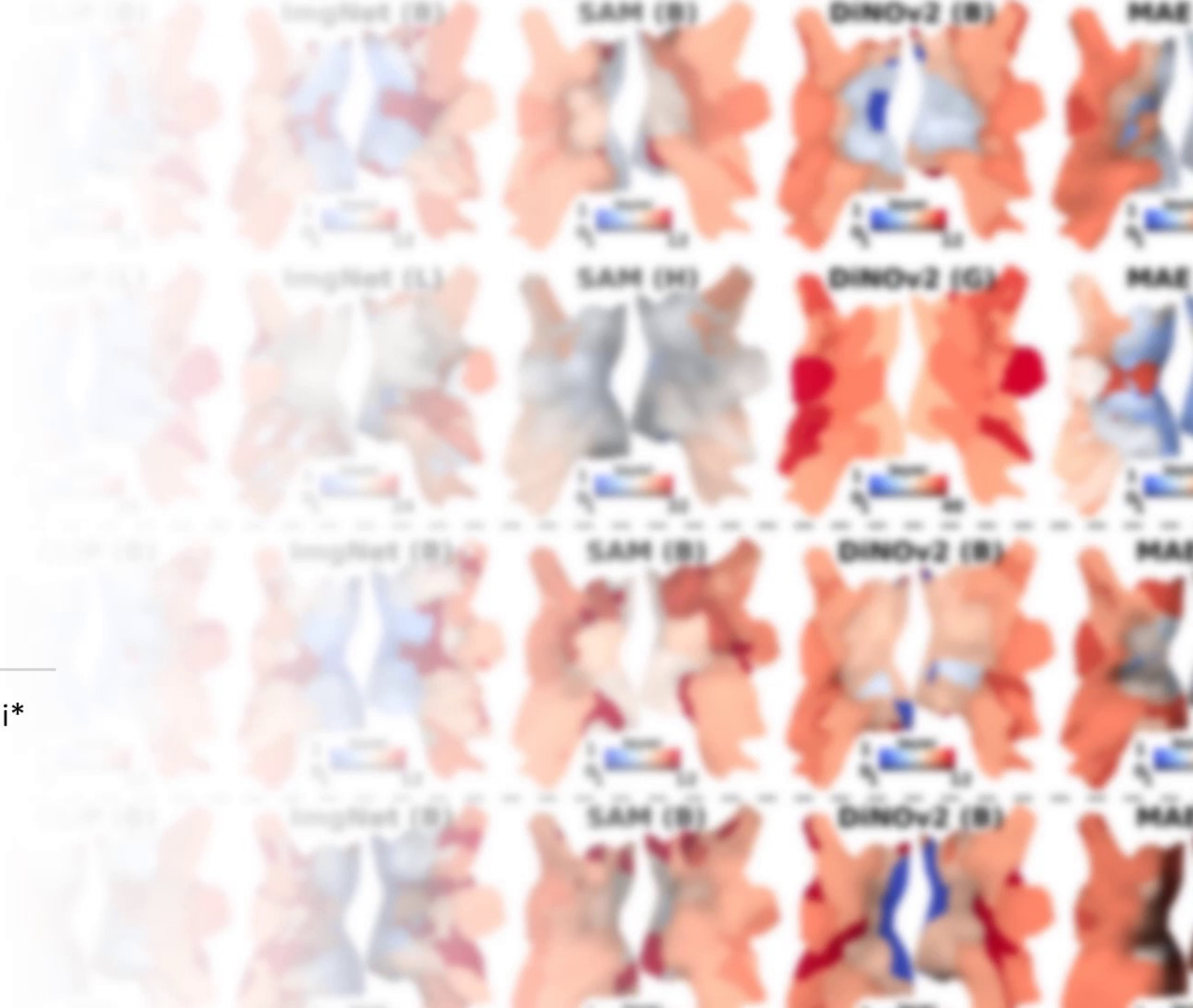
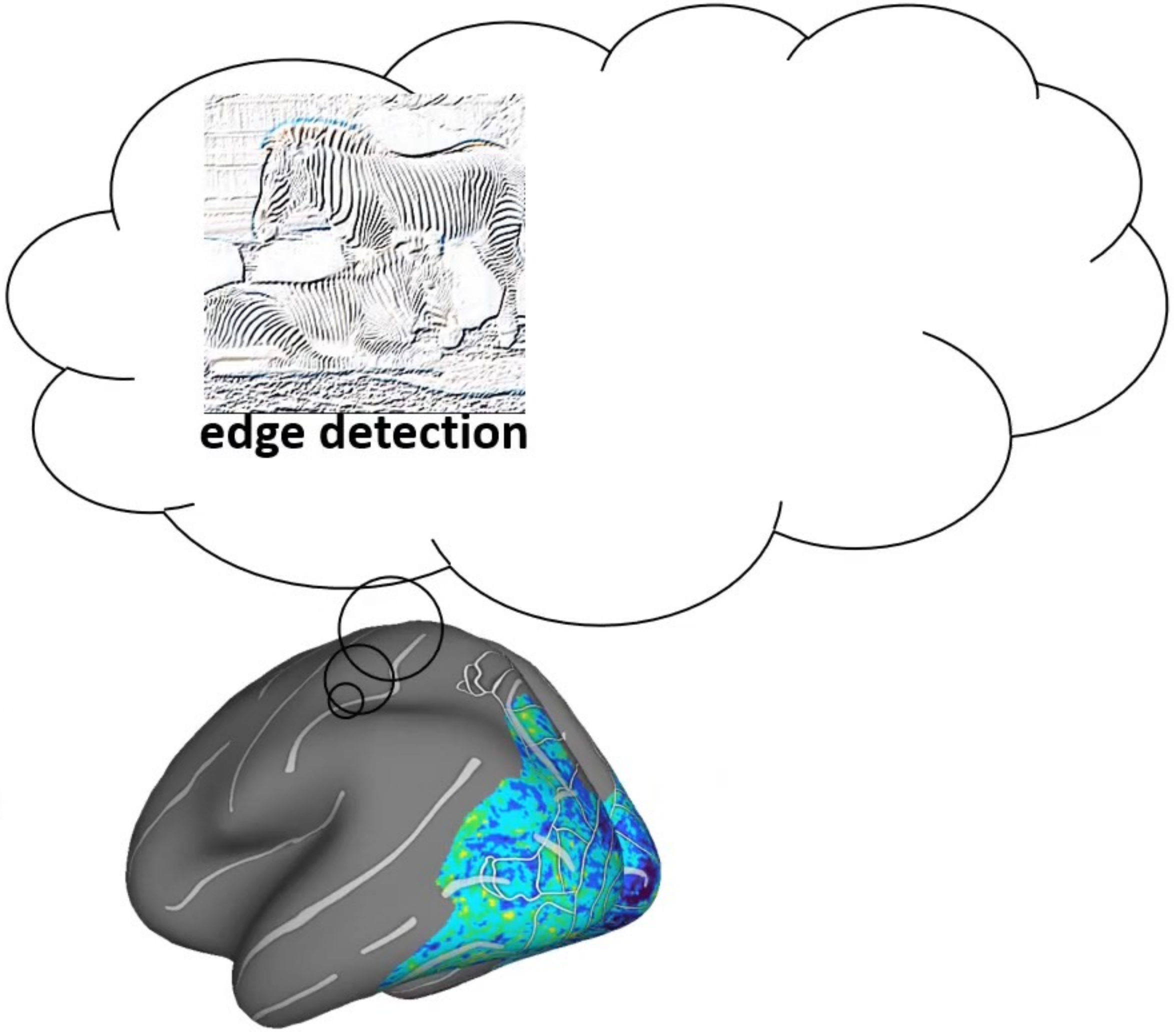
Brain Decodes Deep Nets

Huzheng Yang, James Gee*, Jianbo Shi*
University of Pennsylvania

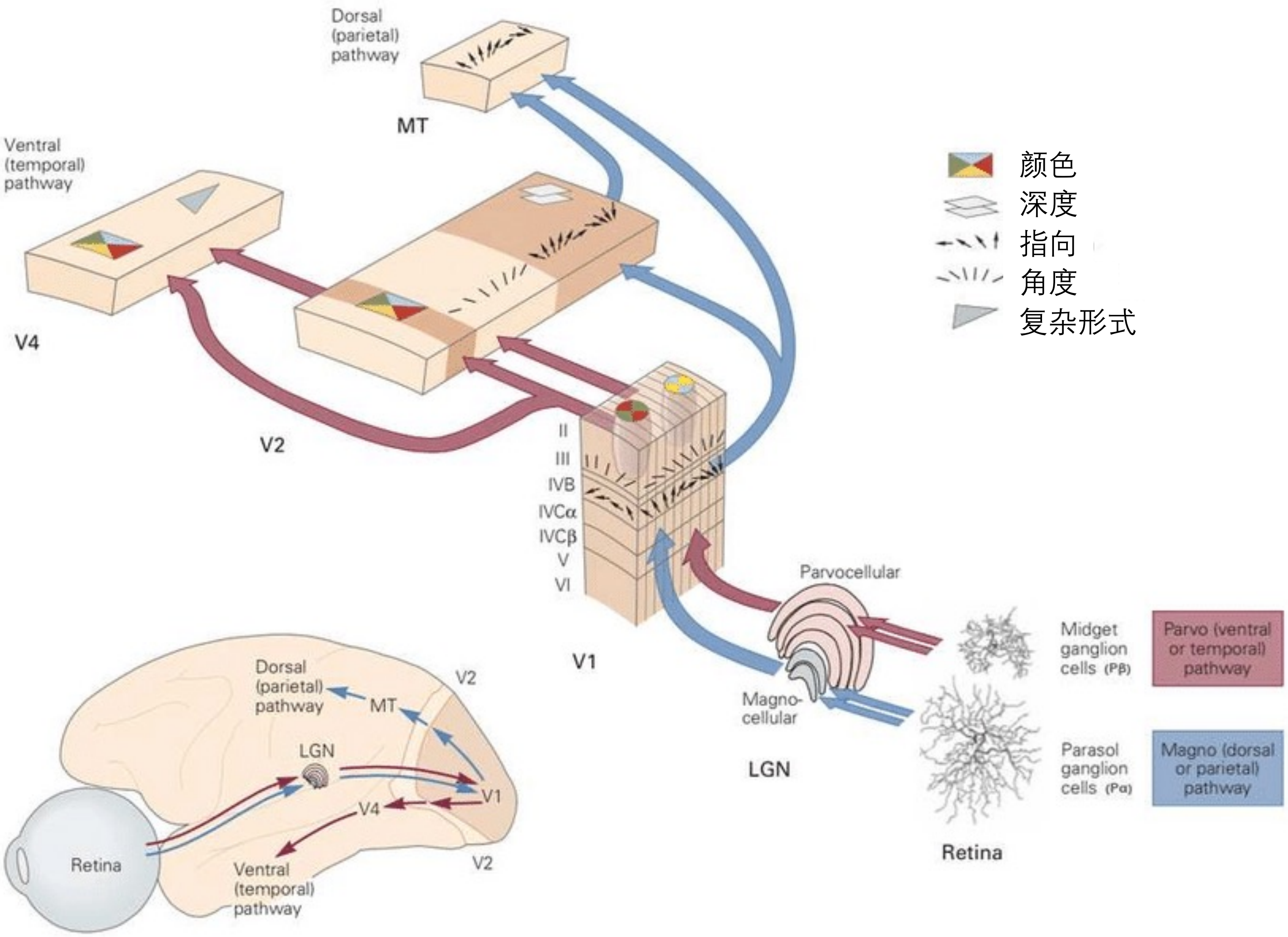


Brain is *multi-tasking*

Input image



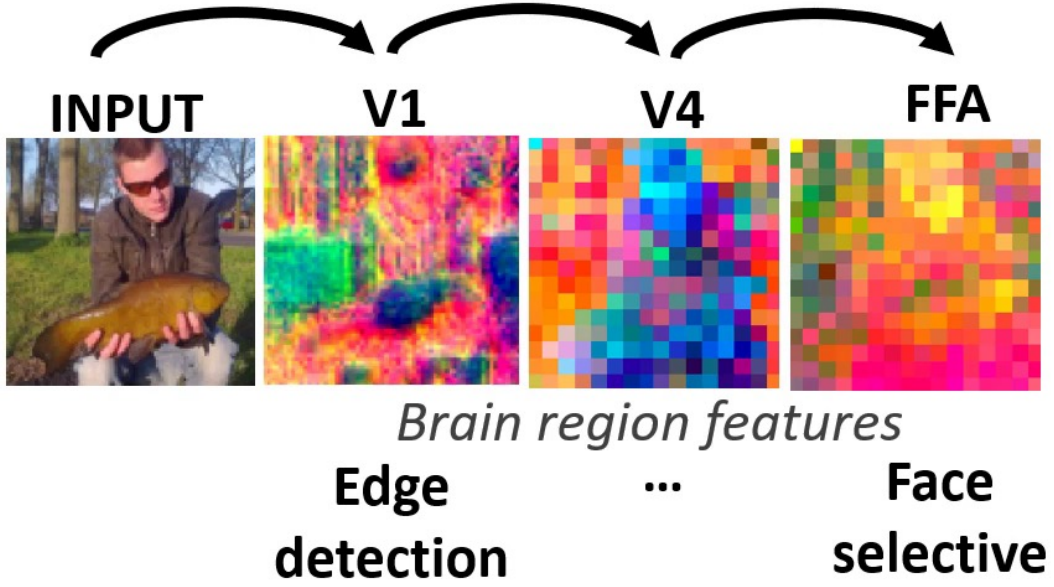
Brain

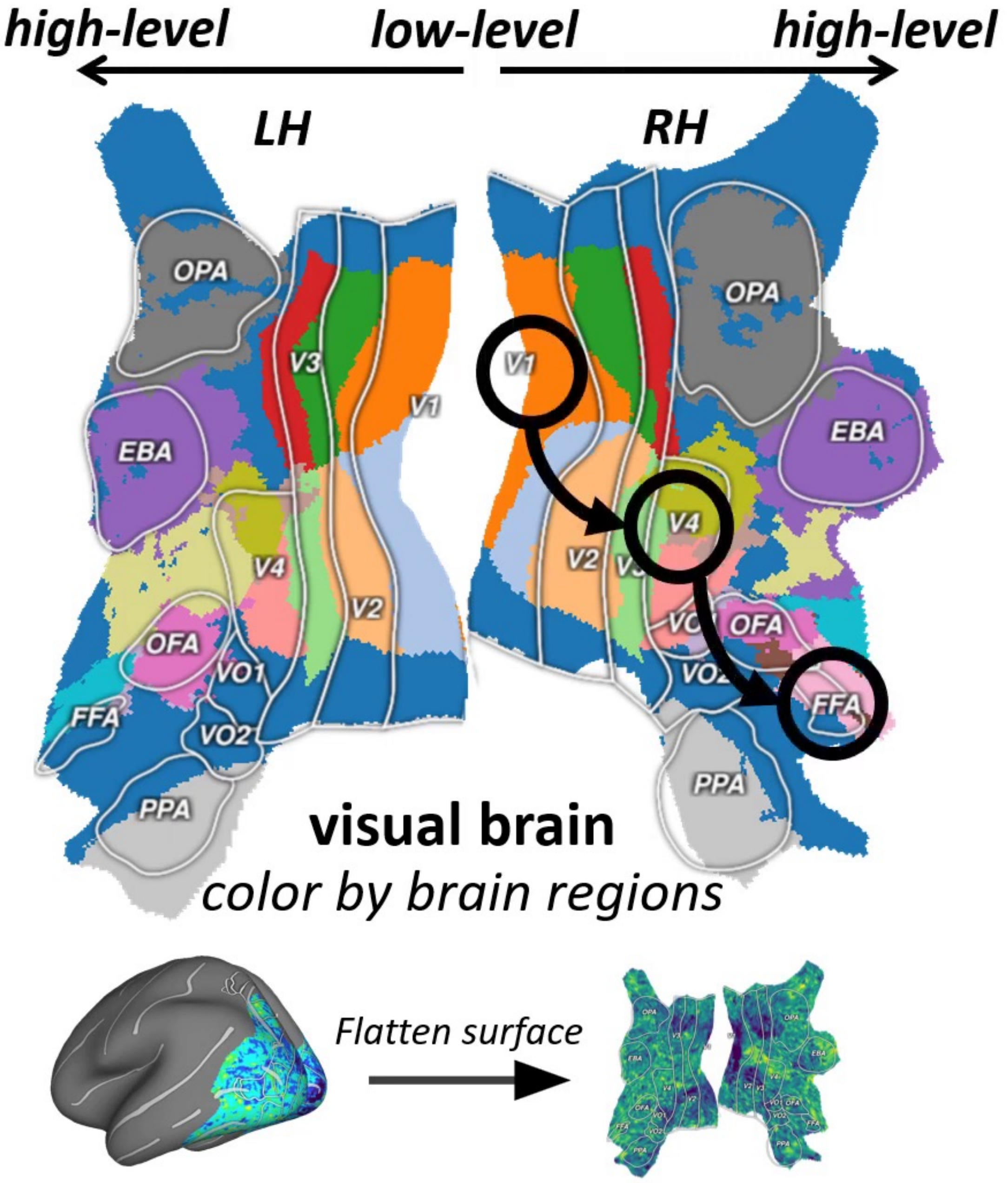


Dorsal
(parietal)
pathway
MT
Ventral
(temporal)
pathway
V4
V2
II
III
IVB
IVCα
IVCβ
V
VI
V1
Parvocellular
Magno-
cellular
LGN
Midget
ganglion
cells (Pβ)
Parvo (ventral
or temporal)
pathway
Parasol
ganglion
cells (Pα)
Magno (dorsal
or parietal)
pathway
Retina
Dorsal
(parietal)
pathway
MT
V2
LGN
V1
V4
Retina
Ventral
(temporal)
pathway
V2
颜色
深度
指向
角度
复杂形式

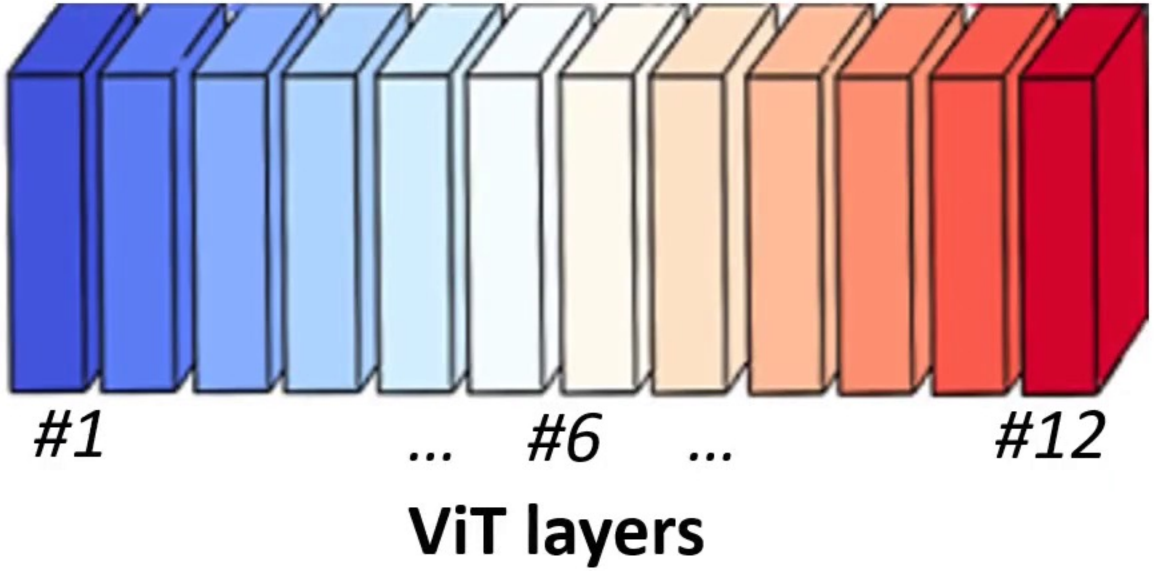
Brain is ***multi-tasking***

Brain is ***hierarchical***

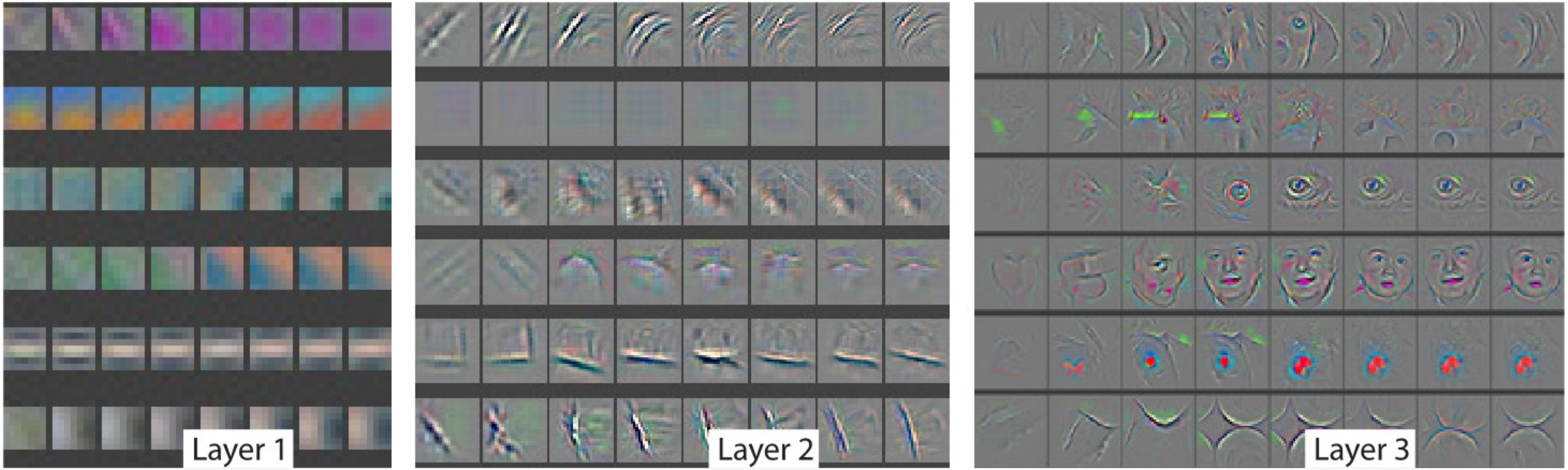




How does ***deep-net*** *compute features over layers?*

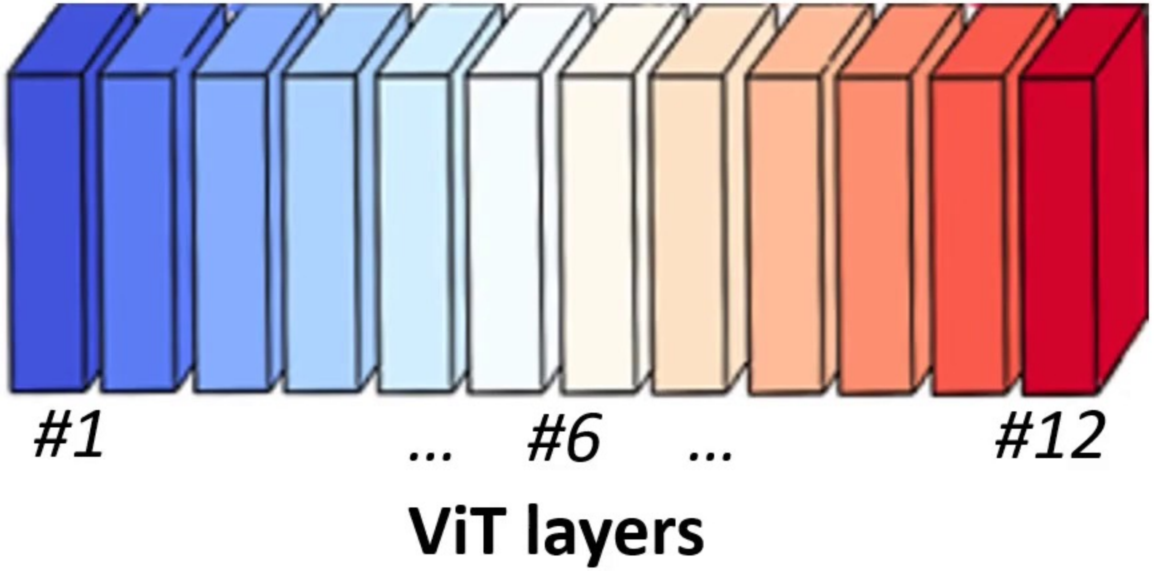


CNN feature map visulization

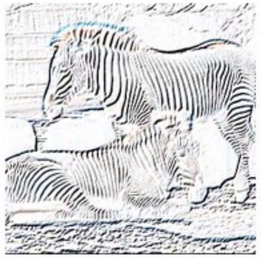


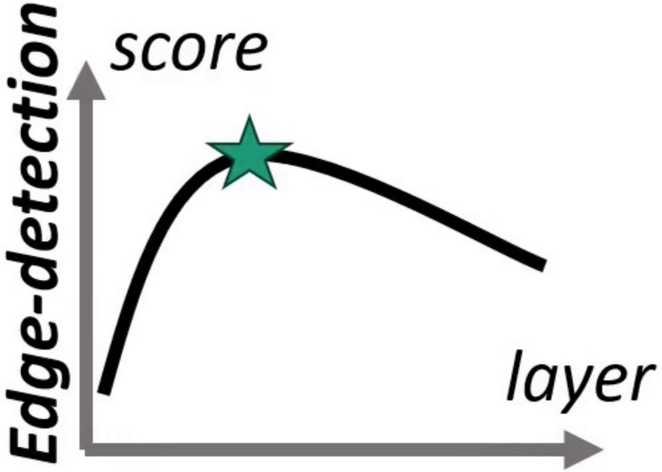
Which layer (ViT) best predict <u>each task?</u>

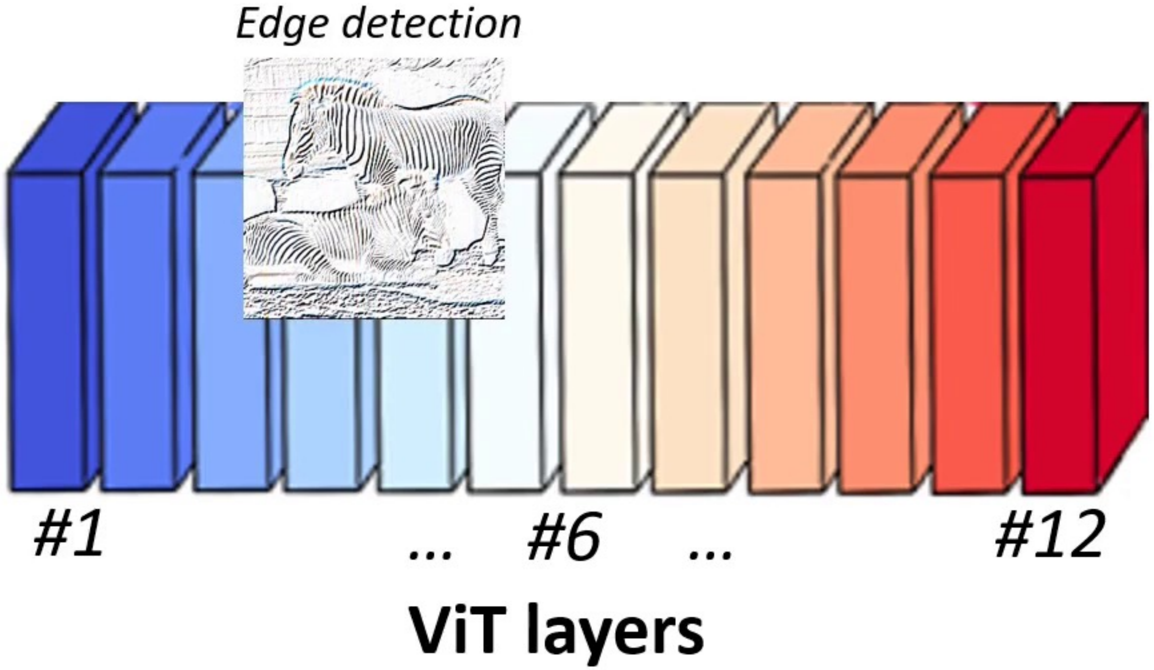
How about linear probing?



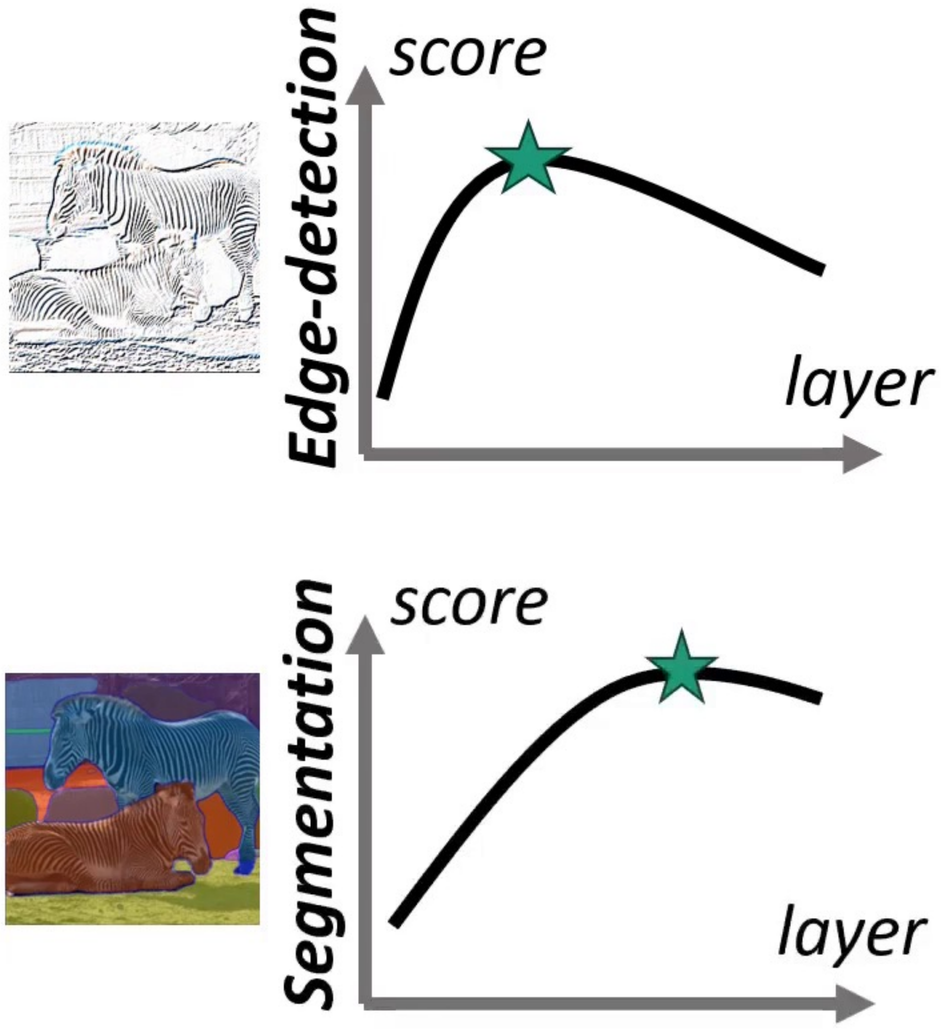
Which layer (ViT) best predict <u>each task?</u>

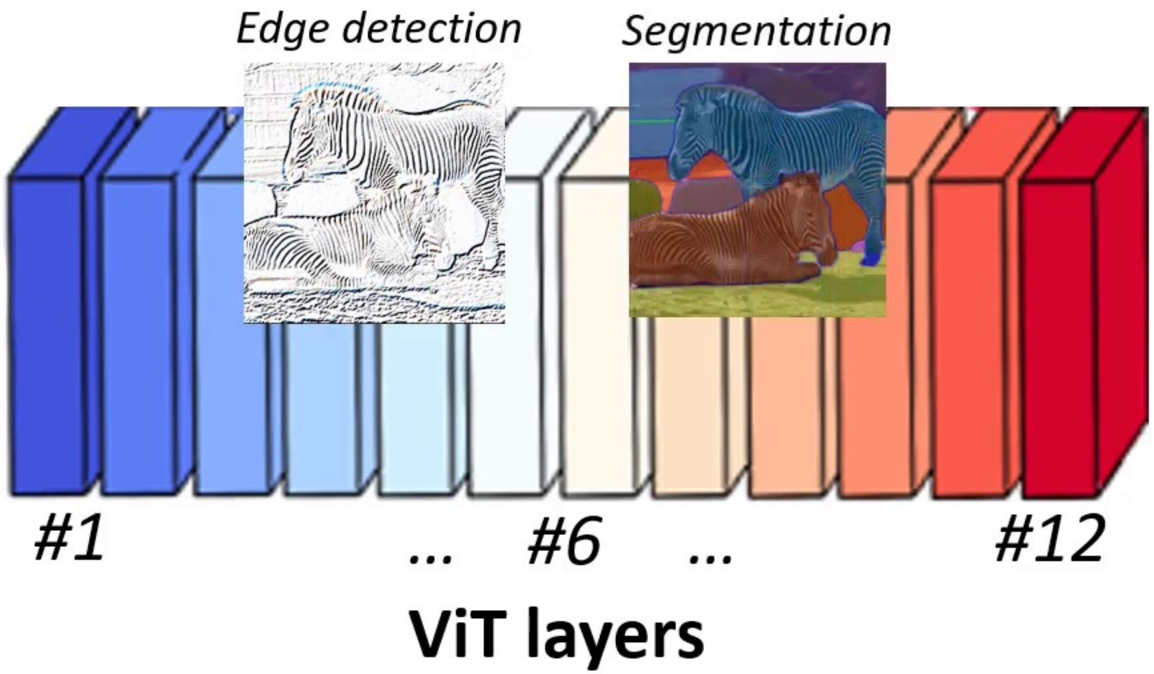






Which layer (ViT) best predict each task?





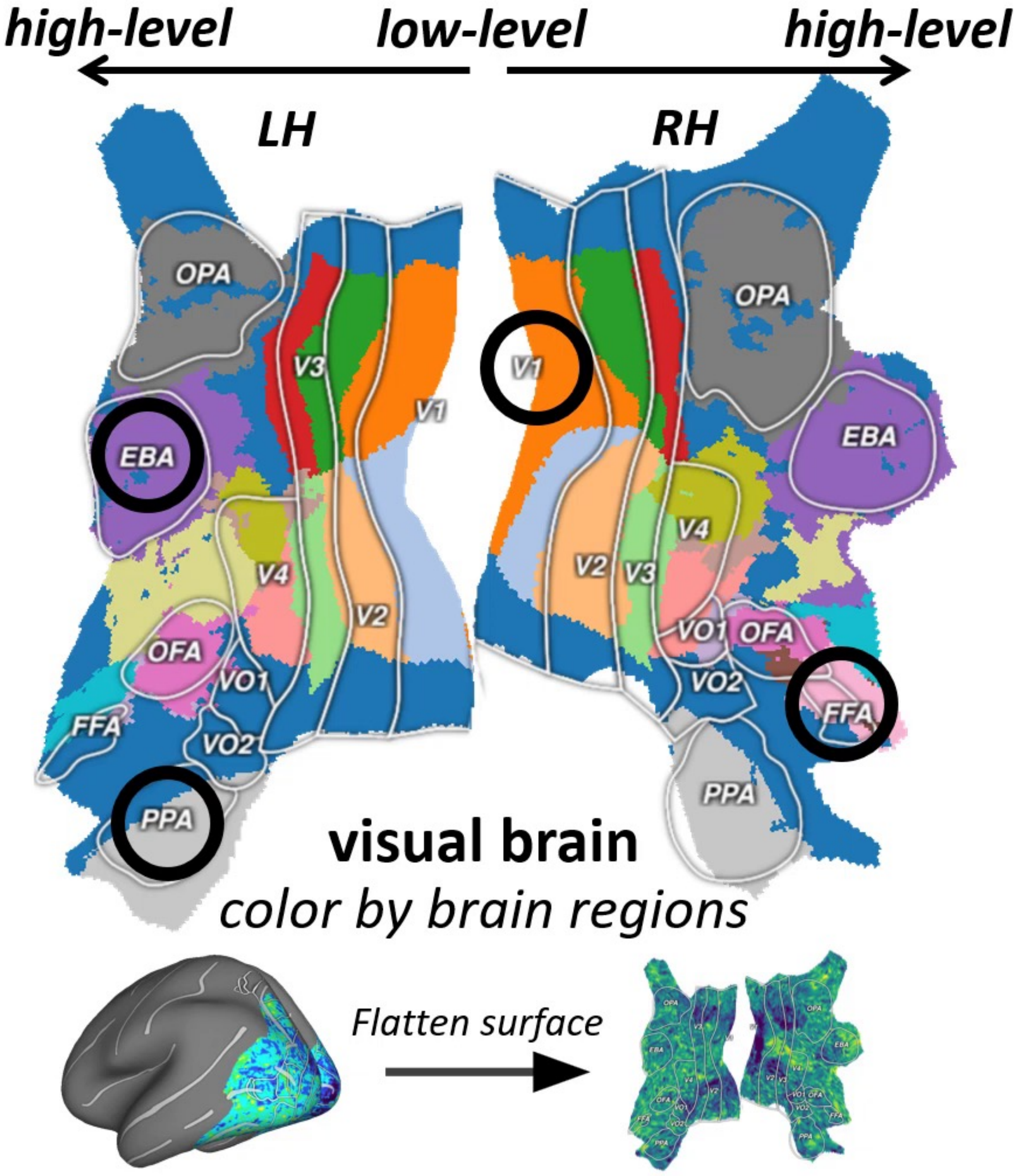
Each brain voxel is a task

V1: *edge-detection*

EBA: *body-selective*

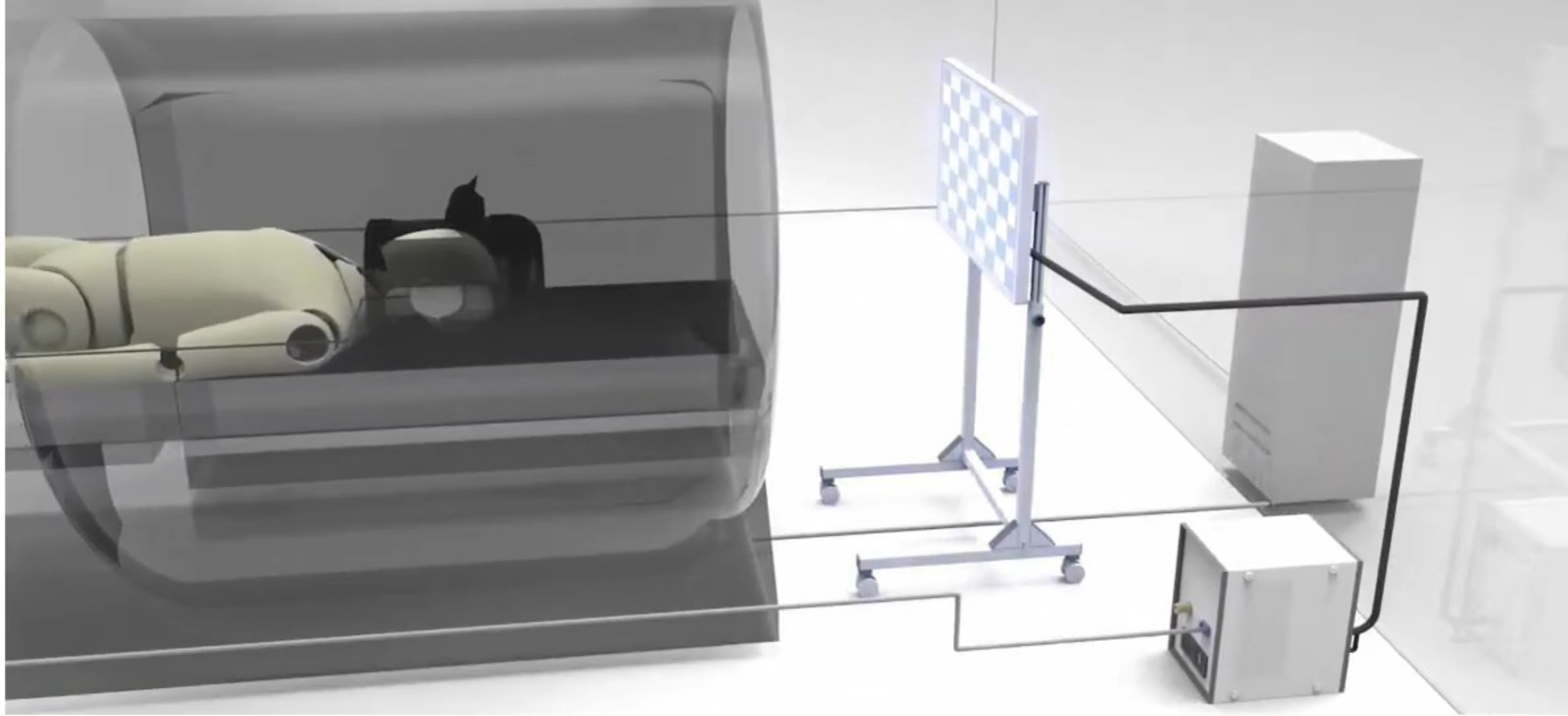
FFA: *face-selective*

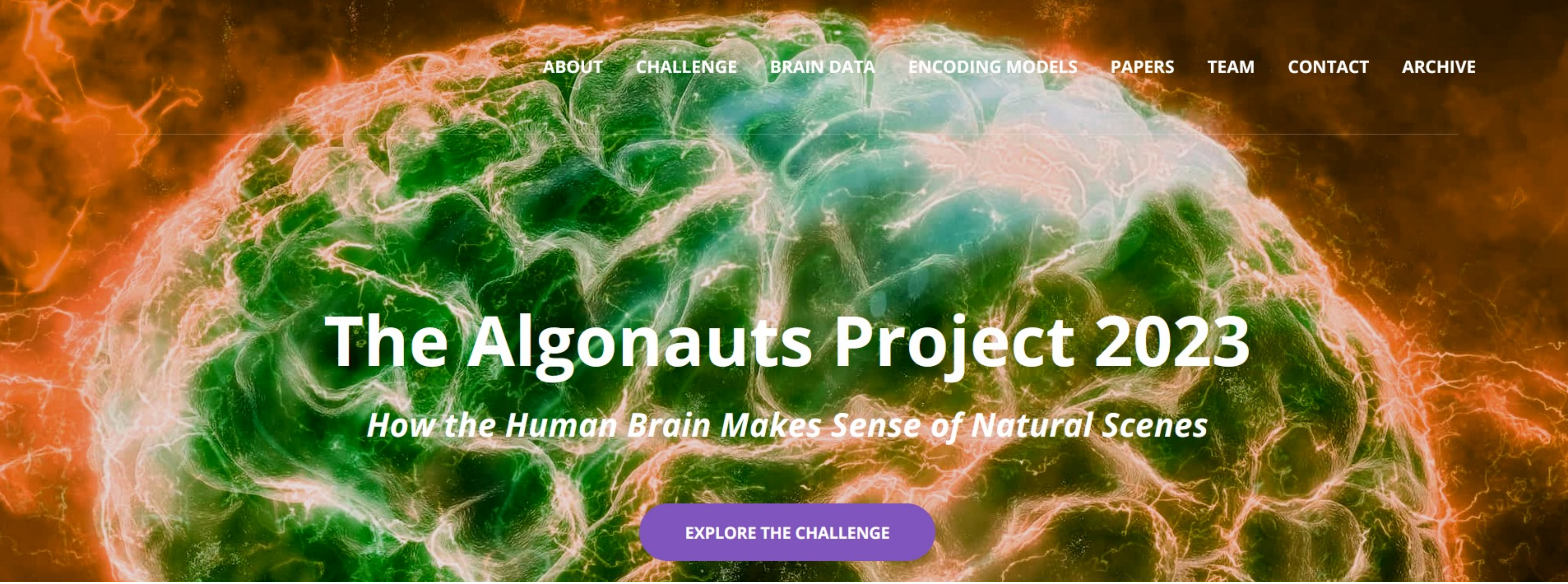
PPA: *place-selective*



Dataset

http://algonauts.csail.mit.edu/



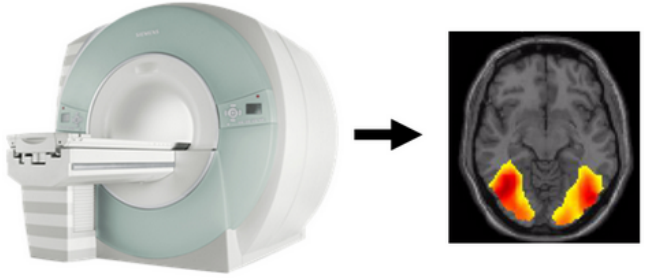


ABOUT CHALLENGE BRAIN DATA ENCODING MODELS PAPERS TEAM CONTACT ARCHIVE

The Algonauts Project 2023

How the Human Brain Makes Sense of Natural Scenes

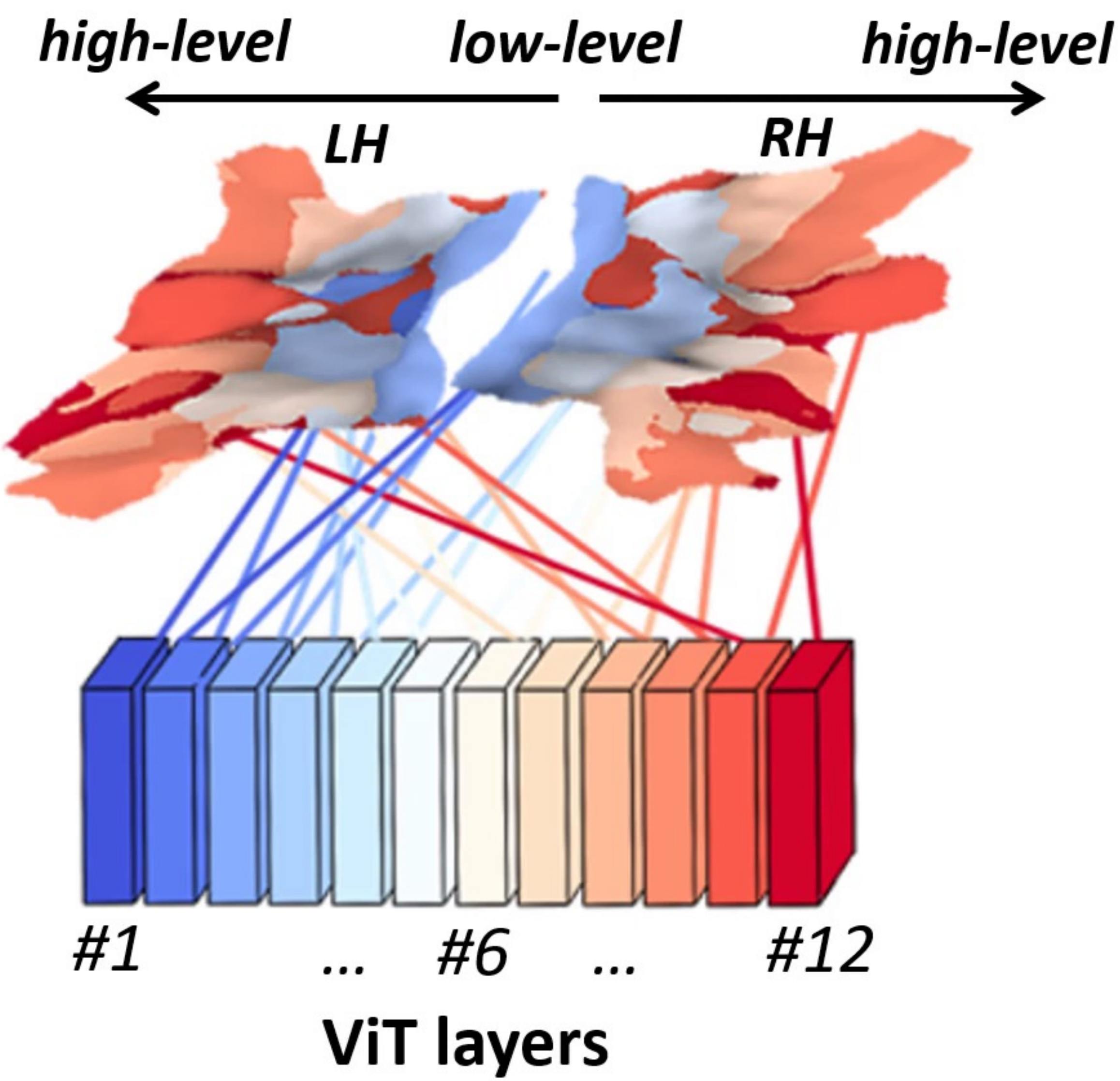
EXPLORE THE CHALLENGE

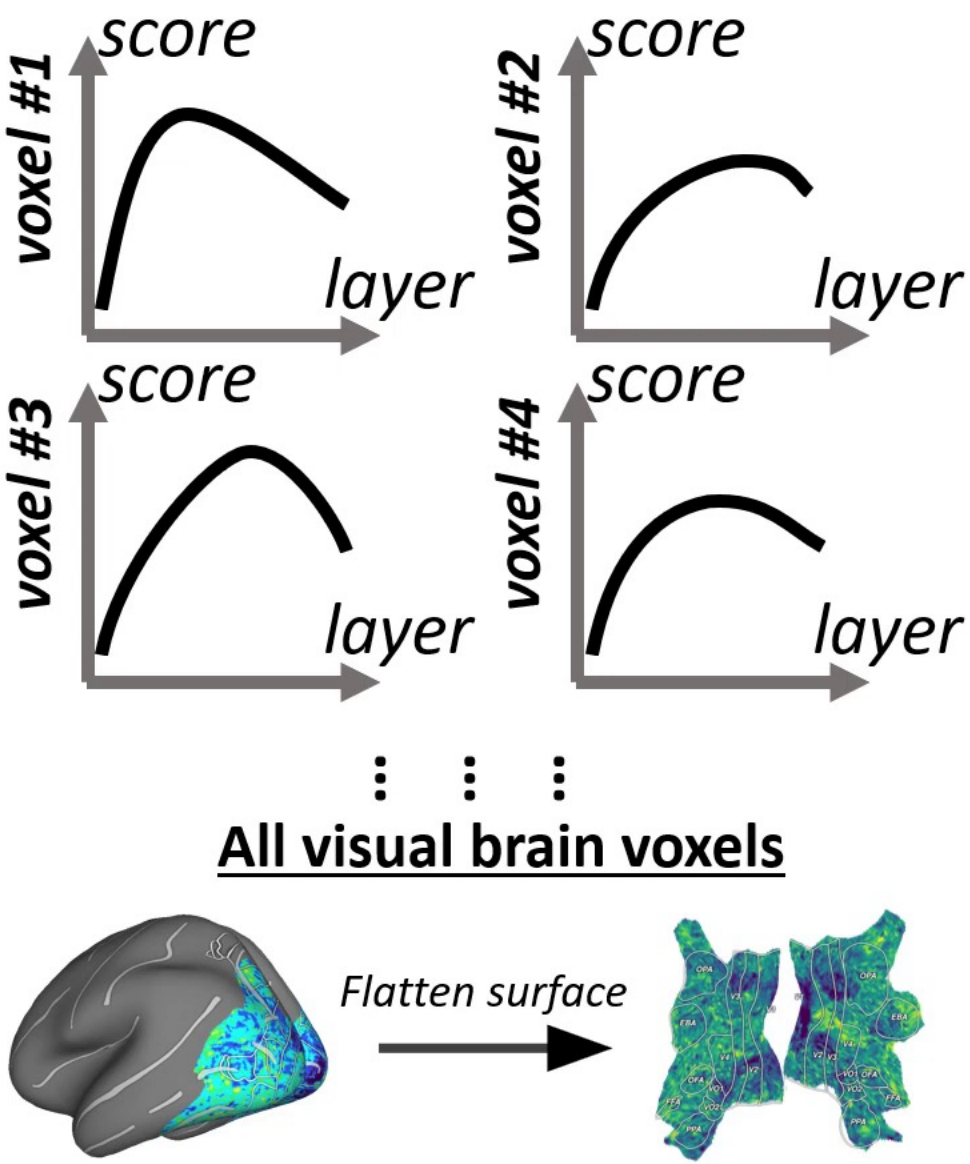


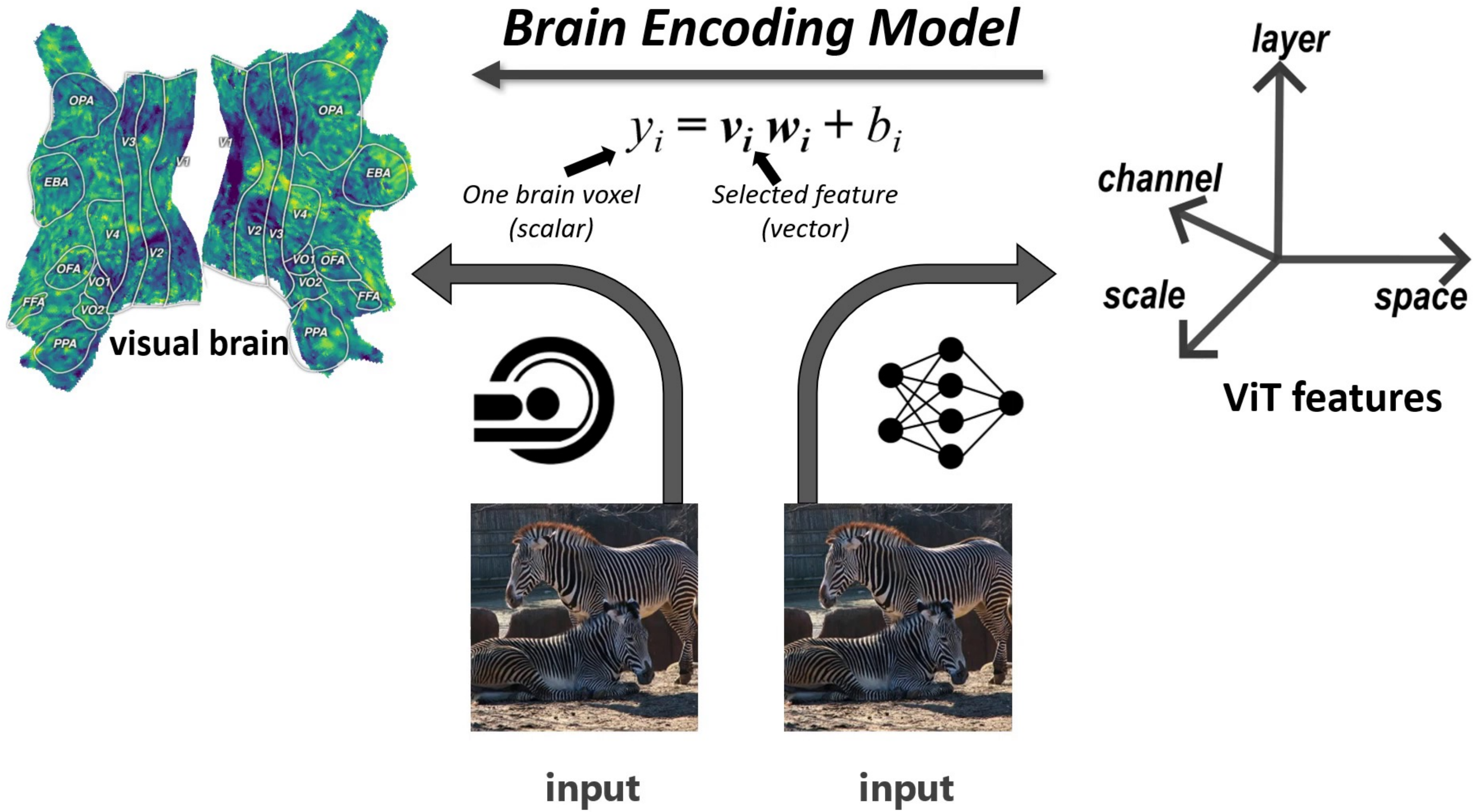
Brain Response Measurement: fMRI

We provide measurements of brain responses using the technique of functional magnetic resonance imaging (fMRI) for millimeter spatial resolution. This technique measures brain activity indirectly by detecting changes in blood flow associated with brain activity. fMRI is a core technique in cognitive neuroscience to observe the human brain in action noninvasively.

Which layer (ViT) best predict <u>each brain voxel?</u>

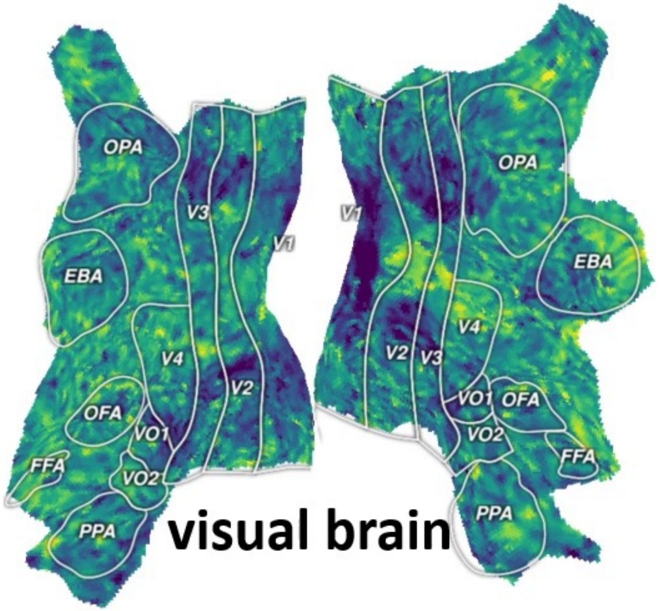






Brain Encoding Model
$y_i = v_i w_i + b_i$
One brain voxel
(scalar)
Selected feature
(vector)
OPA
V3
V1
EBA
V4
OFA
VO1
V2
FFA
VO2
PPA
visual brain
layer
channel
scale
space
ViT features
input
input

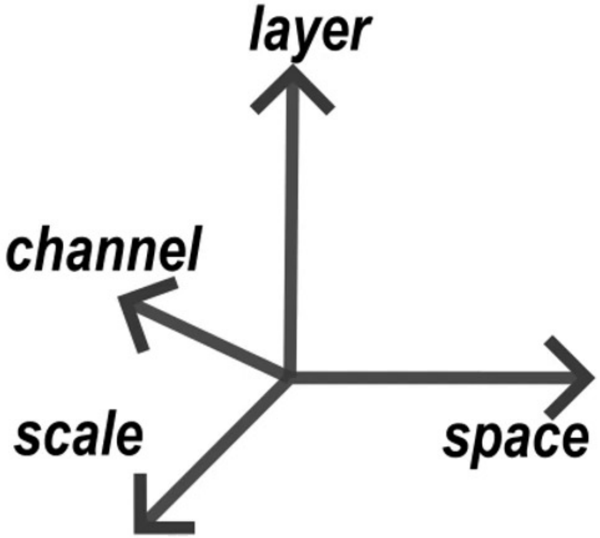
Brain Encoding Model



$$y_i = \boldsymbol{v_i}\, \boldsymbol{w_i} + b_i$$

One brain voxel (scalar)

Selected feature (vector)



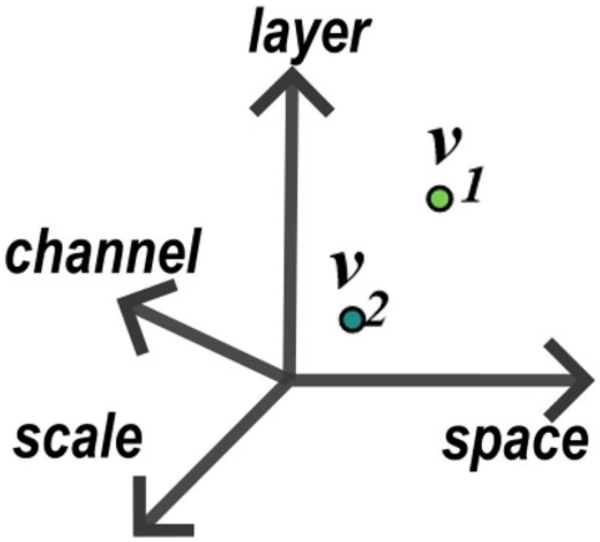
HxW: space

C: channels

Select: TO reduce **[L x (HxW+1) x C]** feature to $\boldsymbol{v_i}$ **[1 x C]**

L: layers

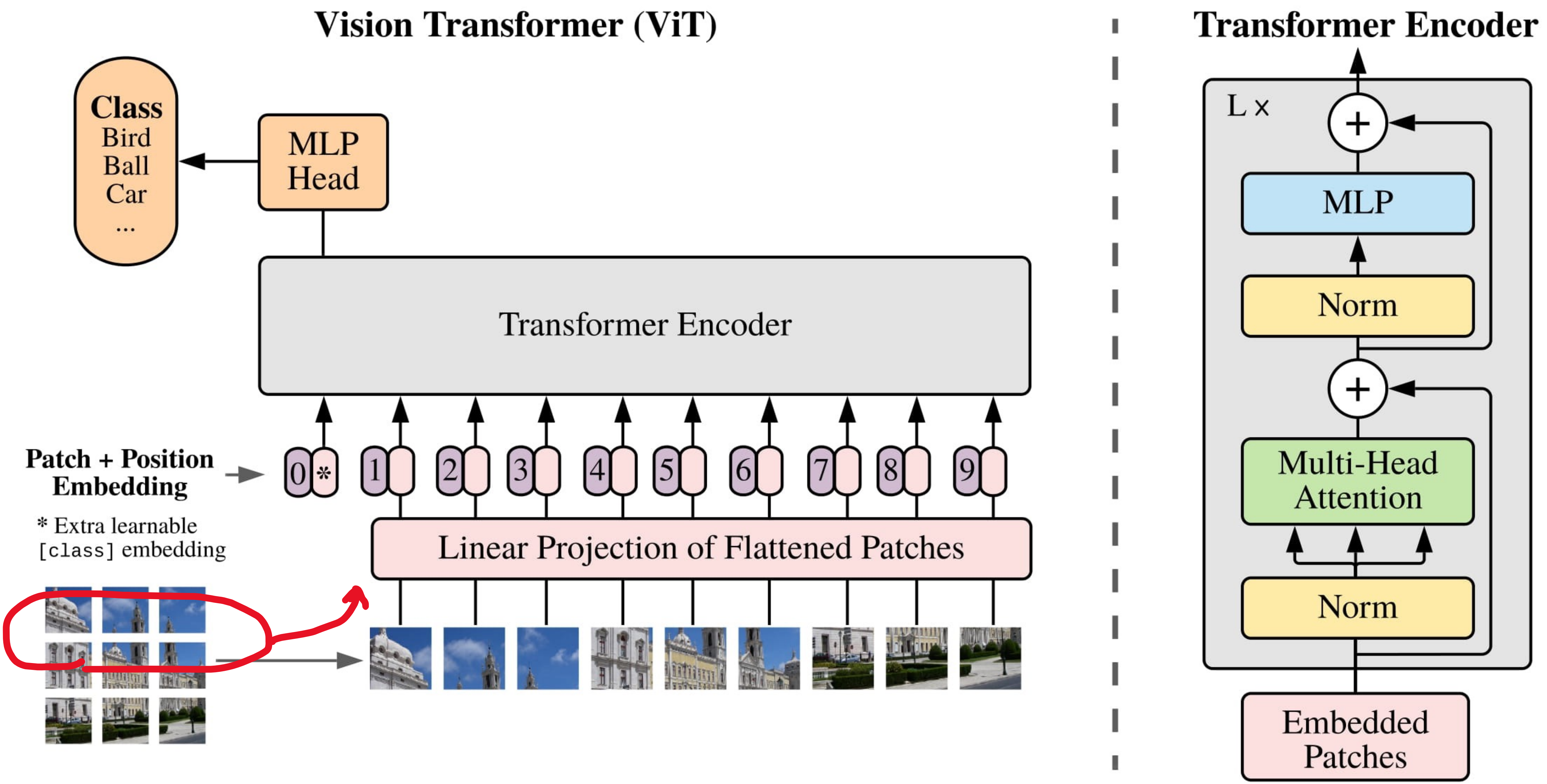
1: scale ([CLS] token)

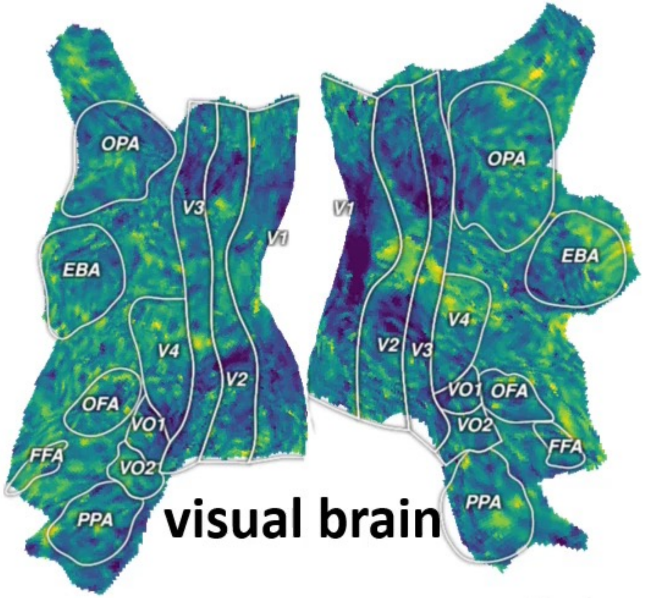


ViT features

During training, <u>each voxel</u> learn an "index" on:

- Layer: weighted sum (softmax) over L layers
- Space: bilinear interpolation at (x, y)
- Scale: weighted sum of space/[CLS]
- Channel: keep all


Vision Transformer (ViT)
Transformer Encoder
Class
Bird
Ball
Car
...
MLP Head
Transformer Encoder
Patch + Position Embedding
* Extra learnable [class] embedding
0 * 1 2 3 4 5 6 7 8 9
Linear Projection of Flattened Patches
L x
MLP
Norm
Multi-Head Attention
Norm
Embedded Patches

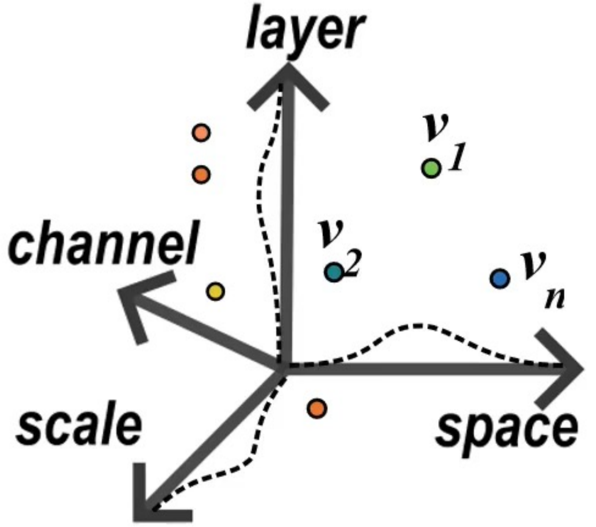


Brain Encoding Model

$$y_i = \boldsymbol{v}_i \boldsymbol{w}_i + b_i$$

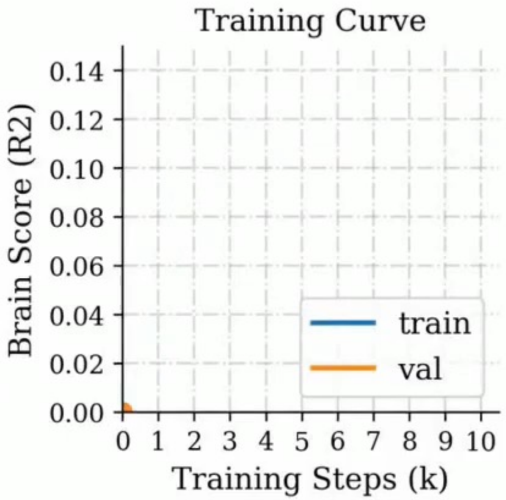
One brain voxel (scalar)

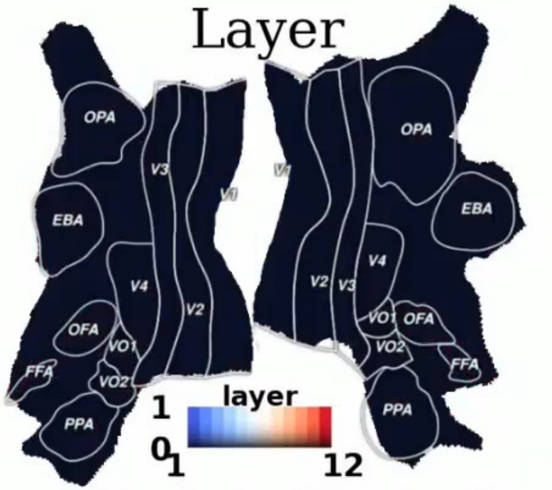
Selected feature (vector)



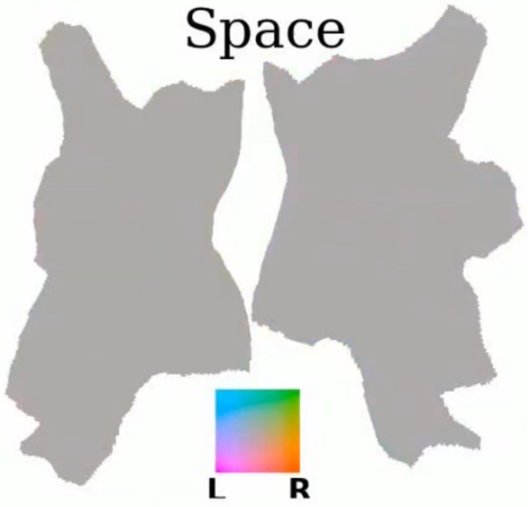
ViT features

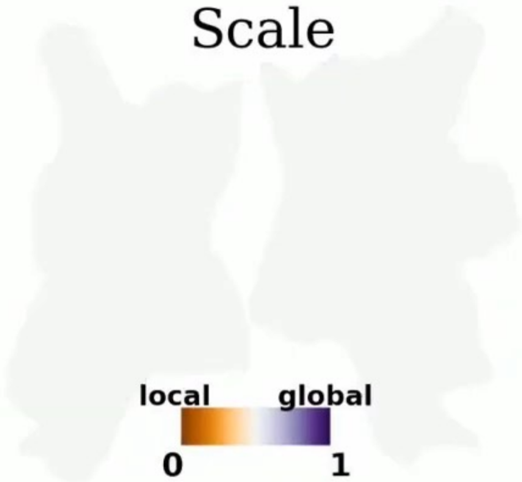
Selection pattern automatically emerges over training
(w/o prior knowledge on selection!)





black: 'soft' selection





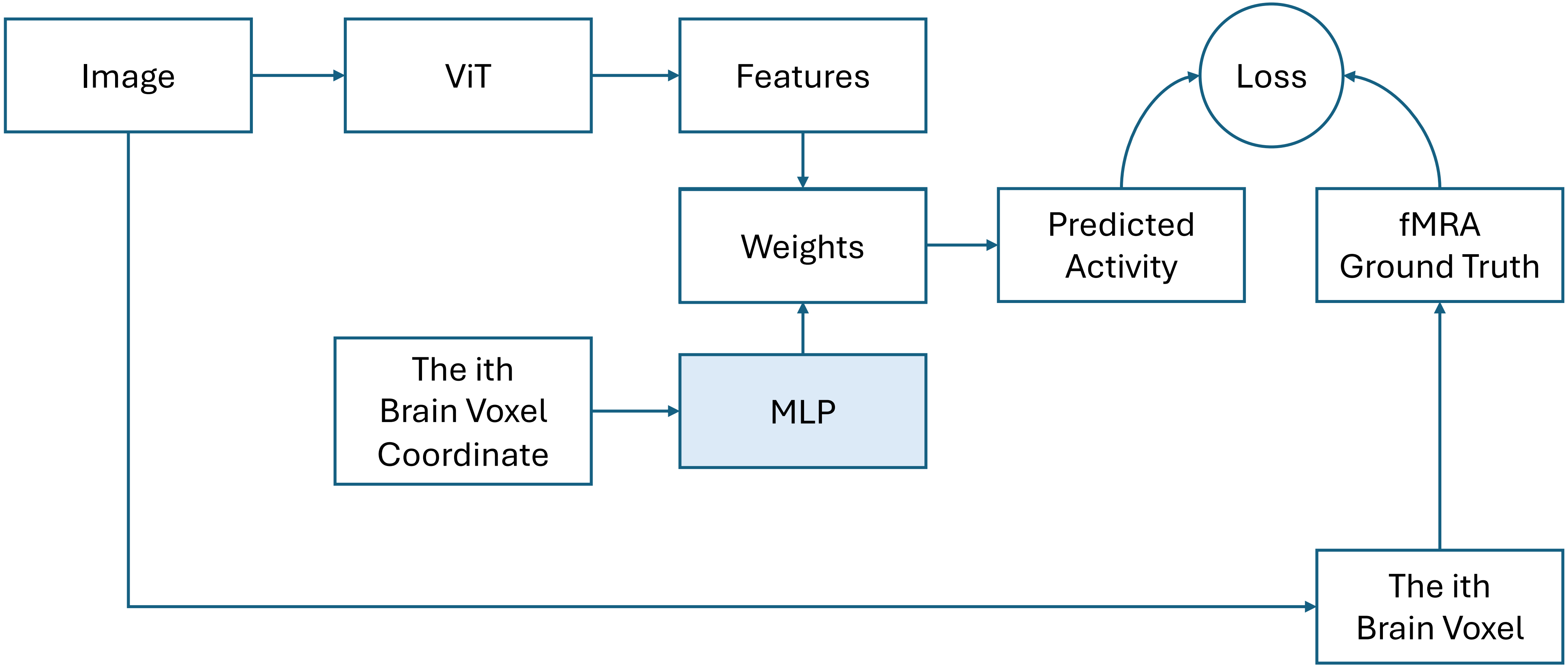
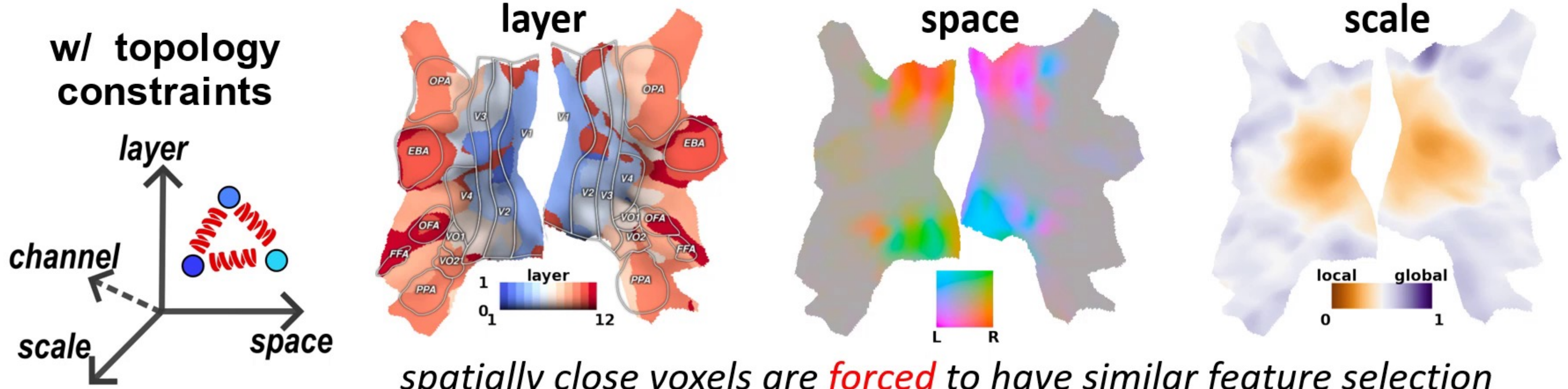
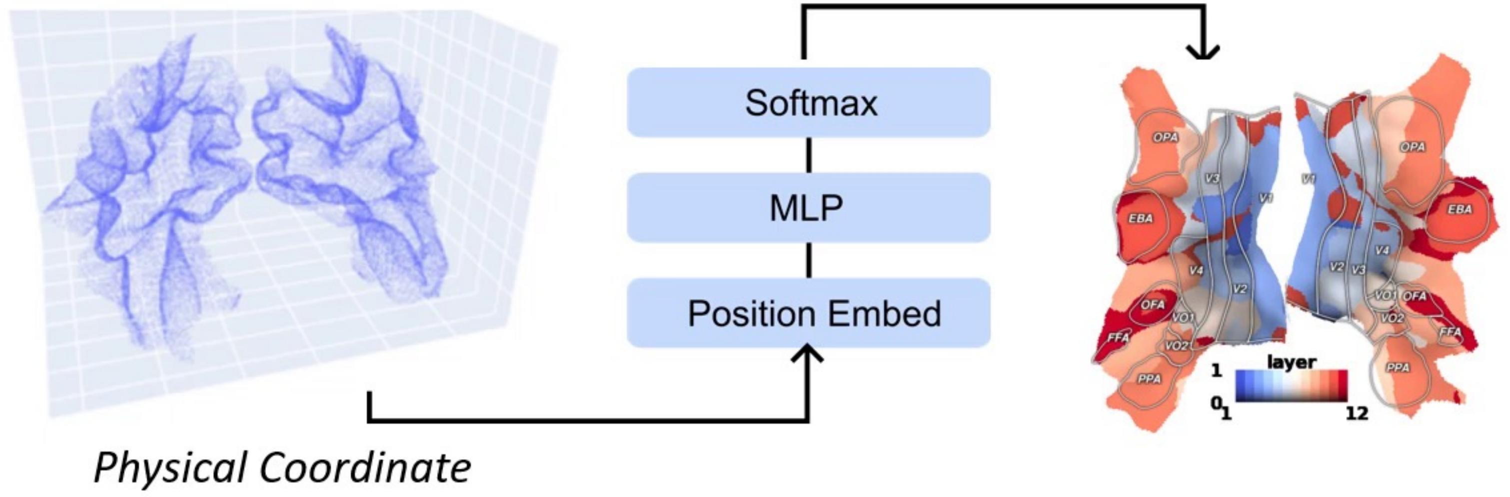


Image
ViT
Features
Loss
Weights
Predicted Activity
fMRA Ground Truth
The ith Brain Voxel Coordinate
MLP
The ith Brain Voxel

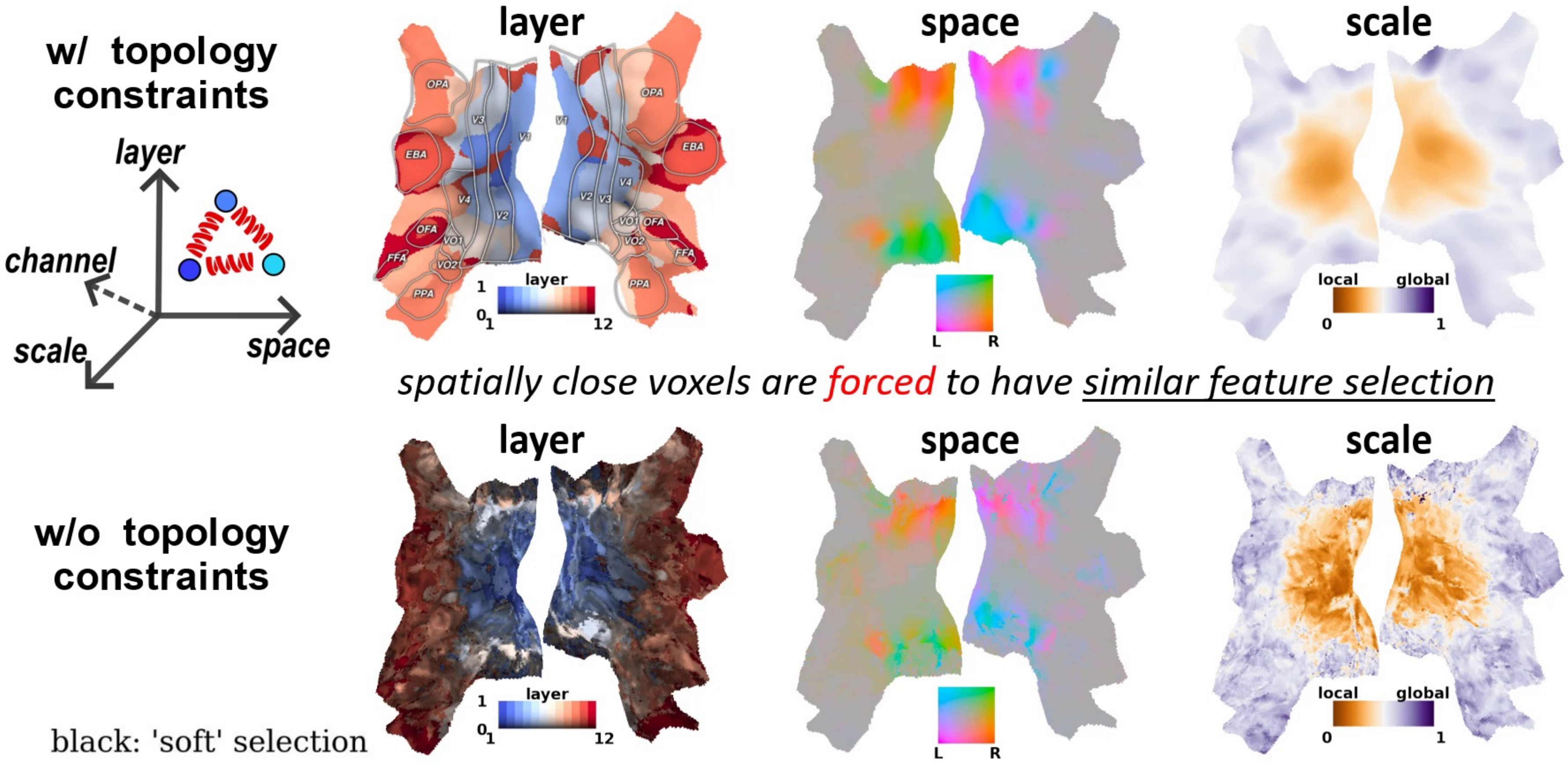
Topological smooth: *voxels are not independent*



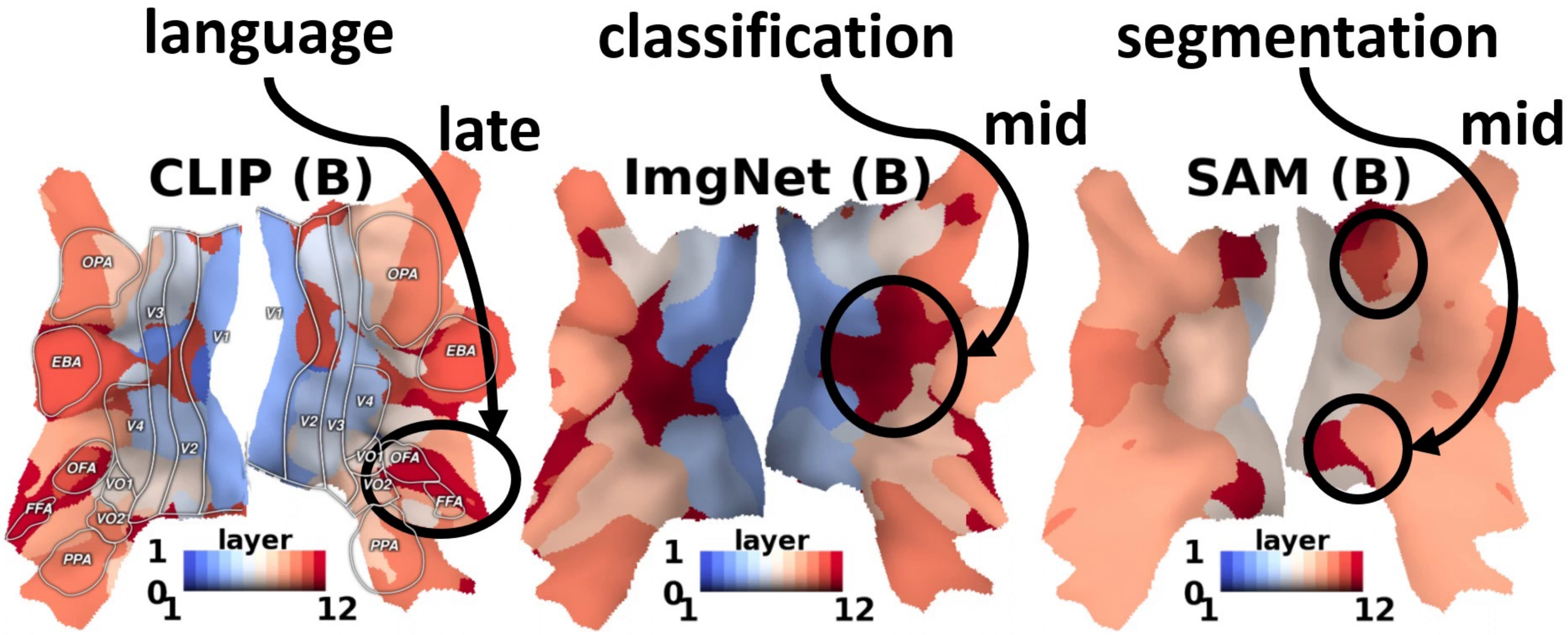
spatially close voxels are forced to have similar feature selection



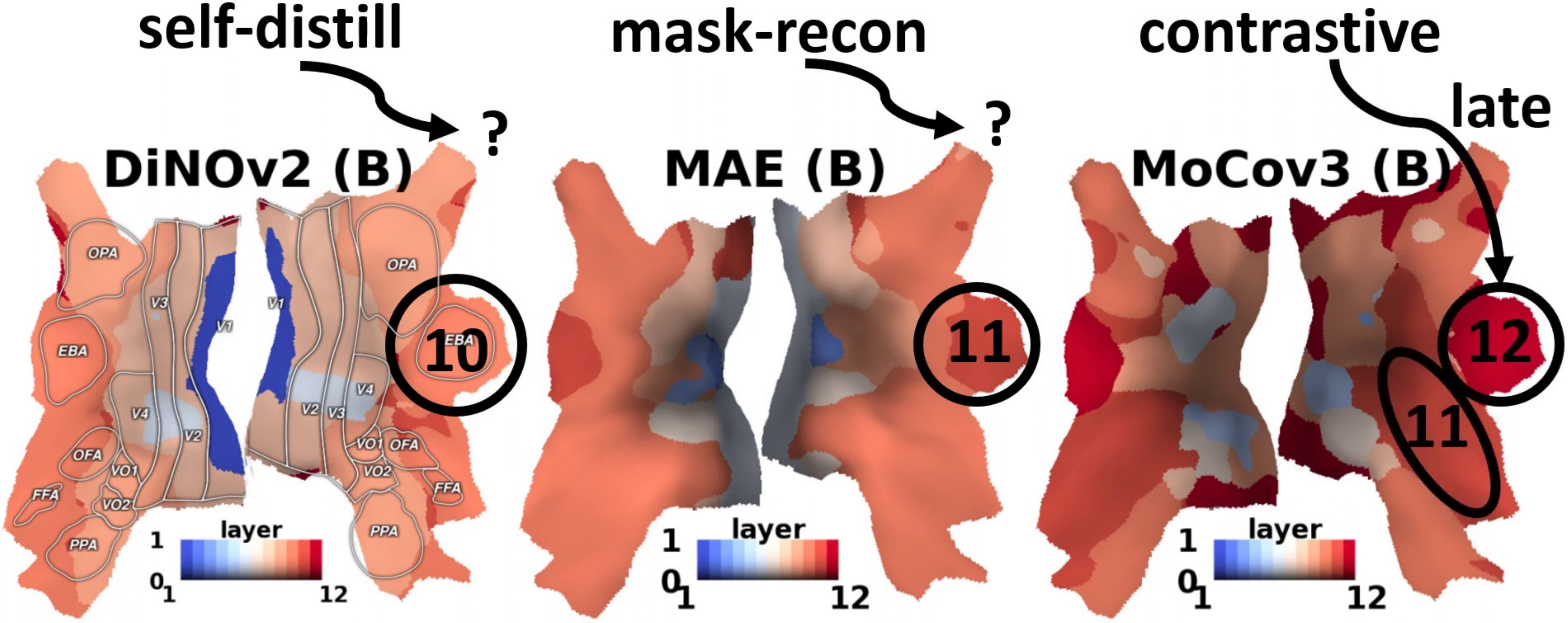
Topological smooth: *voxels are not independent*



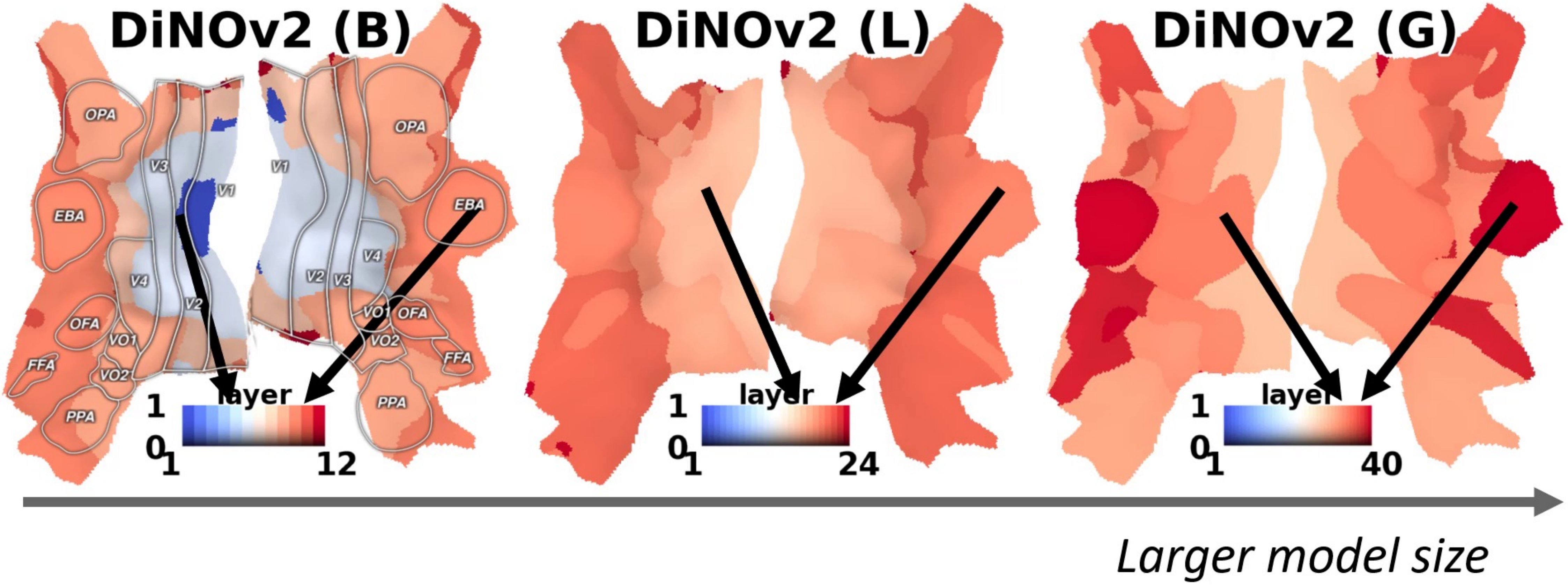
ViT supervised models



ViT un-supervised models

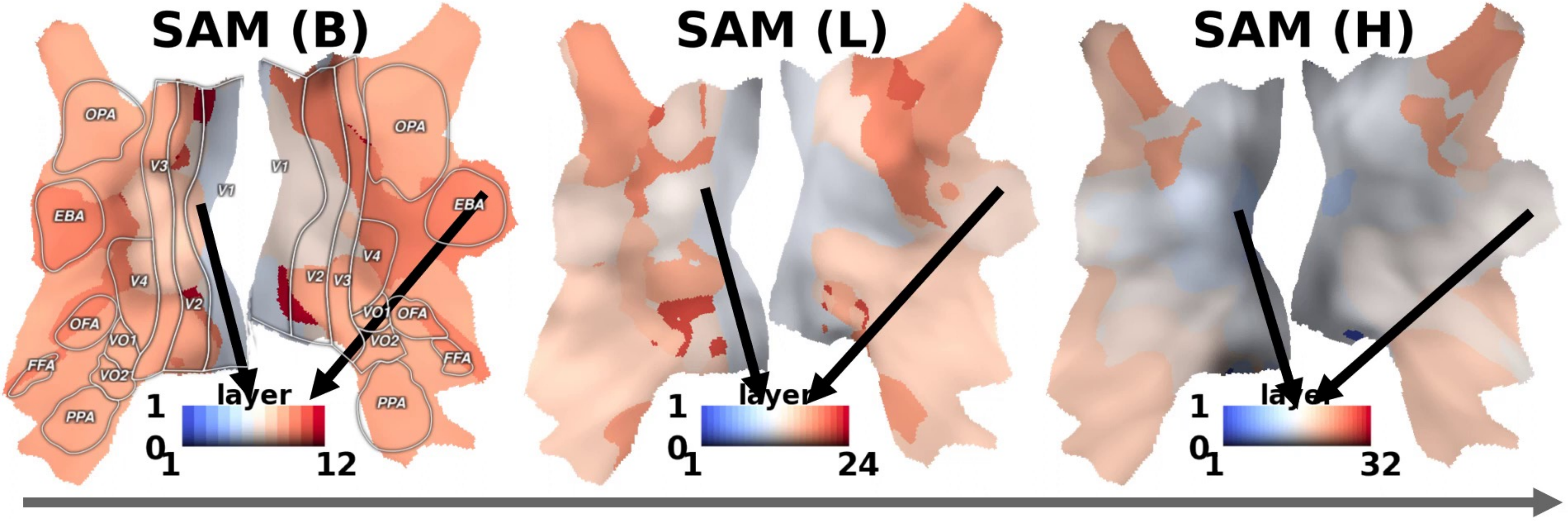


Low level misalignment with increased model size



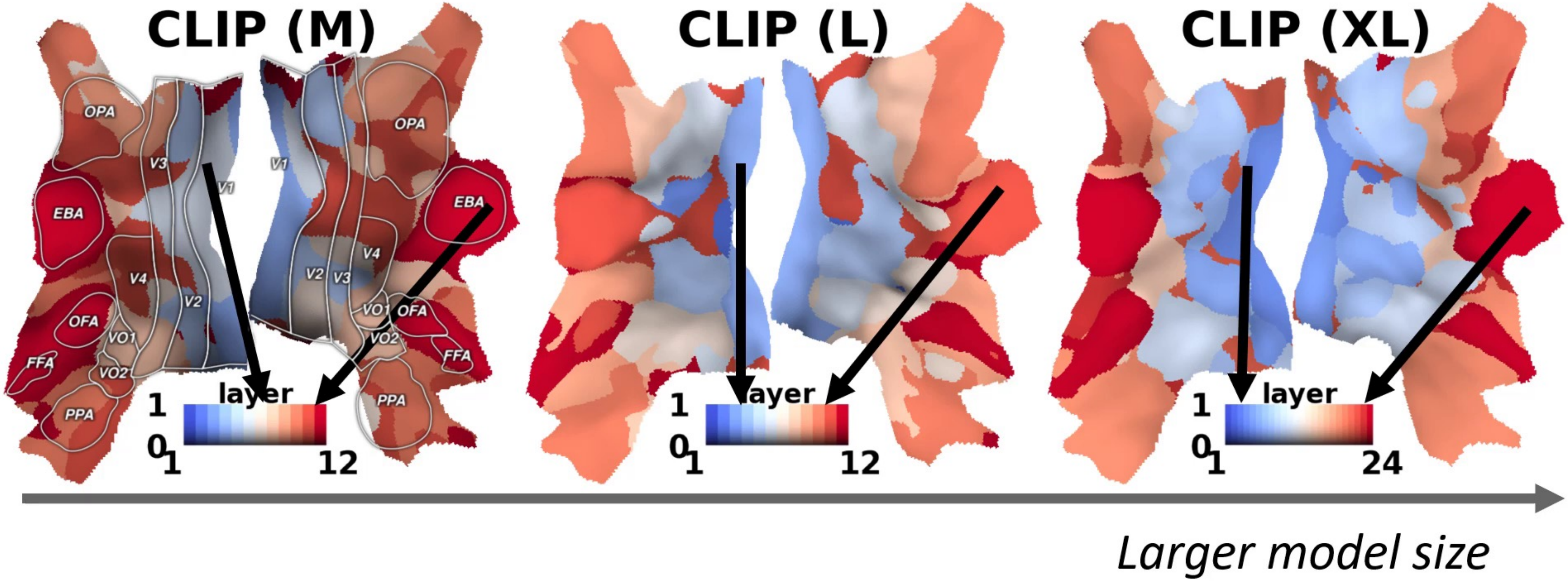
SAM larger model = worse ``brain-alignment''

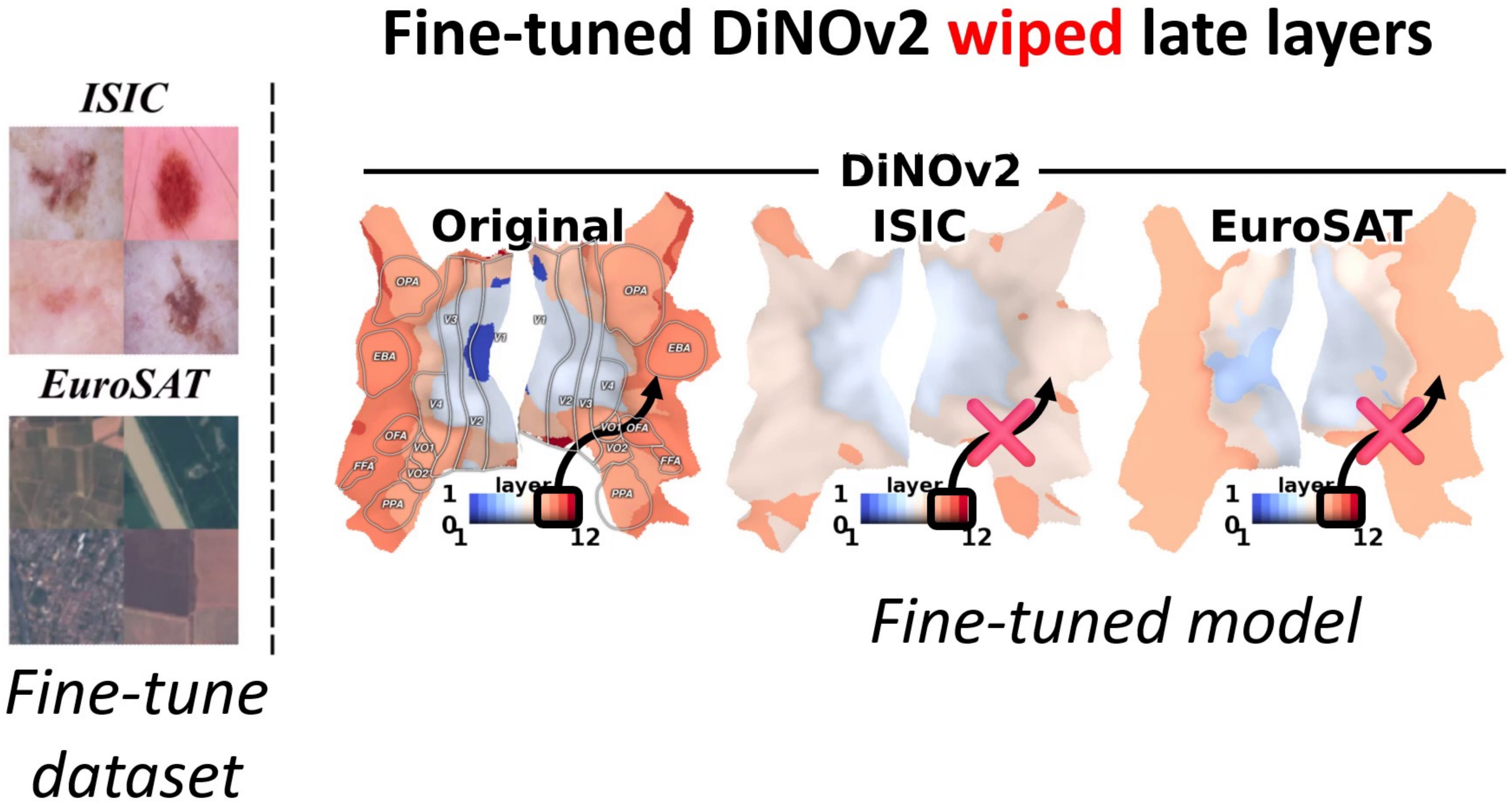
Issue: late layers misalign with the brain



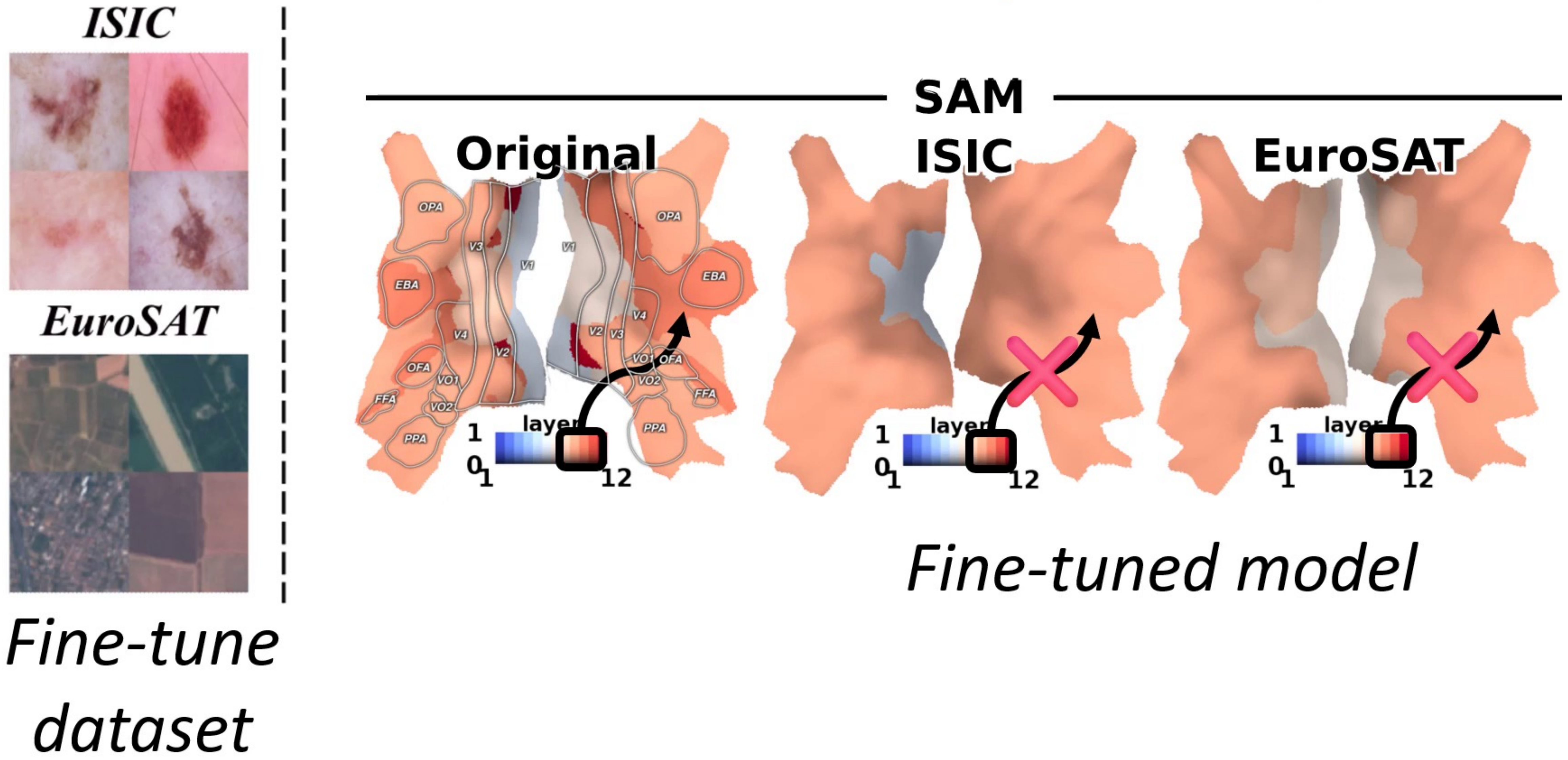
Larger model size

CLIP larger model = better! ``brain-alignment''



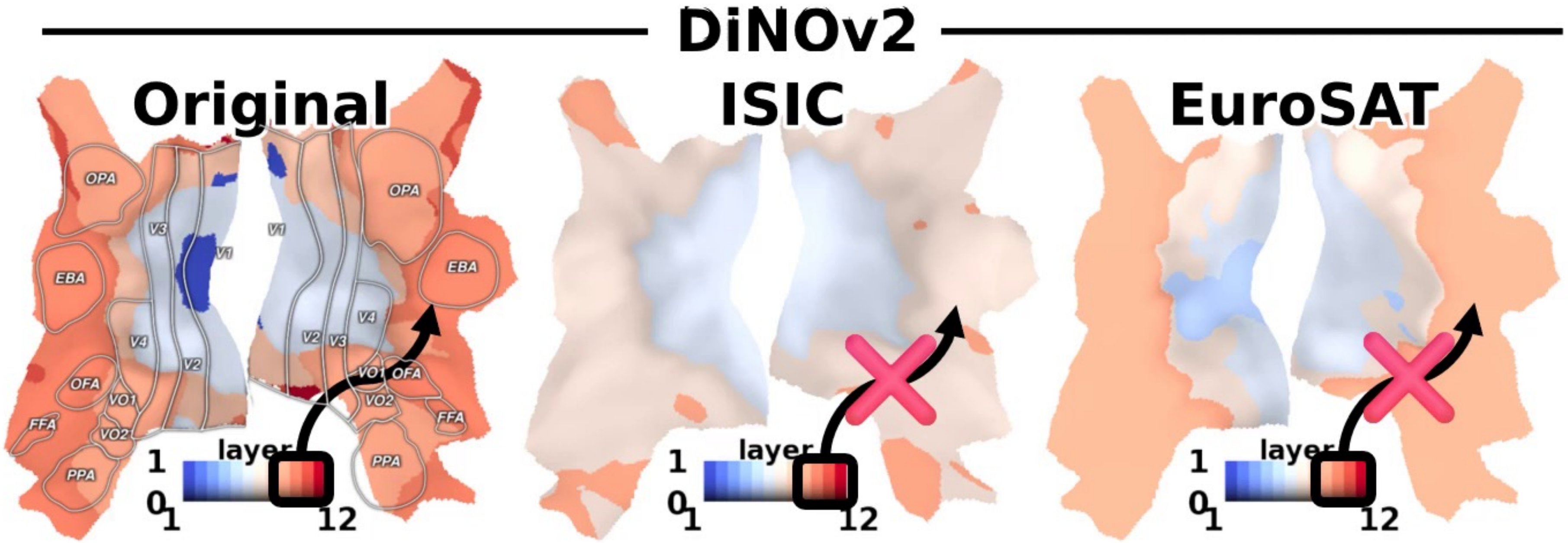

Fine-tuned DiNOv2 wiped late layers
ISIC
EuroSAT
Fine-tune dataset
DiNOv2
Original
ISIC
EuroSAT
OPA
EBA
OFA
FFA
PPA
V1
V2
V3
V4
VO1
VO2
layer
1
0
1
12
Fine-tuned model

Fine-tuned SAM wiped late layers



Fine-tuned DiNOv2 **wiped** late layers

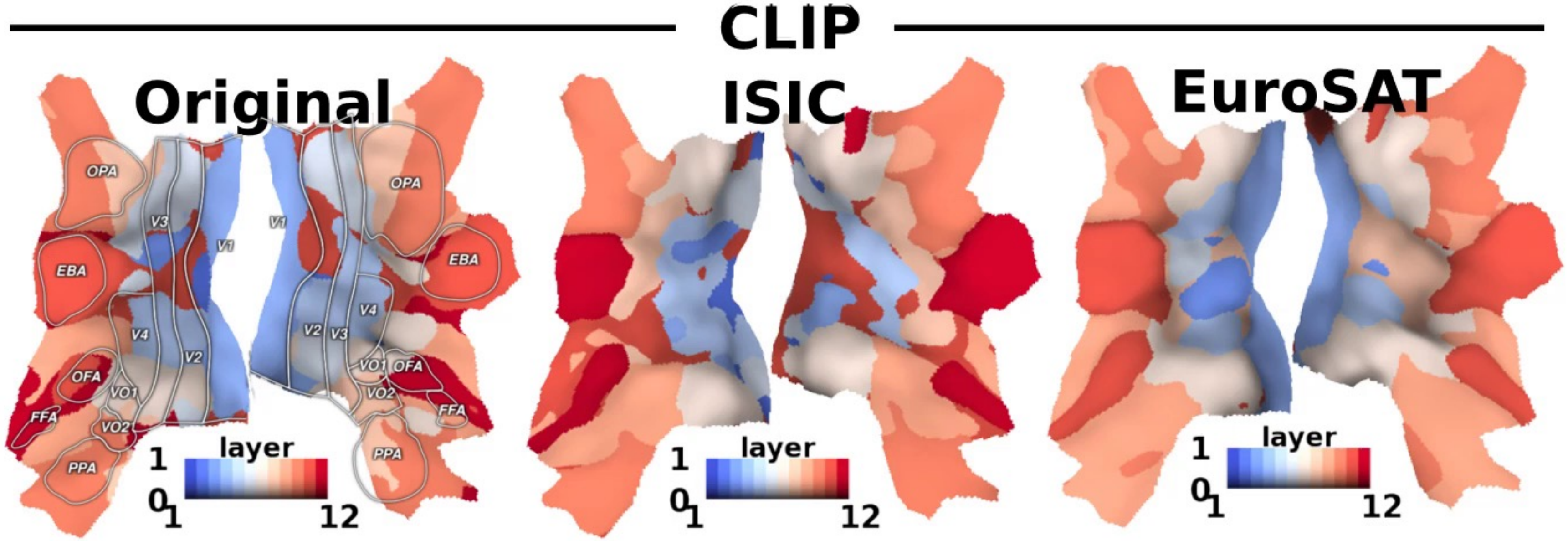
Fine-tune dataset



Fine-tuned model

Fine-tuned CLIP changed less!

Fine-tune dataset



Fine-tuned model

Better brain-alignment -> adapt to dynamic tasks !

Google 学术搜索

brain distillation

文章

找到约 147,000 条结果 （用时**0.08**秒）

时间不限
2024以来
2023以来
2020以来
自定义范围...

按相关性排序
按日期排序

不限语言
中文网页
简体中文网页

类型不限
评论性文章

☐ 包括专利
☑ 包含引用

创建快讯

A single stage knowledge distillation network for brain tumor segmentation on limited MR image modalities
Y Choi, MA Al-Masni, KJ Jung, RE Yoo, SY Lee… - Computer Methods and …, 2023 - Elsevier
… We develop a single-stage knowledge distillation framework that successively trains the teacher and student networks in the same training iteration, which can be used for brain tumor …
☆ 保存 99 引用 被引用次数：11 相关文章 所有 8 个版本

Knowledge distillation for brain tumor segmentation — [PDF] arxiv.org
D Lachinov, E Shipunova, V Turlapov - International MICCAI Brainlesion …, 2019 - Springer
… The variation of knowledge distillation called data distillation … The data distillation was demonstrated on the example of … we employ the knowledge distillation method to train student …
☆ 保存 99 引用 被引用次数：19 相关文章 所有 6 个版本

Cross-modal distillation to improve MRI-based brain tumor segmentation with missing MRI sequences — [PDF] google.com
M Rahimpour, J Bertels, A Radwan… - IEEE Transactions …, 2021 - ieeexplore.ieee.org
… , knowledge distillation is an efficient method to deal with the issue of missing data during inference. Therefore, we used cross-modal distillation approach for MRI-based brain tumor …
☆ 保存 99 引用 被引用次数：32 相关文章 所有 5 个版本

Human-expert-level brain tumor detection using deep learning with data distillation and augmentation — [PDF] arxiv.org
D Lu, N Polomac, I Gacheva… - ICASSP 2021-2021 …, 2021 - ieeexplore.ieee.org
… Here, we study the problem of brain tumor detection from magnetic resonance spectroscopy (MRS) data, where both types of problems are prominent. To overcome these challenges, …
☆ 保存 99 引用 被引用次数：22 相关文章 所有 5 个版本

Brain Decodes Deep Nets

Huzheng Yang, James Gee*, Jianbo Shi*
University of Pennsylvania