

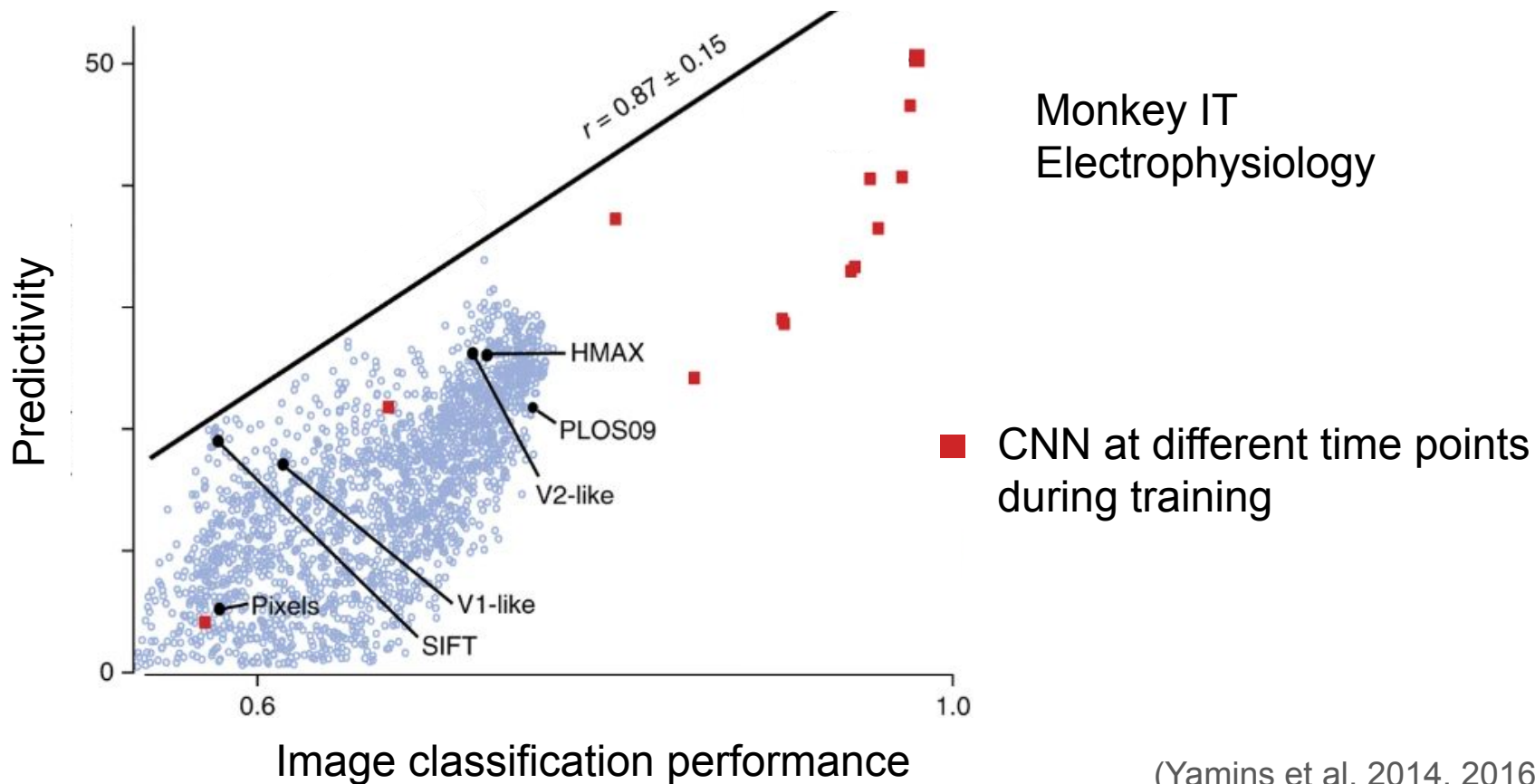
# Do convolutional neural networks show brain-like unilateral processing?

Yota Kawashima

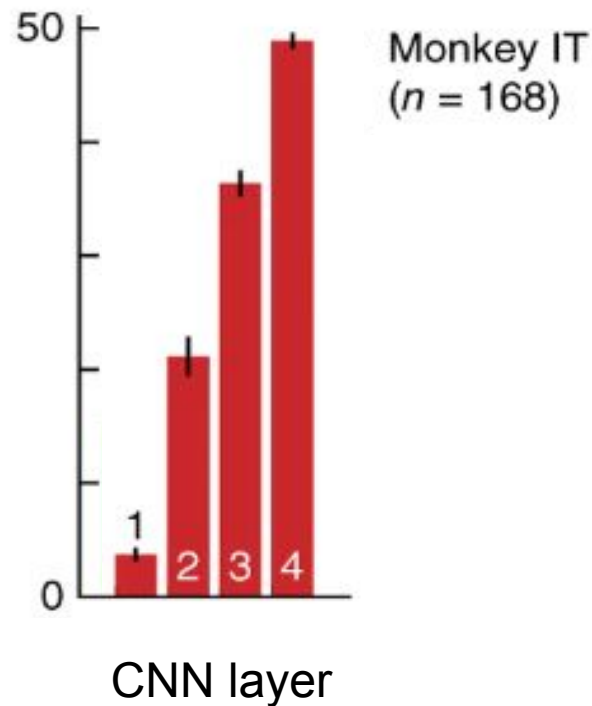
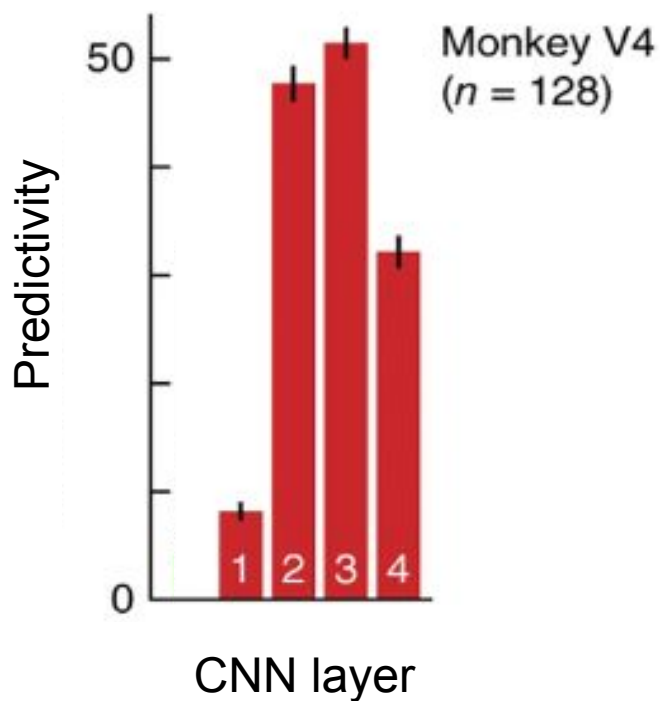
BCCN Berlin

2024/10/18

# Better performance, more brain-like



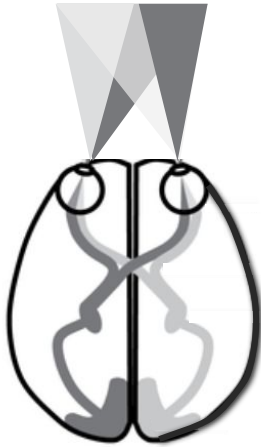
# Similar in what way? Hierarchical structure



# How about unilateral processing?



Better CNNs seem more similar to the visual areas.



## Hypothesis

Better CNNs explain unilateral processing better.

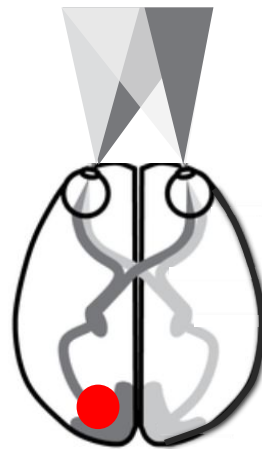
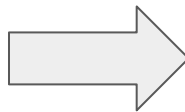
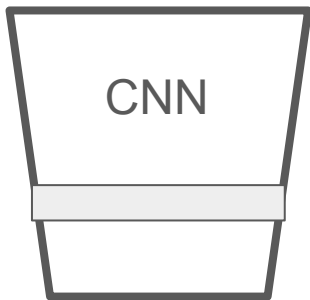
> How can we test this?

# The standard encoding model



Encoding model

Layer  $i$

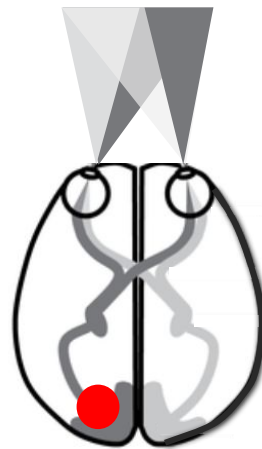
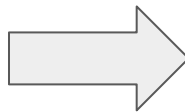
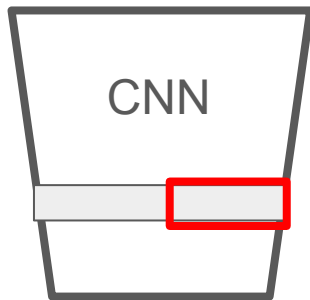


# 'Splitting' NN layers in encoding model



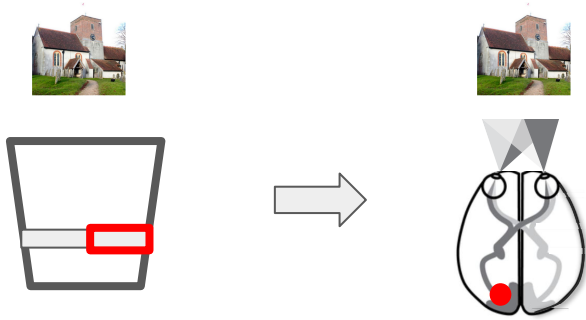
'Split' encoding model

Layer  $i$

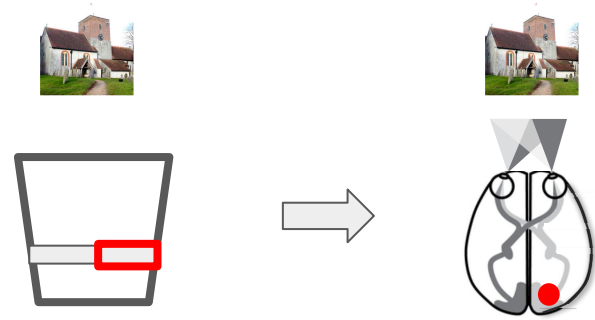


# Two encoding model prediction

Contralateral prediction

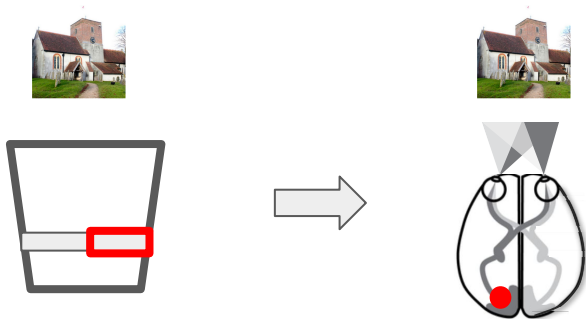


Ipsilateral prediction

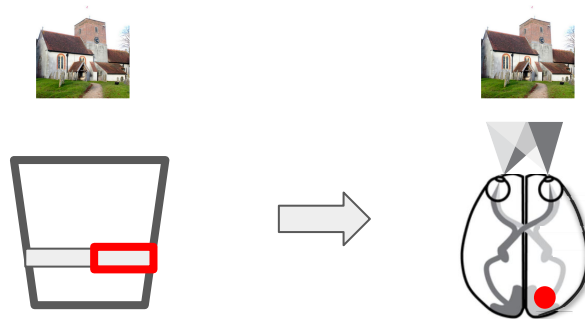


# Contralateral prediction should be better

Contralateral prediction



Ipsilateral prediction



If CNNs are similar to the brain,

- Better contralateral prediction than ipsilateral prediction.
- Large difference in early layers.



# fMRI dataset and CNN models

The Algonauts project fMRI dataset

- 8 participants
- 872 natural scene images



The Efficient network (Tan & Le, 2019)

- Relatively few parameters
- Good performance

Models to be compared

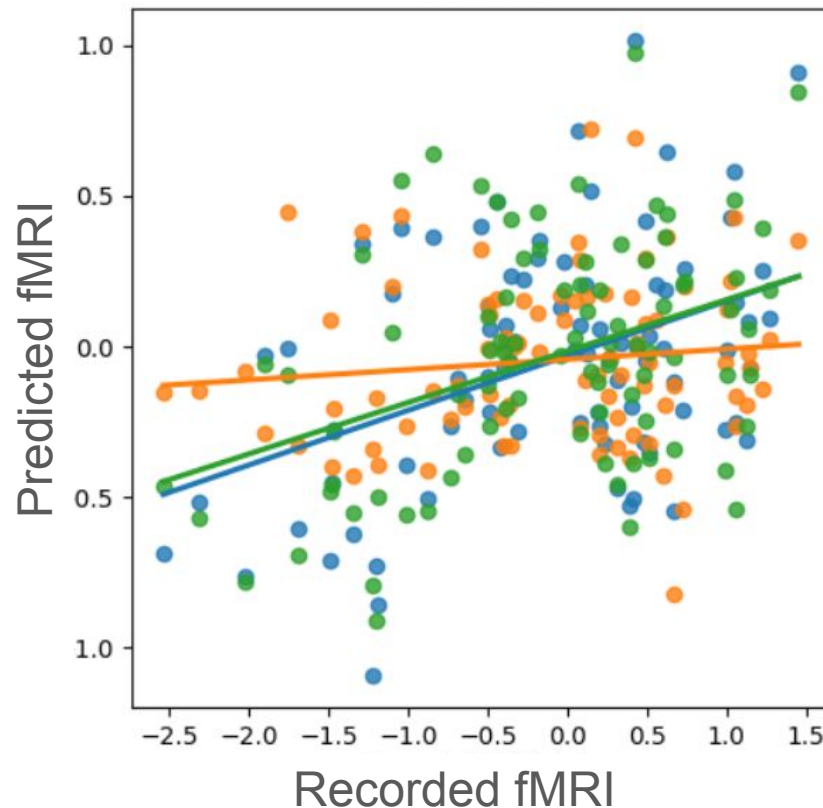
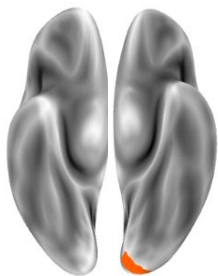
- Trained (ImageNet-1K)
- Not-trained (random weights)

Stage $i$	Operator $\hat{\mathcal{F}}_i$
1	Conv3x3
2	MBConv1, k3x3
→ 3	MBConv6, k3x3
4	MBConv6, k5x5
5	MBConv6, k3x3
→ 6	MBConv6, k5x5
7	MBConv6, k5x5
8	MBConv6, k3x3
→ 9	Conv1x1 & Pooling & FC

# Result: single vertex prediction ( $N = 1$ )

Trained model  
The early layer

Early visual area  
(left)



Full:	0.55
Ipsilateral:	0.19
Contralateral:	0.67

# Contralateral prediction seems better ( $N = 1$ )

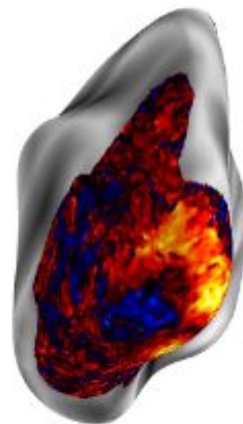
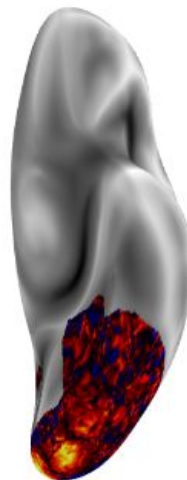
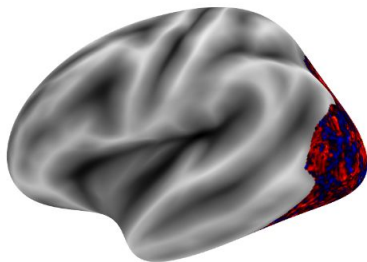
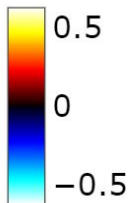
Trained model  
The early layer

Lateral view

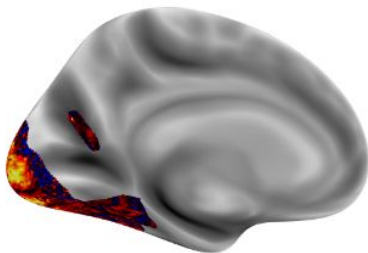
Ventral view

Occipital view

(corr. contra.) - (corr. ipsi.)



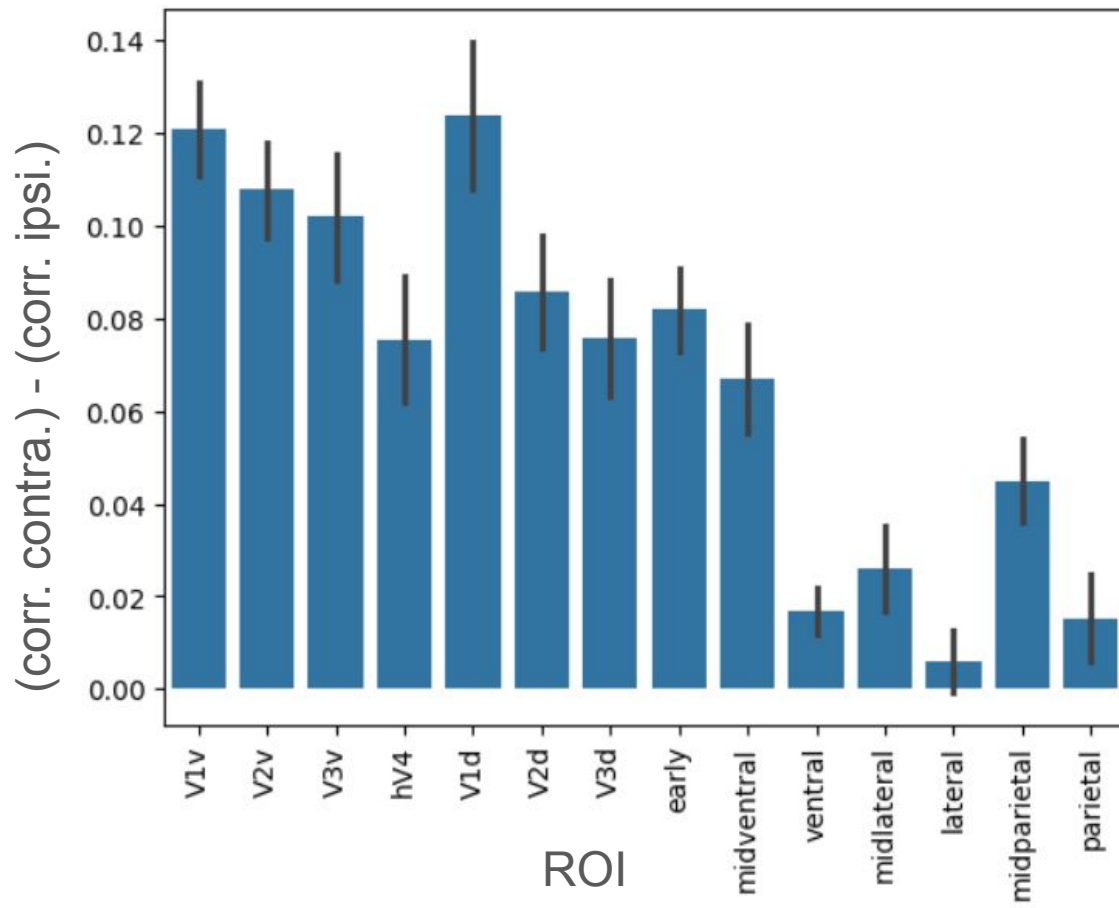
Medial view



# Contralateral prediction is better ( $N = 8$ )

Trained model  
The early layer

Mean & std across  
participants & hemispheres

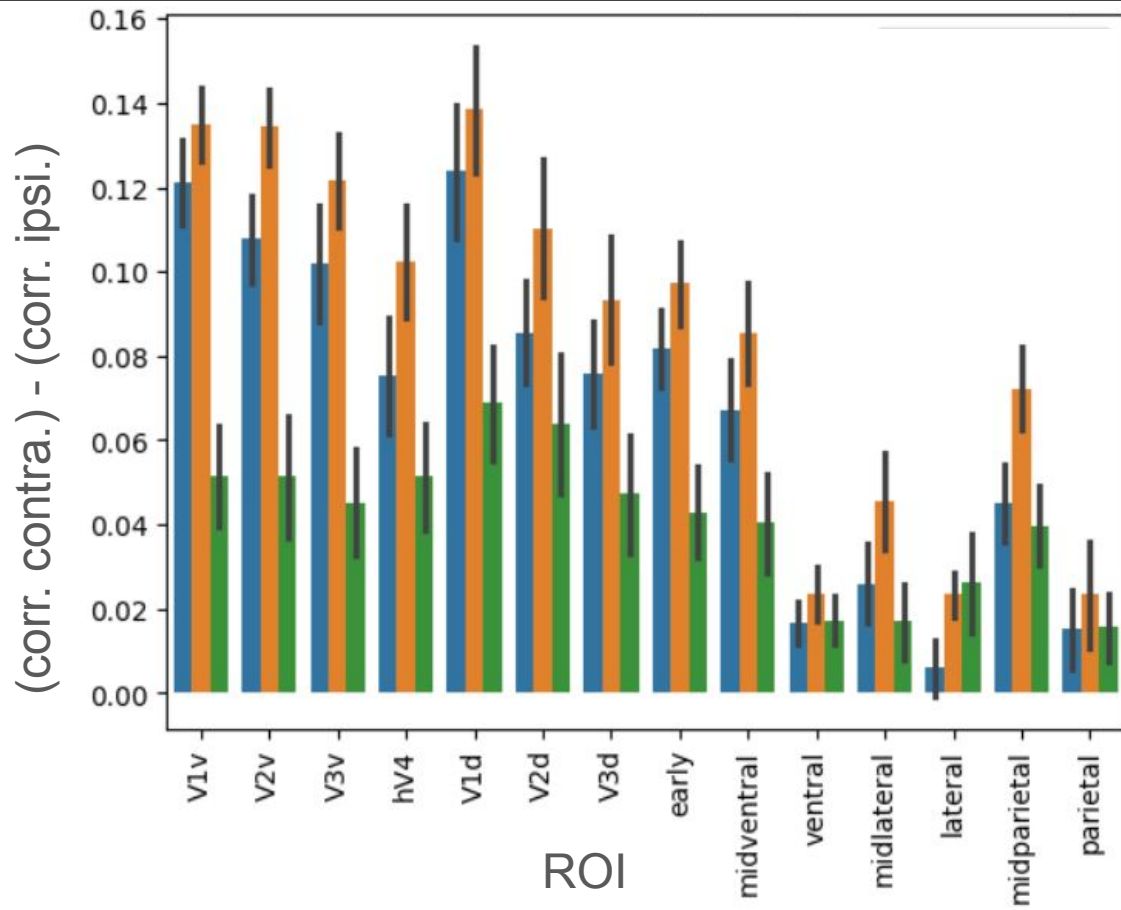


# Early layers show larger difference

Trained model

Mean & std across  
participants & hemispheres

Early layer  
Middle  
Late

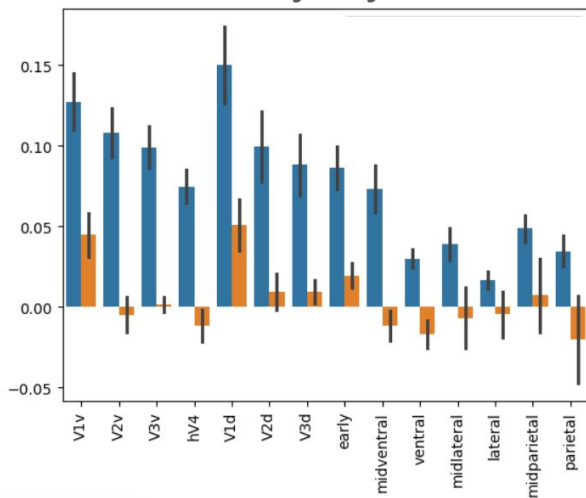


# Trained model shows larger difference

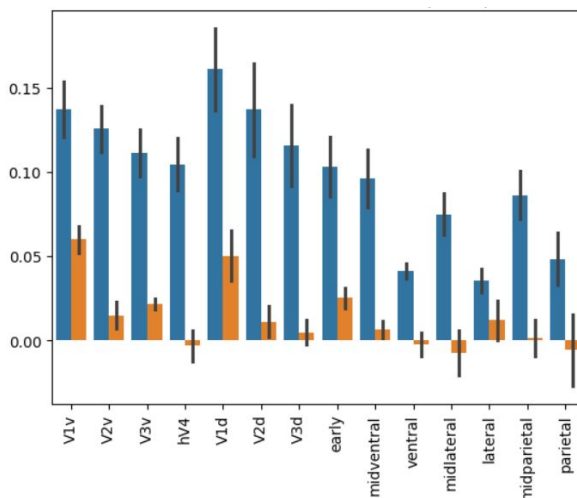
- Trained
- Not-trained

(corr. contra.) - (corr. ipsi.)

## Early layer

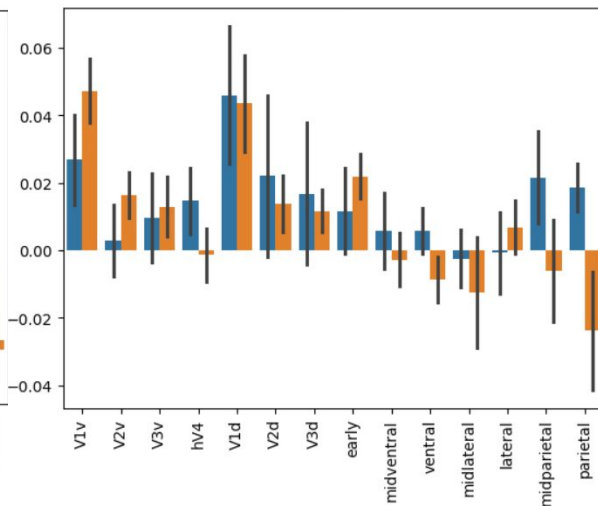


## Middle



ROI

## Late



# Summary & Discussion

- Better CNNs seem to have more brain-like unilateral processing.
  - 'Split' encoding model for the trained effNet
  - Better contralateral prediction than ipsilateral prediction.
  - Larger difference in early layers.
  - But not for the not-trained effNet
- Half-trained (e.g. different time points during training)
- Architecture is important! (Yamins et al 2014)
  - 'Split' in architecture
  - Bilateral visual field maps in a patient with one hemisphere (Muckli et al 2009)

## Code

- <https://drive.google.com/drive/folders/1zDgVxCHiWDRAMLSx30tVdc9bftGcKZXq?usp=sharing>

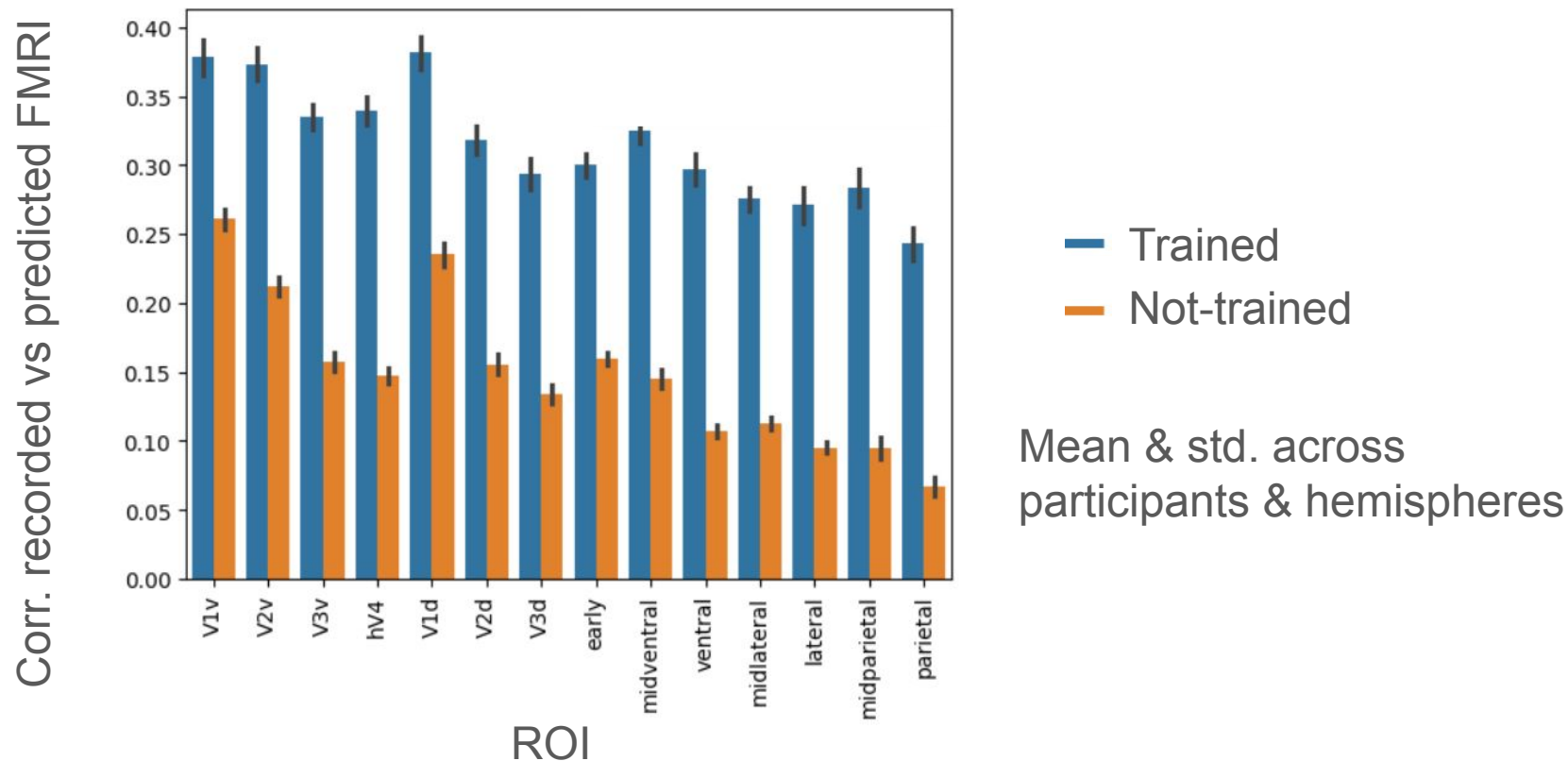
## Reference

- Yamins, D. L. K., Hong, H., Cadieu, C. F., Solomon, E. A., Seibert, D., & DiCarlo, J. J. (2014). Performance-optimized hierarchical models predict neural responses in higher visual cortex. *Proceedings of the National Academy of Sciences of the United States of America*, 111(23), 8619–8624.  
<https://doi.org/10.1073/pnas.1403112111>
- Yamins, D., DiCarlo, J. Using goal-driven deep learning models to understand sensory cortex. *Nat Neurosci* 19, 356–365 (2016). <https://doi.org/10.1038/nn.4244>
- Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional Neural Networks. In arXiv [cs.LG]. arXiv. <http://arxiv.org/abs/1905.11946>
- Muckli, L., Naumer, M. J., & Singer, W. (2009). Bilateral visual field maps in a patient with only one hemisphere. *Proceedings of the National Academy of Sciences of the United States of America*, 106(31), 13034–13039.  
<https://doi.org/10.1073/pnas.0809688106>
- The Algonauts project <http://algonauts.csail.mit.edu/challenge.html>
- Pytorch pretrained models:  
<https://pytorch.org/vision/stable/models.html#table-of-all-available-classification-weights>

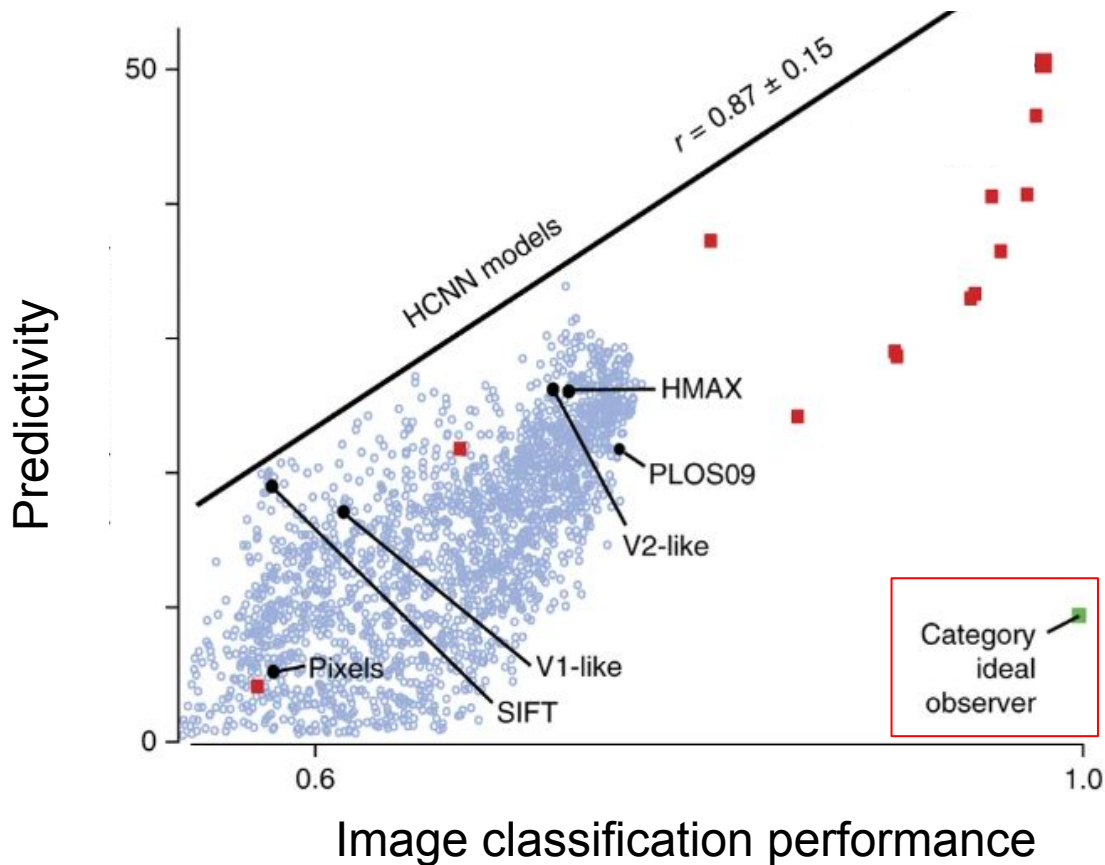


Note

# Performance: the standard encoding model



# Category ideal observer (semantic model)



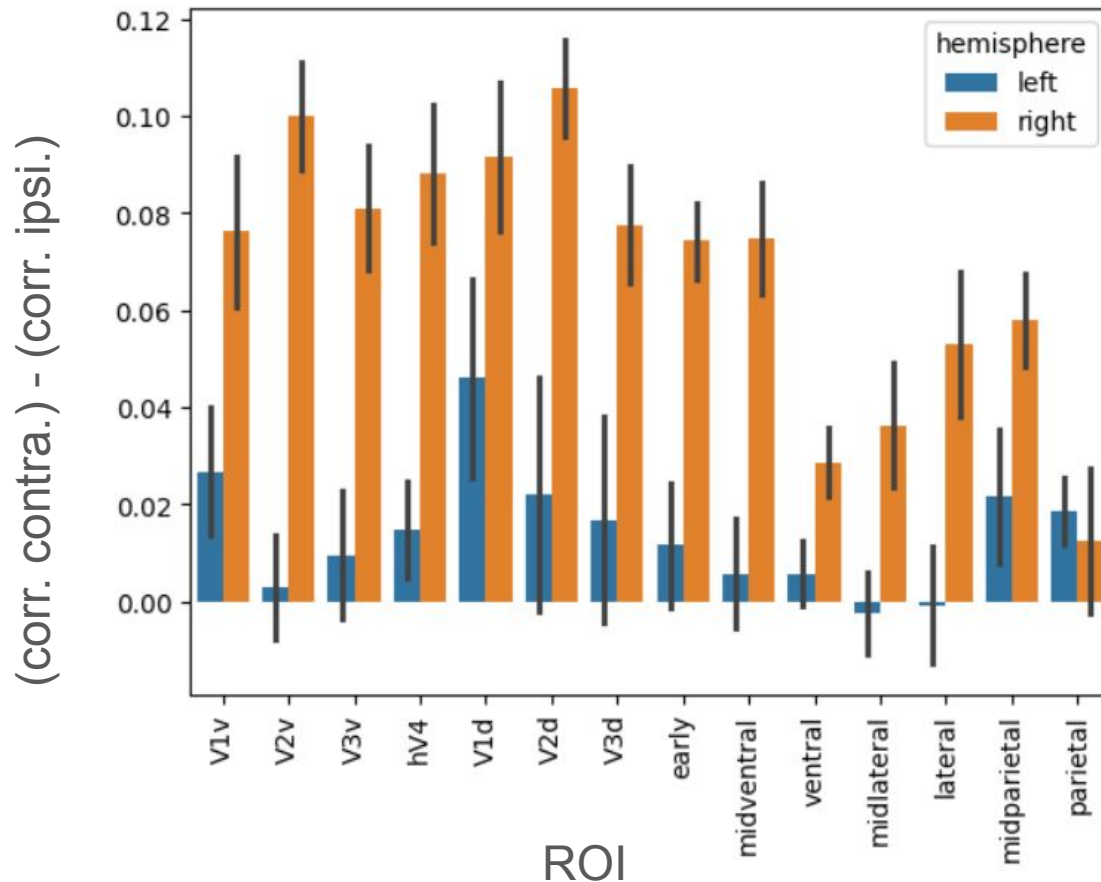
# Comparing hemispheres in the last layer

Trained model

The last layer

Mean & std across  
participants

There are no difference  
between hemisphere in the  
other two early layers. I don't  
know why we see this in the  
late layer...



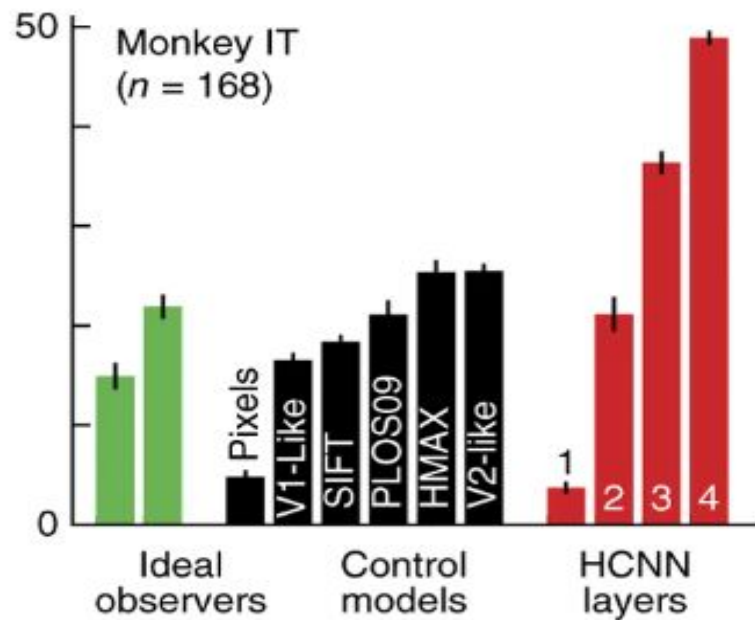
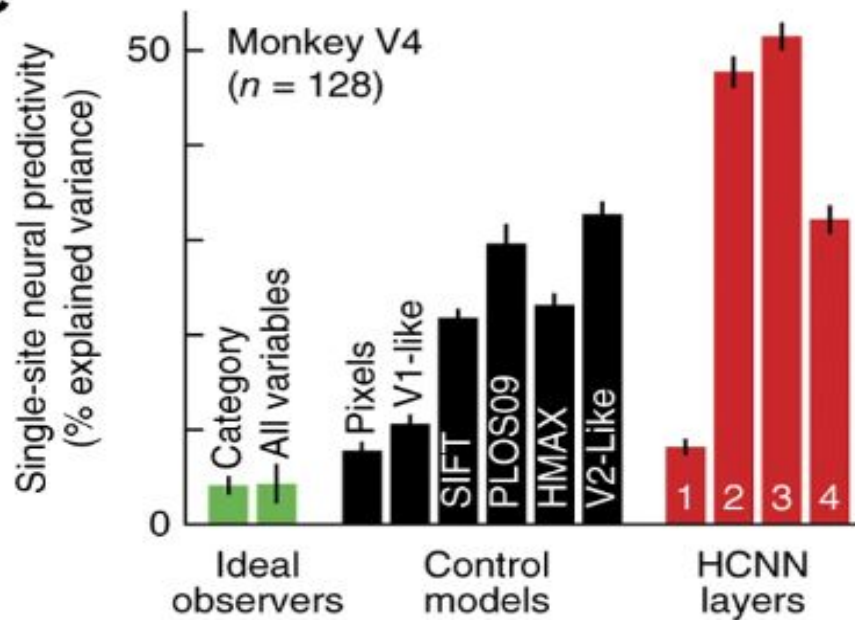
# Efficient network architecture

Stage $i$	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	$224 \times 224$	32	1
2	MBConv1, k3x3	$112 \times 112$	16	1
3	MBConv6, k3x3	$112 \times 112$	24	2
4	MBConv6, k5x5	$56 \times 56$	40	2
5	MBConv6, k3x3	$28 \times 28$	80	3
6	MBConv6, k5x5	$14 \times 14$	112	3
7	MBConv6, k5x5	$14 \times 14$	192	4
8	MBConv6, k3x3	$7 \times 7$	320	1
9	Conv1x1 & Pooling & FC	$7 \times 7$	1280	1

Weight	Acc@1	Acc@5	Params
AlexNet_Weights.IMAGENET1K_V1	56.522	79.066	61.1M
ConvNeXt_Base_Weights.IMAGENET1K_V1	84.062	96.87	88.6M
ConvNeXt_Large_Weights.IMAGENET1K_V1	84.414	96.976	197.8M
ConvNeXt_Small_Weights.IMAGENET1K_V1	83.616	96.65	50.2M
ConvNeXt_Tiny_Weights.IMAGENET1K_V1	82.52	96.146	28.6M
DenseNet121_Weights.IMAGENET1K_V1	74.434	91.972	8.0M
DenseNet161_Weights.IMAGENET1K_V1	77.138	93.56	28.7M
DenseNet169_Weights.IMAGENET1K_V1	75.6	92.806	14.1M
DenseNet201_Weights.IMAGENET1K_V1	76.896	93.37	20.0M
EfficientNet_B0_Weights.IMAGENET1K_V1	77.692	93.532	5.3M
EfficientNet_B1_Weights.IMAGENET1K_V1	78.642	94.186	7.8M
EfficientNet_B1_Weights.IMAGENET1K_V2	79.838	94.934	7.8M
EfficientNet_B2_Weights.IMAGENET1K_V1	80.608	95.31	9.1M
EfficientNet_B3_Weights.IMAGENET1K_V1	82.008	96.054	12.2M
EfficientNet_B4_Weights.IMAGENET1K_V1	83.384	96.594	19.3M
EfficientNet_B5_Weights.IMAGENET1K_V1	83.444	96.628	30.4M
EfficientNet_B6_Weights.IMAGENET1K_V1	84.008	96.916	43.0M
EfficientNet_B7_Weights.IMAGENET1K_V1	84.122	96.908	66.3M
EfficientNet_V2_L_Weights.IMAGENET1K_V1	85.808	97.788	118.5M
EfficientNet_V2_M_Weights.IMAGENET1K_V1	85.112	97.156	54.1M
EfficientNet_V2_S_Weights.IMAGENET1K_V1	84.228	96.878	21.5M
GoogLeNet_Weights.IMAGENET1K_V1	69.778	89.53	6.6M
Inception_V3_Weights.IMAGENET1K_V1	77.294	93.45	27.2M
MNASNet0_5_Weights.IMAGENET1K_V1	67.734	87.49	2.2M
MNASNet0_75_Weights.IMAGENET1K_V1	71.18	90.496	3.2M
MNASNet1_0_Weights.IMAGENET1K_V1	73.456	91.51	4.4M
MNASNet1_3_Weights.IMAGENET1K_V1	76.506	93.522	6.3M
MaxViT_T_Weights.IMAGENET1K_V1	83.7	96.722	30.9M
MobileNet_V2_Weights.IMAGENET1K_V1	71.878	90.286	3.5M
MobileNet_V2_Weights.IMAGENET1K_V2	72.154	90.822	3.5M
MobileNet_V3_Large_Weights.IMAGENET1K_V1	74.042	91.34	5.5M
MobileNet_V3_Large_Weights.IMAGENET1K_V2	75.274	92.566	5.5M
MobileNet_V3_Small_Weights.IMAGENET1K_V1	67.668	87.402	2.5M

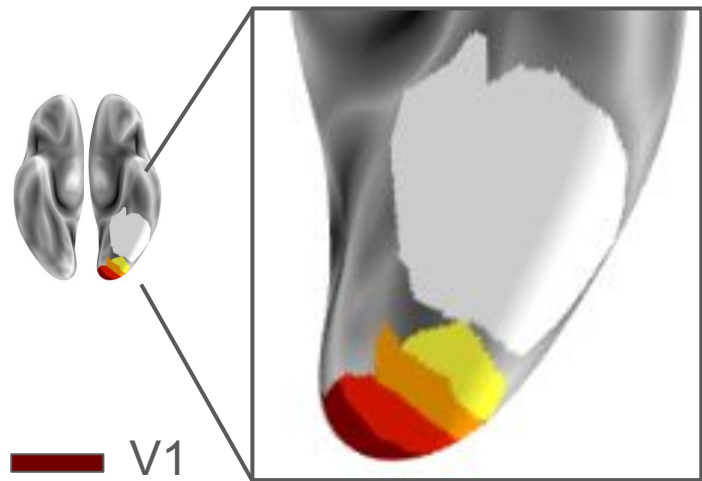
# From Yamins paper






**c**

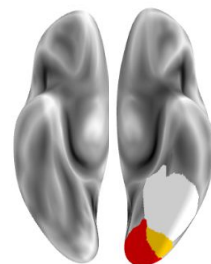
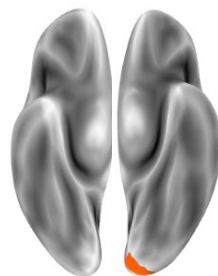


# Single vertex prediction

Left hemisphere (axial)



-  V1
-  V2
-  V3
-  V4
-  Ventral (higher)

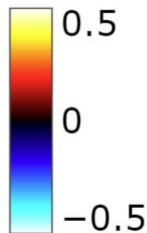




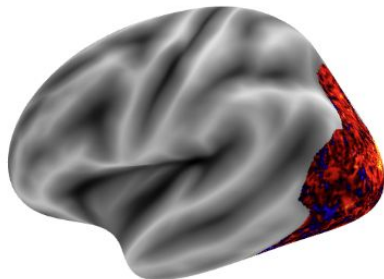
# Contralateral prediction seems better ( $N = 1$ )

Trained model  
The middle layer

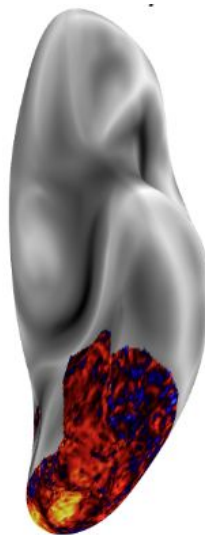
(corr. contra.) - (corr. ipsi.)



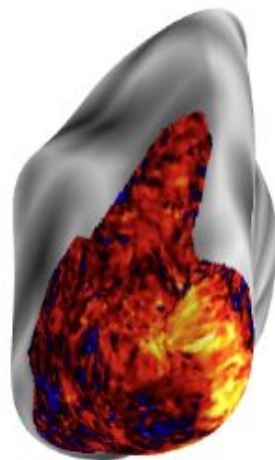
Lateral view



Ventral view



Occipital view



Medial view

