

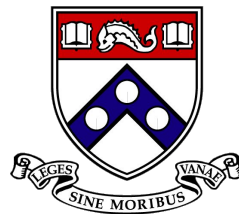
Hand-Engineered Image-Computable Models Can Still Outperform DNNs in V1 Similarity

Tanish Mendki¹, Sudhanshu Srivastava², Ansh Soni³

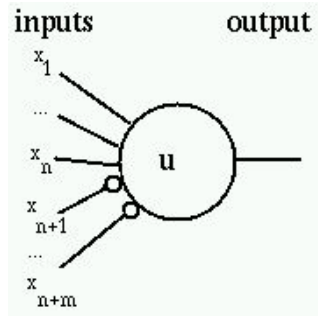
¹University of California, Santa Barbara

²University of California, San Diego

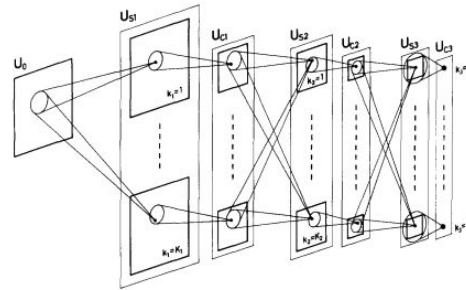
³University of Pennsylvania



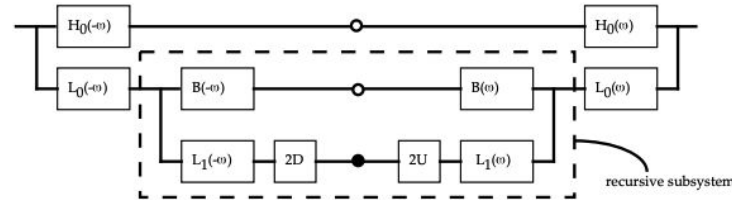
Artificial Neural Systems (ANS)



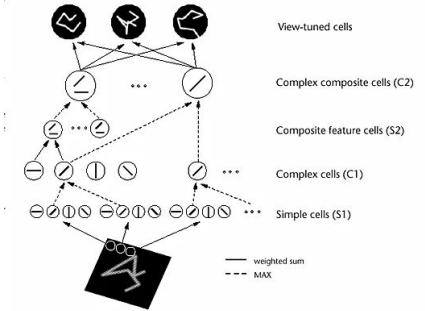
MCP Neuron
(McCulloch & Pitts 1943)



Neocognitron (Fukushima 1980)



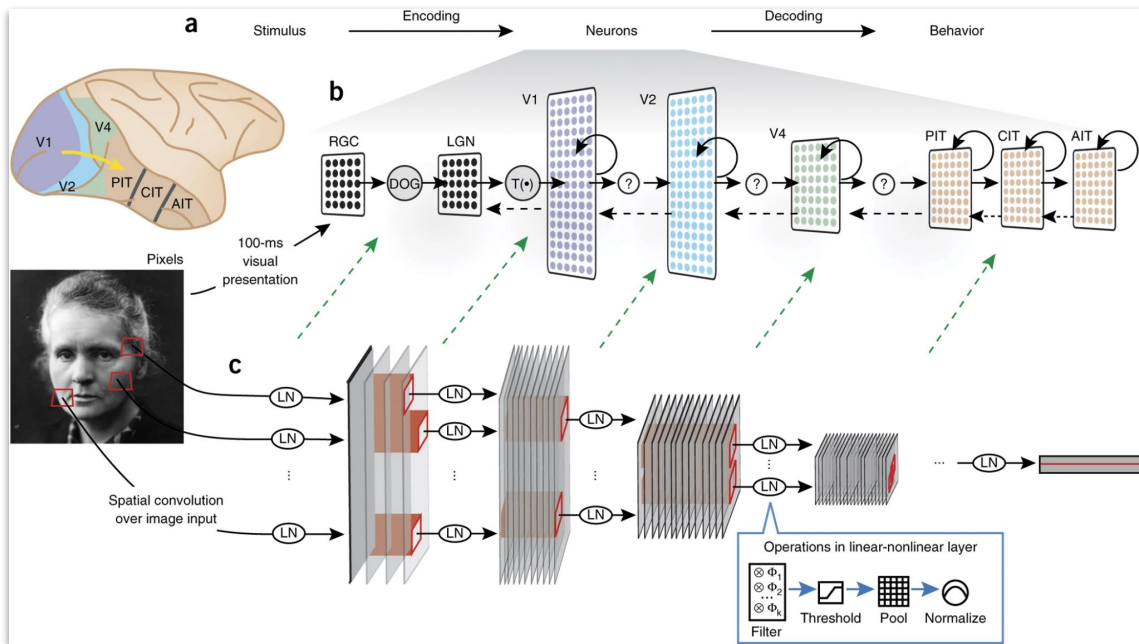
Steerable Pyramid (Simoncelli 1995)



HMAX
(Riesenhuber & Poggio 1999)

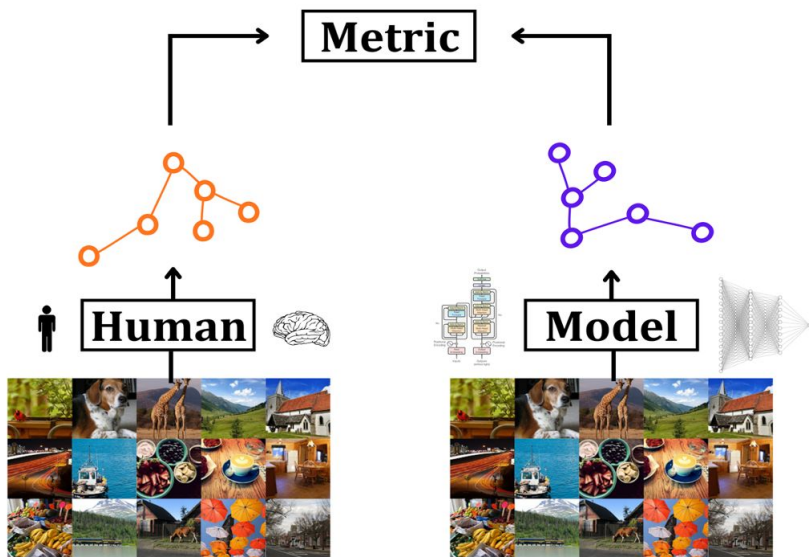
Deep Neural Networks

- Hierarchical network of layers initialized with random weights rather than built-in feature tuned units.
- Learns feature banks simply based on the training and exposure to images + backpropagation.



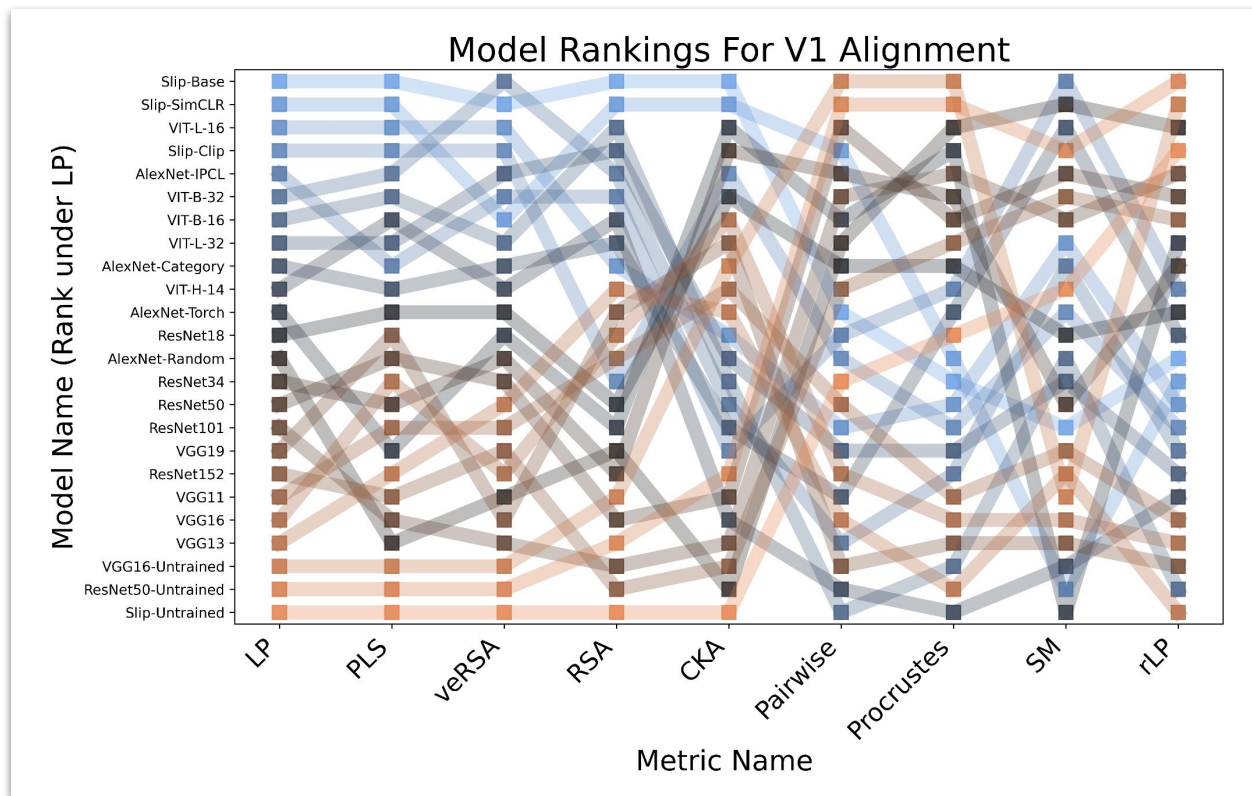
What does it mean for a model to be
brain-like?

How do we compare models to brains?



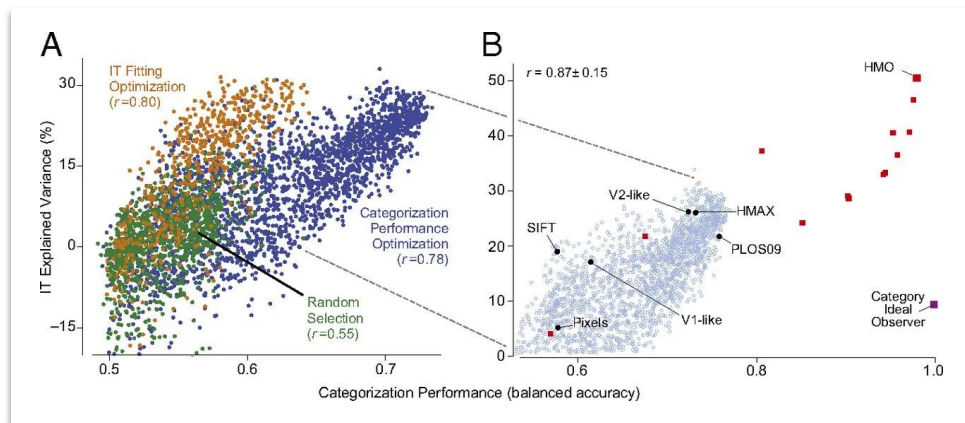
- Evaluate feature similarity between models and brains using some measure.
- Measure choice affects the result achieved, as shown recently by *Soni et al. (2025)*.

Variability of measures



Predictive measures

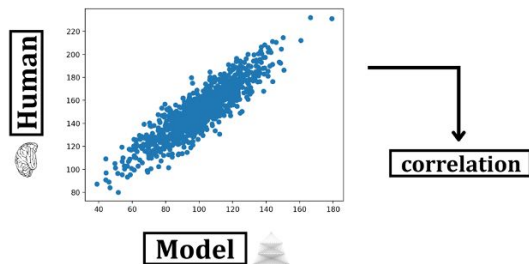
- Take the features from the model and see how it predicts neural responses.
 - *Beyond Prediction* symposium on Friday heavily discussed this!
- See what similarities exist and in principle is a powerful tool if certain conditions are met.
 - Coverage of units
 - Symmetry between networks and brains



Going beyond predictivity

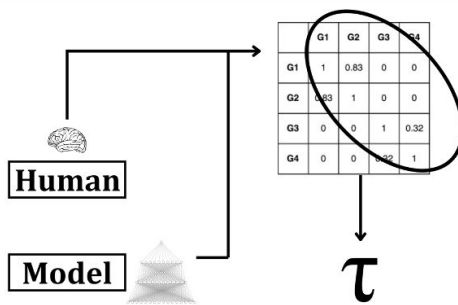
Linear Predictivity

Coarse and asymmetric measure of broadly shared and linearly accessible information.



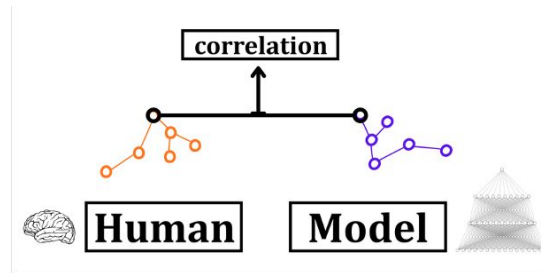
Representational Similarity

Comparing the global distribution of unit selectivity and organization.

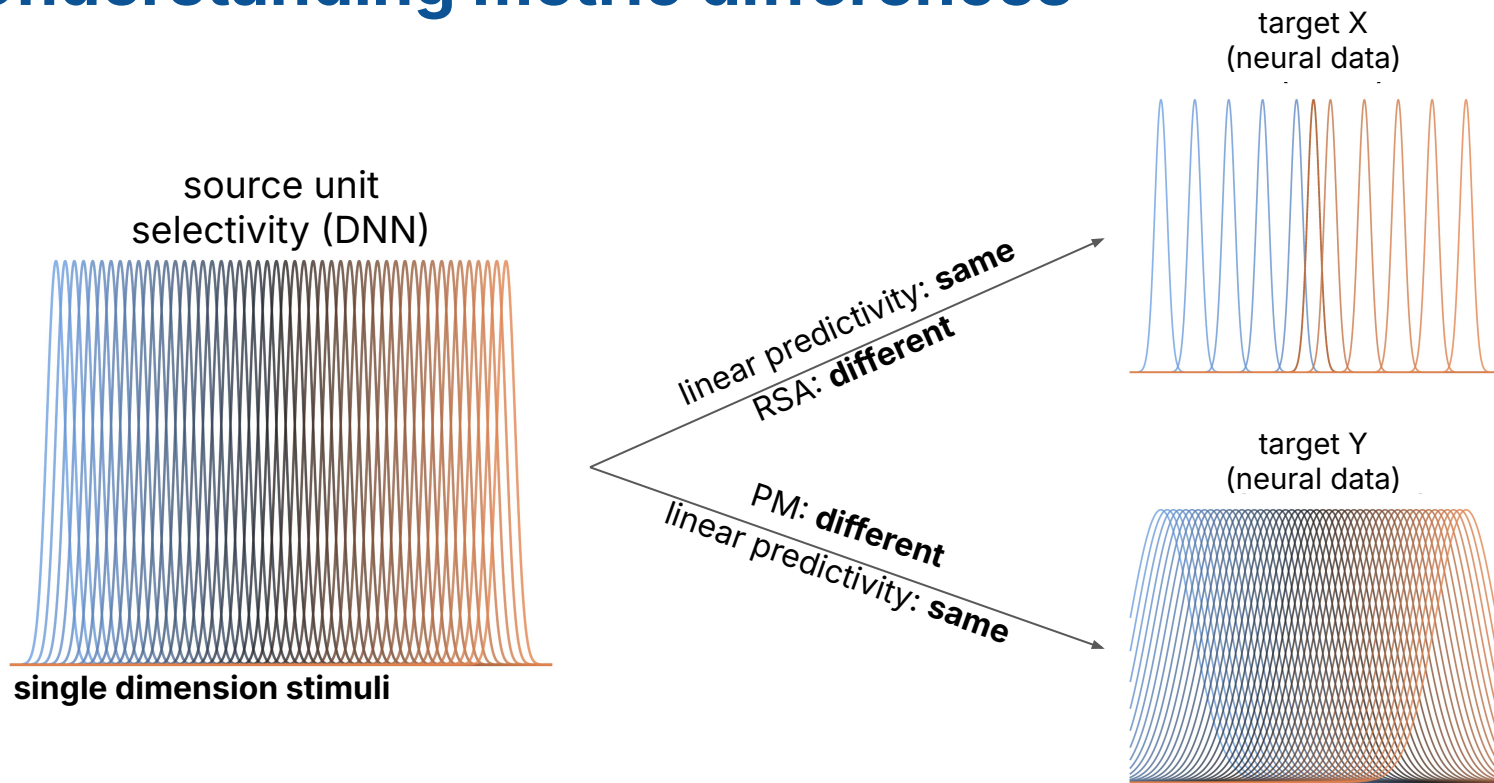


Pairwise Matching

Comparing the individual units to find similarities in response structures.



Understanding metric differences



Primary Visual Cortex (V1)

What do we know about V1?

- Orientation and spatial frequency of visual input - **simple** and **complex** cells.
- Spatially localized receptive fields with specific ON and OFF fields.

Disparity Channels in Early Vision

[Anna W Roe](#)^{1,✉}, [Andrew J Parker](#)², [Richard T Born](#)³, [Gregory C DeAngelis](#)⁴

Binocular disparity

Spatial and chromatic interactions in the lateral geniculate body of the rhesus monkey

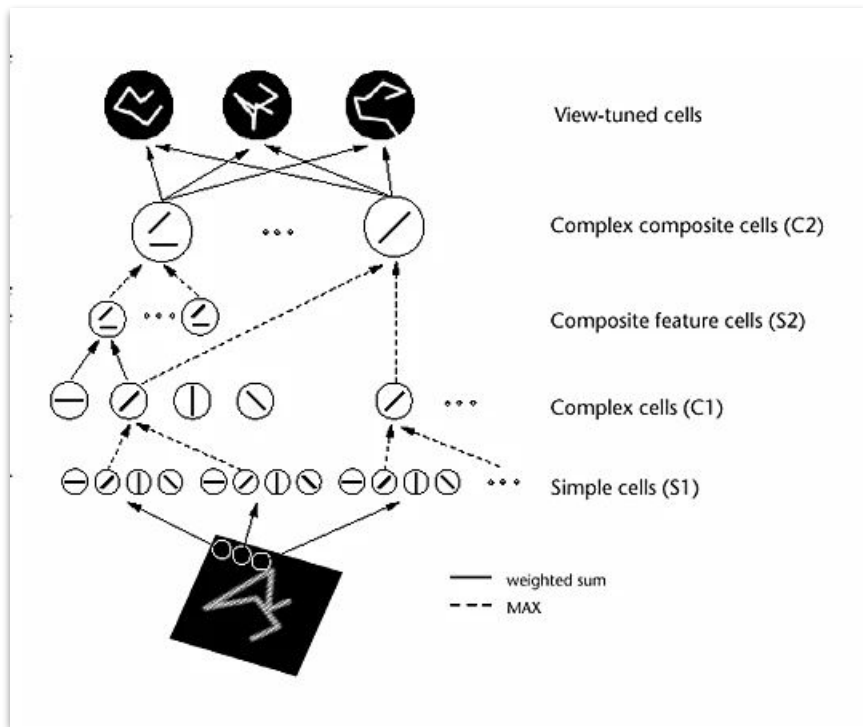
[T N Wiesel](#), [D H Hubel](#)

Color processing and selectivity

Color Blobs in Cortical Areas V1 and V2 of the New World Monkey *Callithrix jacchus*, Revealed by Non-Differential Optical Imaging

[Matthias F. Valverde Salzmänn](#), [Andreas Bartels](#), [Nikos K. Logothetis](#), and [Almut Schüz](#)
Journal of Neuroscience 6 June 2012, 32 (23) 7881-7894; <https://doi.org/10.1523/JNEUROSCI.4832-11.2012>

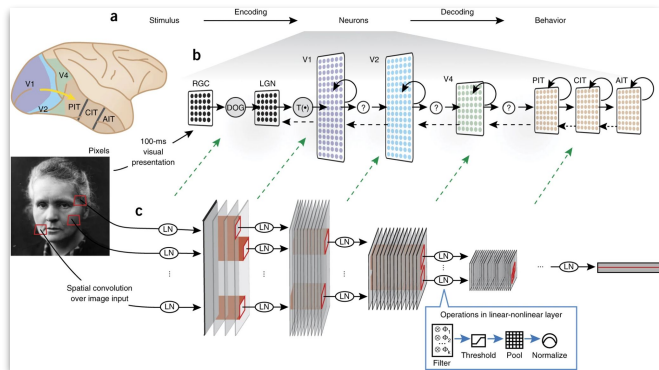
HMAX



- Image-computable model that explicitly tracks what we **know about V1**.
- Simple cells = S1
 - Gabor
- Complex cells = C1
 - Pooling

Other biologically inspired models also tested: Neocognitron, Gabor Wavelet Pyramid, Steerable Pyramid

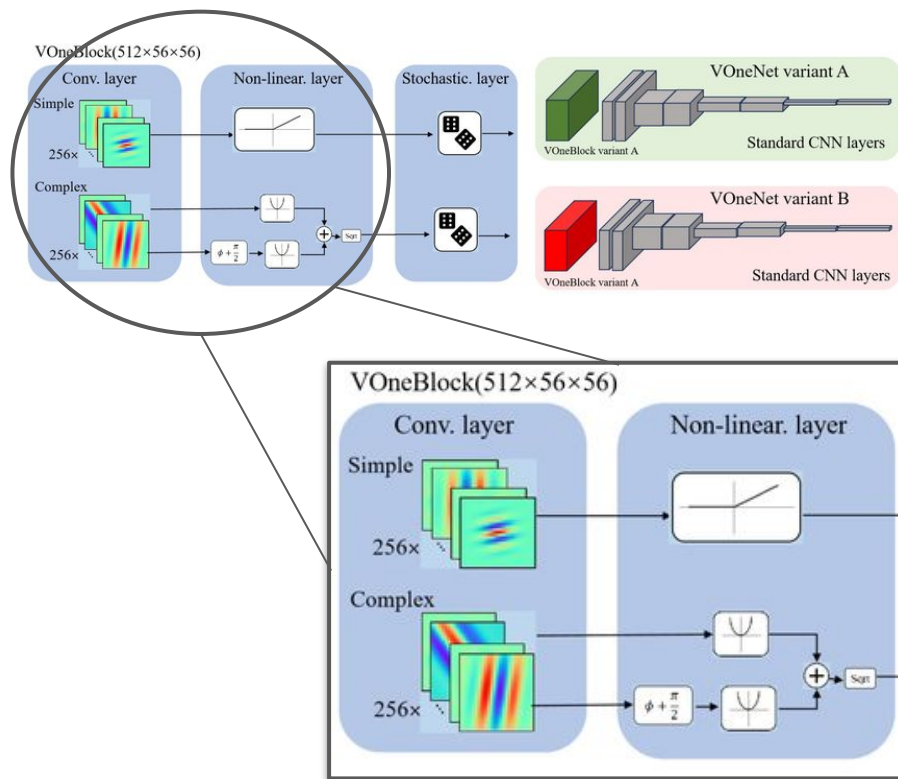
DNNs



No explicit biological constraints on what the internal representations look like.



VOneNet *(Dapello et al. 2020)*



- DNN with a fixed, **biologically constrained front end** that explicitly models V1 simple and complex cells using Gabor filters and noise.
- Pre-defined feature tuning to simulate V1, and then the rest of the model learns from data as usual.

What happens when we compare HMAX to DNNs?

fMRI data

Natural Scenes Dataset (NSD)

Common Objects in Context (COCO) images

8 participants

7T fMRI, 1.8mm

V1 ROI

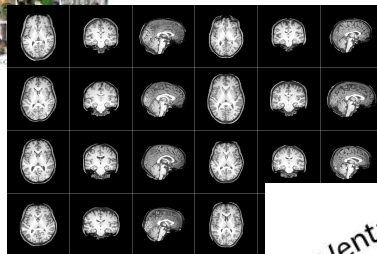
Electrophysiology data

THINGS Ventral-Stream Spiking Dataset (TVSD)

Things Dataset Images

2 macaques

Utah arrays, V1 ROI

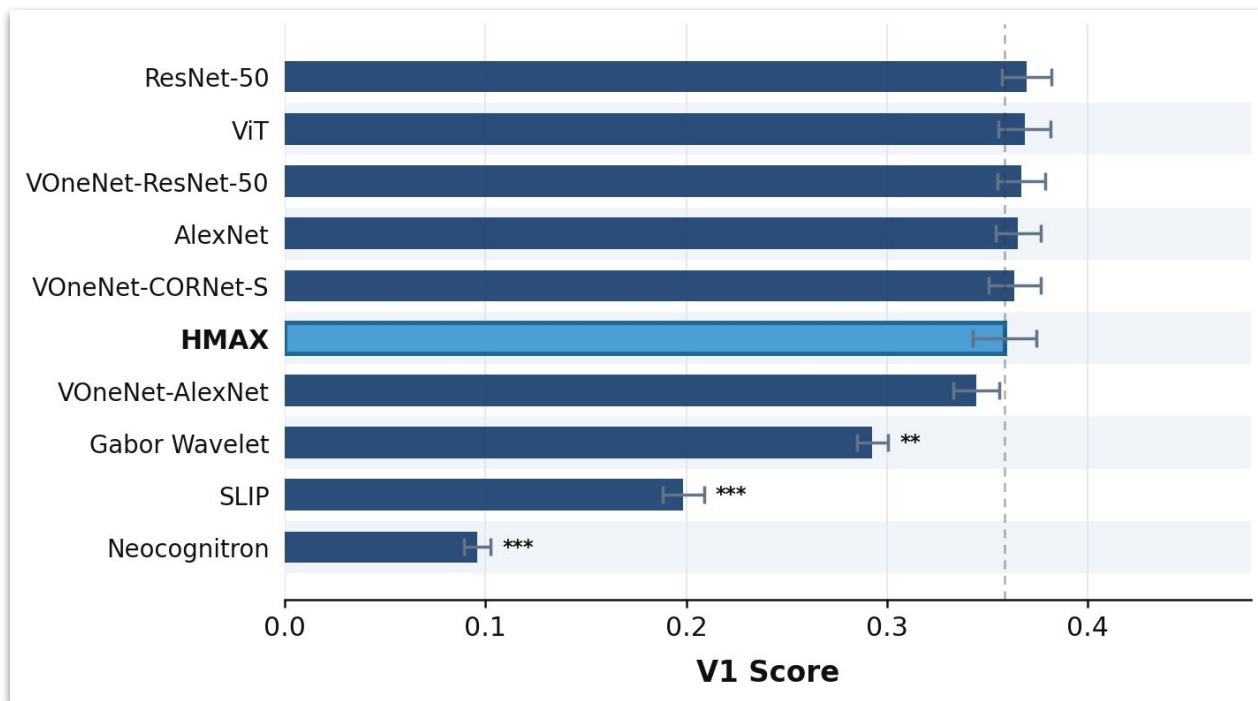


Linear Predictivity - fMRI

Predict voxels and neural spiking using intermediate model features.

Historical measure, and we expected HMAX to perform low.

In V1, HMAX is not distinguishable from other models!

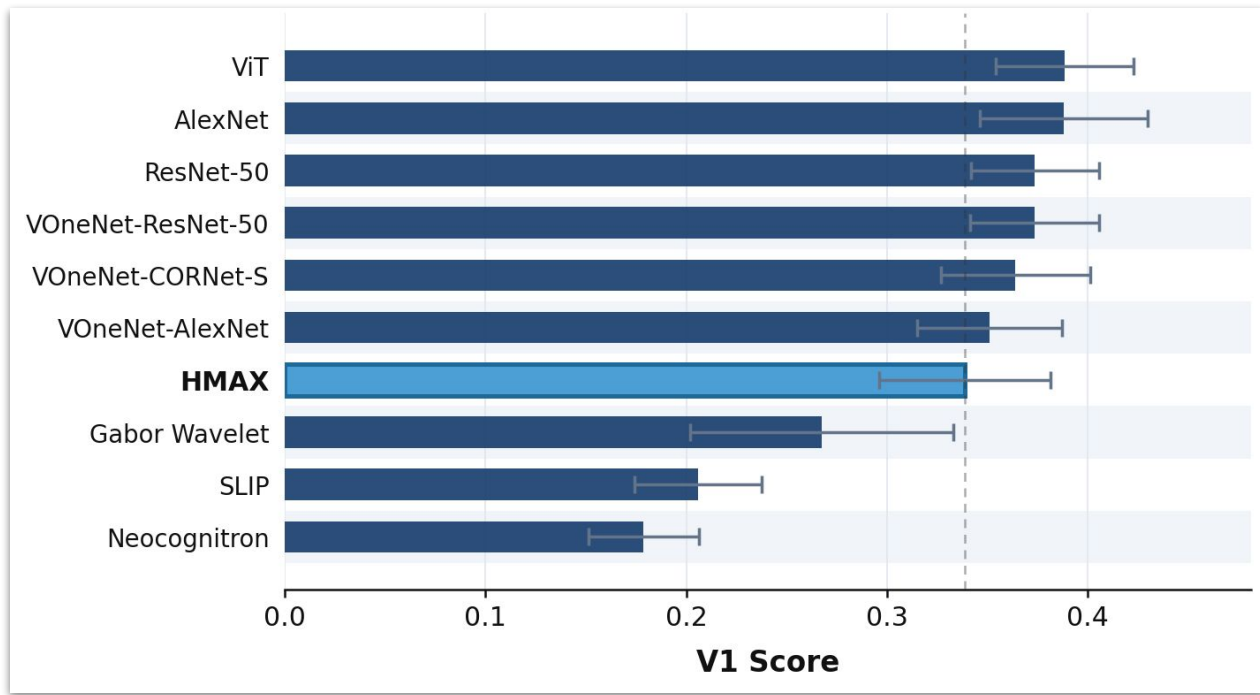


Linear Predictivity - EPhys

Predict voxels and neural spiking using intermediate model features.

Historical measure, and we expected HMAX to perform low.

In V1, HMAX is not distinguishable from other models!

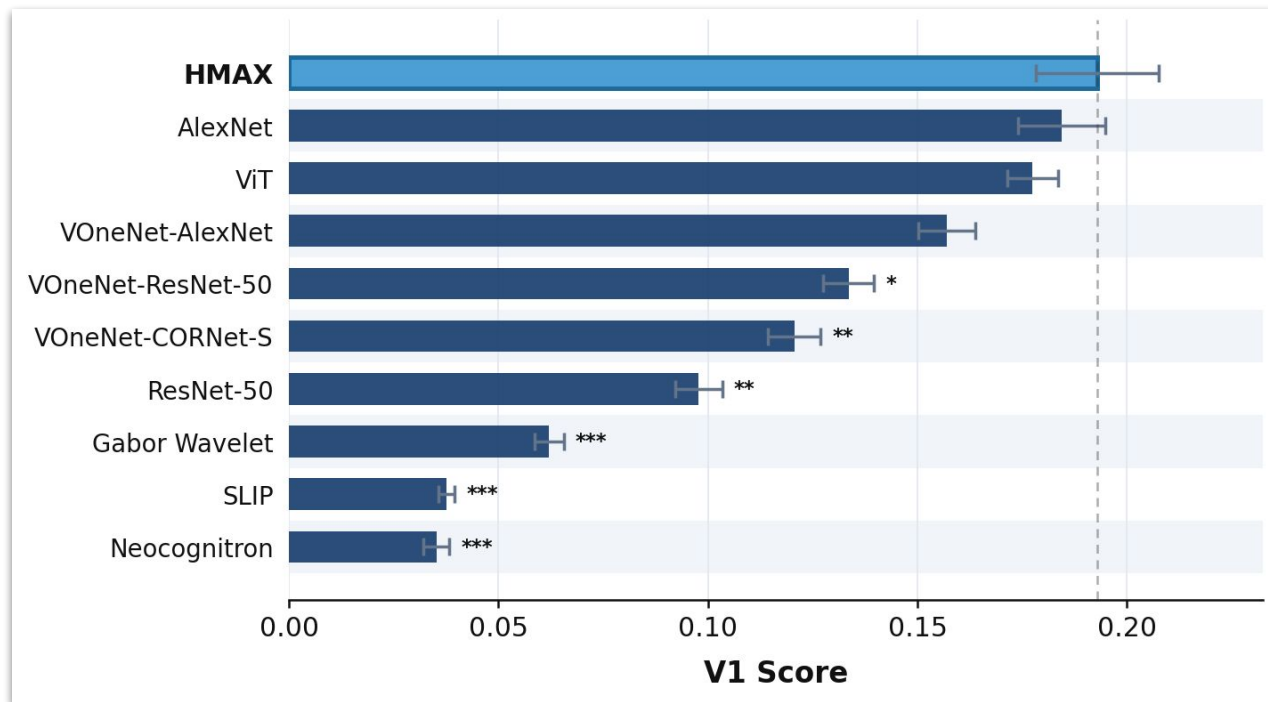


Representational Similarity Analysis - fMRI

Compare the selectivity of units across the entire population.

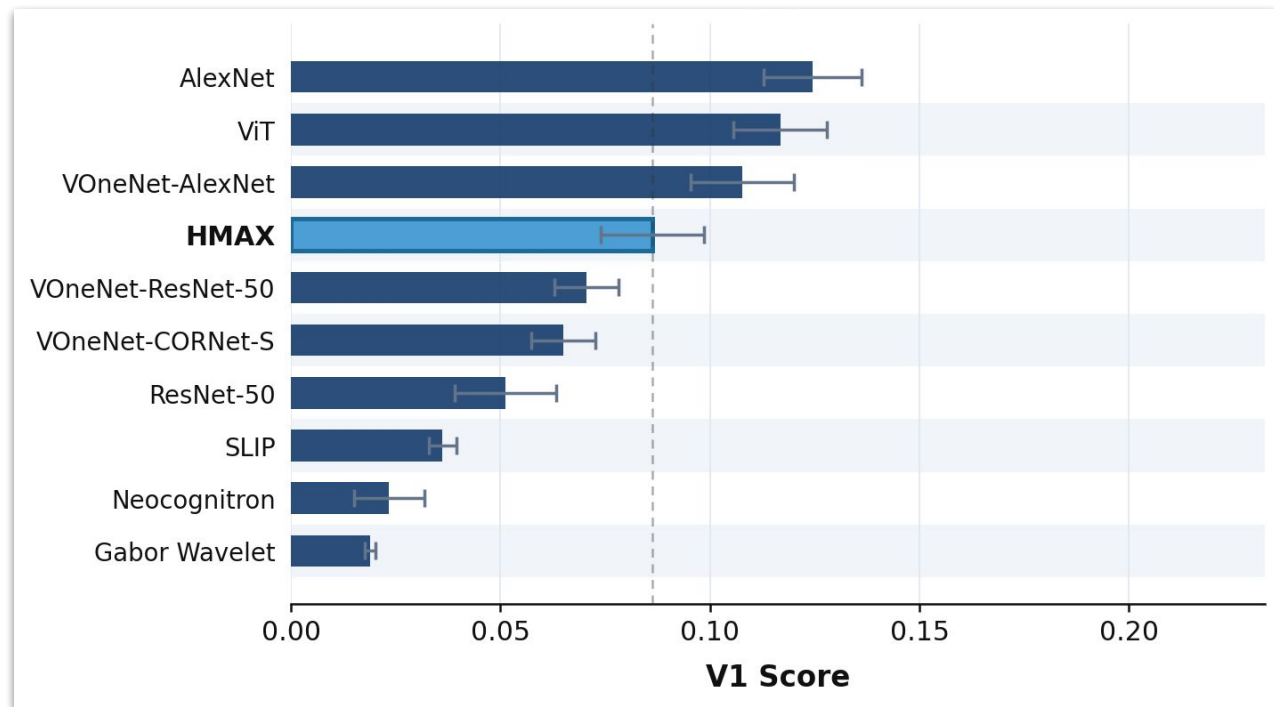
Higher scores indicate that a model organizes its unit selectivity in a similar manner to neural data.

HMAX is the **best model** in terms of this measure!



Representational Similarity Analysis - EPhys

Different results with TVSD, but RSA with electrophysiological data does not track the same way.

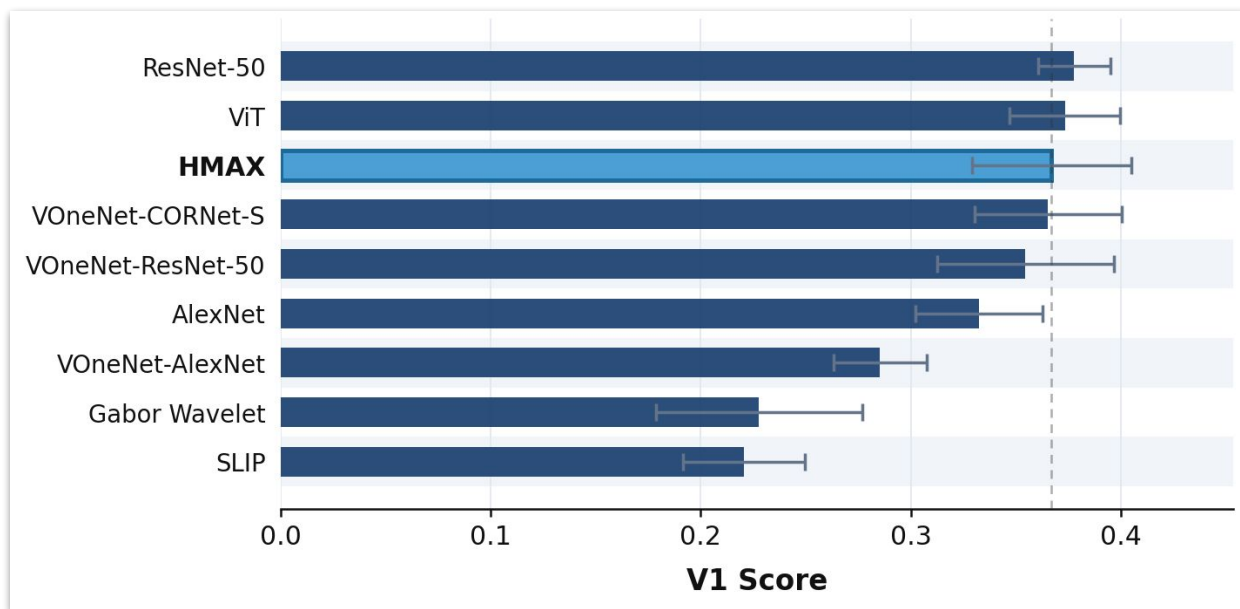


Pairwise Matching - Ephys

Compare the correlations of individual units within the model and neural data.

A higher score on pairwise matching will have more units that act like units contained in neural data.

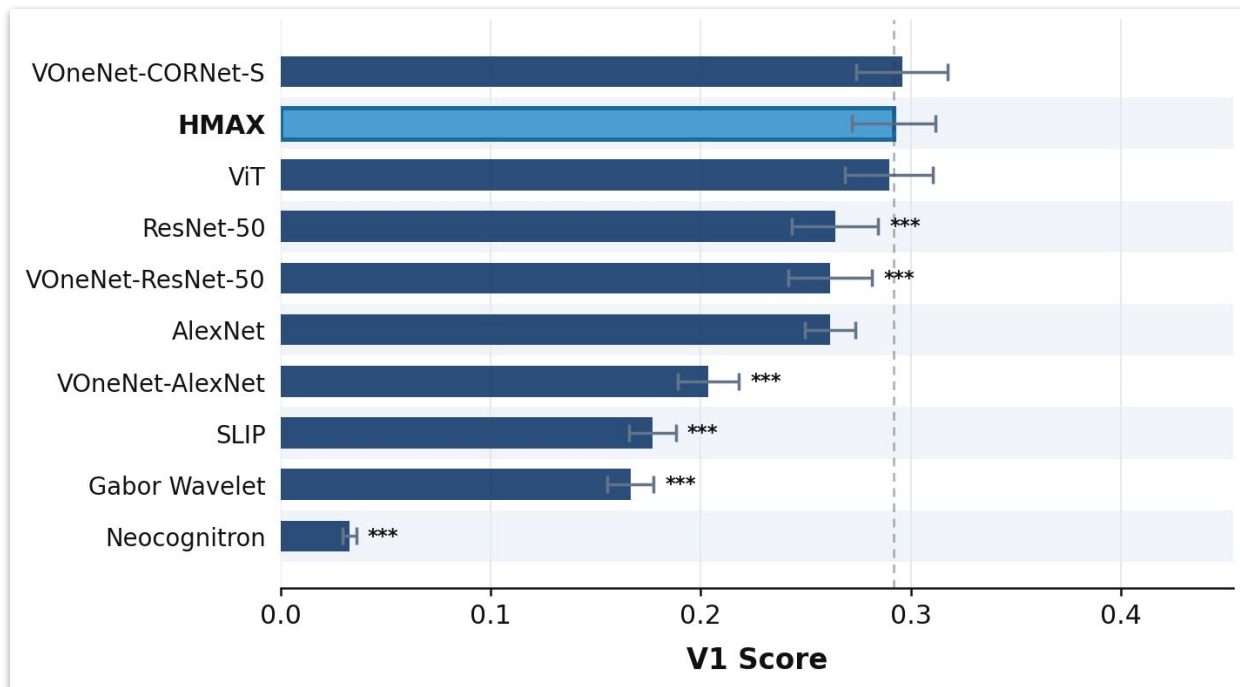
We would expect HMAX, which has explicit modeling simple and complex cells to have correlating units, and it in fact scores very similar to larger models.



Pairwise Matching - fMRI

While we see similar results with fMRI, this measure does not match well with this modality.

PM matches units, but the units here are voxels - a pooling over many individual neurons.

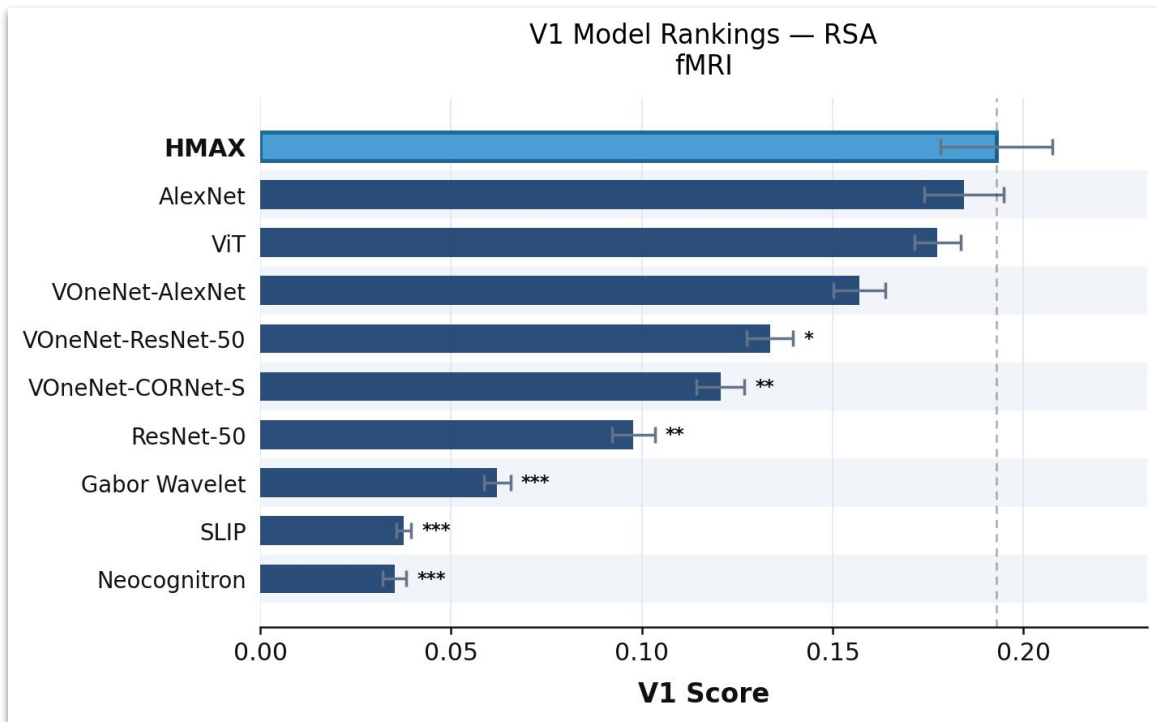


Summary

DNNs predict neural activity well, so does HMAX.

HMAX has a more “brain-like” organization of unit selectivity across the population.

Individual units in HMAX correlate highly with individual units in neural data.



So what?

How do we use ANS to understand the brain?

While we didn't increase our understanding of V1, this analysis gives us a future direction to work in.

How do we use ANS to understand the brain?

ResNet-50 and HMAX both rank very high on Pairwise Matching, so it begs the question - *what units are they correlating with?*

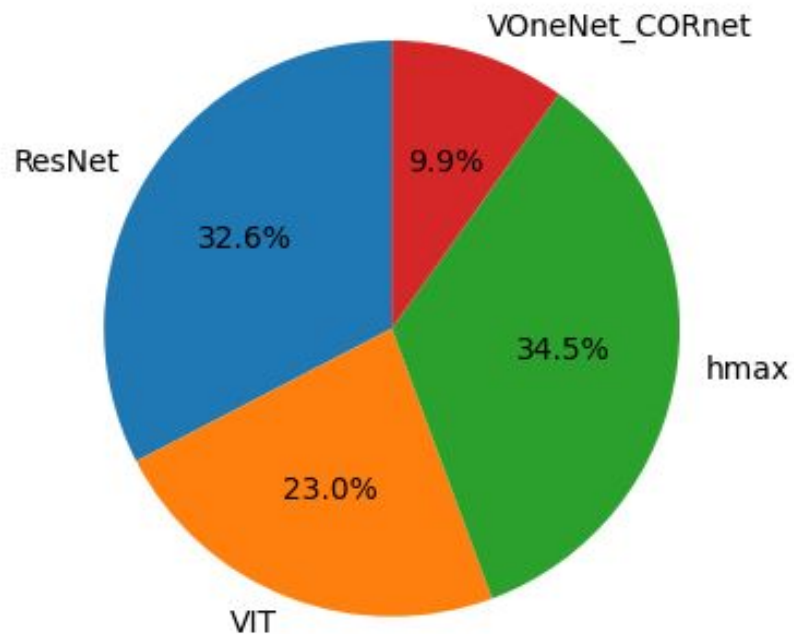


Based on preliminary analysis, some of the units that are **worst matched** by HMAX, are in the **best matching units** for ResNet.

We freely allow neurons to match with units in multiple models.

An equal subset of units correlate highly with HMAX and ResNet, with a few to ViT and the best VOneNet.

Majority-vote attribution
(% of neurons where model wins most folds)



Looking ahead

Similarity matters, but specifically, **what is similar** matters.

- Utilizing metrics that align with research goals leads to results that give actual insight into understanding the brain and computations.
- DNNs offer valuable insights if paired with biological constraints which add a level of interpretability.
 - See the next talk, which will tell us about efficient coding and how that affects similarity.
- More work to be done in terms of looking into the unit-wise differences and learning more about the functions of V1 beyond just simple and complex cells.

Before we ask if a model is brain-like, we need to consider what ***"brain-like"*** **actually means**, and how it **increases our understanding of the brain.**

Acknowledgements



Ansh Soni



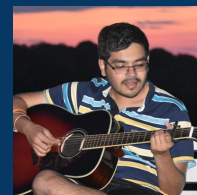
Dr. Srivastava

Dr. Konrad Kording (University of Pennsylvania)

Dr. Miguel Eckstein (UC Santa Barbara)

VIU Lab @ UCSB

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship under Grant No. DGE-2236662.



Looking for positions!

Currently looking for post-bac positions if anyone has any opportunities, would love to hear about it!

[Link to CV →](#)

