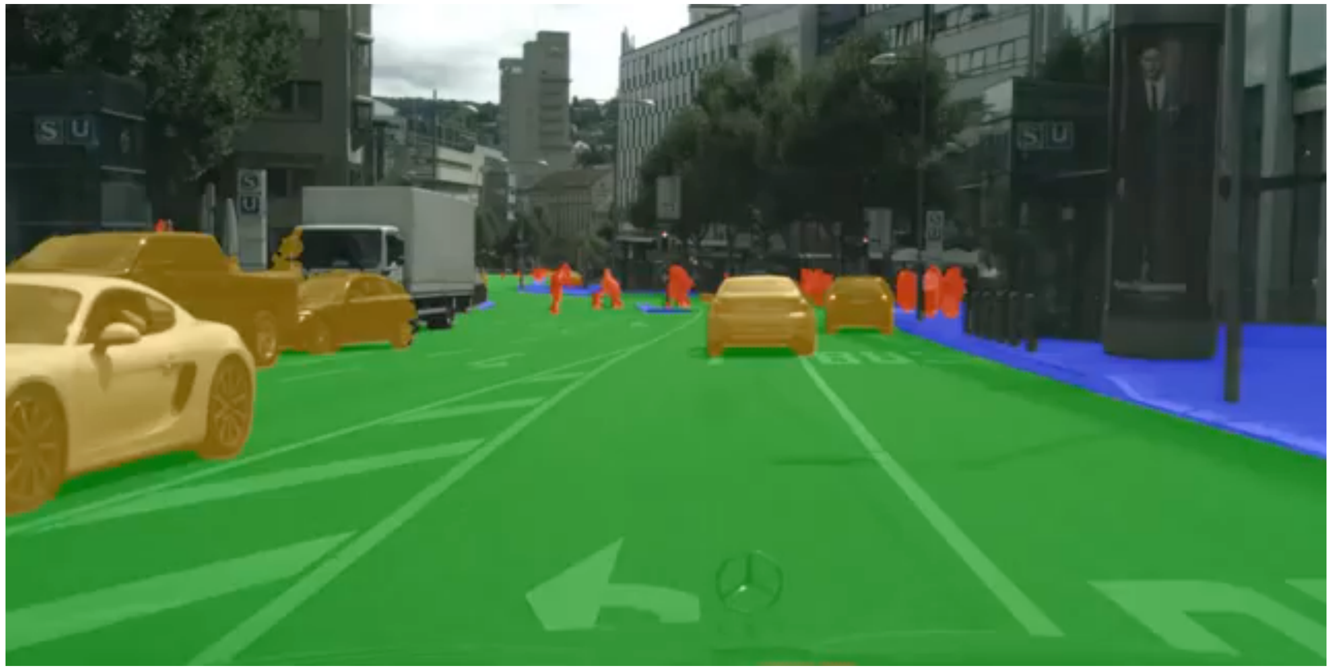

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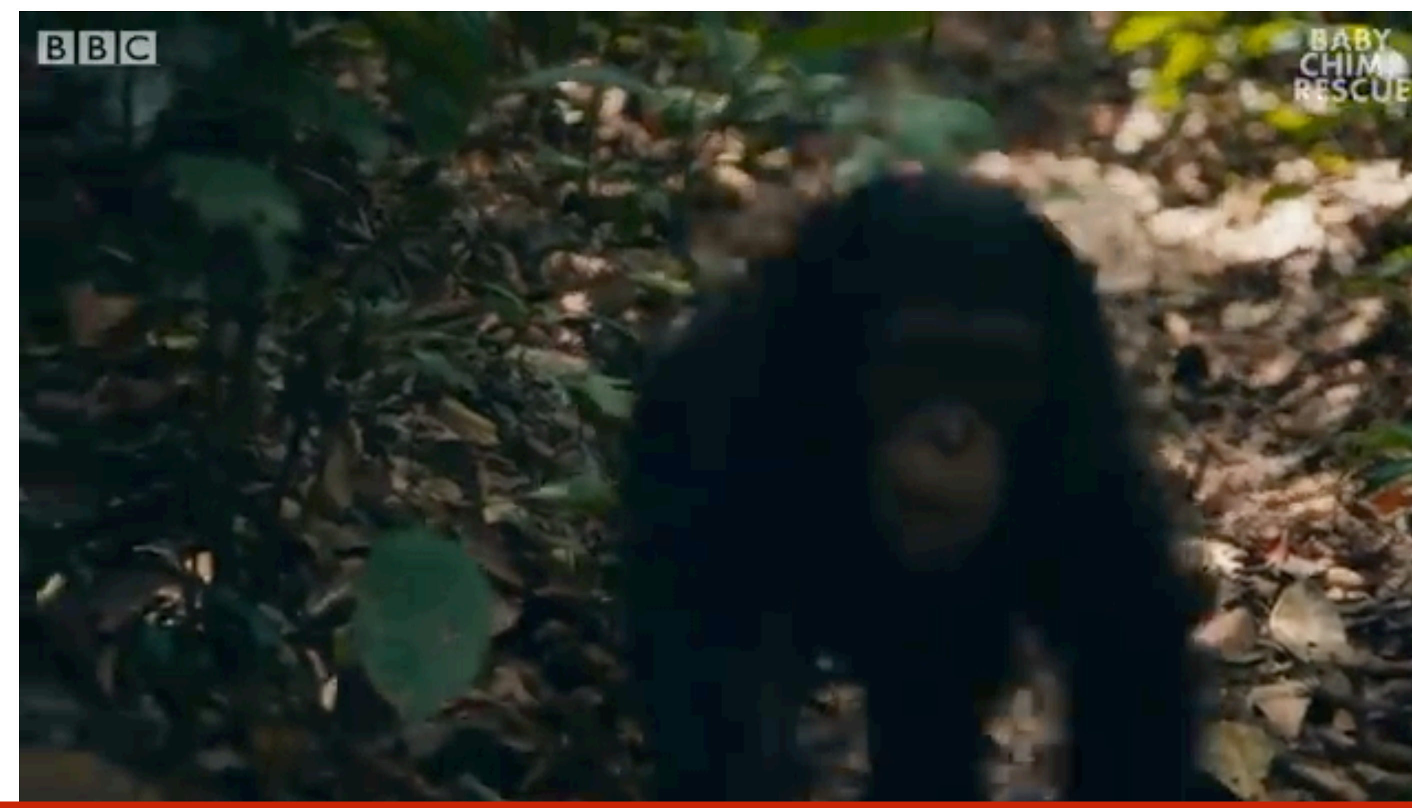

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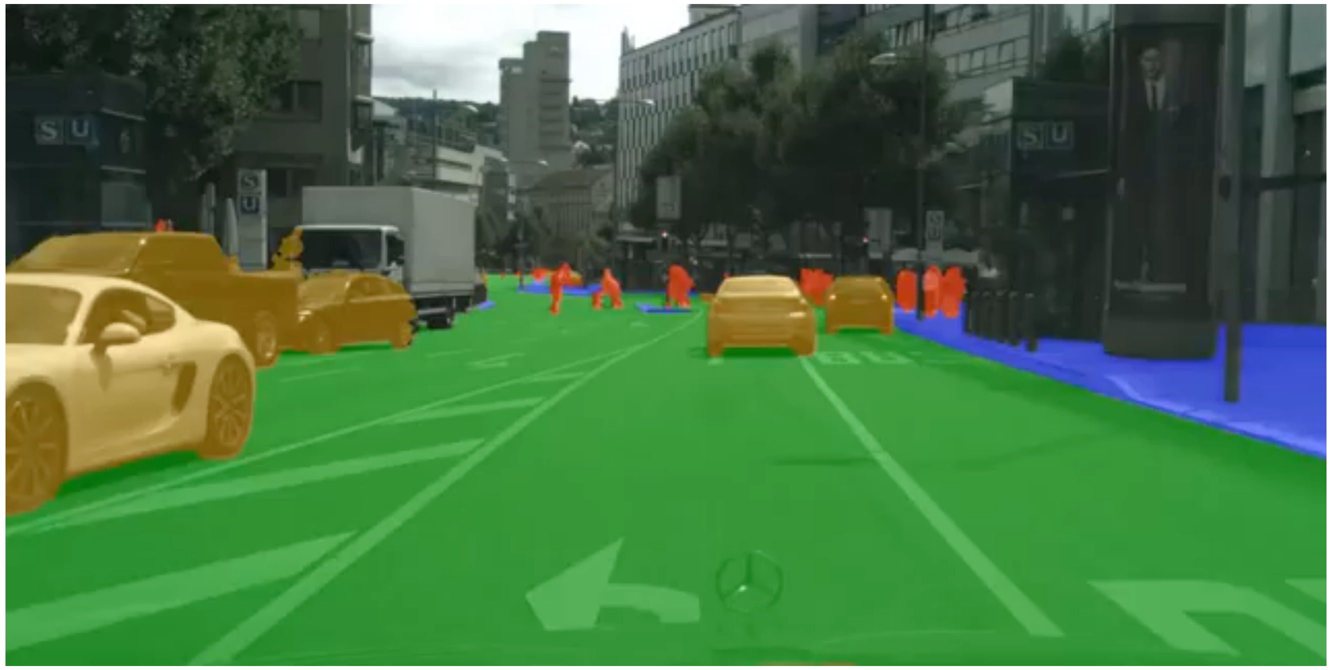

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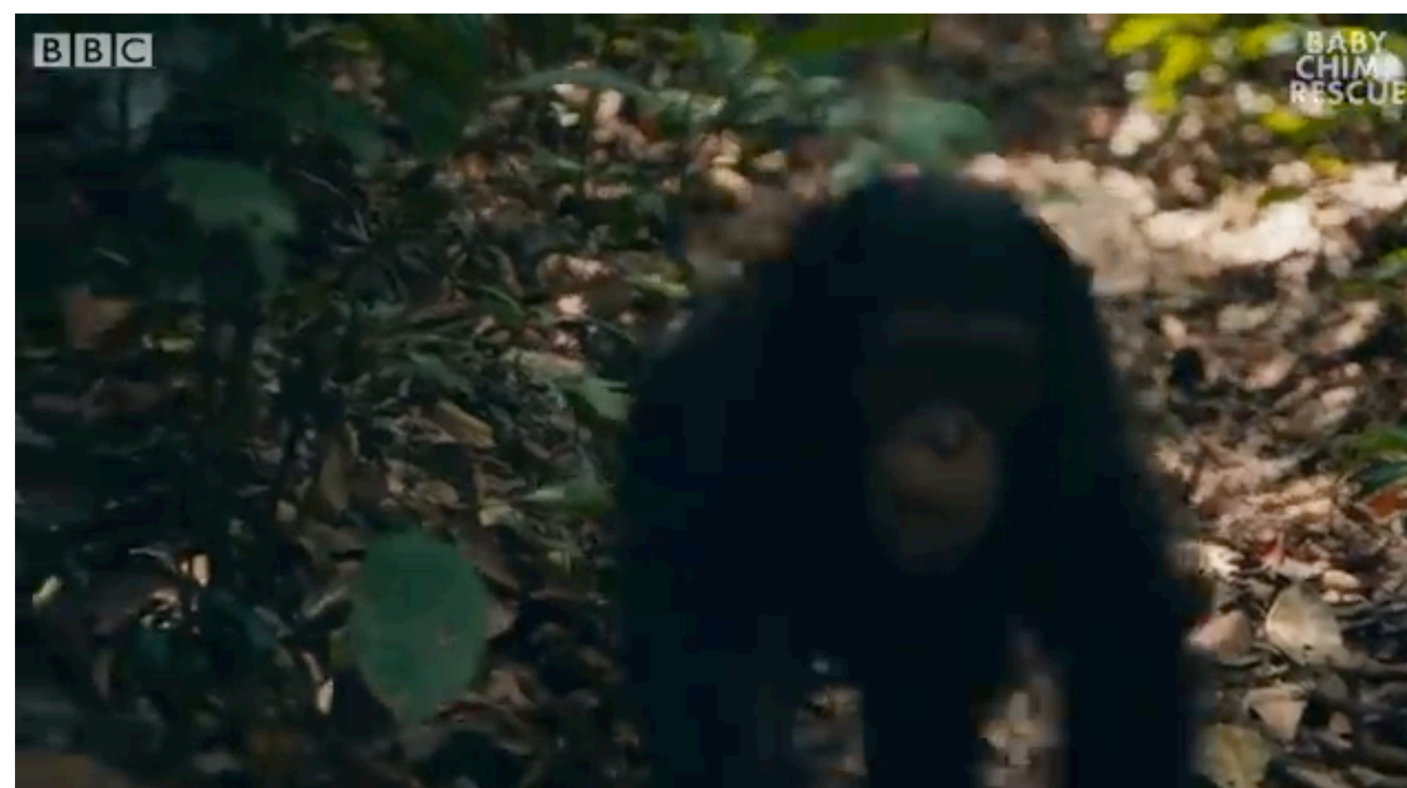

Outline

- Mouse Visual Cortex as a Task-General, Limited Resource System

- Reusable Latent Representations for Primate Mental Simulation

- Heuristics for Interrogating Natural Intelligence

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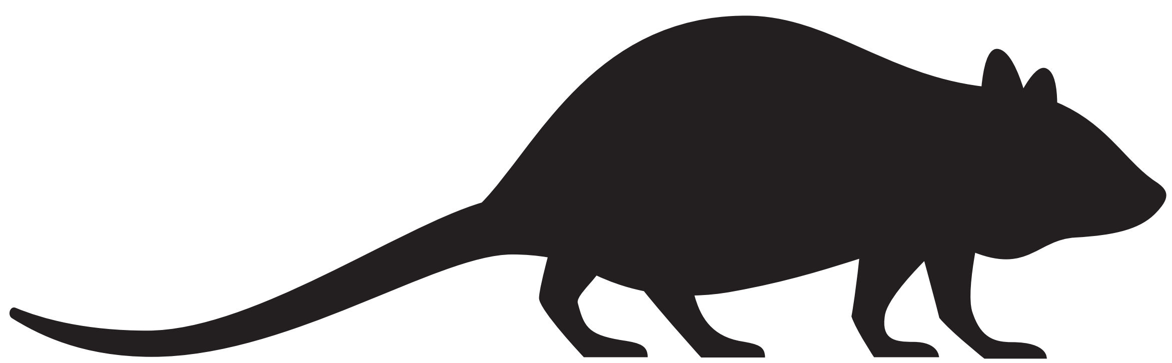
Mouse visual cortex as a limited resource system that self-learns an ecologically-general representation.
PLOS Computational Biology 2023


Nathan C.L. Kong*

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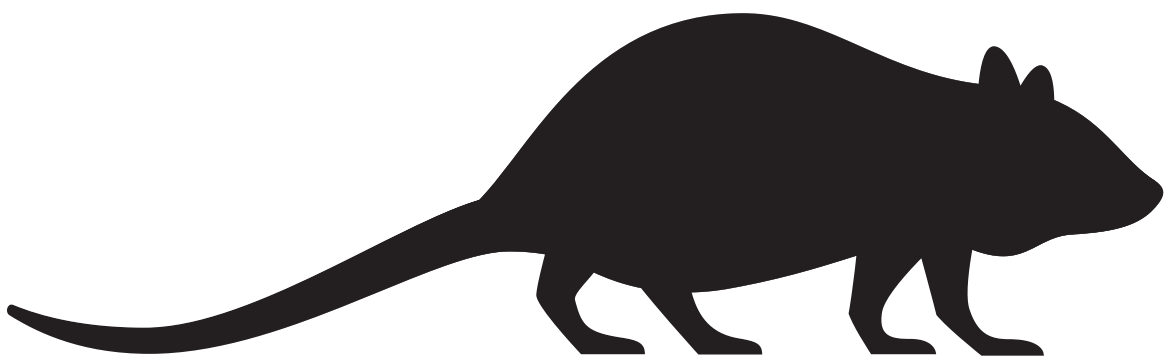


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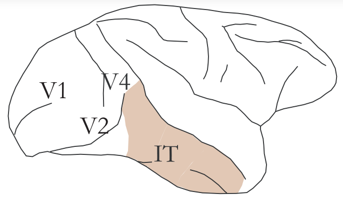
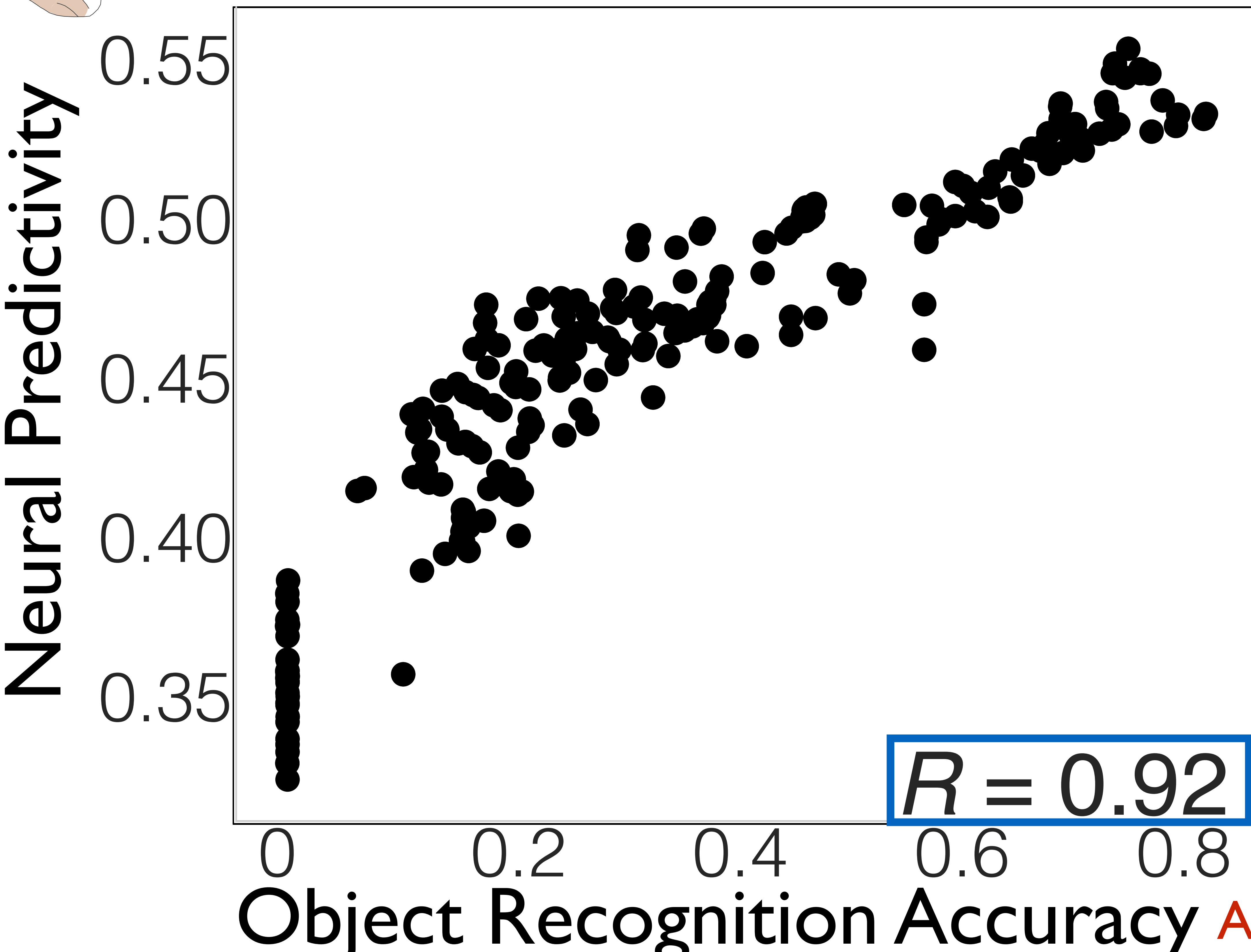
Task Performance Correlated with Neural Predictivity



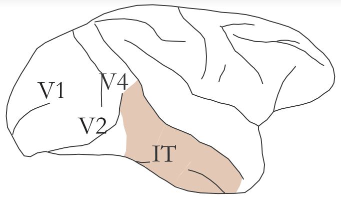
A Neuroscience Goal

Schrimpf, Kubilius* et al. 2018*



An AI Goal

Task Performance Correlated with Neural Predictivity



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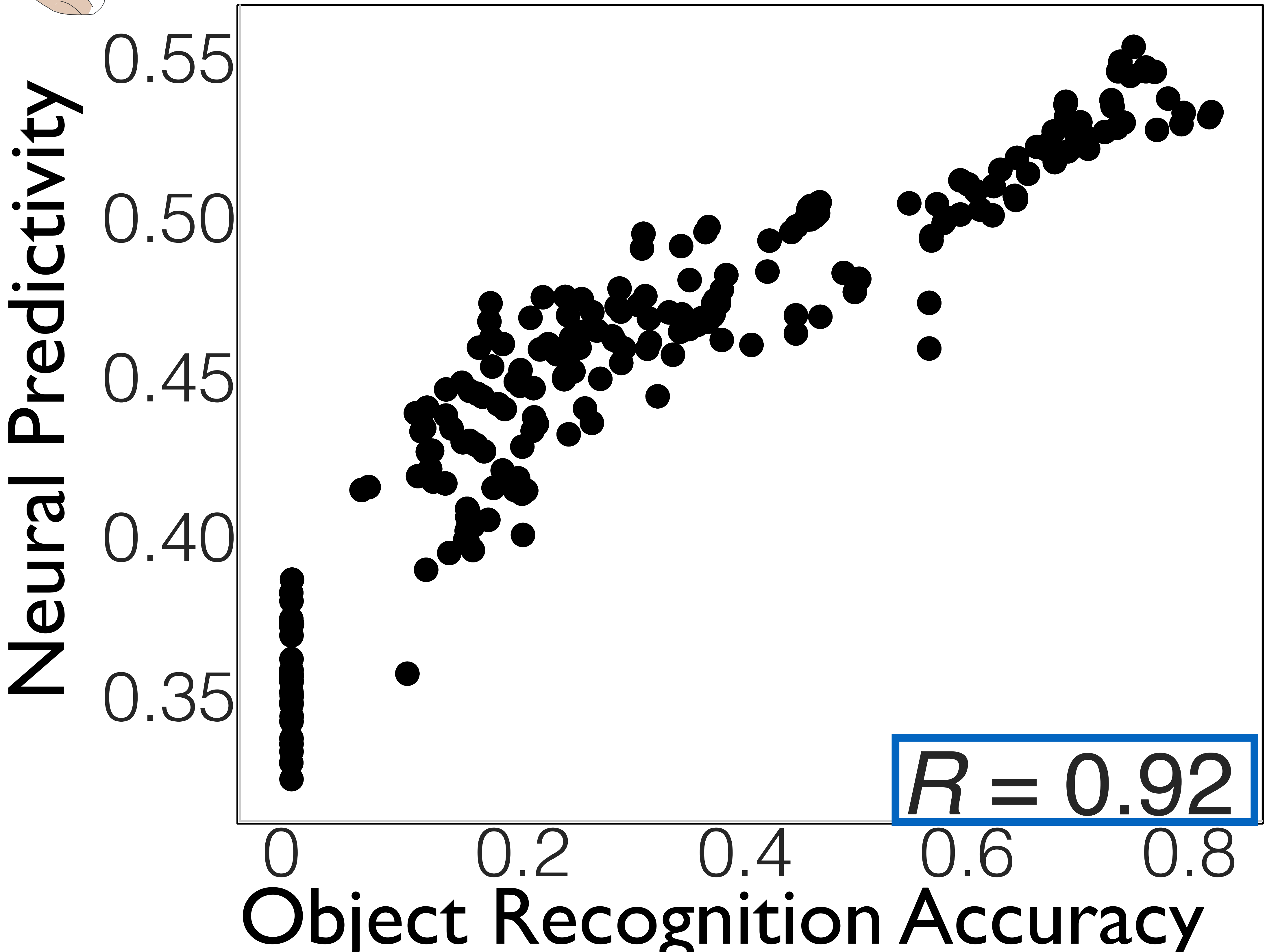

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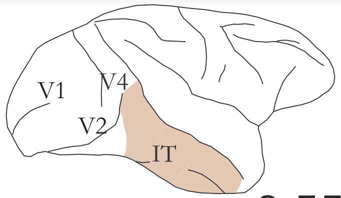
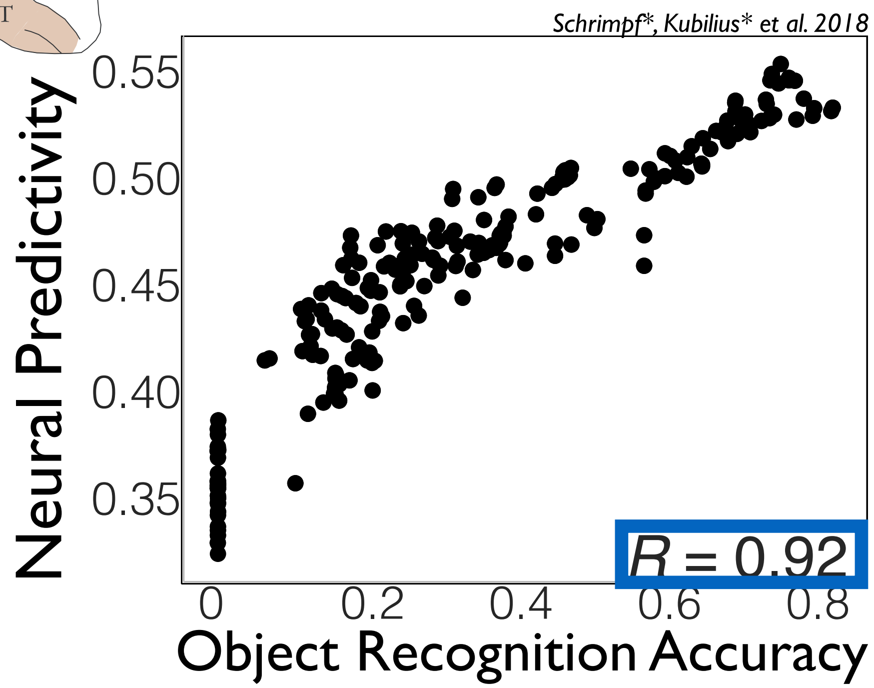
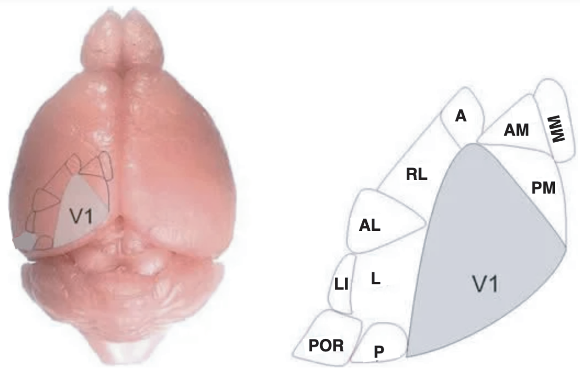


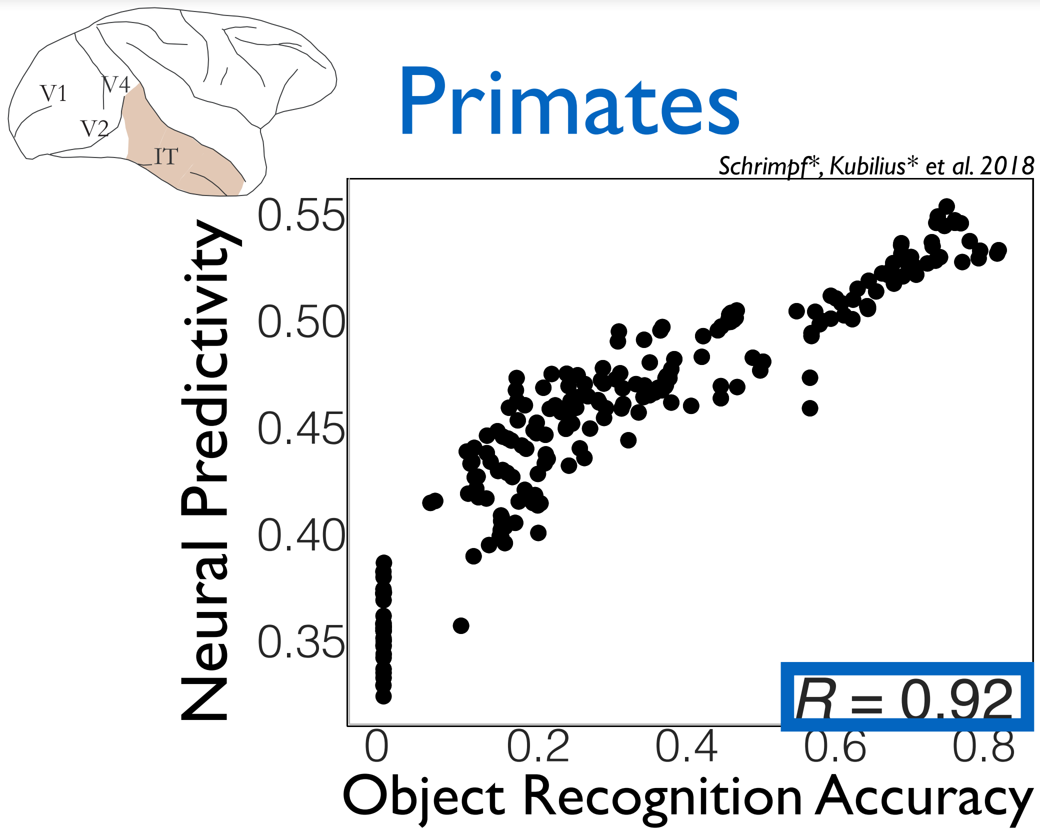
Primates

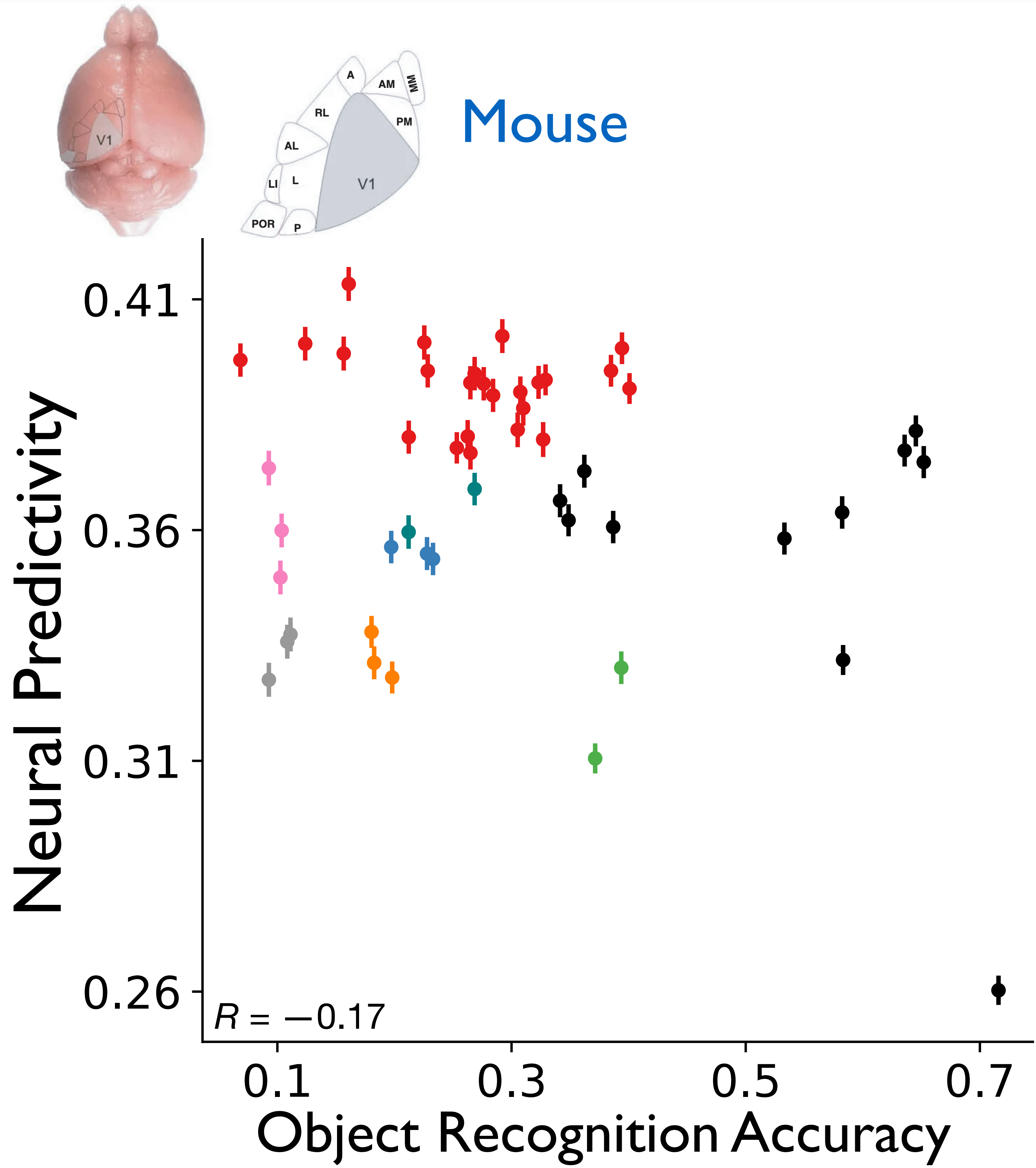




Mouse?

Object Categorization Ability **NOT** Correlated with Neural Predictivity





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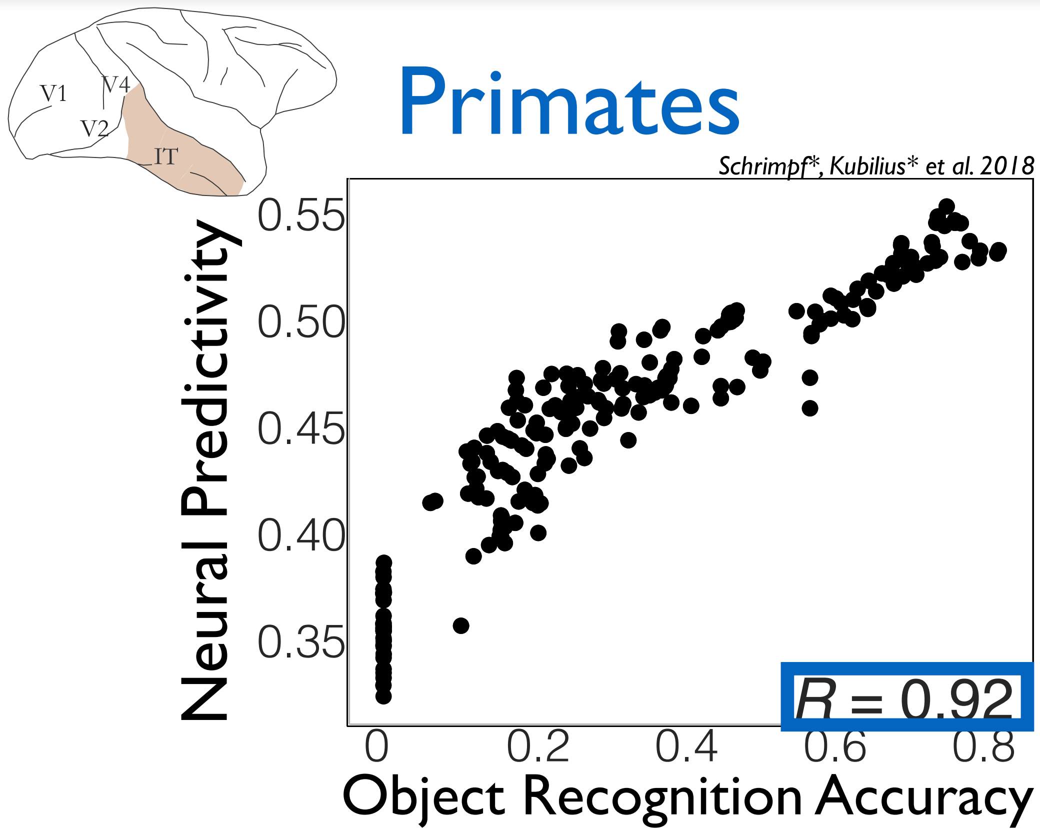

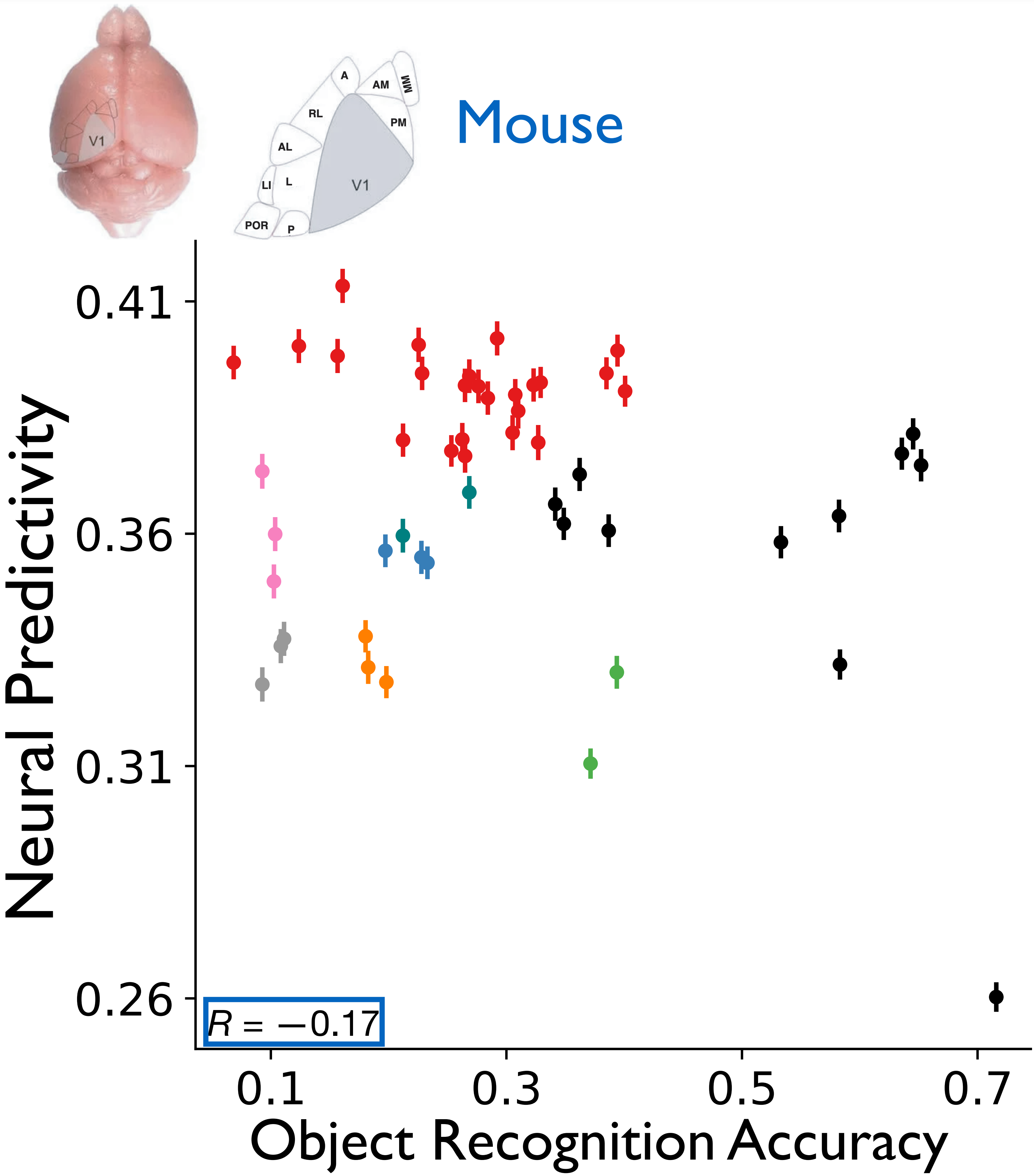

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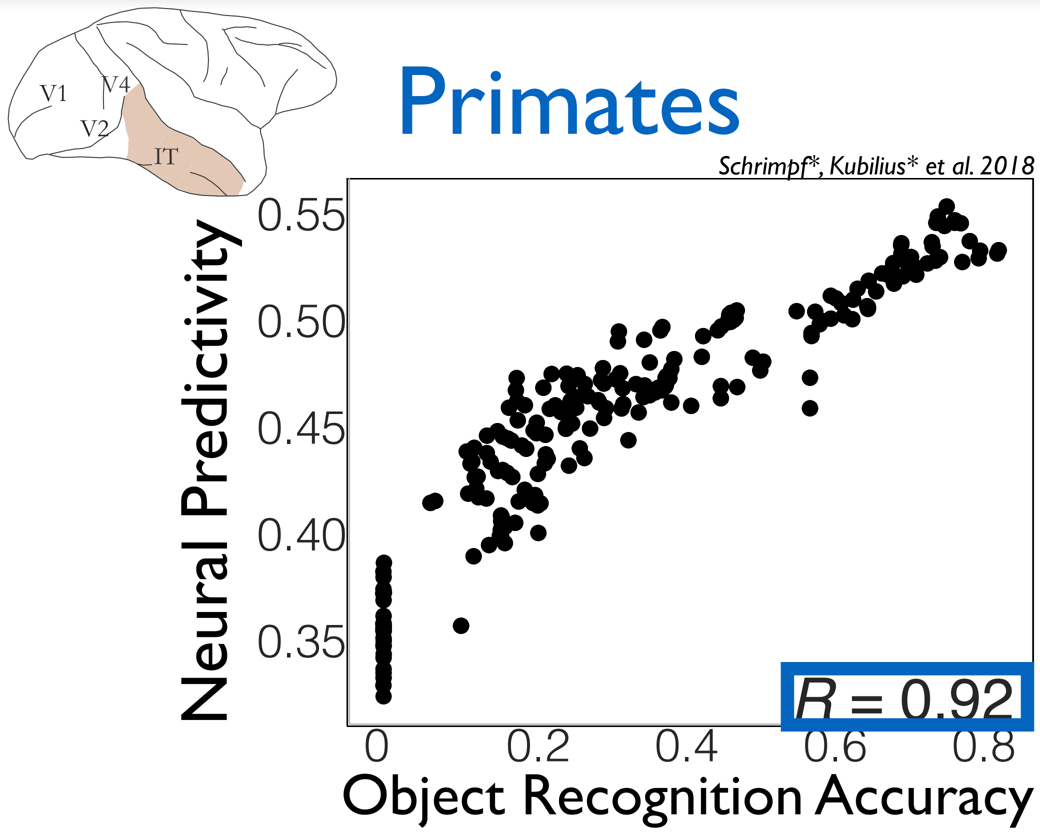

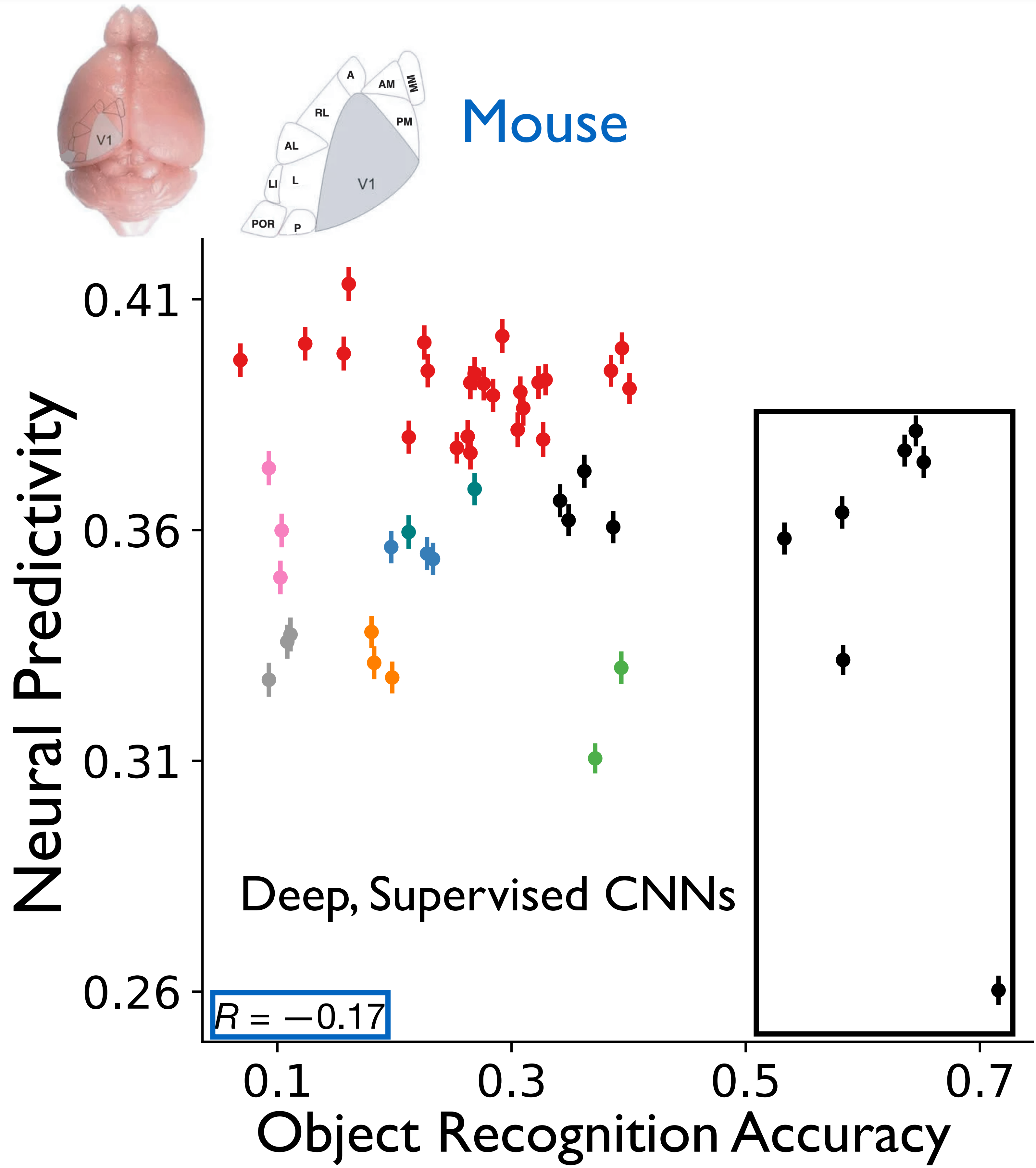

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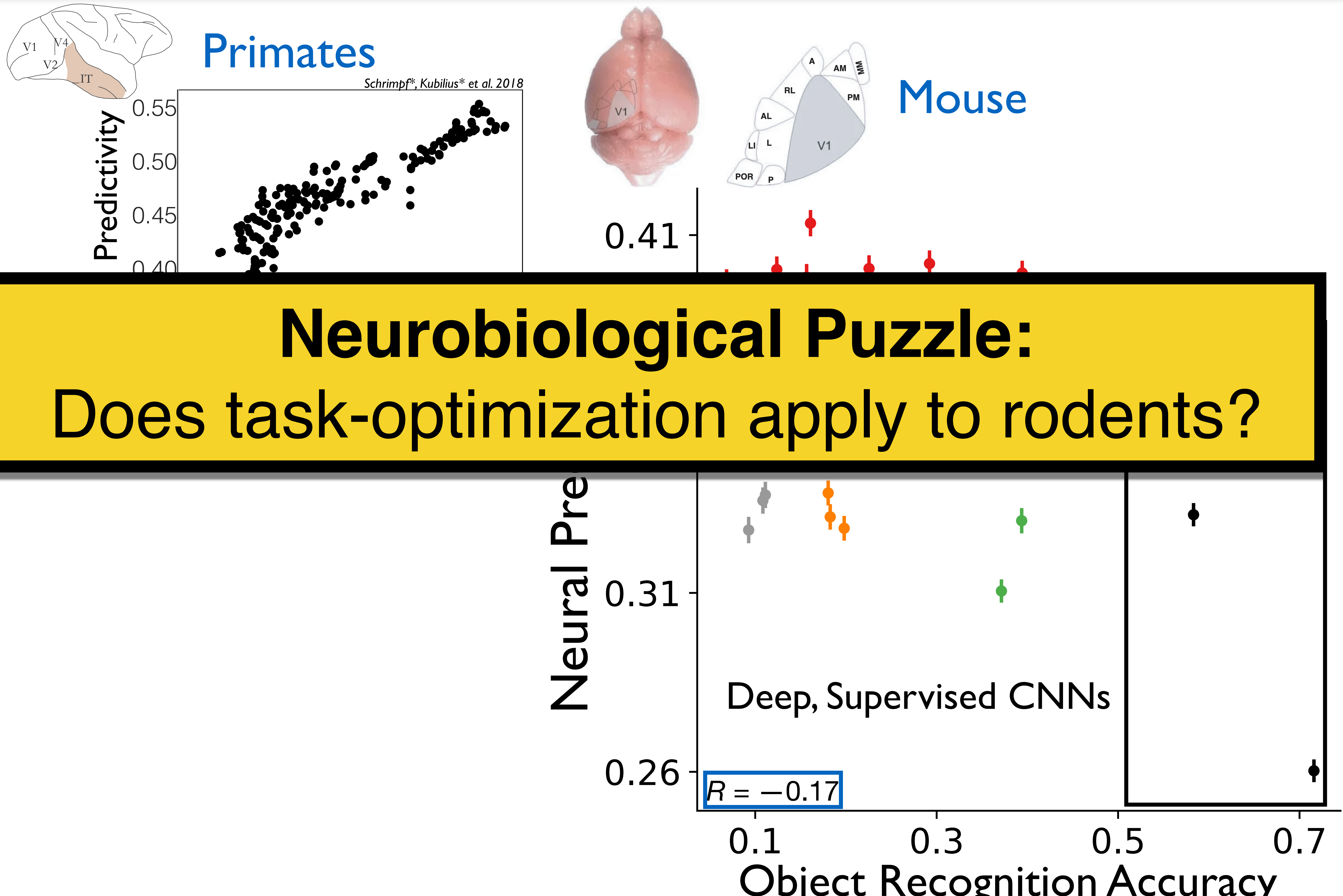
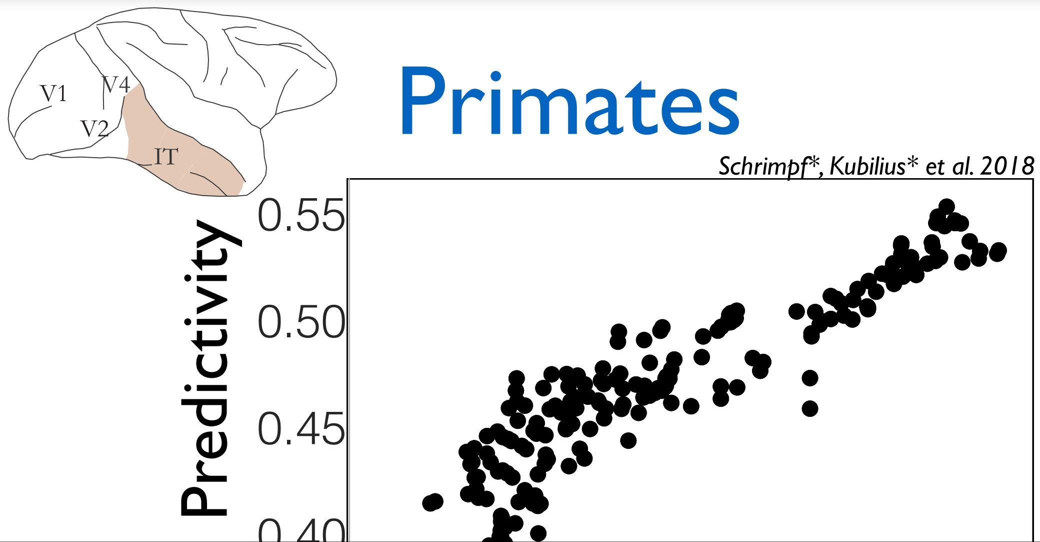
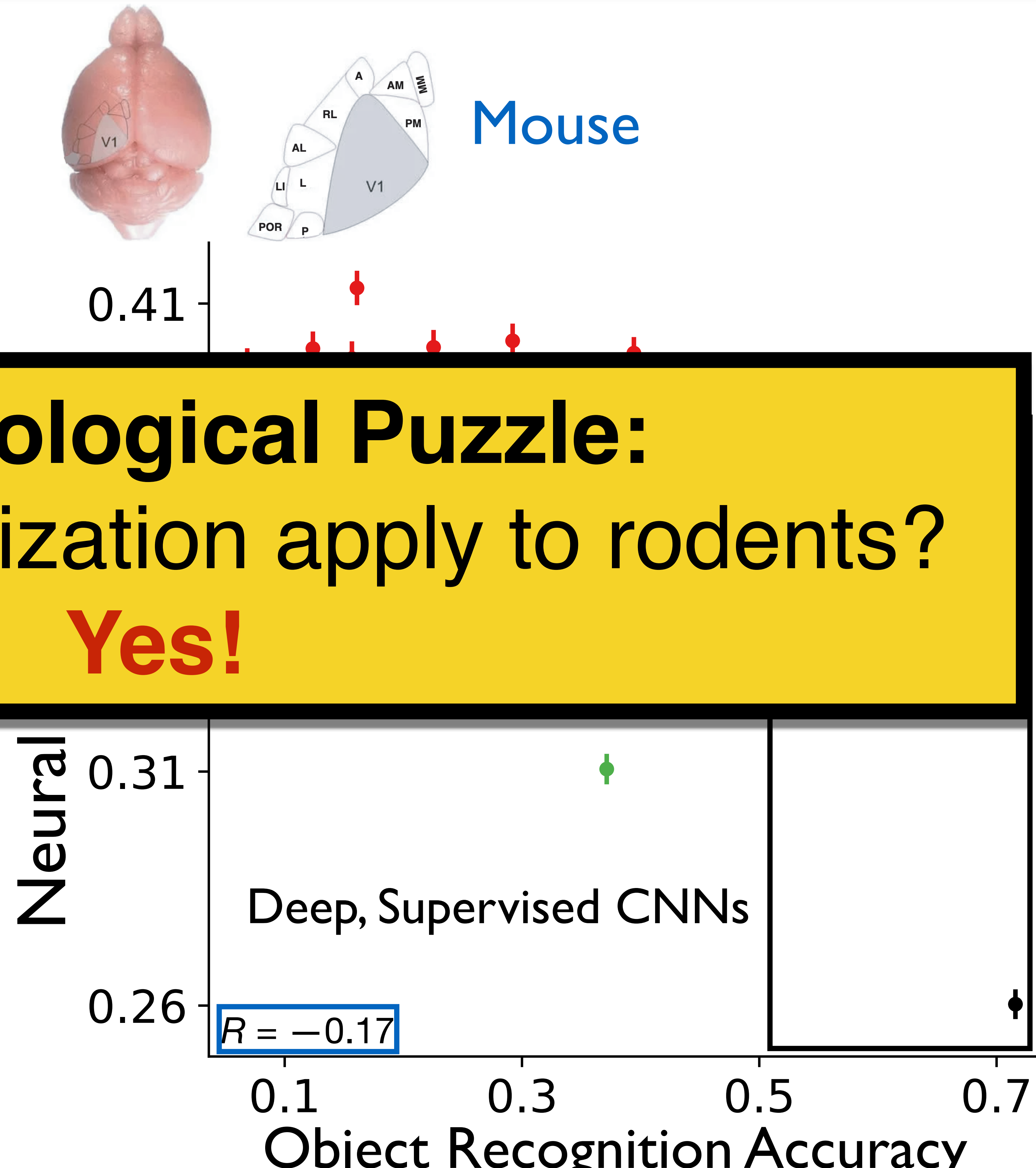


Neurobiological Puzzle:
Does task-optimization apply to rodents?

Object Categorization Ability **NOT** Correlated with Neural Predictivity





Neurobiological Puzzle:

Does task-optimization apply to rodents?

Yes!

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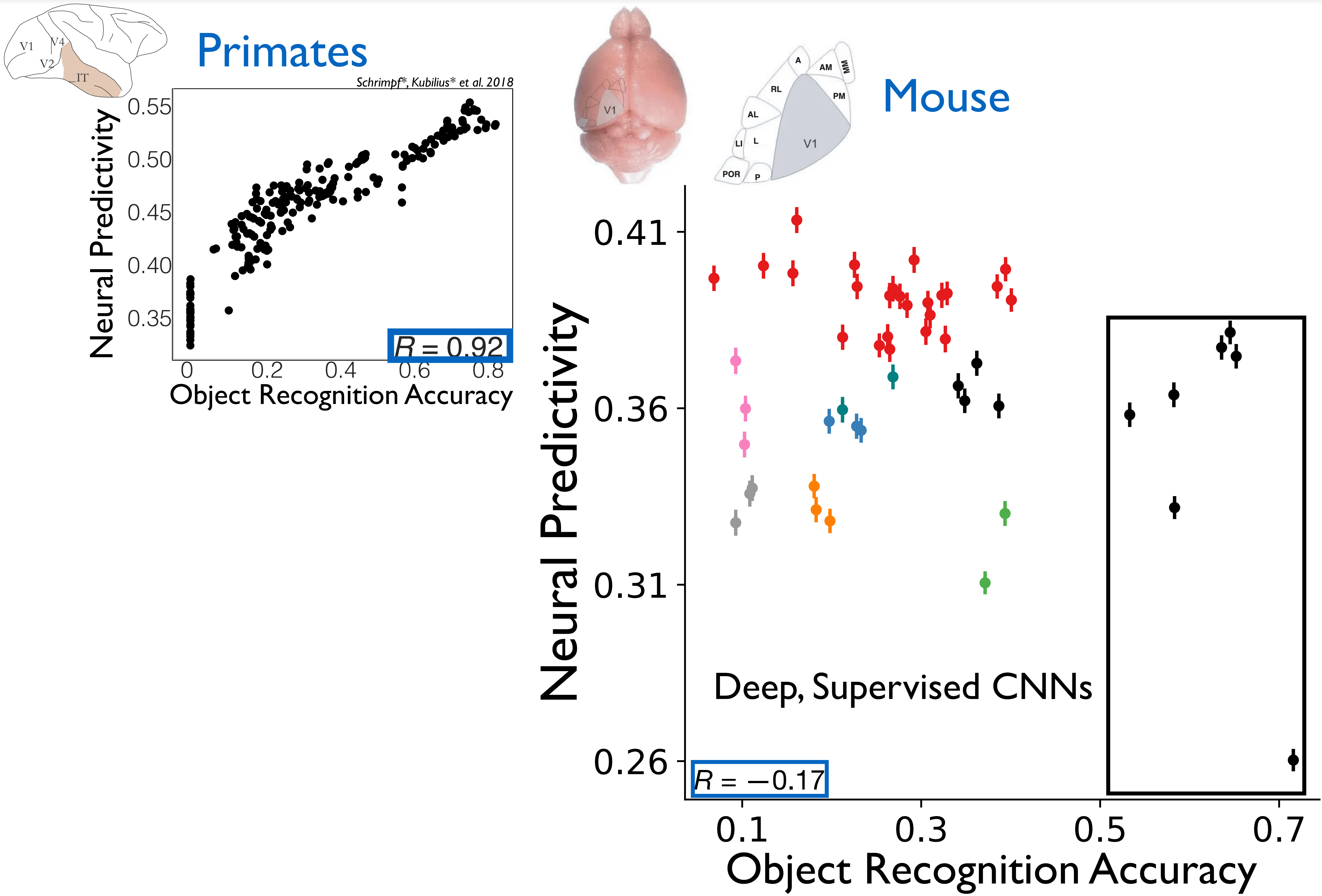

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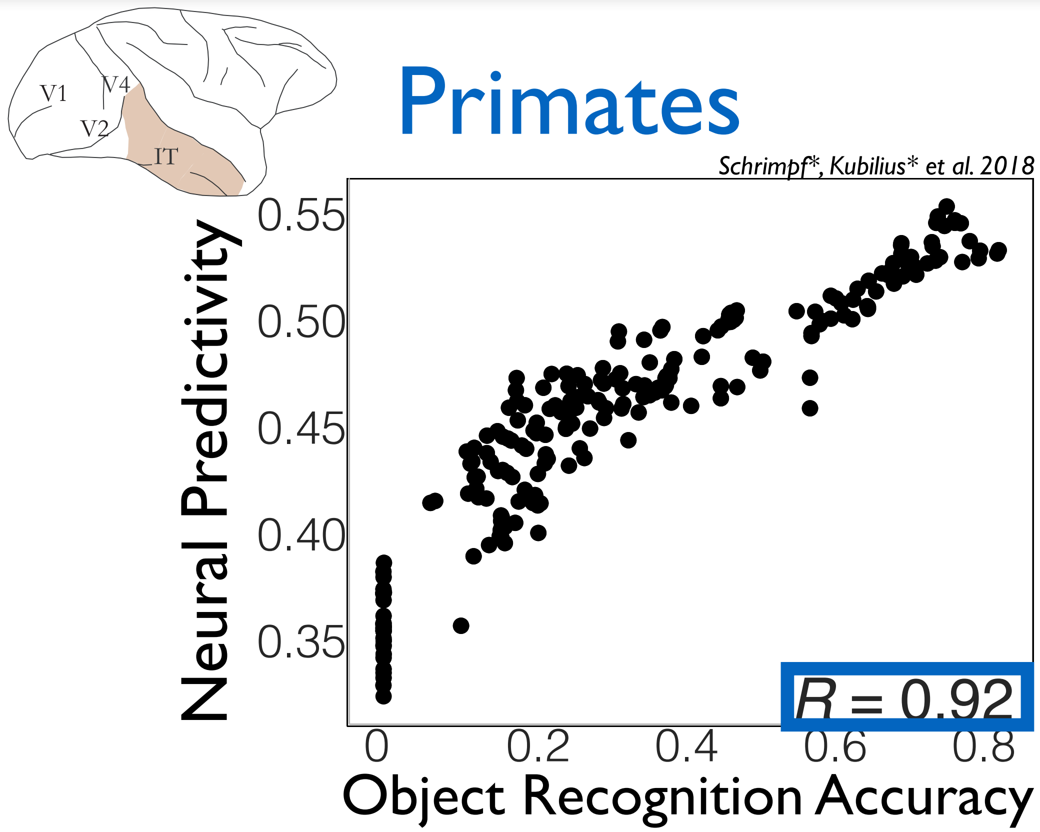

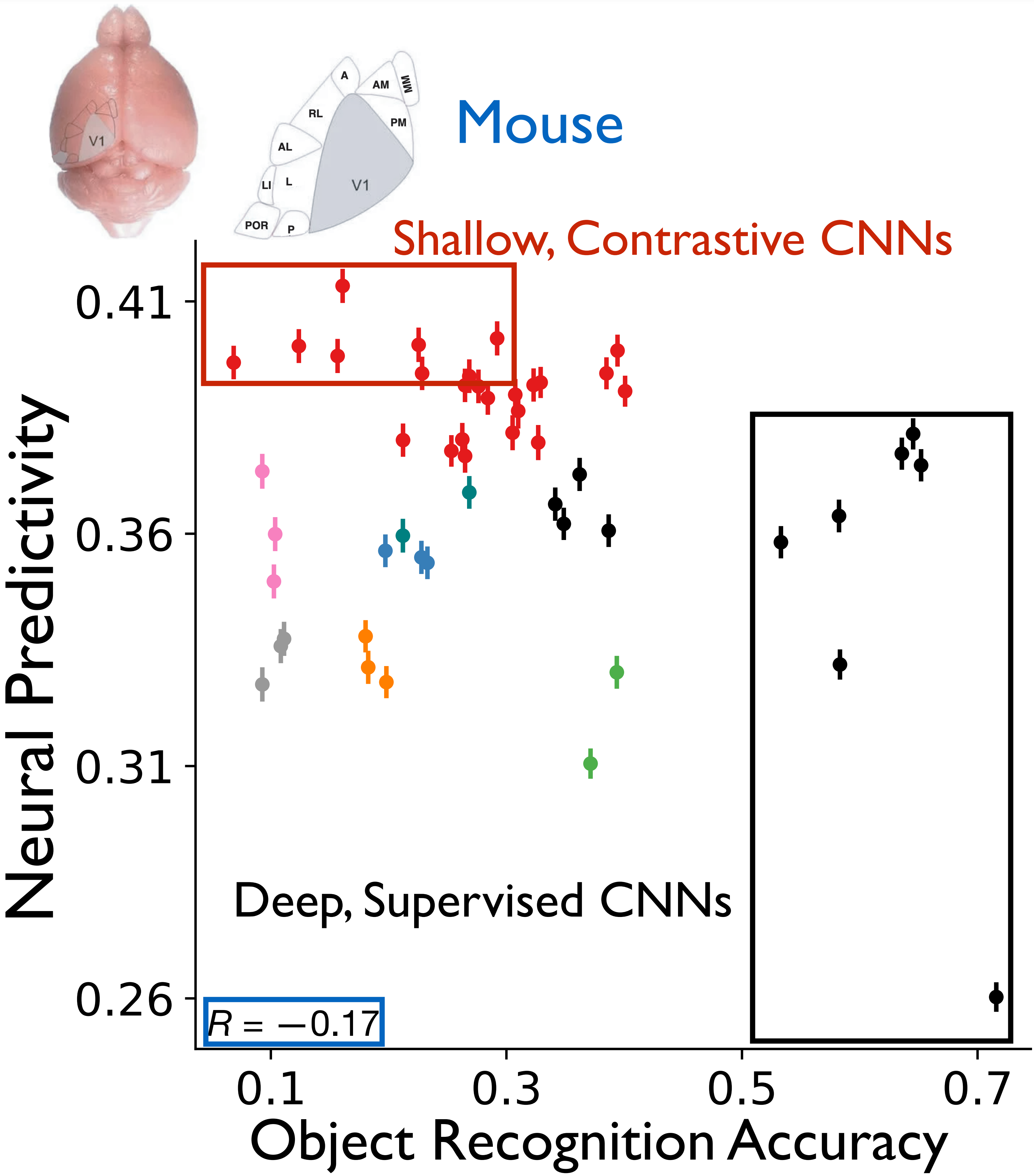

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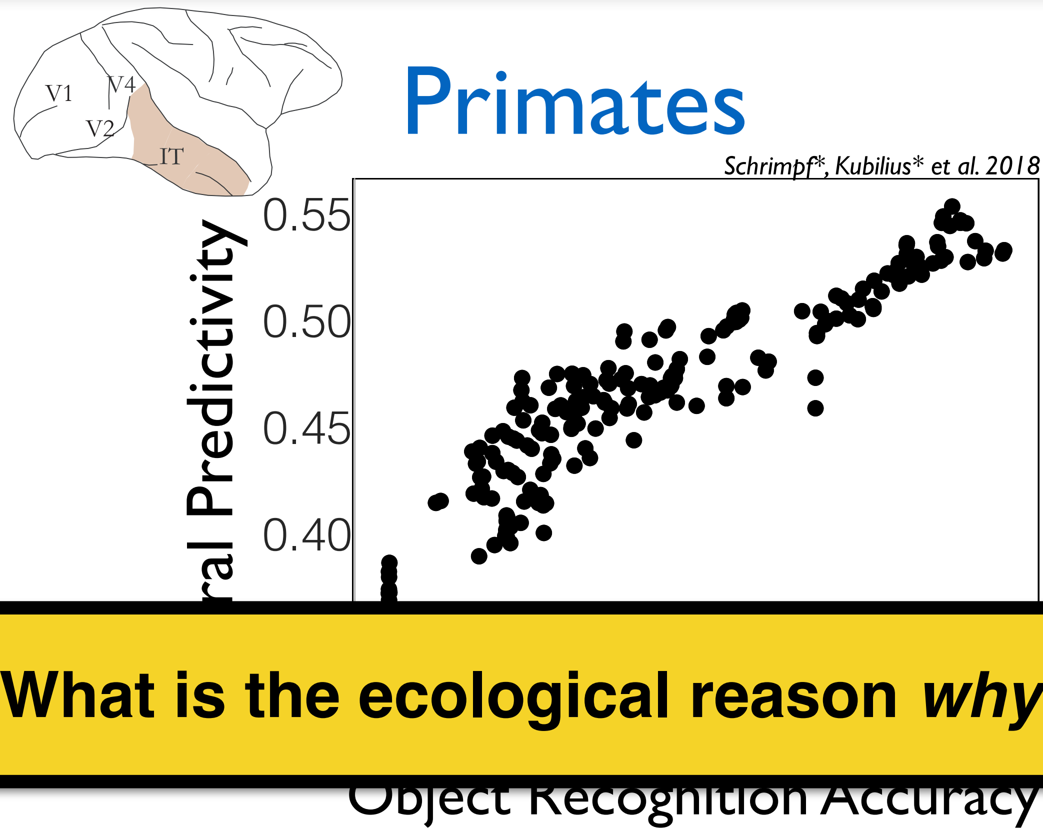
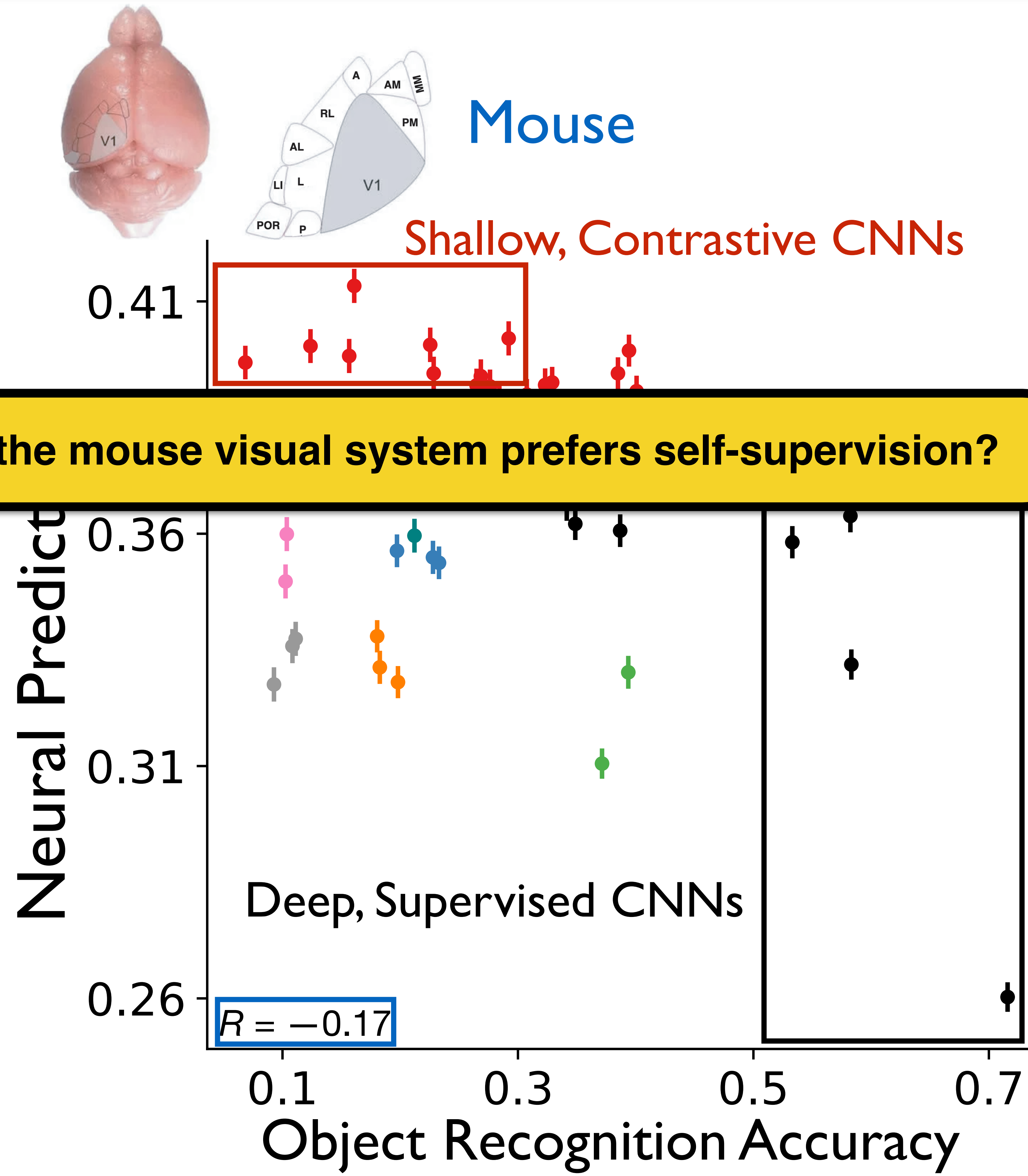
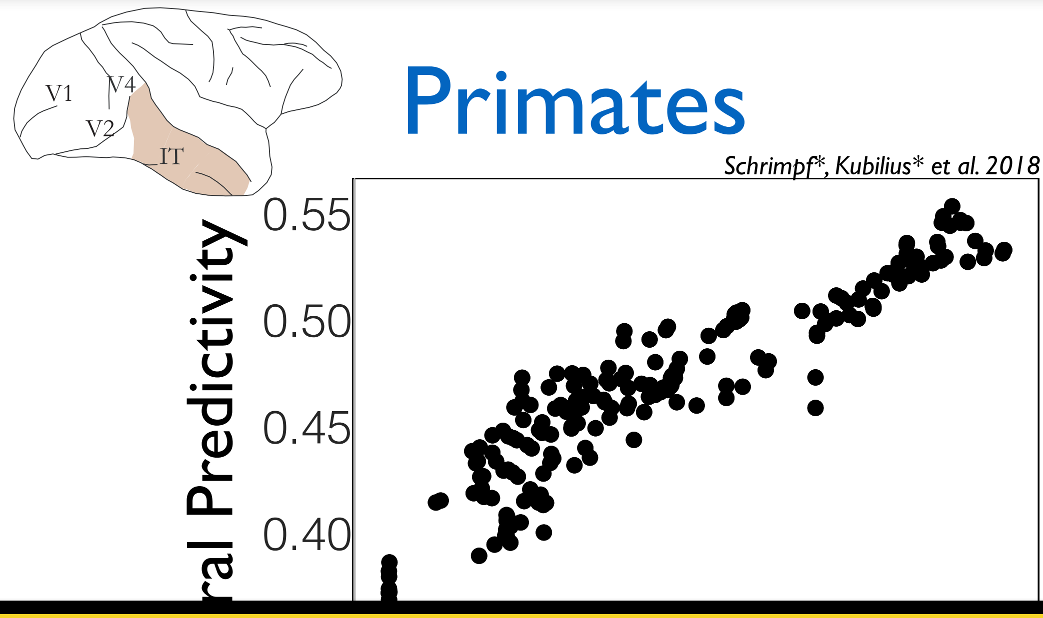
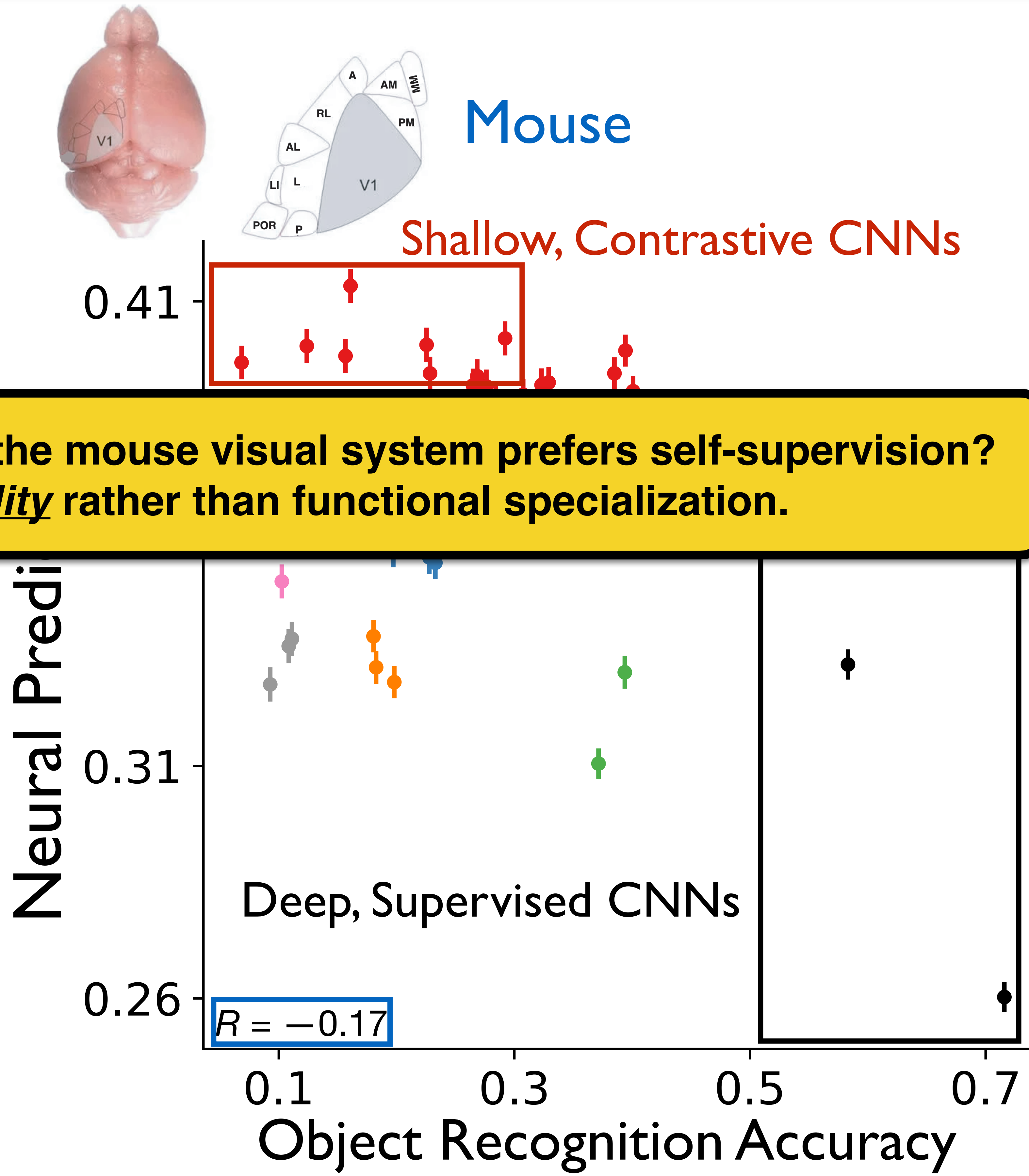




What is the ecological reason *why* the mouse visual system prefers self-supervision?

Object Categorization Ability **NOT** Correlated with Neural Predictivity





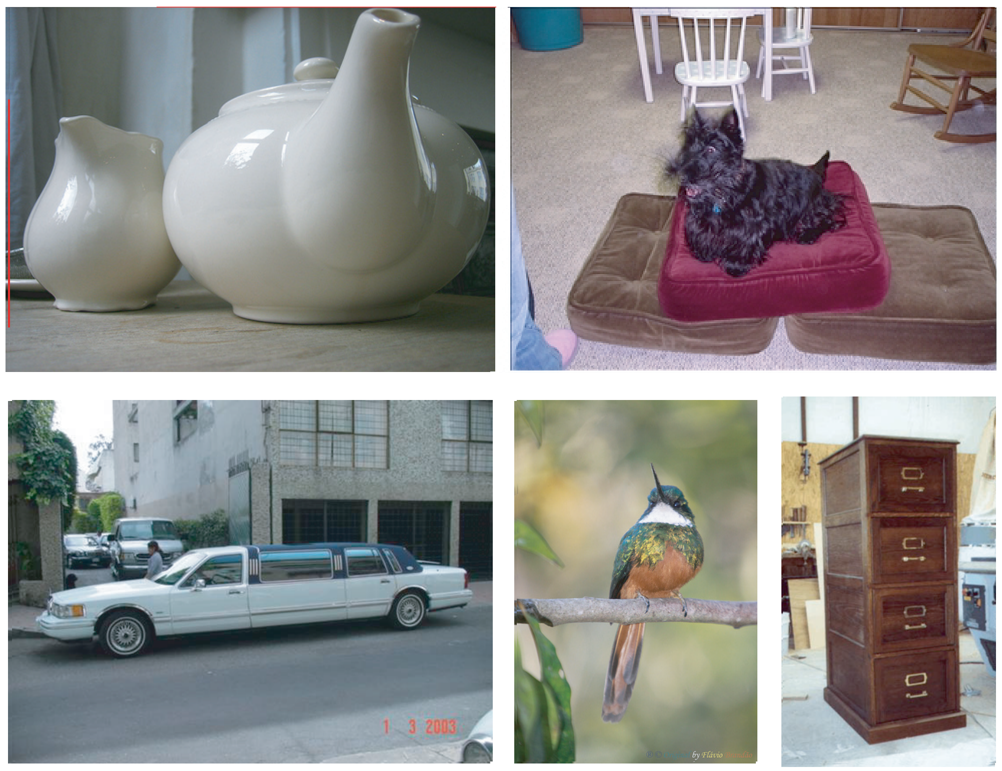
What is the ecological reason *why* the mouse visual system prefers self-supervision?
Hypothesis: *task-generality* rather than functional specialization.

Assessing Task-Generality

Assessing Task-Generality

Train

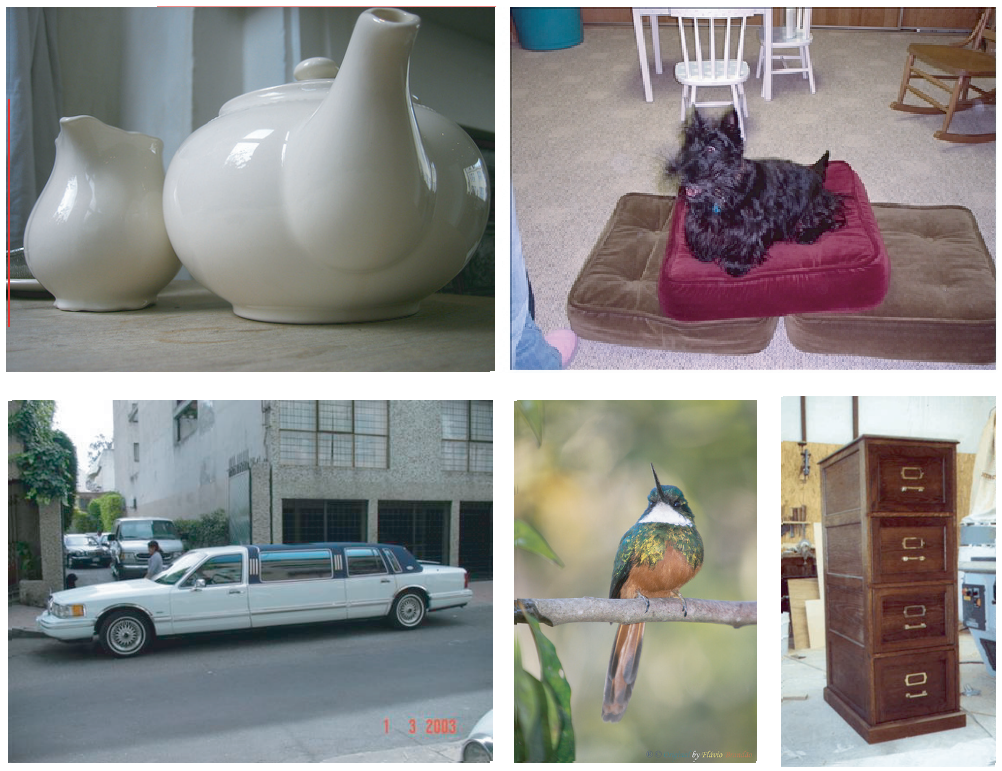
ImageNet



Assessing Task-Generality

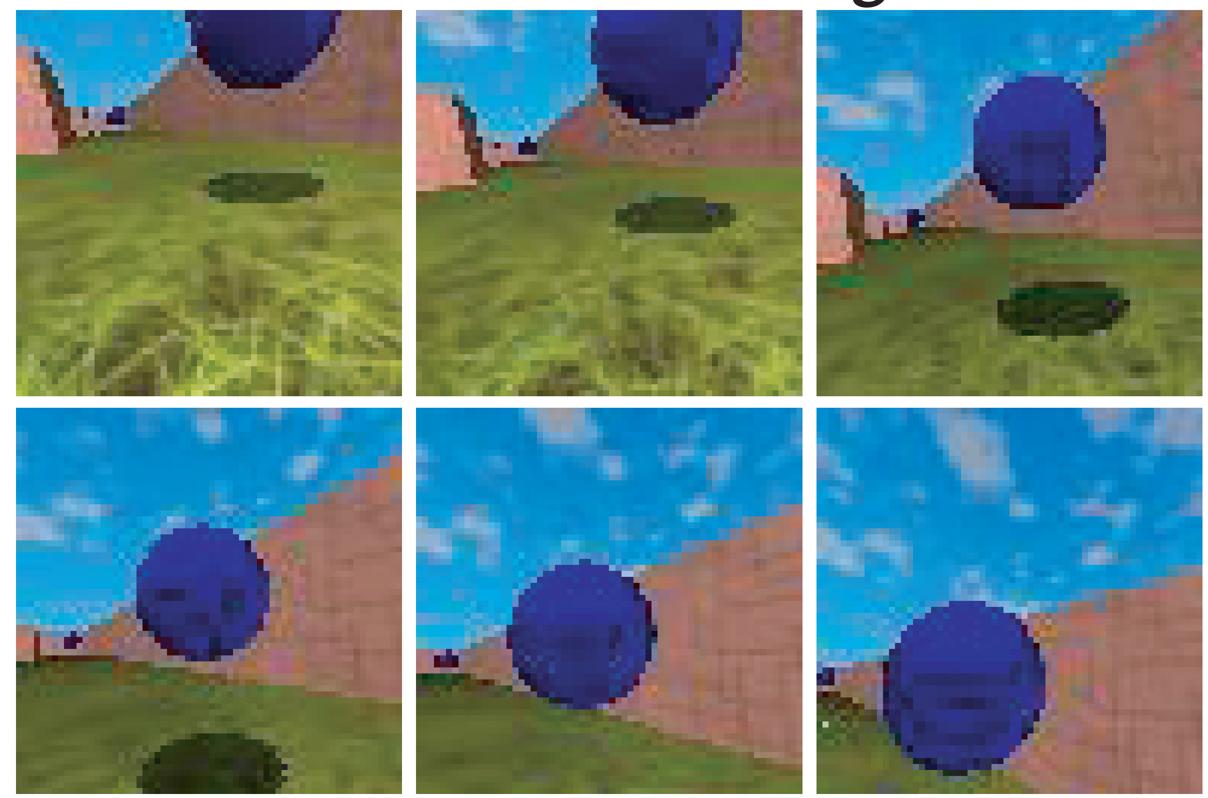
Train

ImageNet



Evaluate

Reward-Based Navigation



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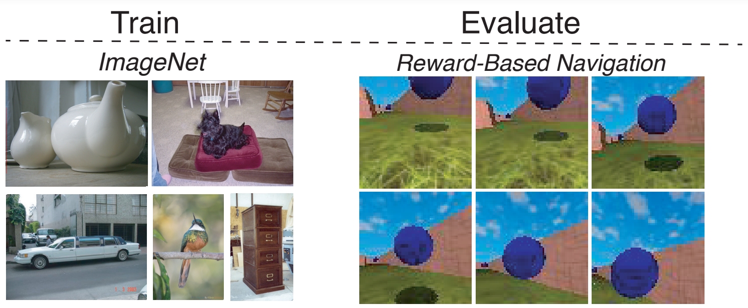

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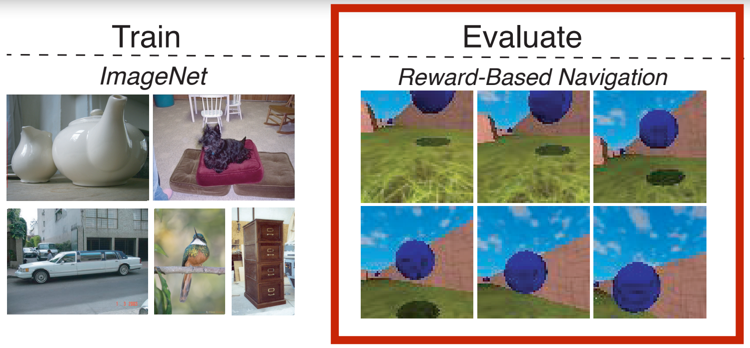
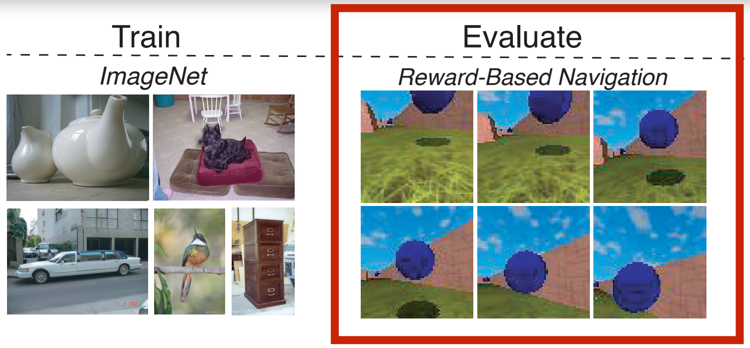


Embodied Virtual Rodent Navigation



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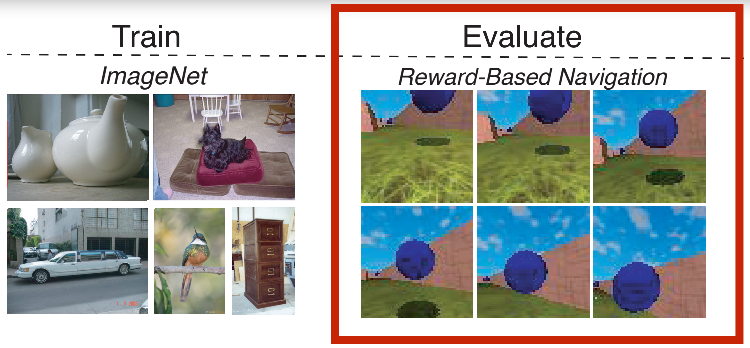
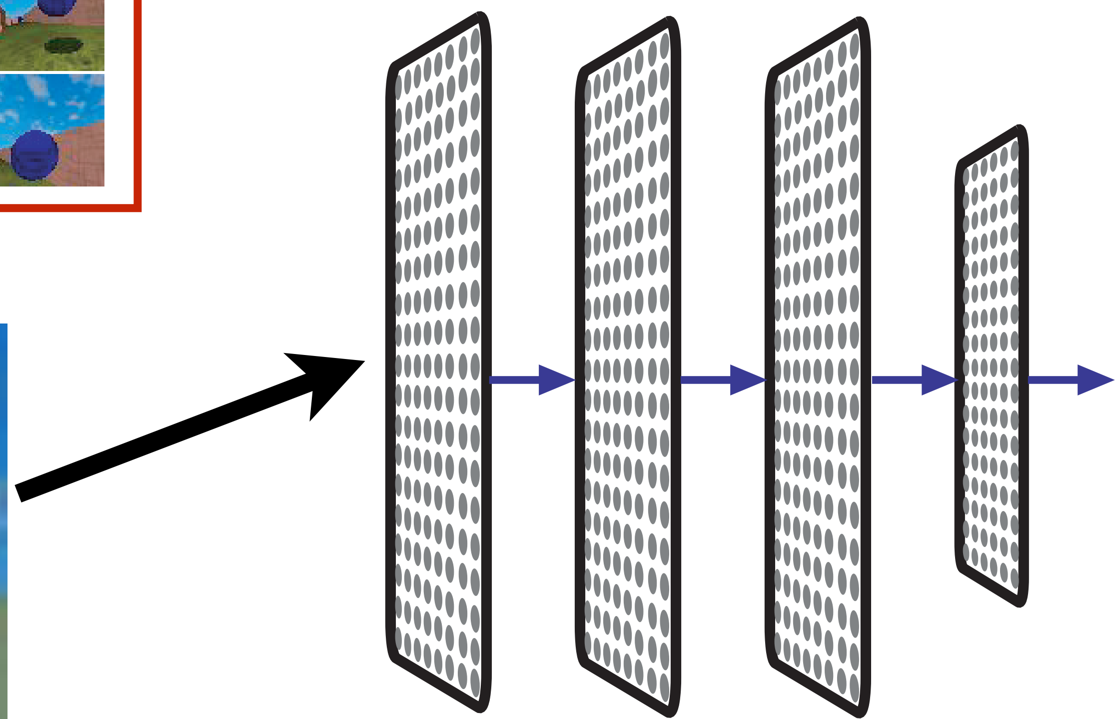


Vision Network



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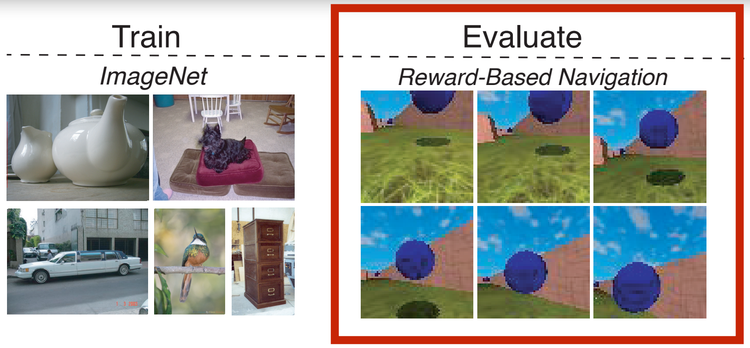

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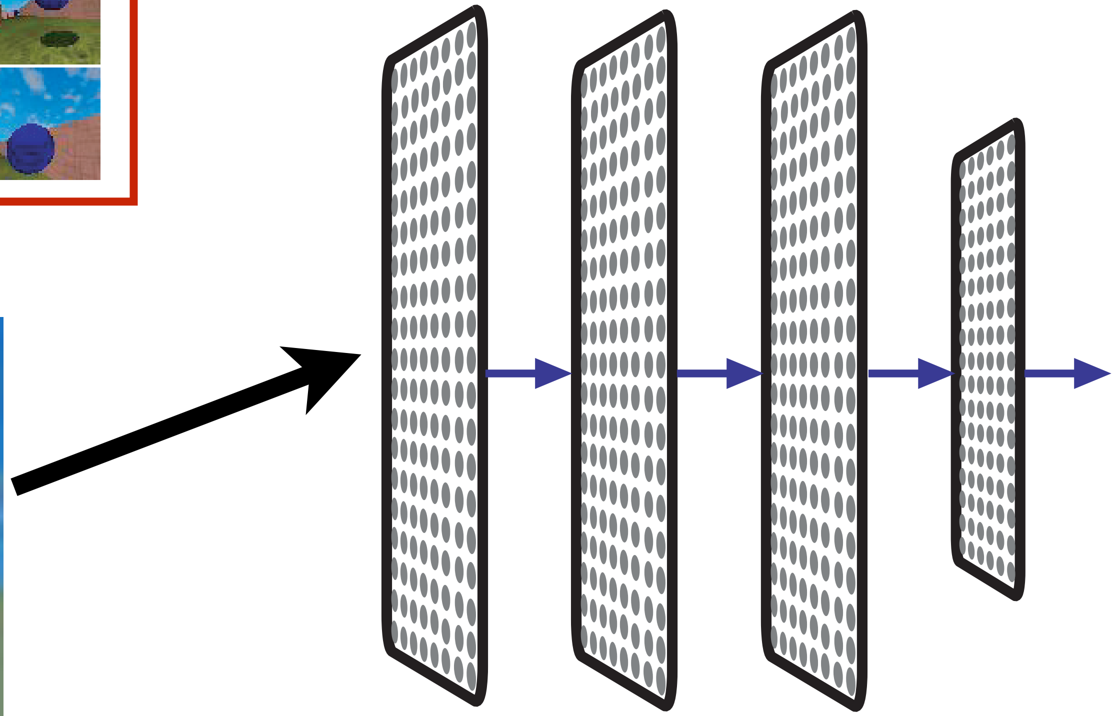
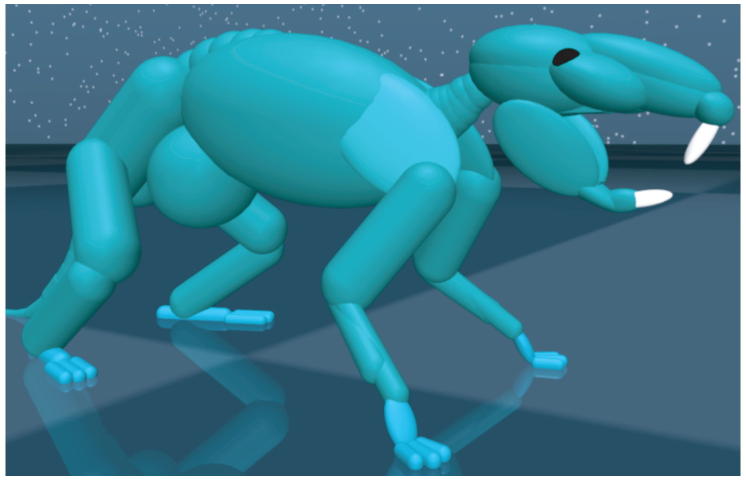
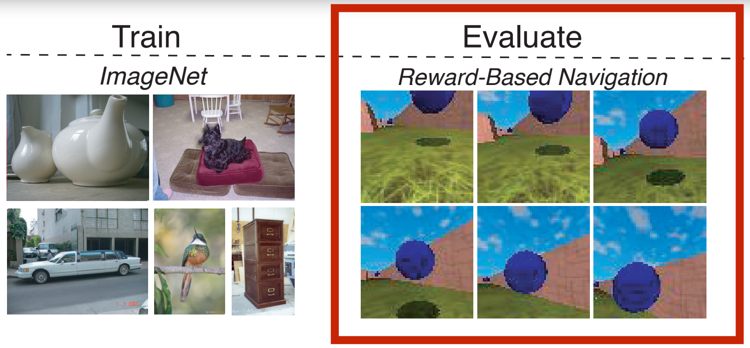




Biomechanical Model
(Joint angles, accelerometer, etc.)

Bence Ölveczky

Embodied Virtual Rodent Navigation



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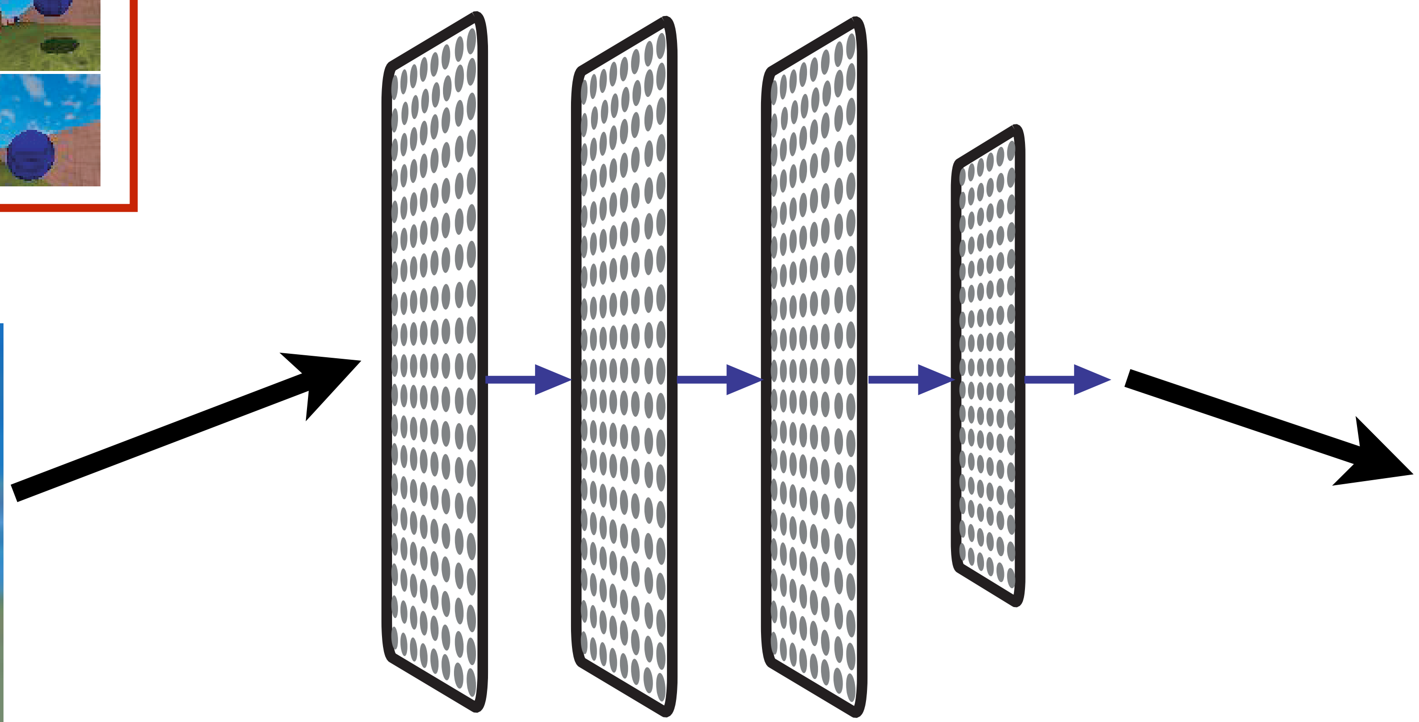

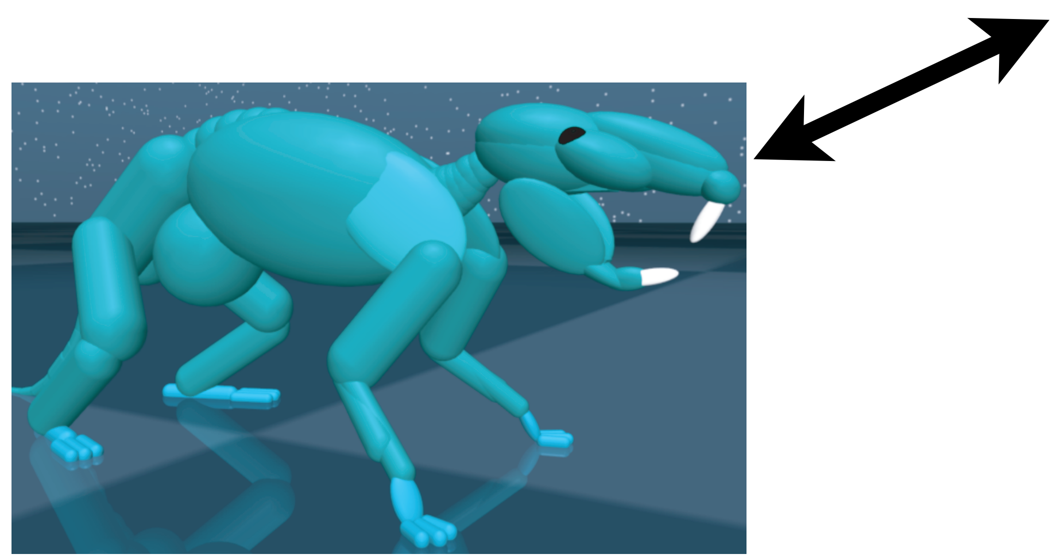

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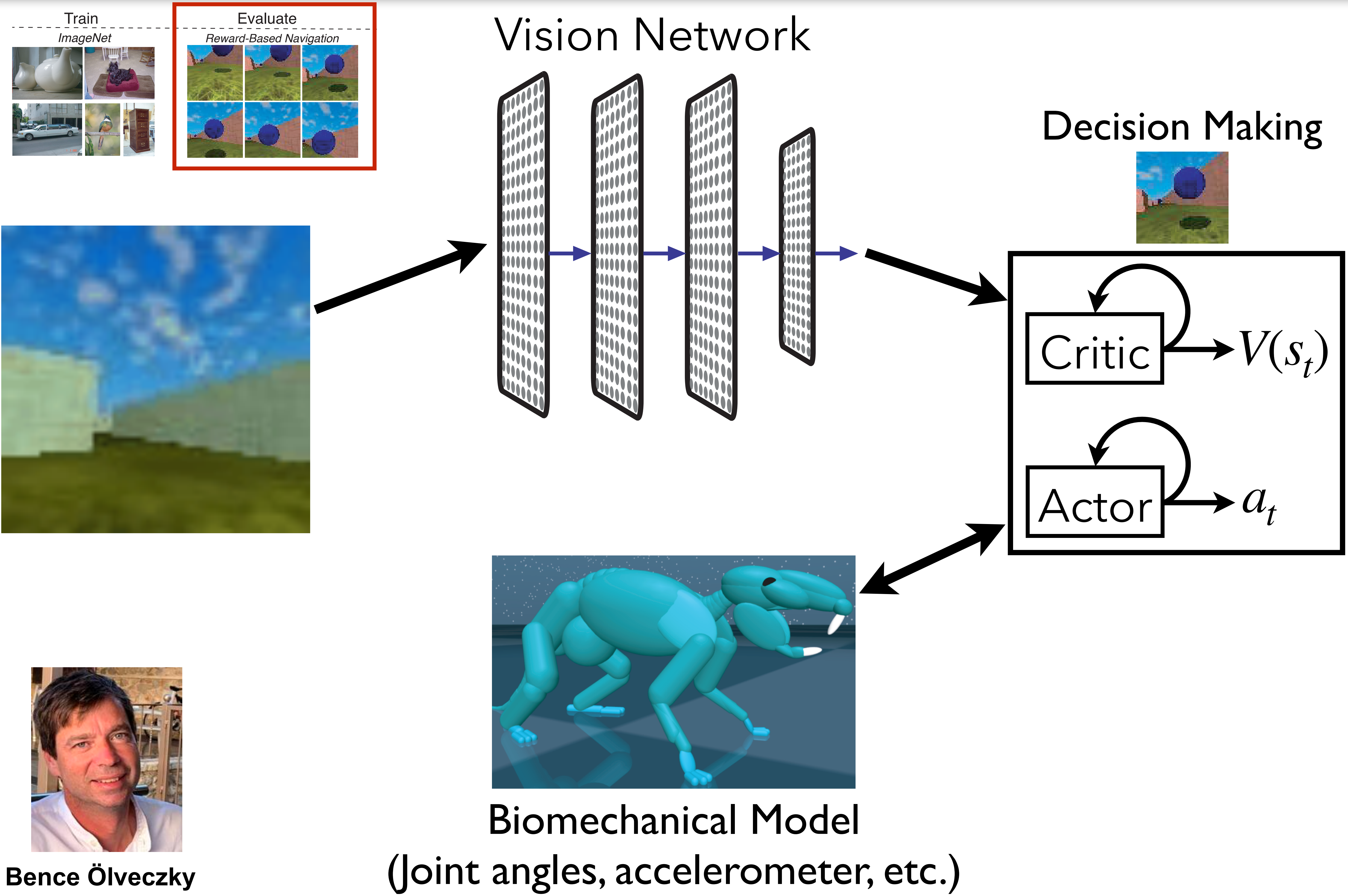

Bence Ölveczky

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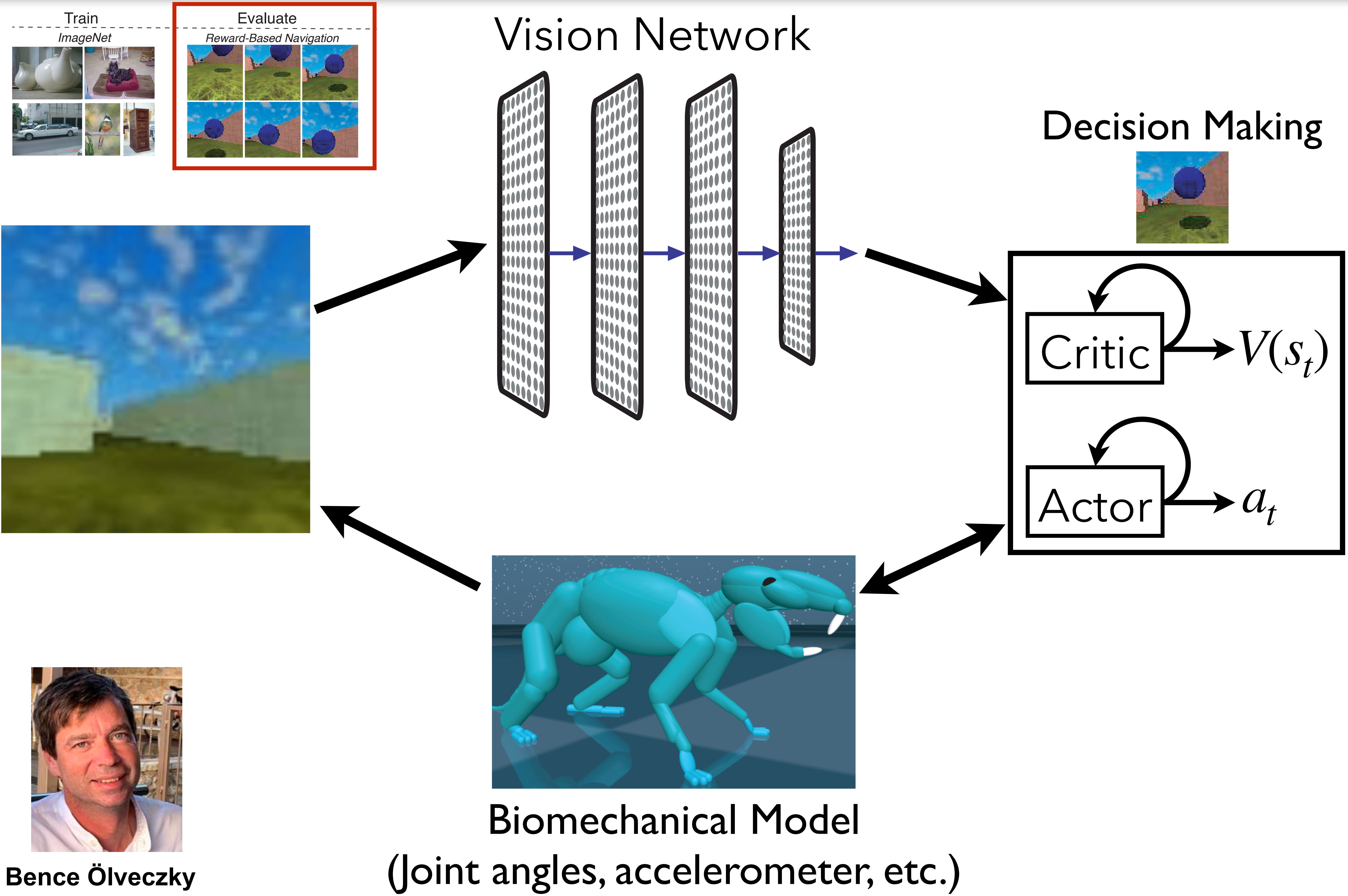
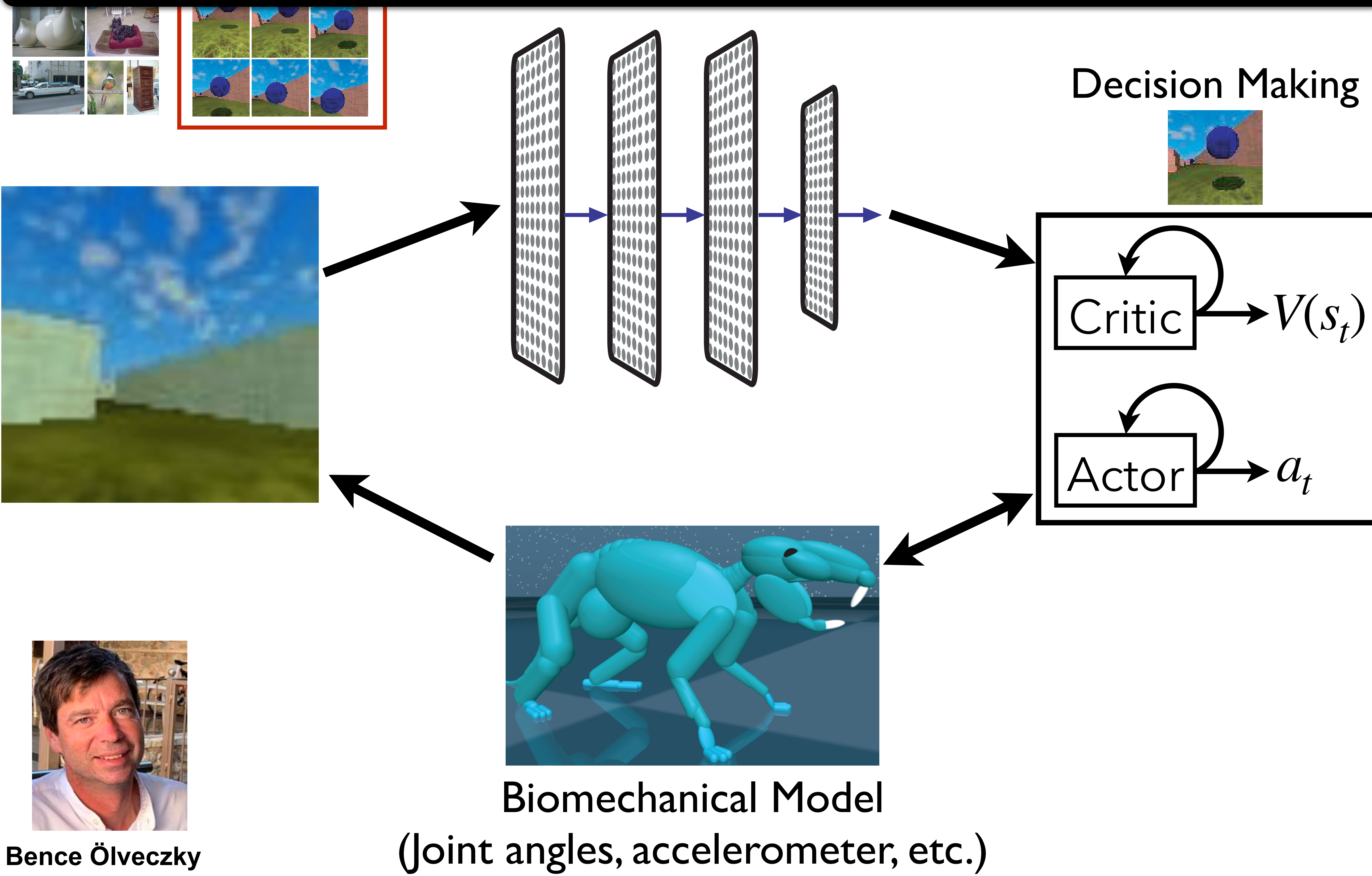


High degree-of-freedom body, keeping track of history over long timescales with high-dimensional, continuous inputs



Bence Ölveczky

Contrastive Models Yield Better Transfer Performance

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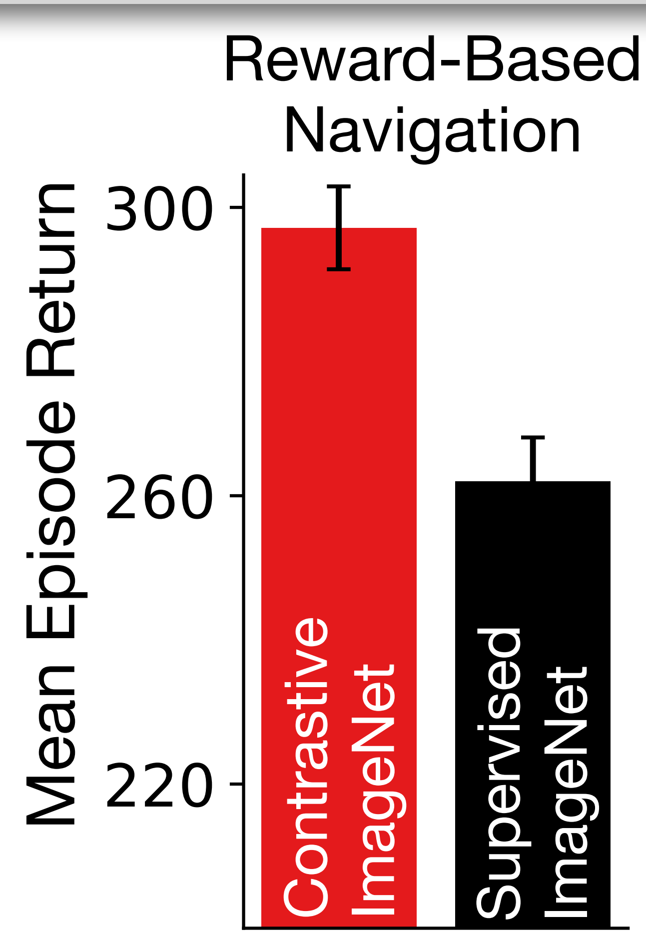
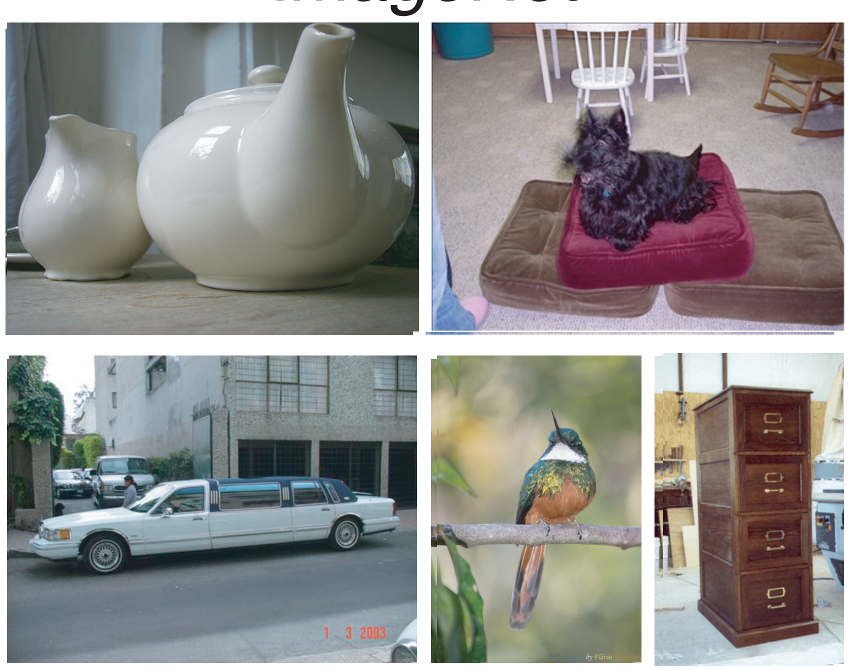
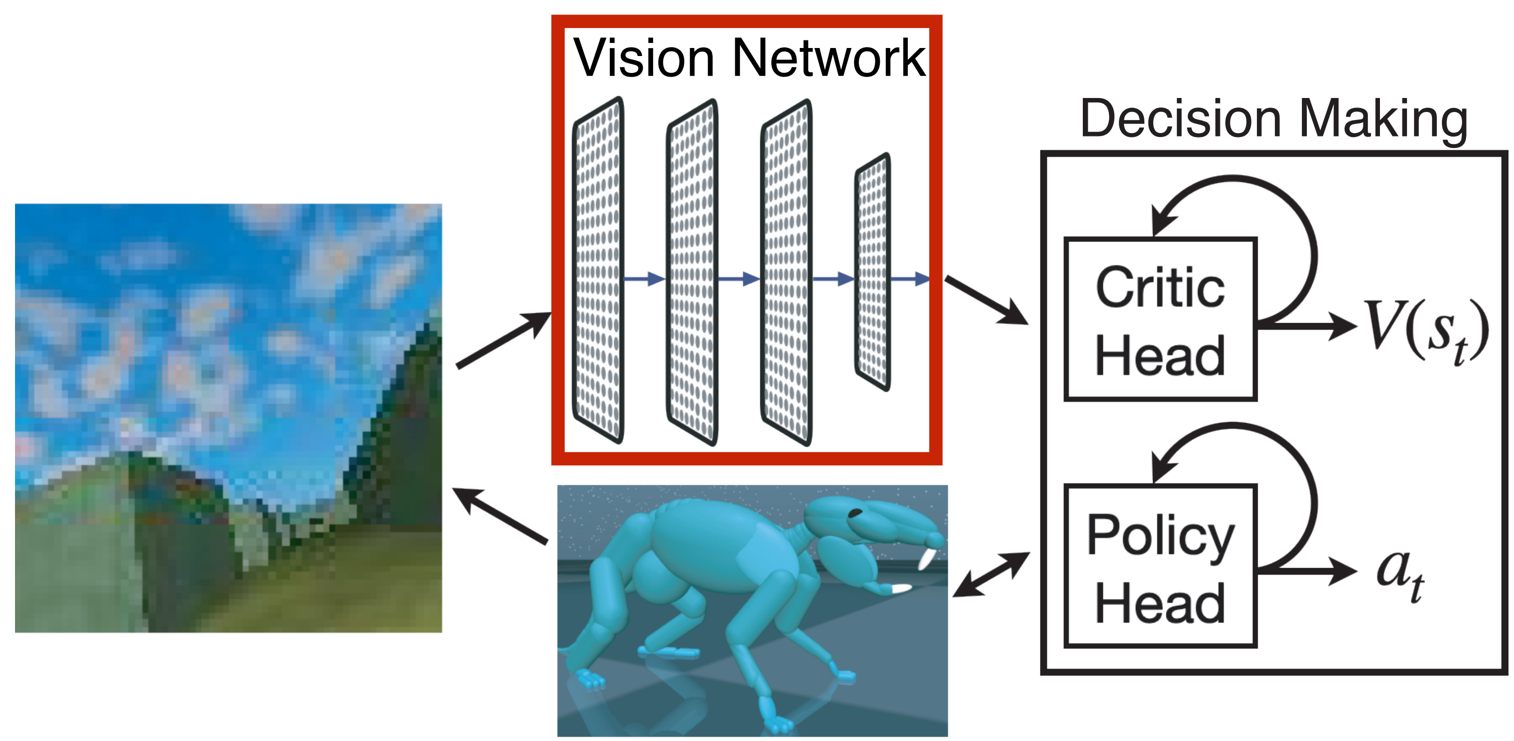


Train

ImageNet



Evaluate



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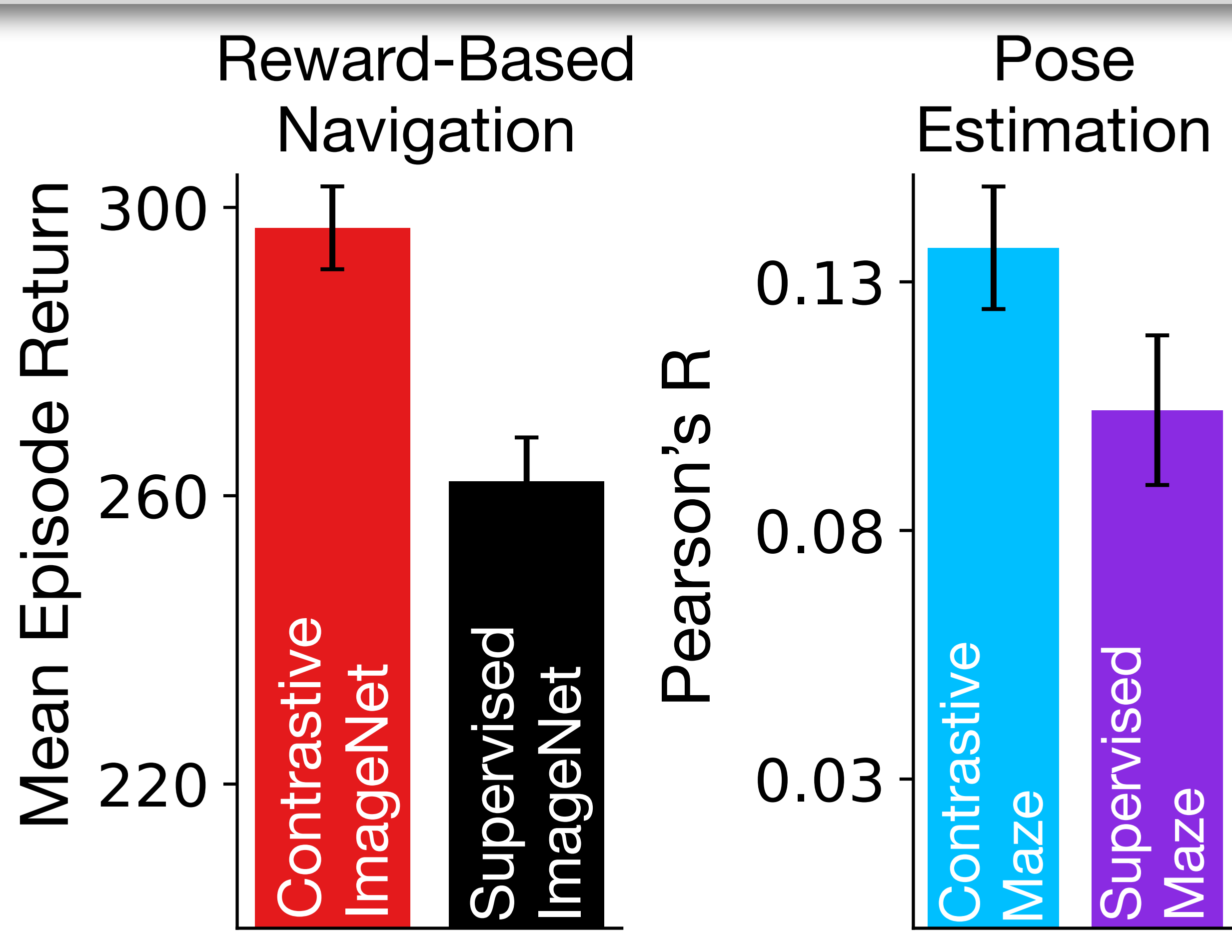
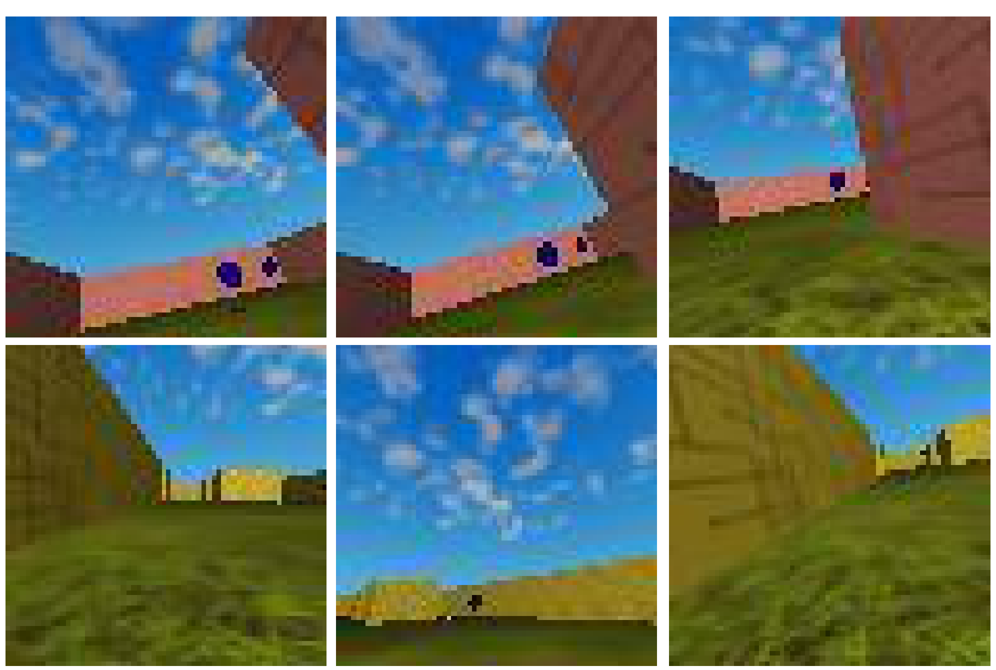


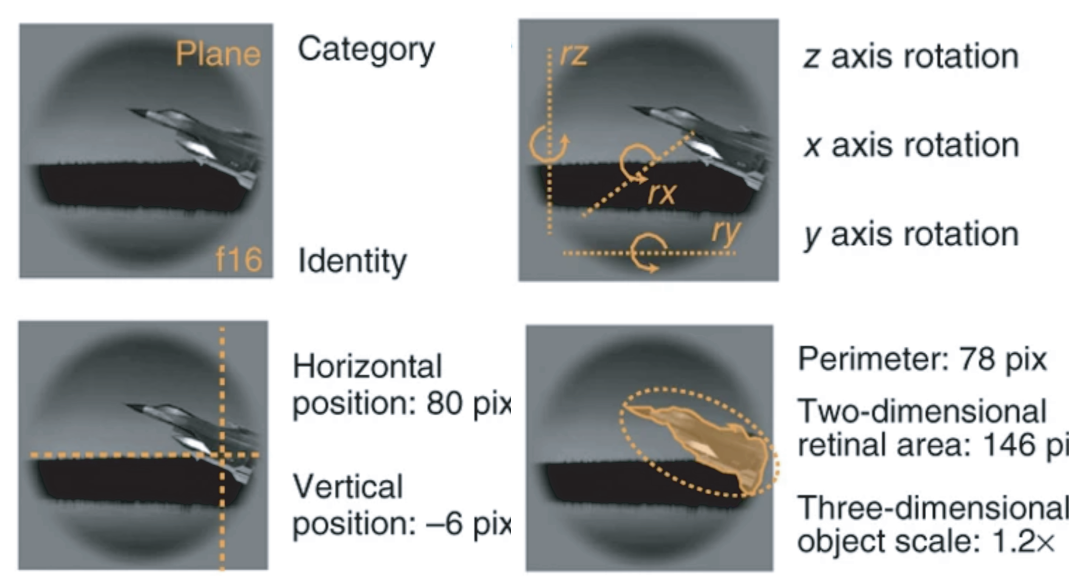
Train

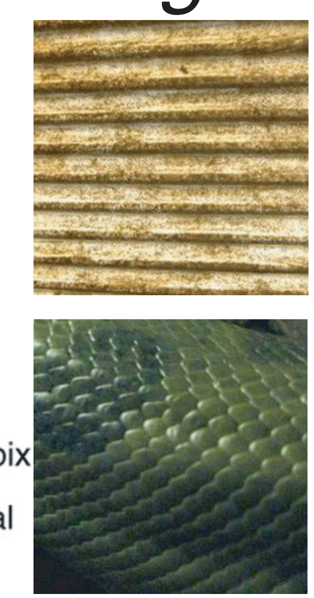
Maze Environment



Evaluate

Visual Scene Understanding





Object properties *Texture*

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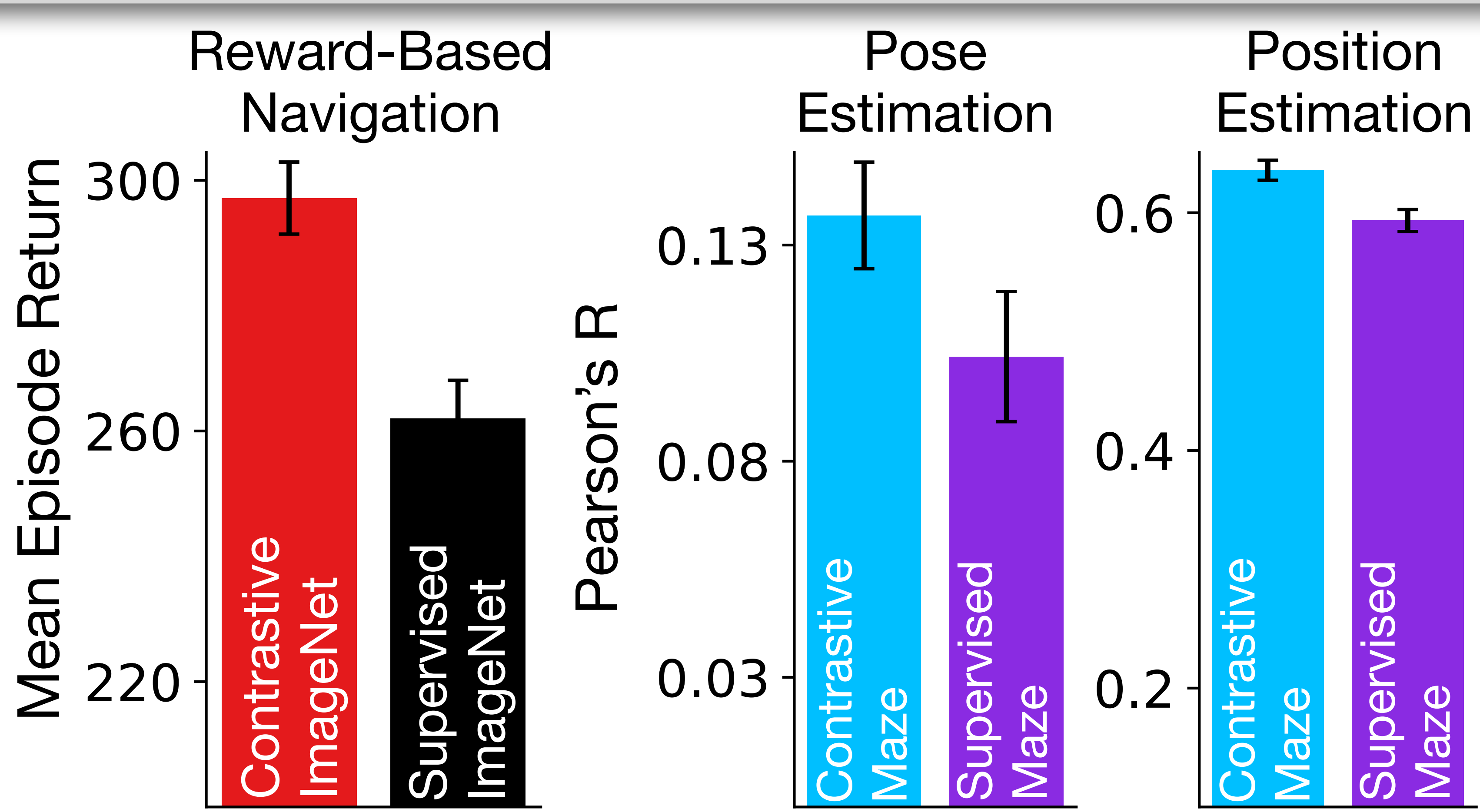

Train

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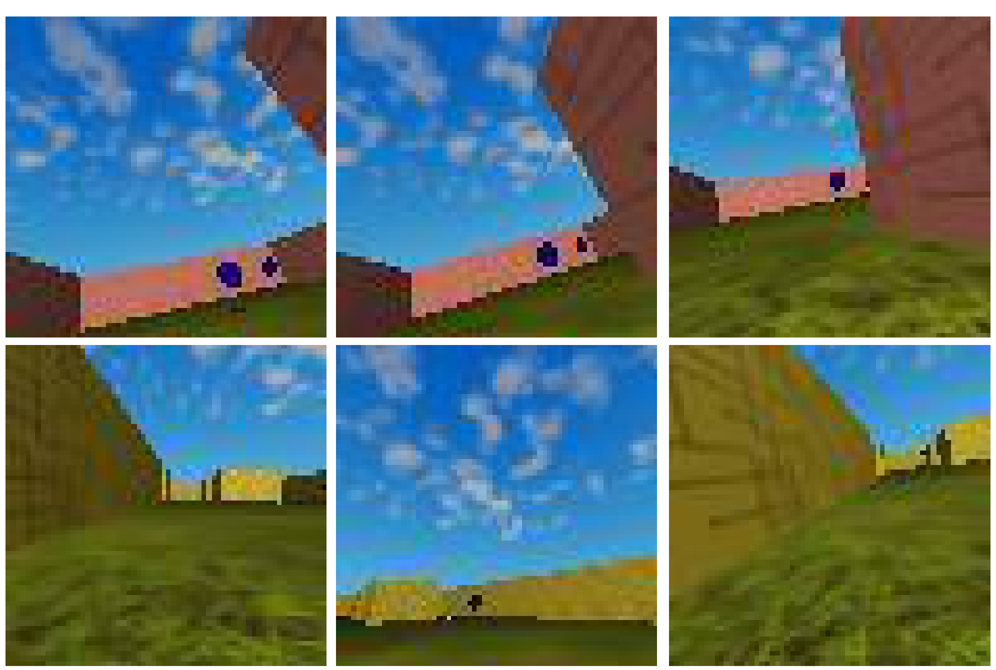

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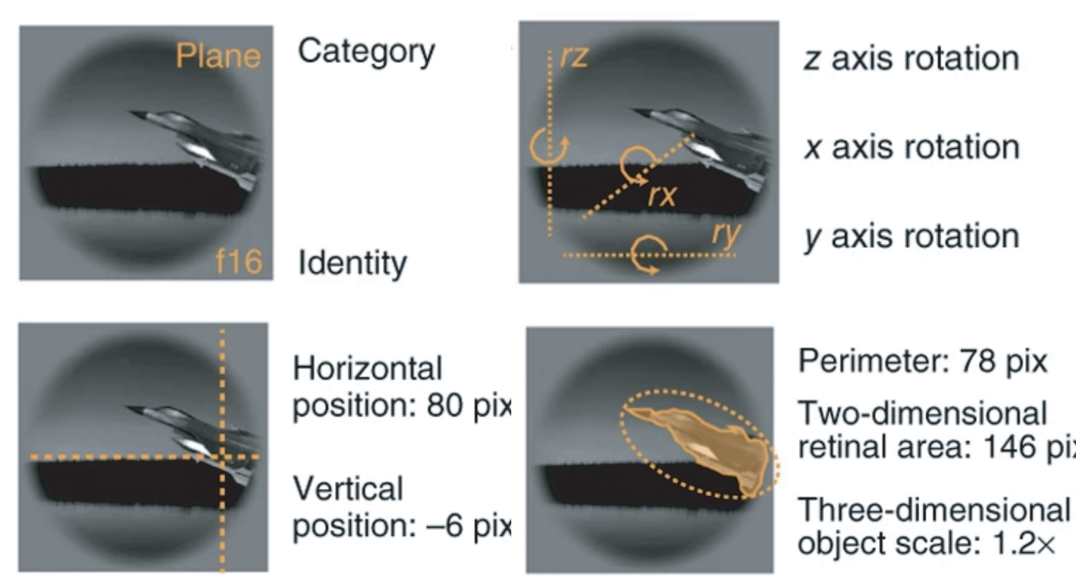

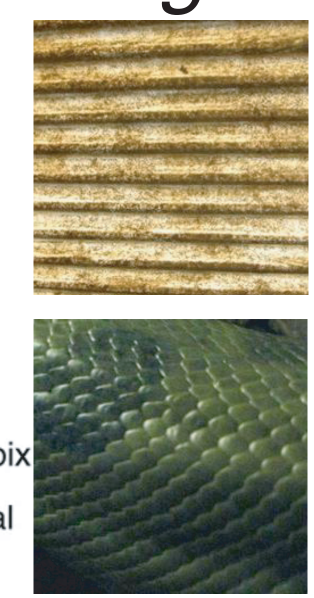

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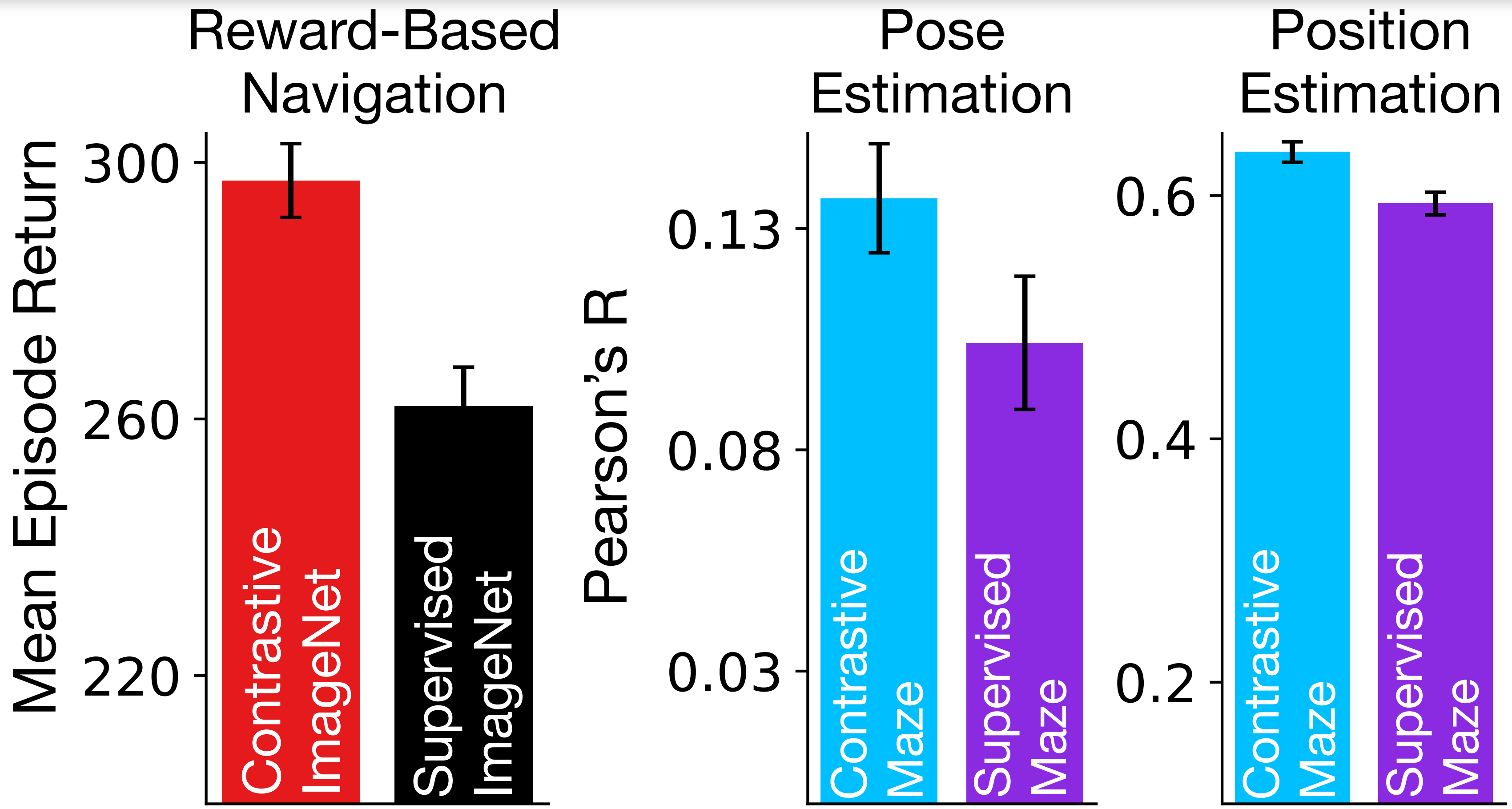

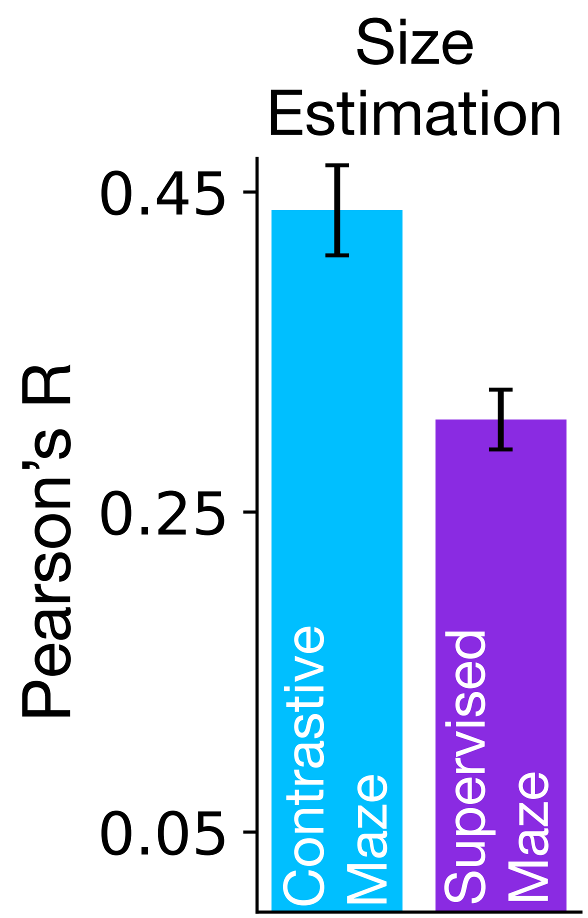

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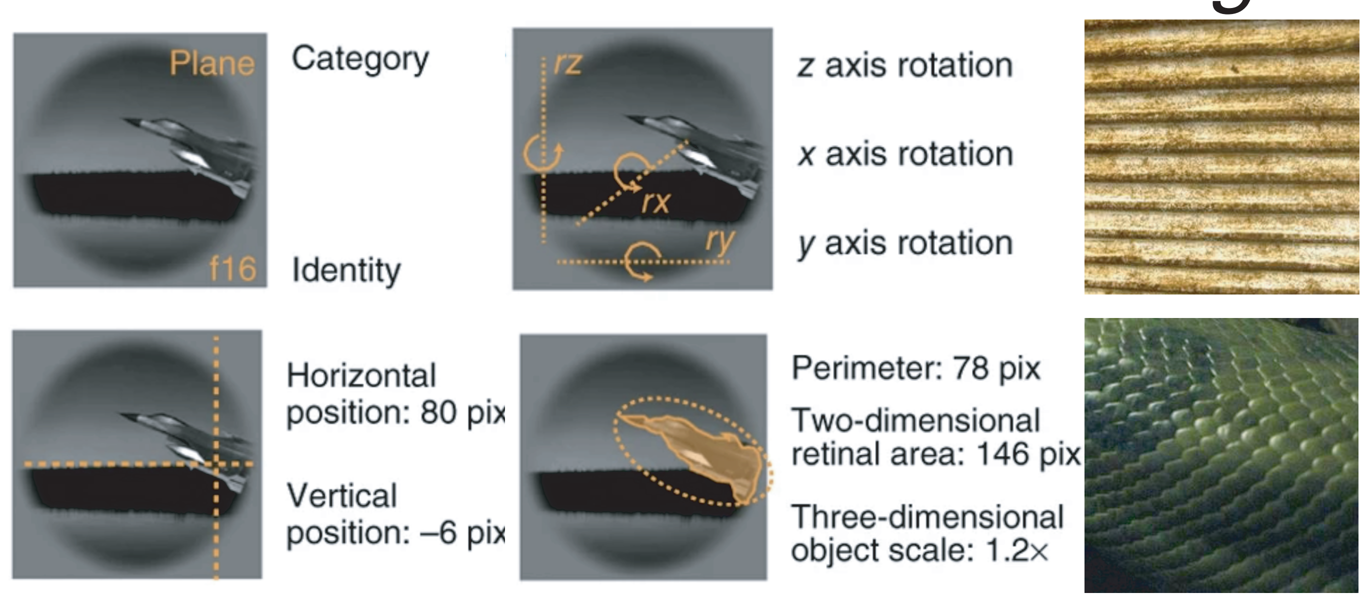

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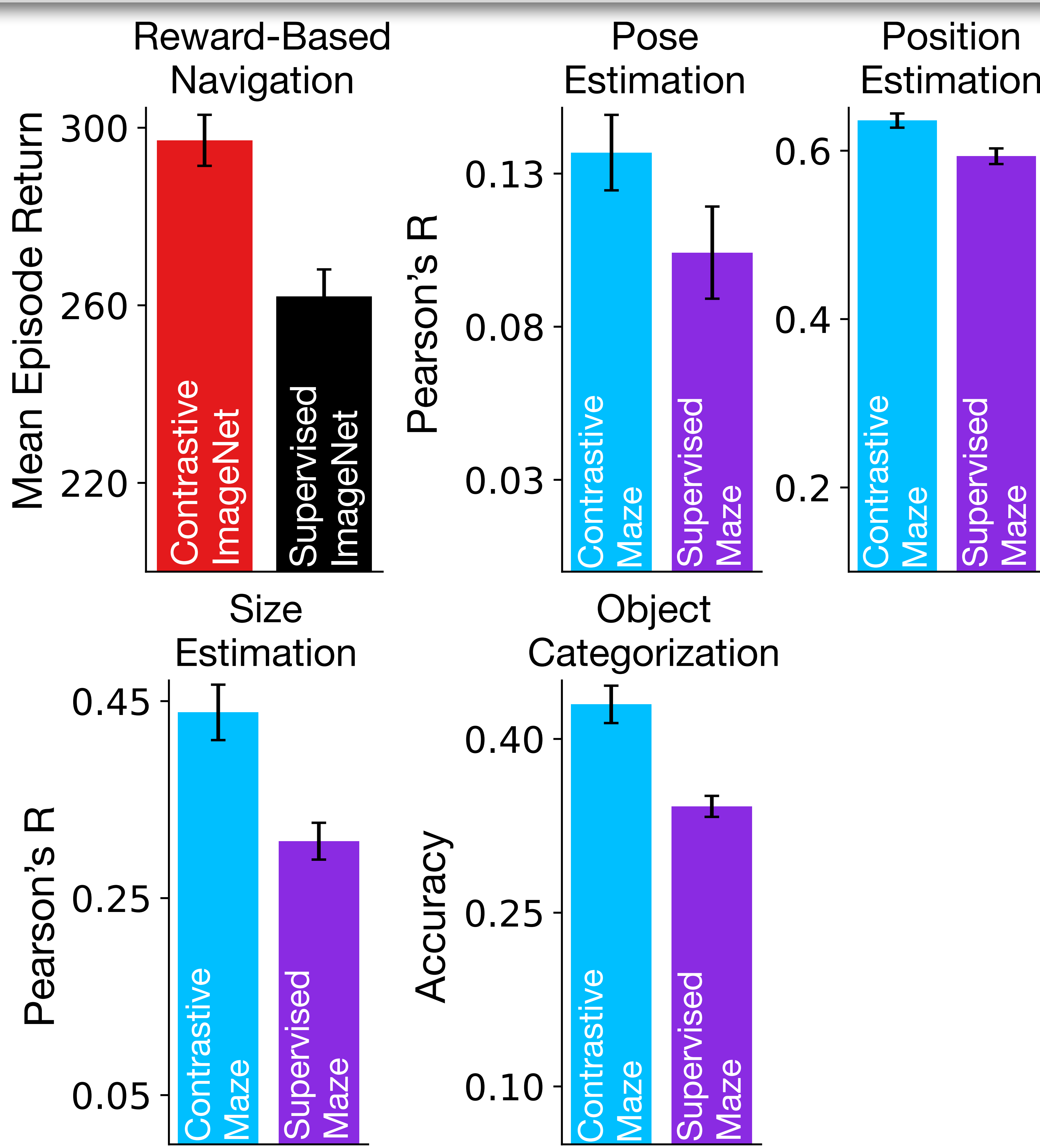

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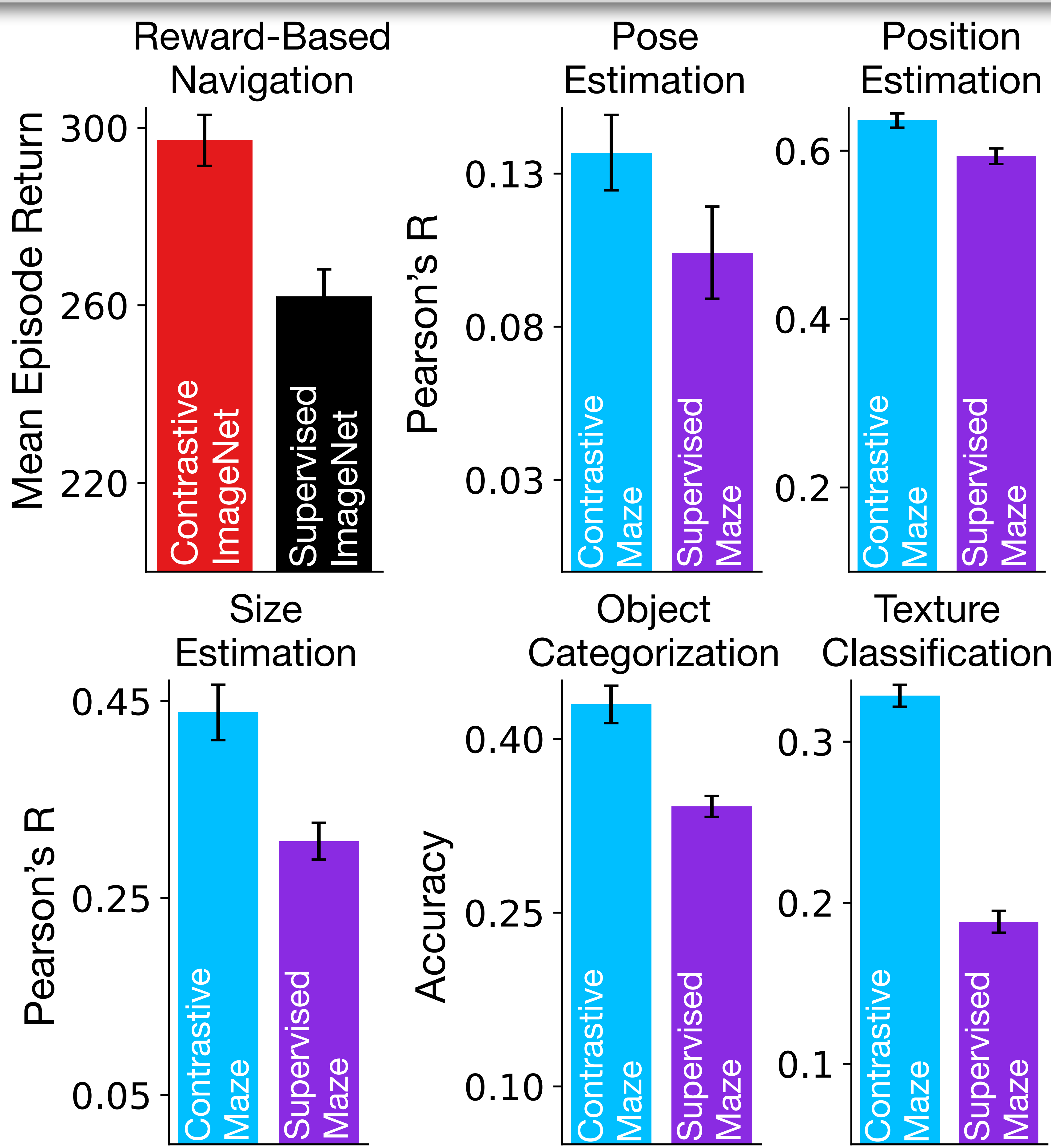

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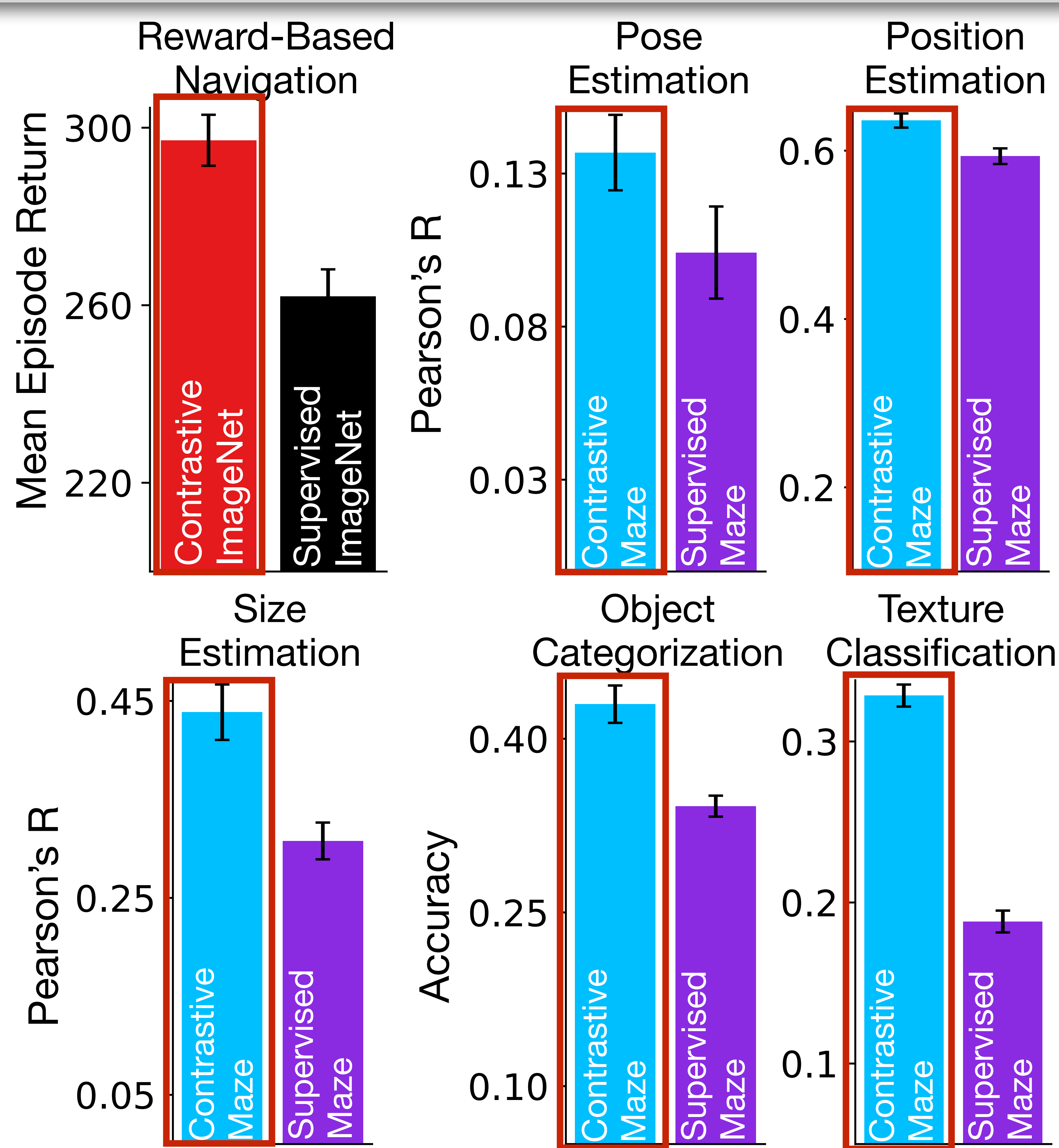
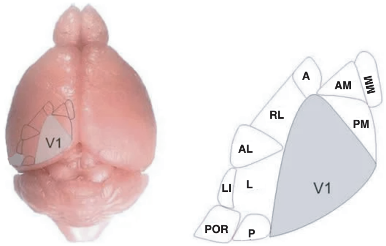
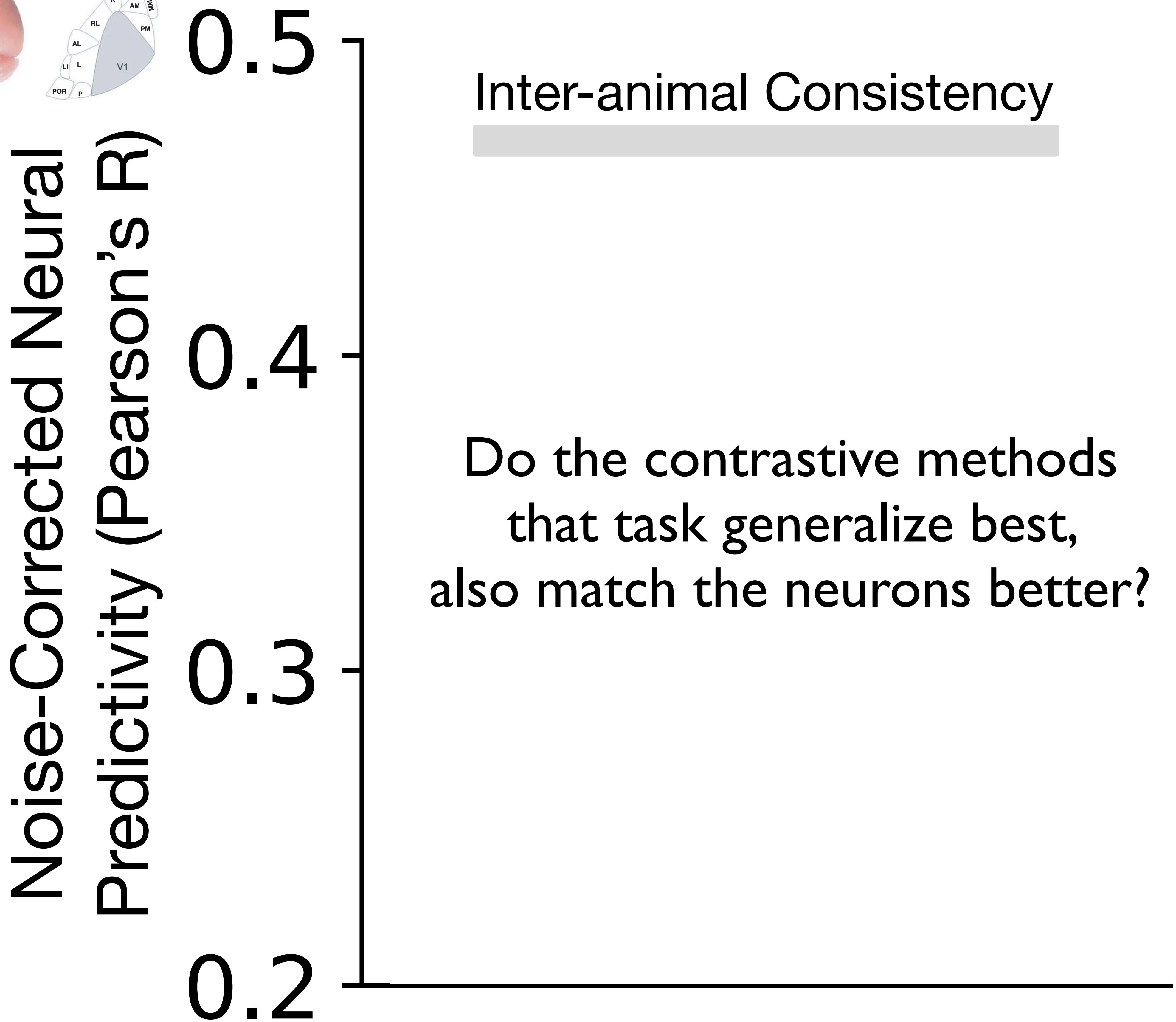


The best neural models have the best task transfer





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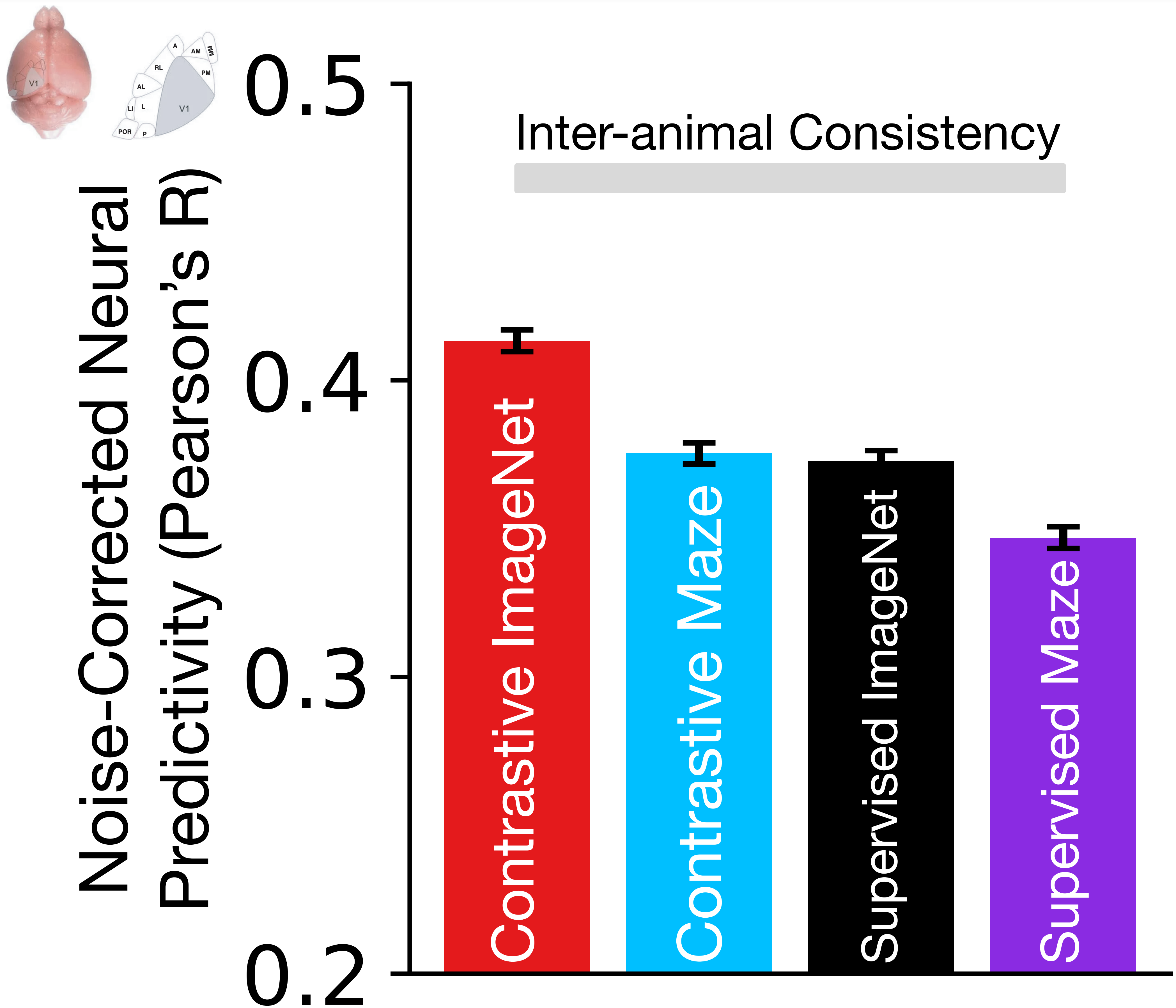

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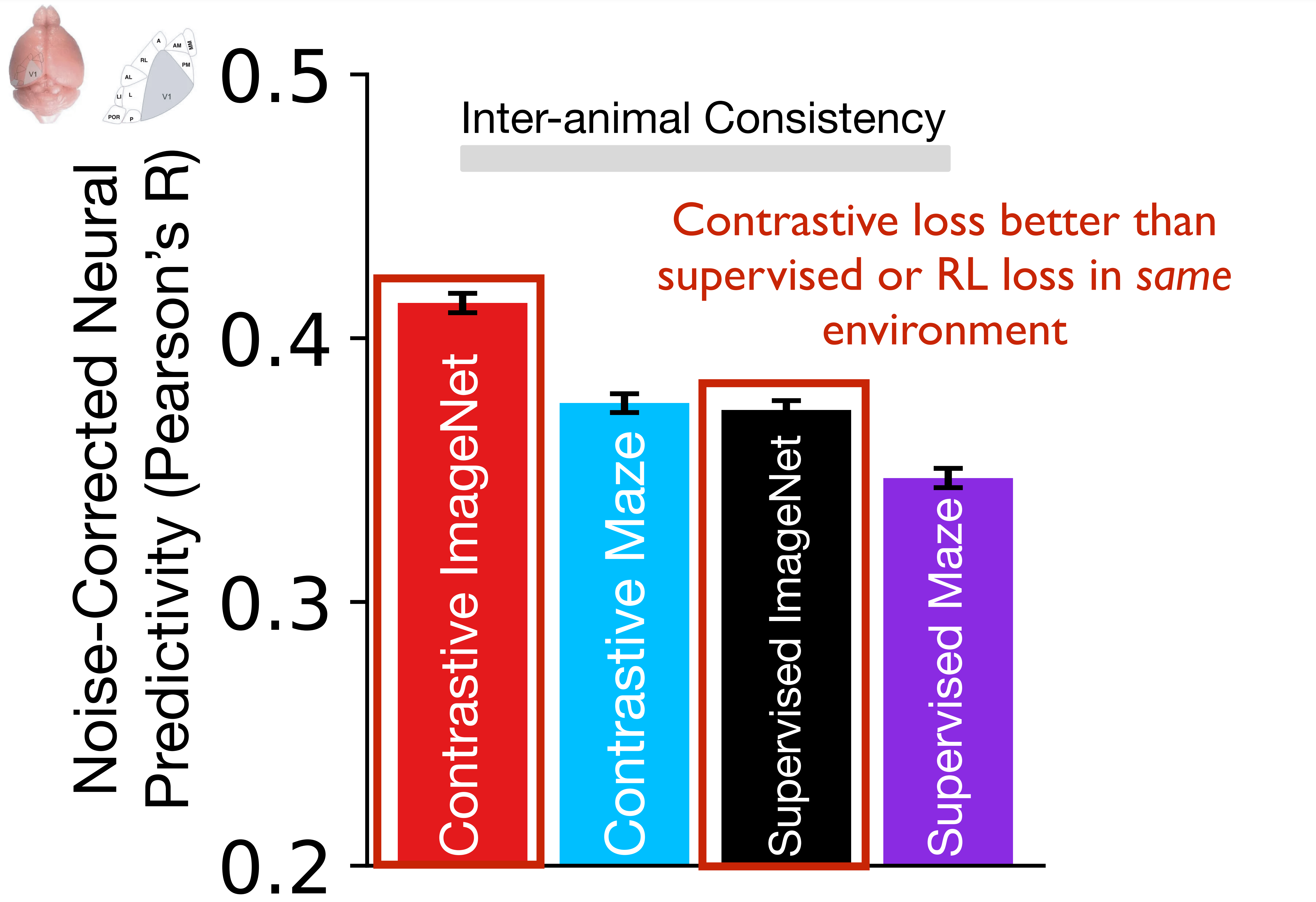

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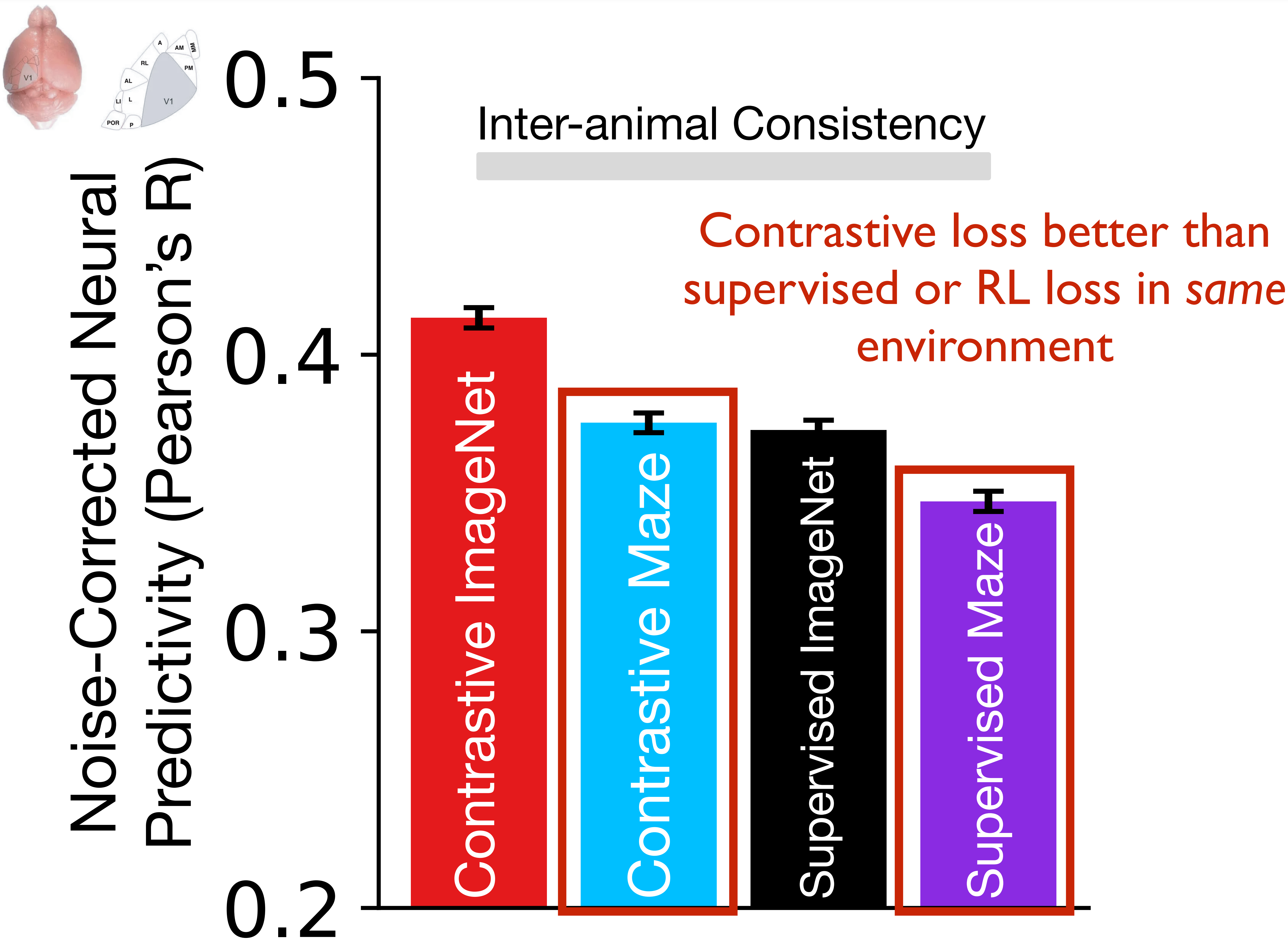

Outline

- Mouse Visual Cortex as a Task-General, Limited Resource System
- Reusable Latent Representations for Primate Mental Simulation
- Heuristics for Interrogating Natural Intelligence

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Mouse visual cortex (so far) is a low-acuity, shallow network that makes best use of the mouse's limited resources to create a general-purpose visual system, that can be deployed in novel environments and embodied contexts.

- Reusable Latent Representations for Primate Mental Simulation

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- Reusable Latent Representations for Primate Mental Simulation

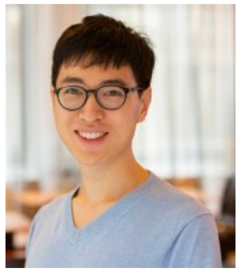
- Heuristics for Interrogating Natural Intelligence

Reusable Latent Representations for Primate Mental Simulation

A. Nayebi, R. Rajalingham, M. Jazayeri, G.R. Yang
Neural foundations of mental simulation: future prediction of latent representations on dynamic scenes.
NeurIPS 2023 (spotlight)


Rishi Rajalingham


Mehrdad Jazayeri


Guangyu Robert Yang

Visually-Grounded Mental Simulation

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<u>Infer:</u>
Has this ice block been out longer?

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Visually-Grounded Mental Simulation

Infer:
Has this ice block been out longer?

Predict:
Will this box support me?

Visually-Grounded Mental Simulation

Infer:
Has this ice block been out longer?

Plan:
How would I take these hats off the rack?

Predict:
Will this box support me?

Visually-Grounded Mental Simulation

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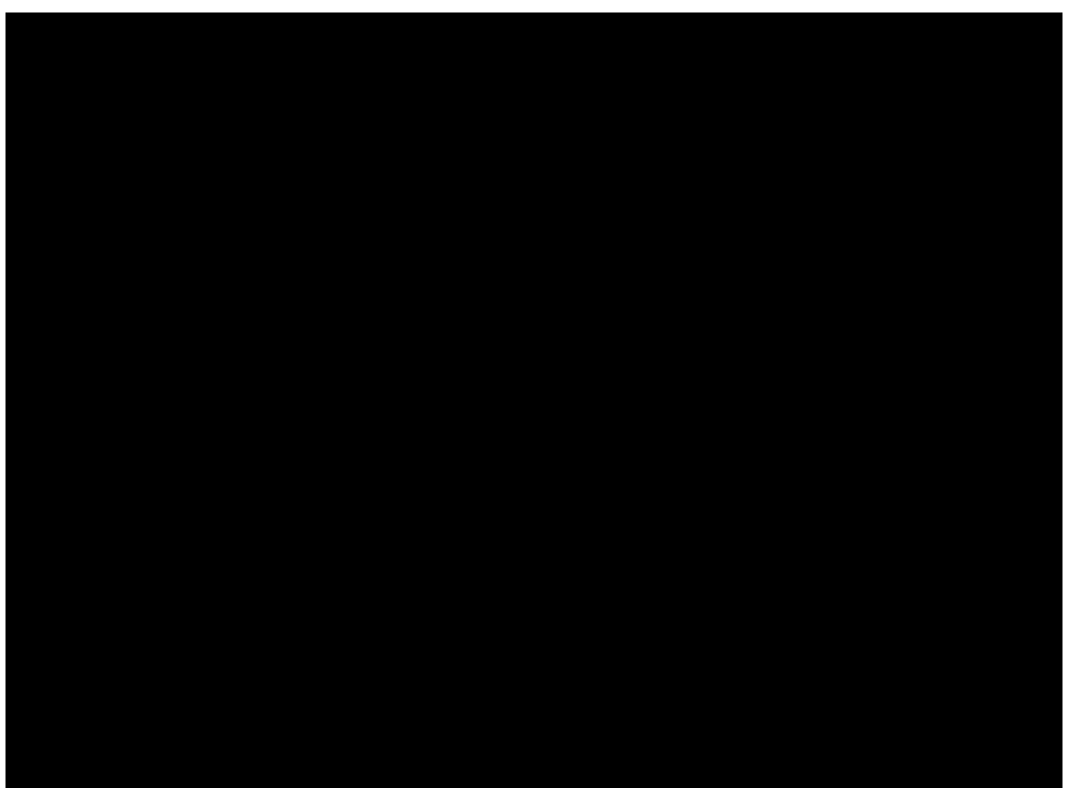

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Visually-Grounded Mental Simulation

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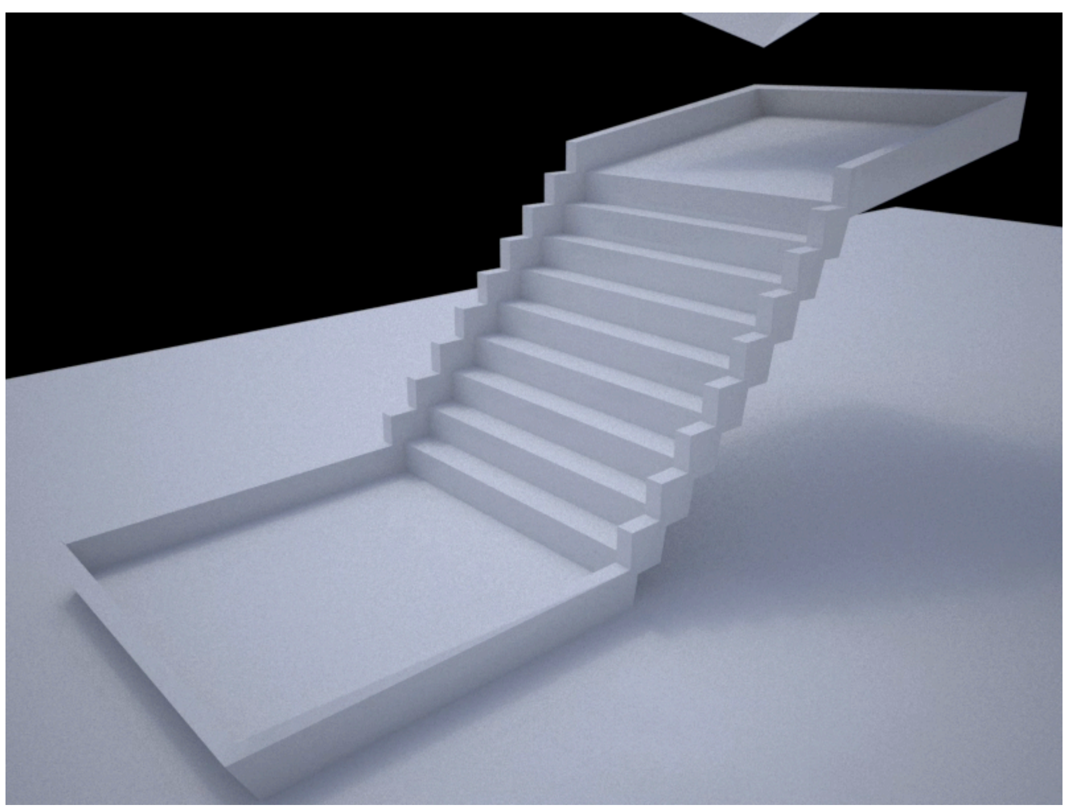

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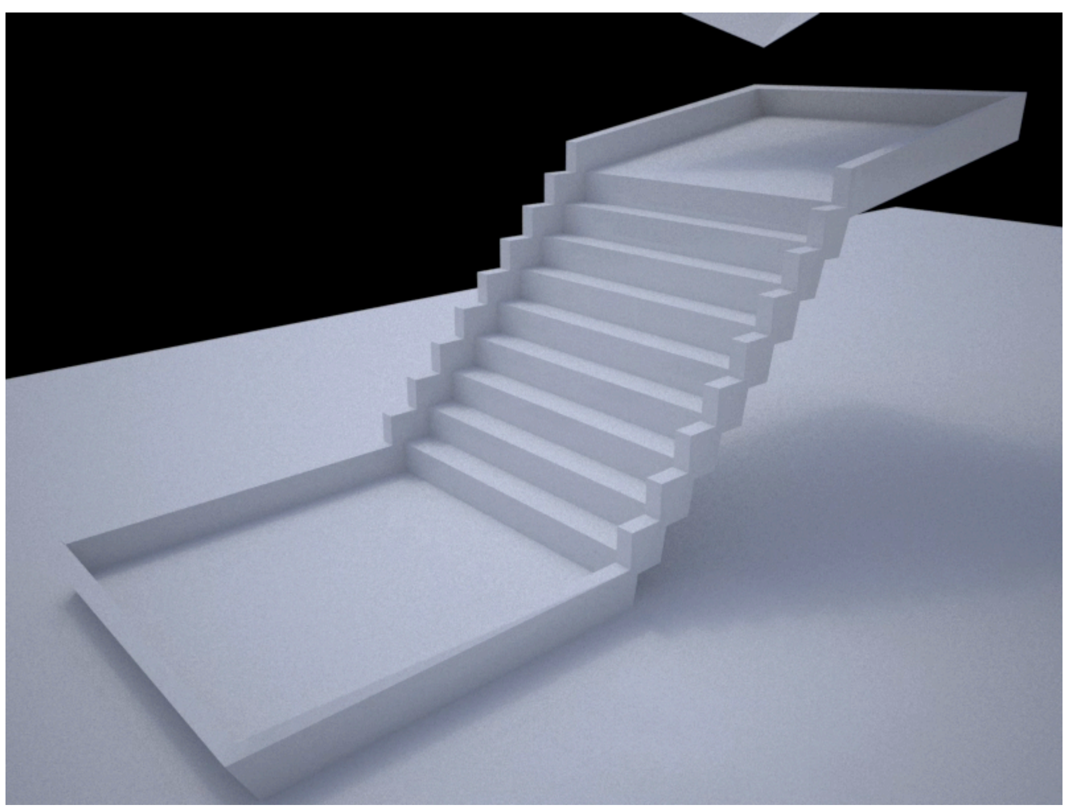

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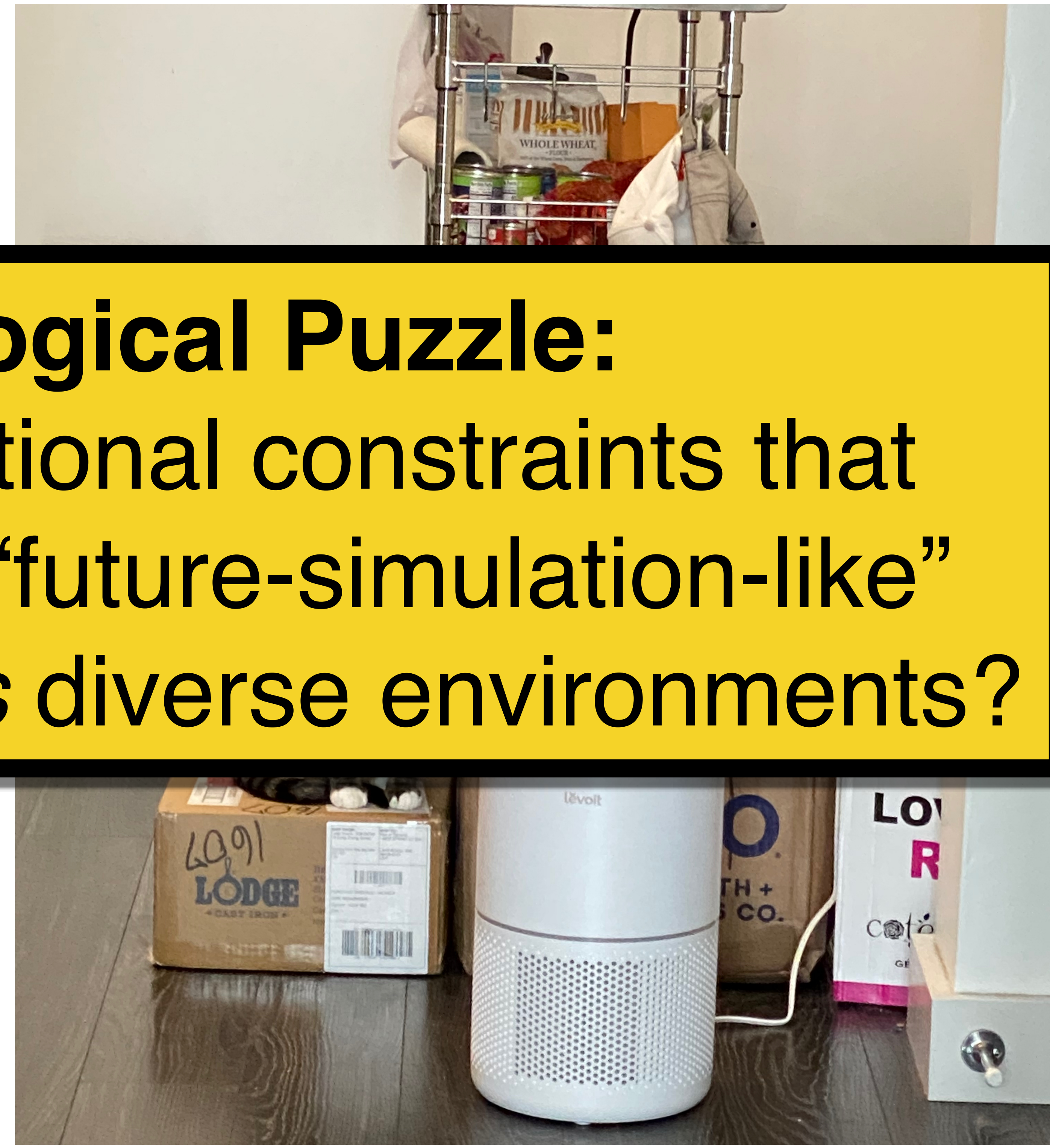
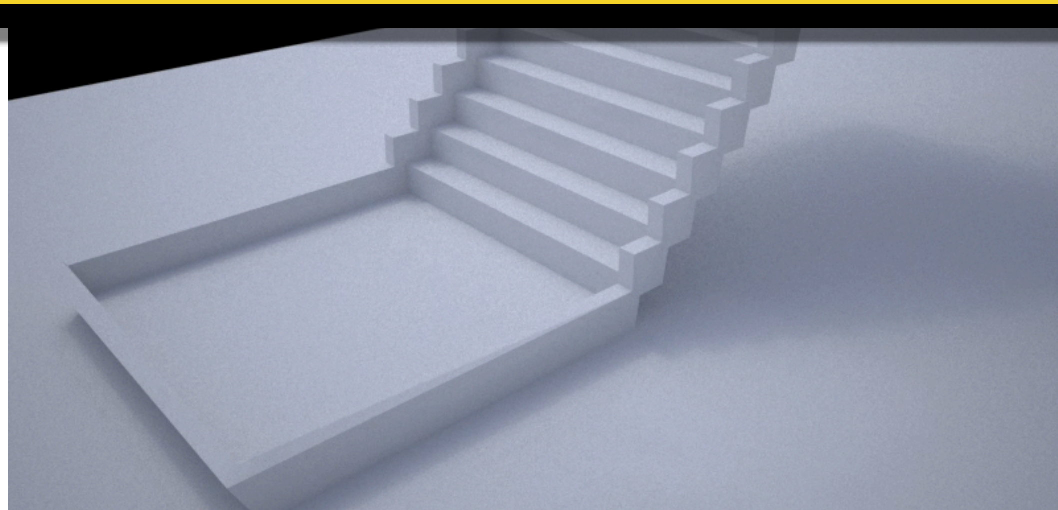


Neurobiological Puzzle:
What are the functional constraints that enable the brain's "future-simulation-like" computations *across* diverse environments?



Visually-Grounded Mental Simulation

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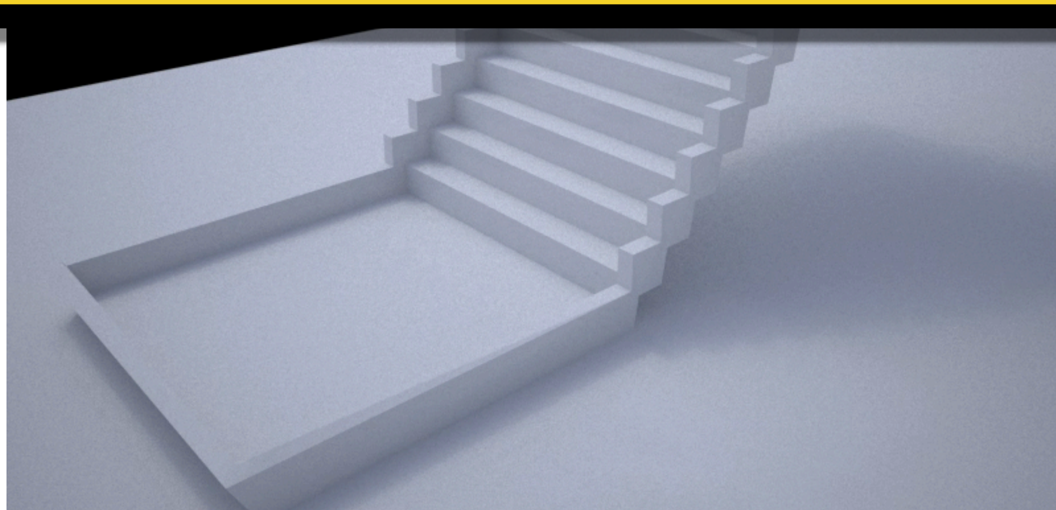

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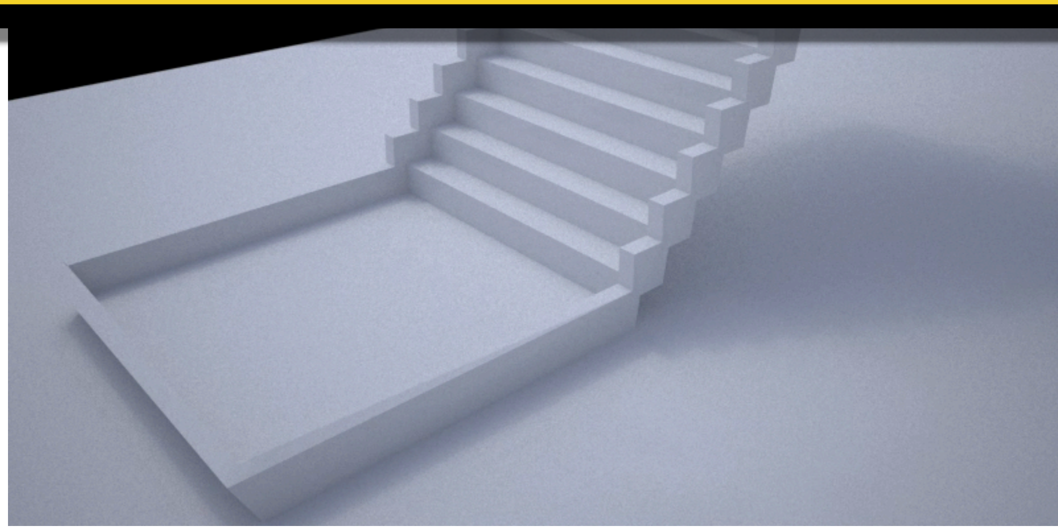
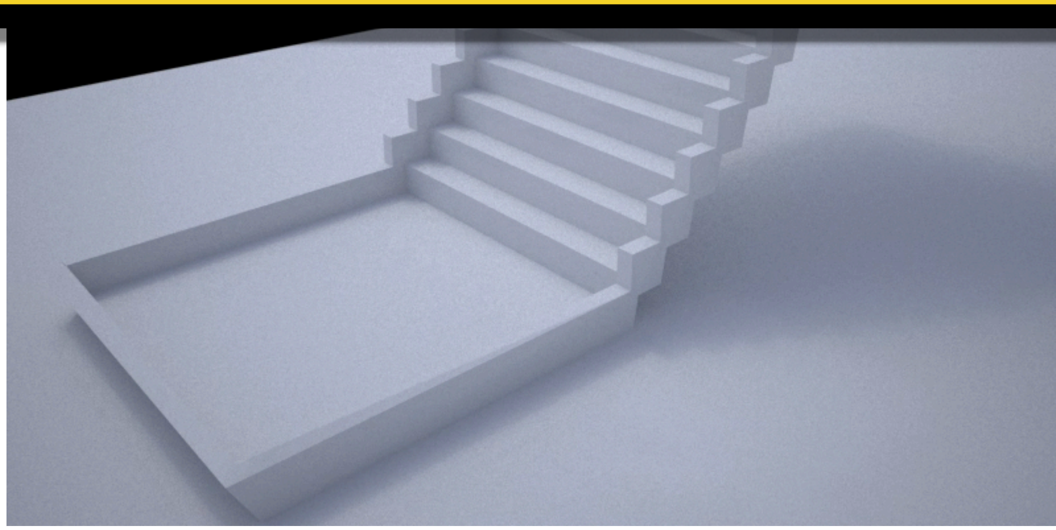


Visually-Grounded Mental Simulation

Neurobiological Puzzle:

What are the functional constraints that enable the brain's "future-simulation-like" computations *across* diverse environments?



Defining Hypotheses

Defining Hypotheses

“Sensory-Cognitive Networks”

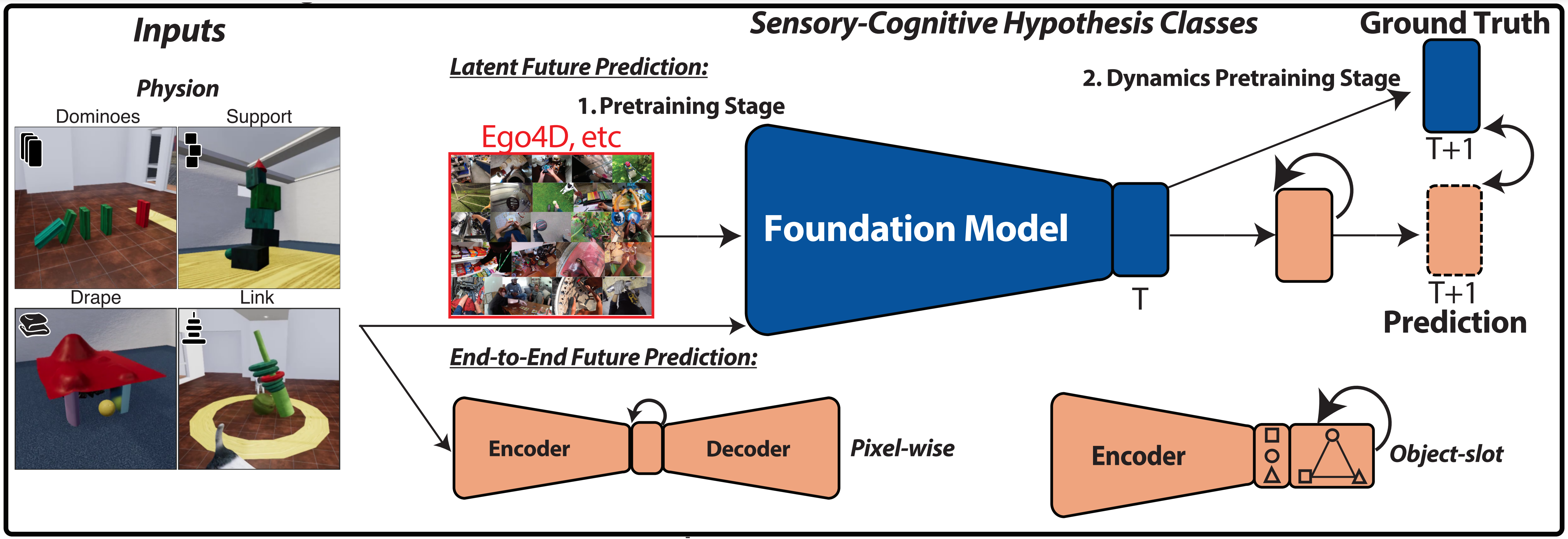
R1 (Input-Driven): Take in unstructured visual inputs across a range of physical phenomena.

R2 (Behavioral Outputs): Generate physical predictions for each scenario (“behavior”).

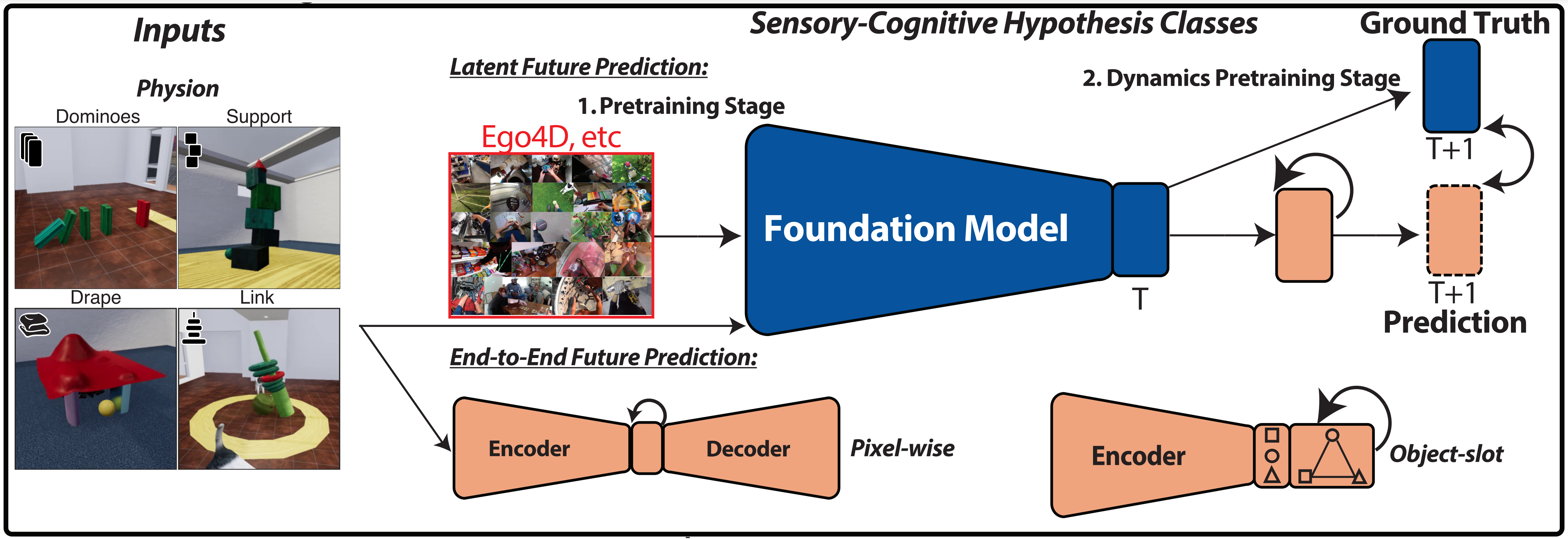
R3 (Neural Representations): Consist of internal units that can be compared to biological units (e.g. containing “artificial neurons”).

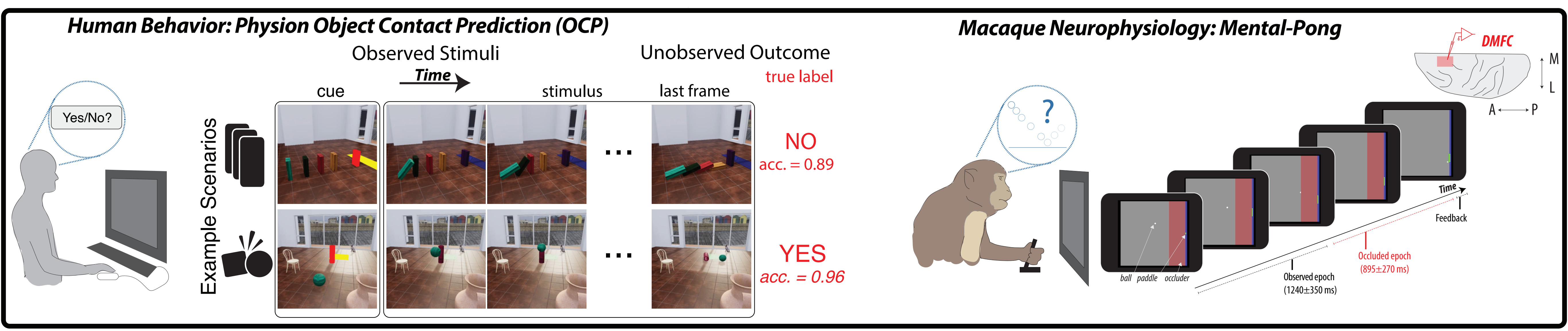
Overall Approach: Sensory-Cognitive Hypotheses

Overall Approach: Sensory-Cognitive Hypotheses

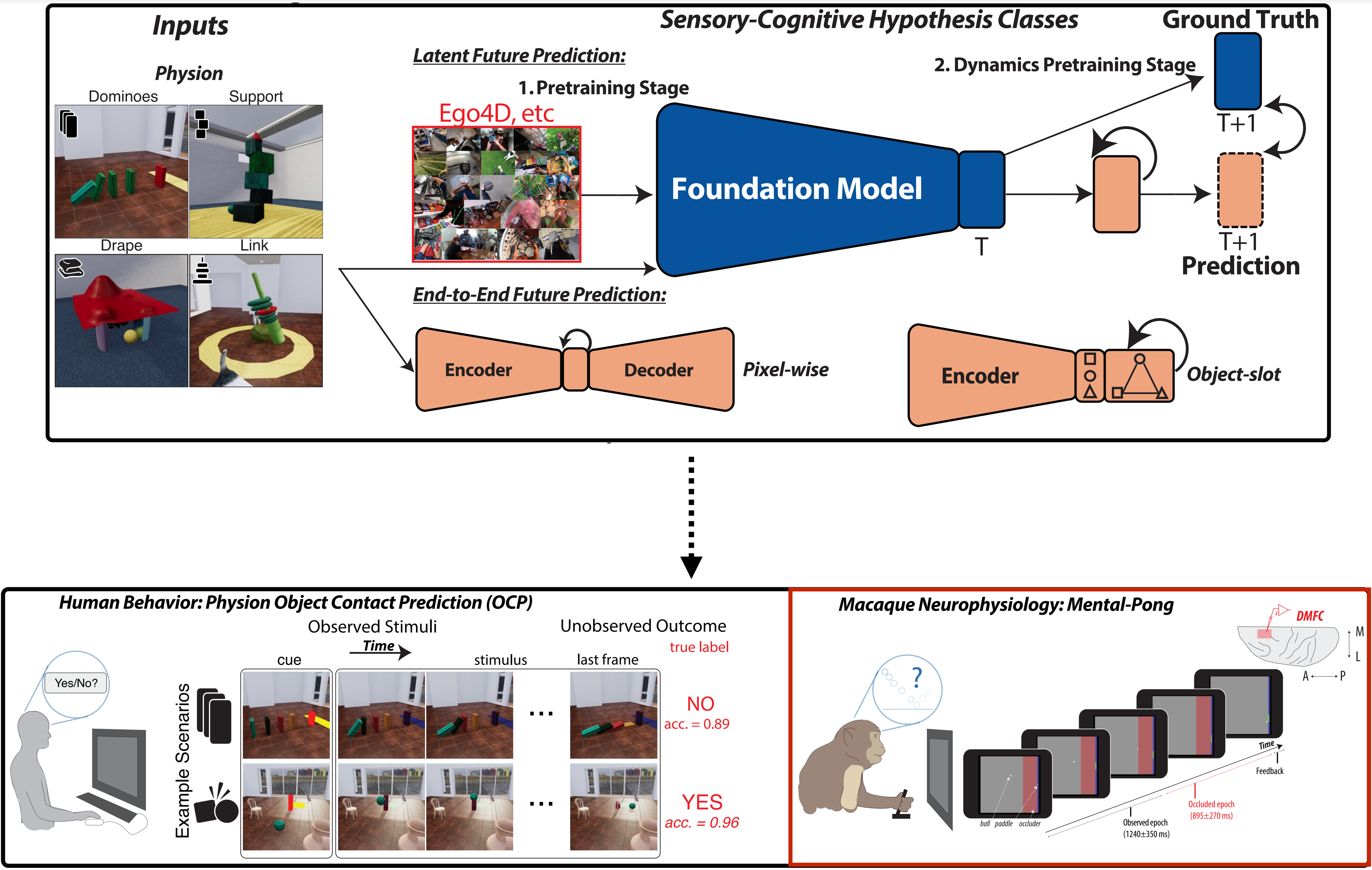


Overall Approach: Sensory-Cognitive Hypotheses





Macaque Neurophysiology: Mental Pong



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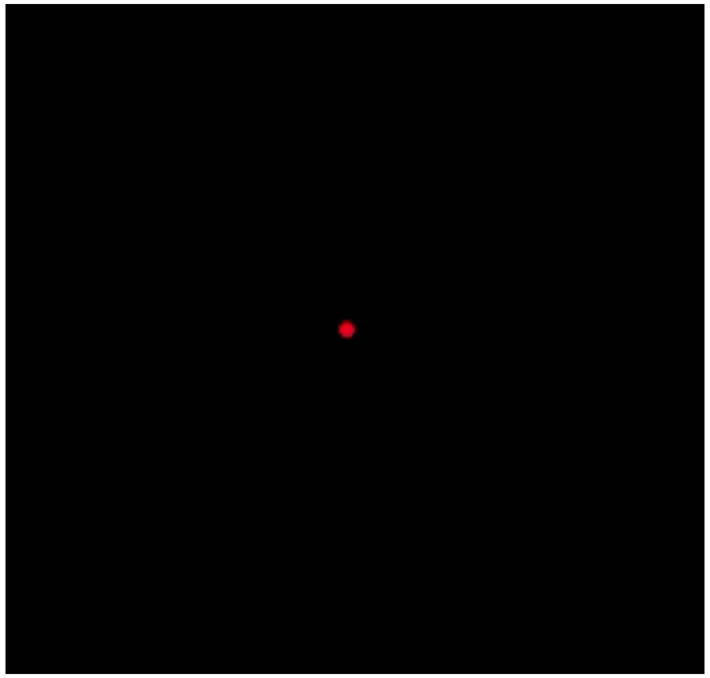
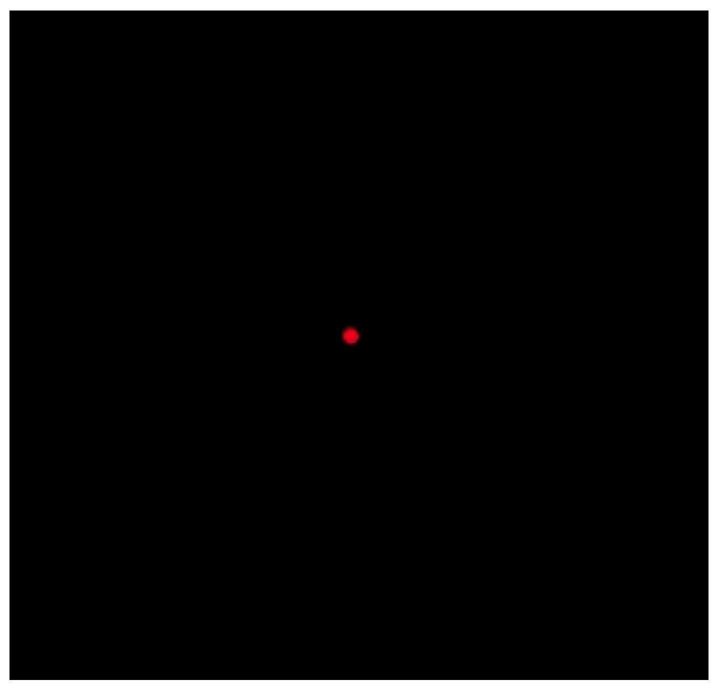
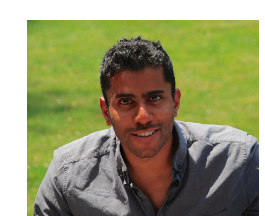


Rishi Rajalingham

Macaque Neurophysiology: Mental Pong

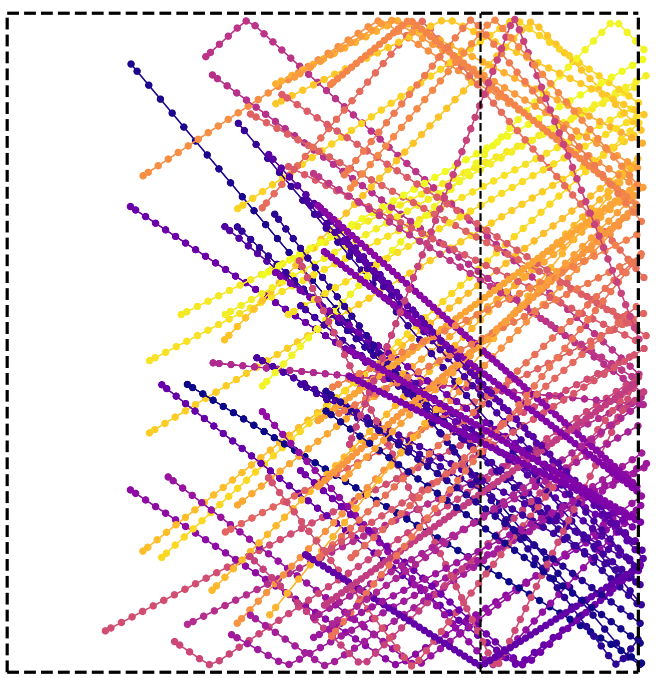


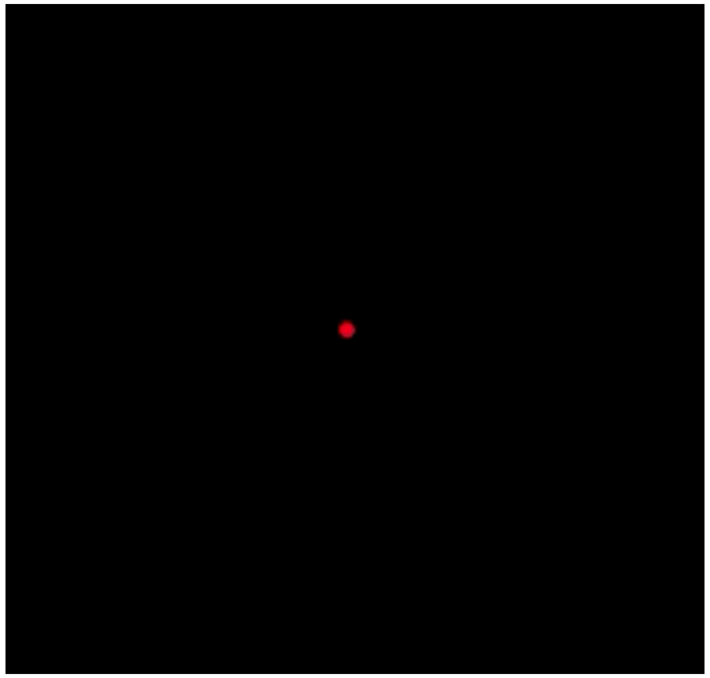


Rishi Rajalingham

Macaque Neurophysiology: Mental Pong

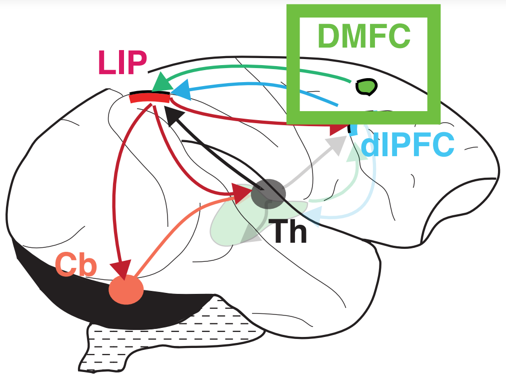
79 conditions





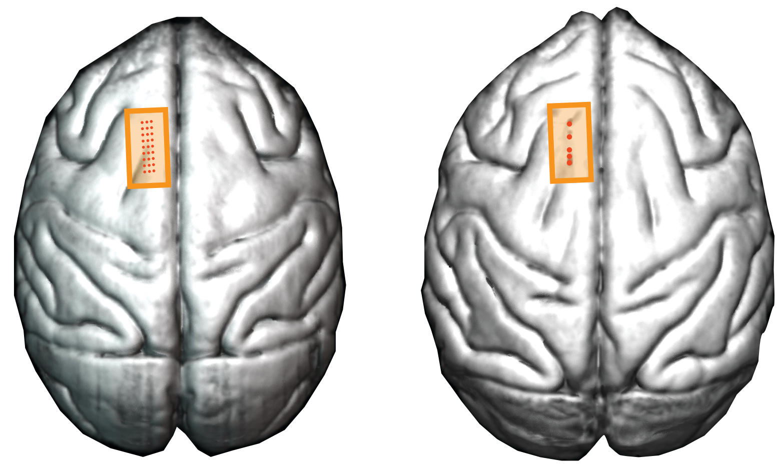
Rishi Rajalingham

Macaque Neurophysiology: Mental Pong

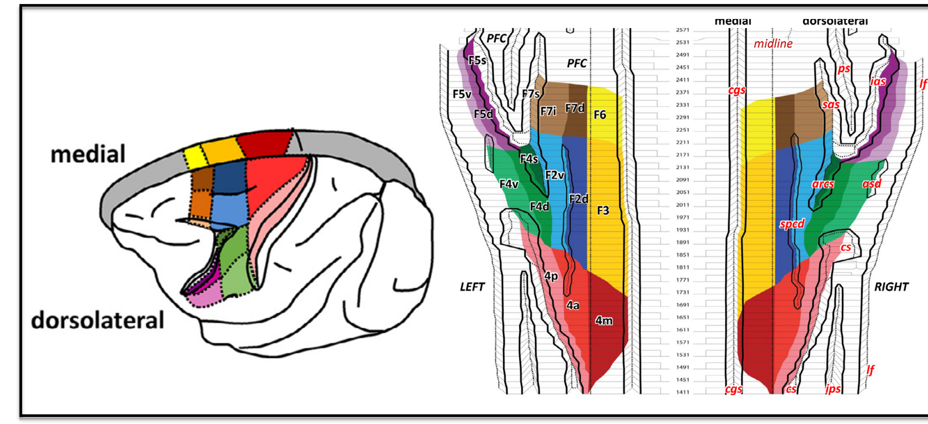


Fronto-Parietal Network

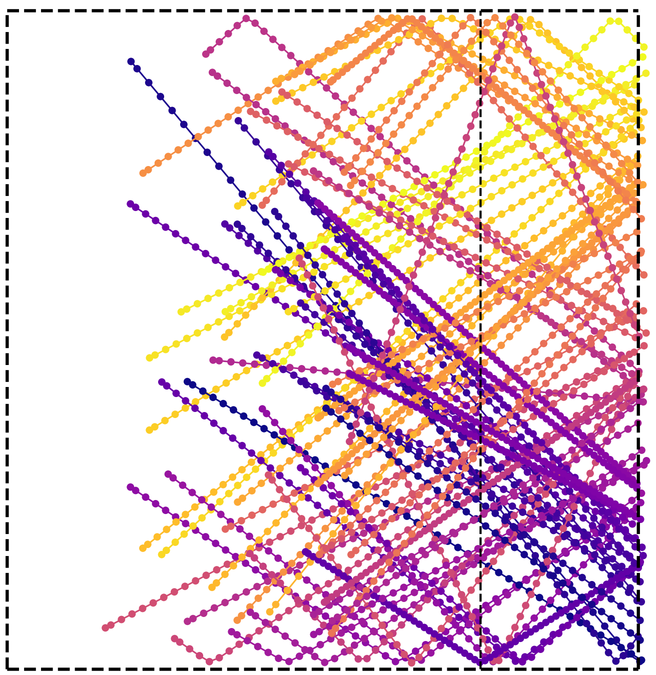
Dorsomedial frontal cortex (DMFC)

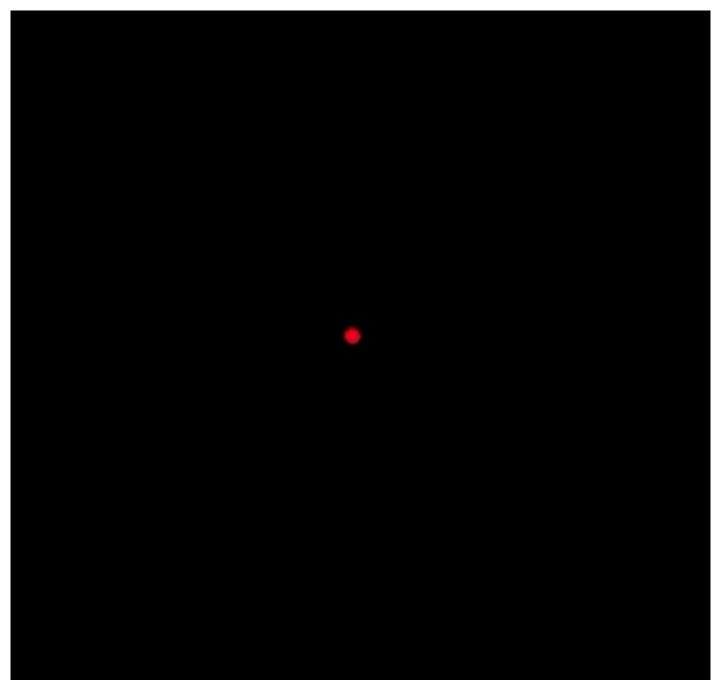


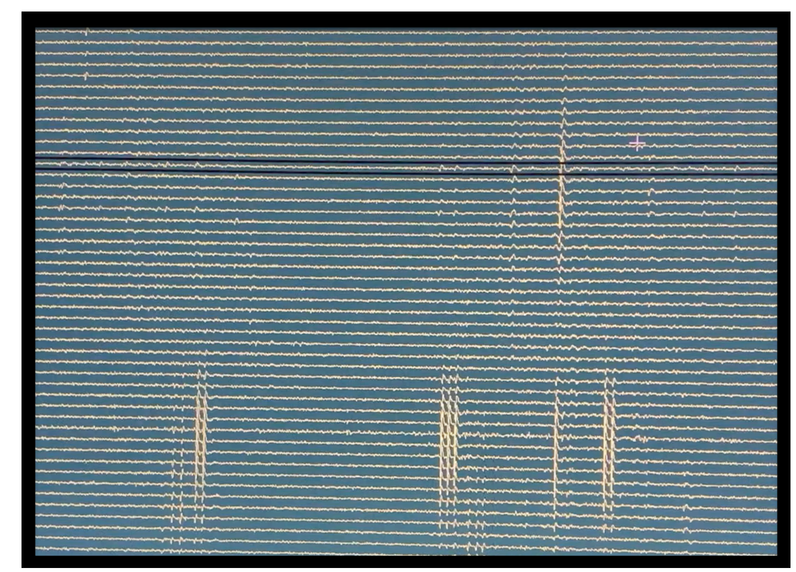
Monkey P   *Monkey M*



79 conditions

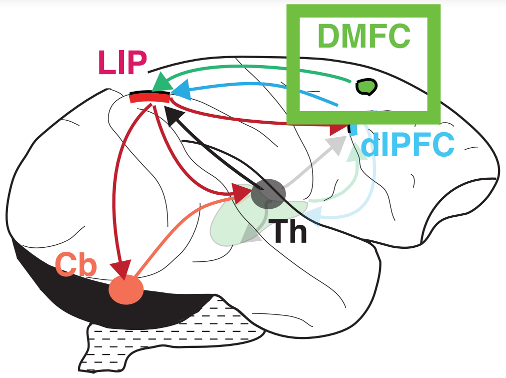






Rishi Rajalingham

Macaque Neurophysiology: Mental Pong



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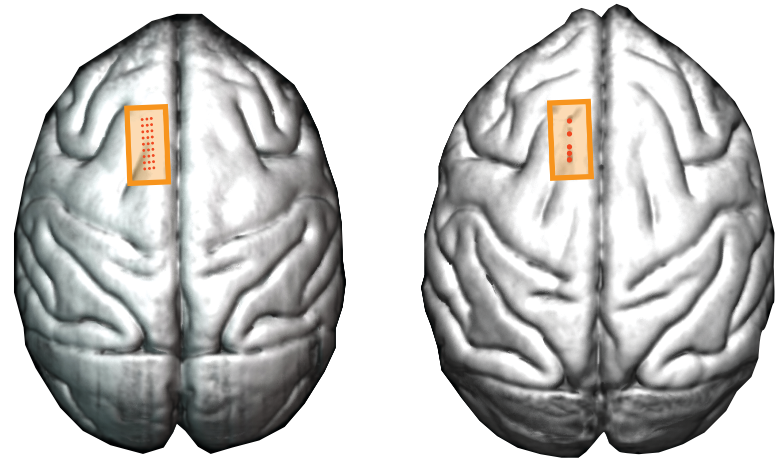
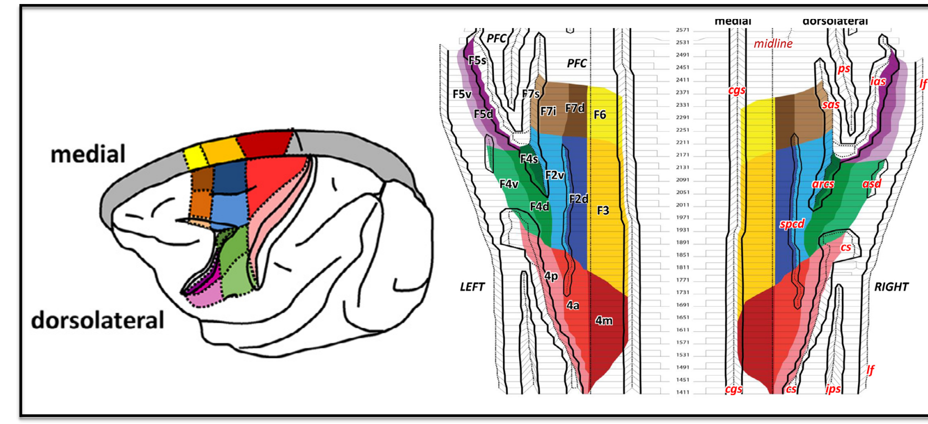
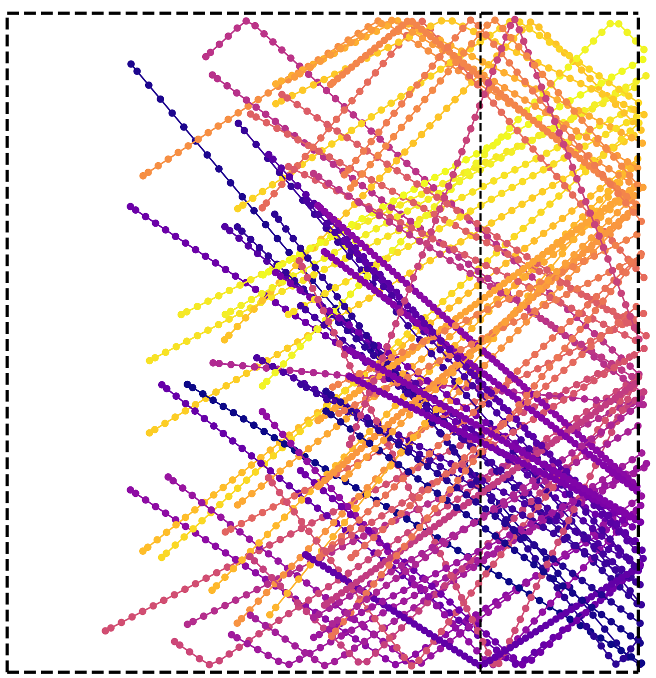
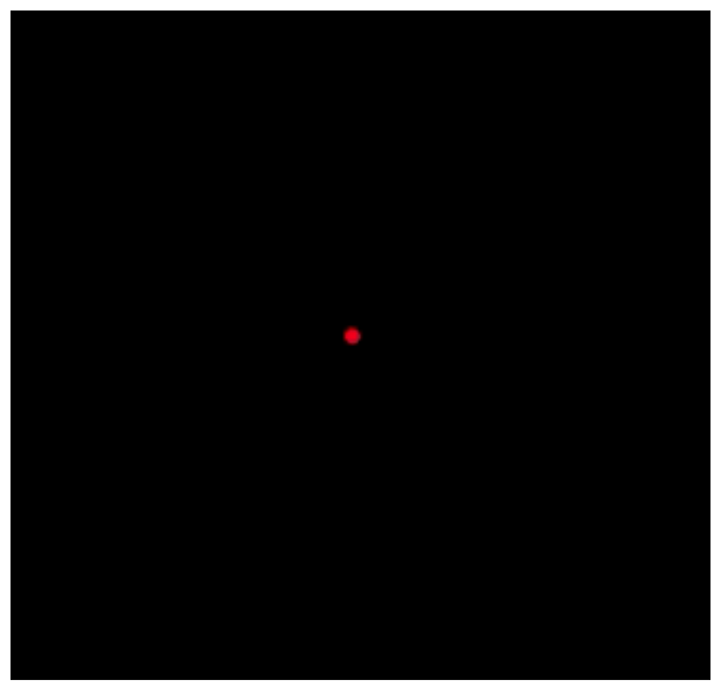


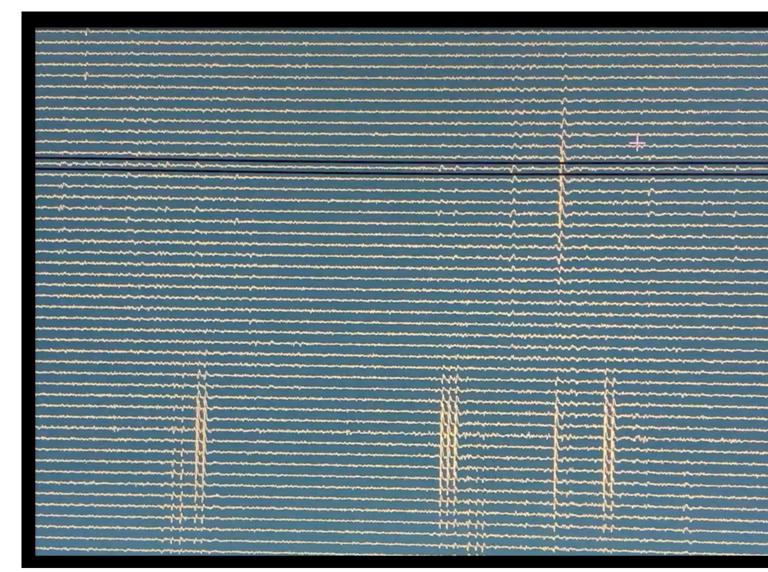
Monkey P *Monkey M*



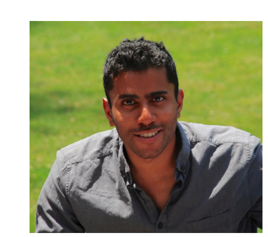
79 conditions





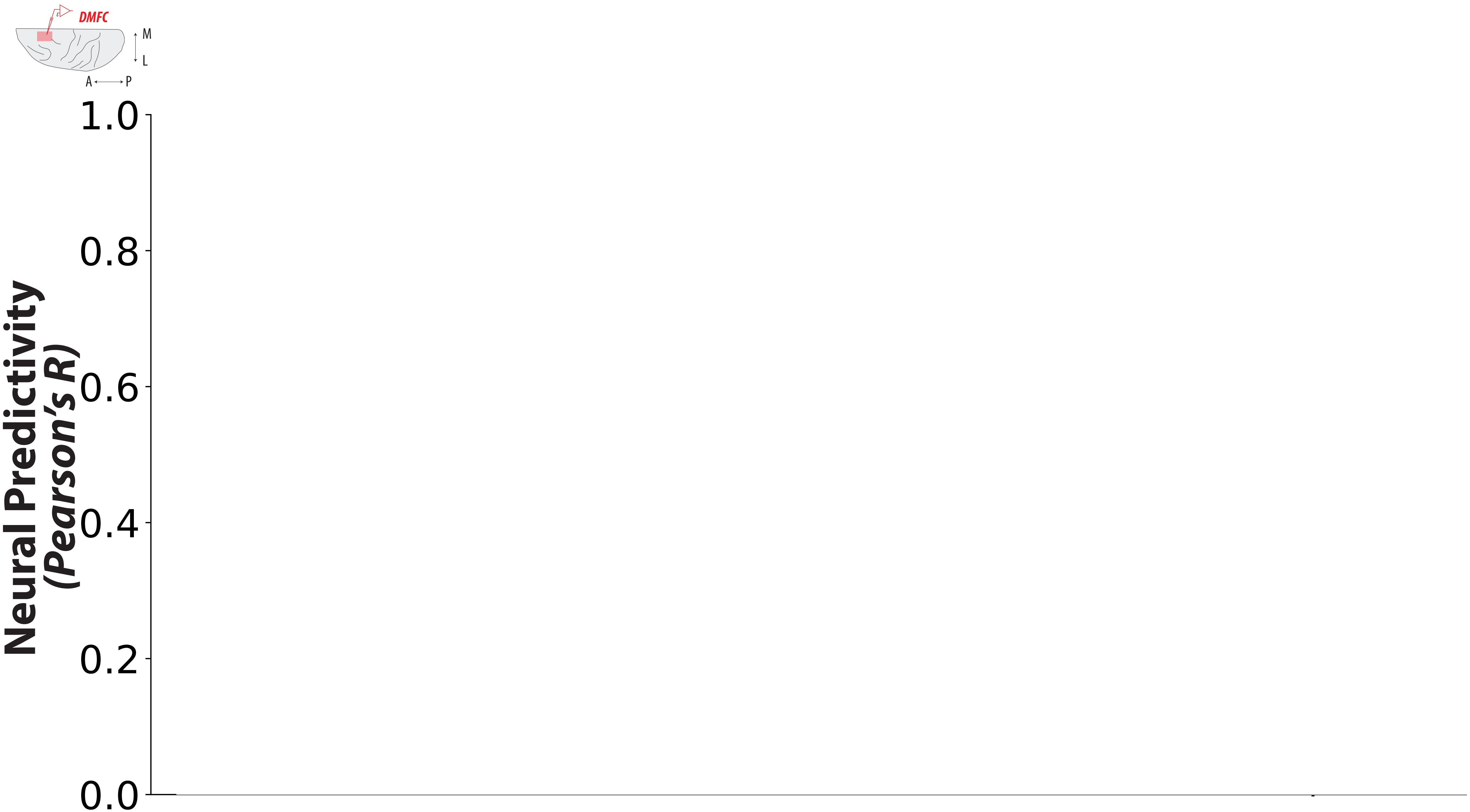


- *Data from two male adult monkeys*
- *79 subsampled M-Pong conditions*
- *64 channel v-probe (monkey P) and 384-channel Neuropixel probe (monkey M)*
- *Total of 1889 stable & reliable neurons recorded from DMFC*

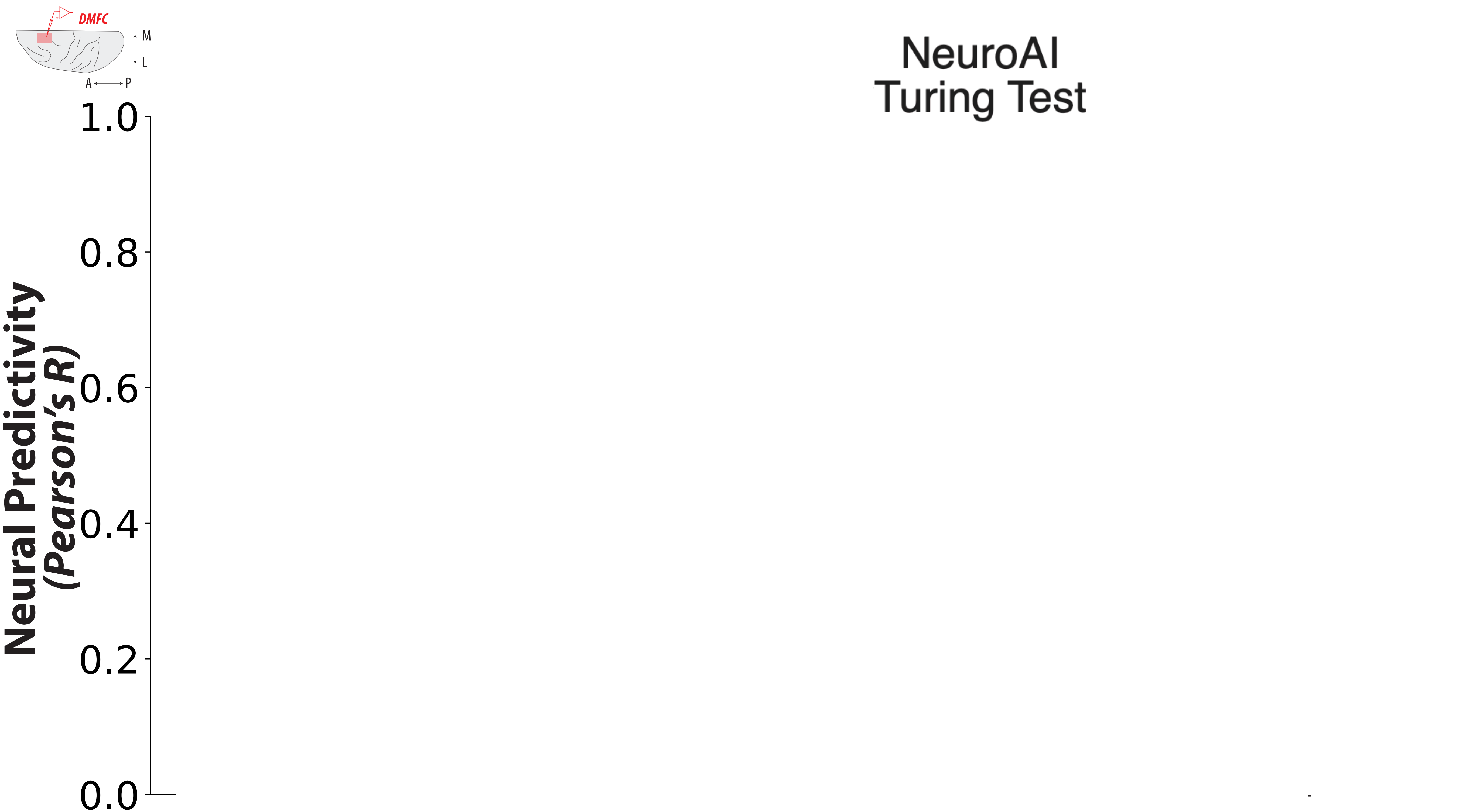


Rishi Rajalingham

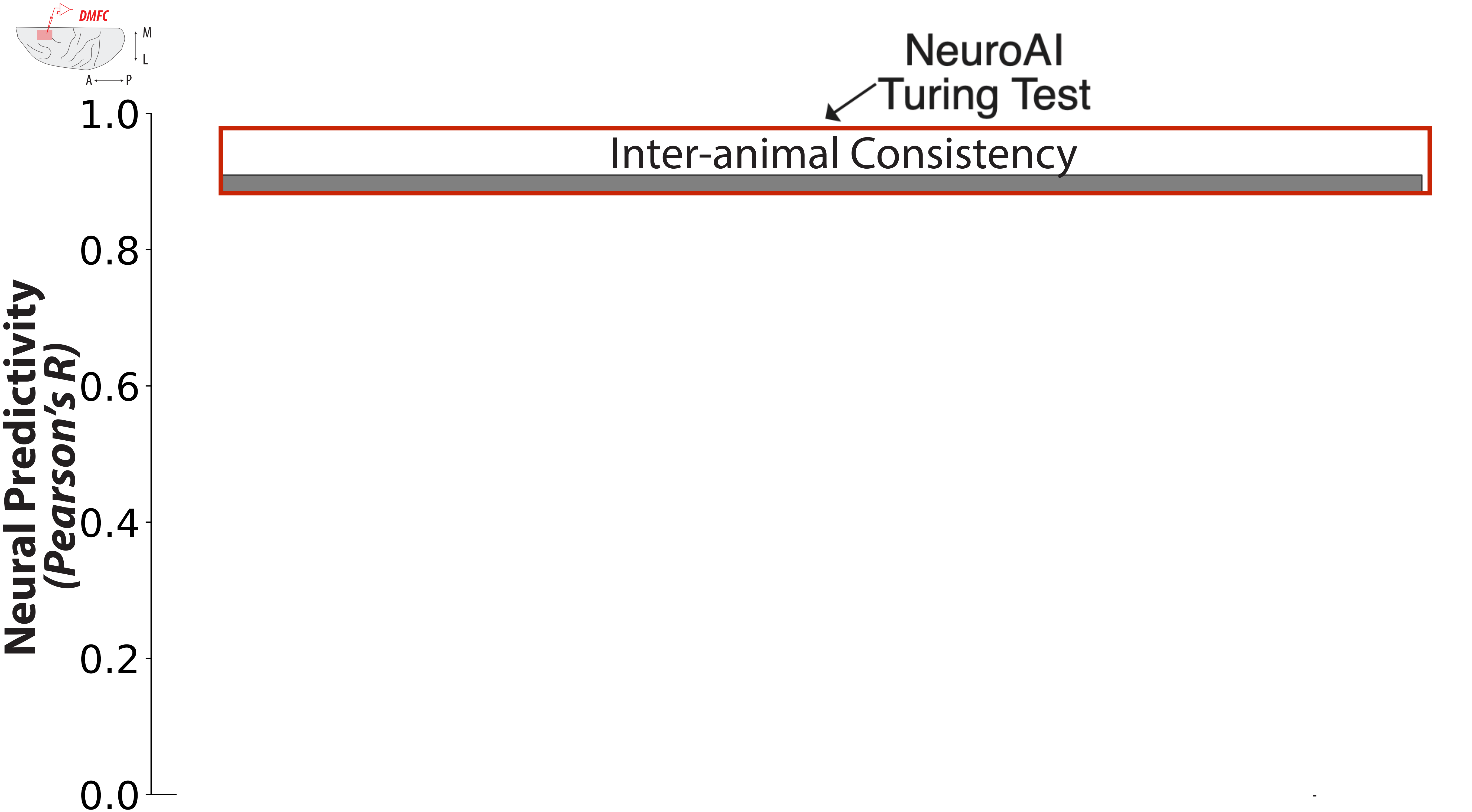
Macaque Neurophysiology: Mental Pong



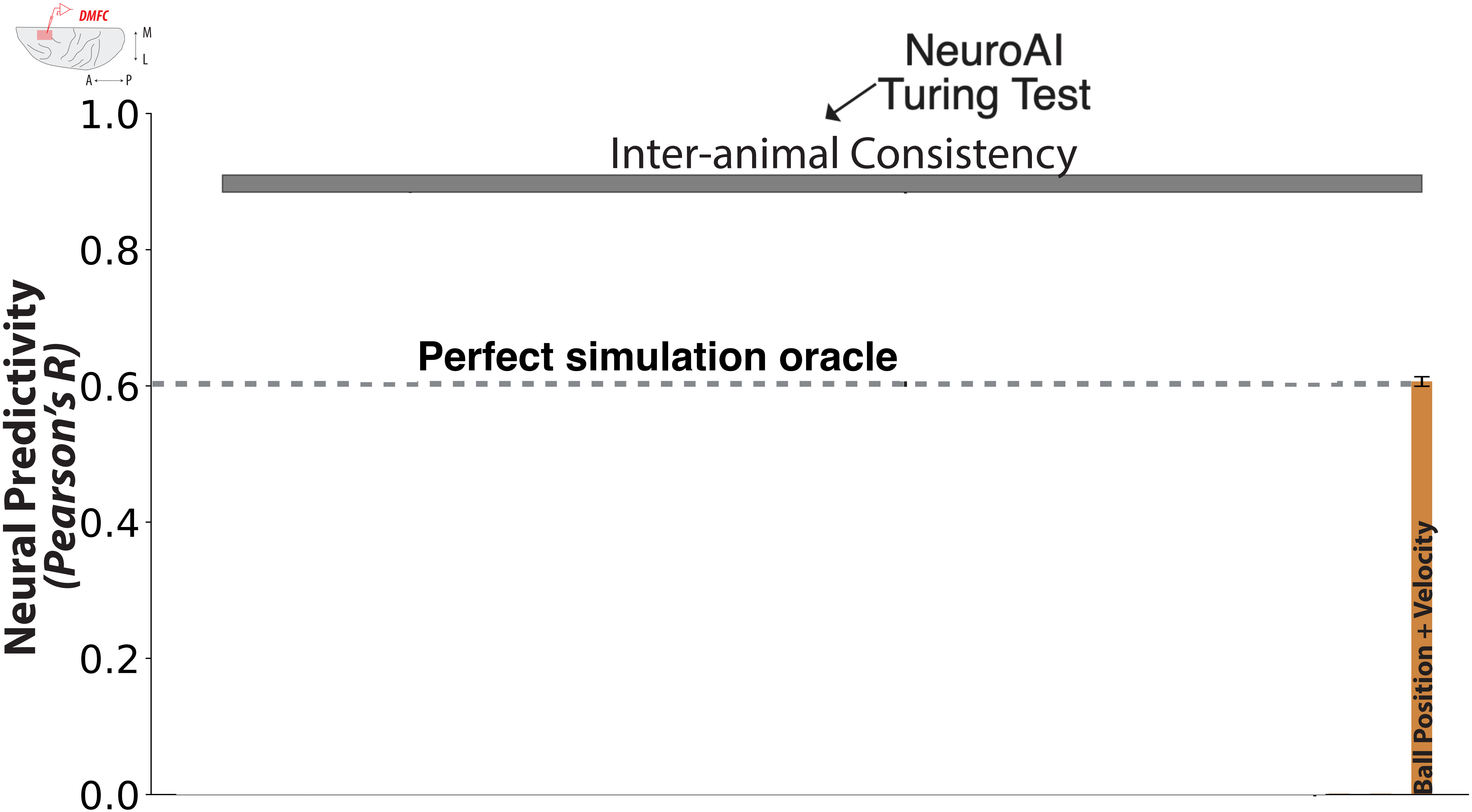
Macaque Neurophysiology: Mental Pong



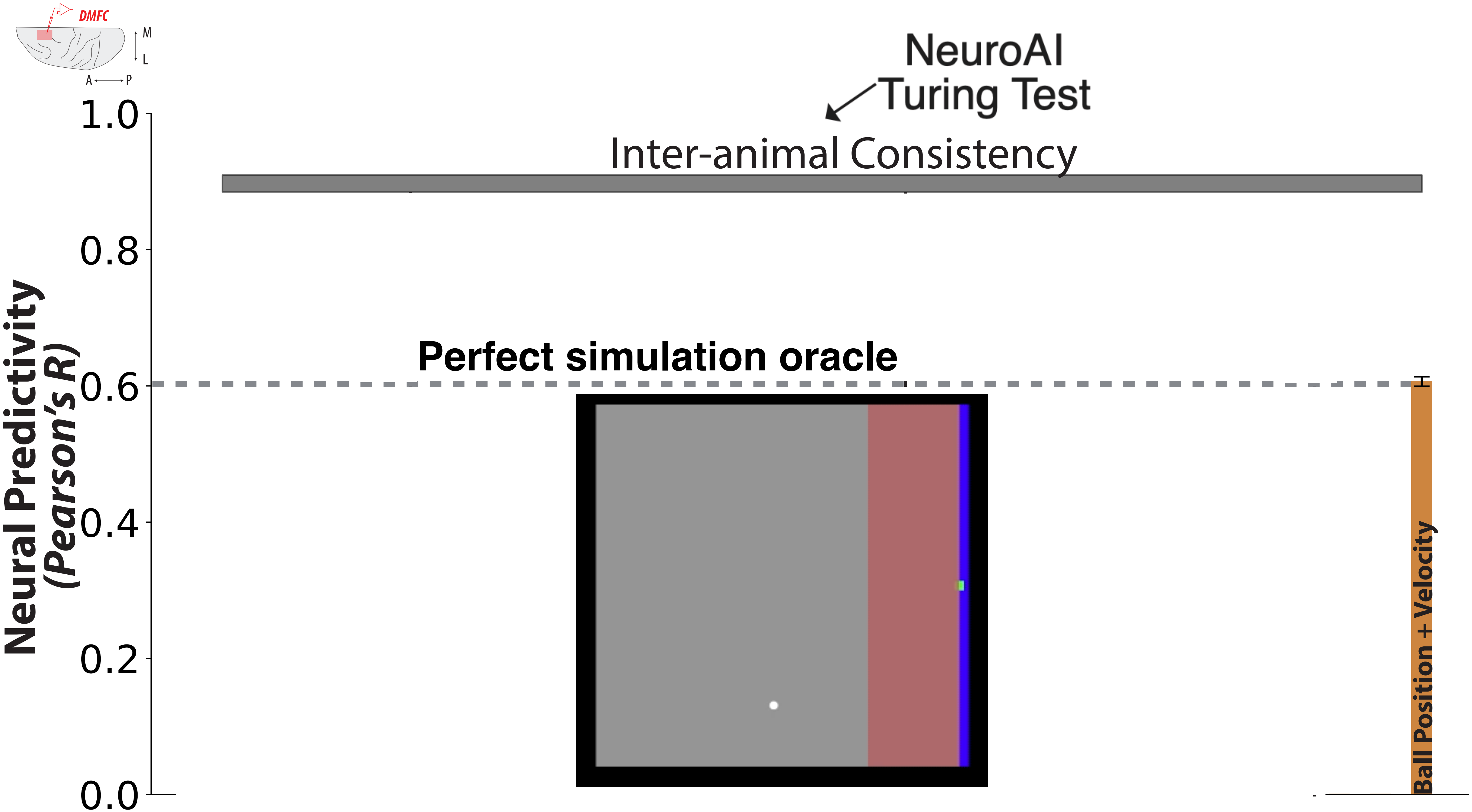
Macaque Neurophysiology: Mental Pong



Perfect Simulation Oracle Predicts Neural Data Well



Perfect Simulation Oracle Predicts Neural Data Well

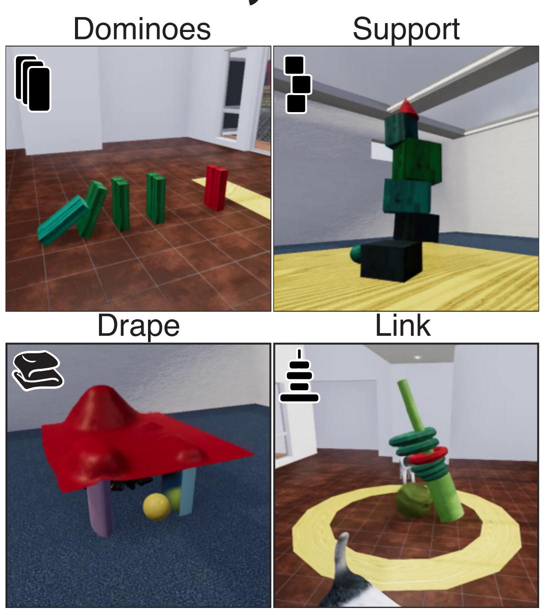


Functional Constraint Hypotheses

Inputs

Sensory-Cognitive Hypothesis Classes

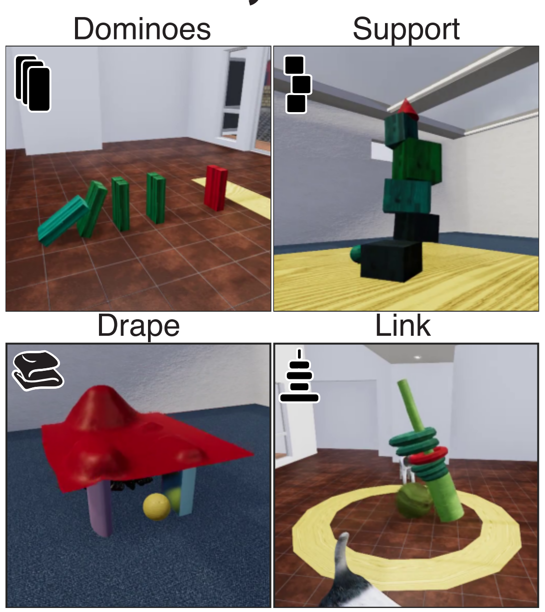
Physion



Hypothesis Class 1: Pixel-wise Future Prediction

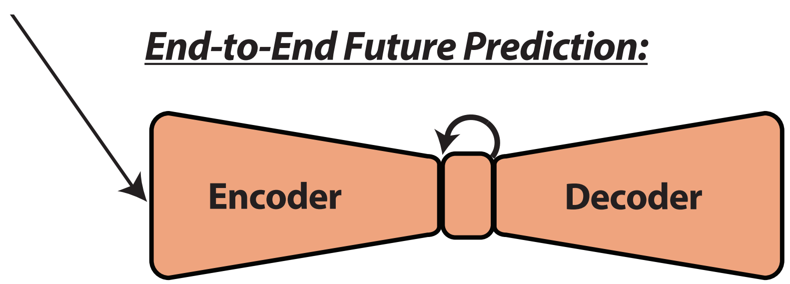
Inputs

Physion



Sensory-Cognitive Hypothesis Classes

<u>End-to-End Future Prediction:</u>

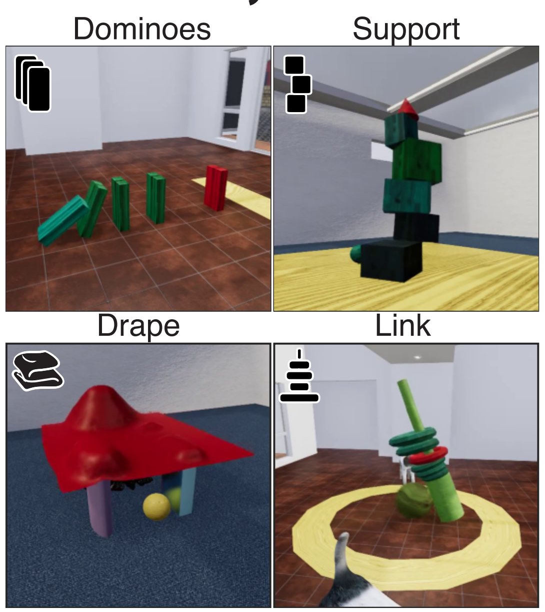


Pixel-wise

Hypothesis Class I: Pixel-wise Future Prediction

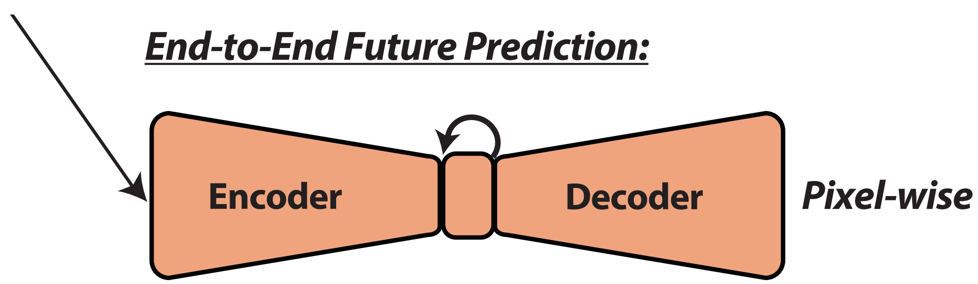
Inputs

Physion

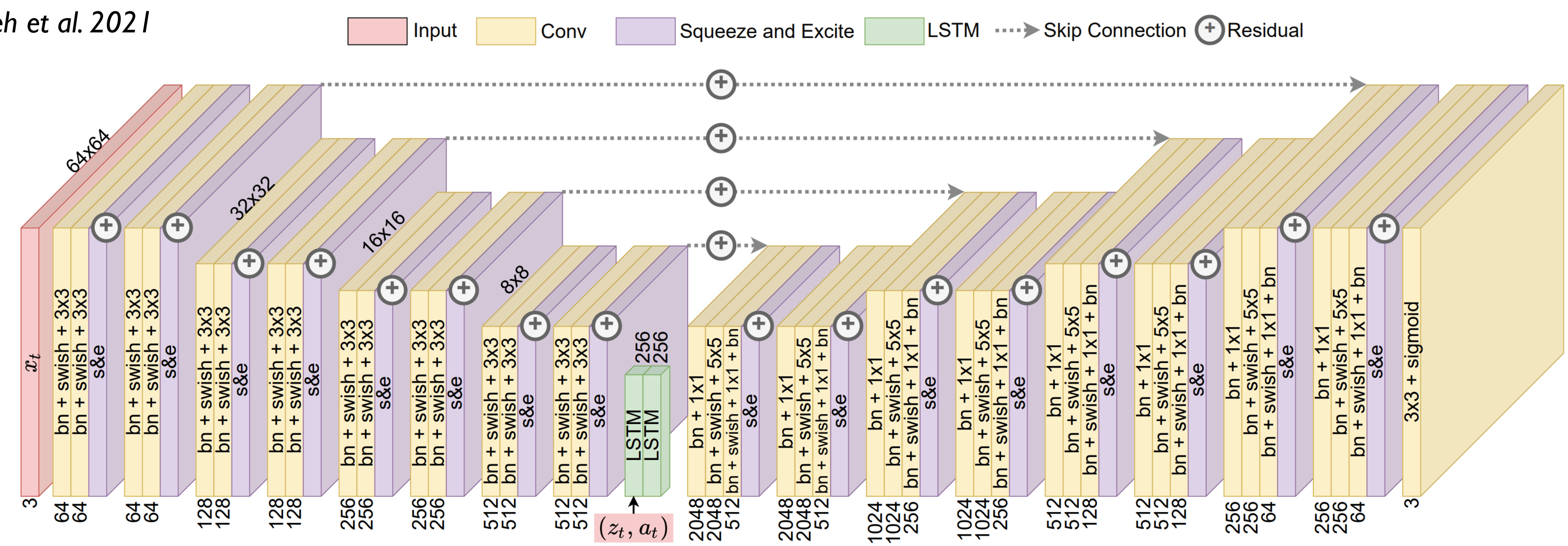


Sensory-Cognitive Hypothesis Classes

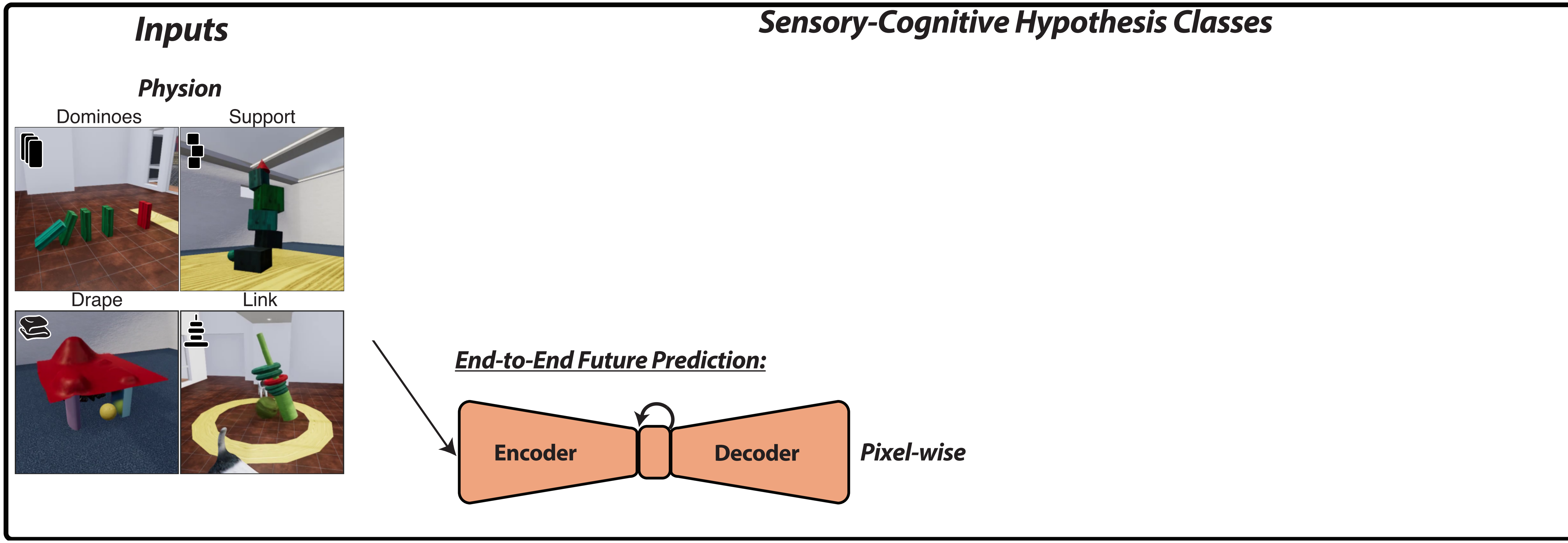
End-to-End Future Prediction:



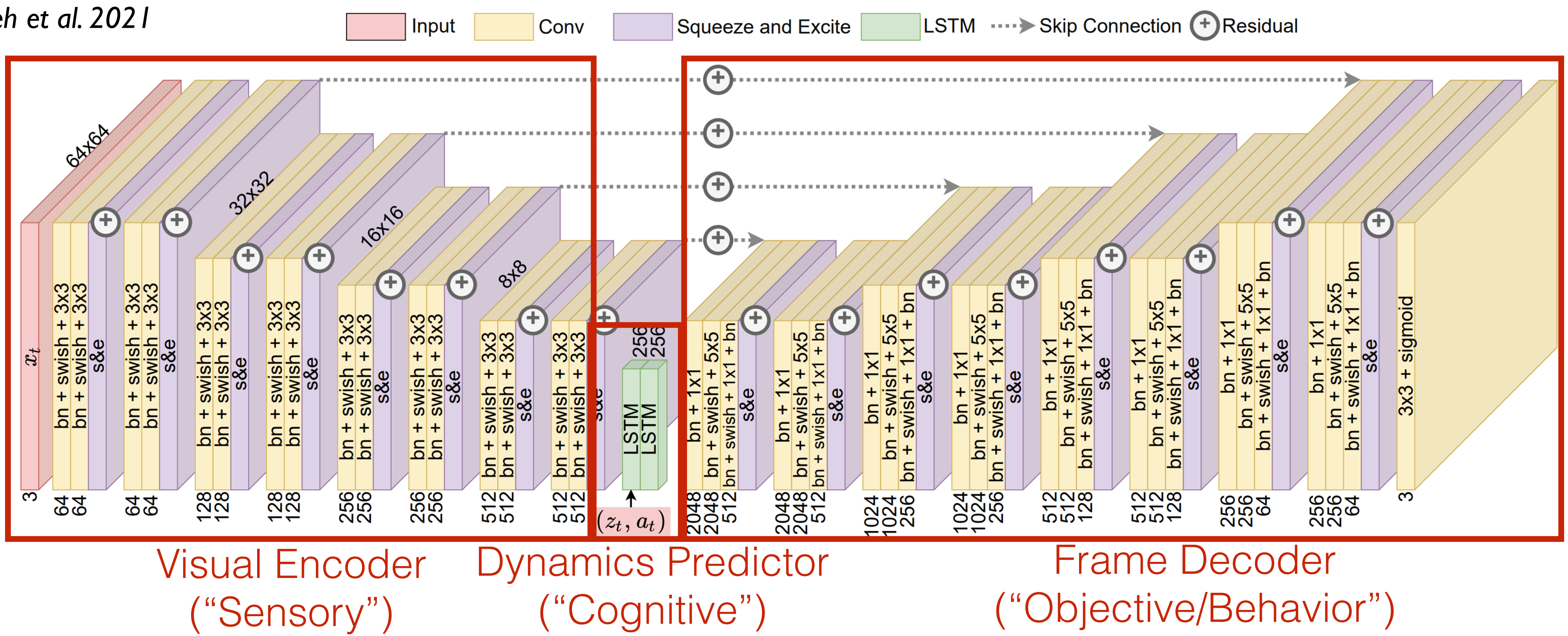
Babaeizadeh et al. 2021



Hypothesis Class I: Pixel-wise Future Prediction



Babaeizadeh et al. 2021

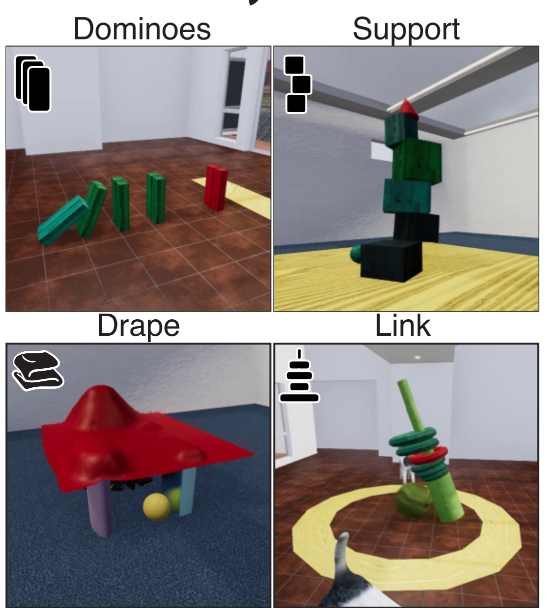


Hypothesis Class 1: Pixel-wise Future Prediction

Inputs

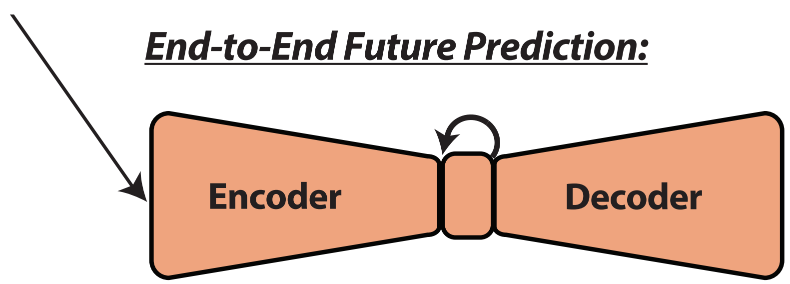
Sensory-Cognitive Hypothesis Classes

Physion



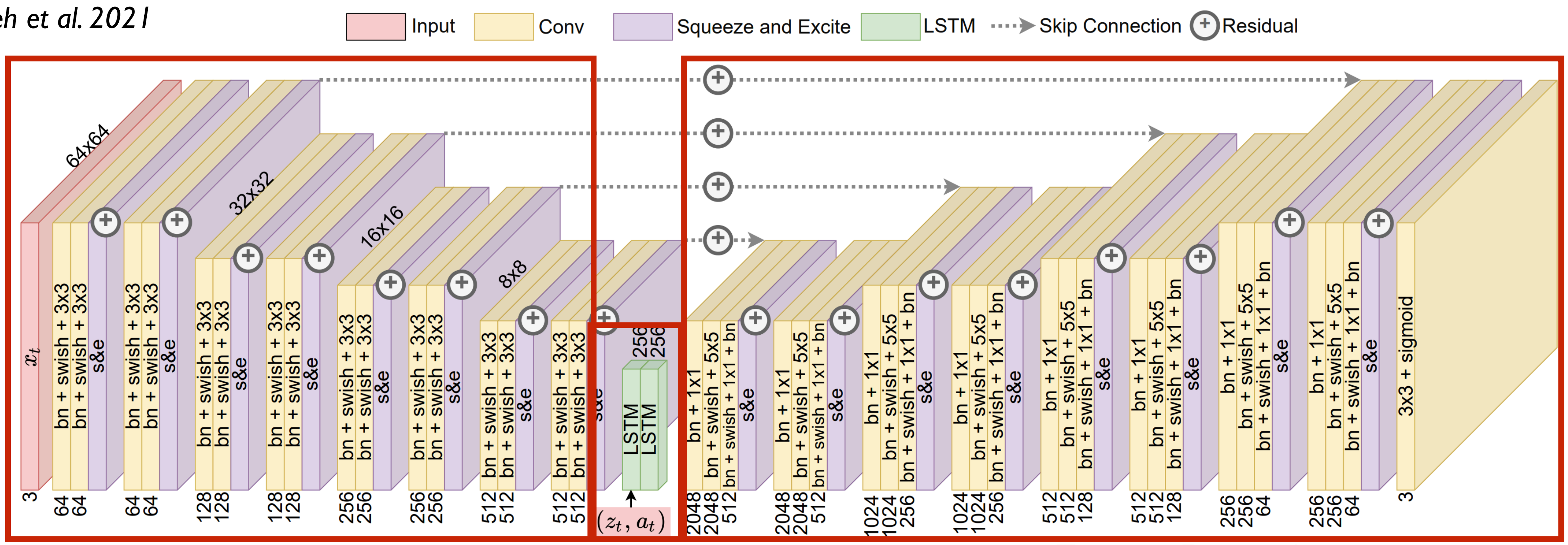
$$\mathcal{L} = \|\mathbf{x}_{t+1} - \hat{\mathbf{x}}_{t+1}\|_2^2 + \beta D_{KL}(\mathcal{N}(\mu, \sigma)\|\mathcal{N}(0, \mathbf{I}))$$

End-to-End Future Prediction:



Pixel-wise

Babaeizadeh et al. 2021



Visual Encoder ("Sensory")

Dynamics Predictor ("Cognitive")

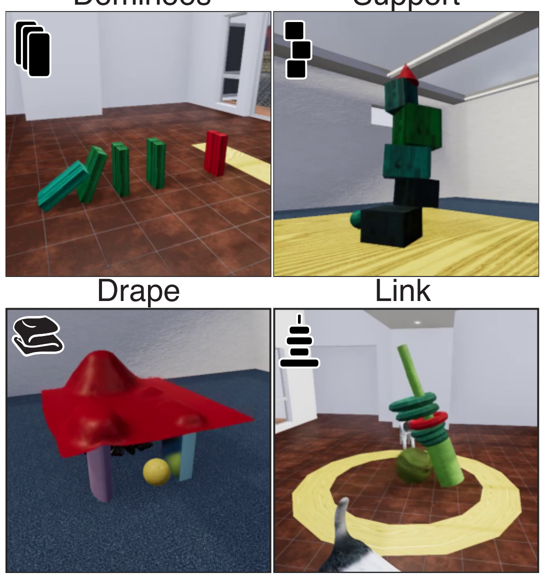
Frame Decoder ("Objective/Behavior")

Hypothesis Class I: Pixel-wise Future Prediction

Inputs

Sensory-Cognitive Hypothesis Classes

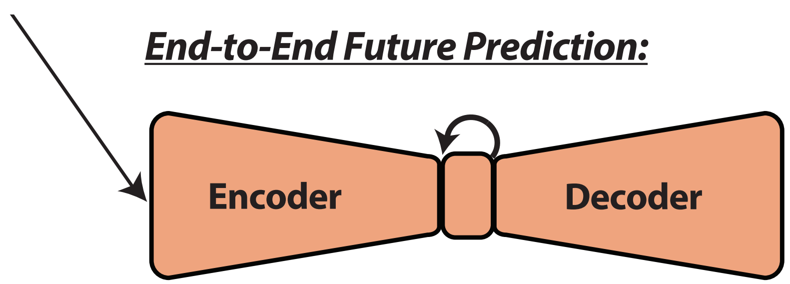
Physion



Predicts the future at the *pixel* resolution of the sensory input
(very detailed)

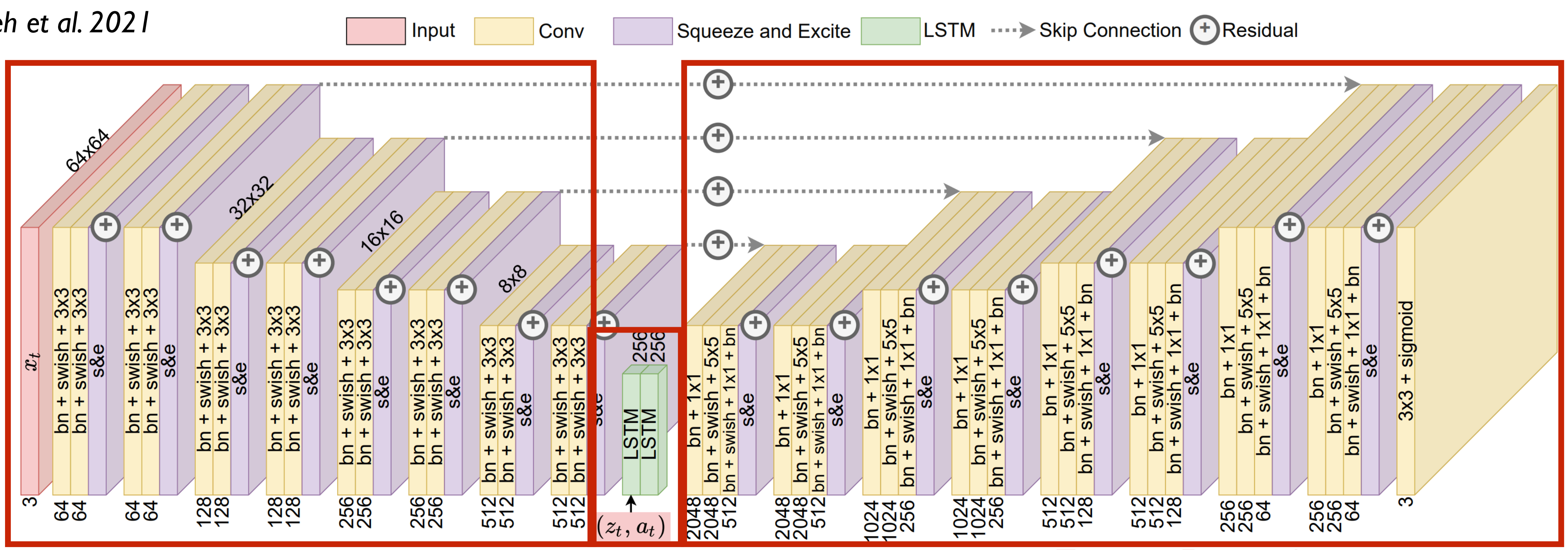
$$\mathcal{L} = \|\mathbf{x}_{t+1} - \hat{\mathbf{x}}_{t+1}\|_2^2 + \beta D_{KL}(\mathcal{N}(\mu, \sigma)\|\mathcal{N}(0, \mathbf{I}))$$

End-to-End Future Prediction:



Pixel-wise

Babaeizadeh et al. 2021



Visual Encoder ("Sensory")

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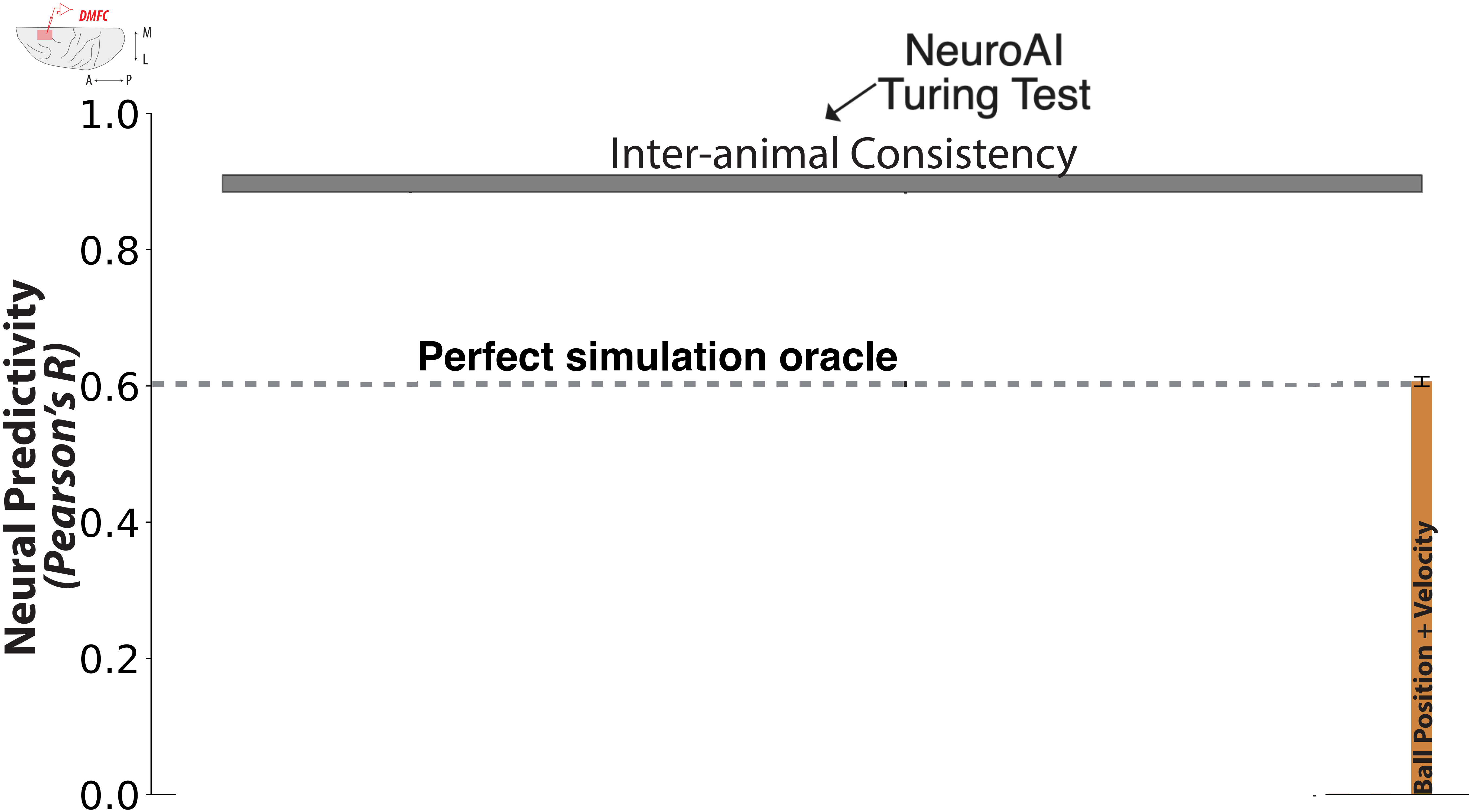
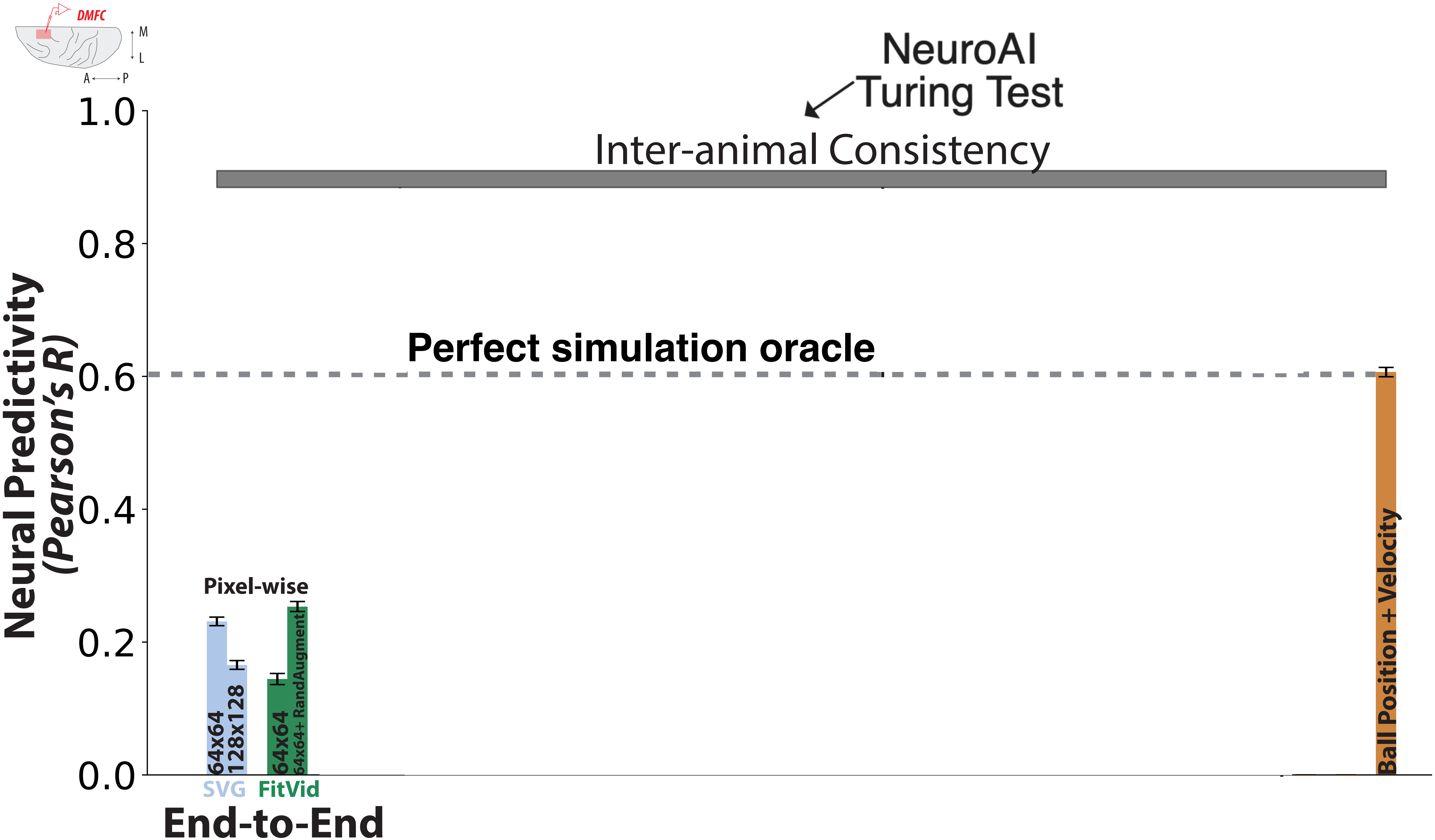
Physical Simulation Oracles Predict Neural Data Well



Pixel-wise Future Prediction Poorly Predicts Neurons



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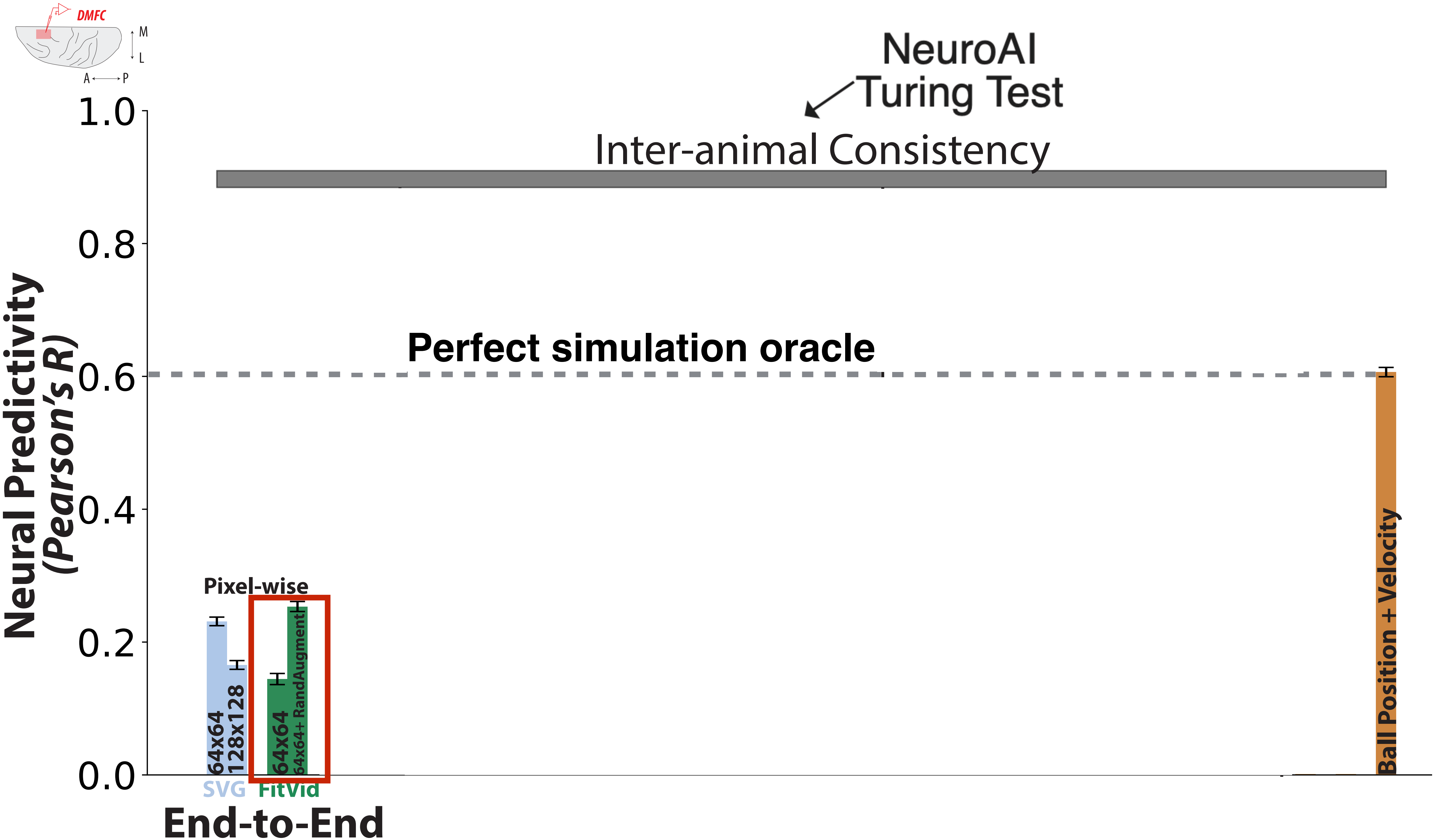
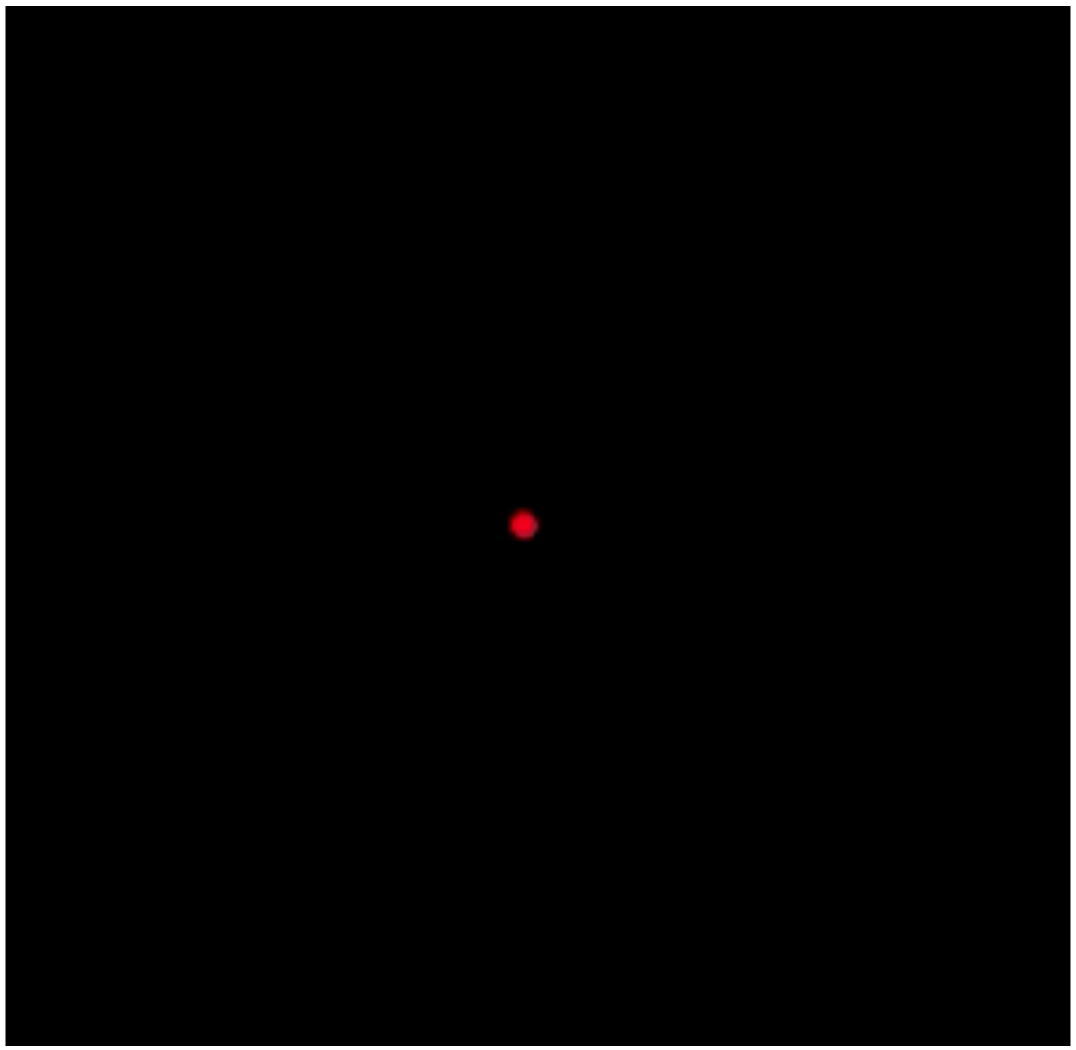


…and they struggle to generalize to Pong

Input Frames

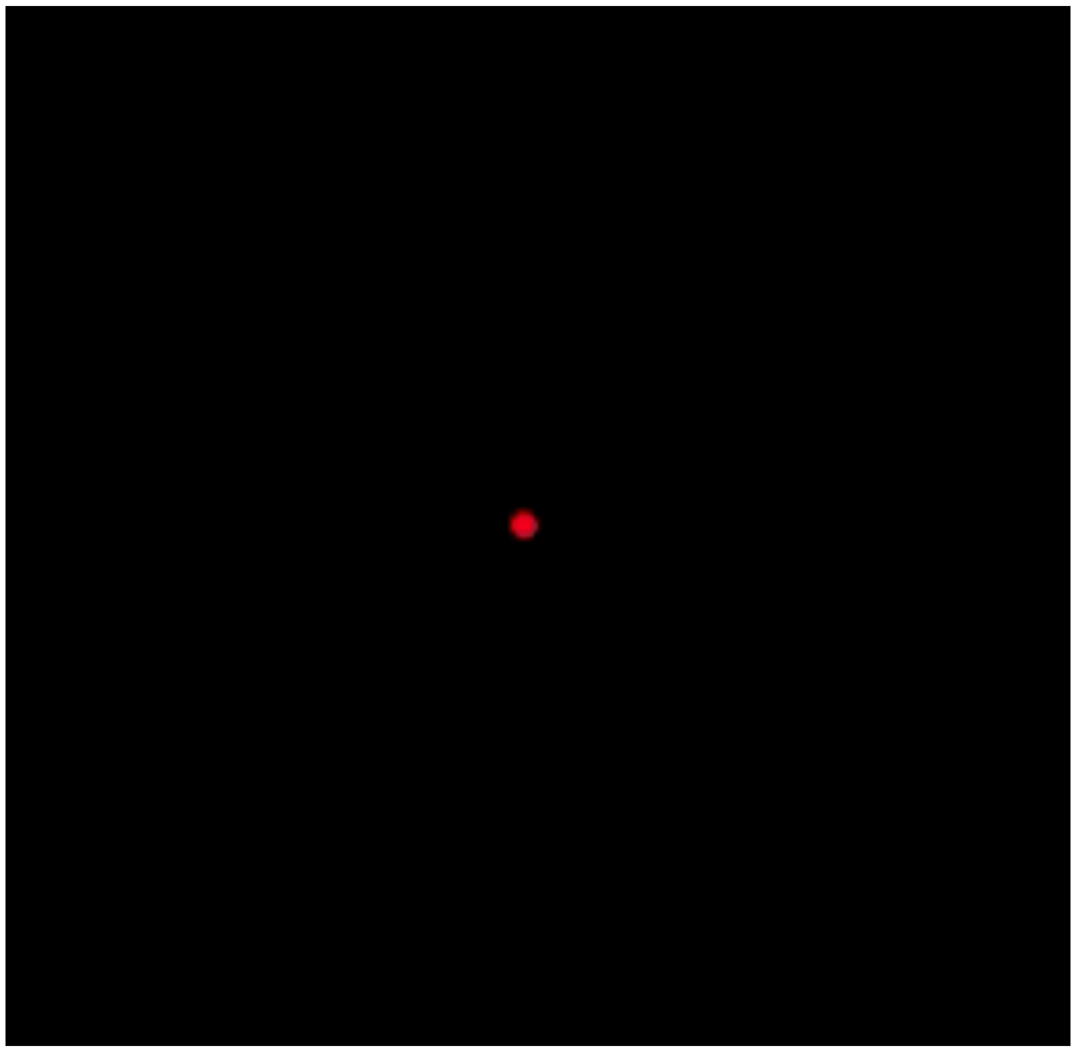
…and they struggle to generalize to Pong

Input Frames



…and they struggle to generalize to Pong

Input Frames



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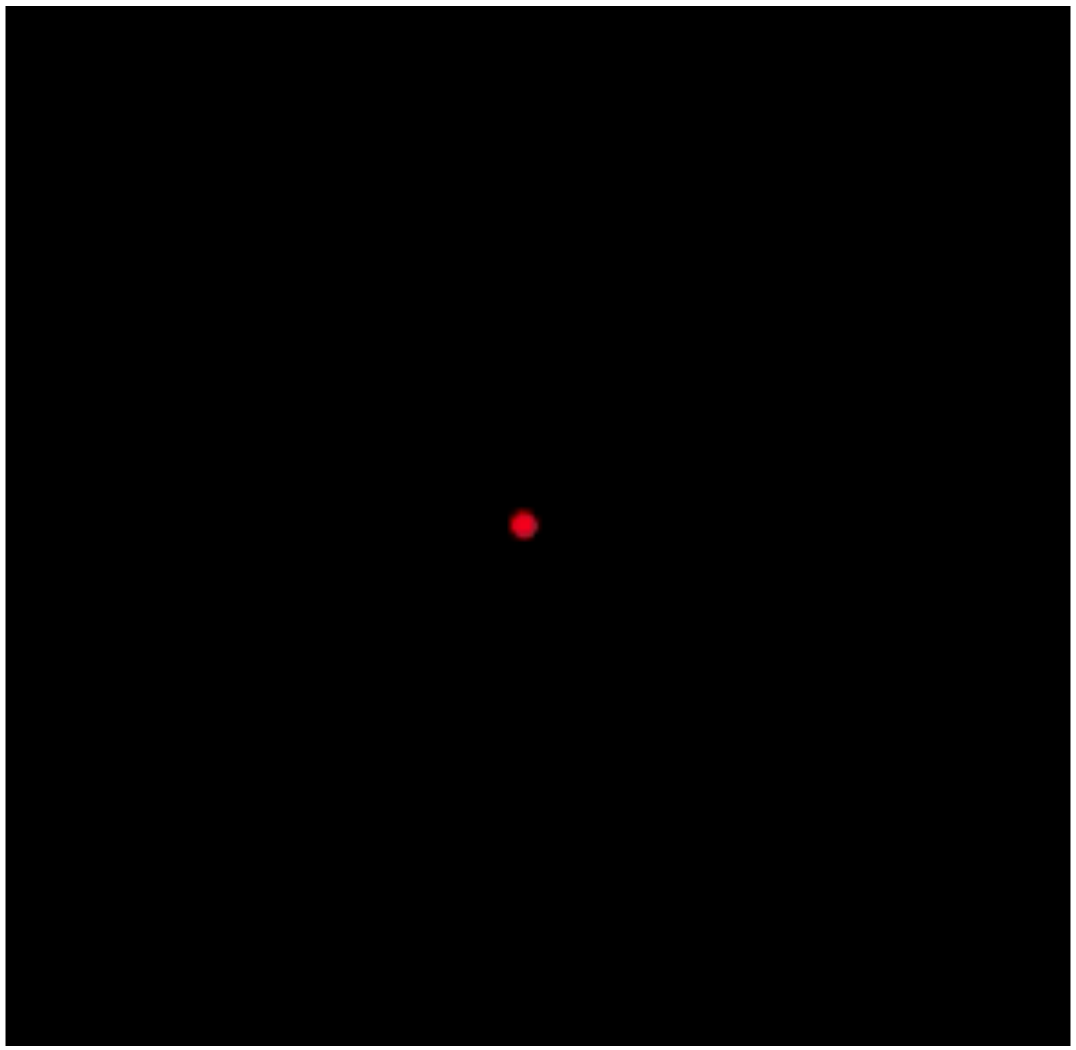
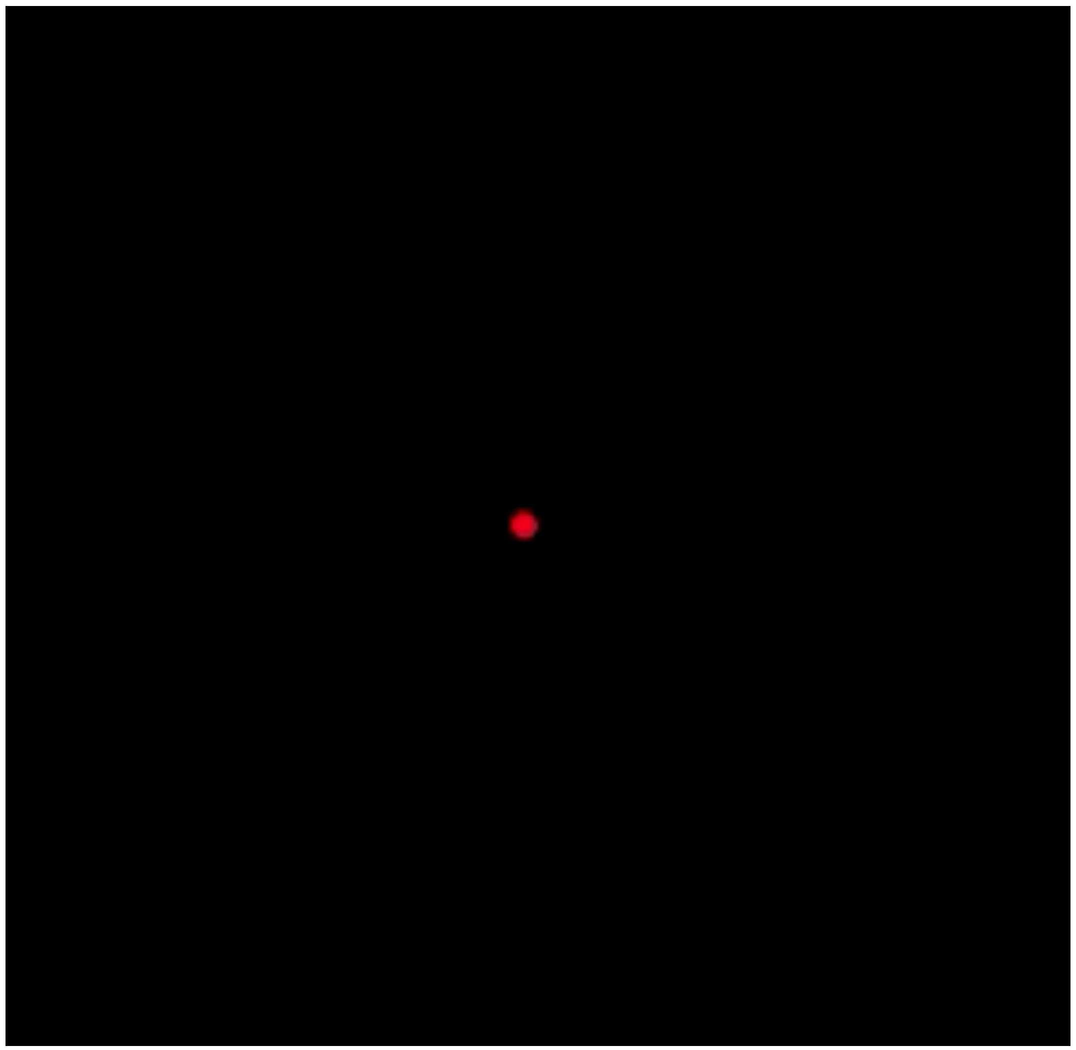
Input Frames



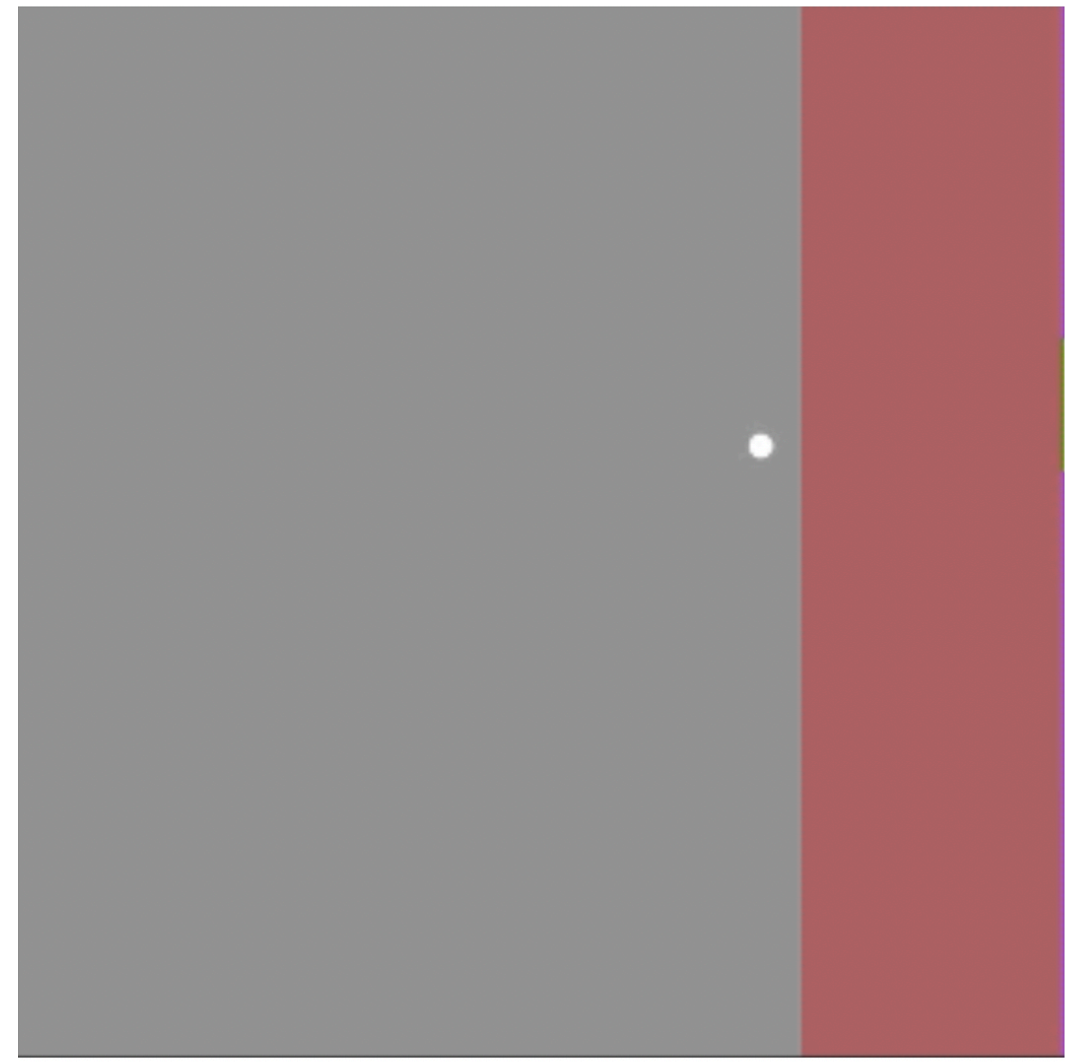
Predicted Frames

…and they struggle to generalize to Pong

Input Frames



Predicted Frames



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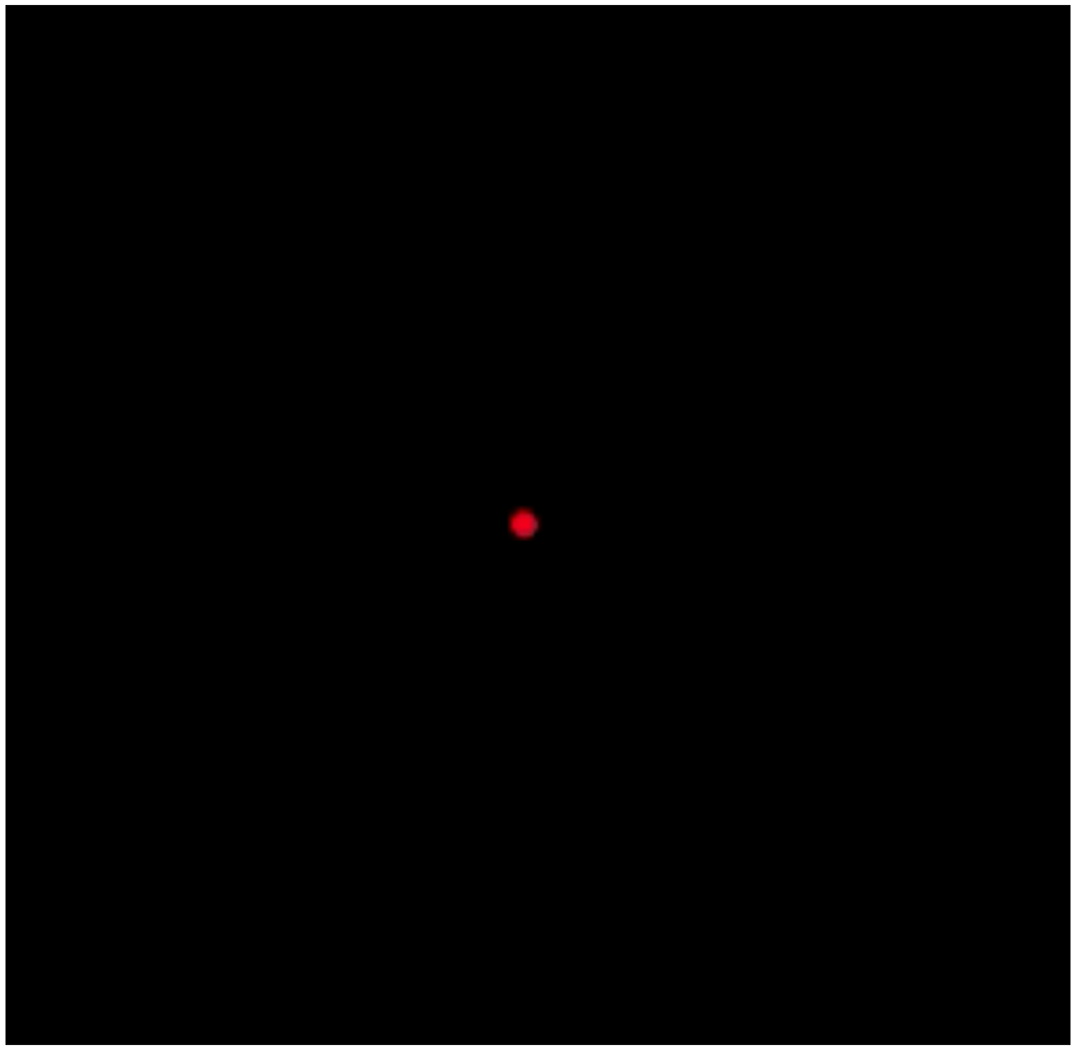

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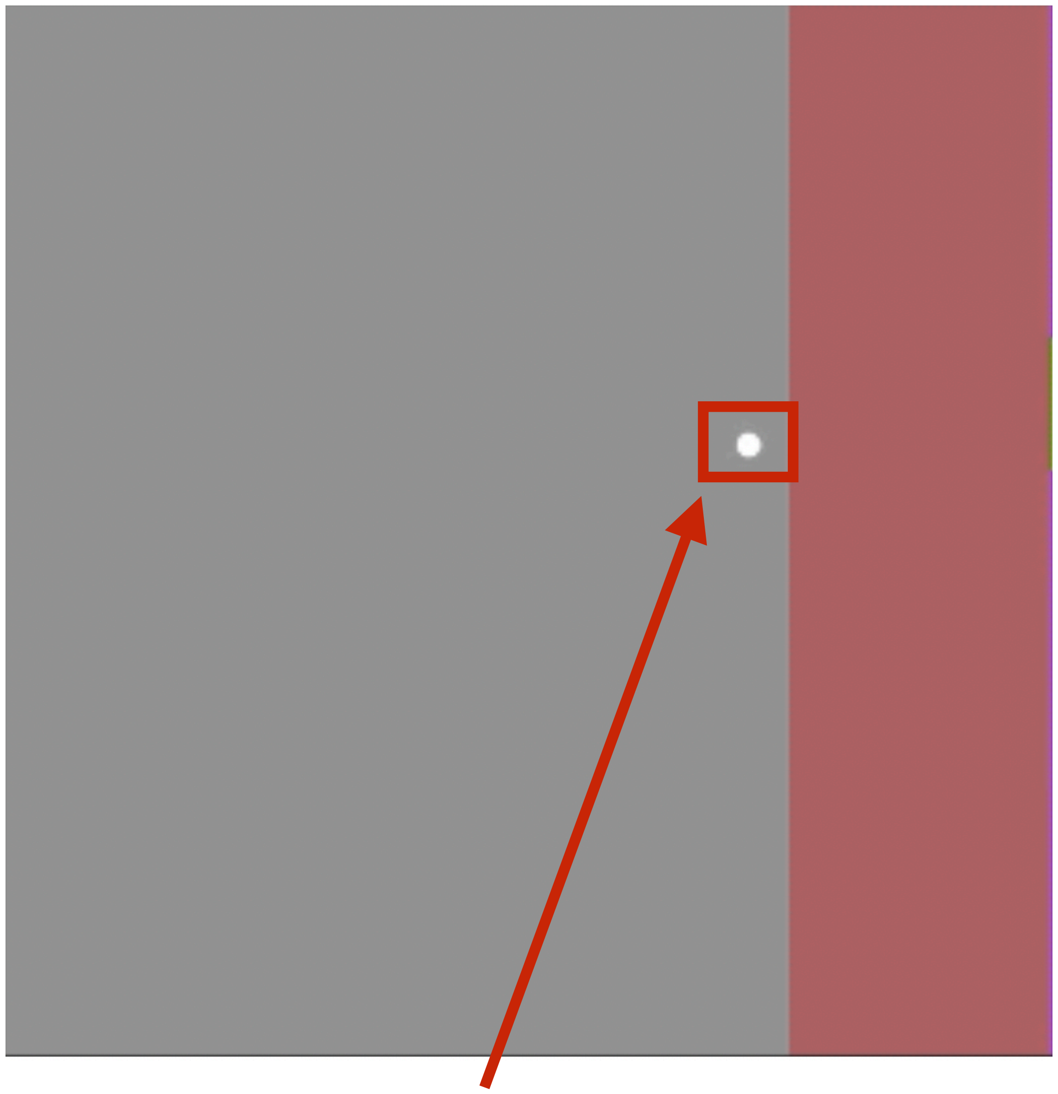
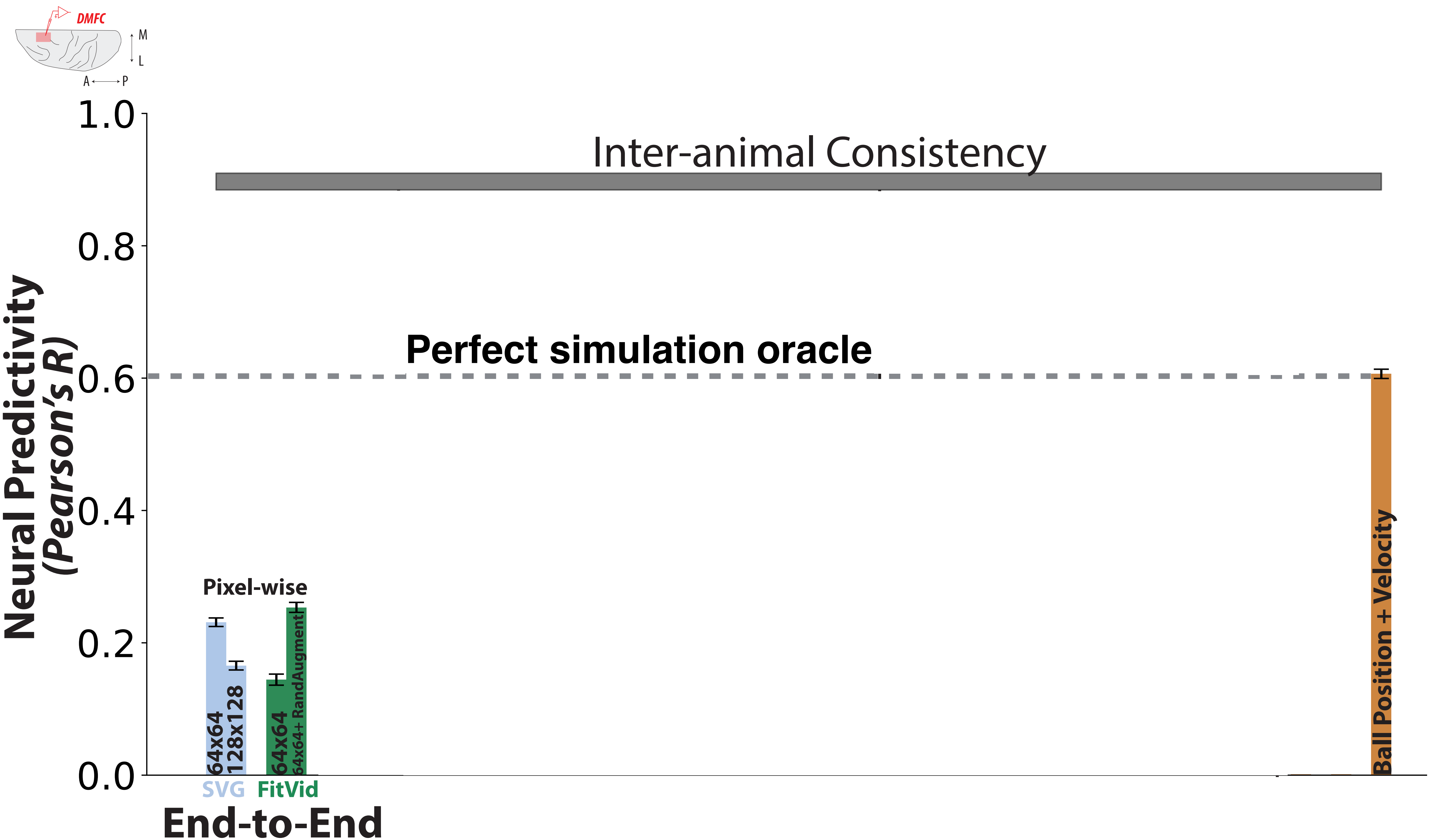
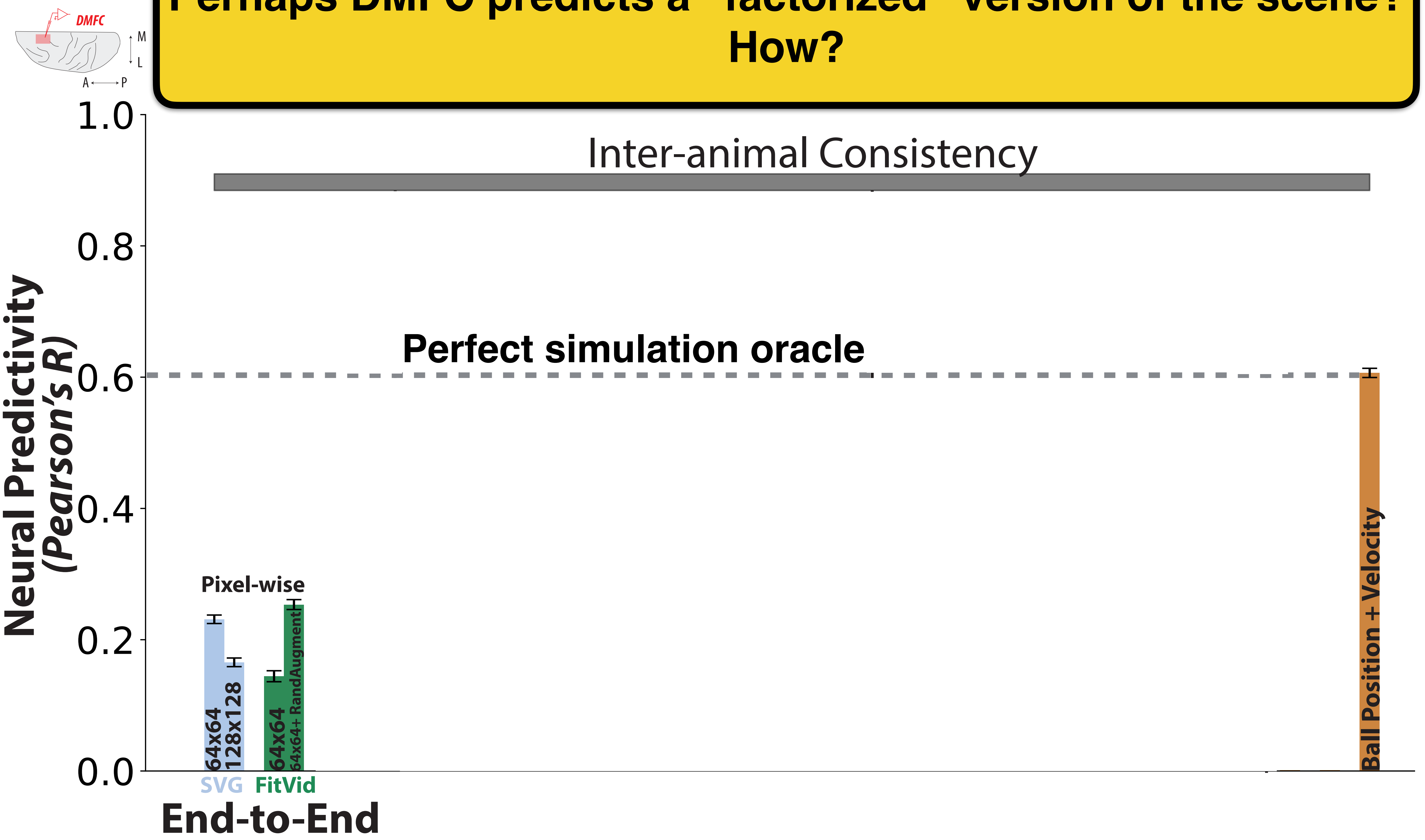


Pixel-wise Future Prediction Poorly Predicts Neurons

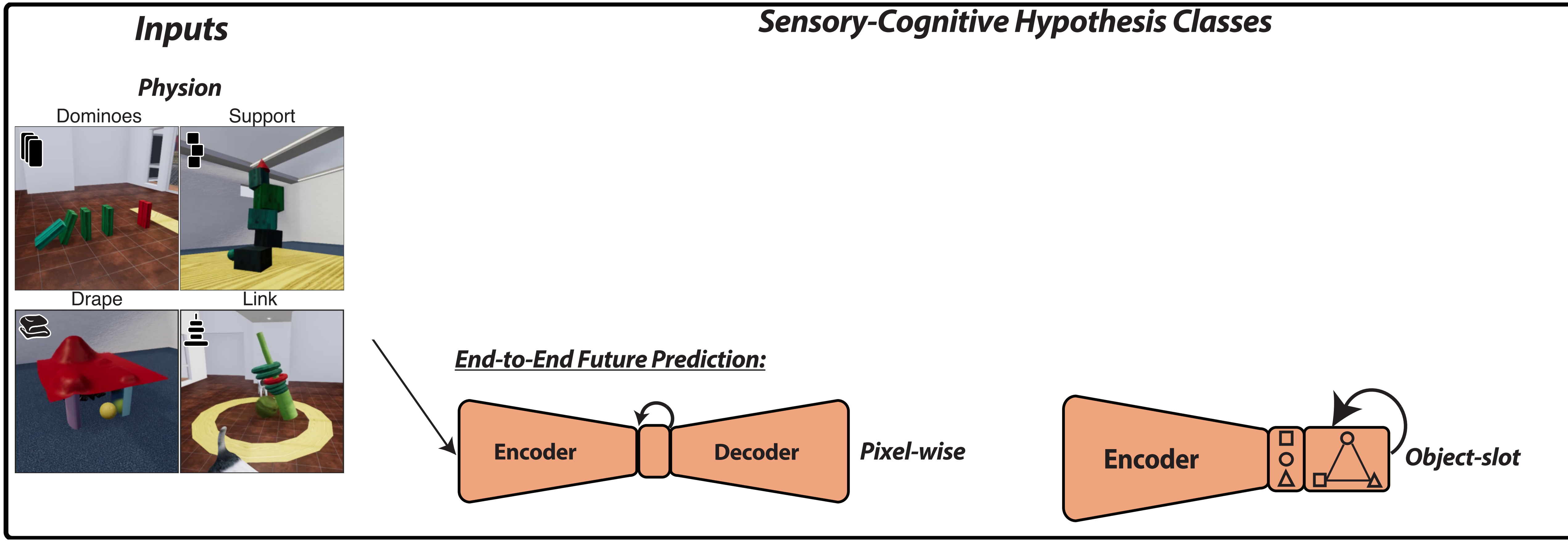


Pixel-wise Future Prediction Poorly Predicts Neurons

Perhaps DMFC predicts a "factorized" version of the scene? How?



Hypothesis Class 2: Object Slots



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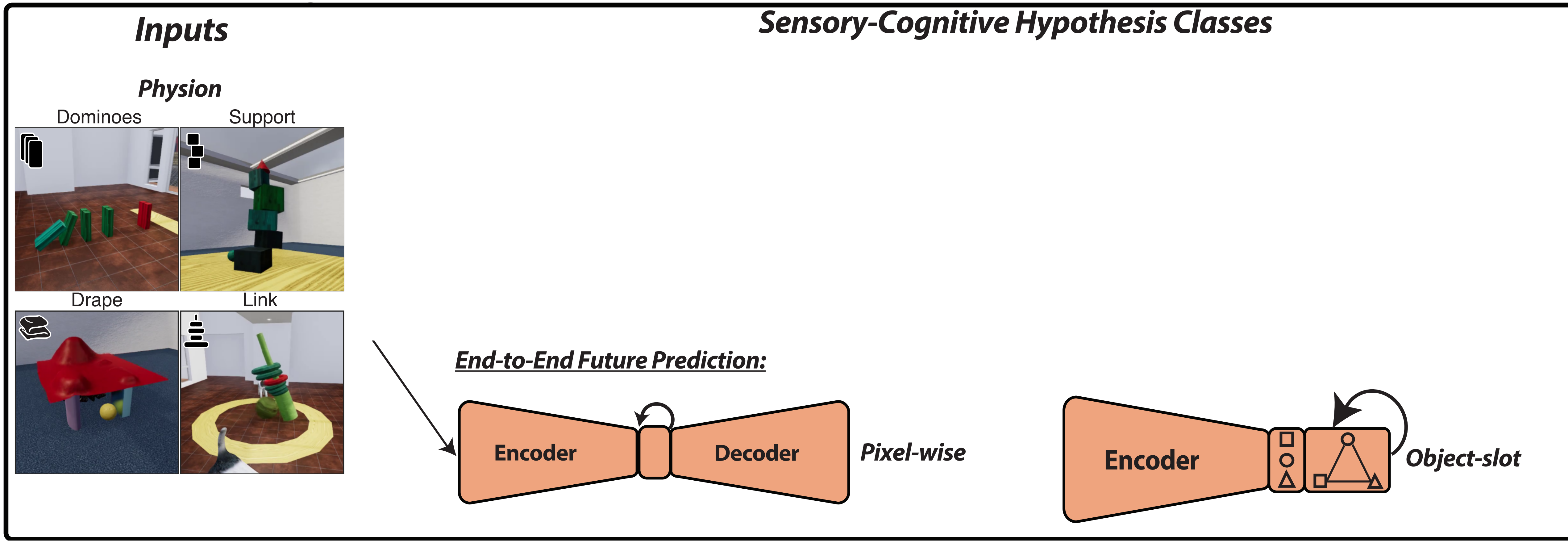
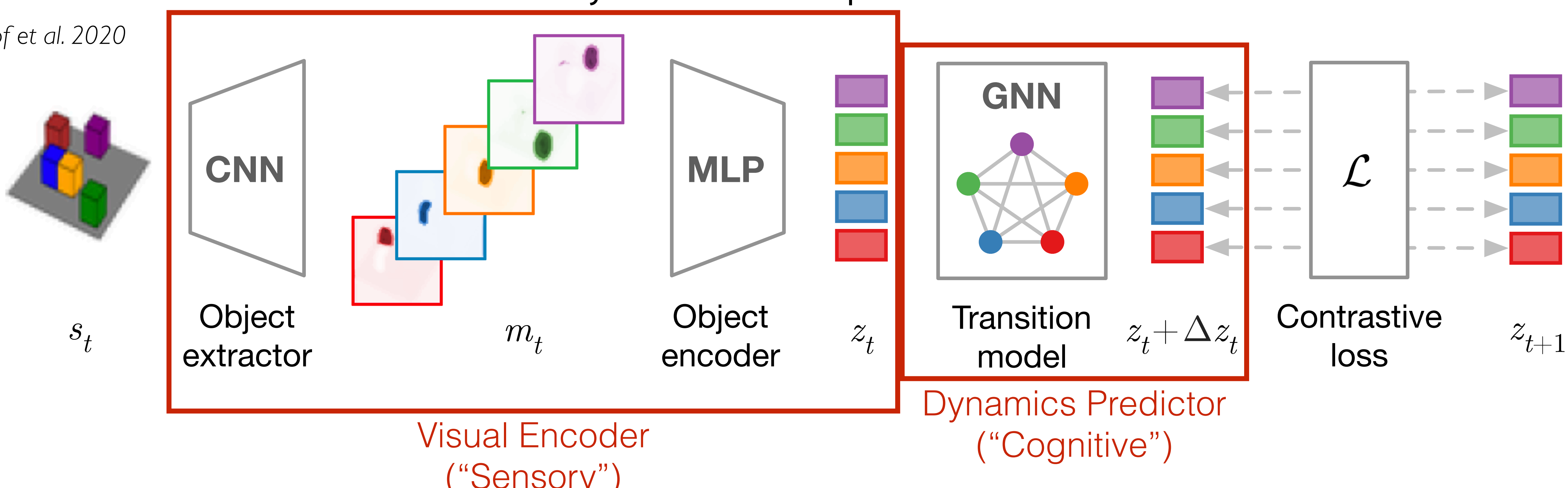


Predicts at the level of object slot representations and their relations

Kipf et al. 2020



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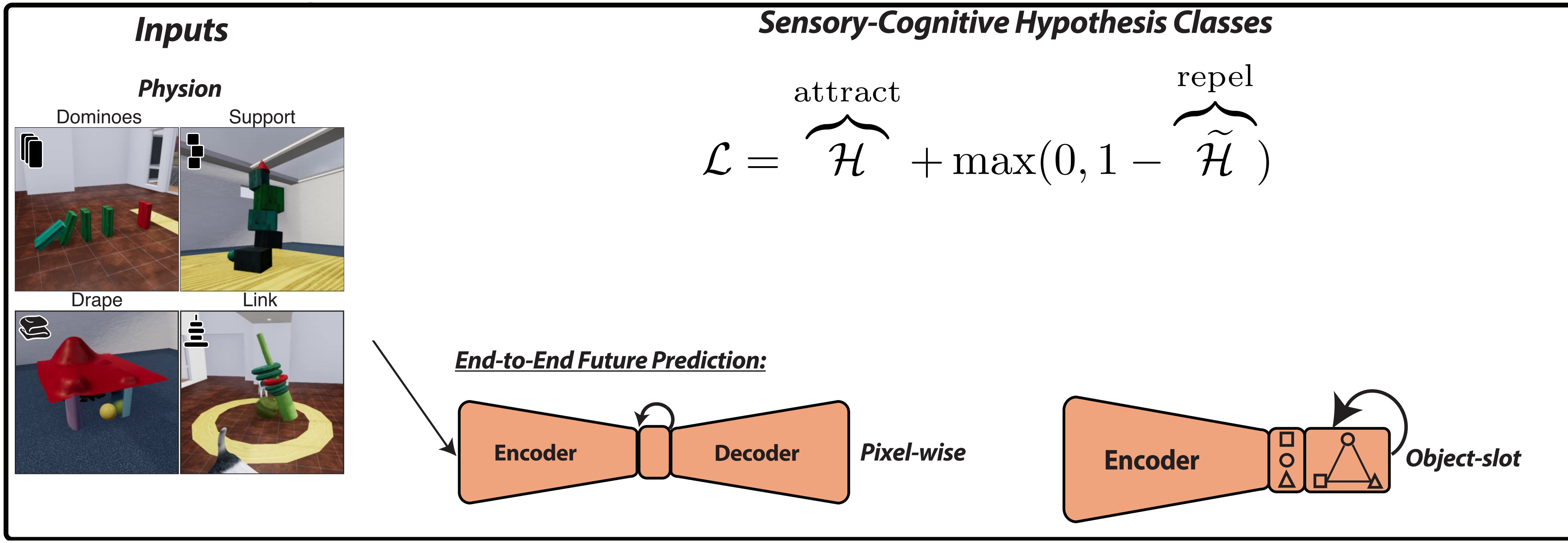

Predicts at the level of object slot representations and their relations

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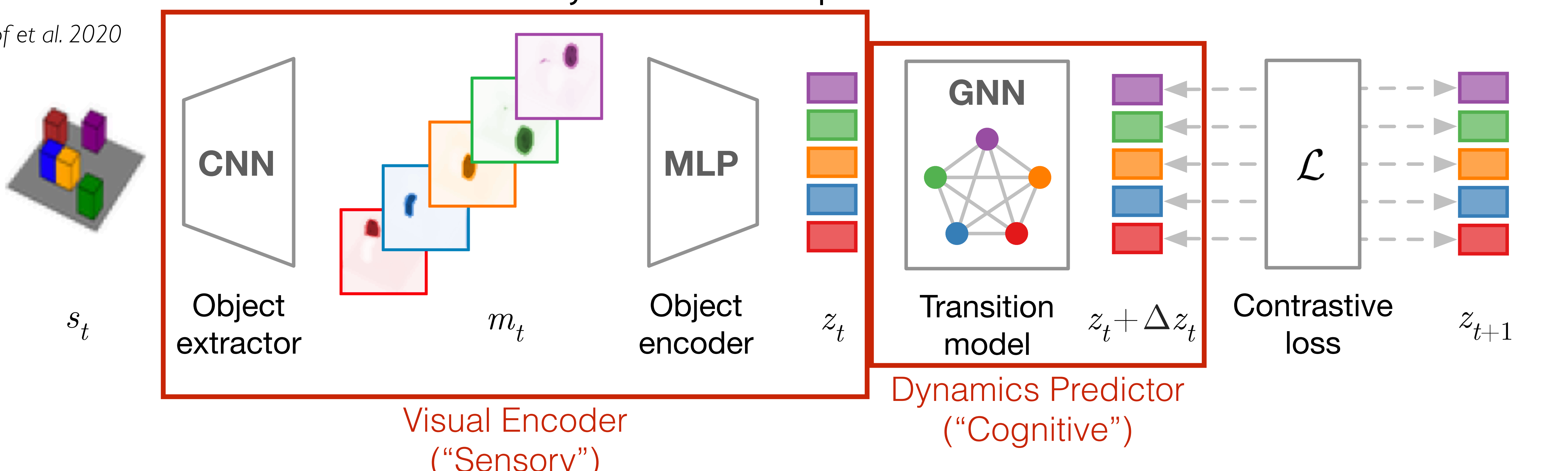
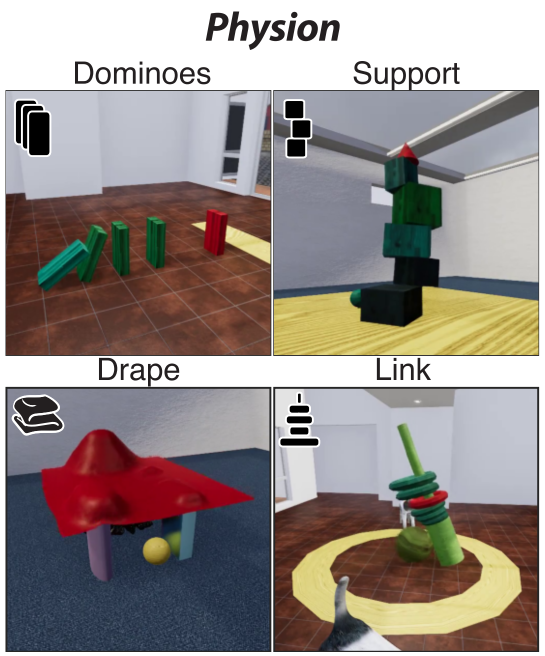


Hypothesis Class 2: Object Slots

Inputs

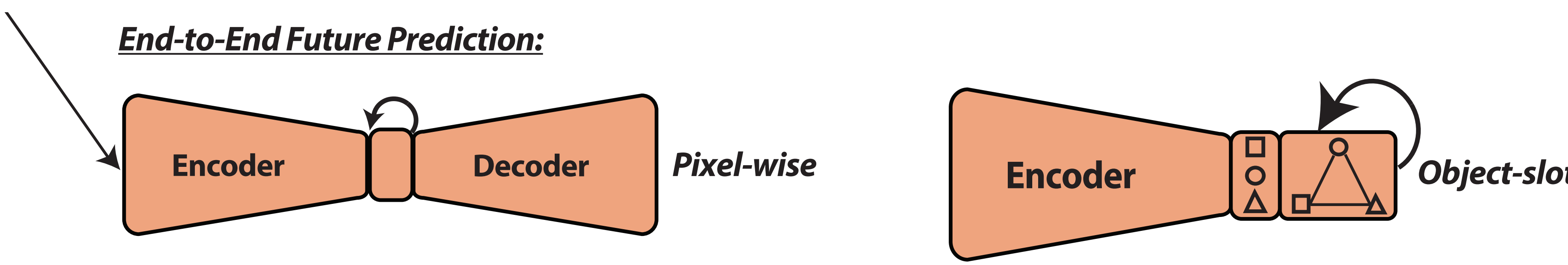
Sensory-Cognitive Hypothesis Classes



$$\mathcal{L} = \overbrace{\mathcal{H}}^{\text{attract}} + \max(0, 1 - \overbrace{\widetilde{\mathcal{H}}}^{\text{repel}})$$

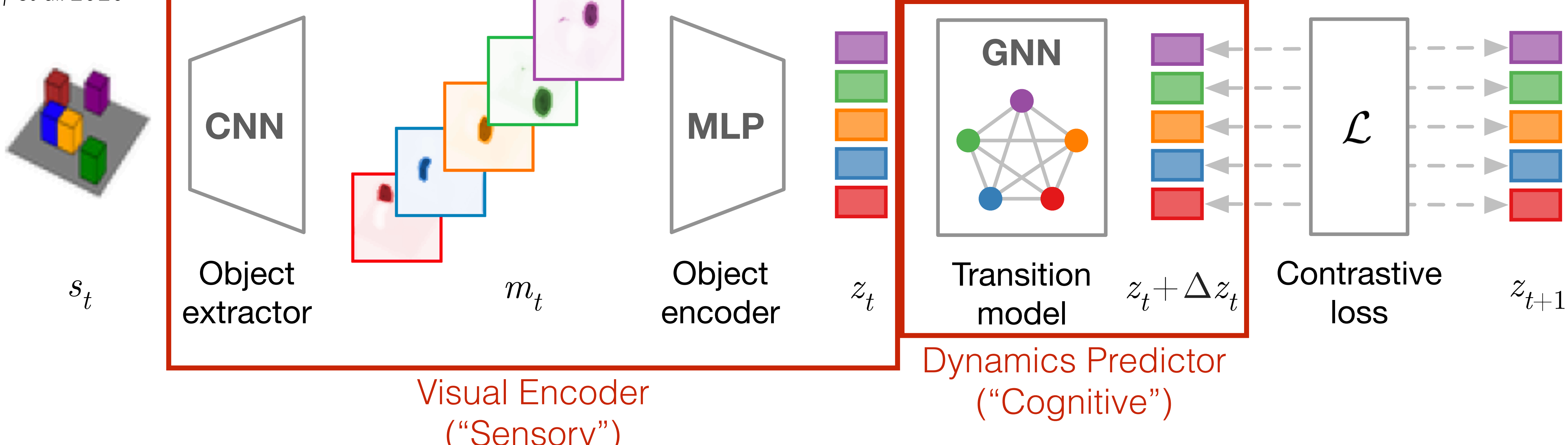
$$\mathcal{H} = \frac{1}{K}\sum_{k=1}^{K} \left\| (\mathbf{z}_t^k + \Delta\mathbf{z}_t^k) - \mathbf{z}_{t+1}^k \right\|_2^2$$

End-to-End Future Prediction:



Predicts at the level of object slot representations and their relations

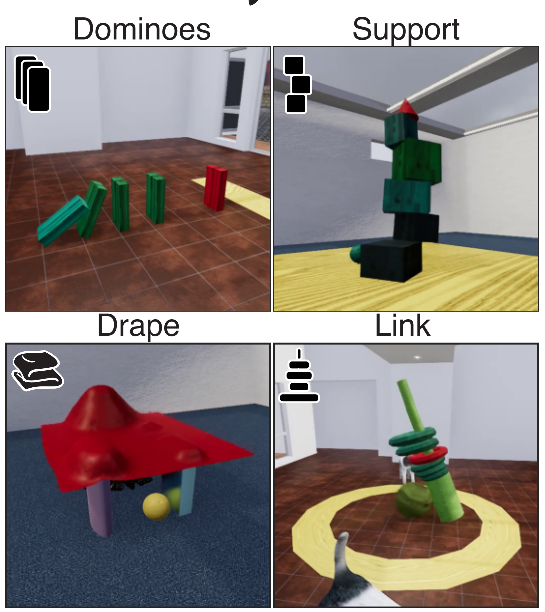
Kipf et al. 2020



Hypothesis Class 2: Object Slots

Inputs

Physion



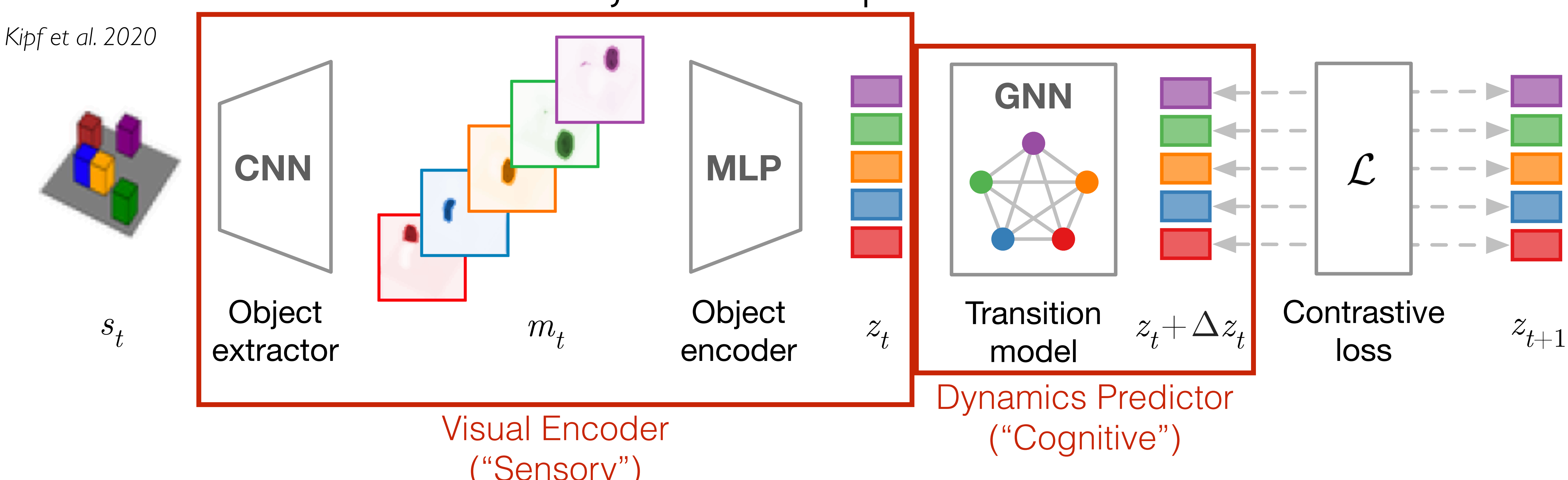
Sensory-Cognitive Hypothesis Classes

$$\mathcal{L} = \overbrace{\mathcal{H}}^{\text{attract}} + \max(0, 1 - \overbrace{\widetilde{\mathcal{H}}}^{\text{repel}})$$

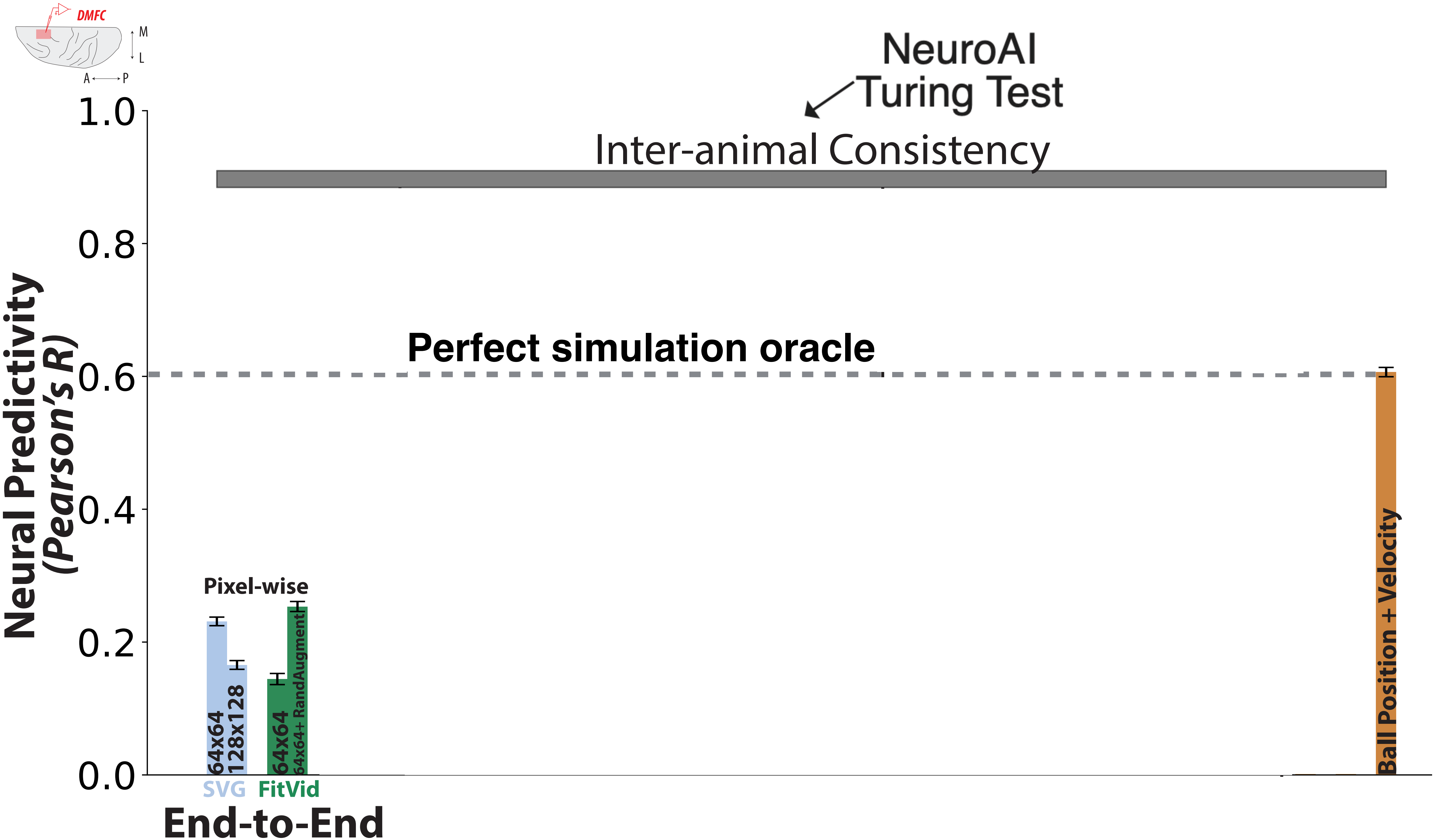
$$\mathcal{H} = \frac{1}{K}\sum_{k=1}^{K} \left\| (\mathbf{z}_t^k + \Delta\mathbf{z}_t^k) - \mathbf{z}_{t+1}^k \right\|_2^2, \quad \widetilde{\mathcal{H}} = \frac{1}{K}\sum_{k=1}^{K} \left\| \widetilde{\mathbf{z}}_t^k - \mathbf{z}_{t+1}^k \right\|_2^2$$

End-to-End Future Prediction:

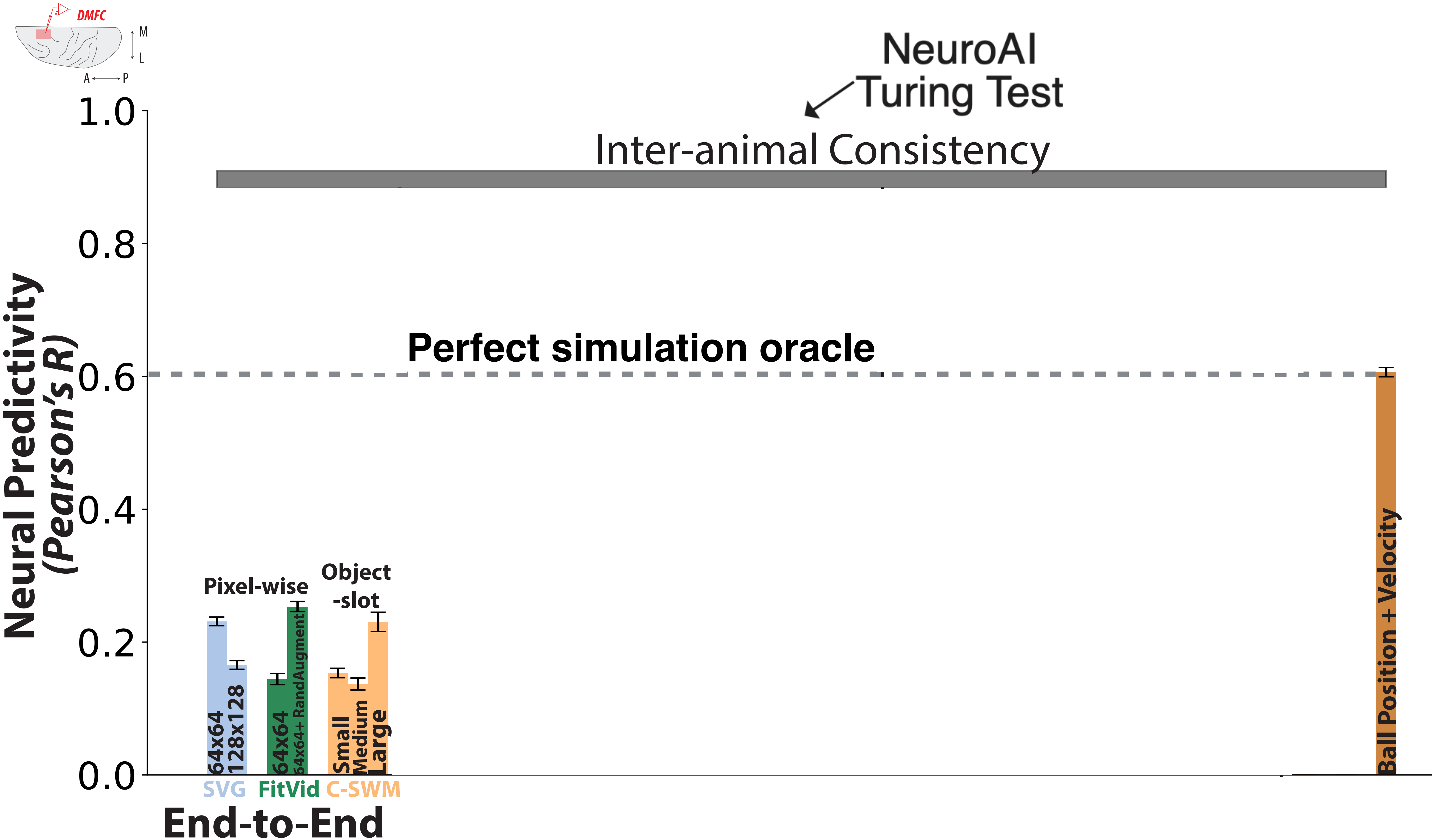
Predicts at the level of object slot representations and their relations



Pixel-wise Future Prediction Poorly Predicts Neurons

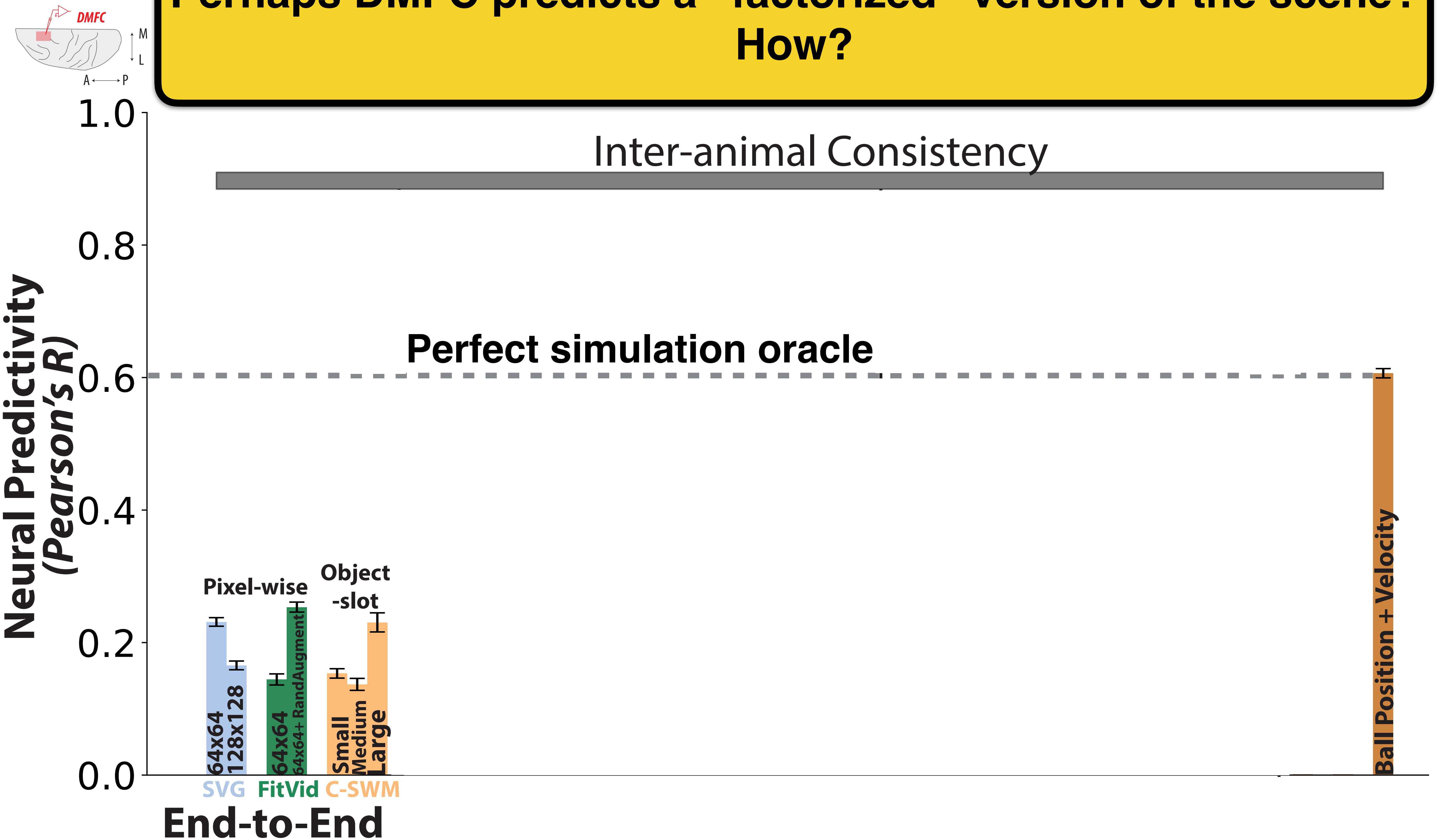


Object Slot Future Prediction Poorly Predicts Neurons



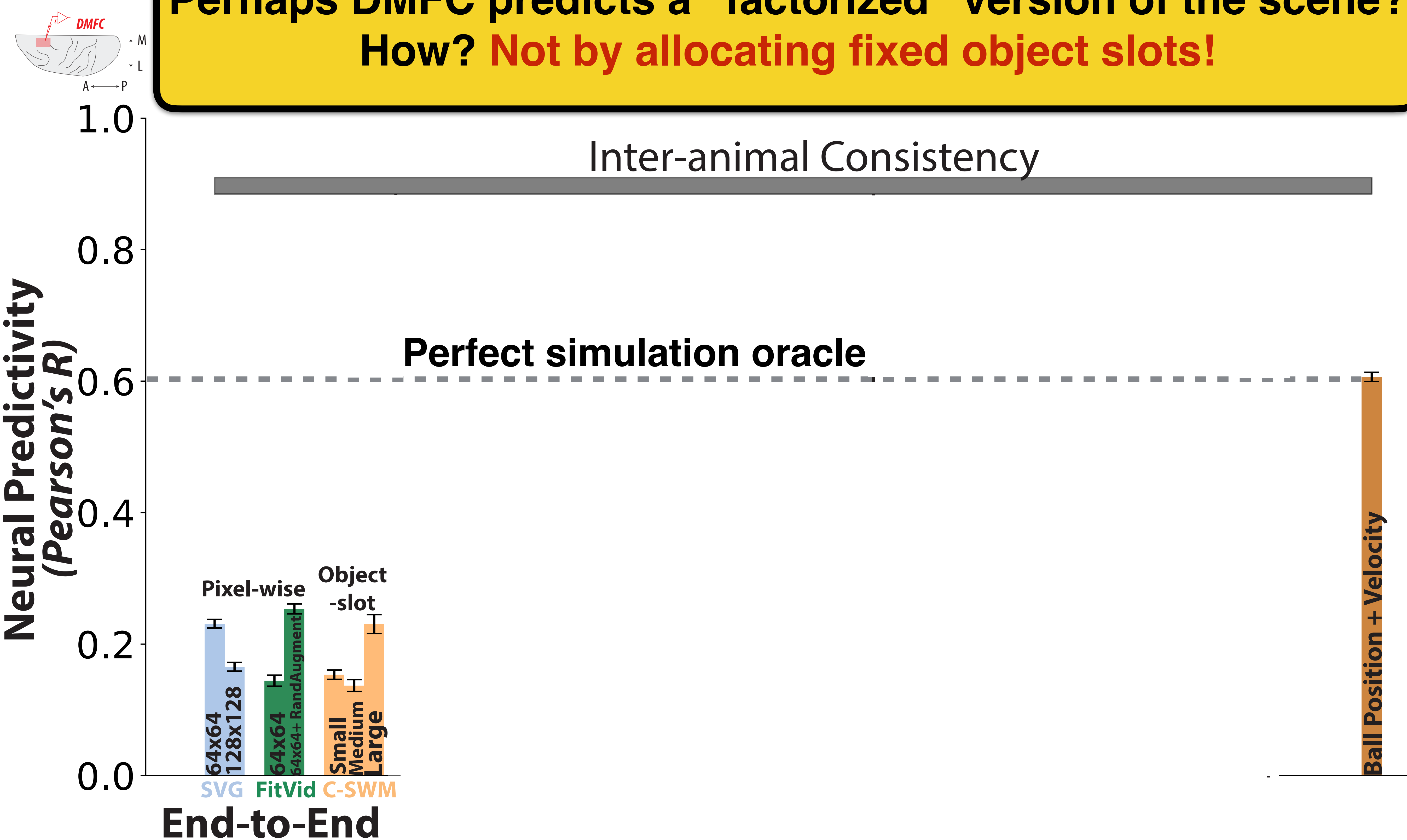
Object Slot Future Prediction Poorly Predicts Neurons

Perhaps DMFC predicts a "factorized" version of the scene? How?

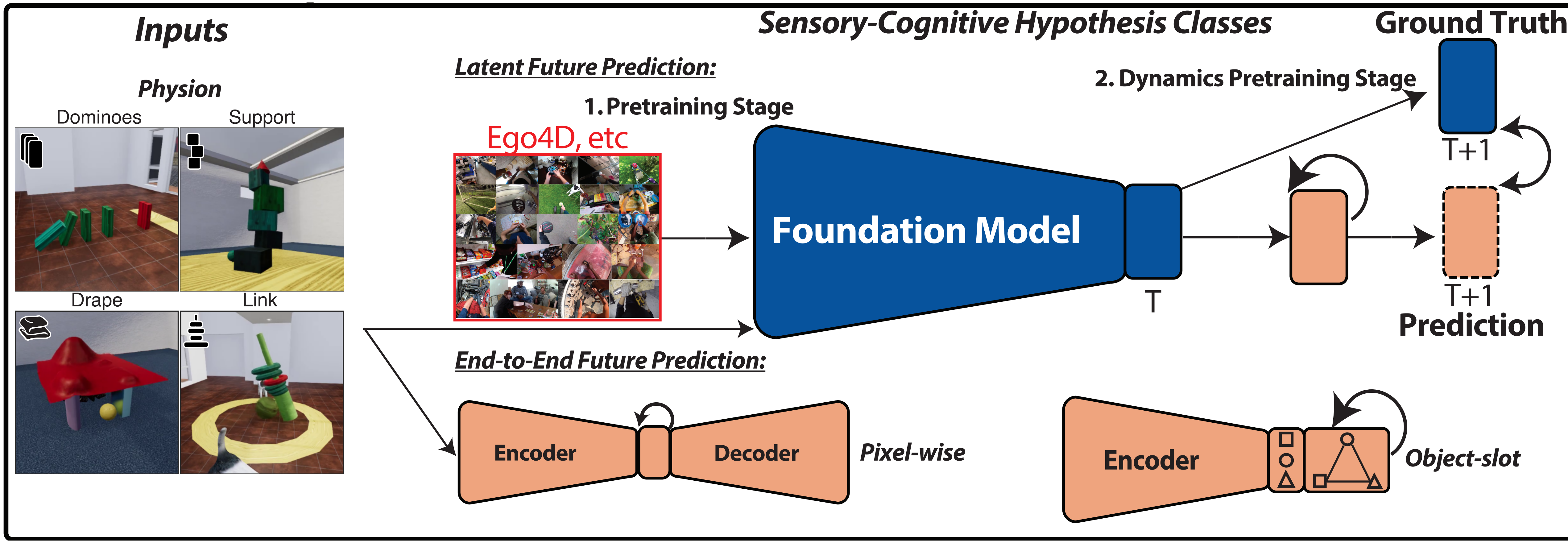


Object Slot Future Prediction Poorly Predicts Neurons

Perhaps DMFC predicts a "factorized" version of the scene?
How? Not by allocating fixed object slots!



Hypothesis Class 3: Latent Future Prediction



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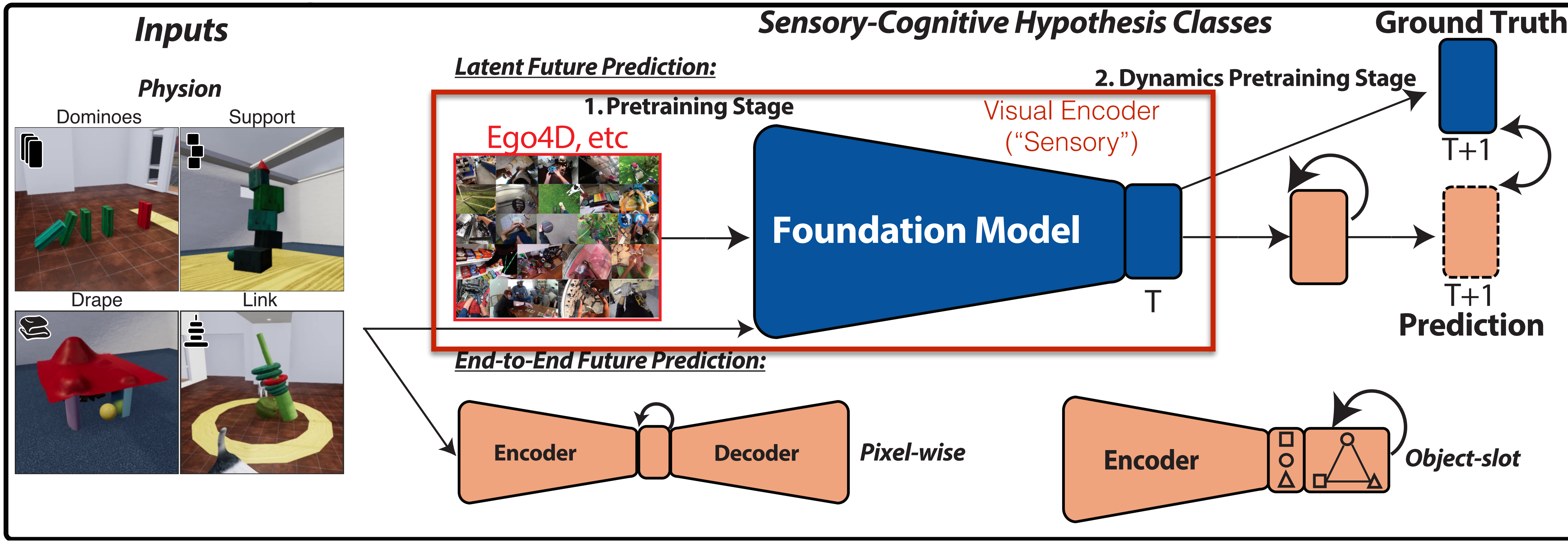
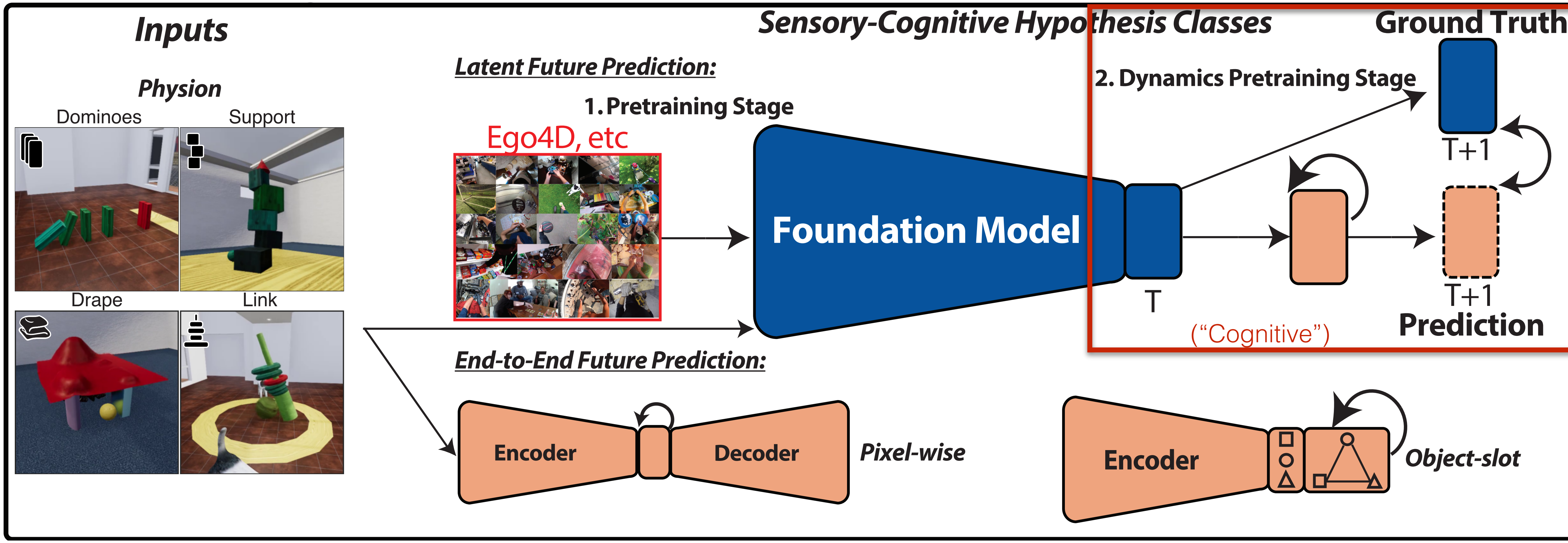


Learn a partial, *implicit* representation of the physical world by performing a challenging vision task ("foundation model")

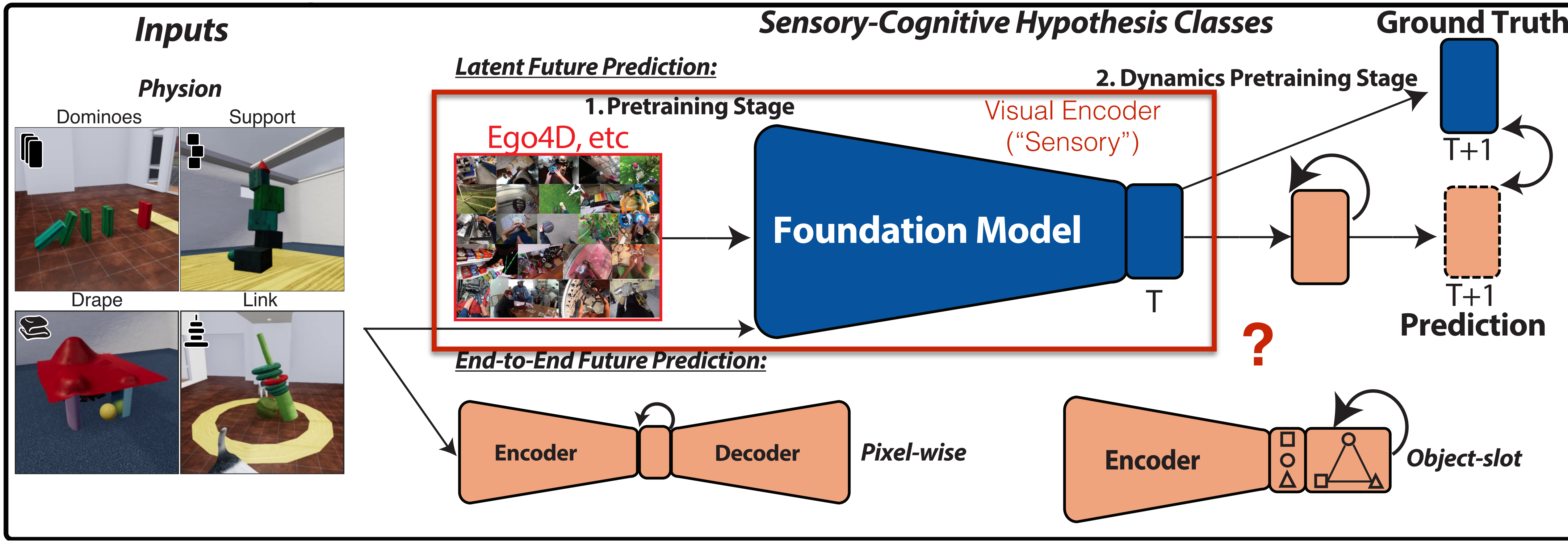
Hypothesis Class 3: Latent Future Prediction



Learn a partial, *implicit* representation of the physical world by performing a challenging vision task ("foundation model")

Leverage these dynamics to do explicit future prediction

Hypothesis Class 3: Foundation Models



Learn a partial, *implicit* representation of the physical world by performing a challenging vision task ("foundation model")

What vision task?

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Hypothesis Class 3: Static Image Foundation Models

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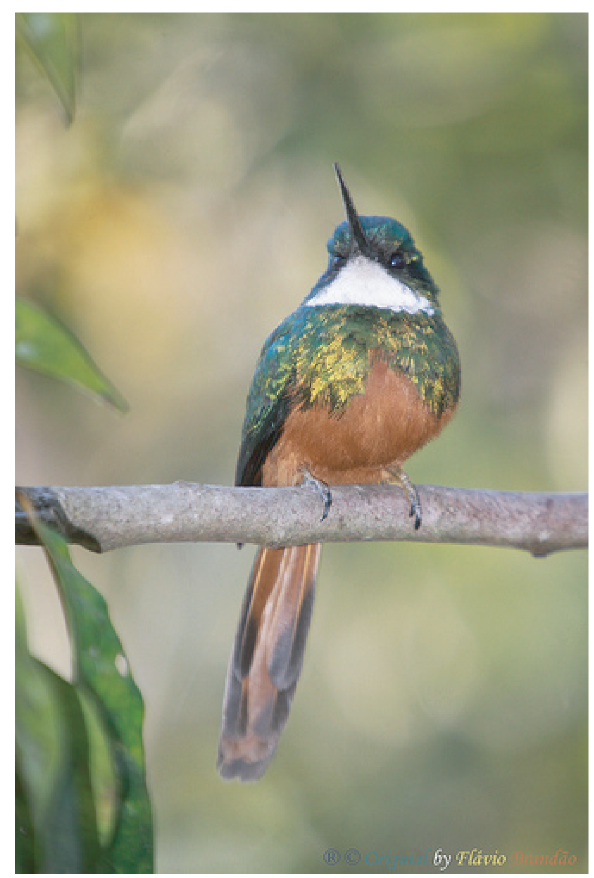

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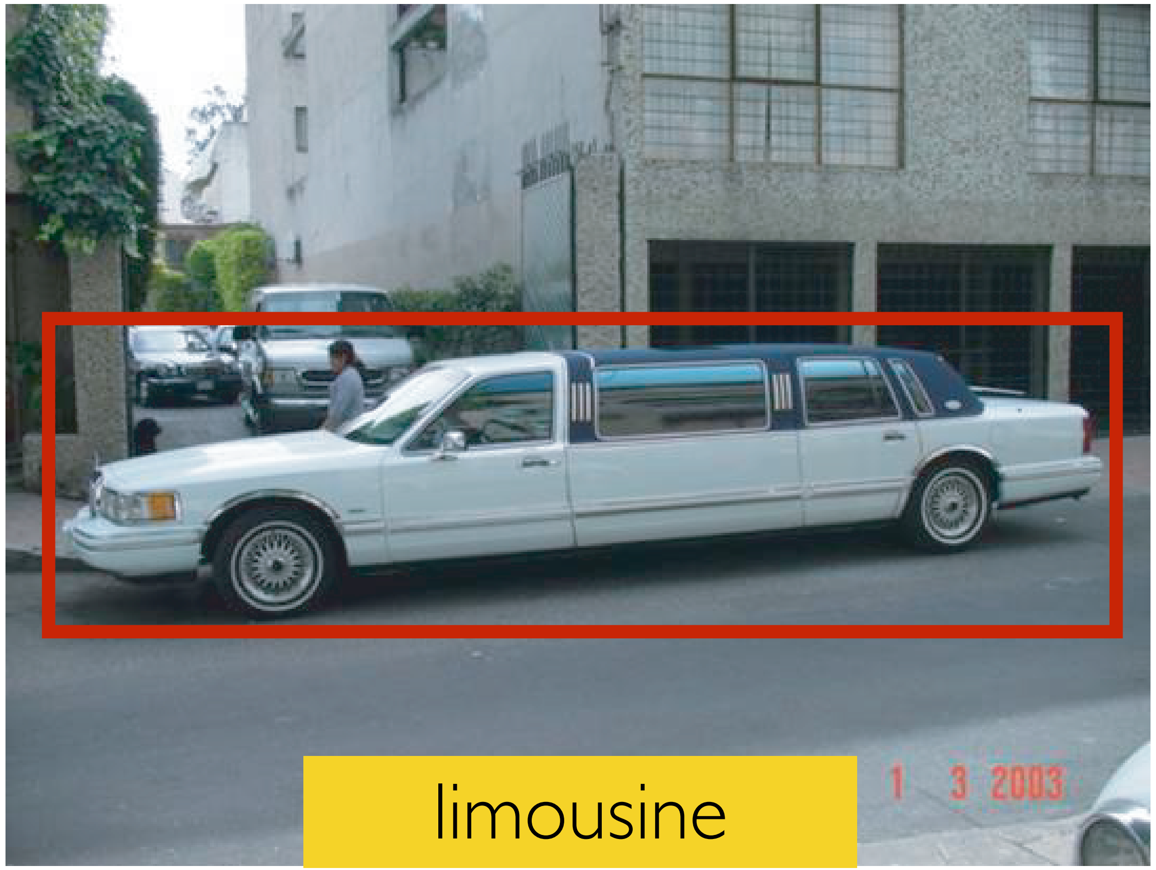

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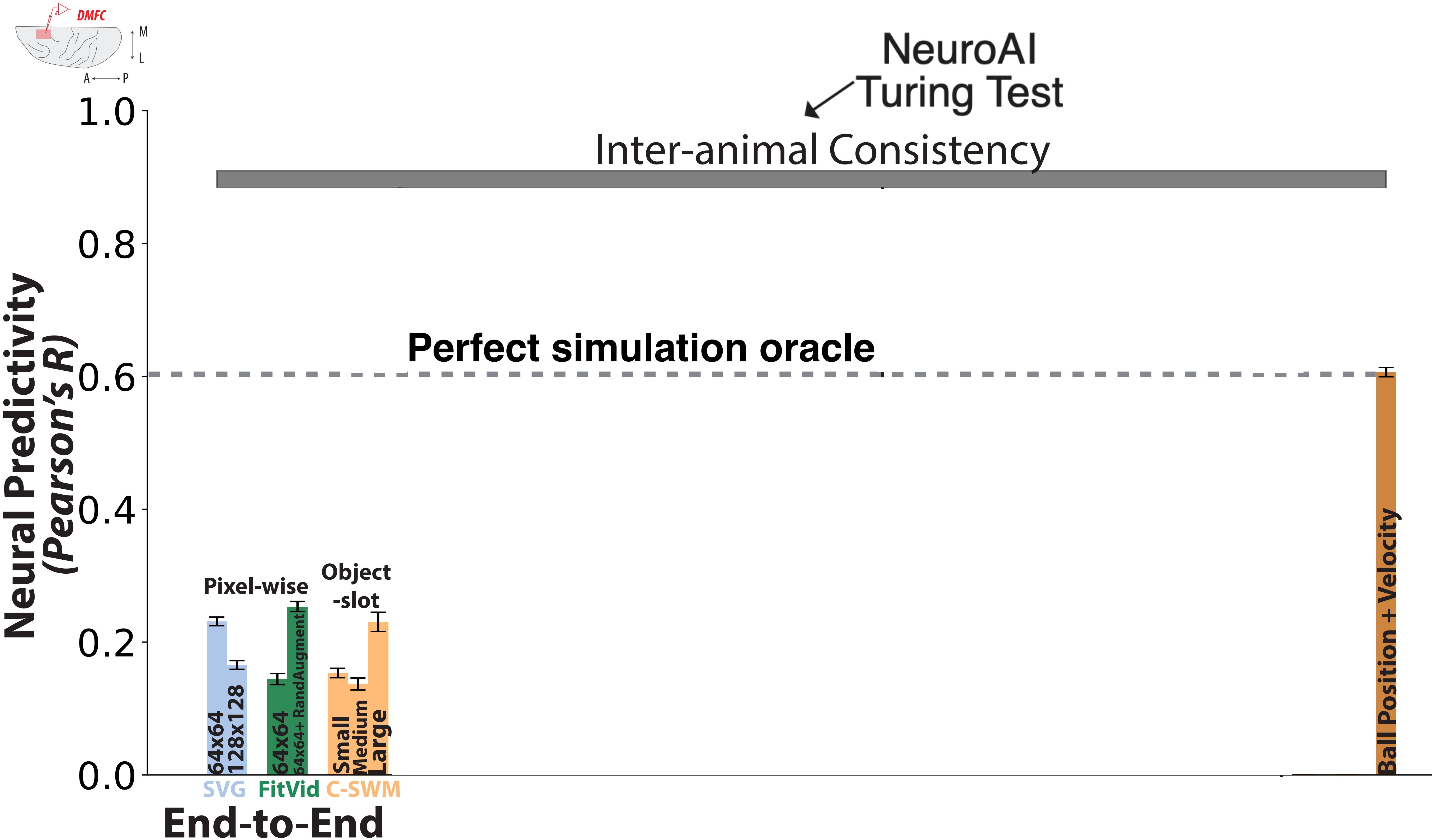

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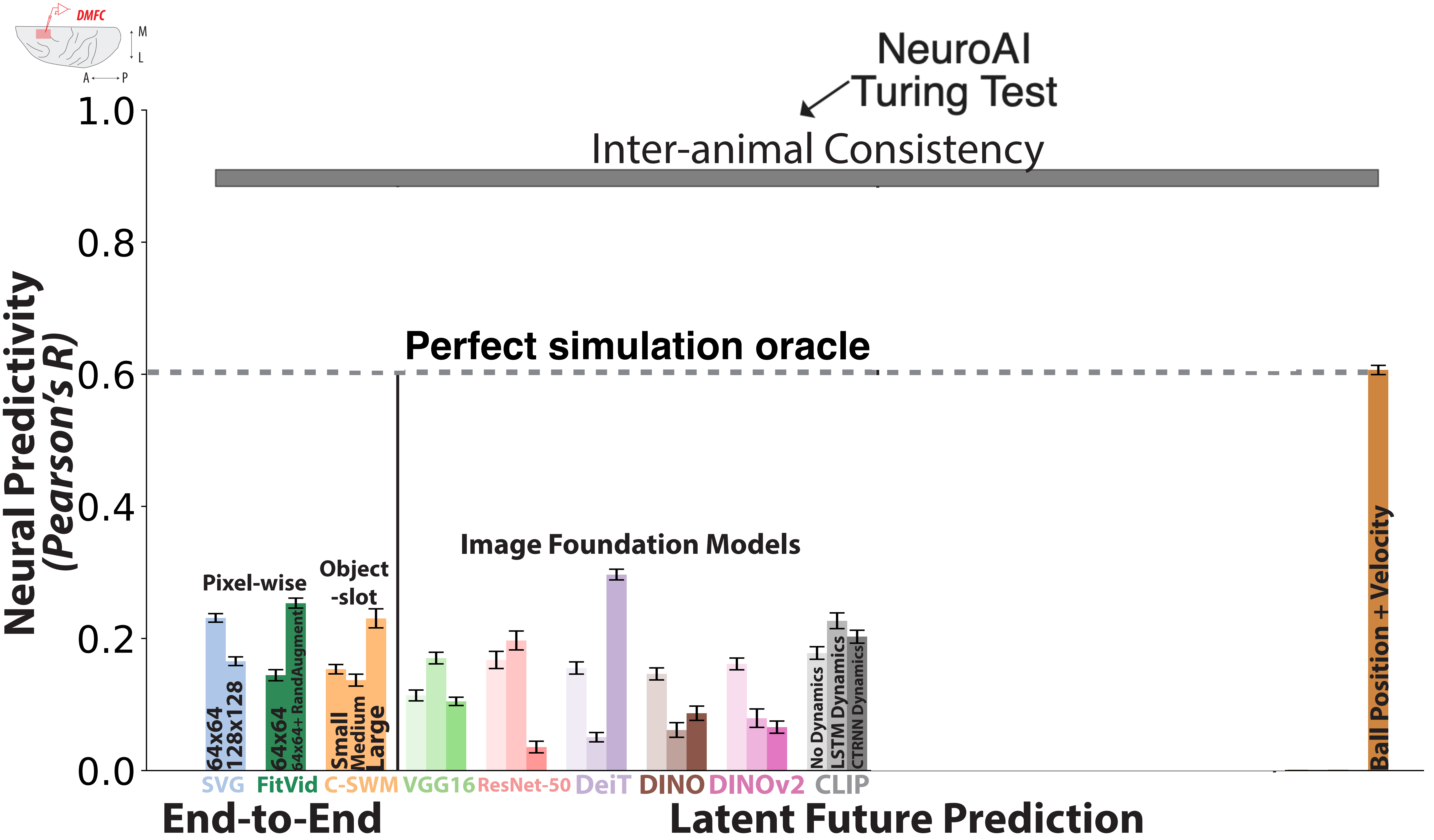

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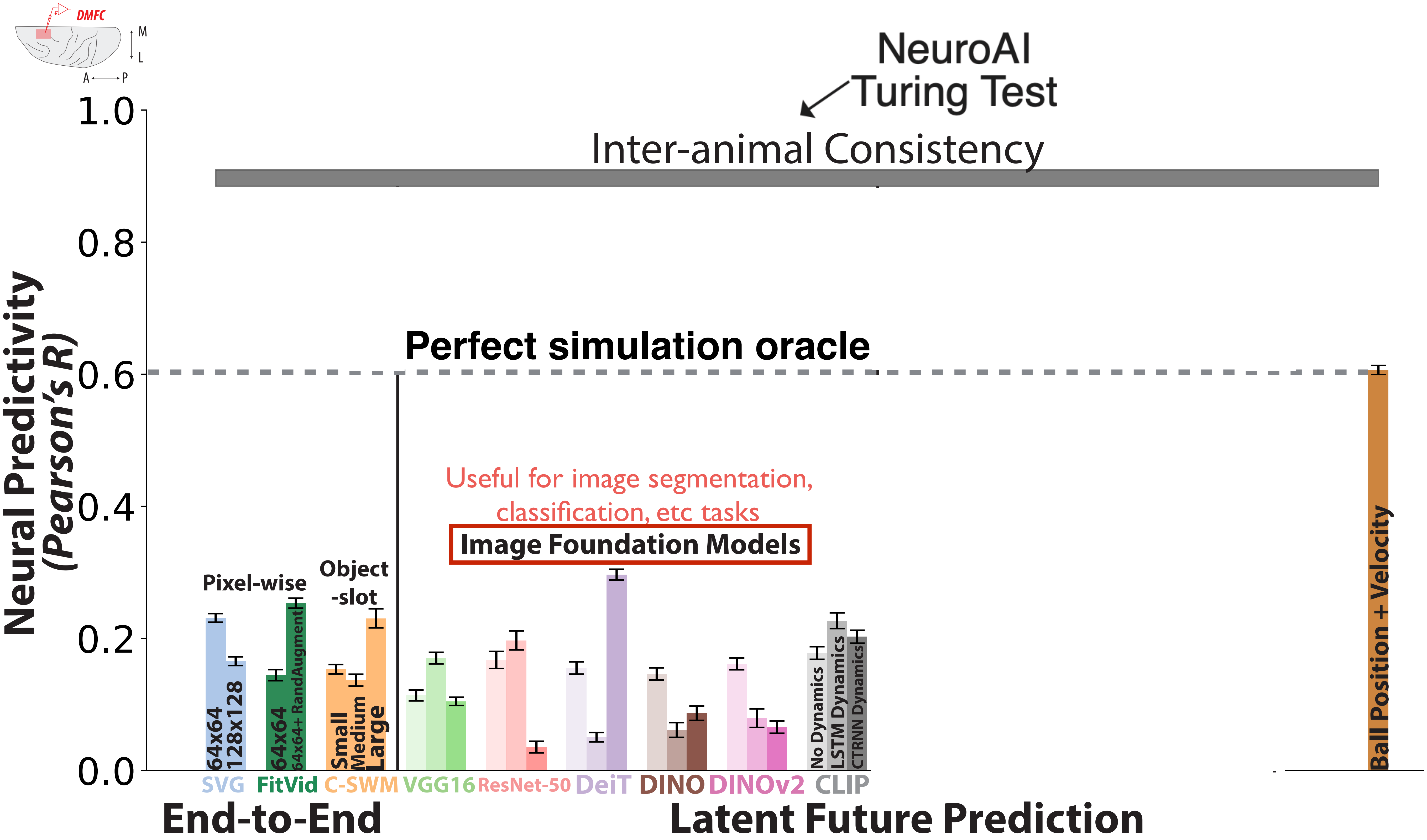

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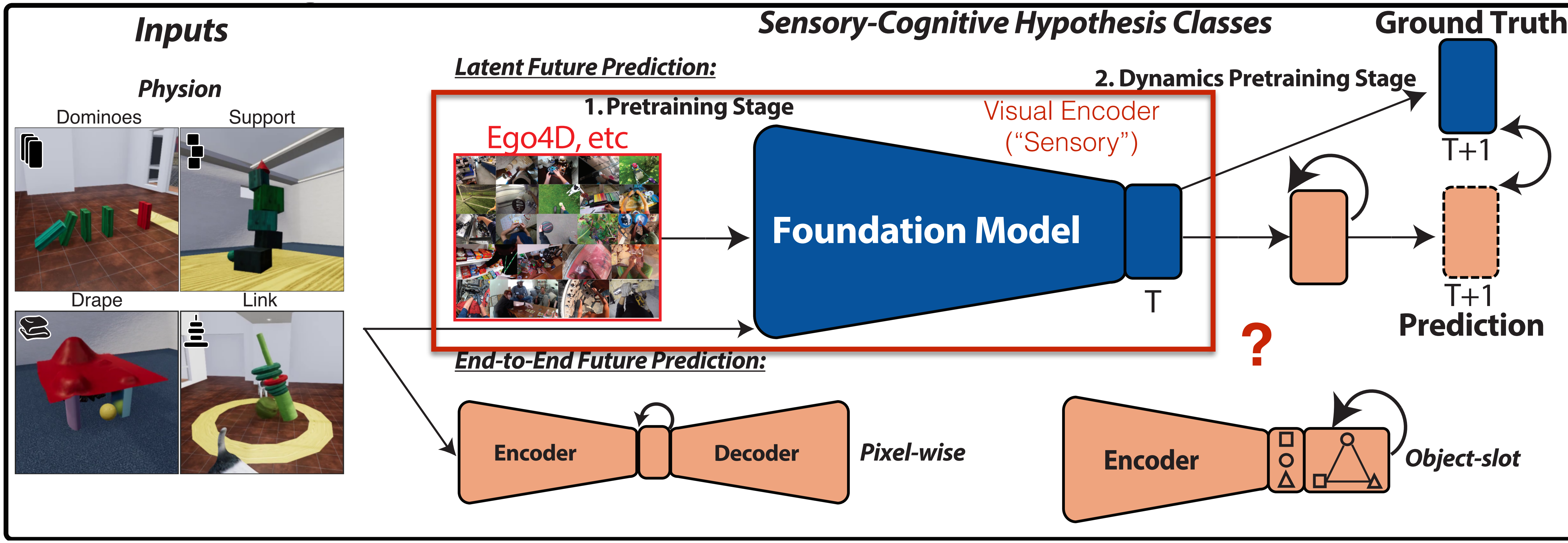

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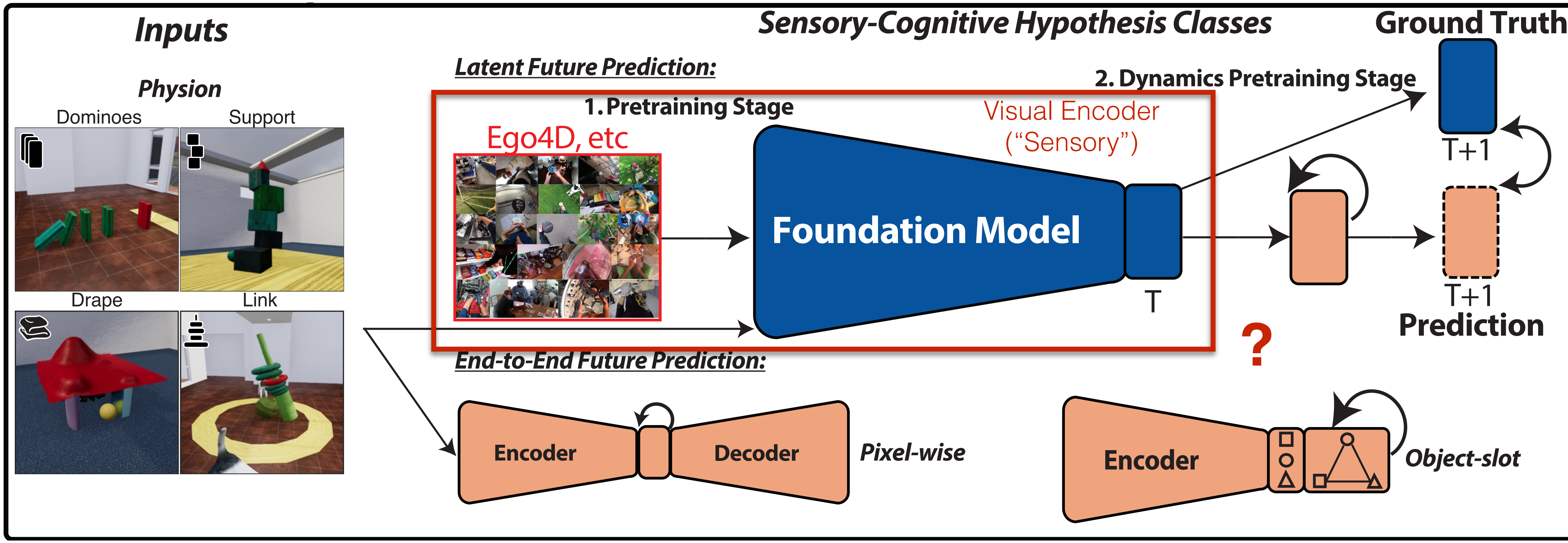
What vision task?

Leverage these dynamics to do explicit future prediction

Hypothesis Class 3: Foundation Models



Learn a partial, *implicit* representation of the physical world by performing a challenging vision task ("foundation model")

What vision task?

We do far more than engage with static images!

Leverage these dynamics to do explicit future prediction

Hypothesis Class 3: Video Foundation Models

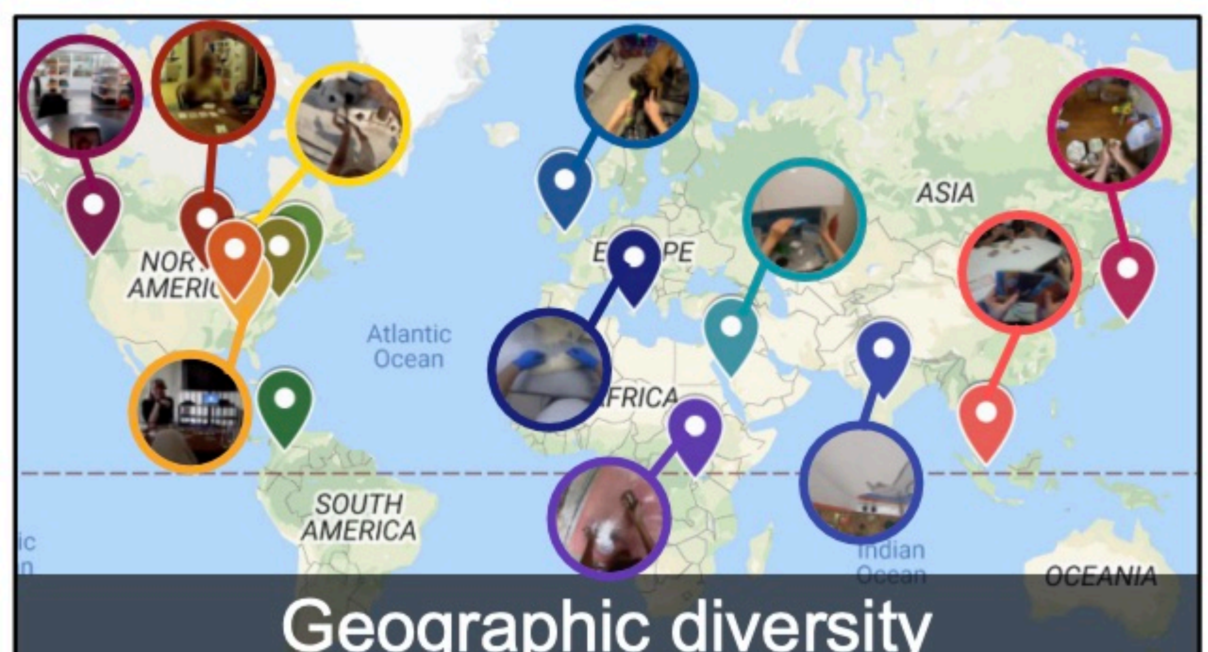
Ego4D: everyday activity around the world

Ego4D: A massive-scale egocentric dataset

3,670 hours of in-the-wild daily life activity

931 participants from 74 worldwide locations

Multimodal: audio, 3D scans, IMU, stereo, multi-camera



Grauman et al. 2022

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Grauman et al. 2022

Hypothesis Class 3: Video Foundation Models

Ego4D: everyday activity around the world

$$\mathcal{L}_{contrastive} =$$

$$-\sum_{b \in B} \log \frac{\overbrace{e^{\mathcal{S}(\mathbf{z}_i^b, \mathbf{z}_j^b)}}^{\text{attract}}}{e^{\mathcal{S}(\mathbf{z}_i^b, \mathbf{z}_j^b)} + \overbrace{e^{\mathcal{S}(\mathbf{z}_i^b, \mathbf{z}_k^b)}}^{\text{repel}} + \overbrace{e^{\mathcal{S}(\mathbf{z}_i^b, \widetilde{\mathbf{z}}_i^b)}}^{\text{repel}}}$$

$$[I_i, I_{j>i}, I_{k>j}]^{1:B}$$

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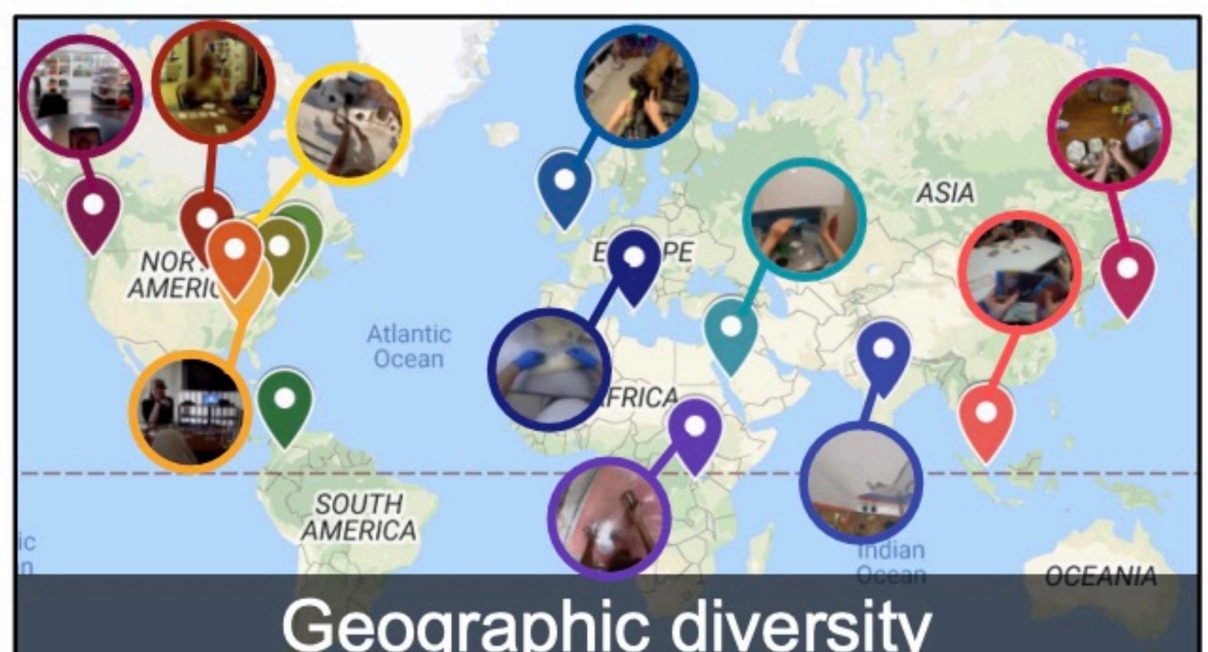

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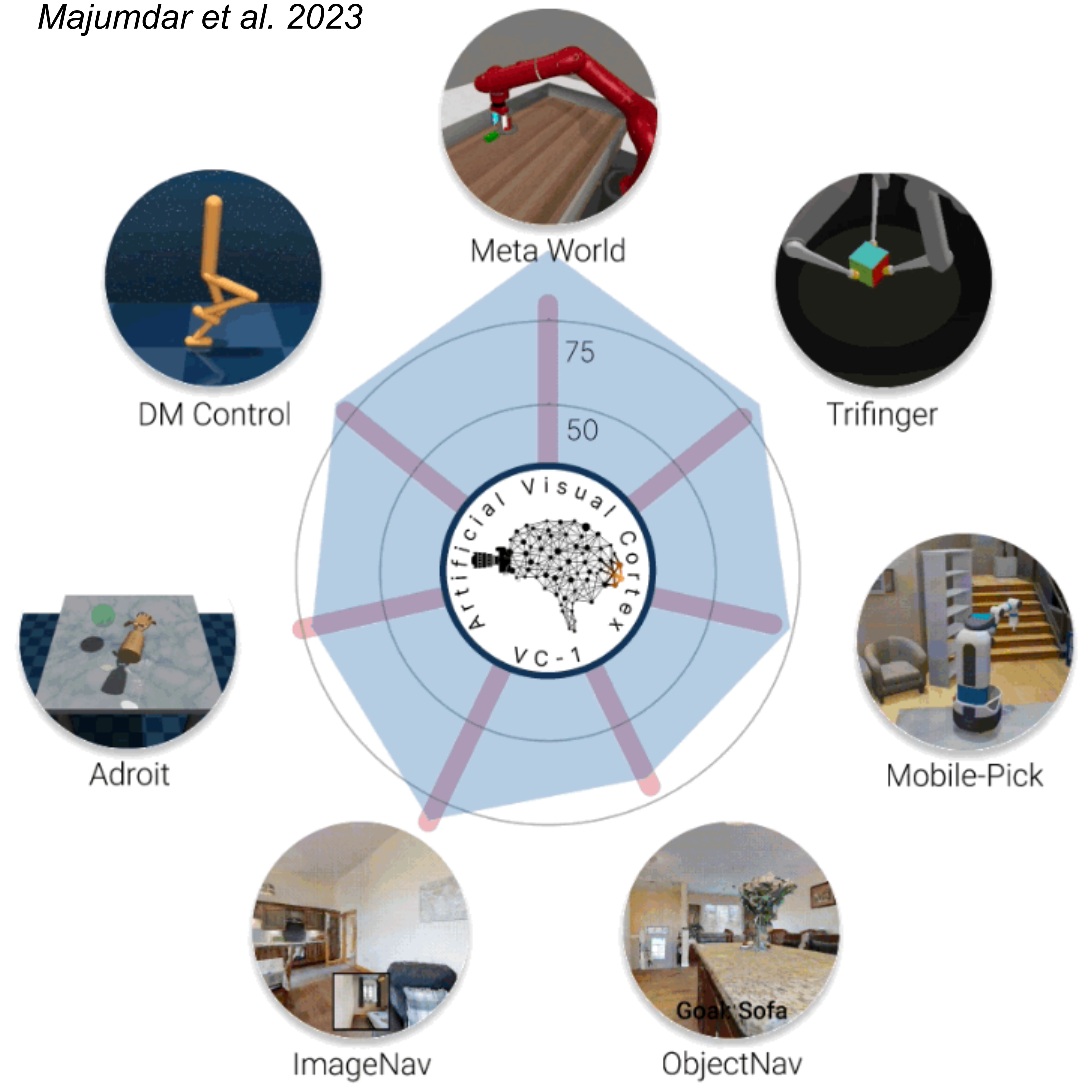
Majumdar et al. 2023



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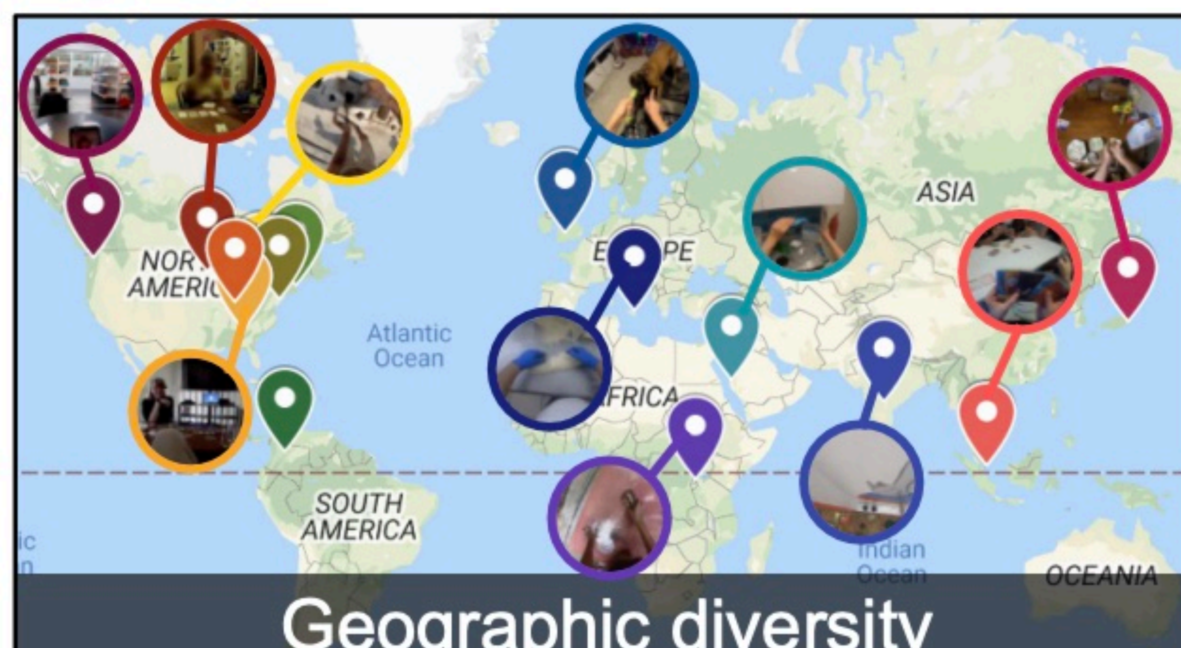

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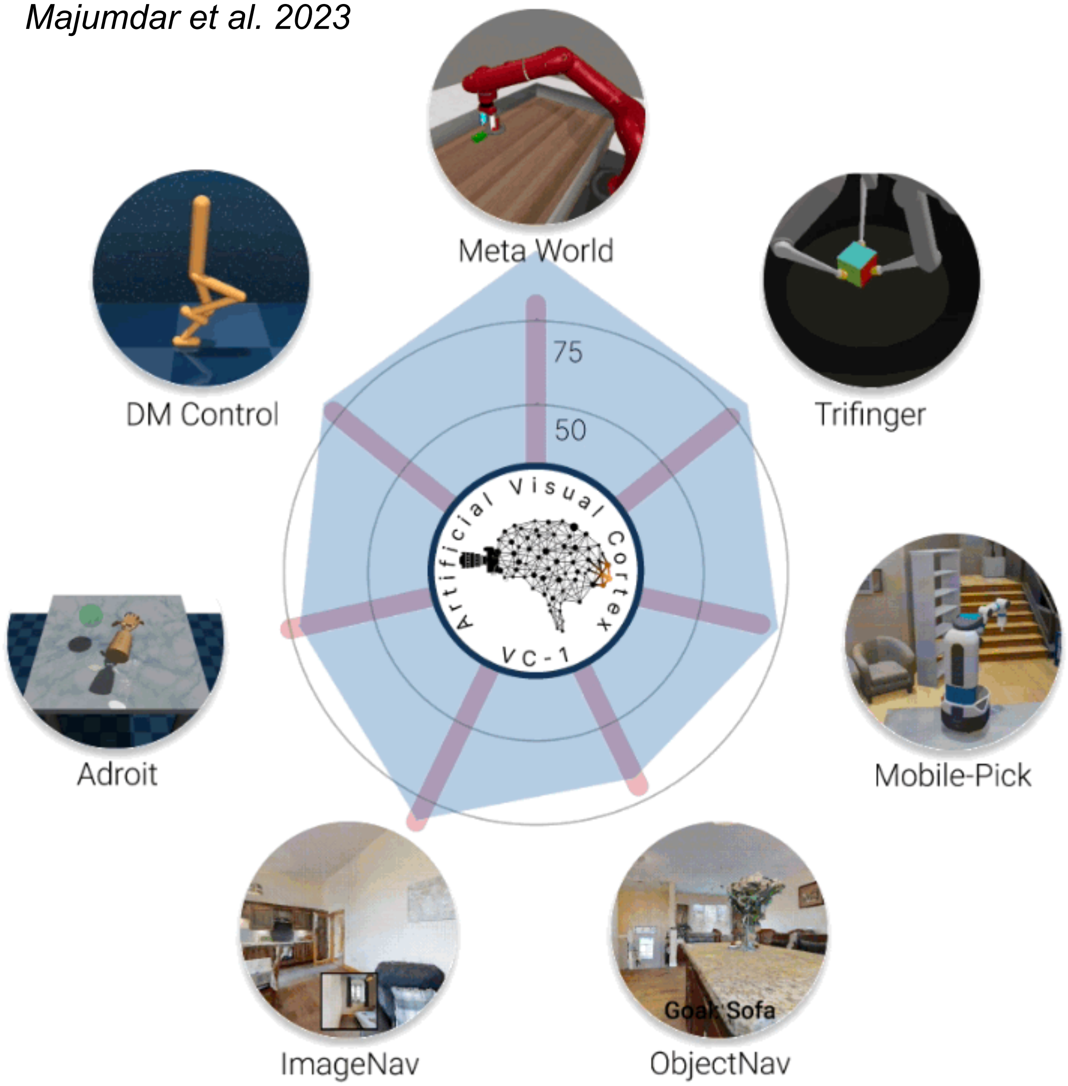

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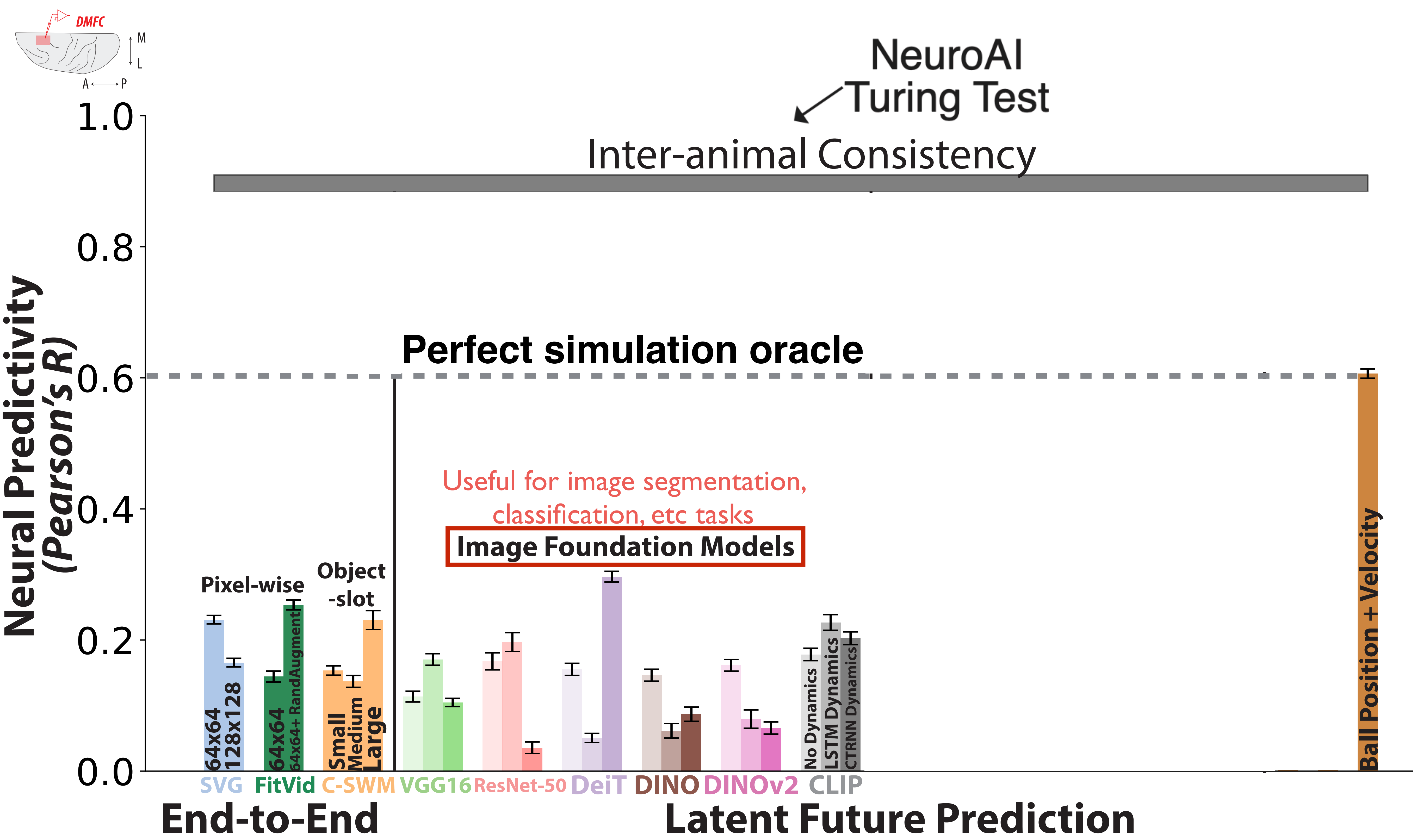
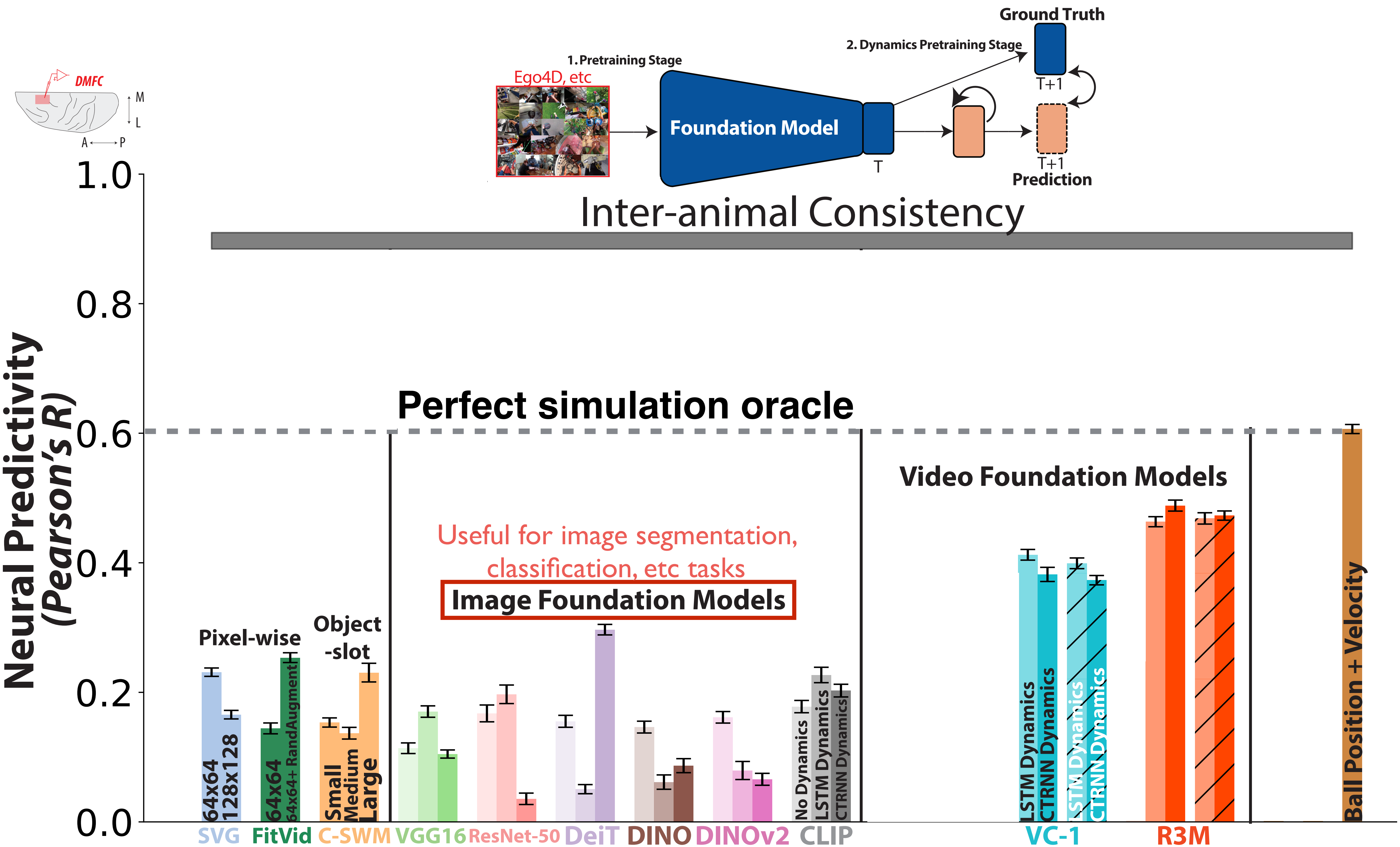
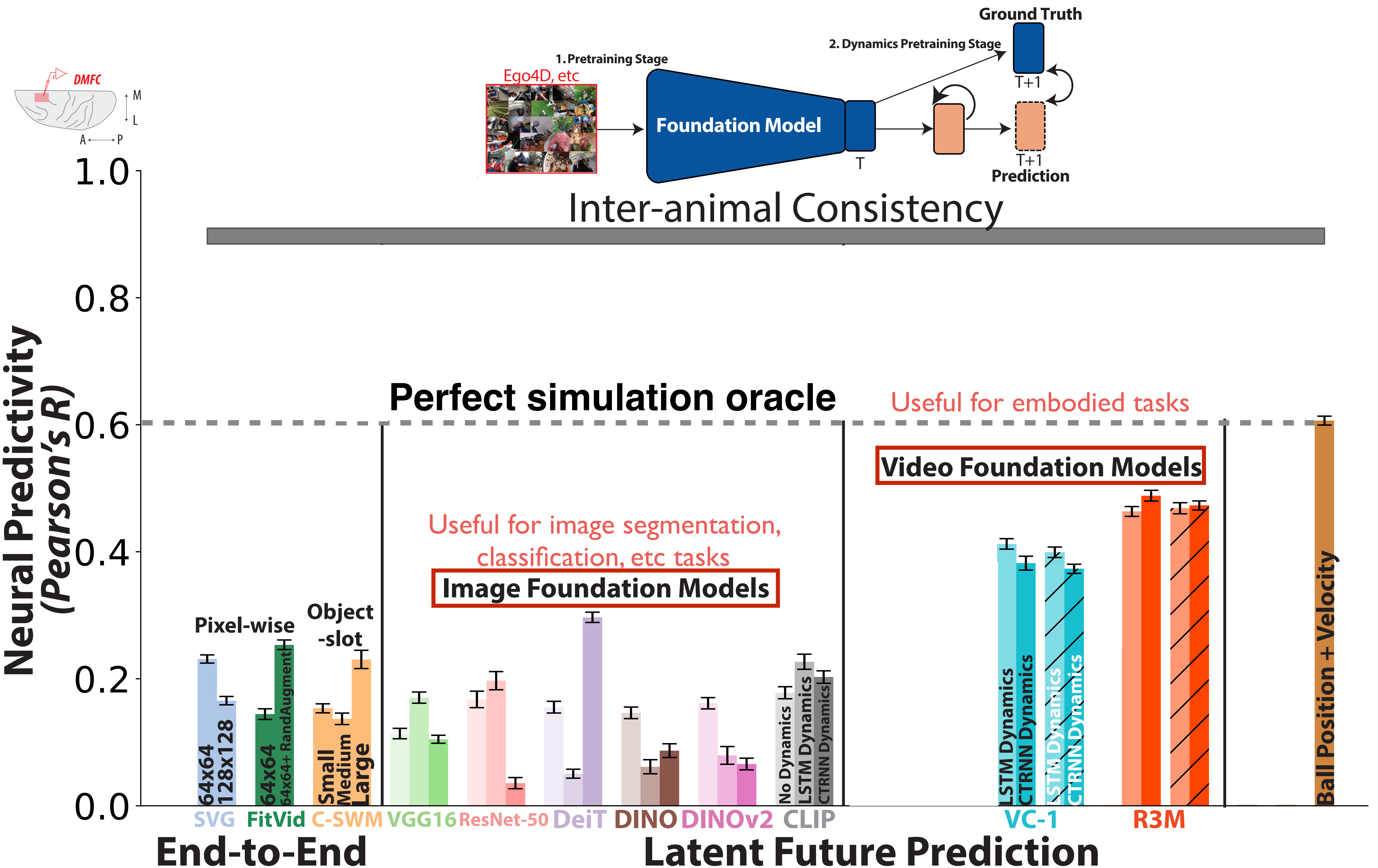


Video Foundation Future Prediction Best Predict Neurons



End-to-End **Latent Future Prediction**

Video Foundation Future Prediction Best Predict Neurons



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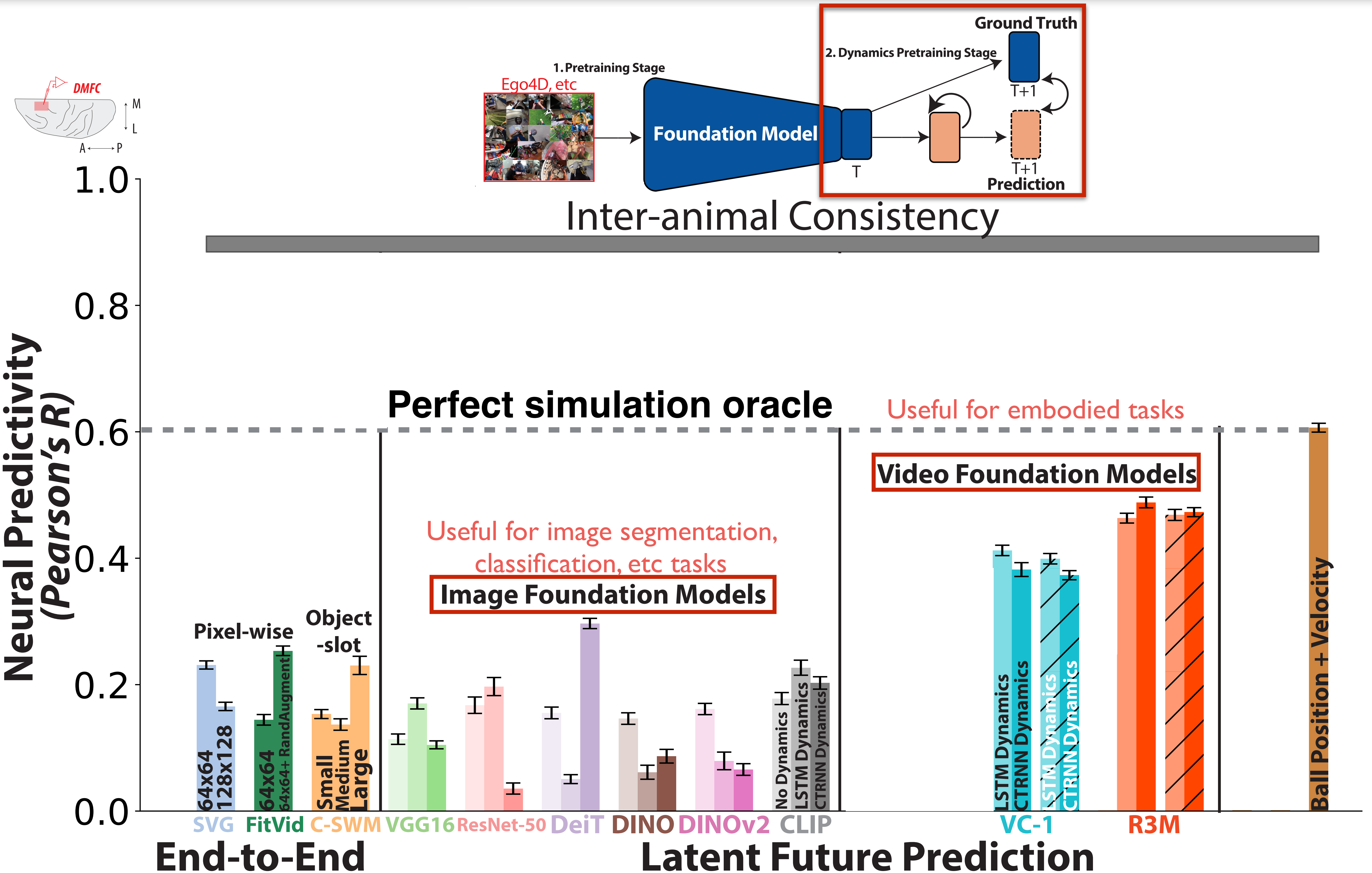

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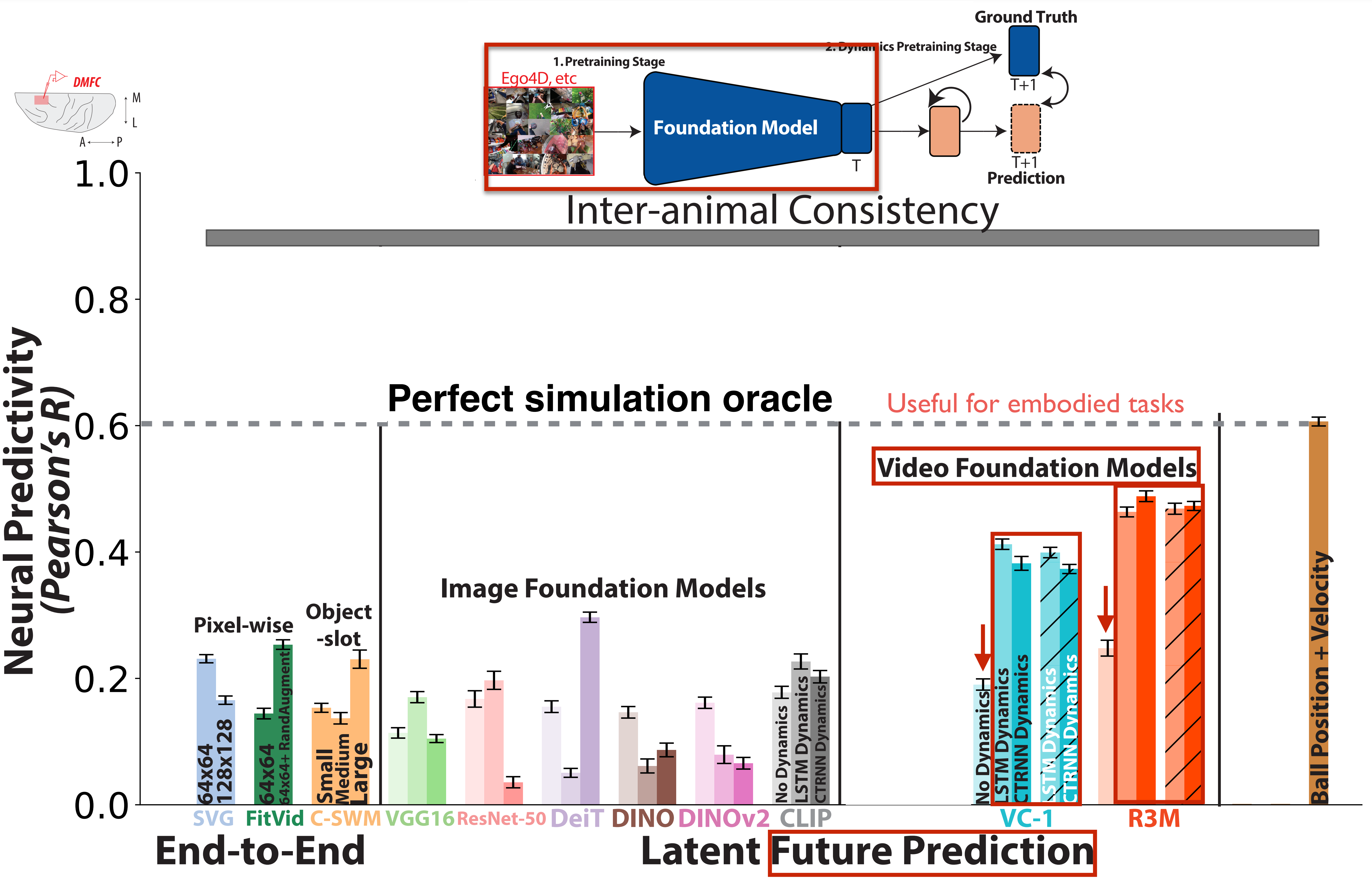

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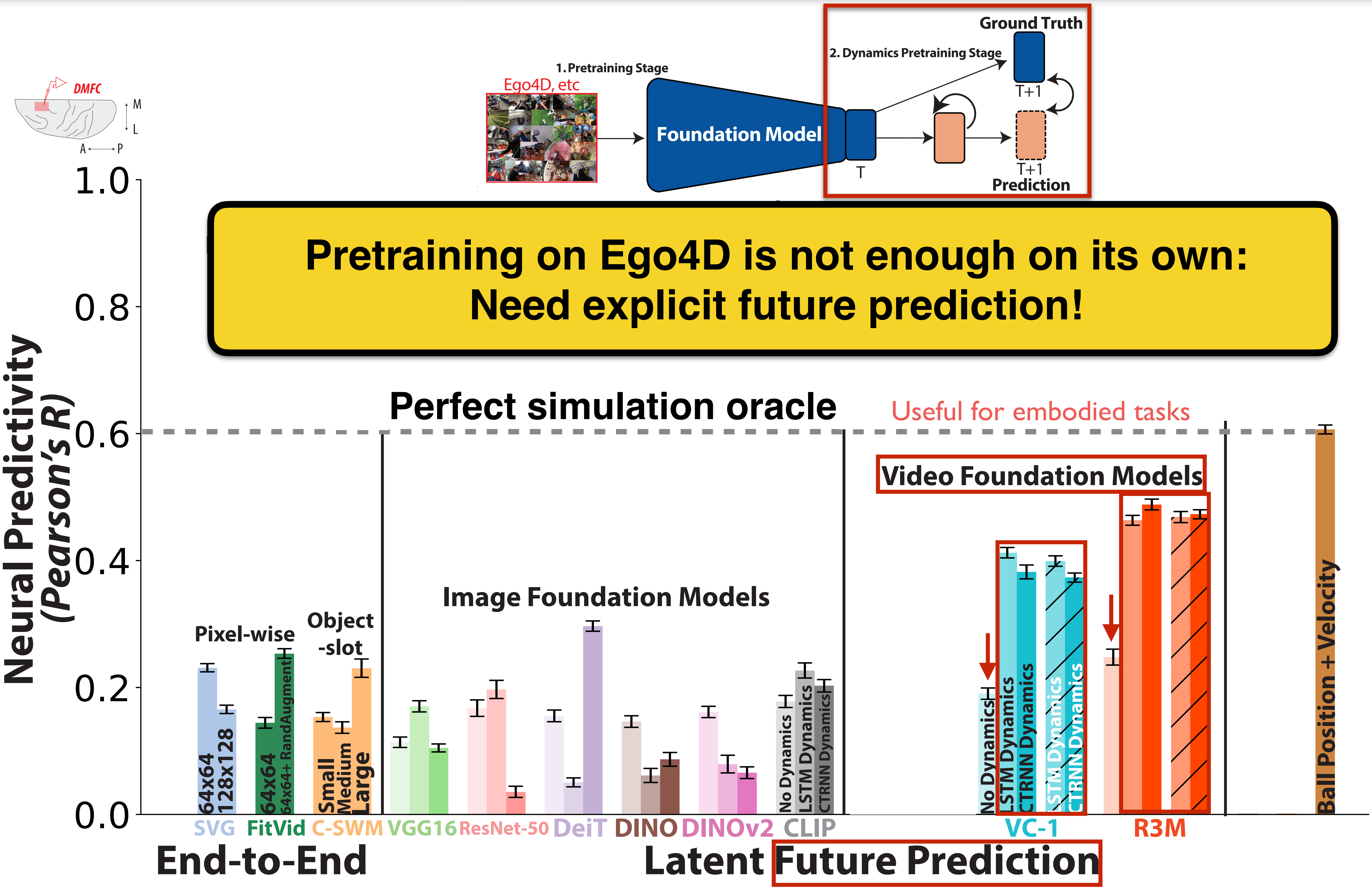

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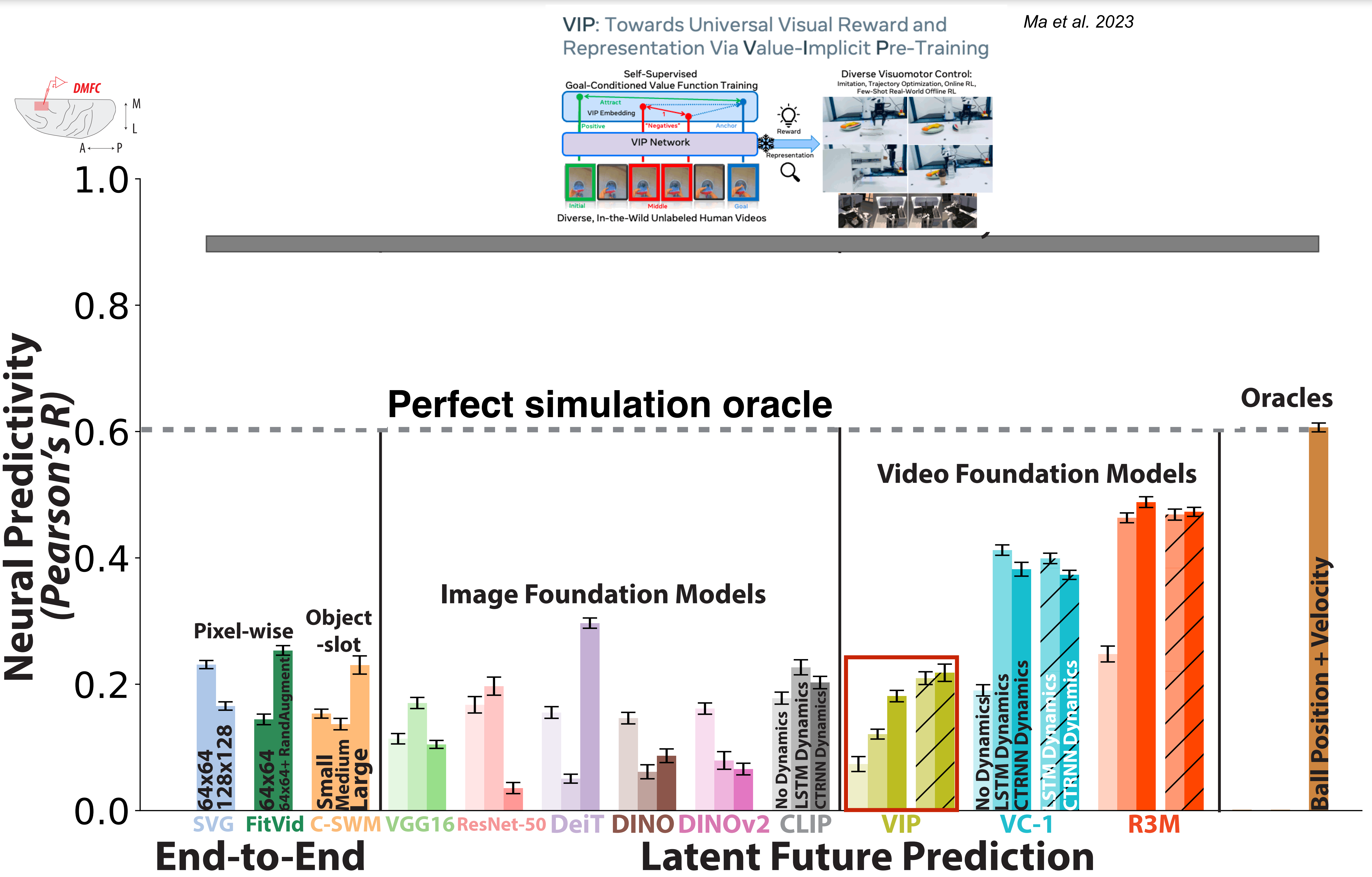
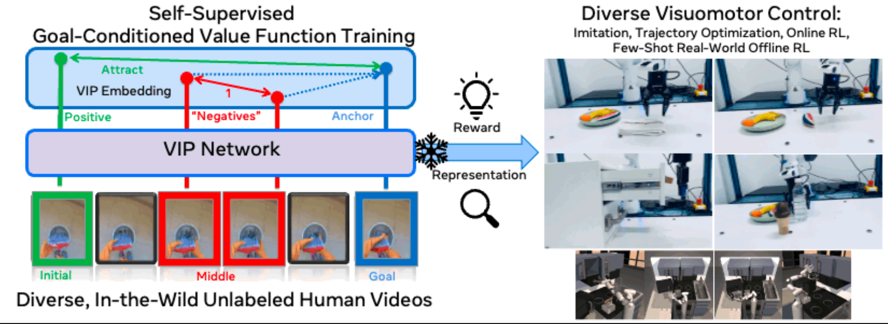


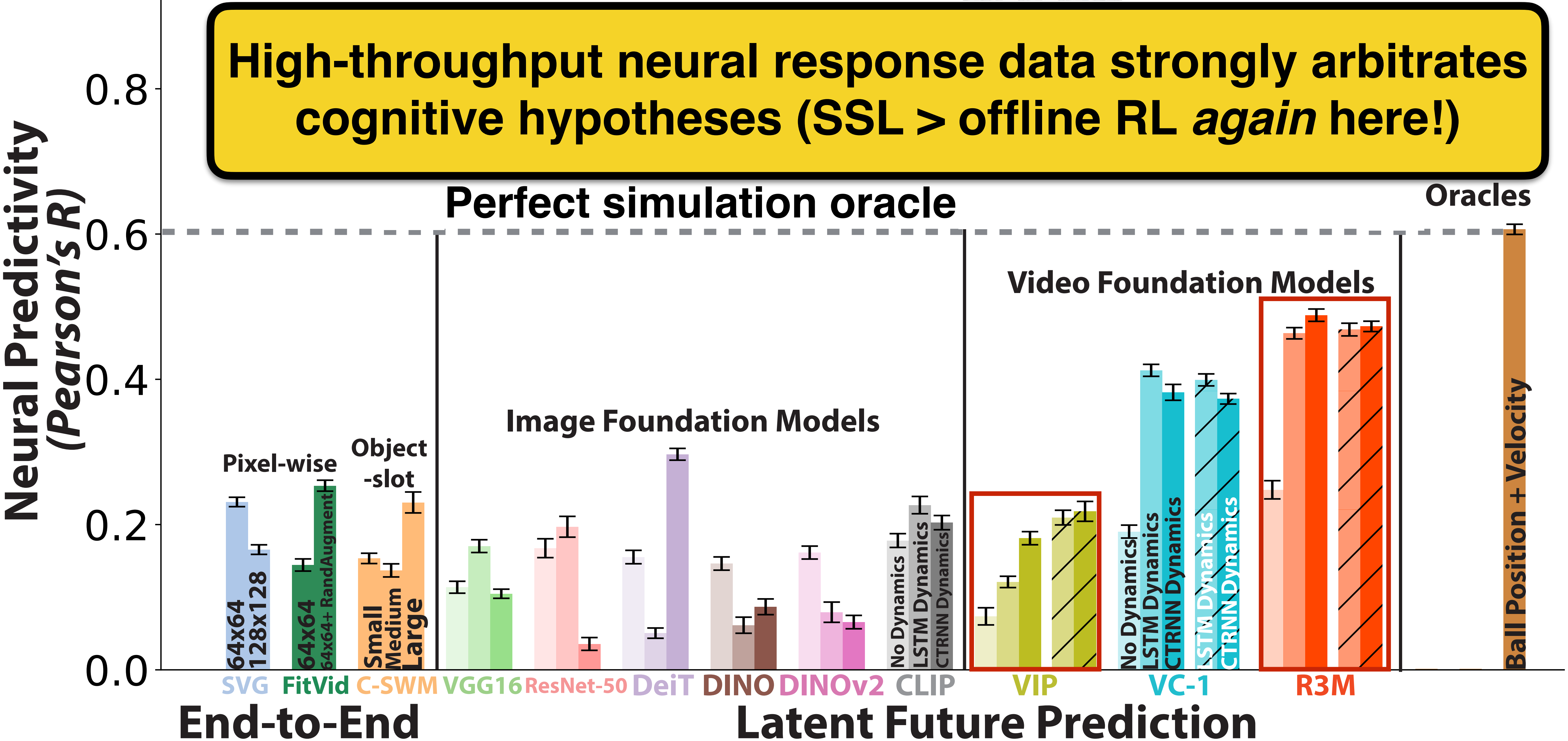
Video Foundation Future Prediction Best Predict Neurons

VIP: Towards Universal Visual Reward and Representation Via Value-Implicit Pre-Training

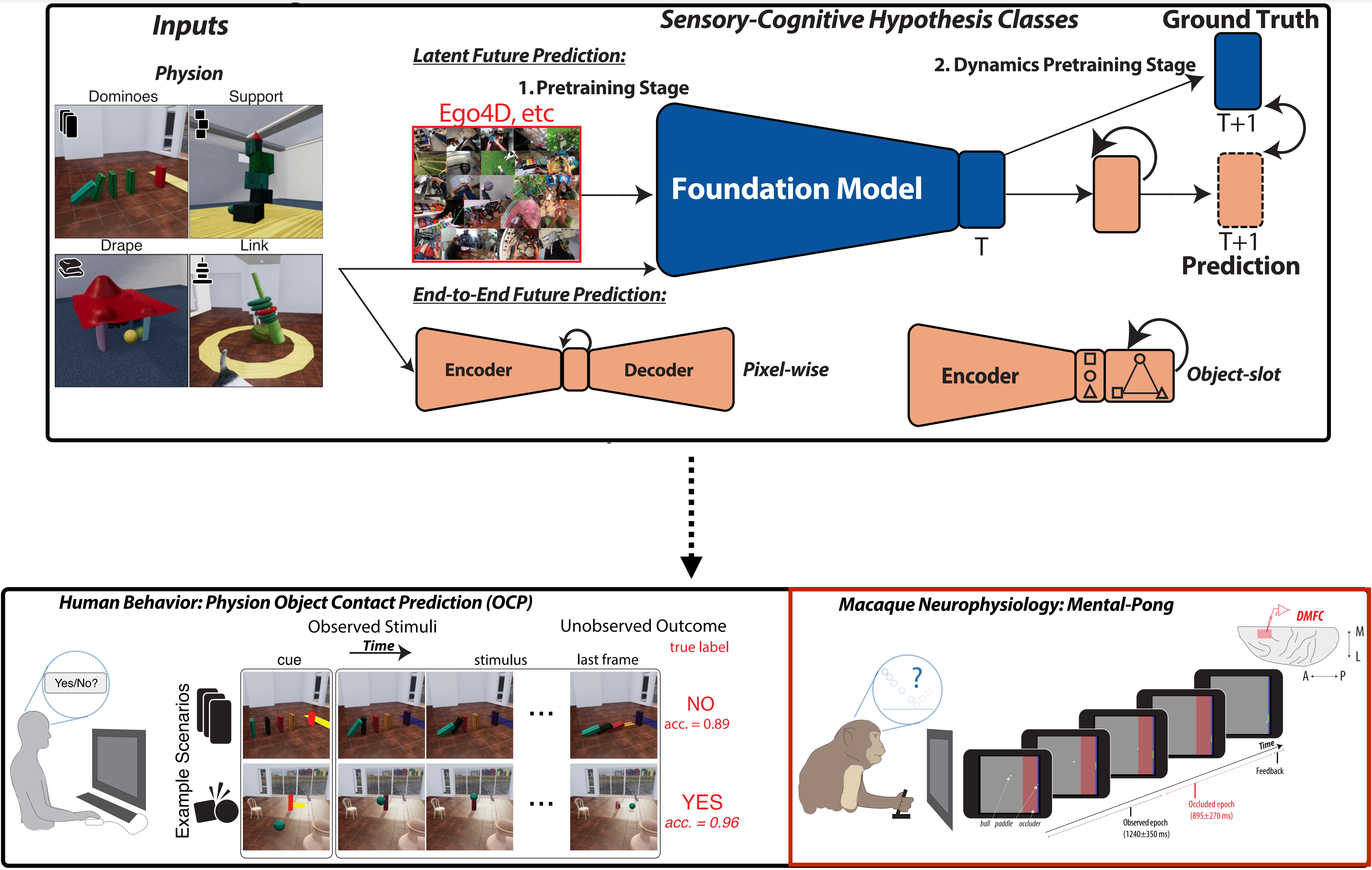
Ma et al. 2023



High-throughput neural response data strongly arbitrates cognitive hypotheses (SSL > offline RL *again* here!)



Macaque Neurophysiology: Mental Pong



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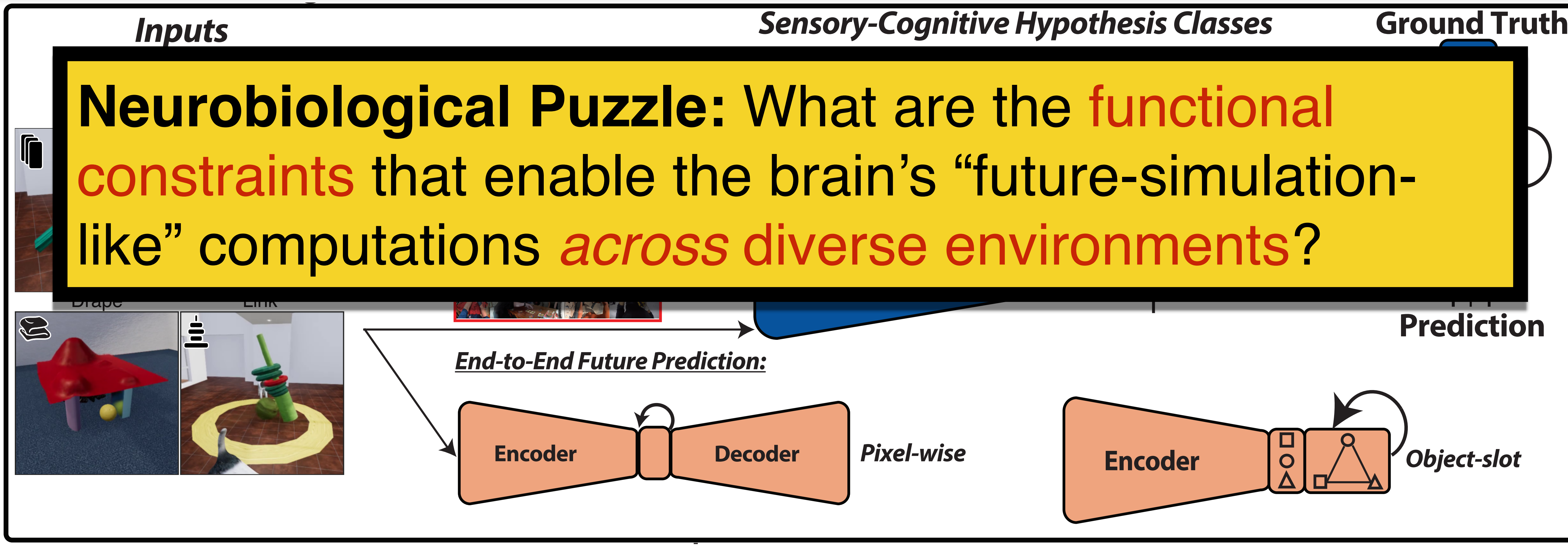
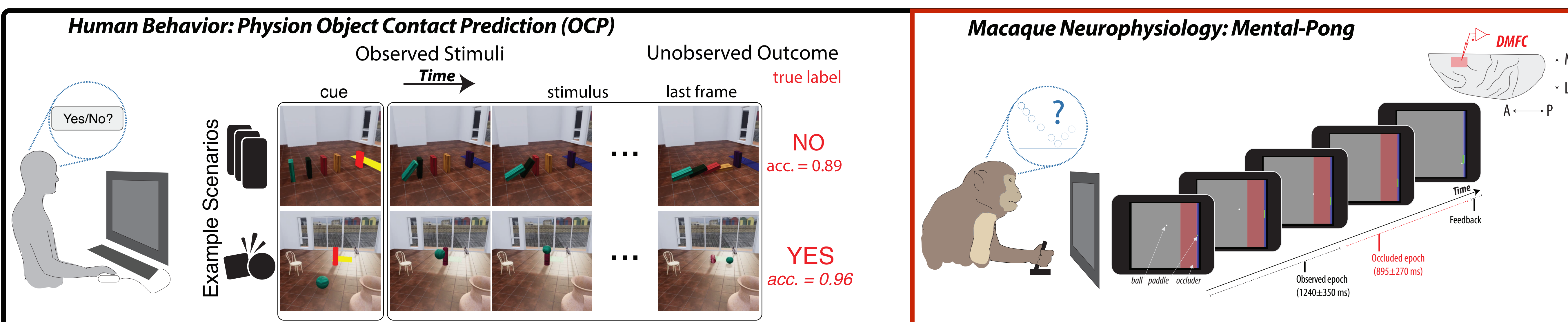
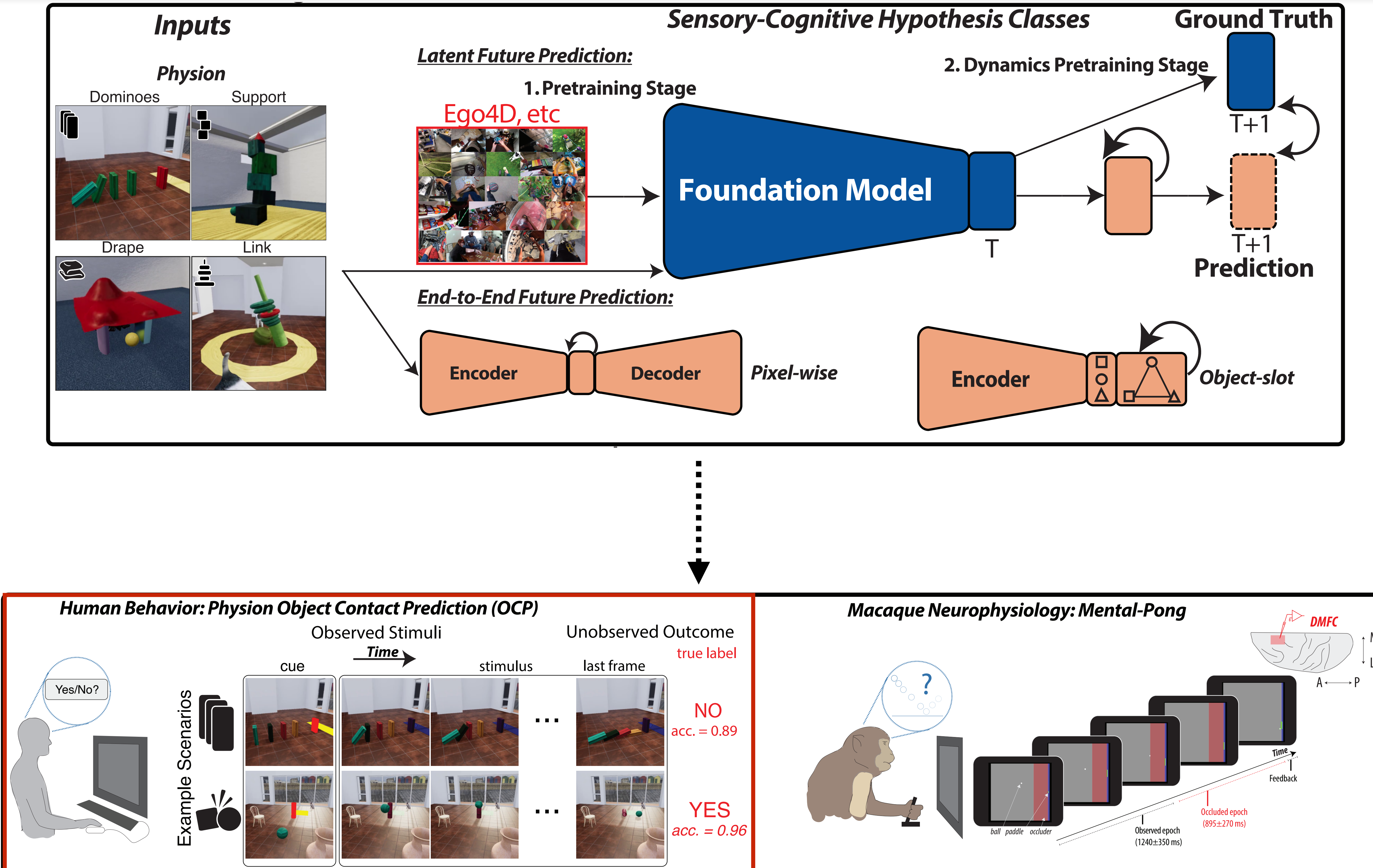


Neurobiological Puzzle: What are the functional constraints that enable the brain's "future-simulation-like" computations *across* diverse environments?



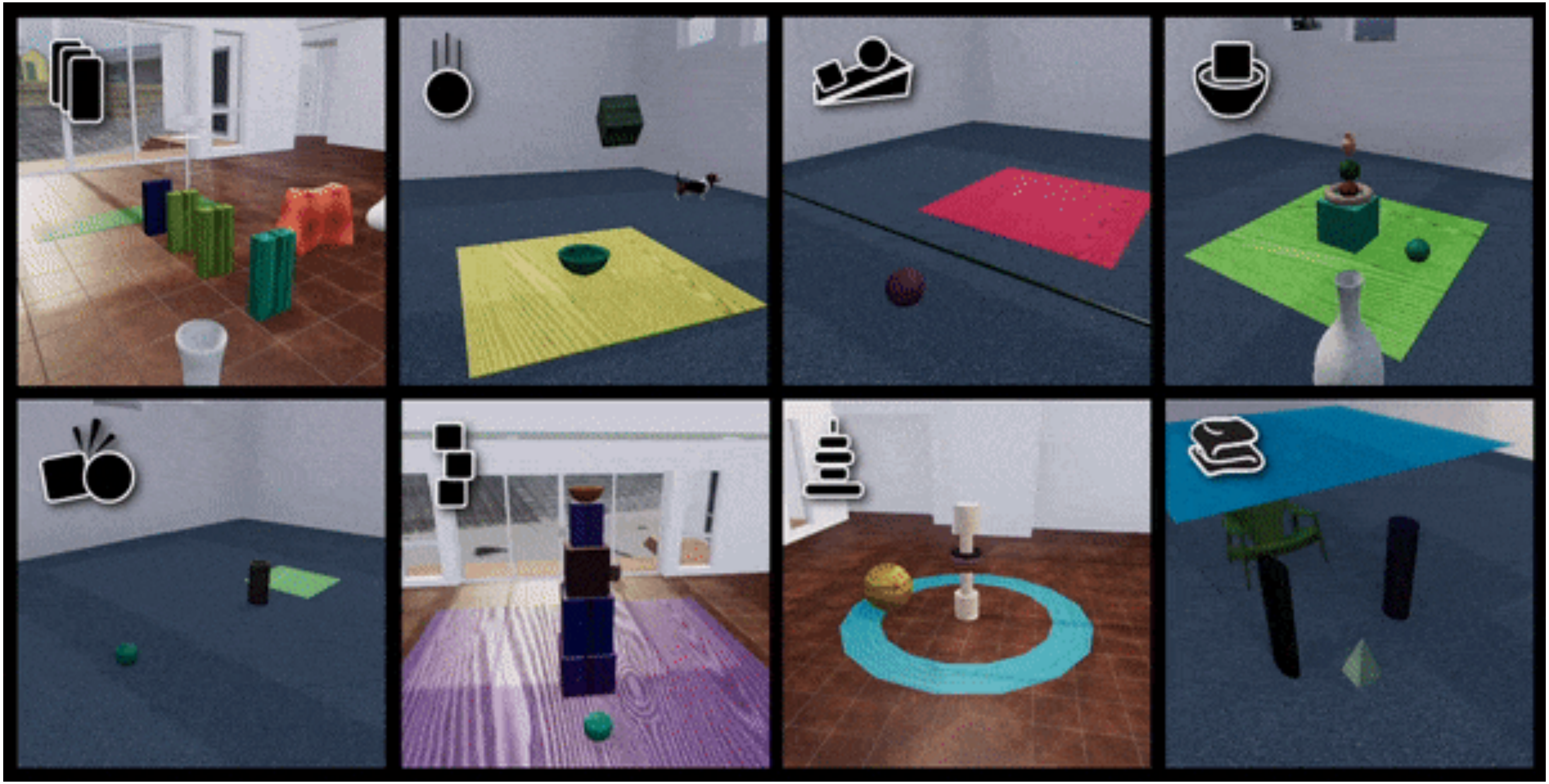
Human Behavior: Object Contact Prediction



Object Contact Prediction Environment

Physion/ThreeD World (TDW)

Bear et al. 2021



Focus on everyday physical understanding

Daniel Bear   Joshua Tenenbaum   Daniel Yamins   Judith Fan

Object Contact Prediction Environment

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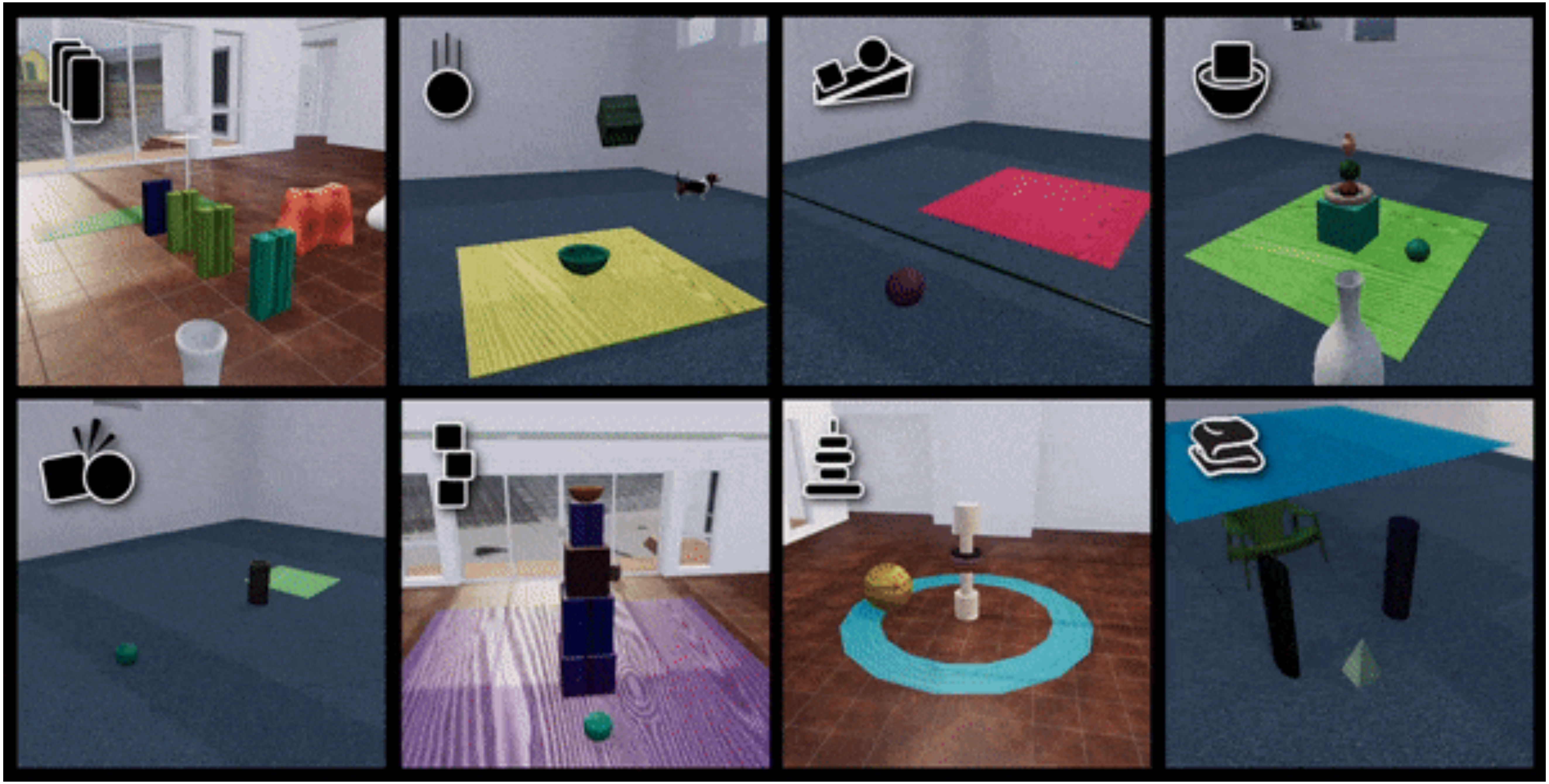


Focus on everyday physical understanding

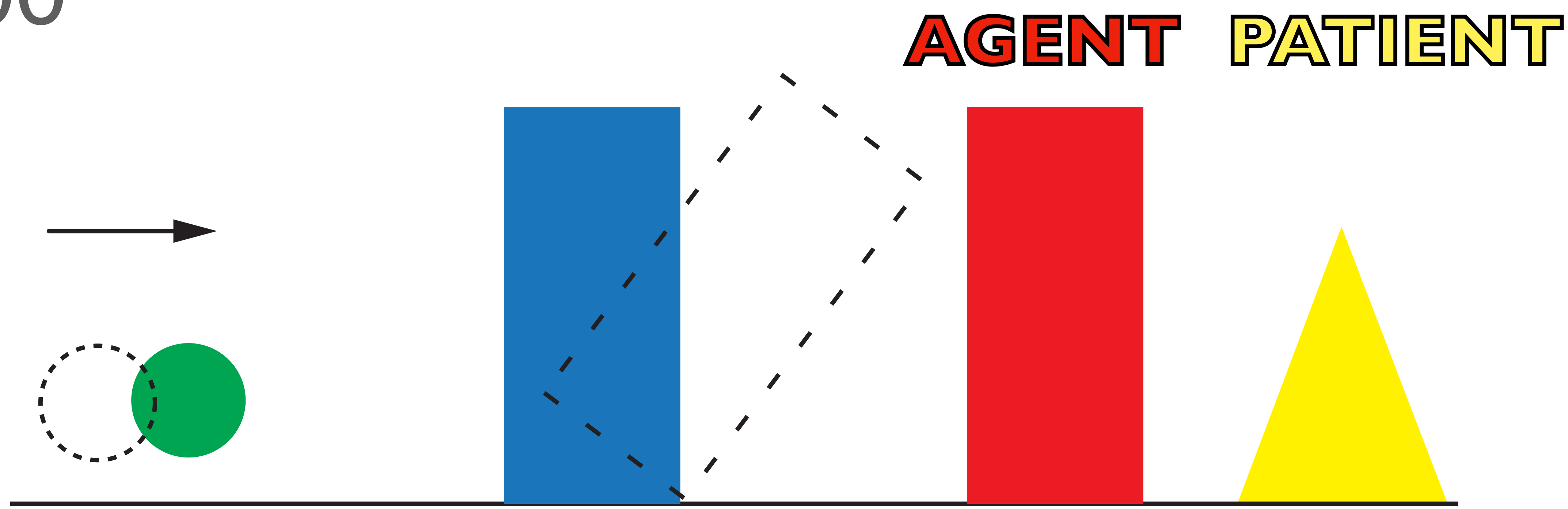
Daniel Bear Joshua Tenenbaum Daniel Yamins Judith Fan

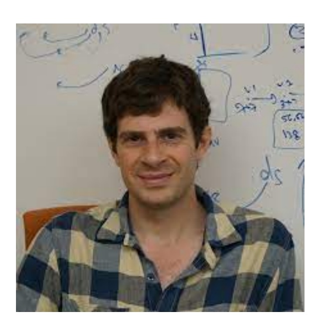
Human Behavior: Object Contact Prediction

Bear et al. 2021

n=100

"Will the agent object contact the patient object?"




Daniel Bear

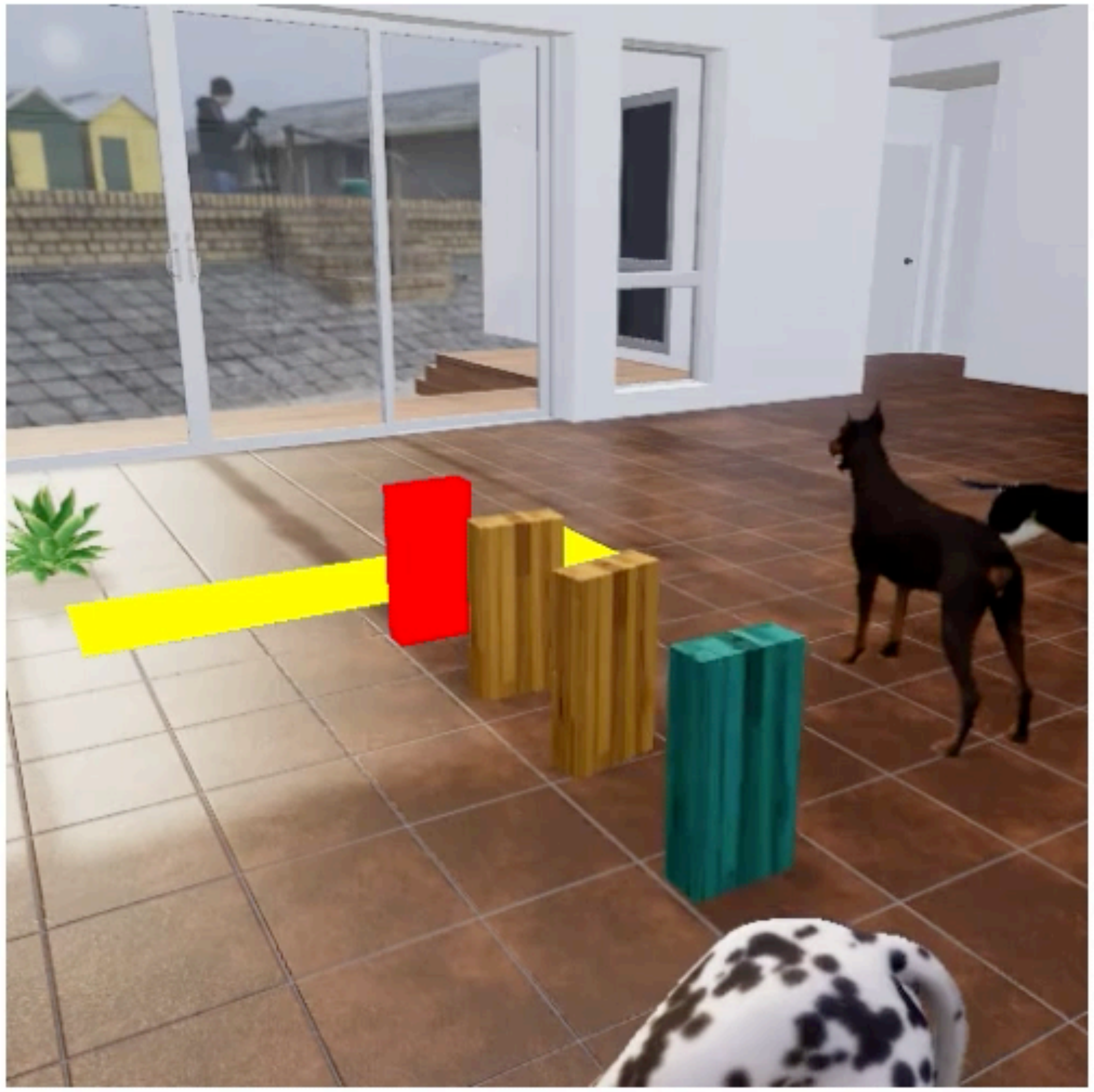

Joshua Tenenbaum


Daniel Yamins


Judith Fan

Completion Progress

Bear et al. 2021

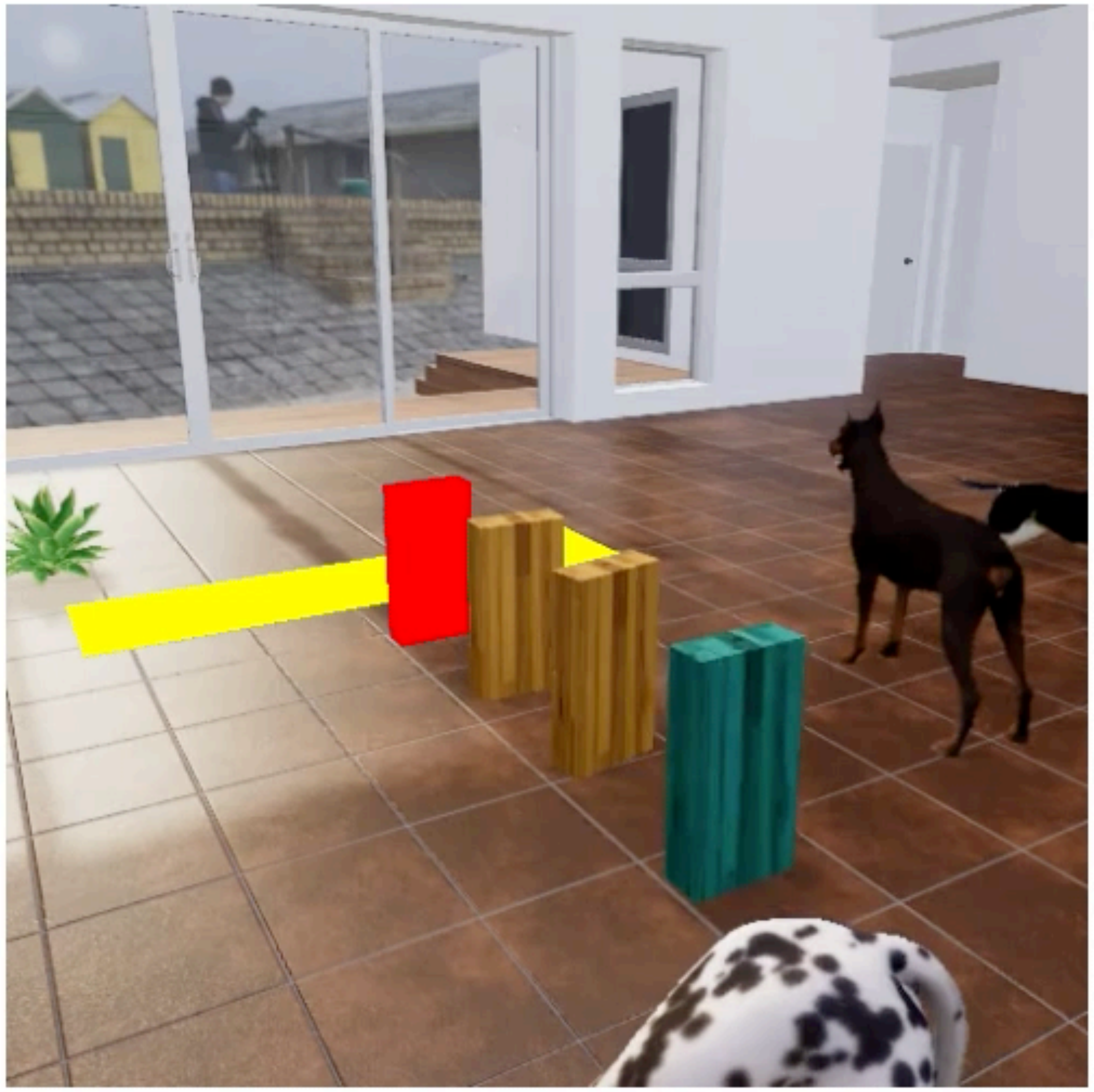


YES NO

Is the red object going to hit the yellow area?

Completion Progress

Bear et al. 2021



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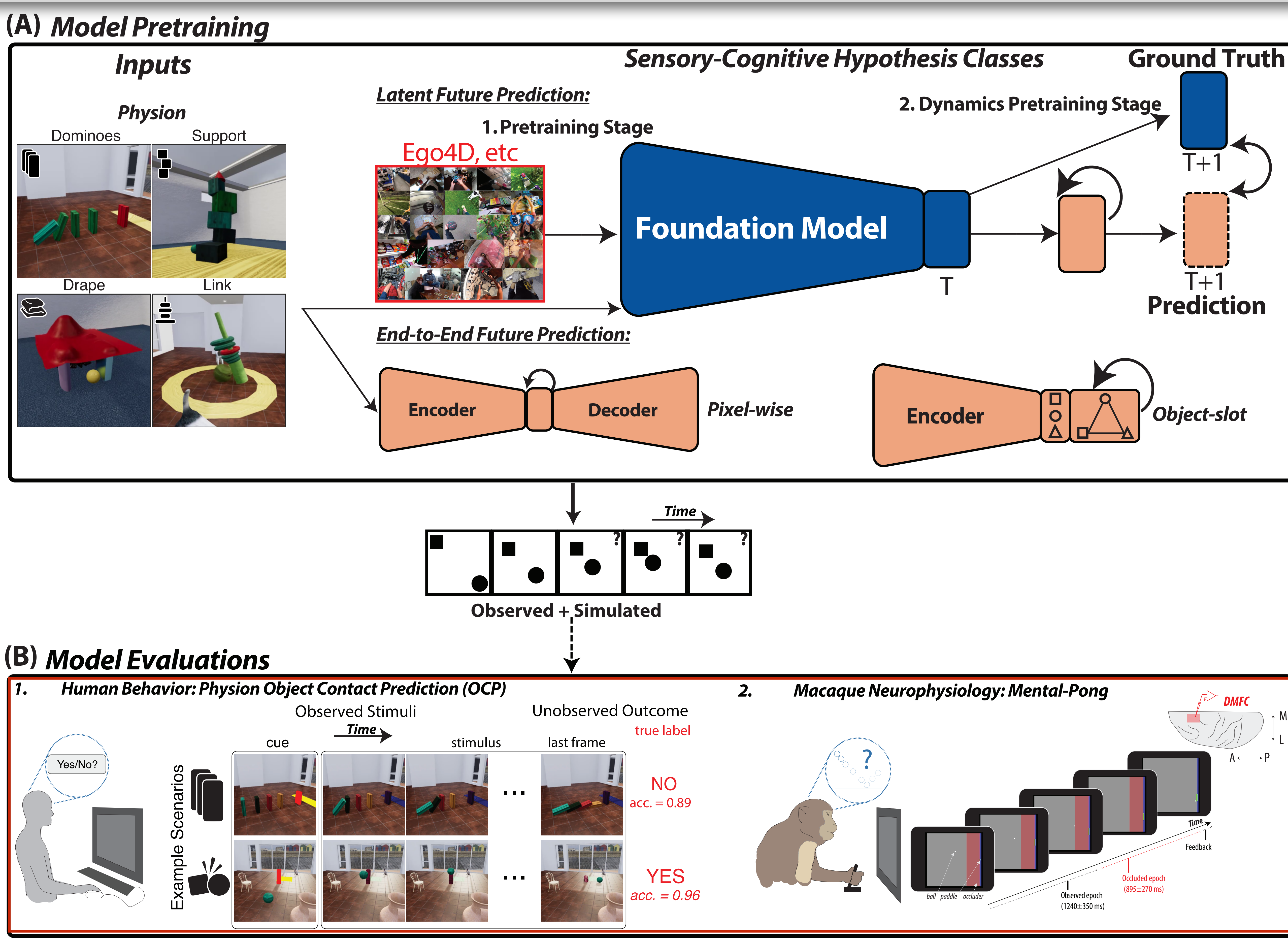
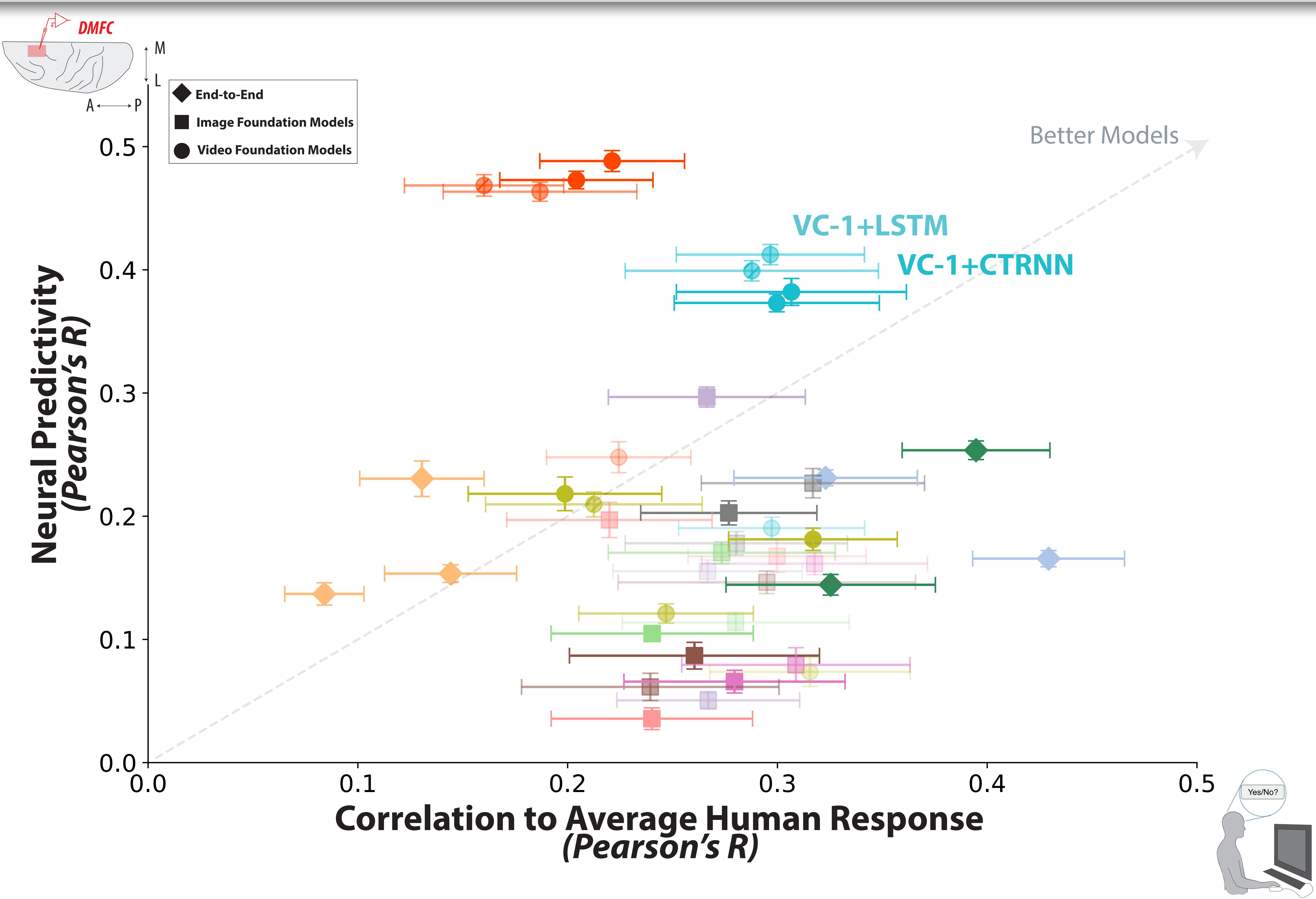
Model Evaluations: Both Metrics



Dynamically-Equipped Video Foundation Models Can Match Both



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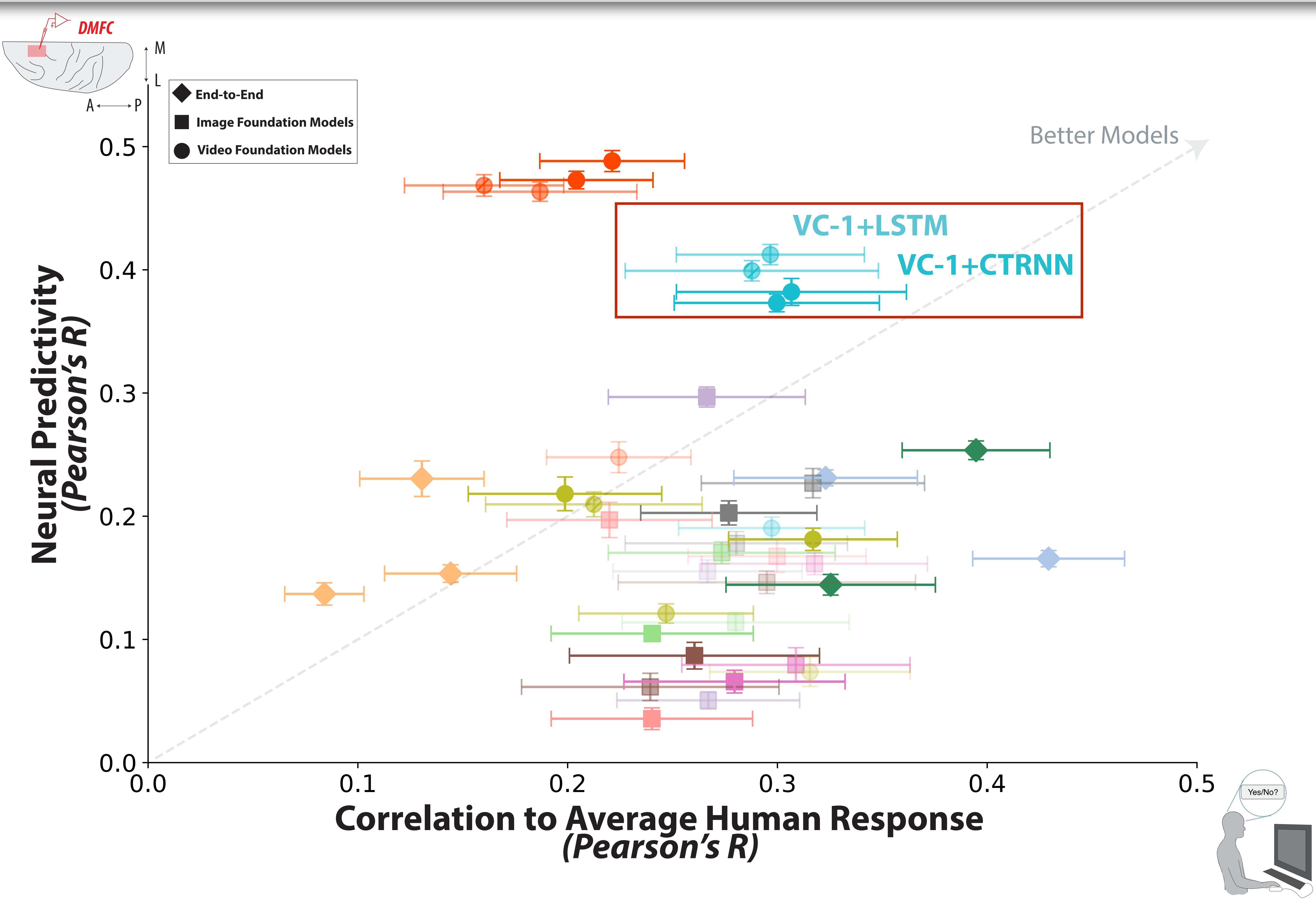
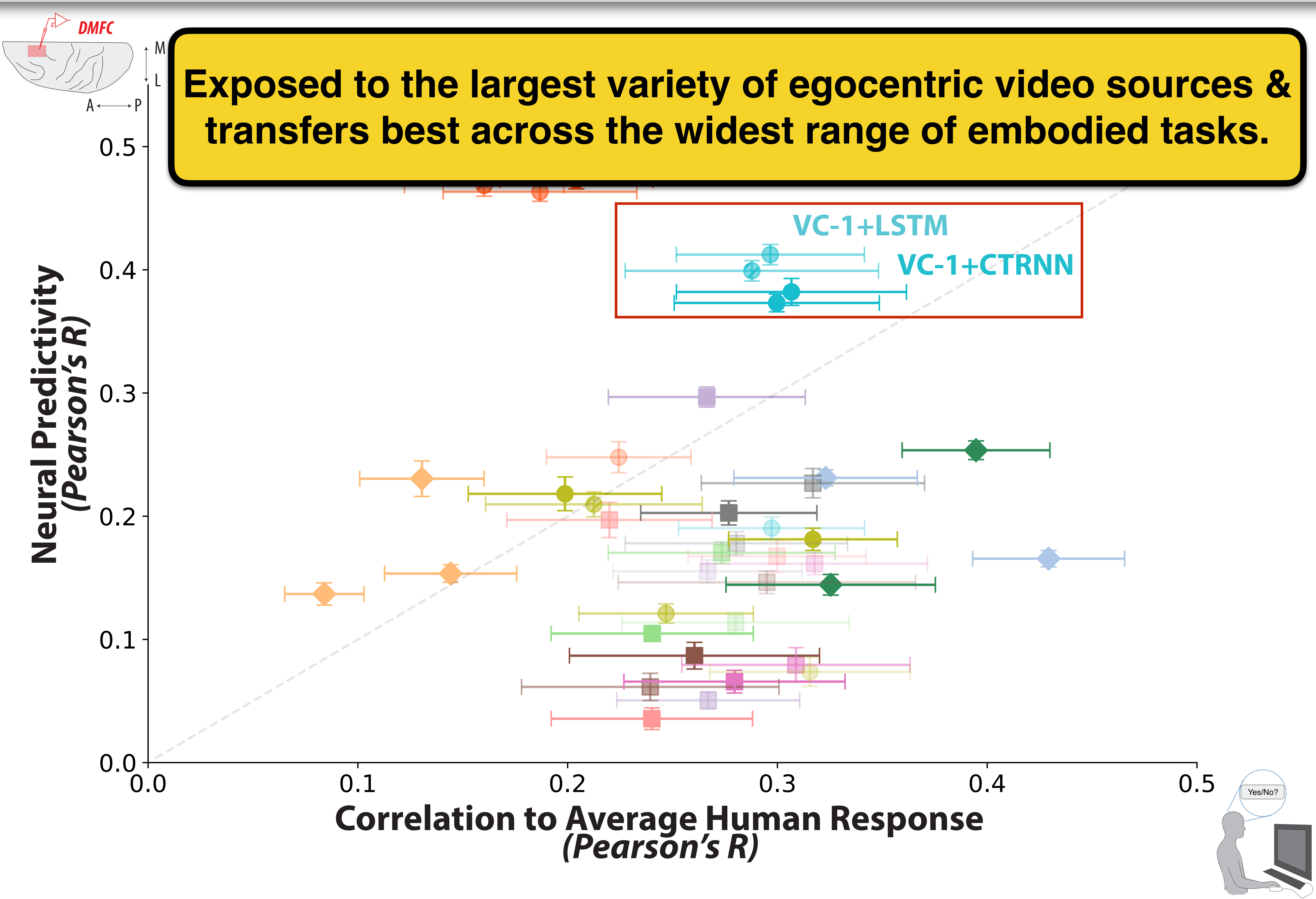
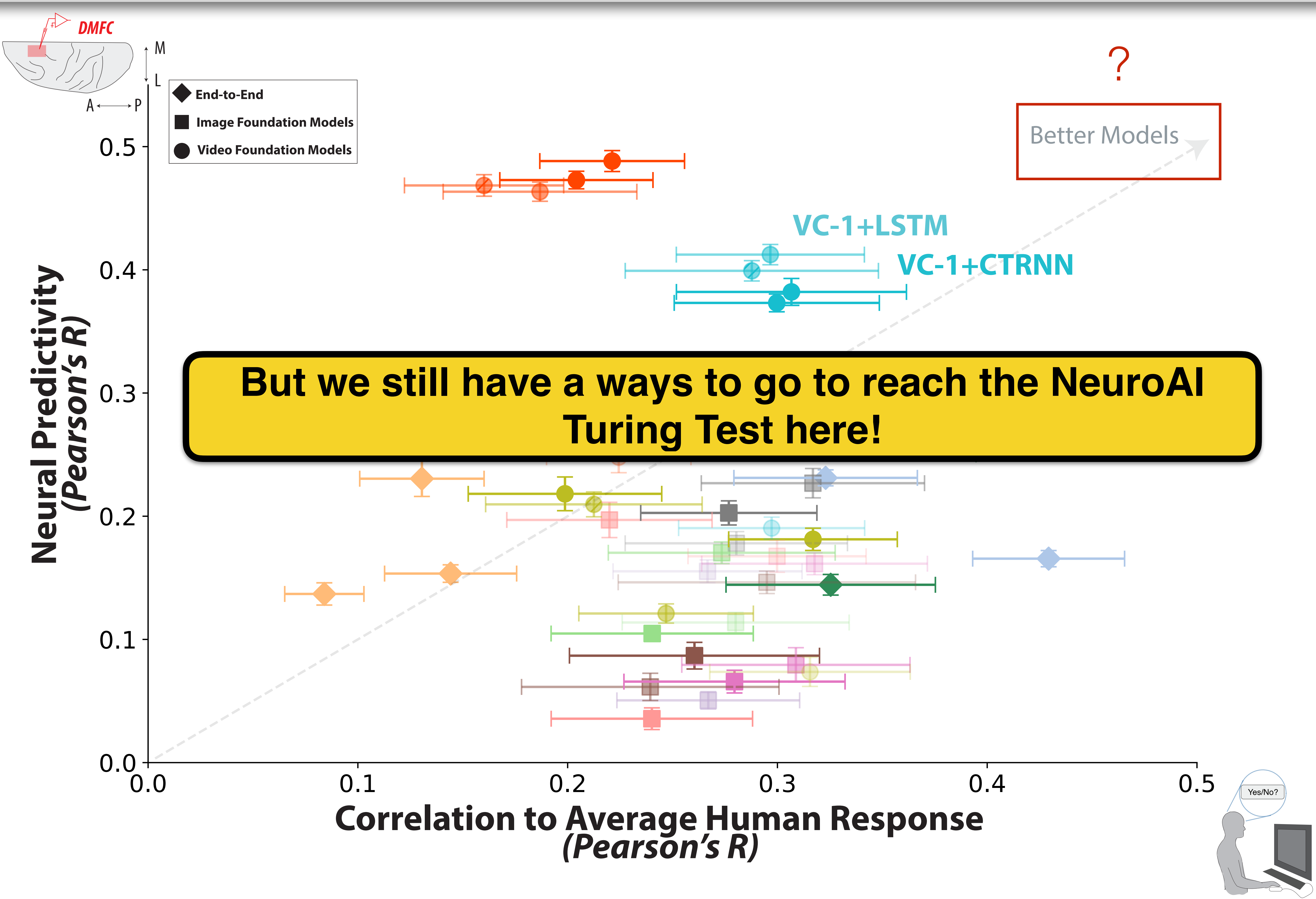


Dynamically-Equipped Video Foundation Models Can Match Both

Exposed to the largest variety of egocentric video sources & transfers best across the widest range of embodied tasks.



Future Directions: The Need for New World Models



But we still have a ways to go to reach the NeuroAI Turing Test here!

Outline

- Mouse Visual Cortex as a Task-General, Limited Resource System

Mouse visual cortex (so far) is a low-acuity, shallow network that makes best use of the mouse's limited resources to create a general-purpose visual system, that can be deployed in novel environments and embodied contexts.

- Reusable Latent Representations for Primate Mental Simulation

- Heuristics for Interrogating Natural Intelligence

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Mental simulation crucially relies on explicit future prediction of a "factorized description" of visual scenes, where this "factorized description" is strongly constrained and must enable a wide range of dynamic <u>embodied</u> abilities.

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- **Incorporating Neuroscience Insights:**

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Heuristics for Interrogating Natural Intelligence

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Heuristics for Interrogating Natural Intelligence

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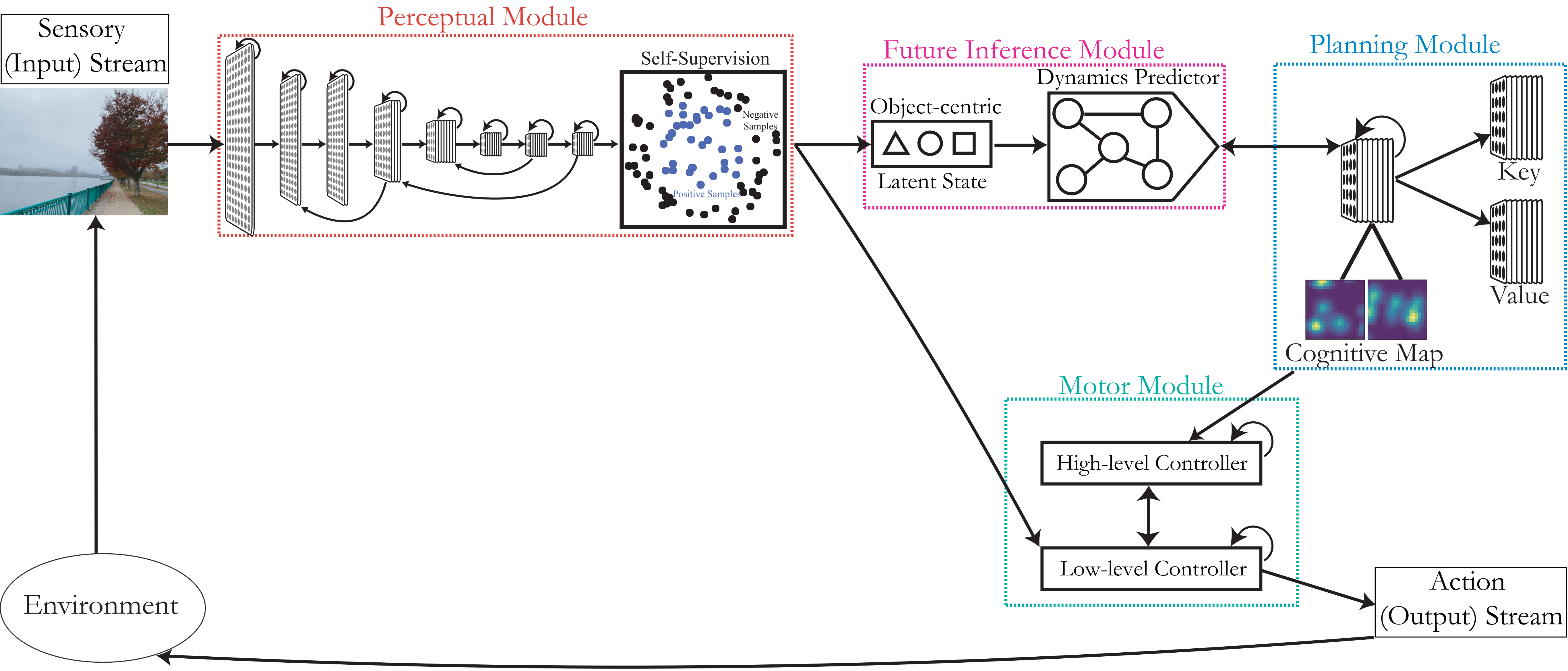
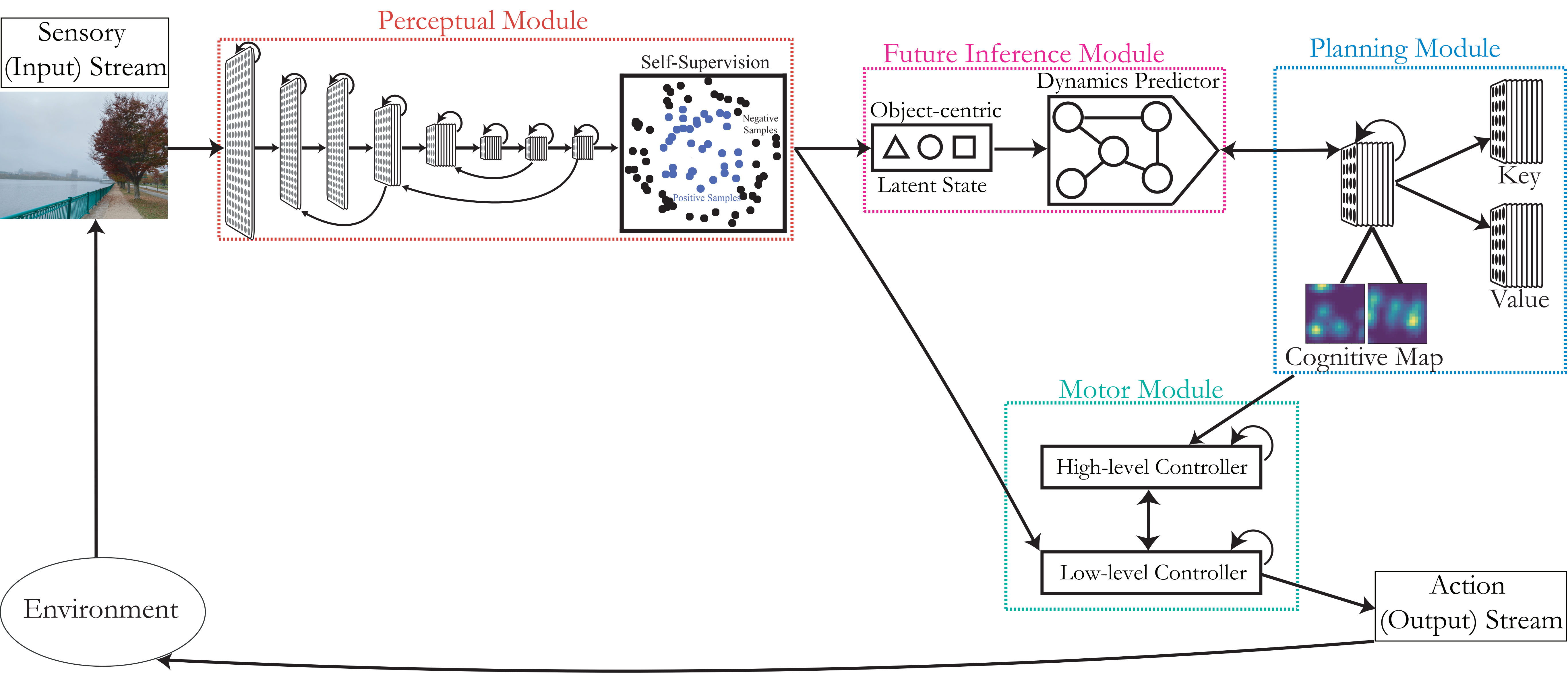


Next Steps: Modularized, Embodied Agents?

How does the brain *represent*, *predict*, *plan*, and enable *action*?



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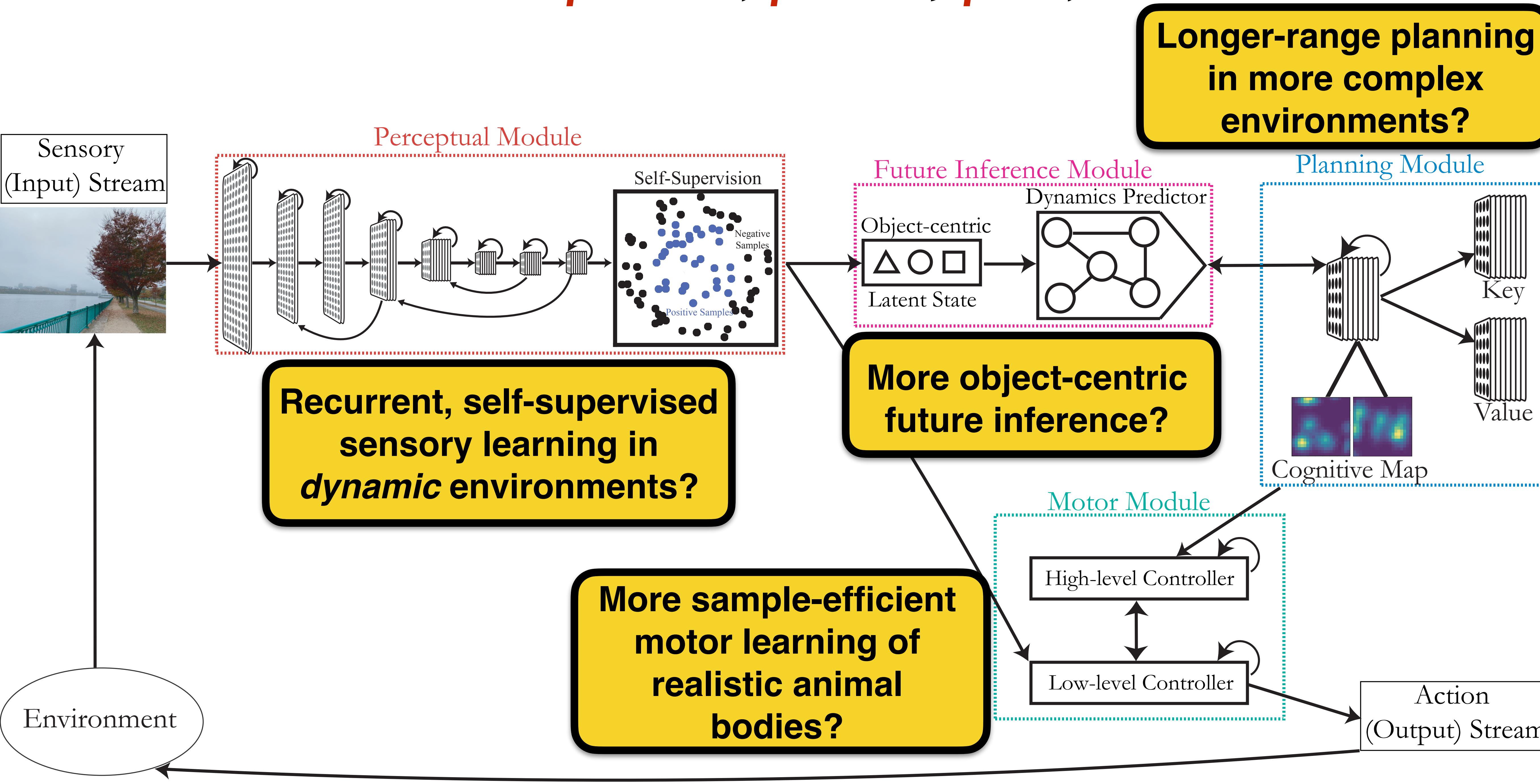

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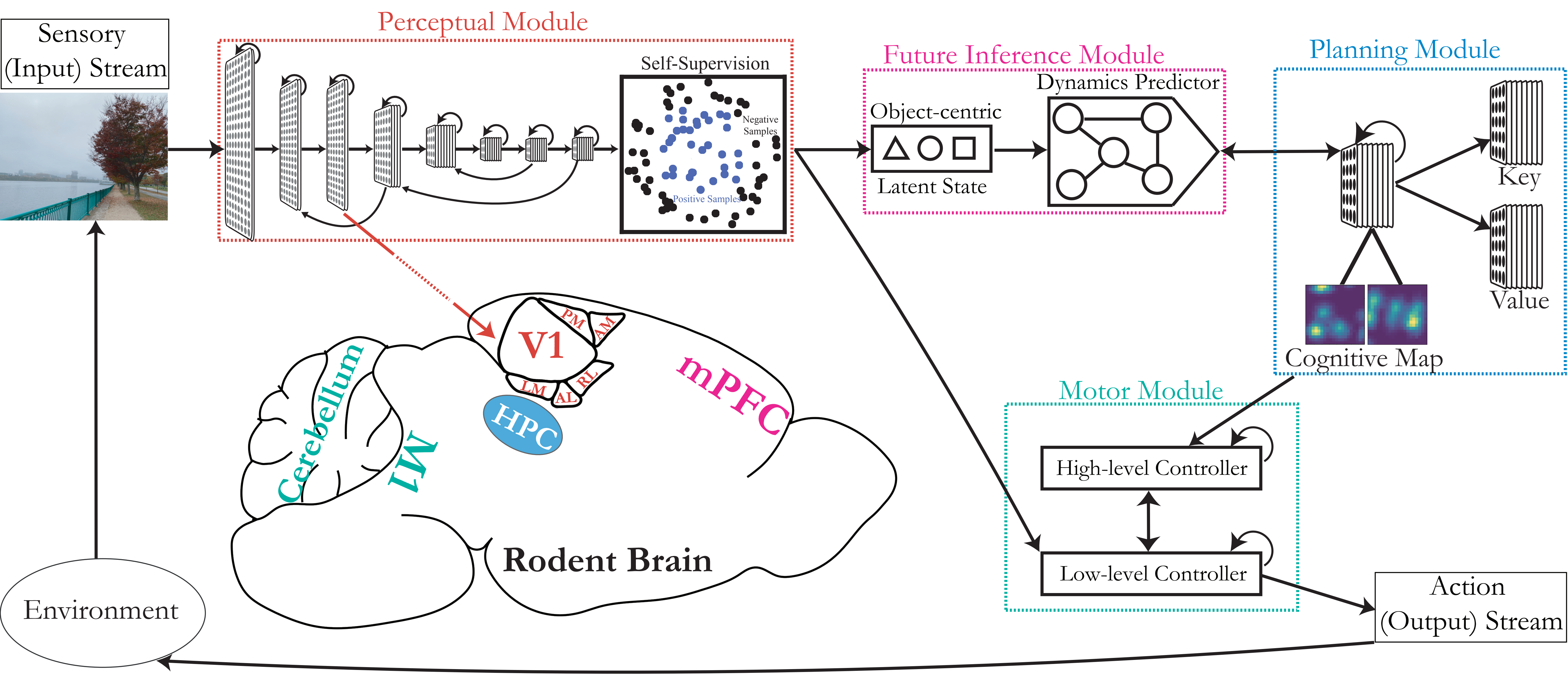


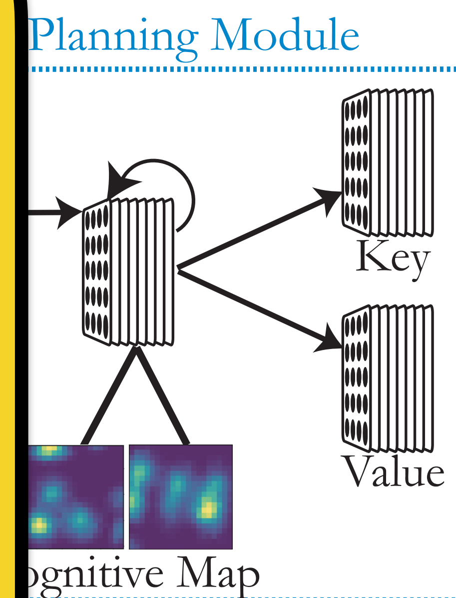
Next Steps: *Applying* Integrative, Embodied Agents

How does the brain *represent*, *predict*, *plan*, and enable *action*?

Sensory (Input) Stream

Practical Outcomes of NeuroAgents:

1. Open-source benchmarks
2. Predict outcomes for new experiments
3. Systems-level understanding of an organism:
   - Hard-wired *intrinsic* goals
   - Identifying biological learning rules
   - Species-conserved algorithms across modules



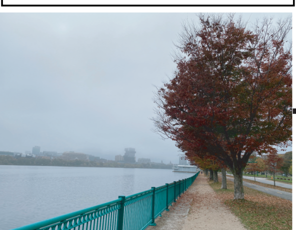
Environment

Action (Output) Stream

Next Steps: *Applying* Integrative, Embodied Agents

How does the brain *represent*, *predict*, *plan*, and enable *action*?

Sensory (Input) Stream



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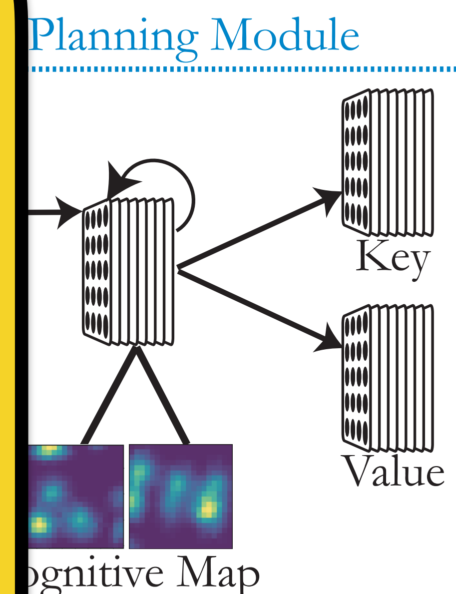
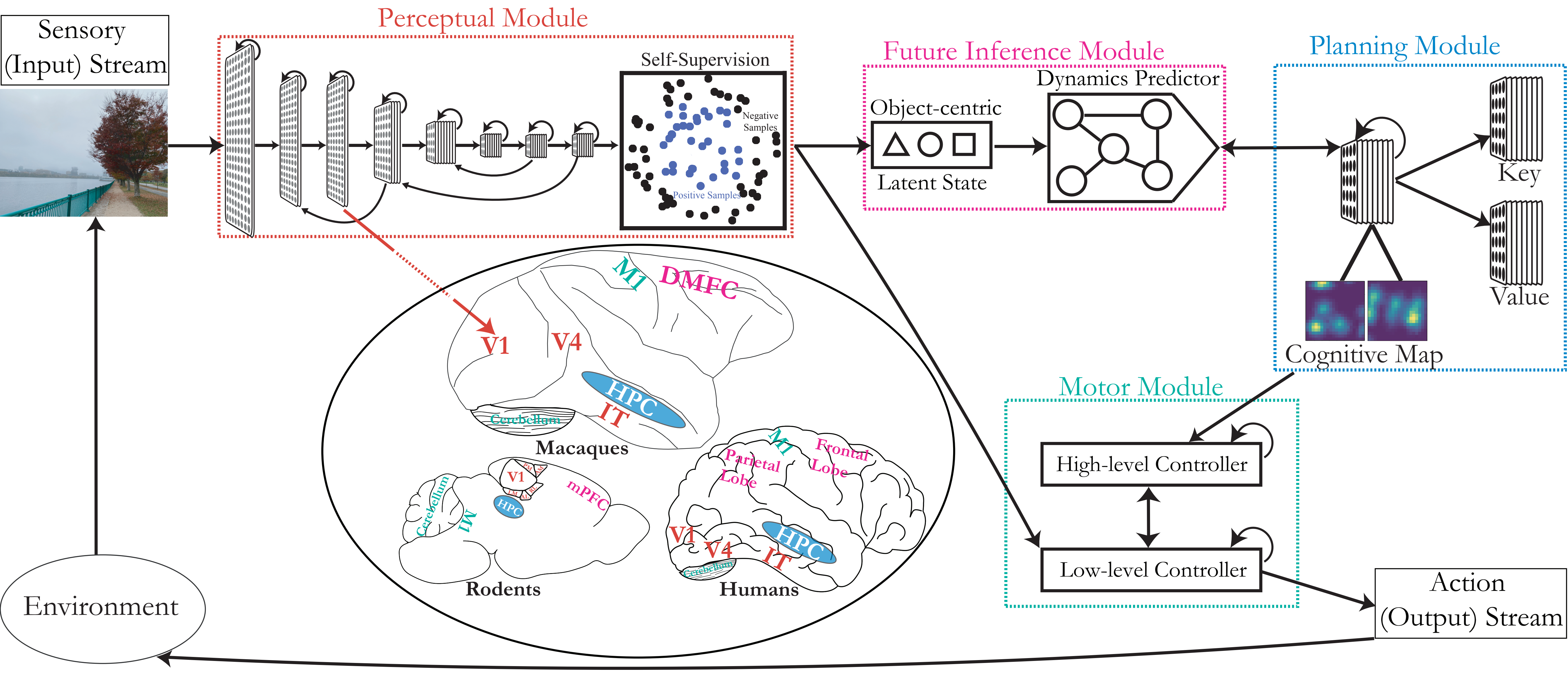


Environment

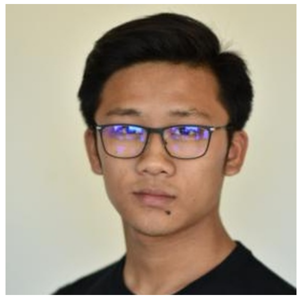
Action (Output) Stream

Long-Term Outcome: Artificial **Organisms**

How does the brain *represent*, *predict*, *plan*, and enable *action*?



Acknowledgements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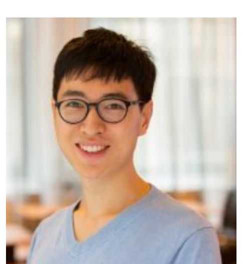
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