Encoding & Decoding in fMRI

Brain Imaging 2024/5

What does fMRI allow us to say?

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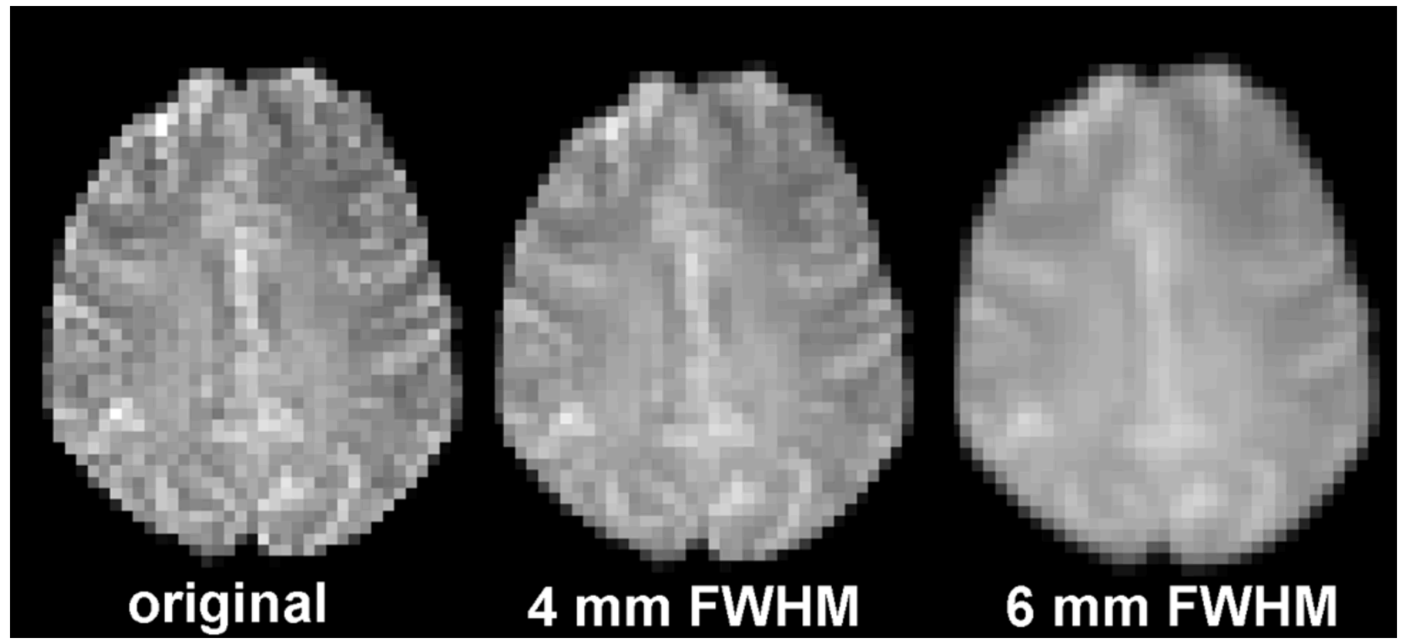

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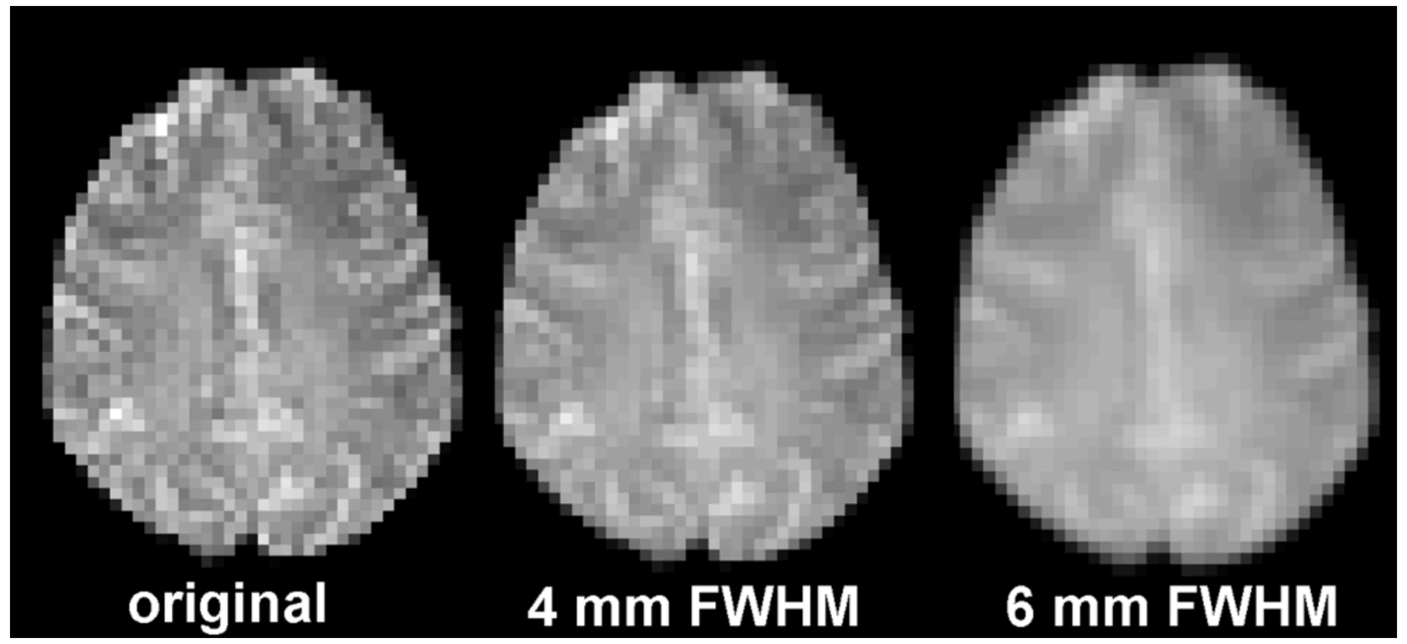

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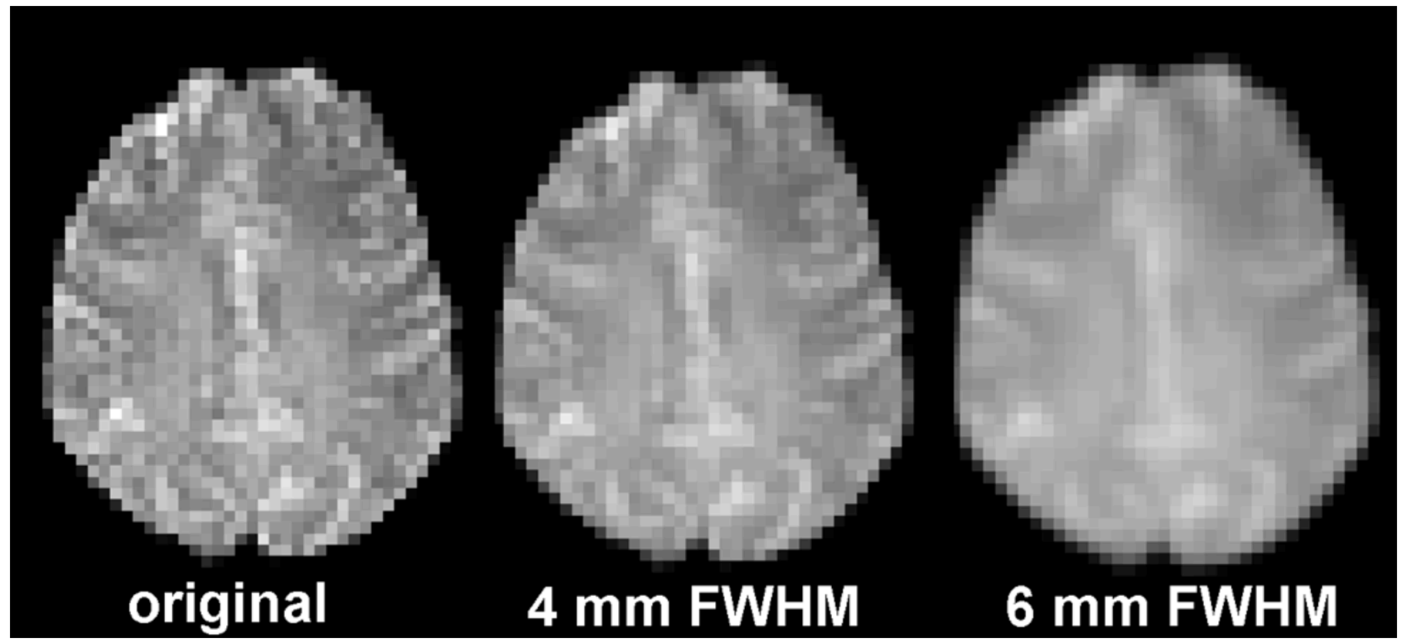

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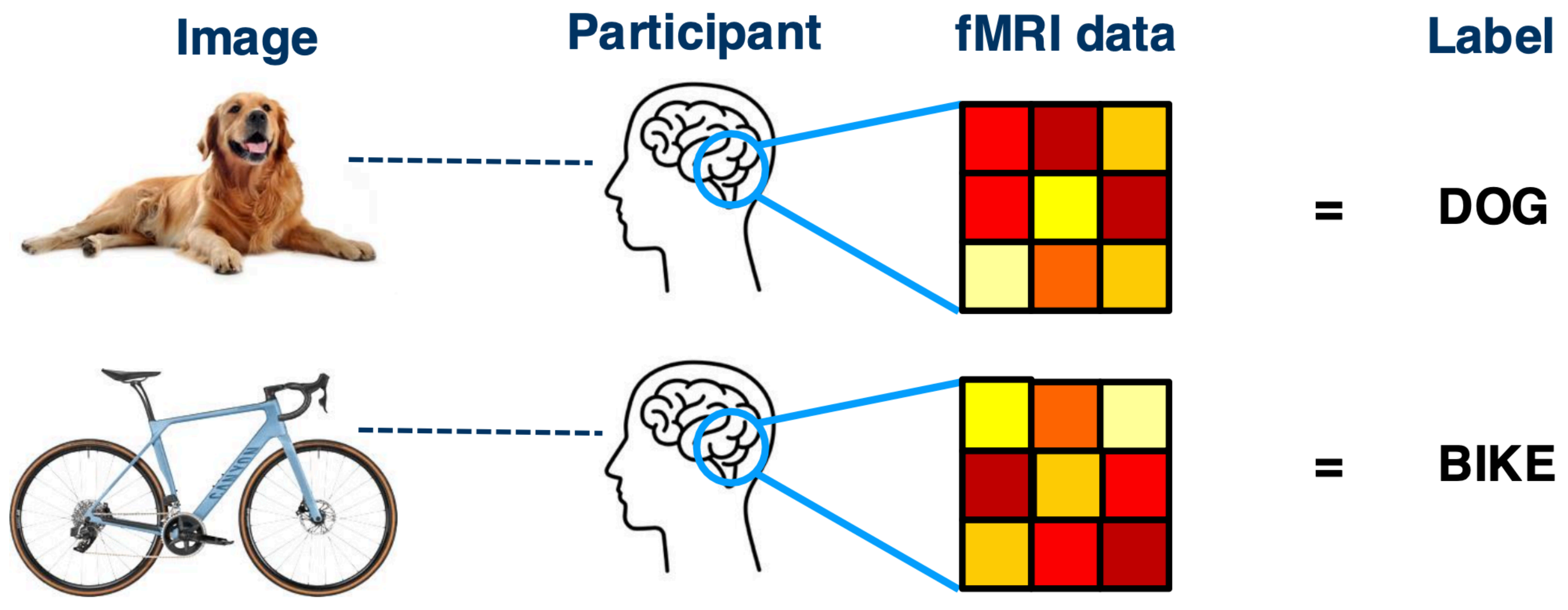

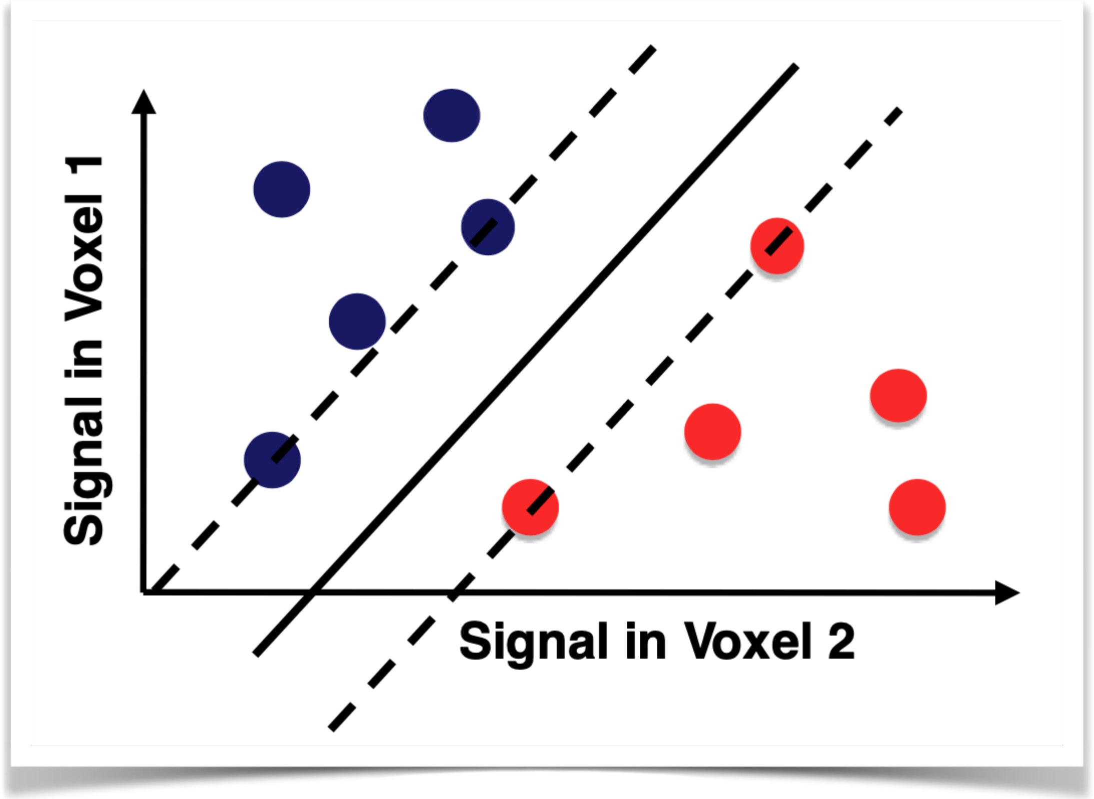

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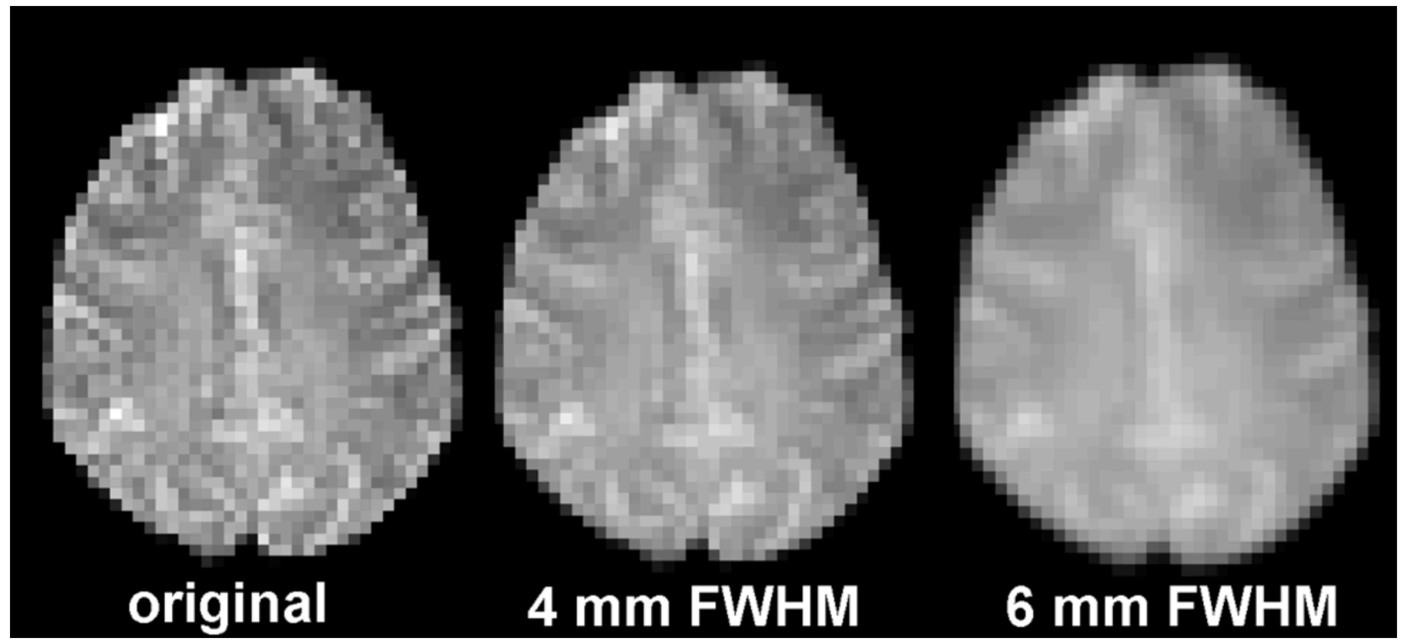

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- ***BUT: won't everything necessarily look like a BLOB?***
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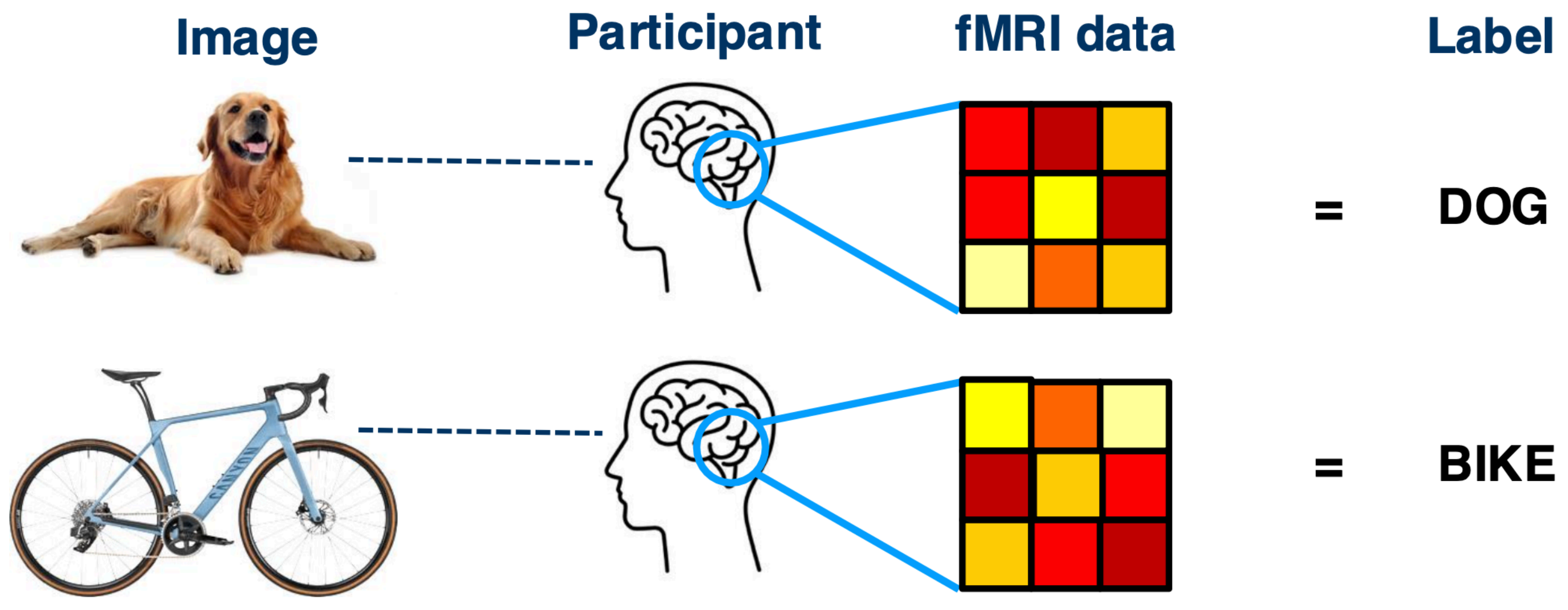
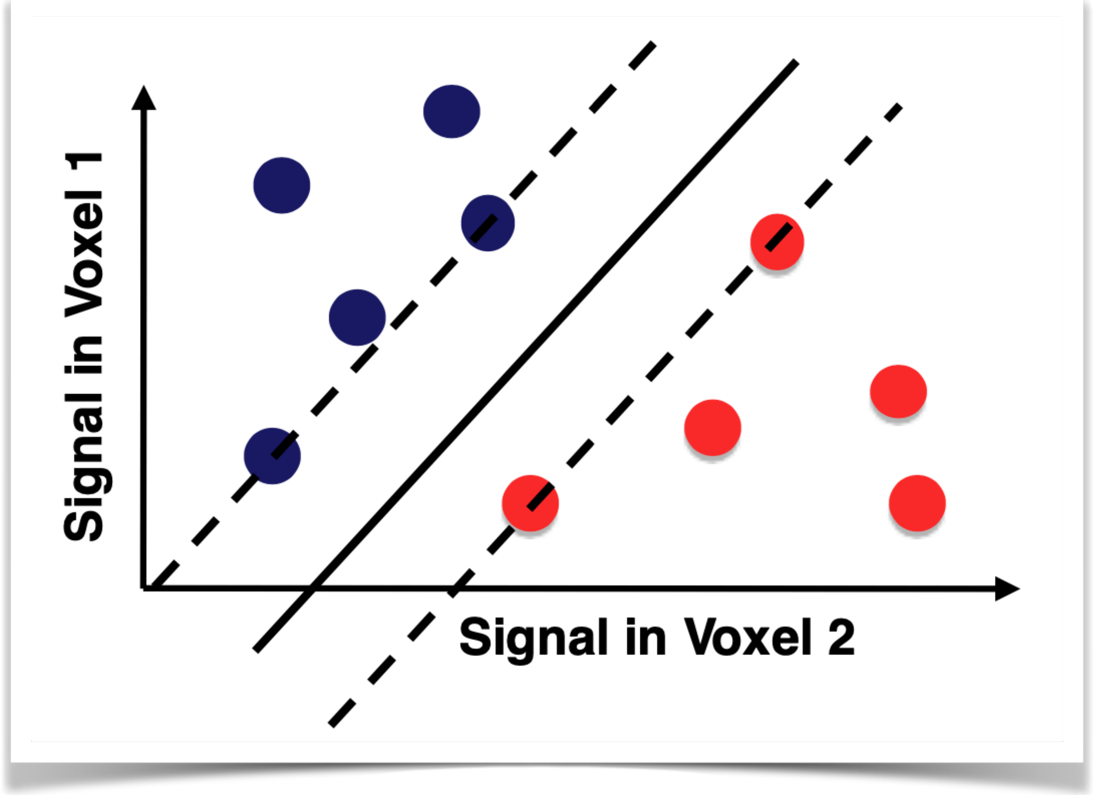
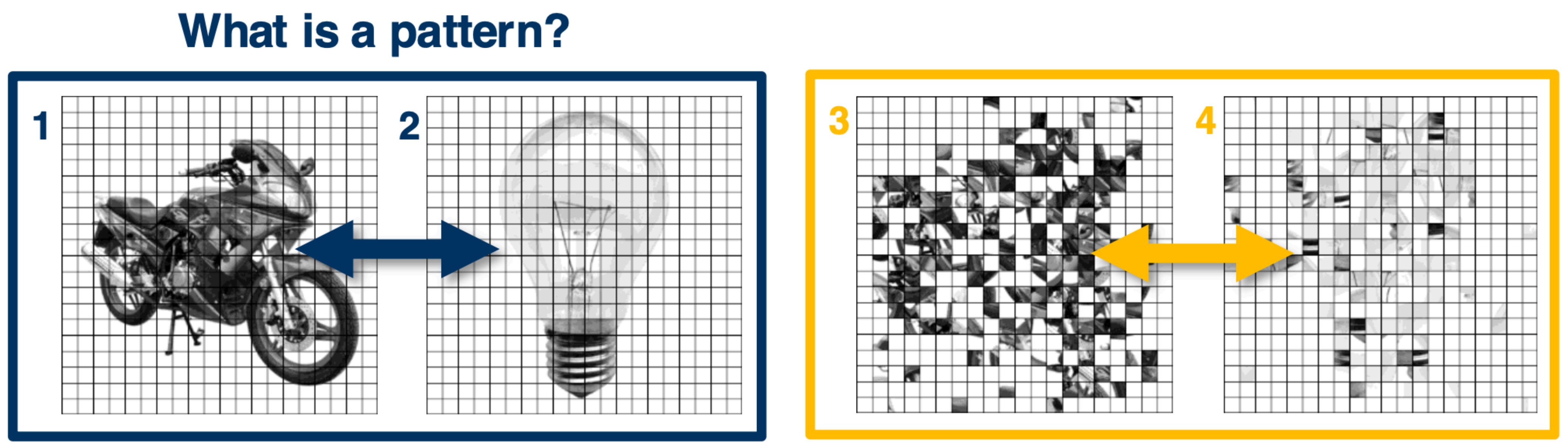
- Analysing patterns across voxels will also increase SNR by pooling across voxels, and help us get results.
- ***BUT: what does a pattern of responses across voxels mean?***
  No explicit model of what process generates this response pattern…

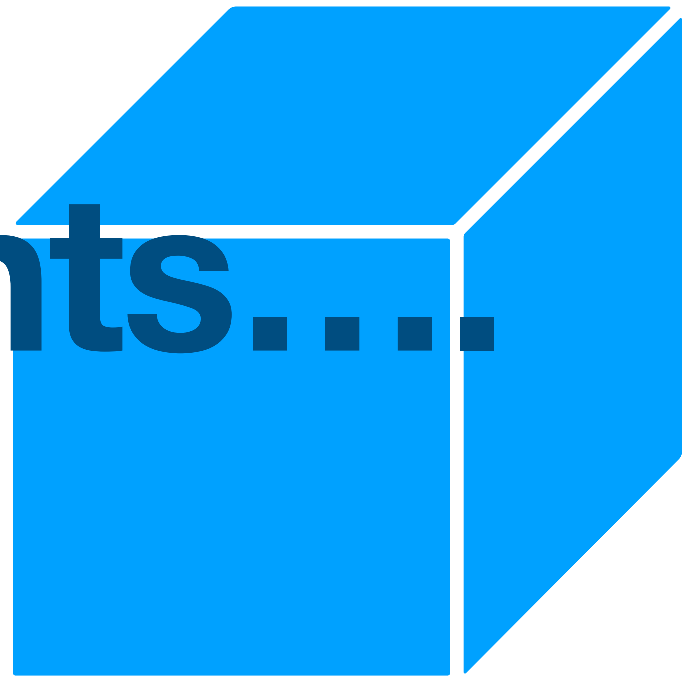






Let’s think deeply about our measurements….

What information does a voxel’s signal contain?



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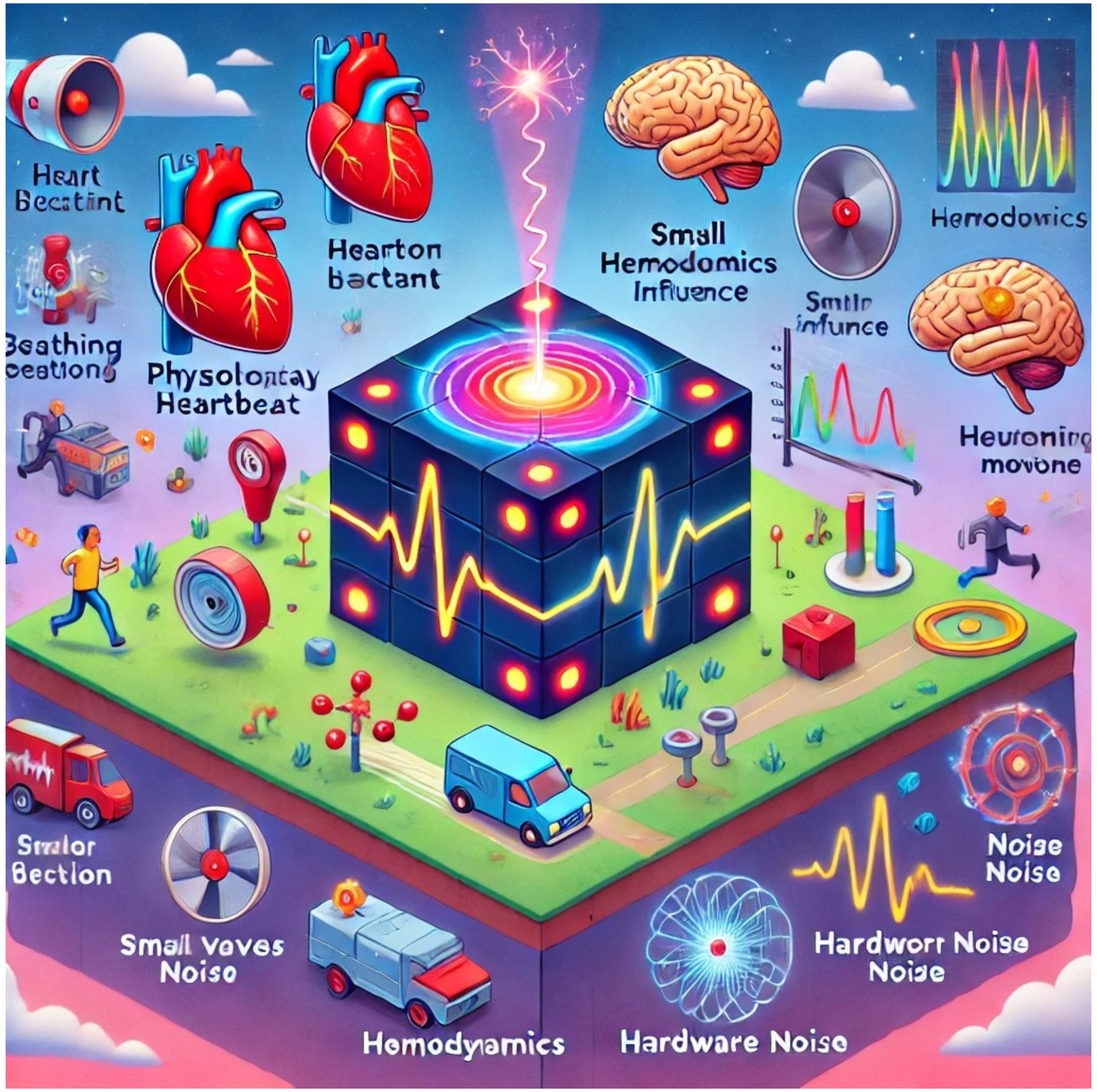

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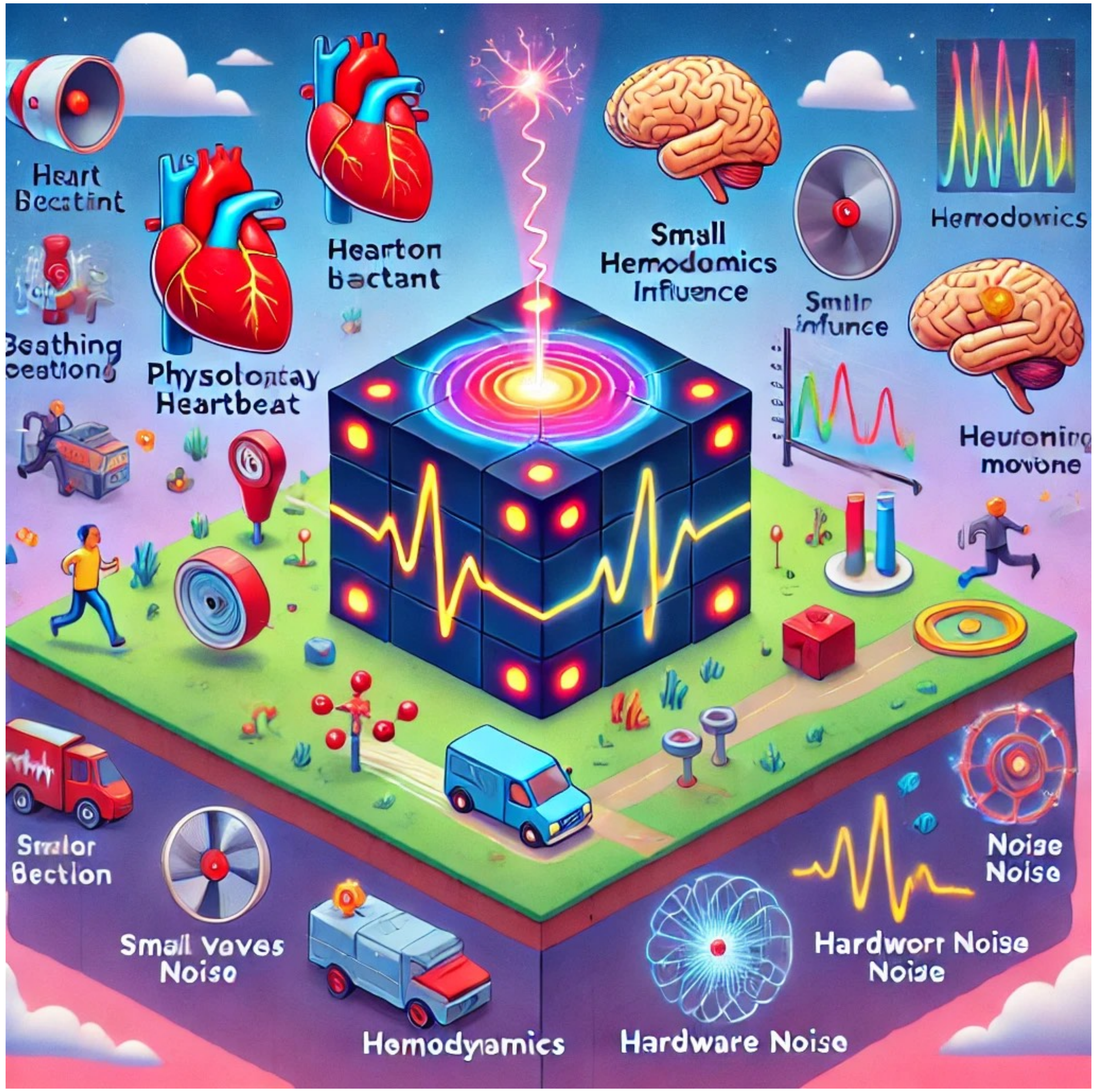
  Interpret our measurements as ***neurons firing***?



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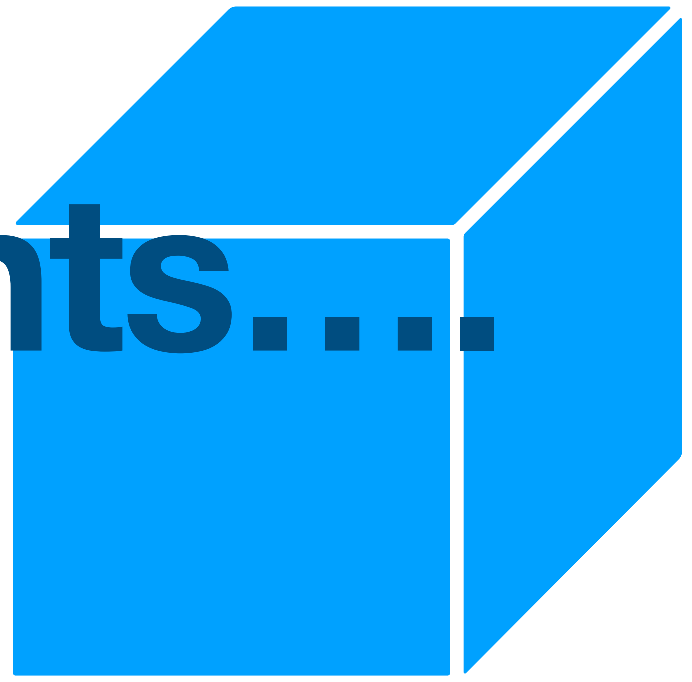

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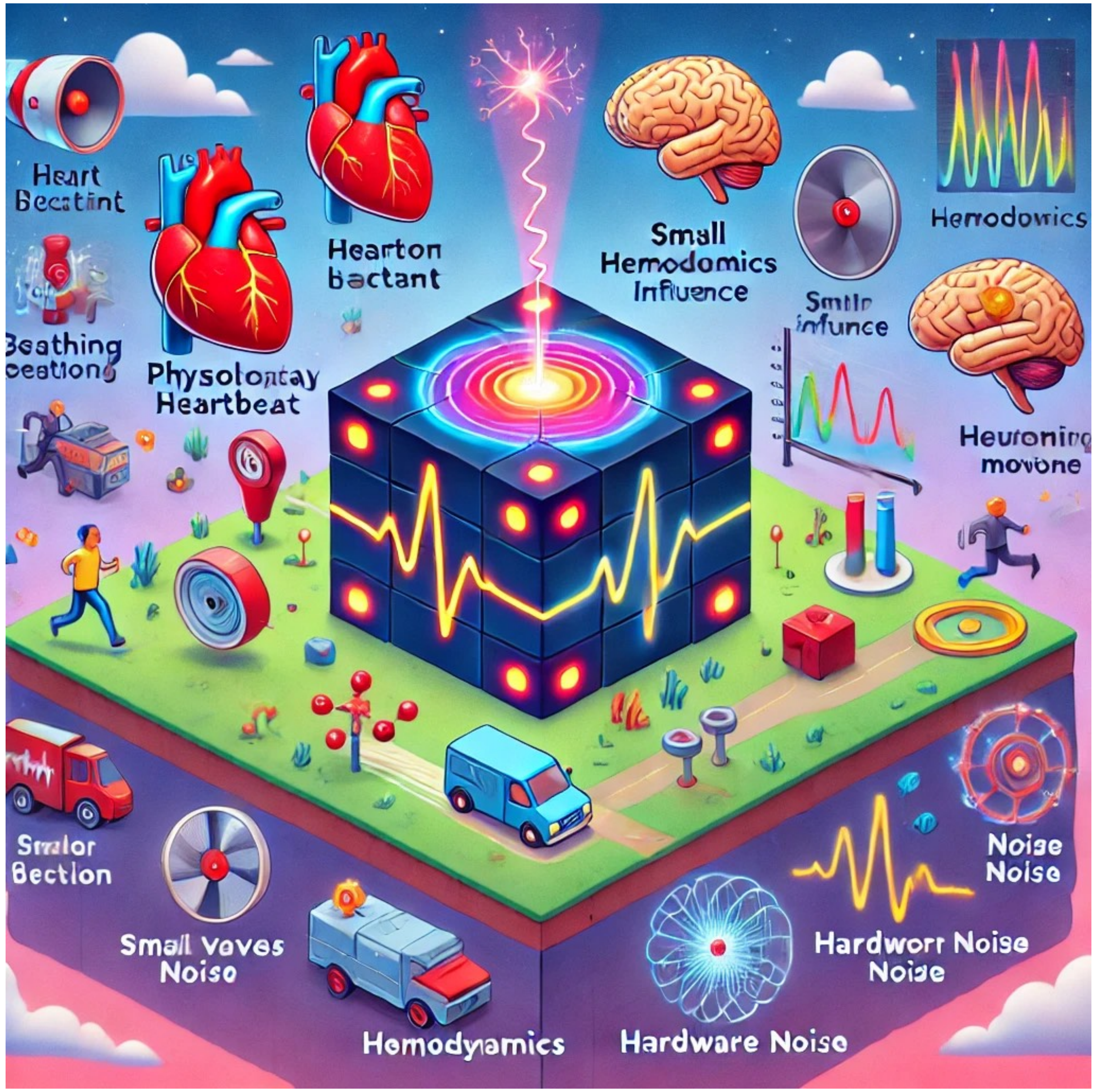

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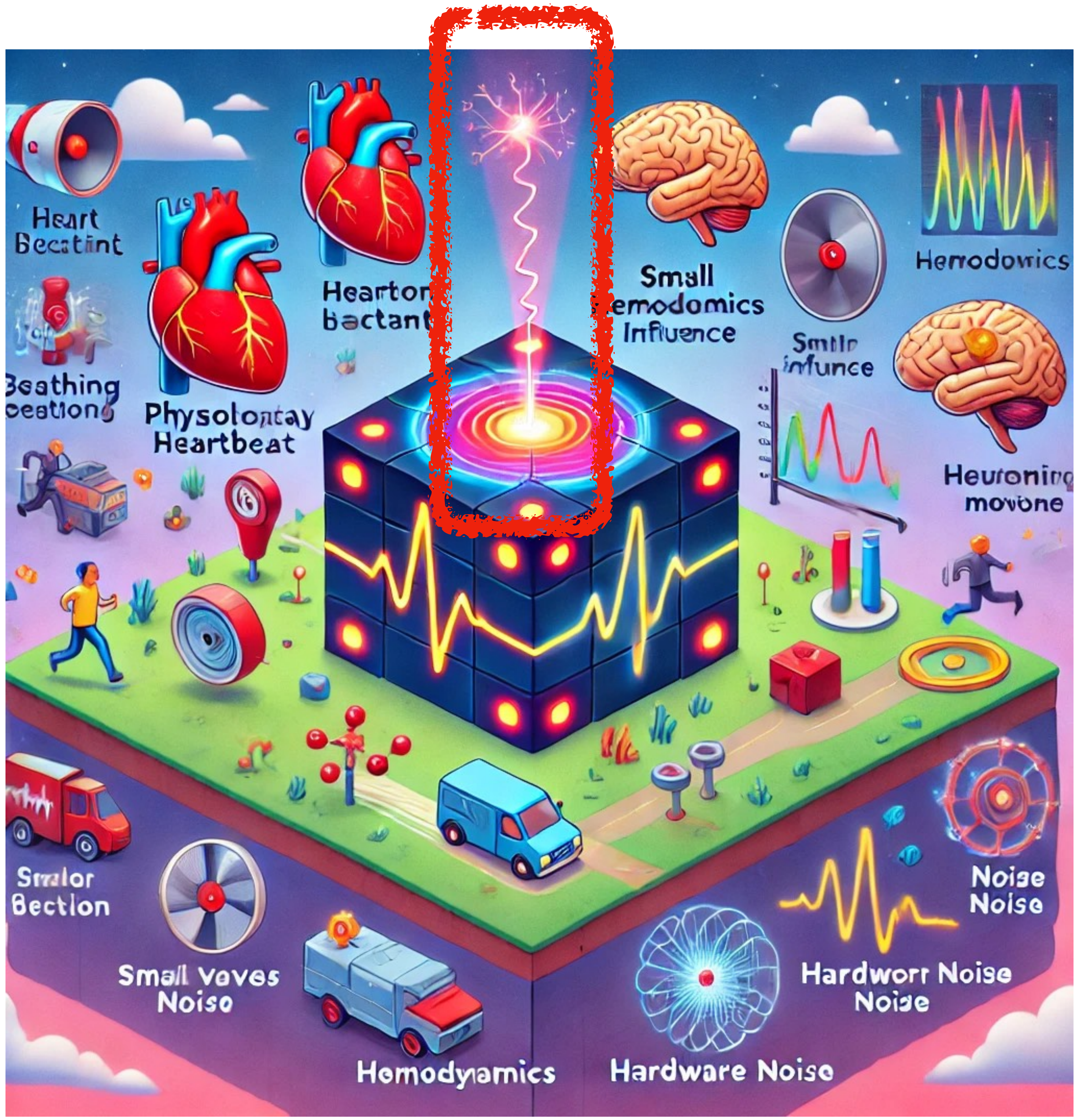
- With recent improvements in fMRI signal fidelity, we want to:

1. *Make explicit models of what neurons in **single voxels** are doing*

2. *how this processing generates **patterns across voxels**.*



Receptive fields?

Hubel & Wiesel

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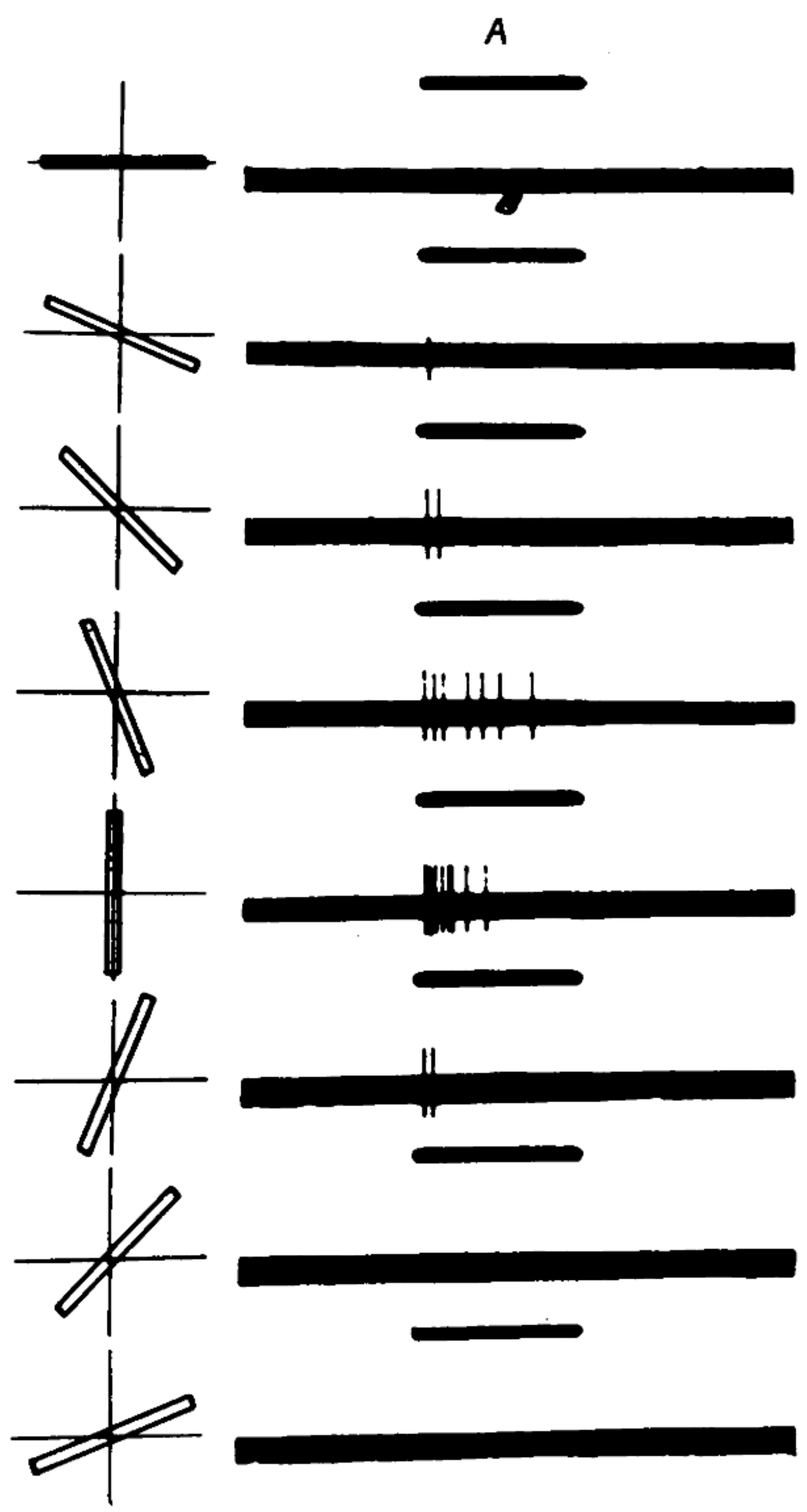

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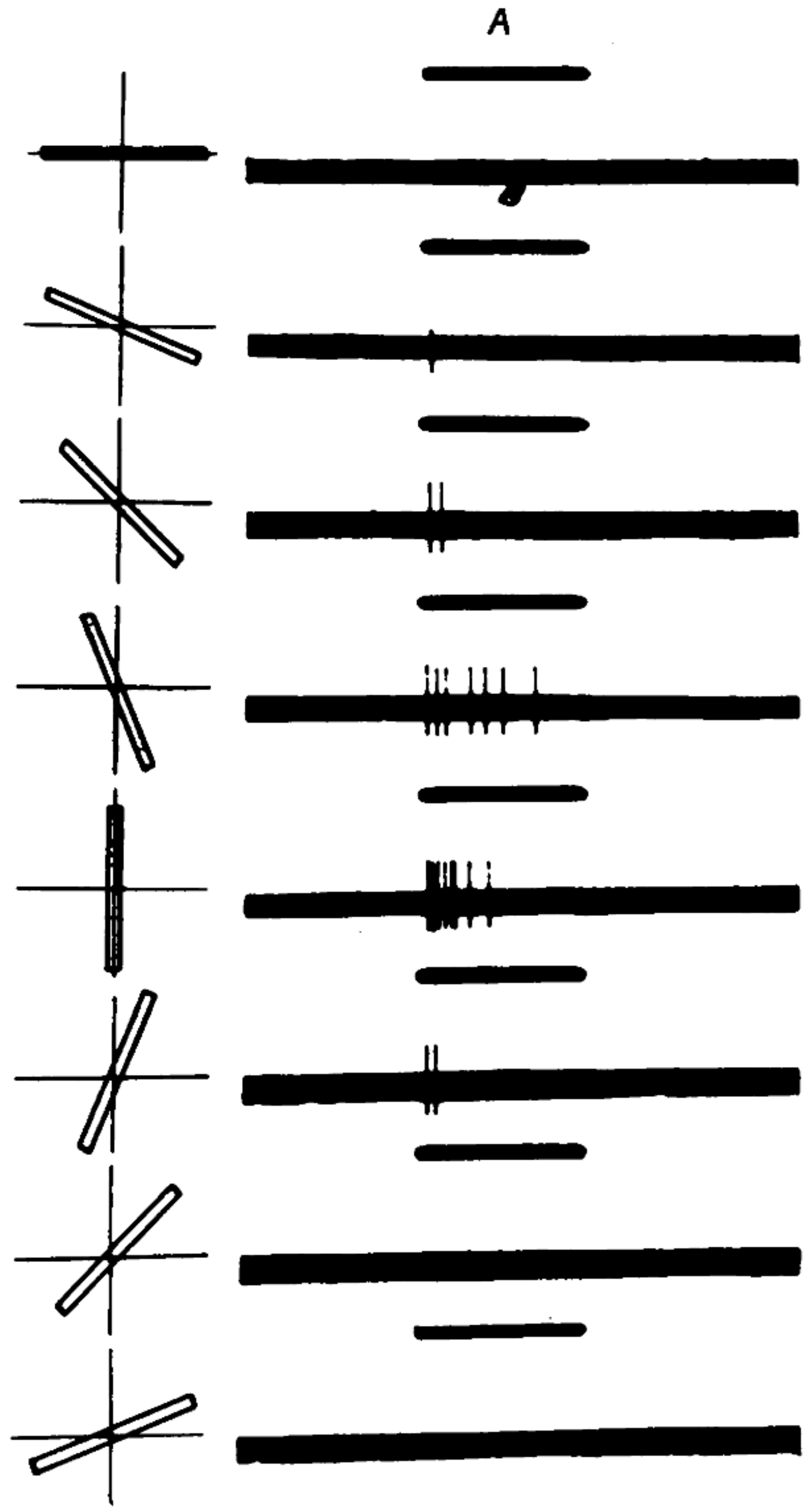
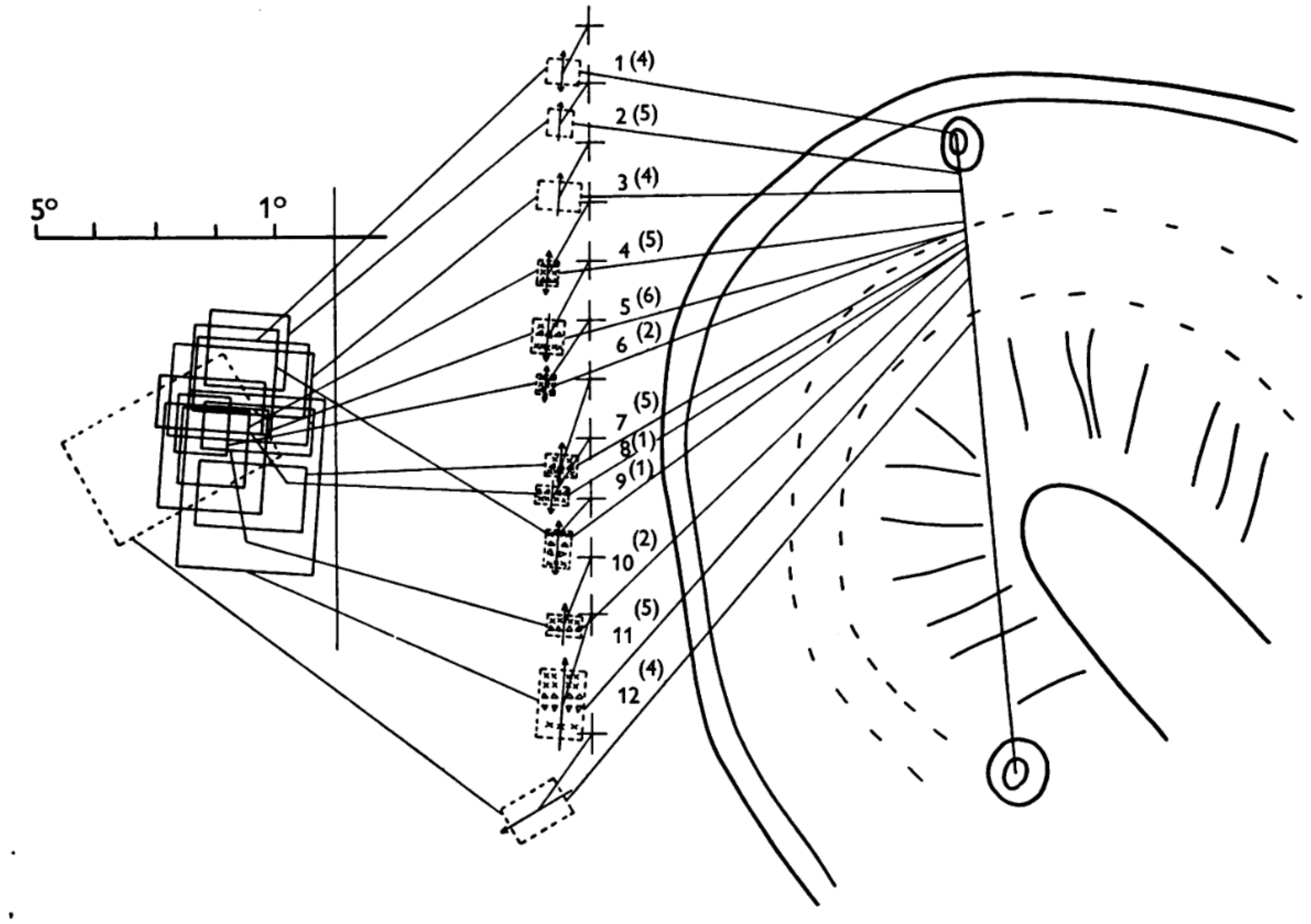
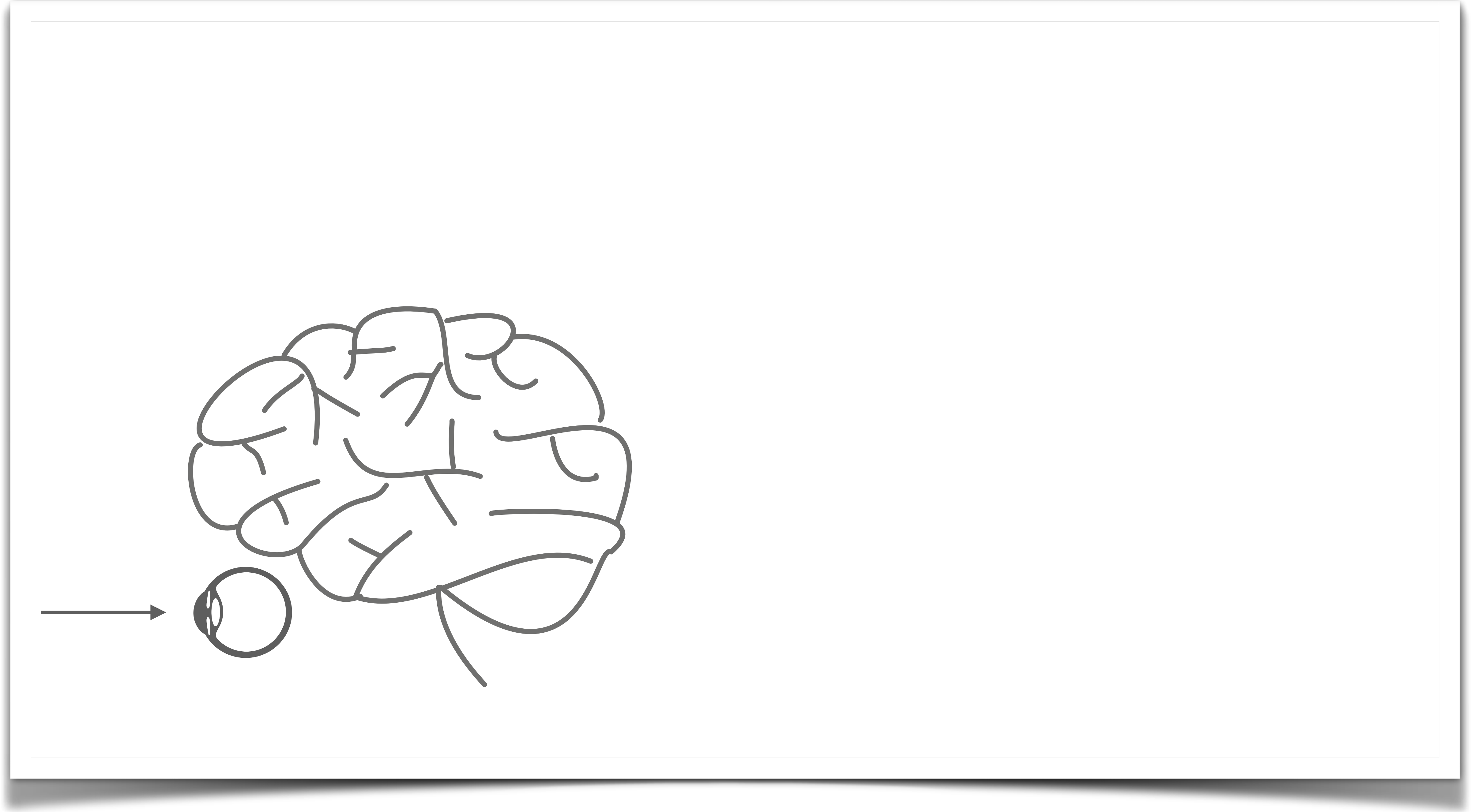




Population Receptive Fields using fMRI



Dumoulin & Wandell, 2008

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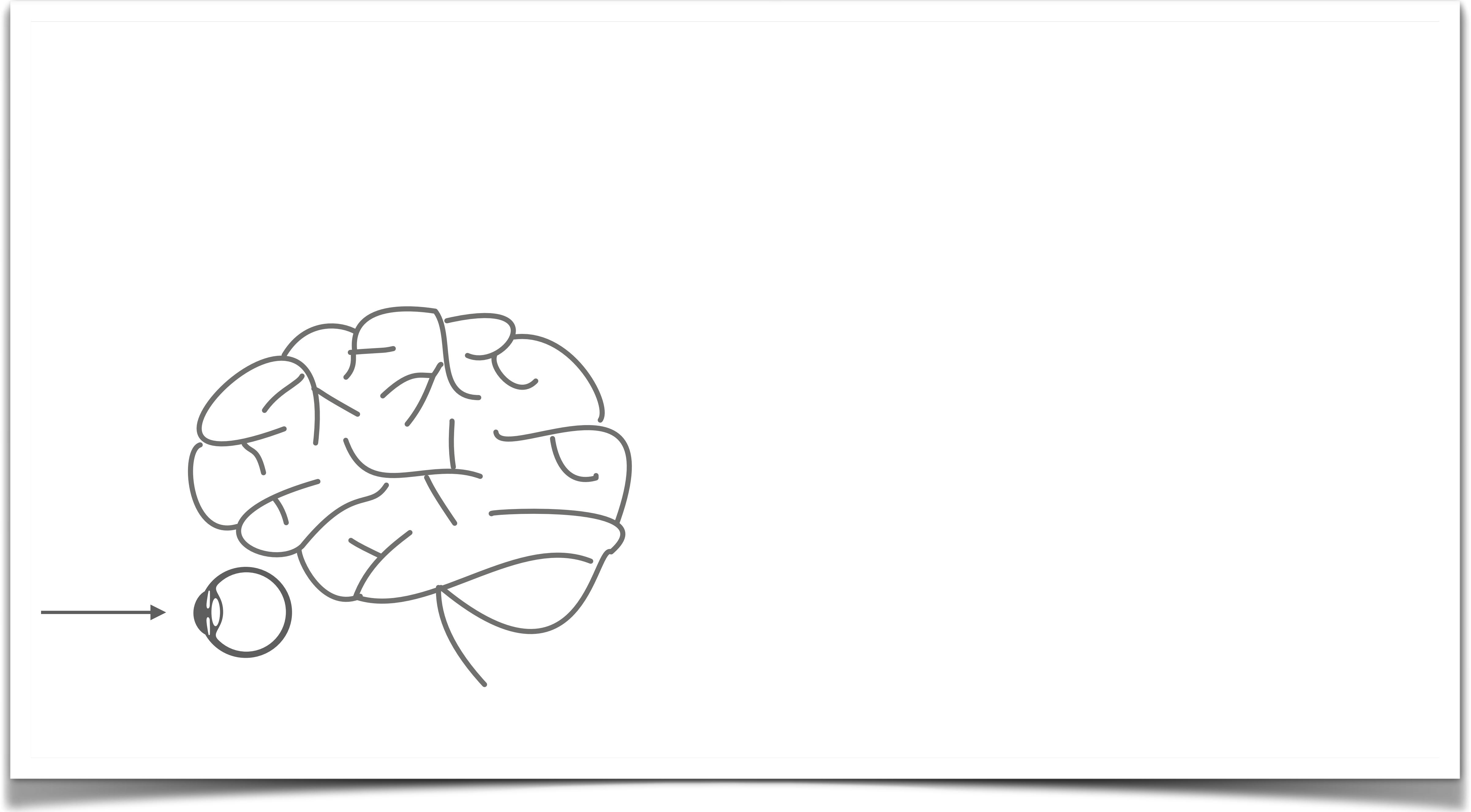

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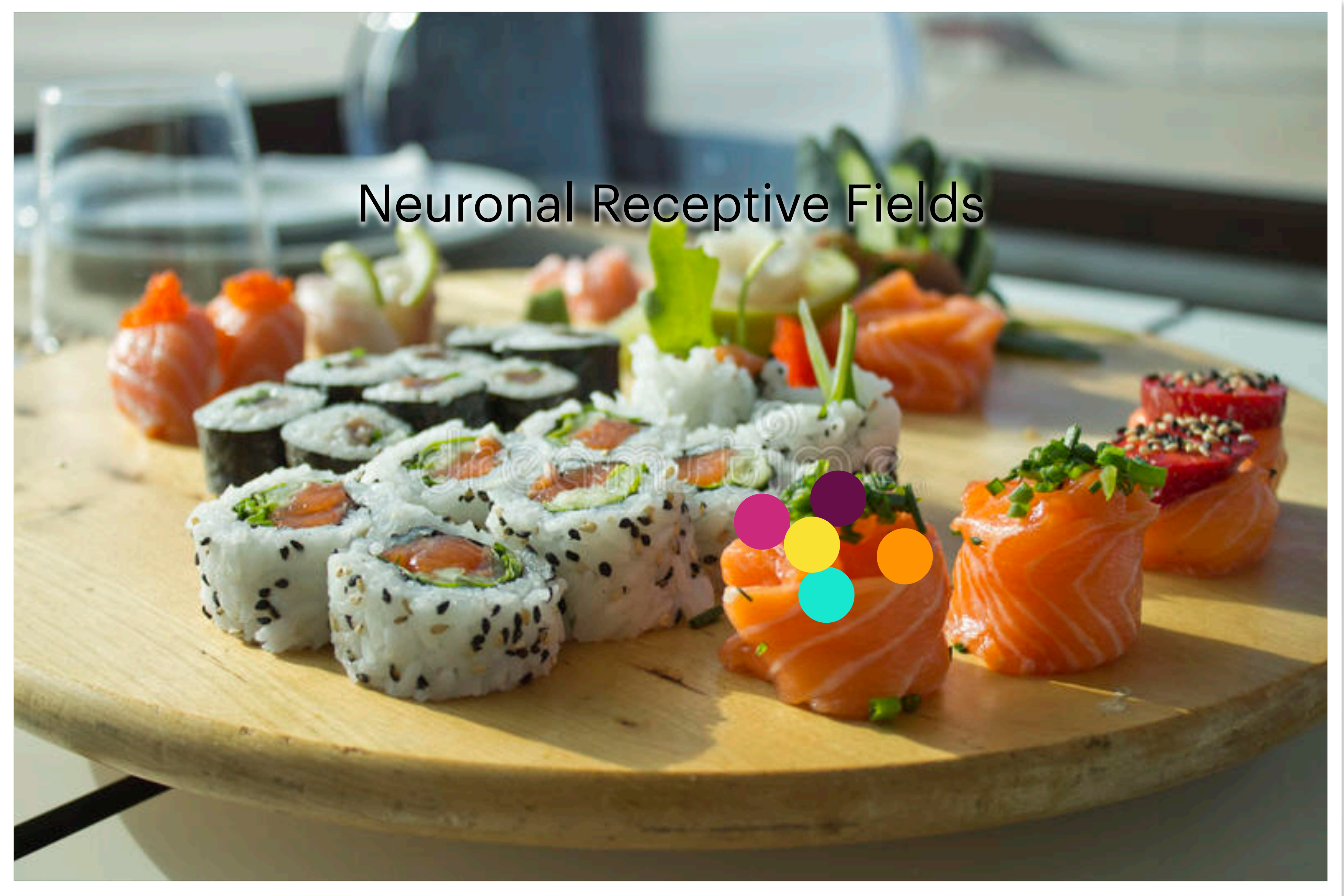

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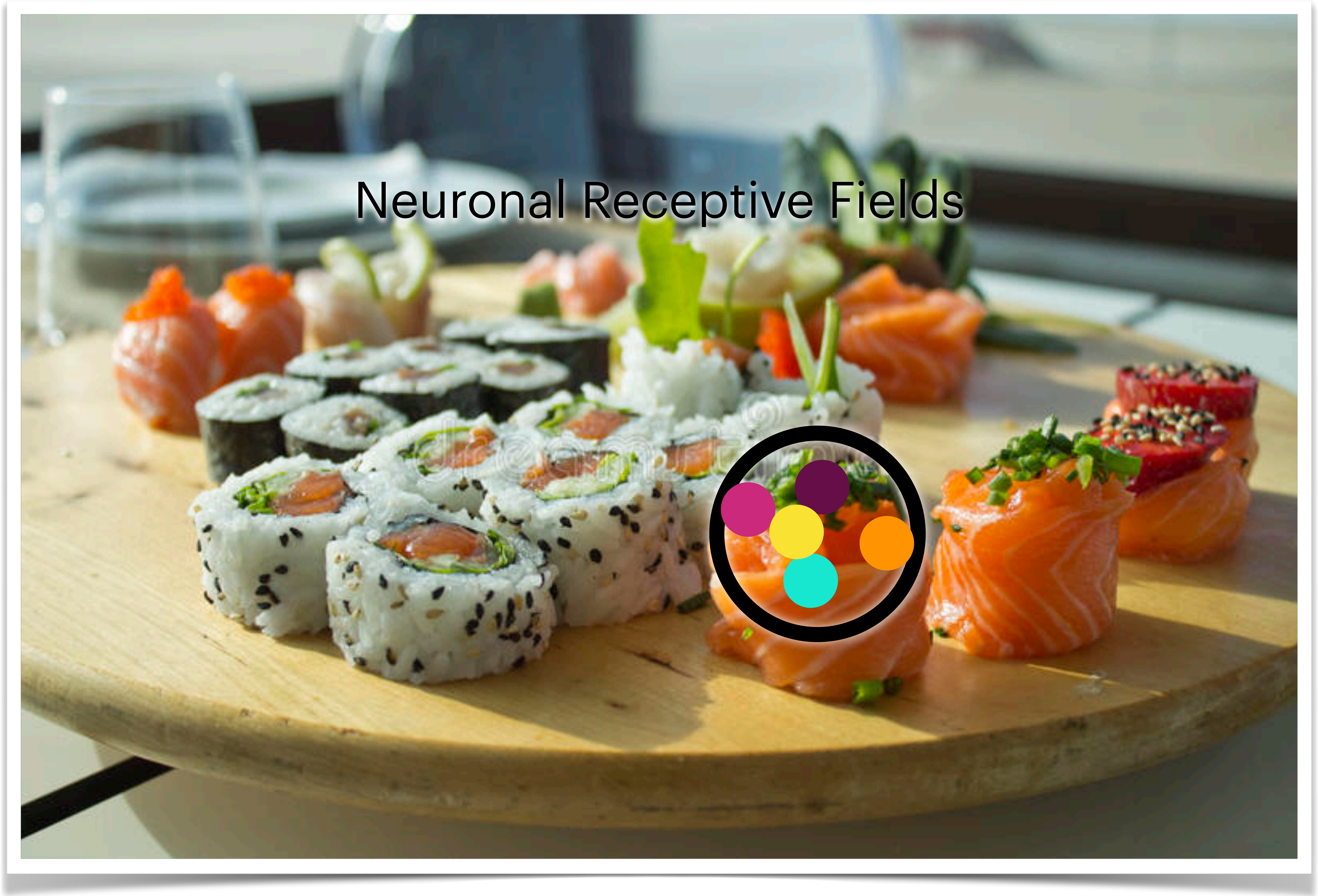

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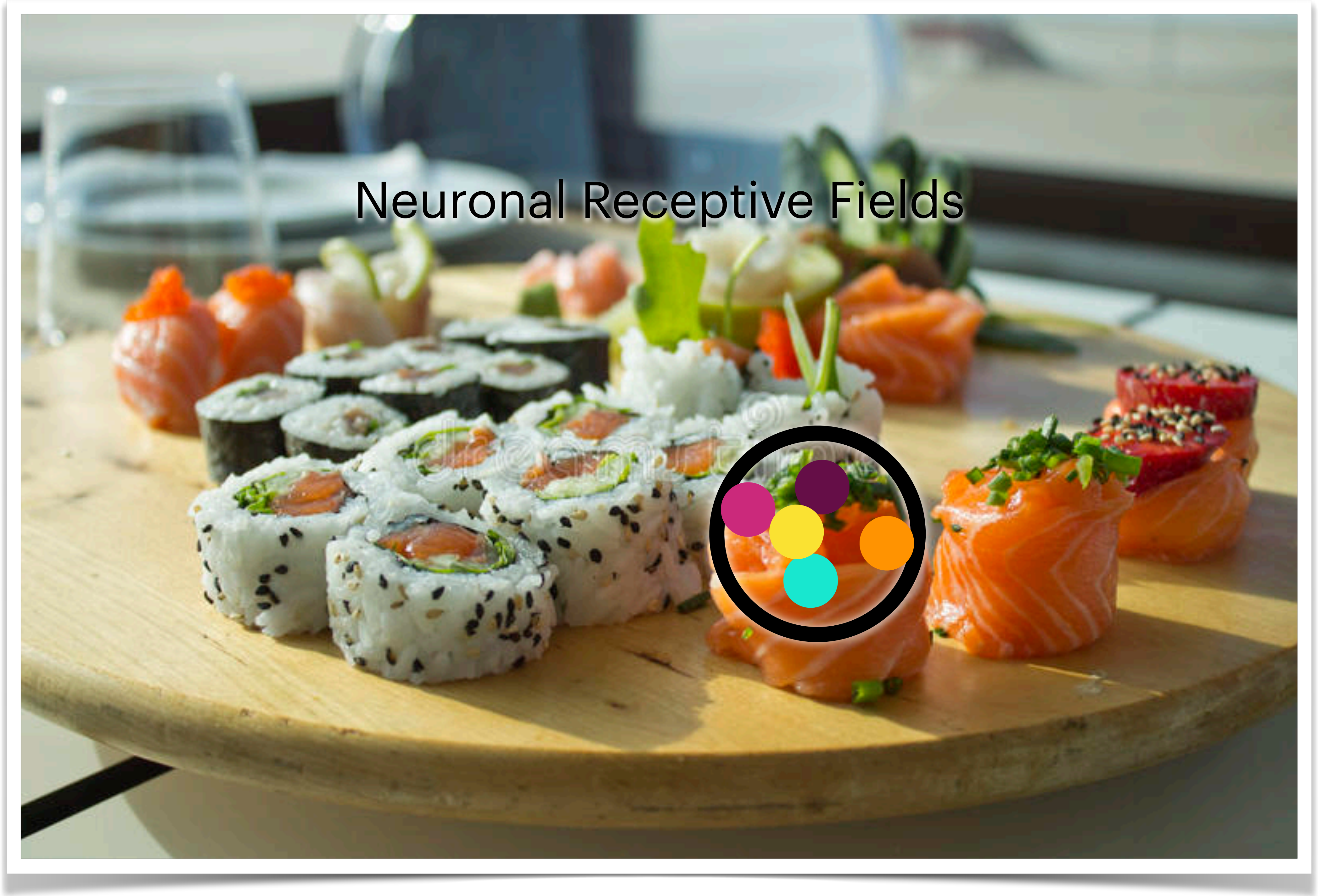

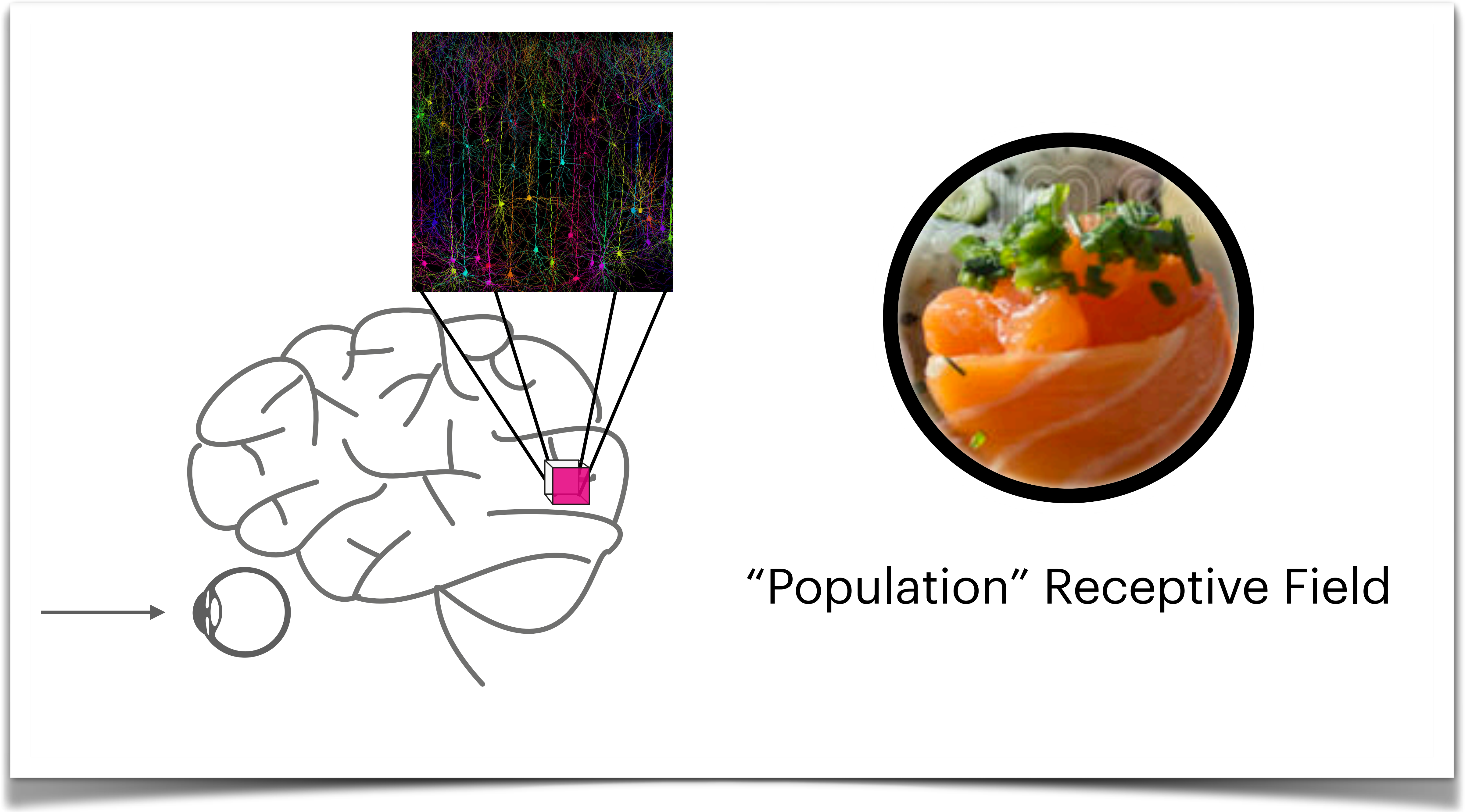

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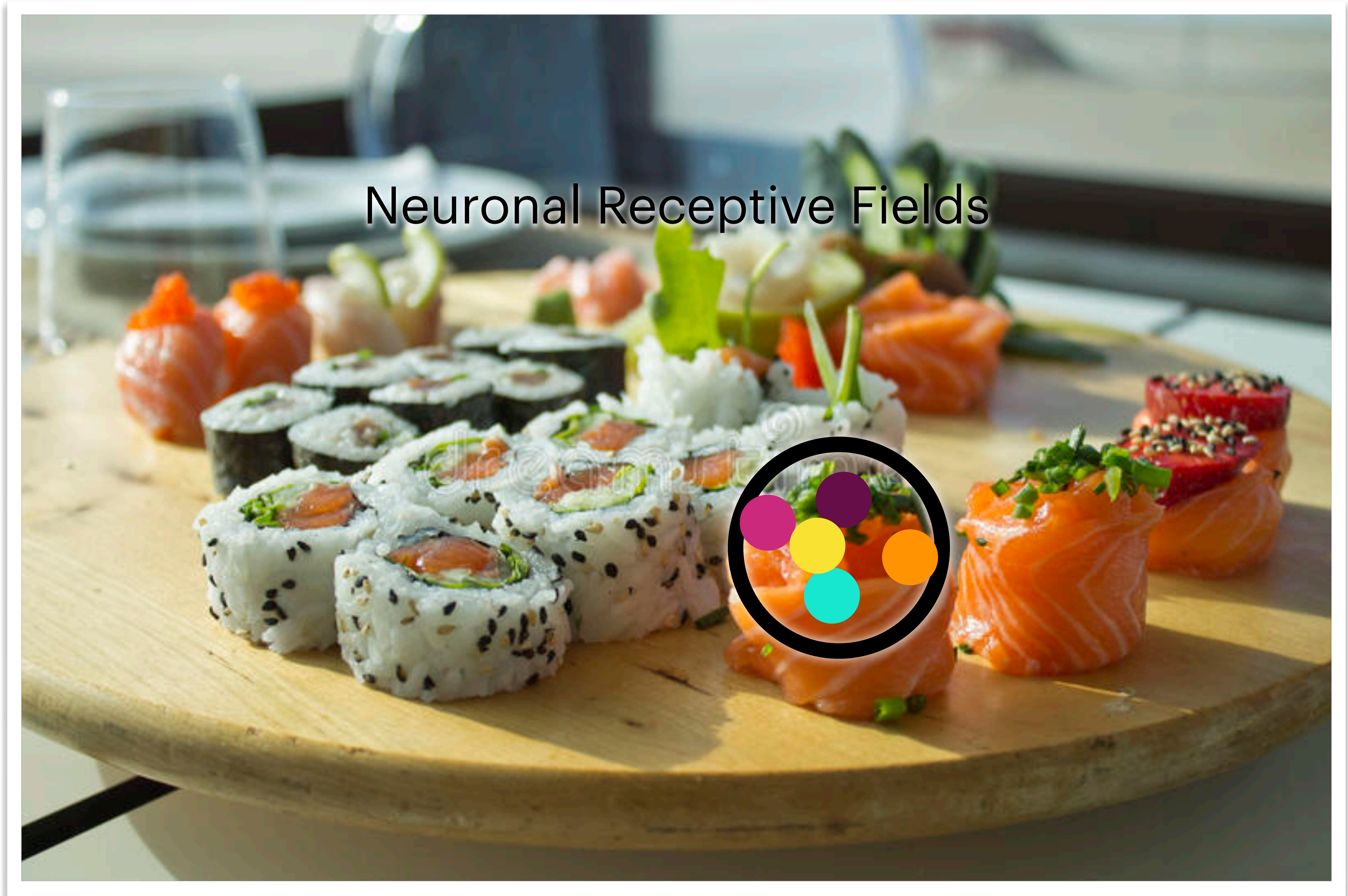

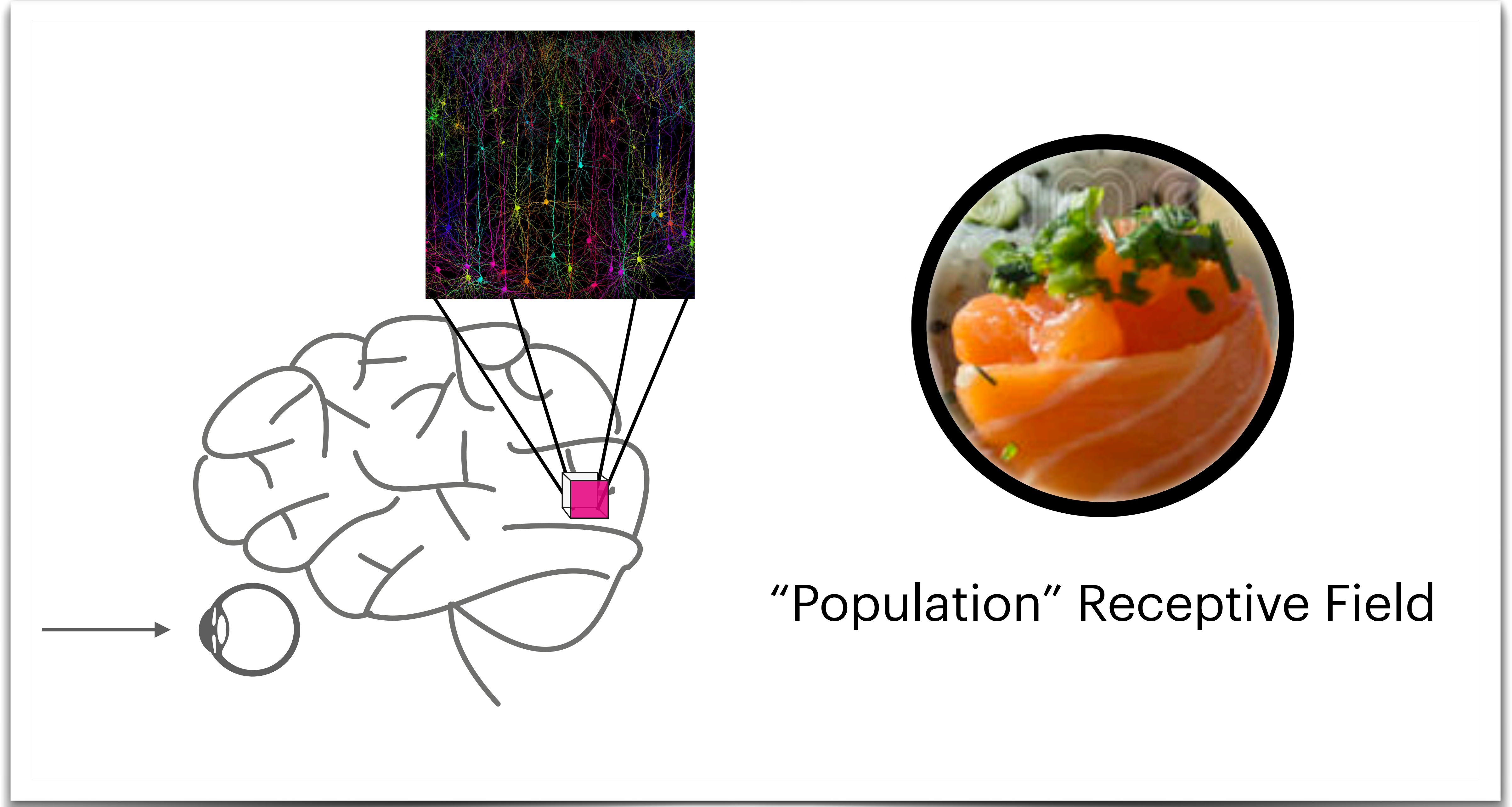

Extend the receptive field computational motif to voxels:
a voxel's neural population (if tuned similarly) has a
population receptive field (pRF)

Dumoulin & Wandell, 2008

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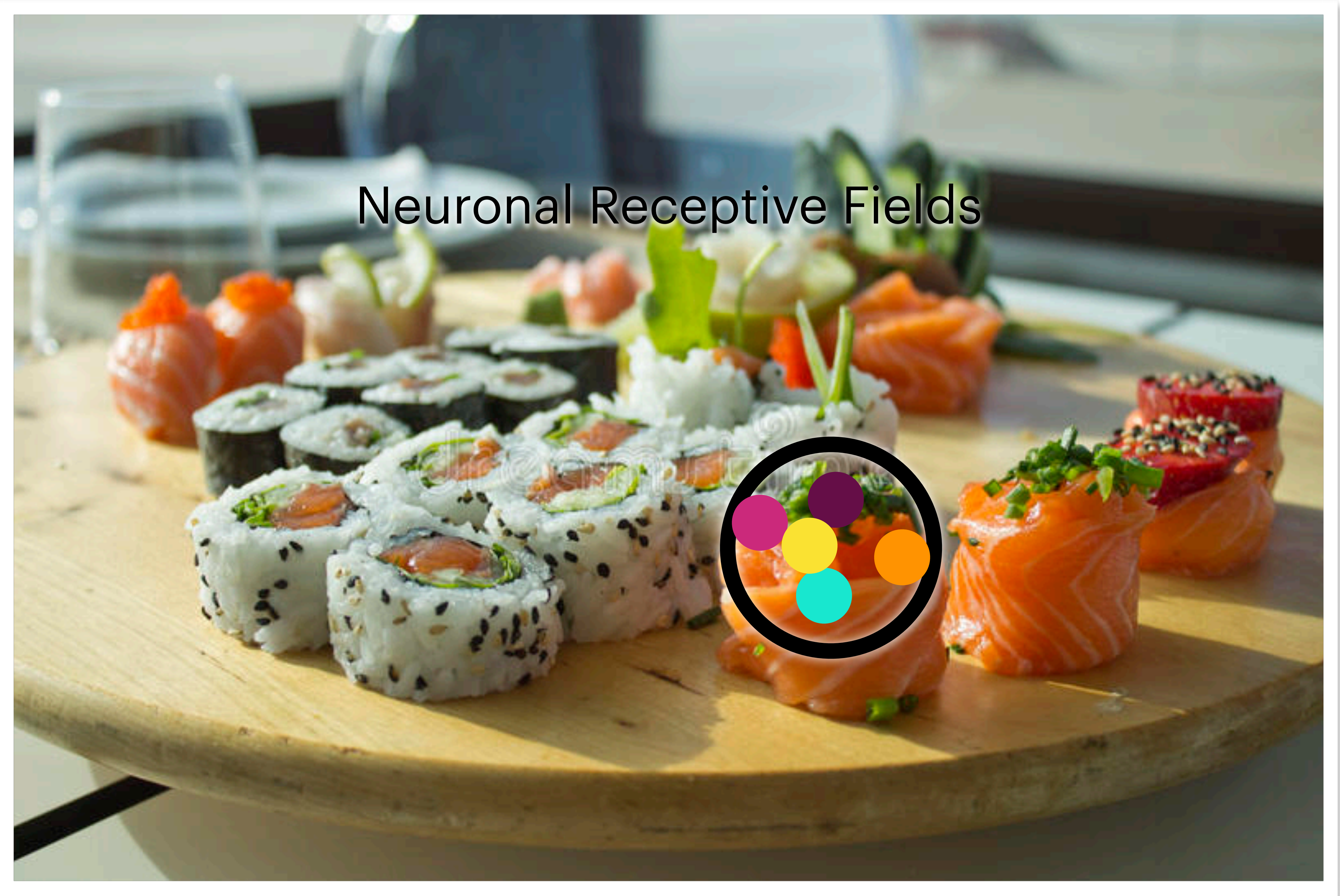

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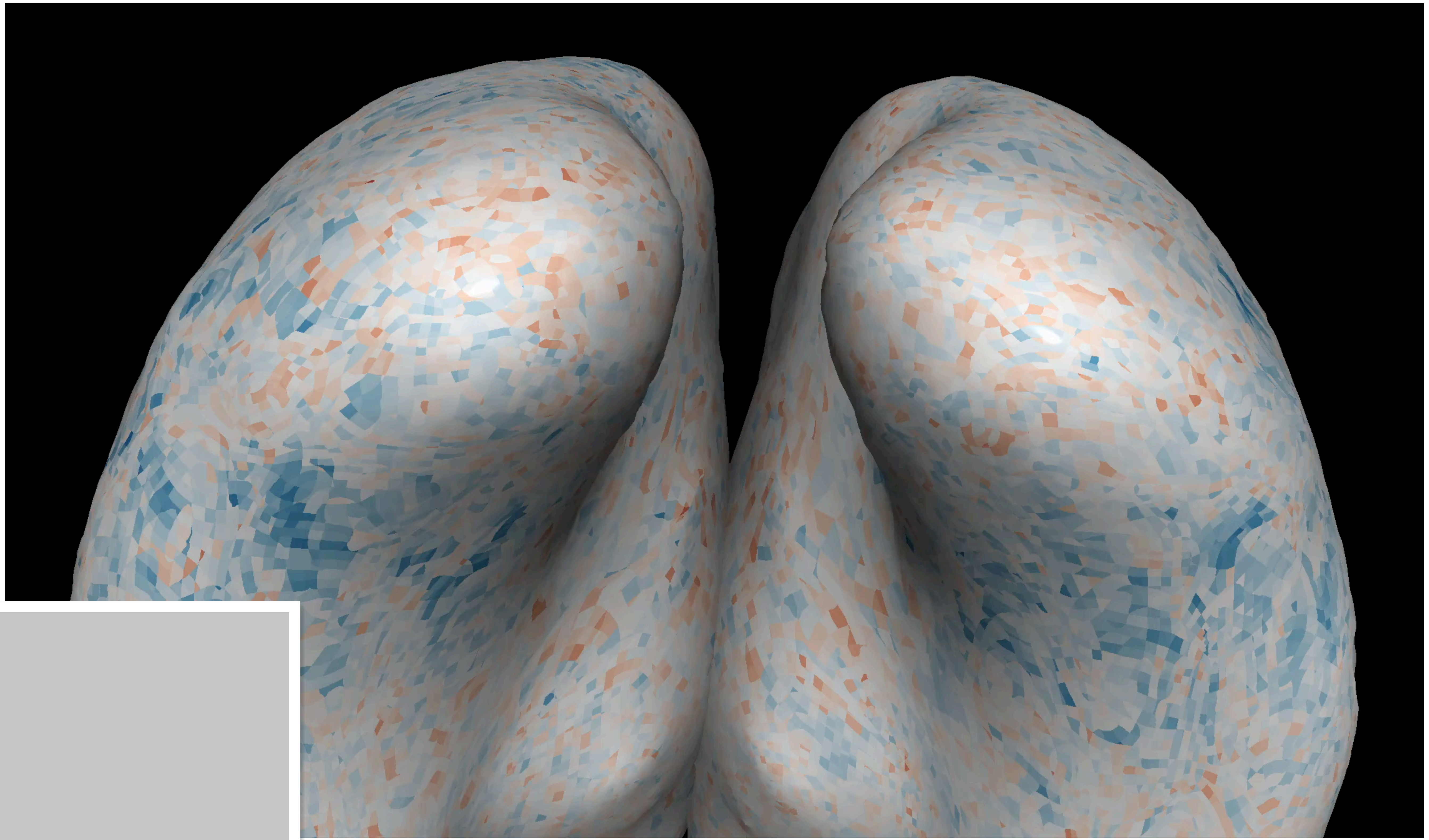
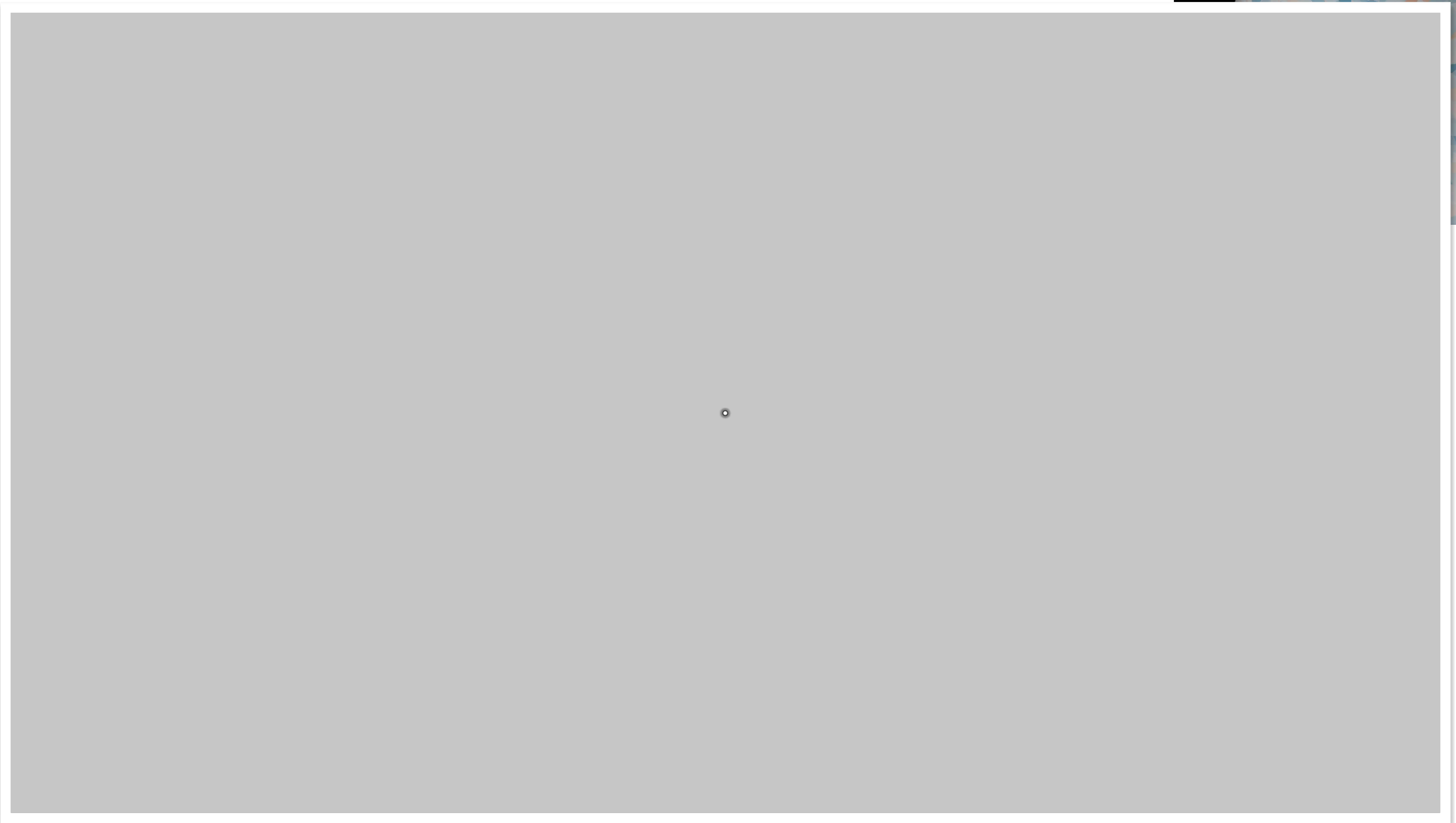
Leaves out orientation, focuses on just location!

Dumoulin & Wandell, 2008

Taking RFs To fMRI





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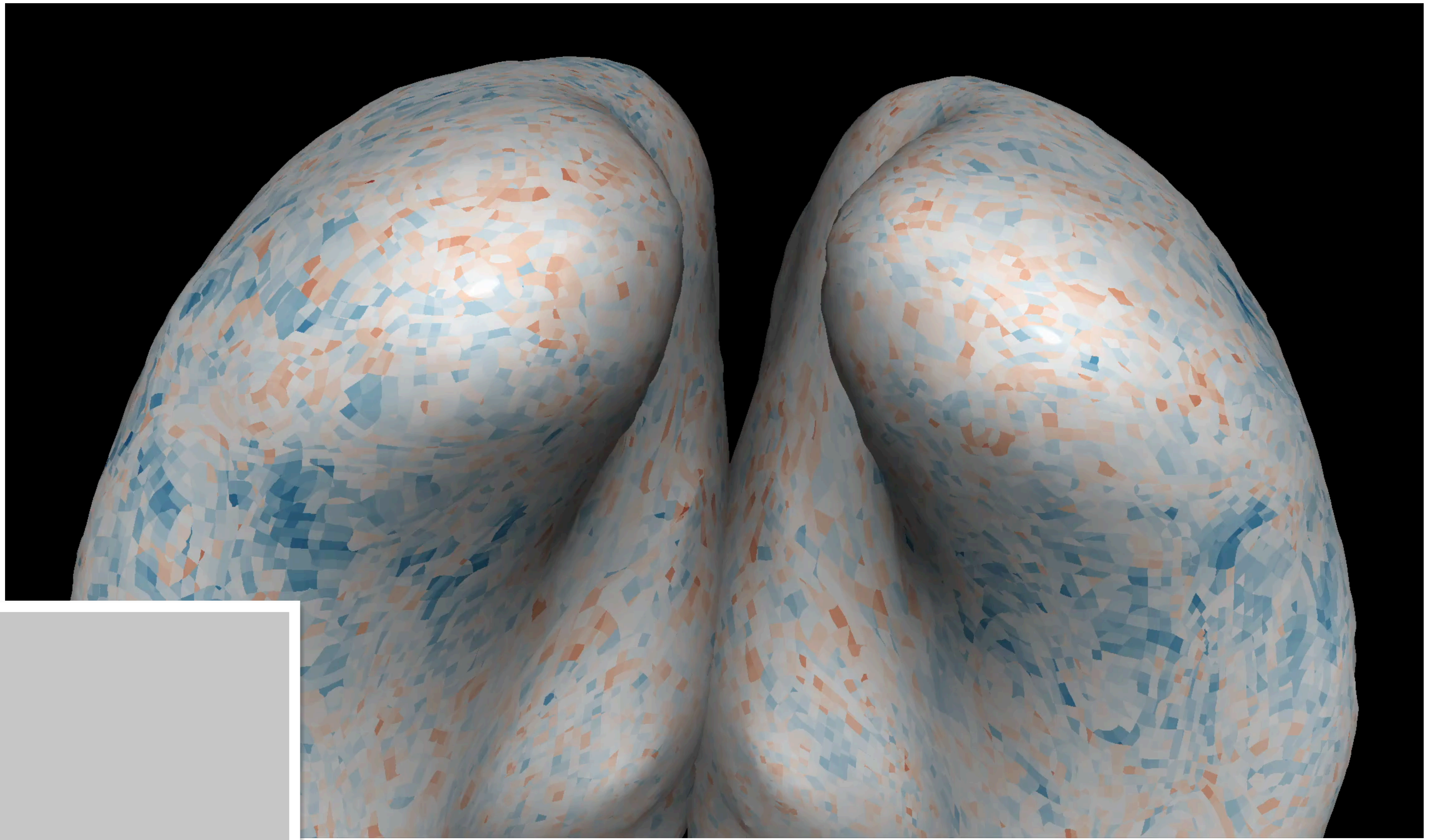

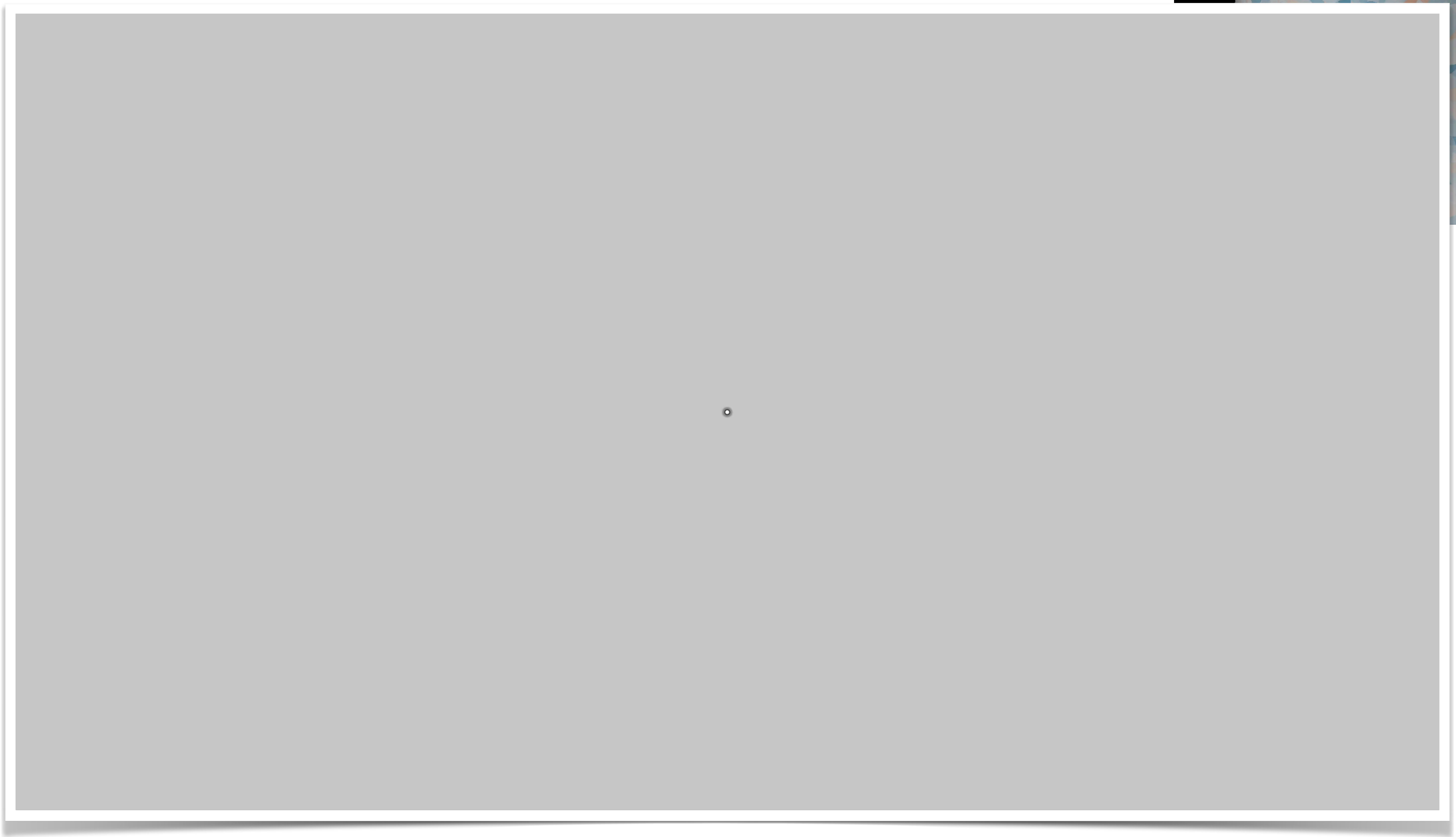

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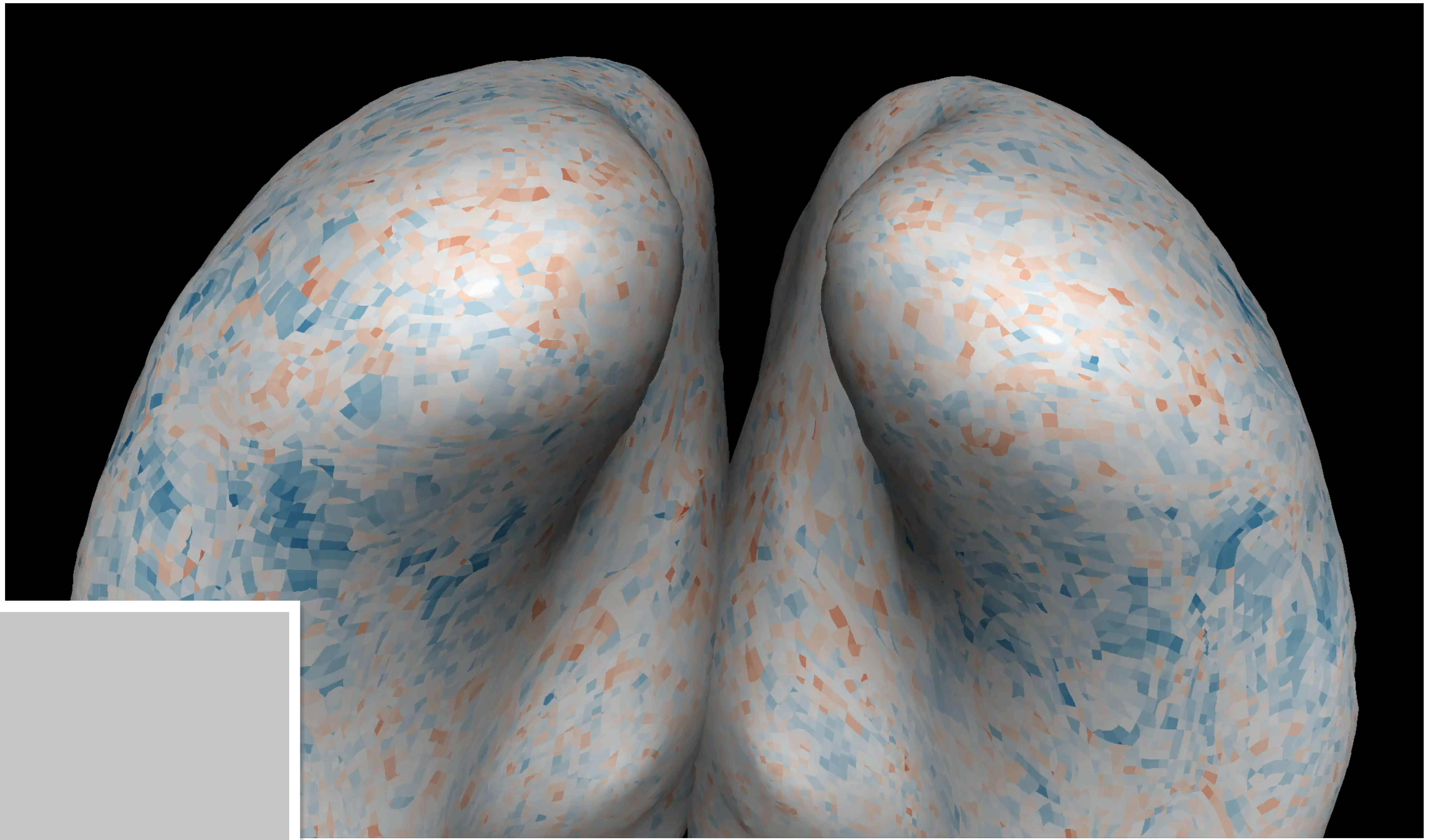
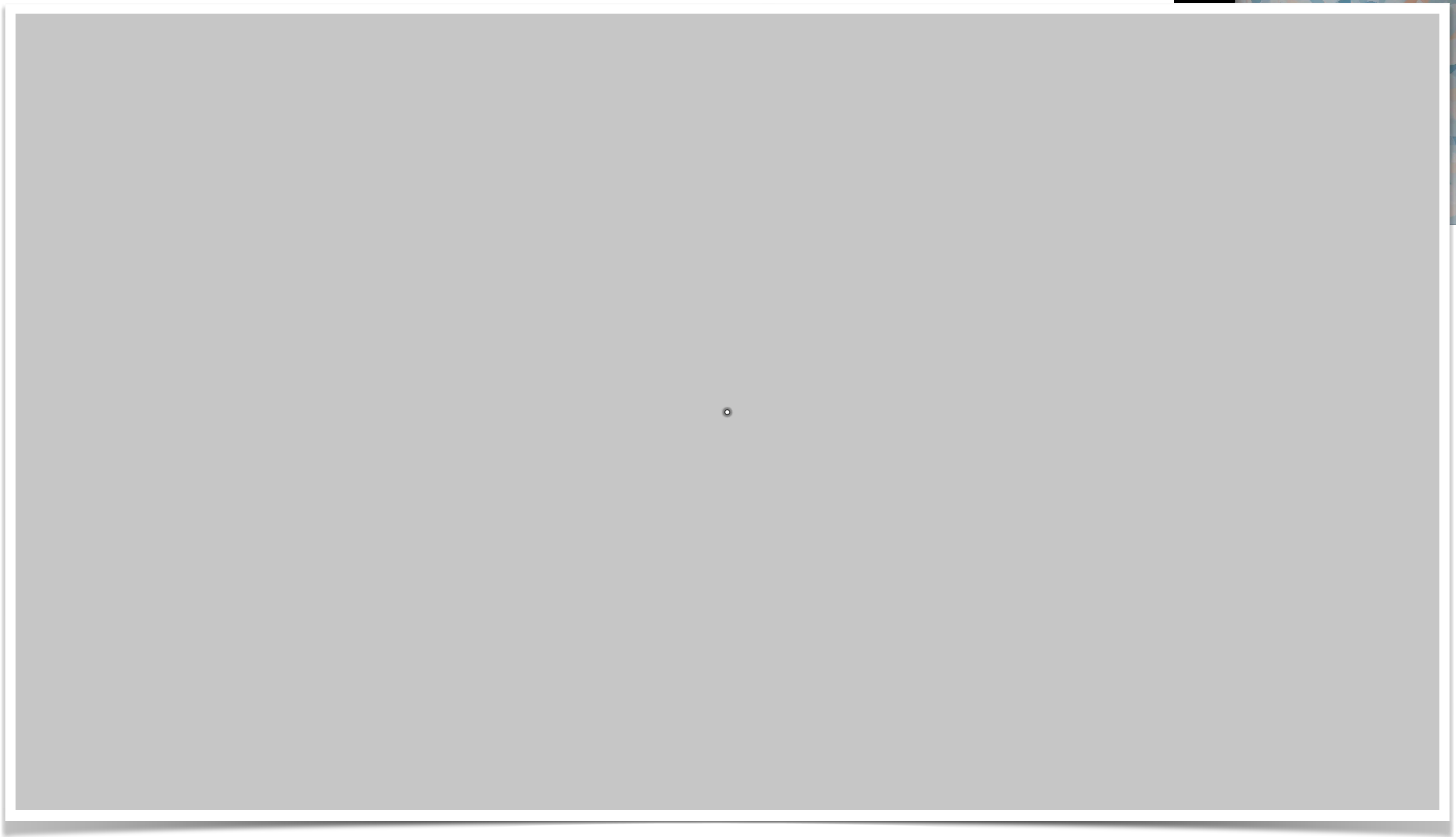




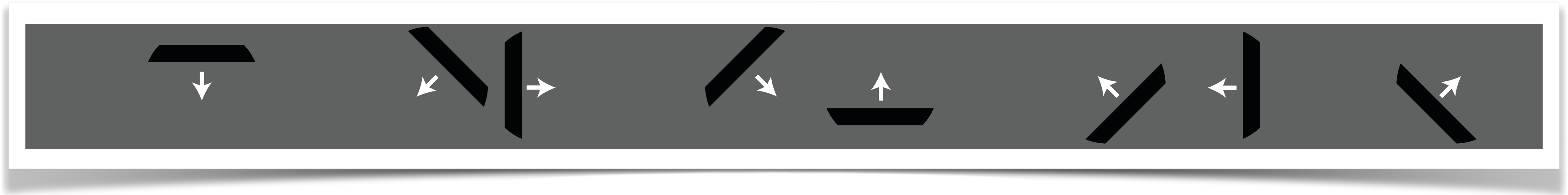
*Structured single-voxel BOLD time course: we can **fit PRF parameters***

Position

$$g(x_0, y_0, \sigma) = exp(-\frac{(x - x_0)^2 + (y - y_0)^2}{2\sigma^2}),$$

Size

Estimate best-fitting model parameters given the data



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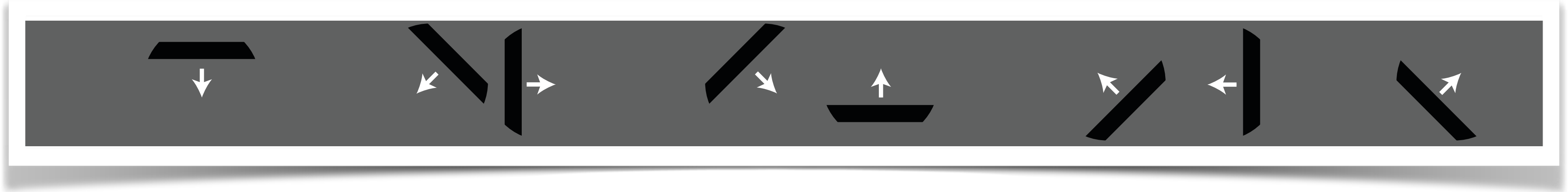

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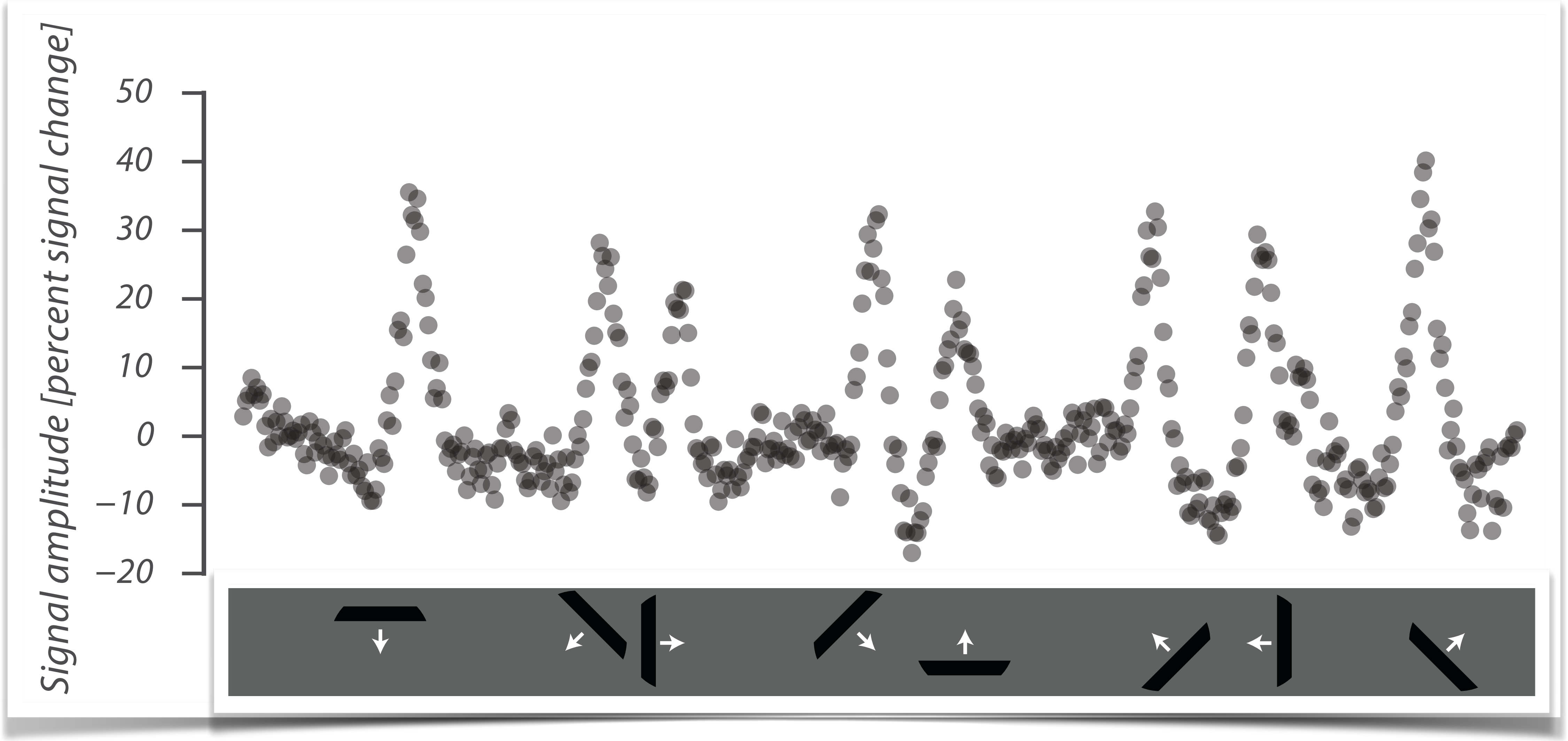

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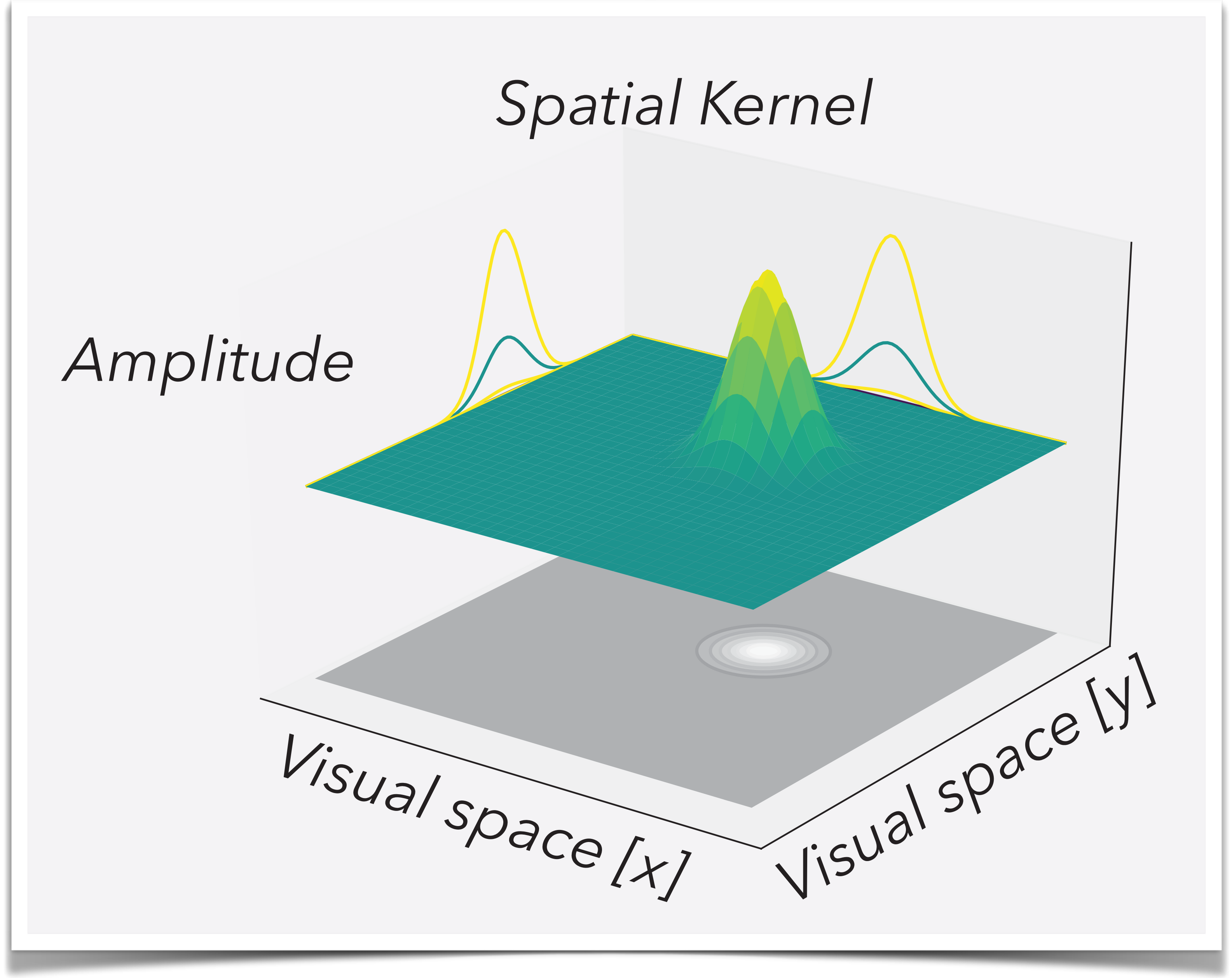

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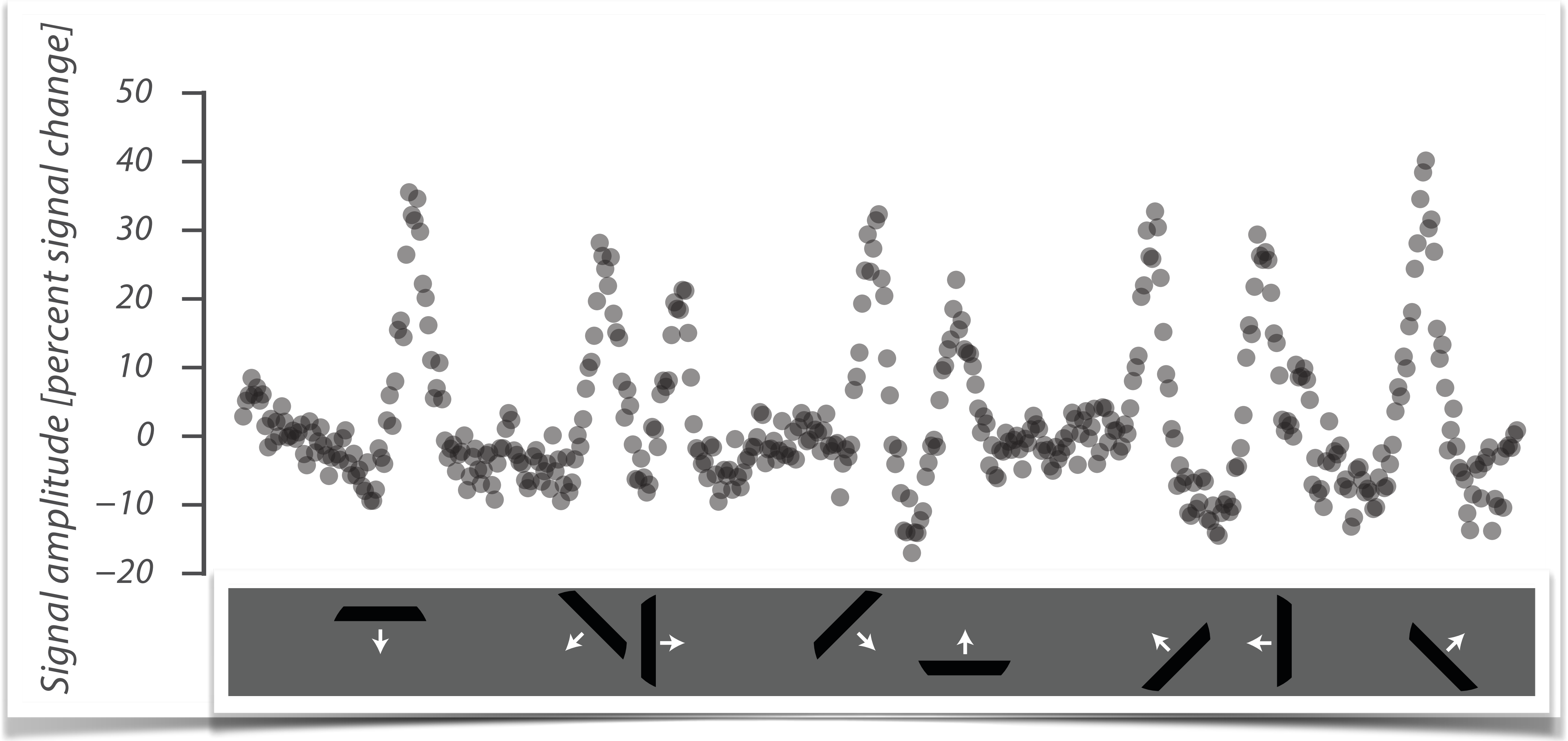

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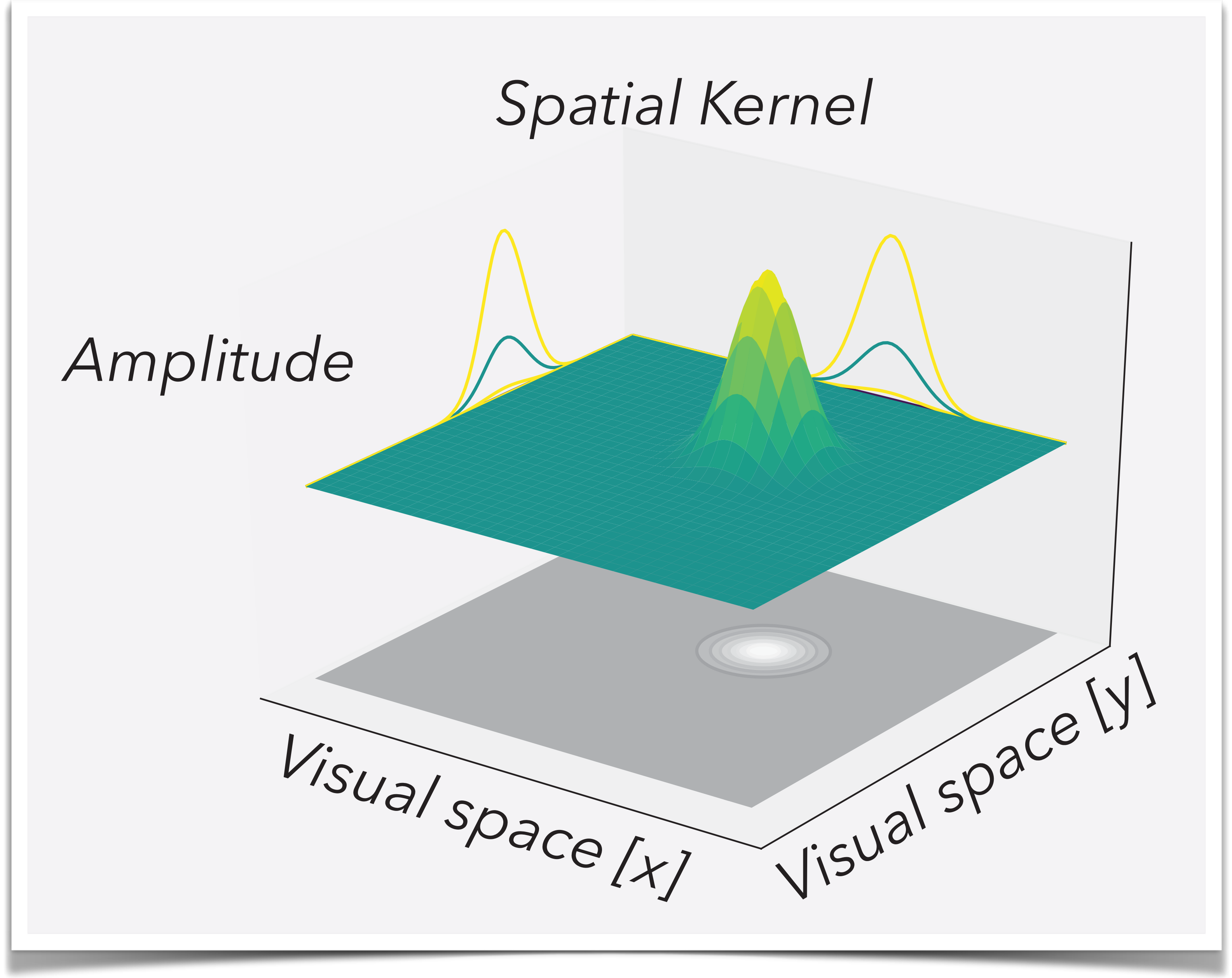

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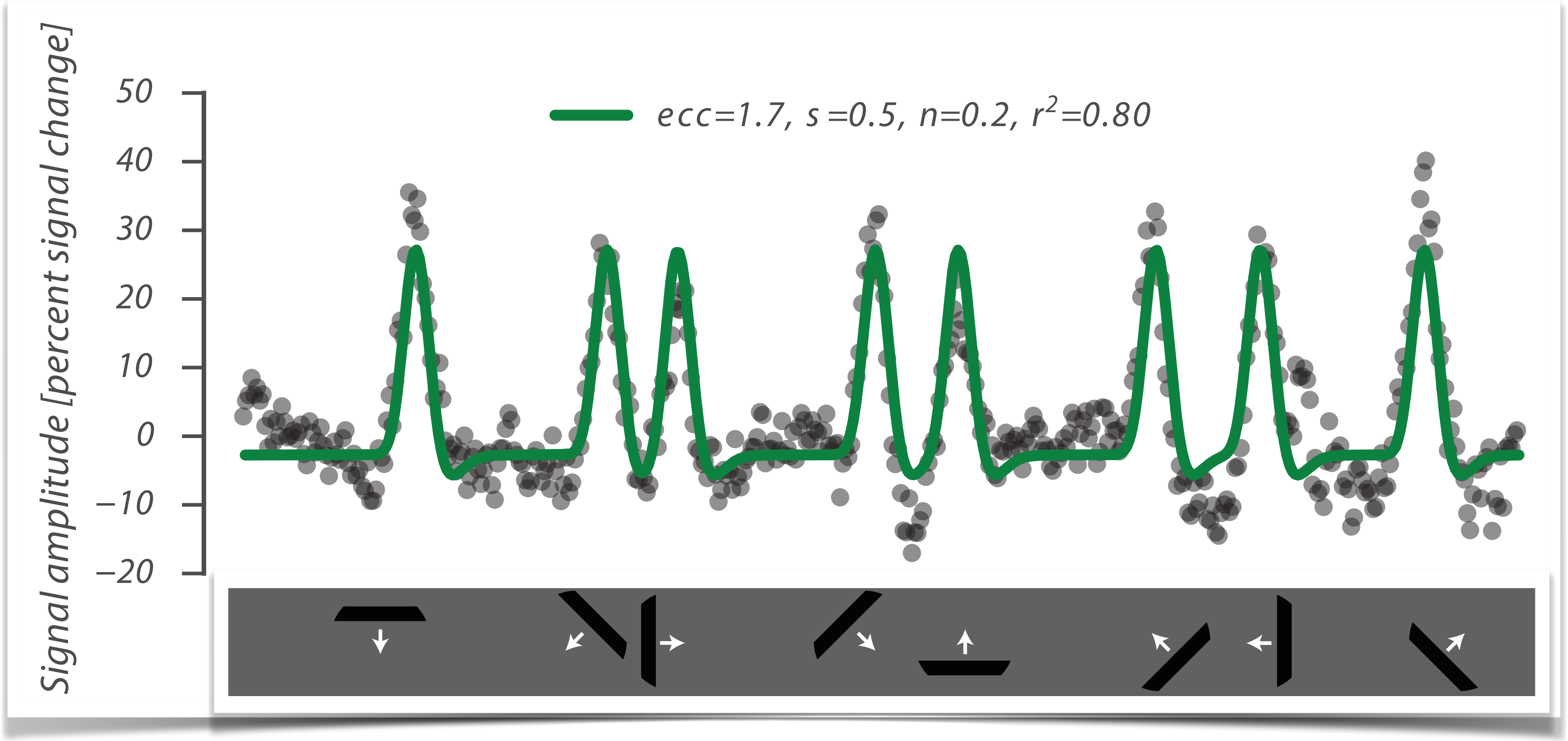

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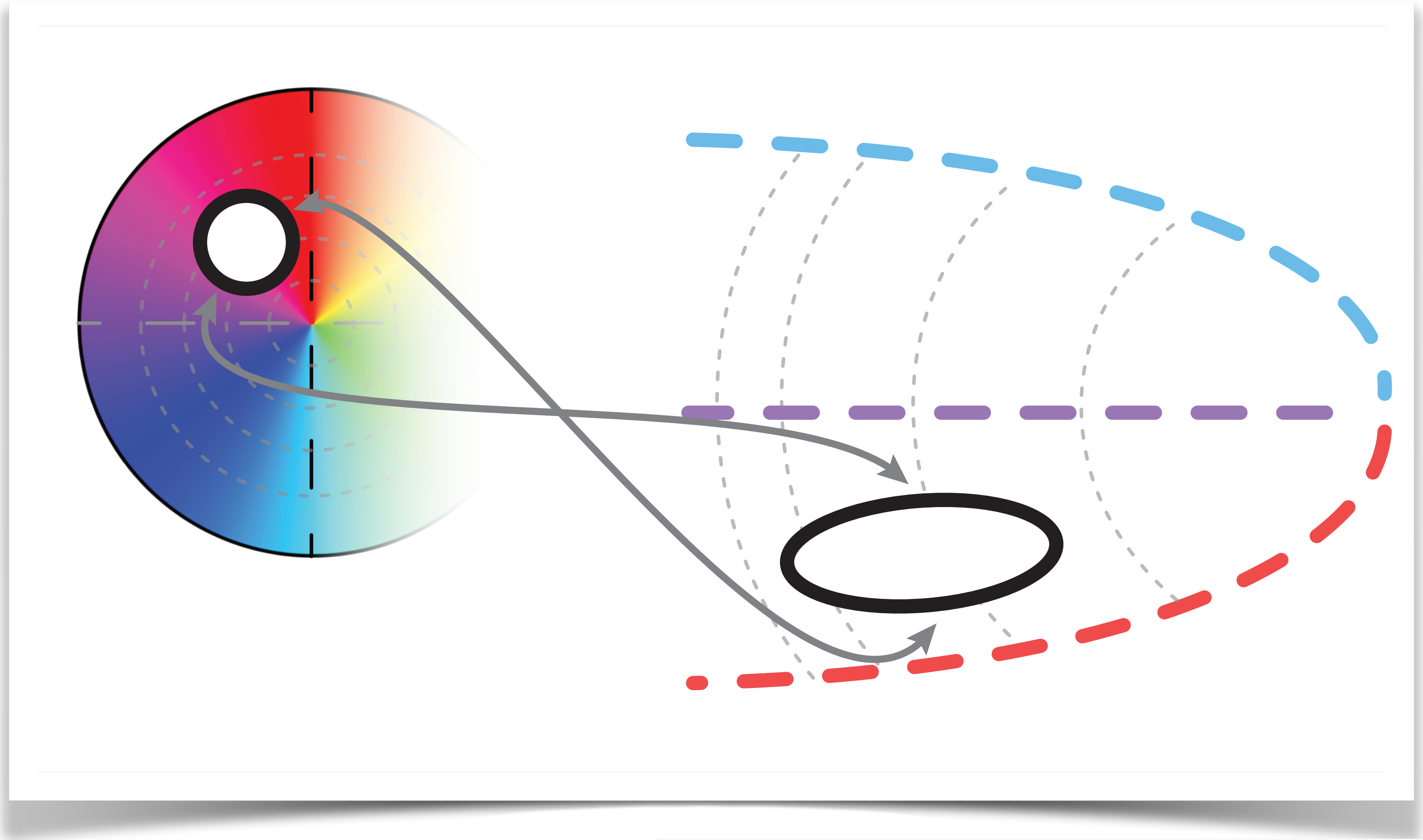

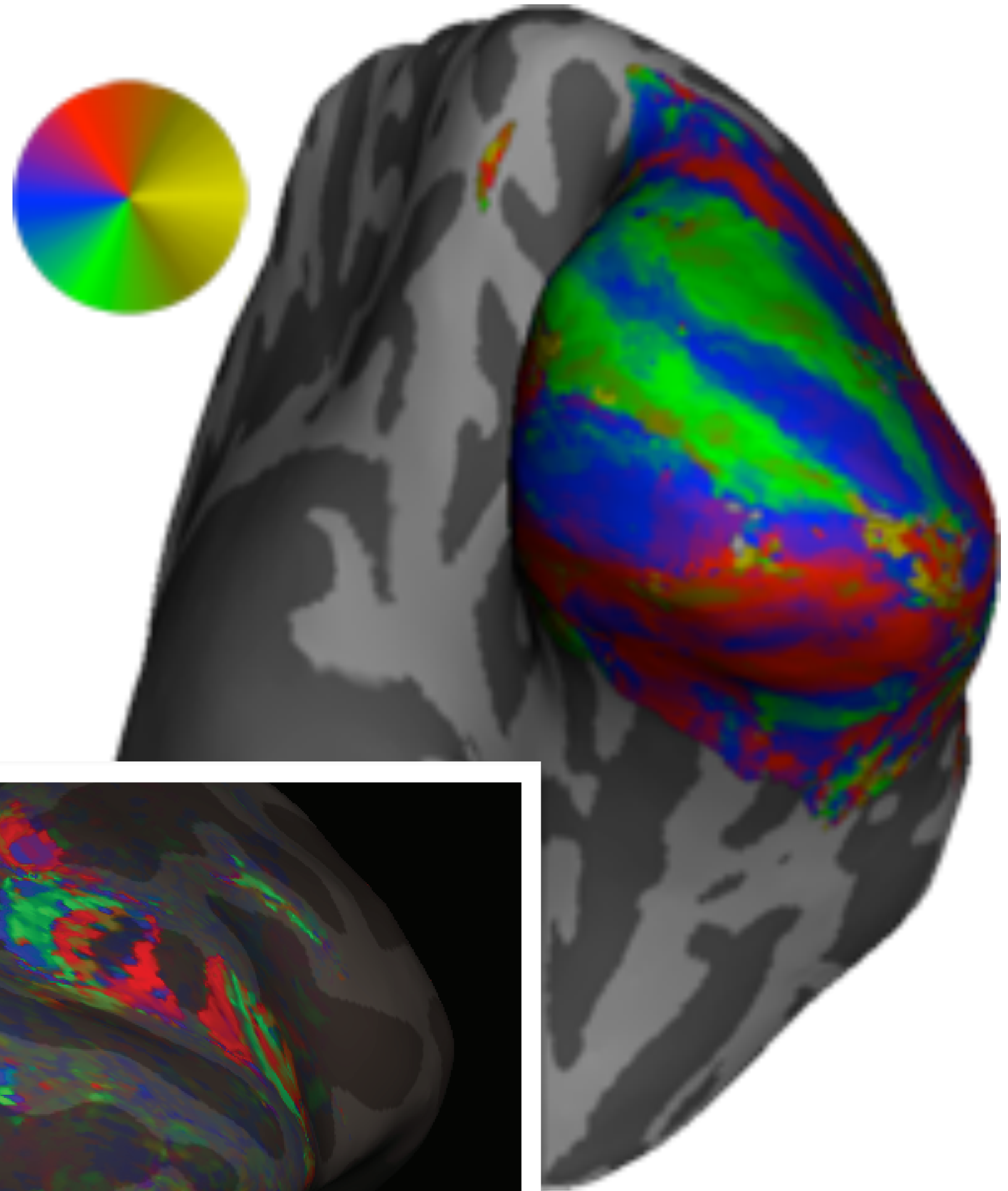

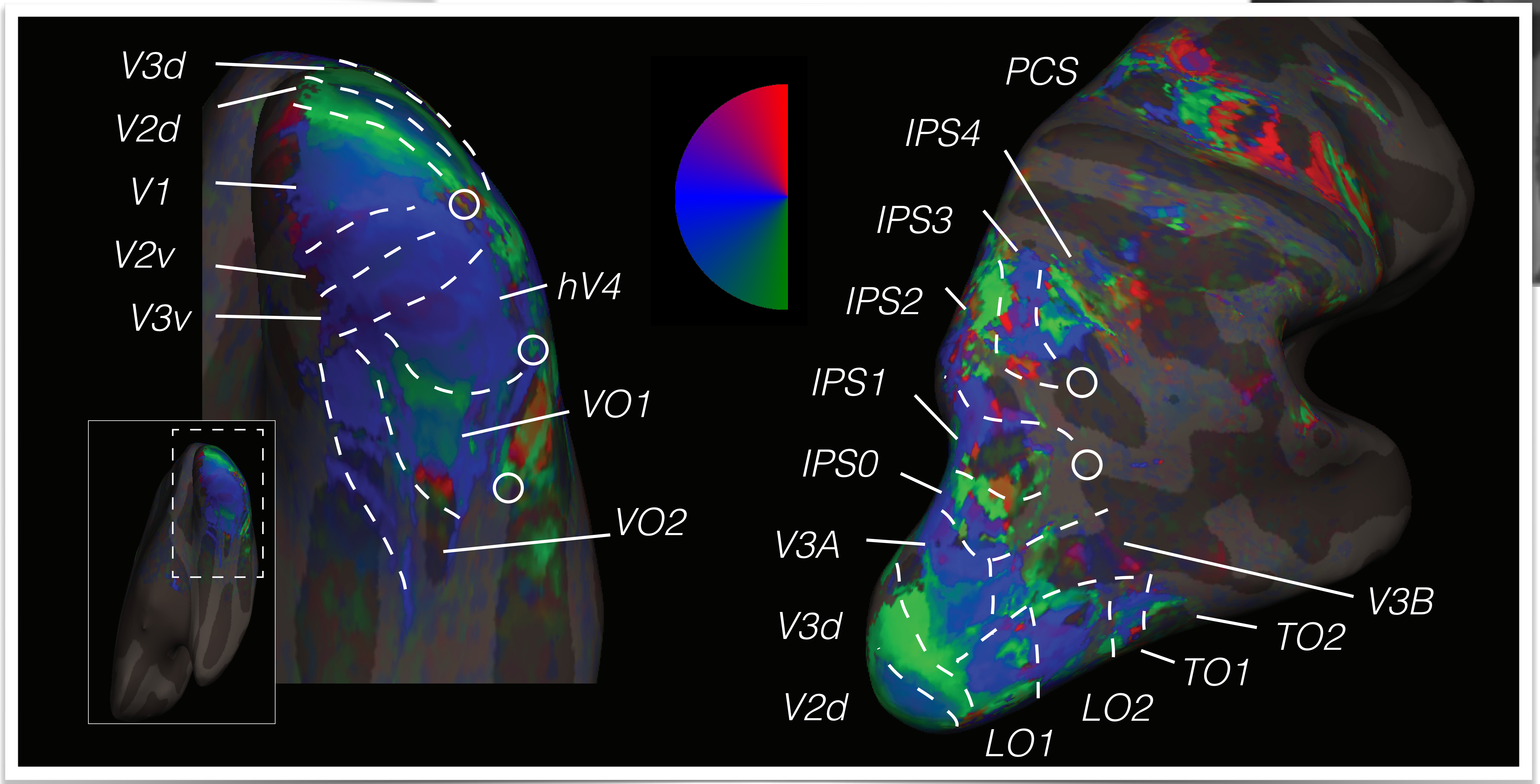
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V2d
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VO1
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PCS
IPS4
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LO1
LO2
TO1
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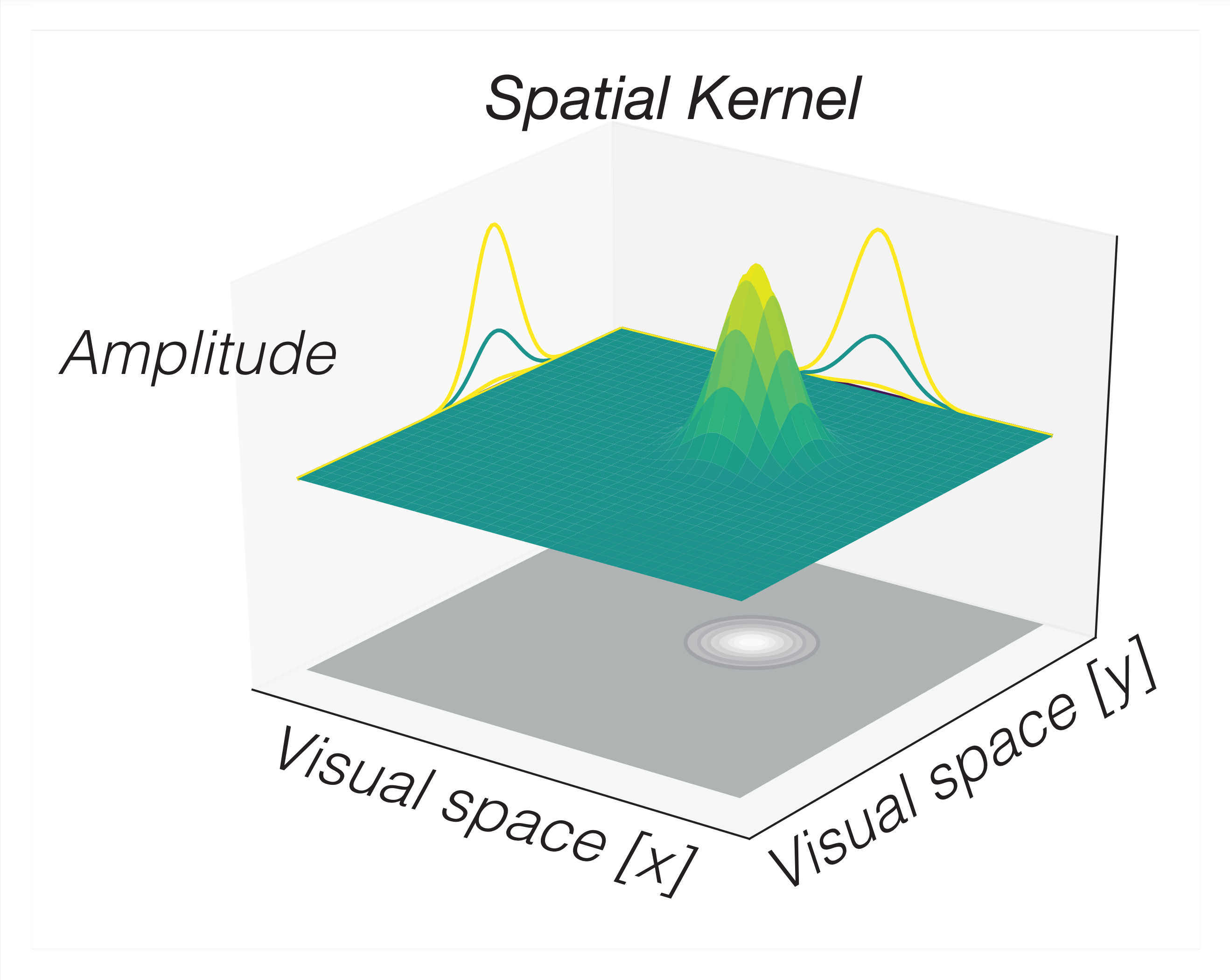
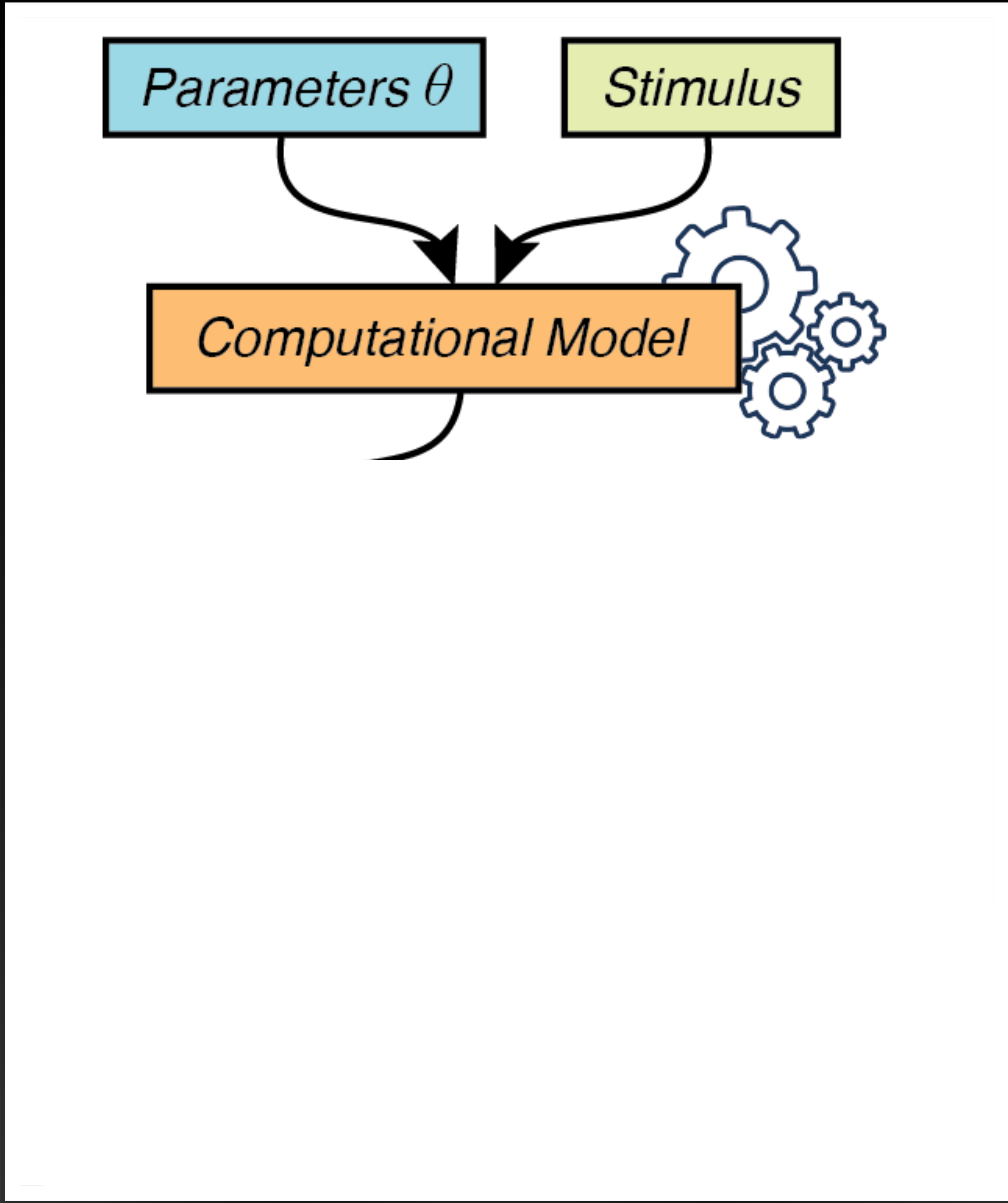
V3B

Computational Cognitive Neuroscience





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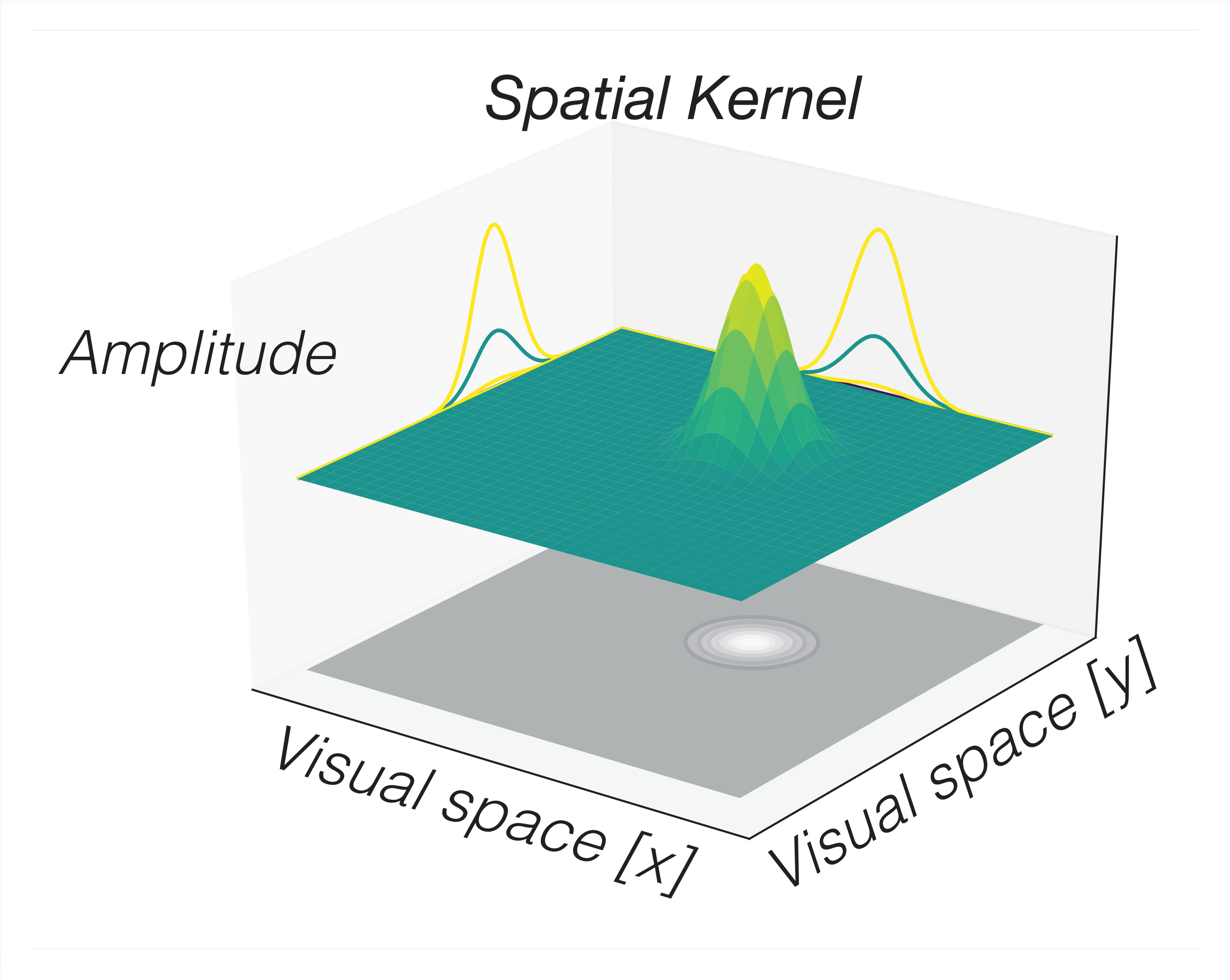

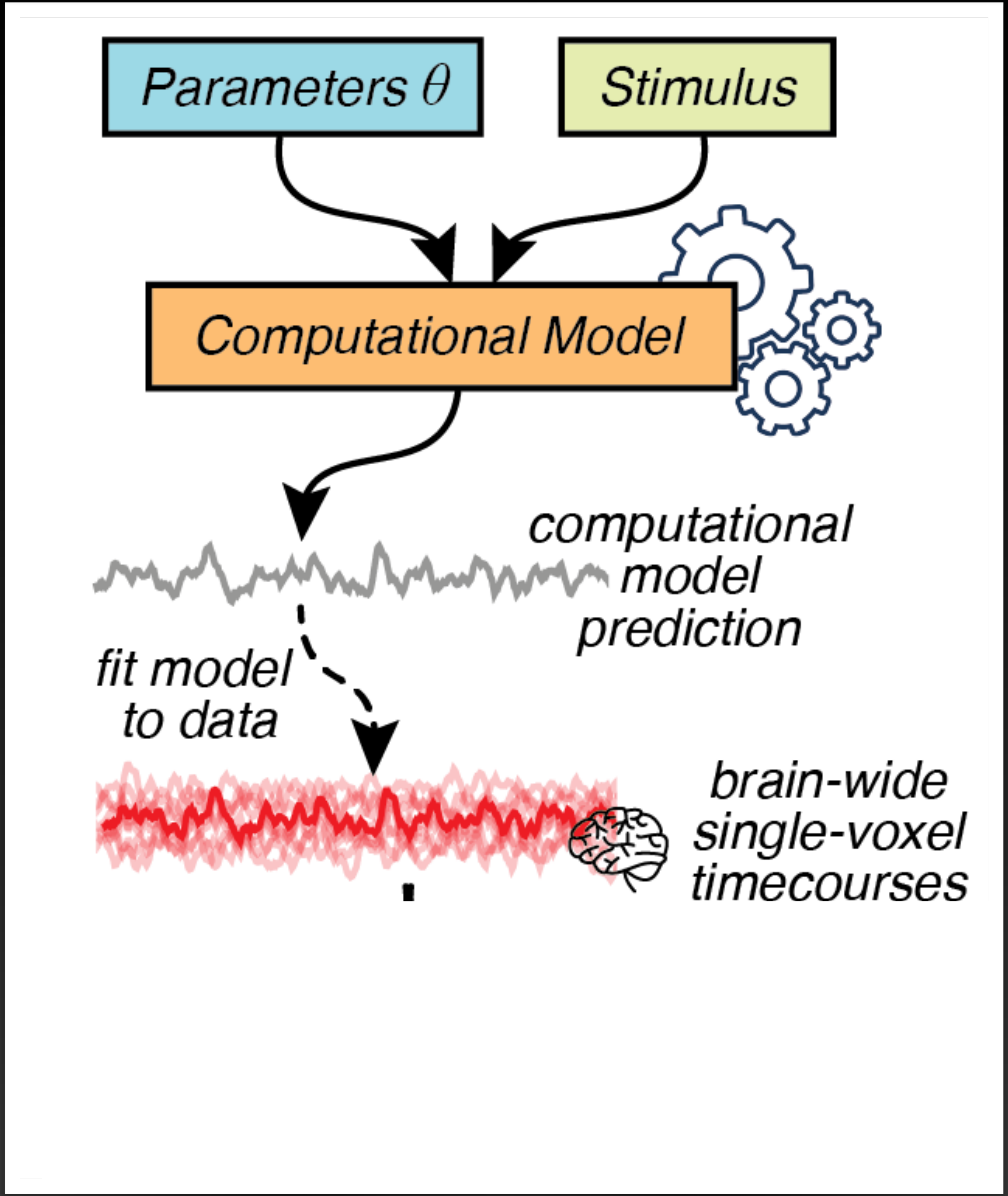

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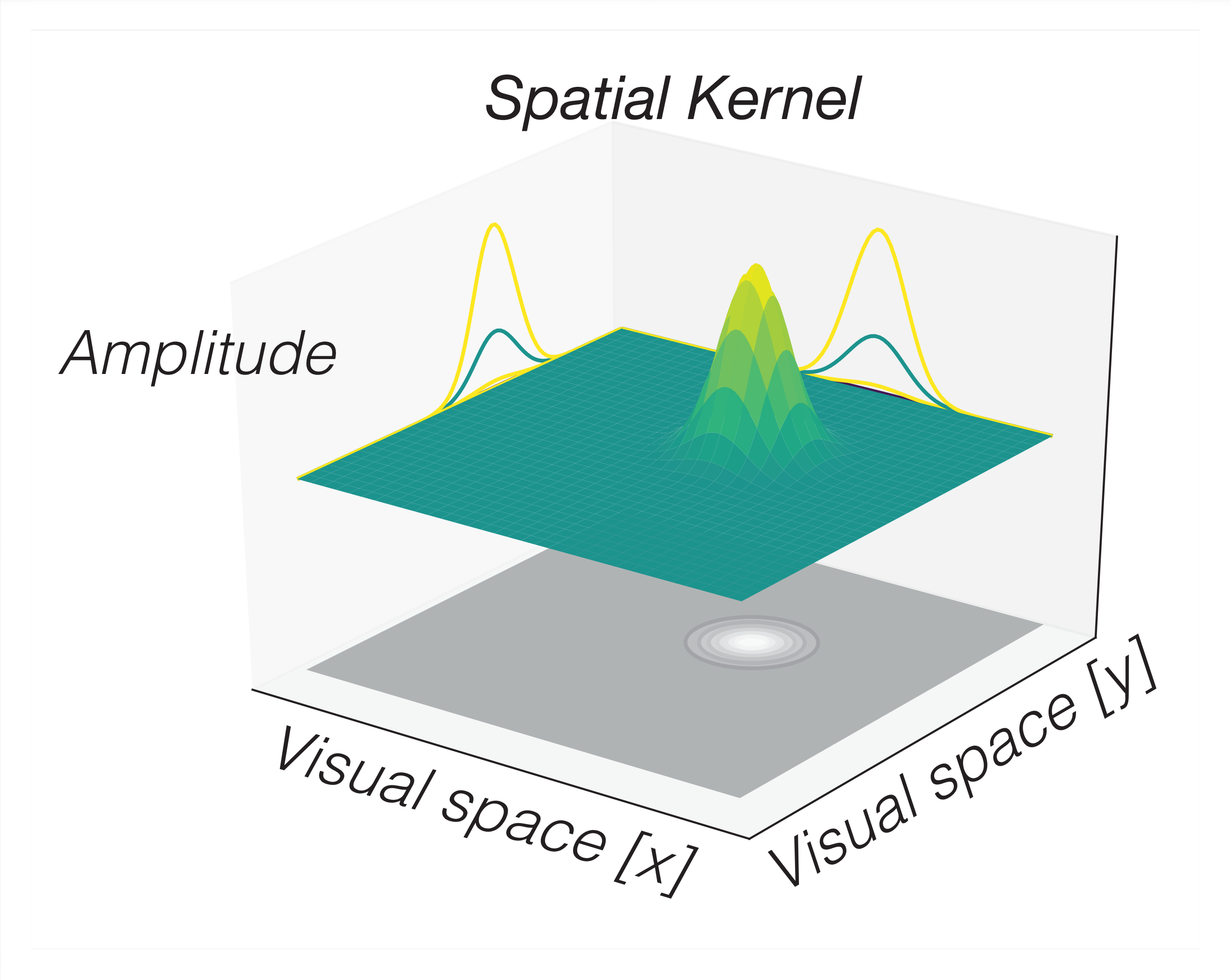

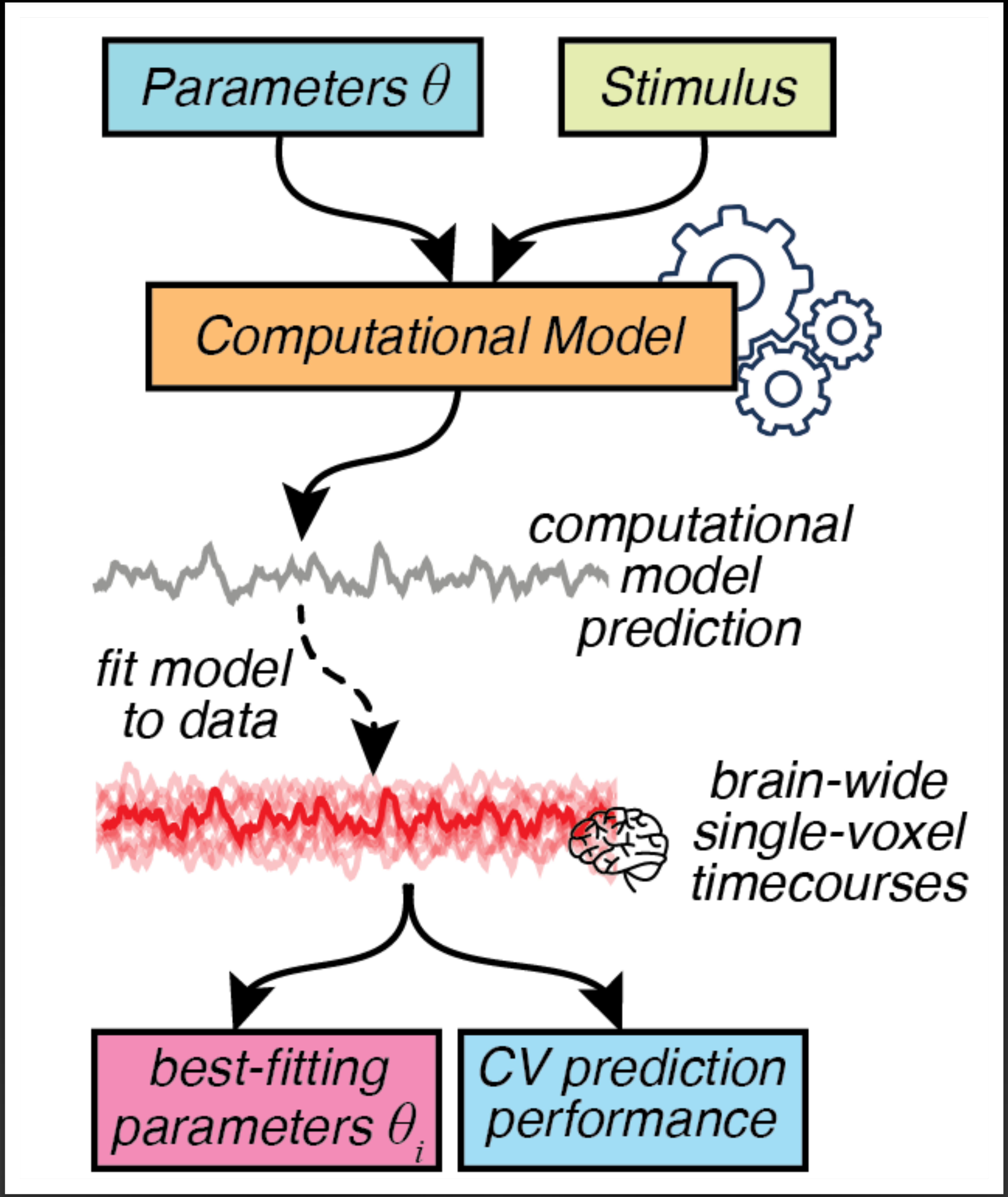

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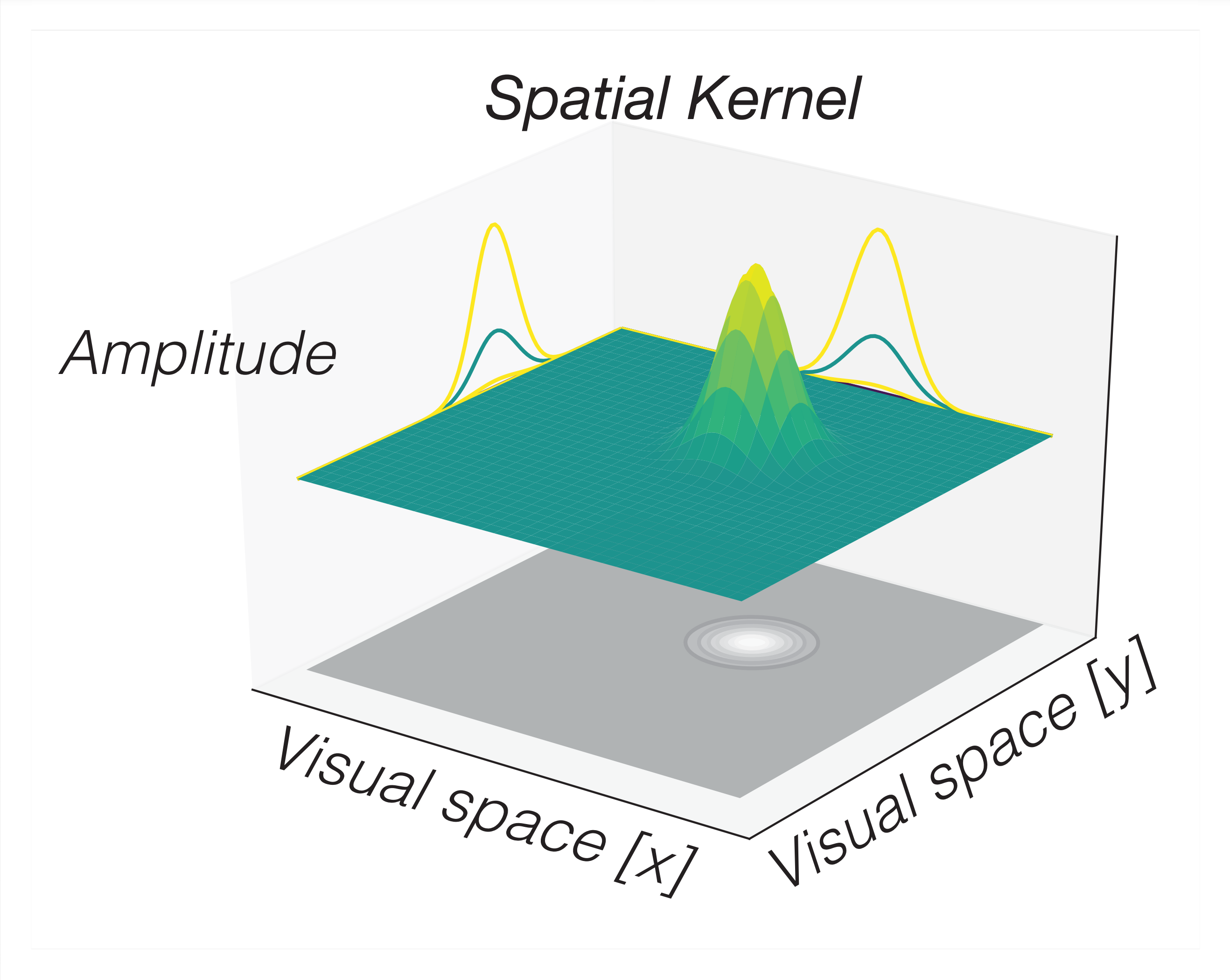
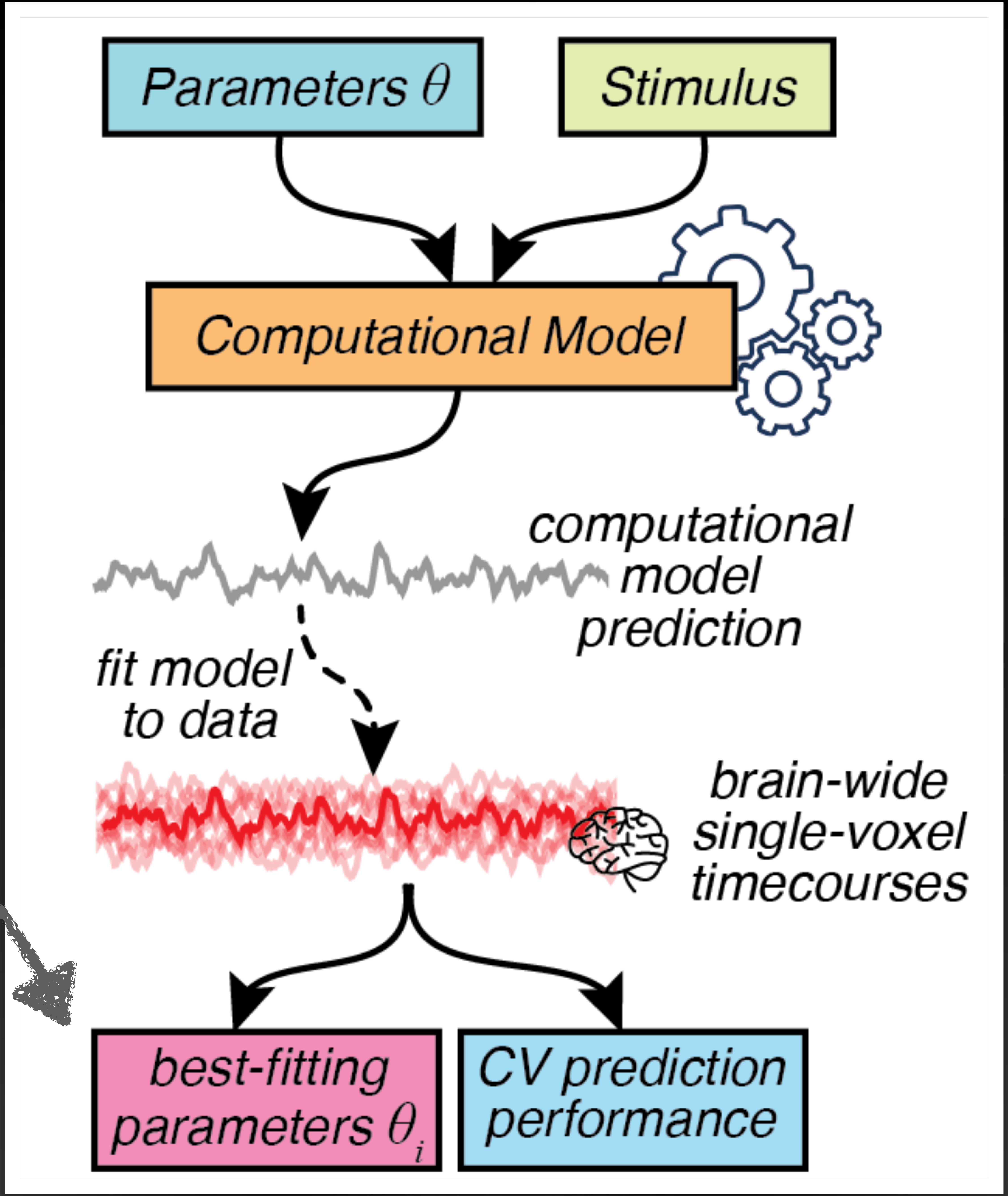
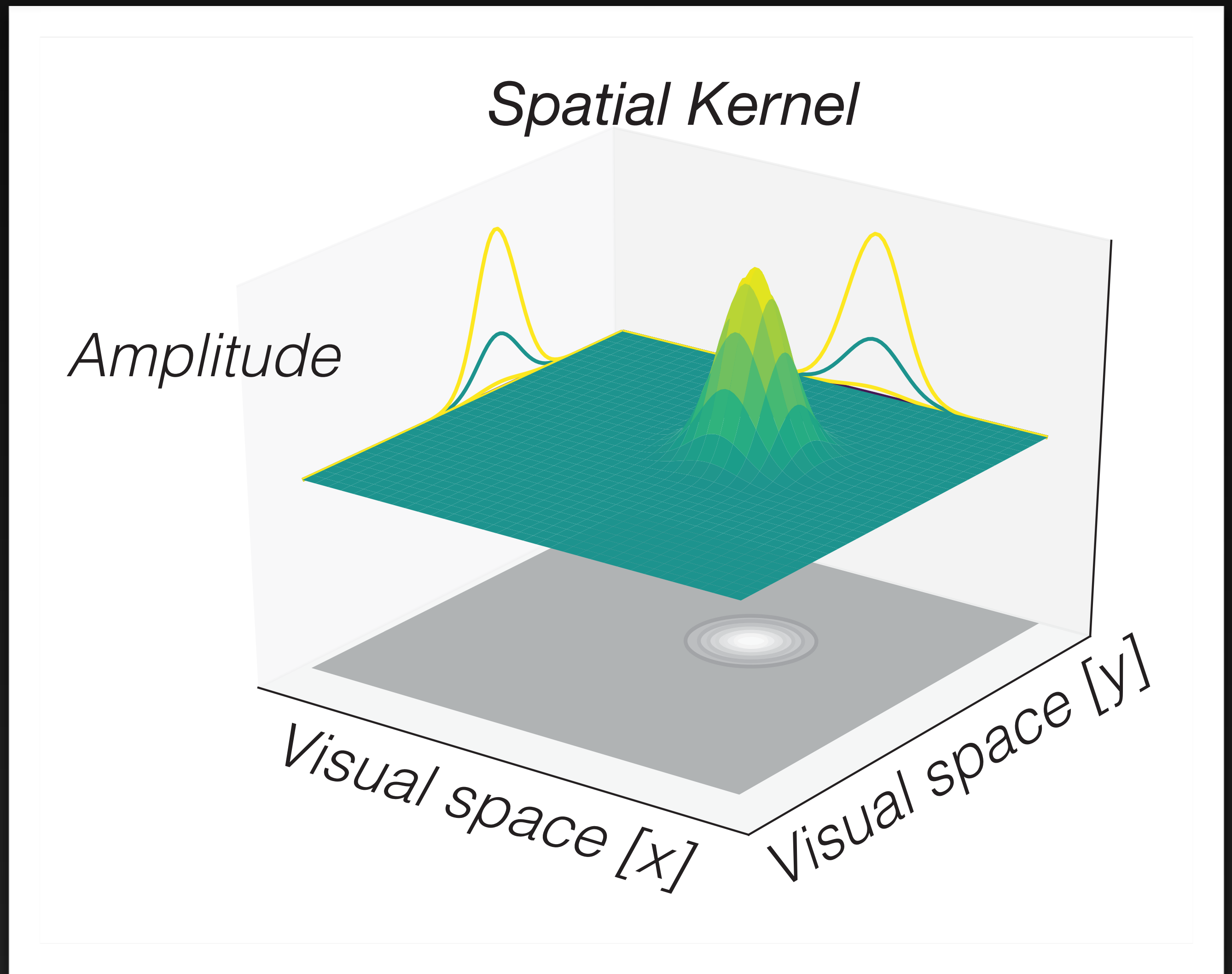
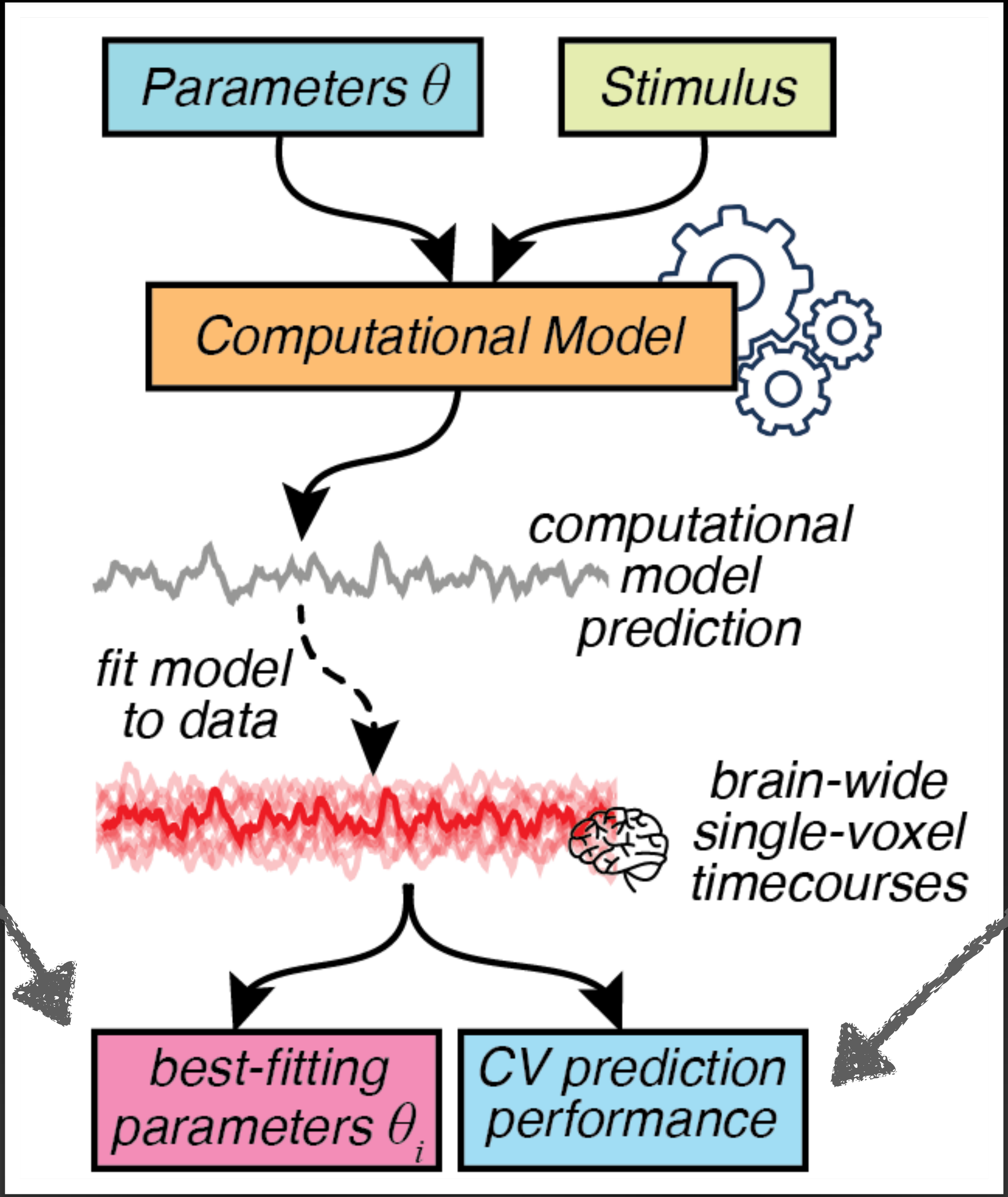




PROBE COMPUTATION, REPRESENTATION

Computational Cognitive Neuroscience





Probe Computation, Representation

Compare Computational Models

Encoding

Kay et al, 2008

Encoding

What is the 'receptive field' of a voxel?

Let's expand to more complex receptive fields

Kay et al, 2008

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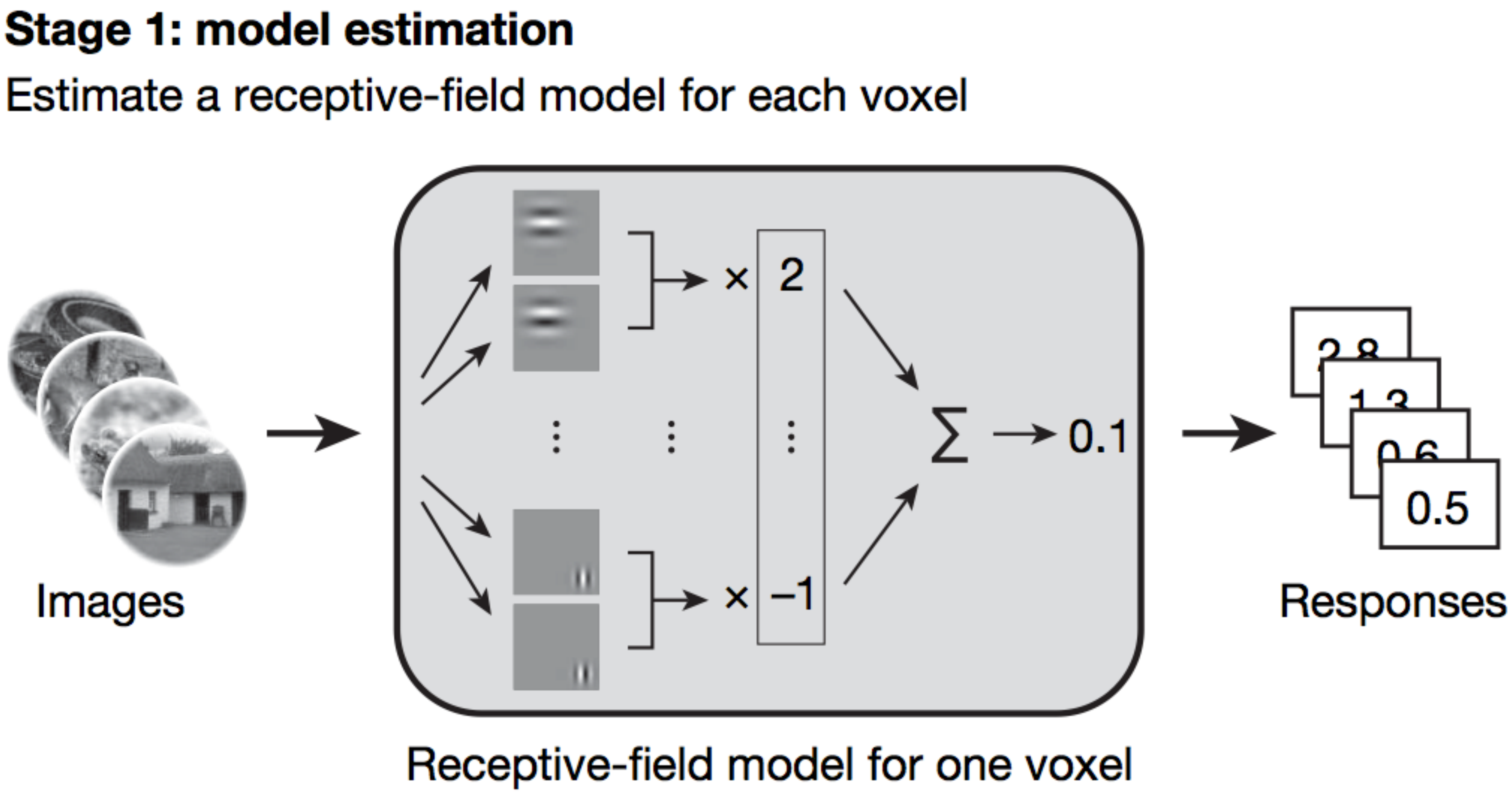

Kay et al, 2008

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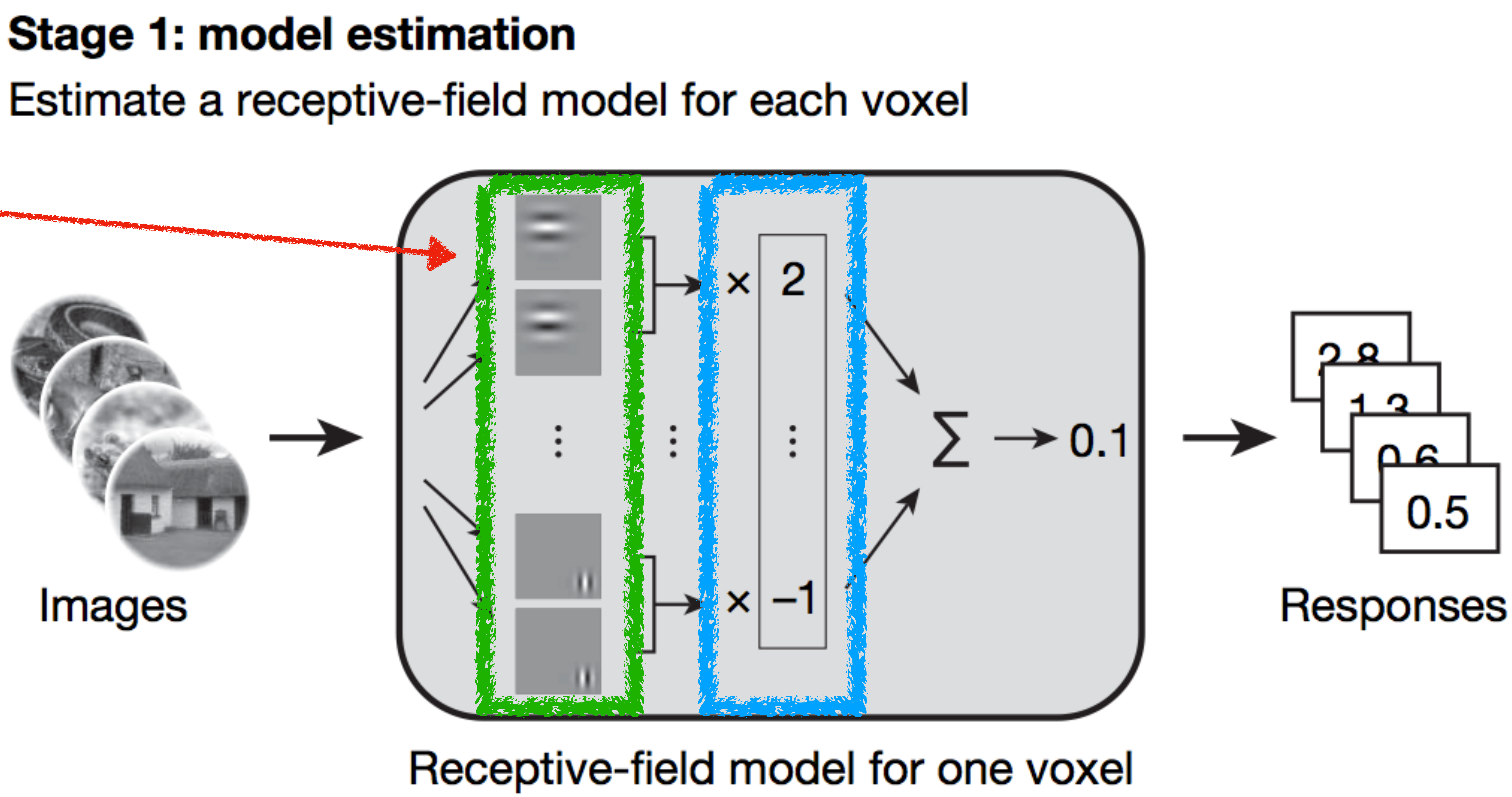
Many different models and their predictions



Kay et al, 2008

Encoding: adding orientation

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Kay et al, 2008

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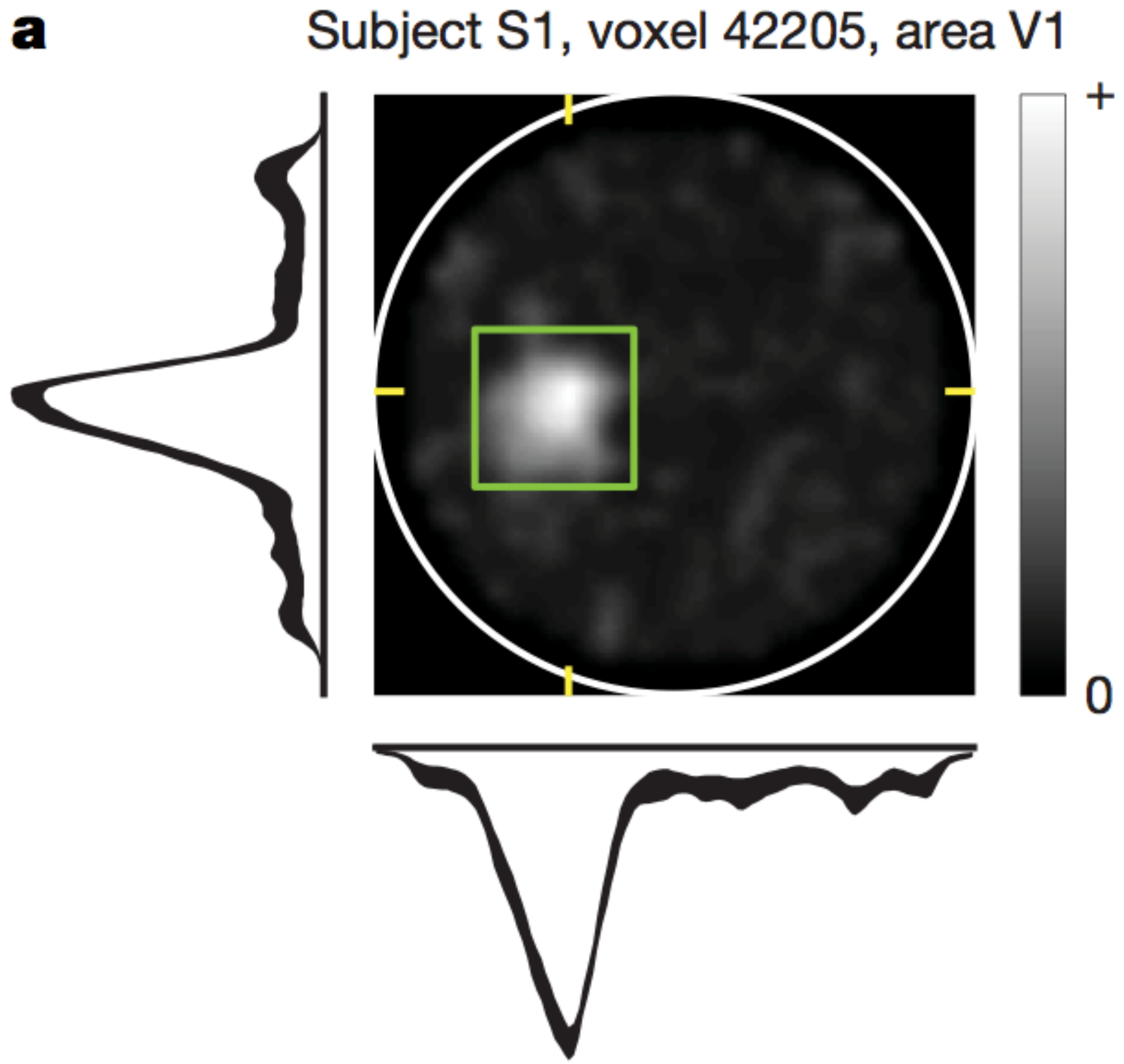

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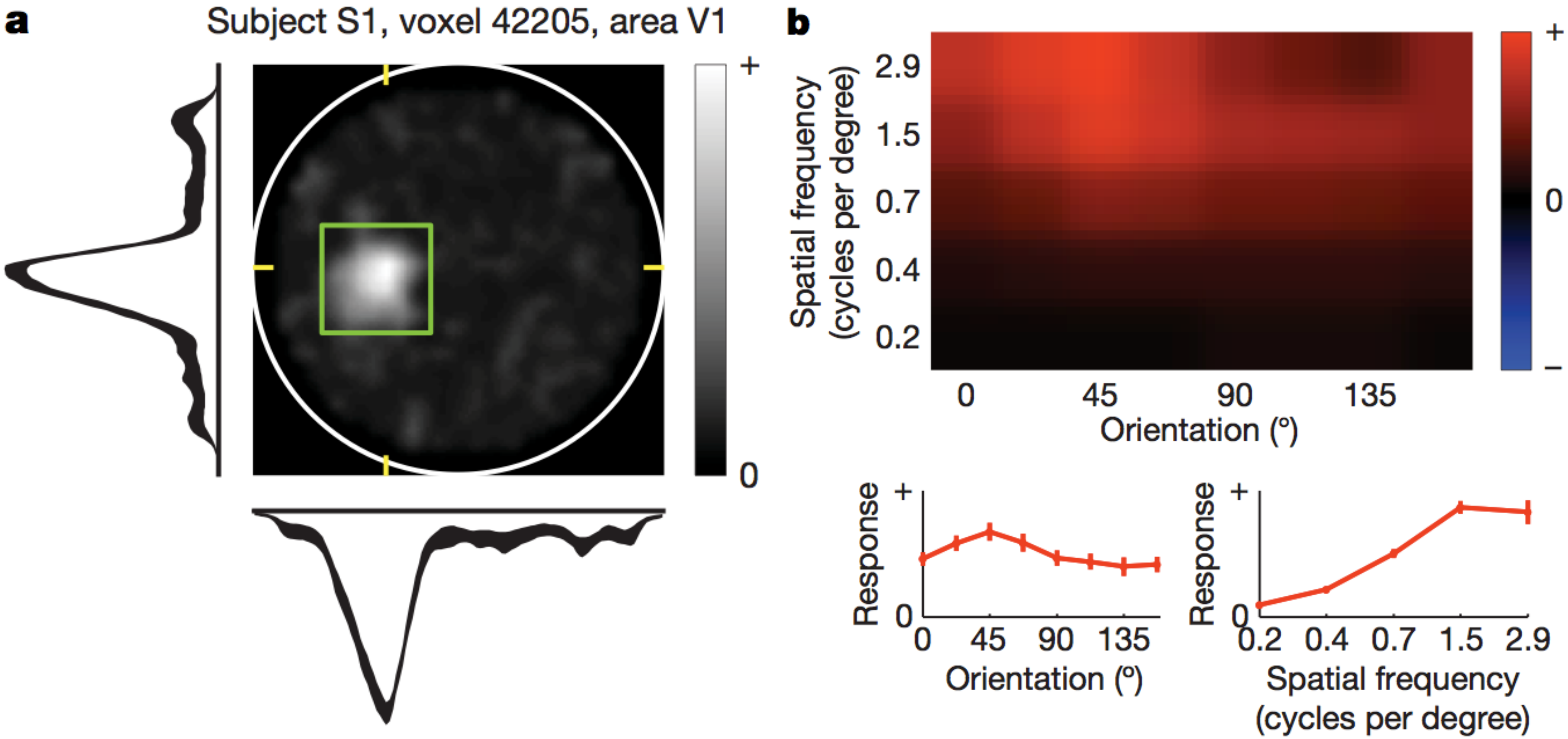

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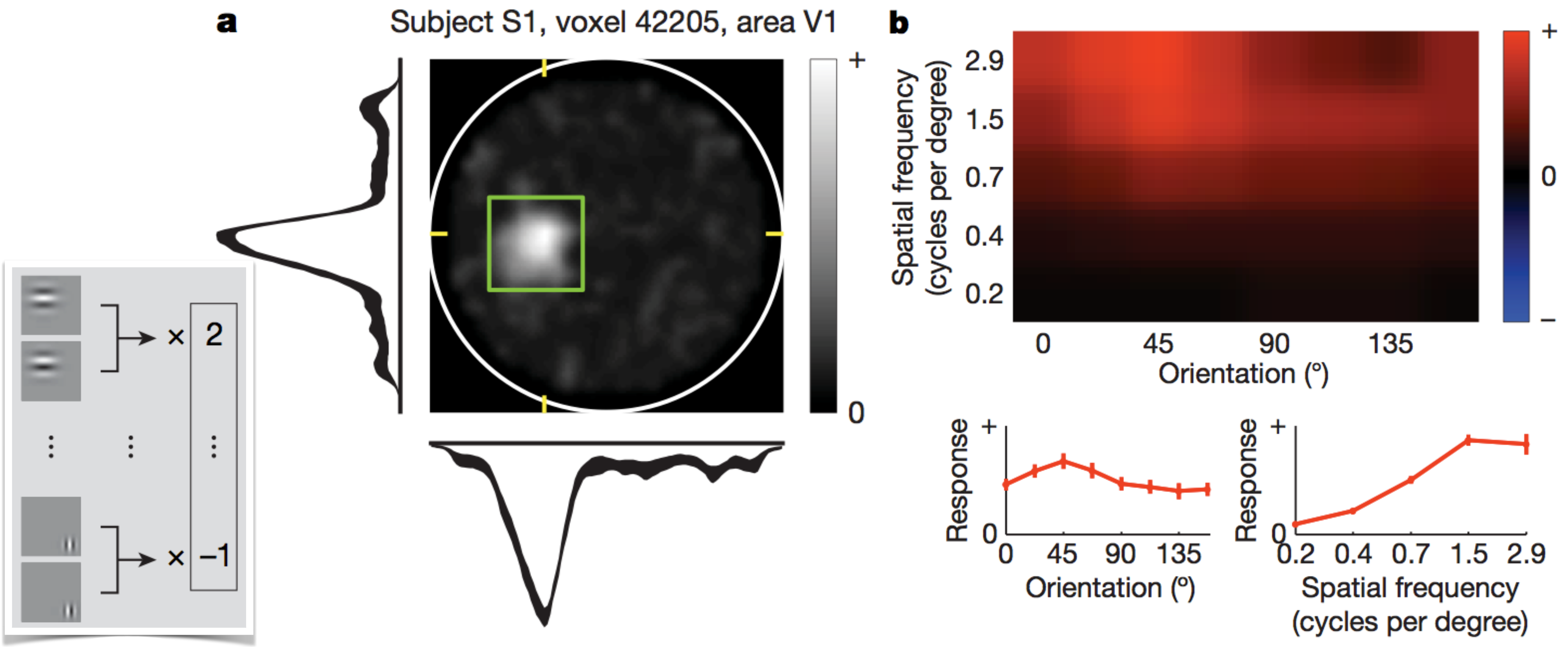

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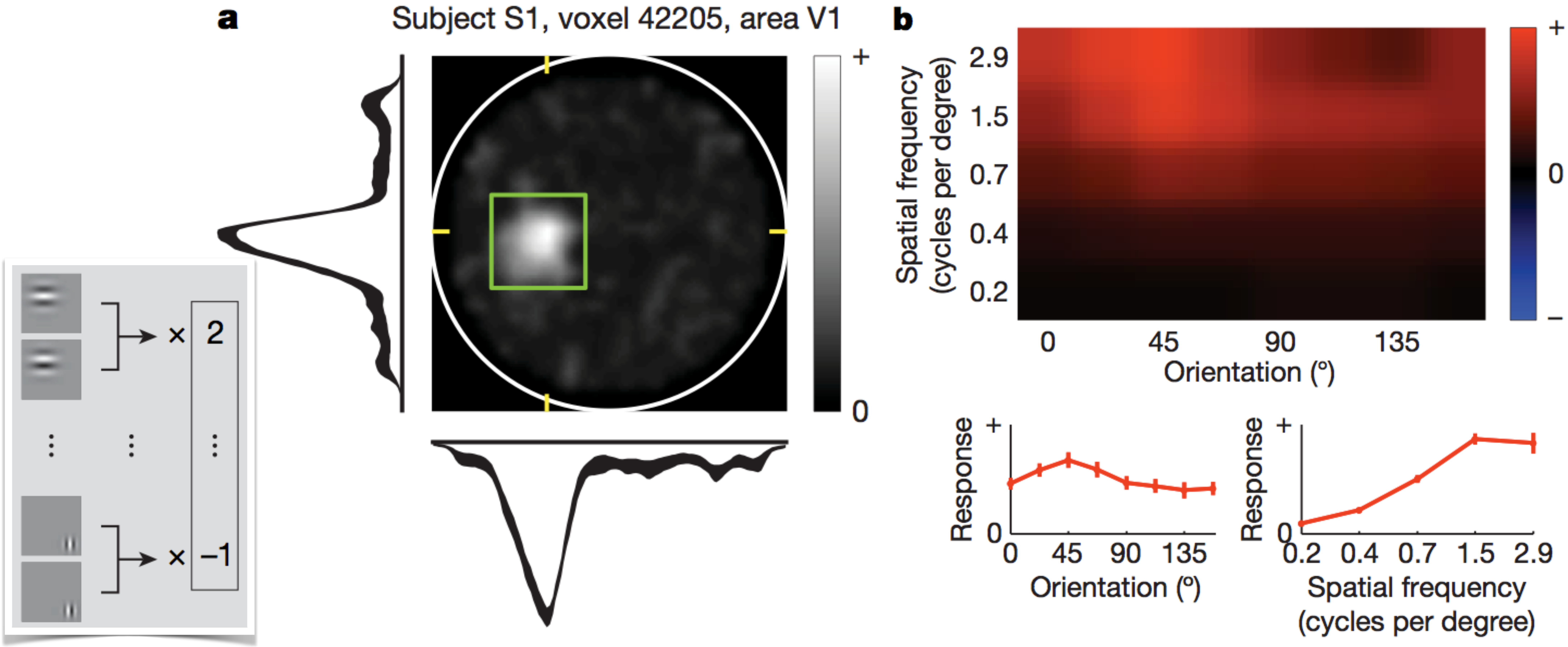
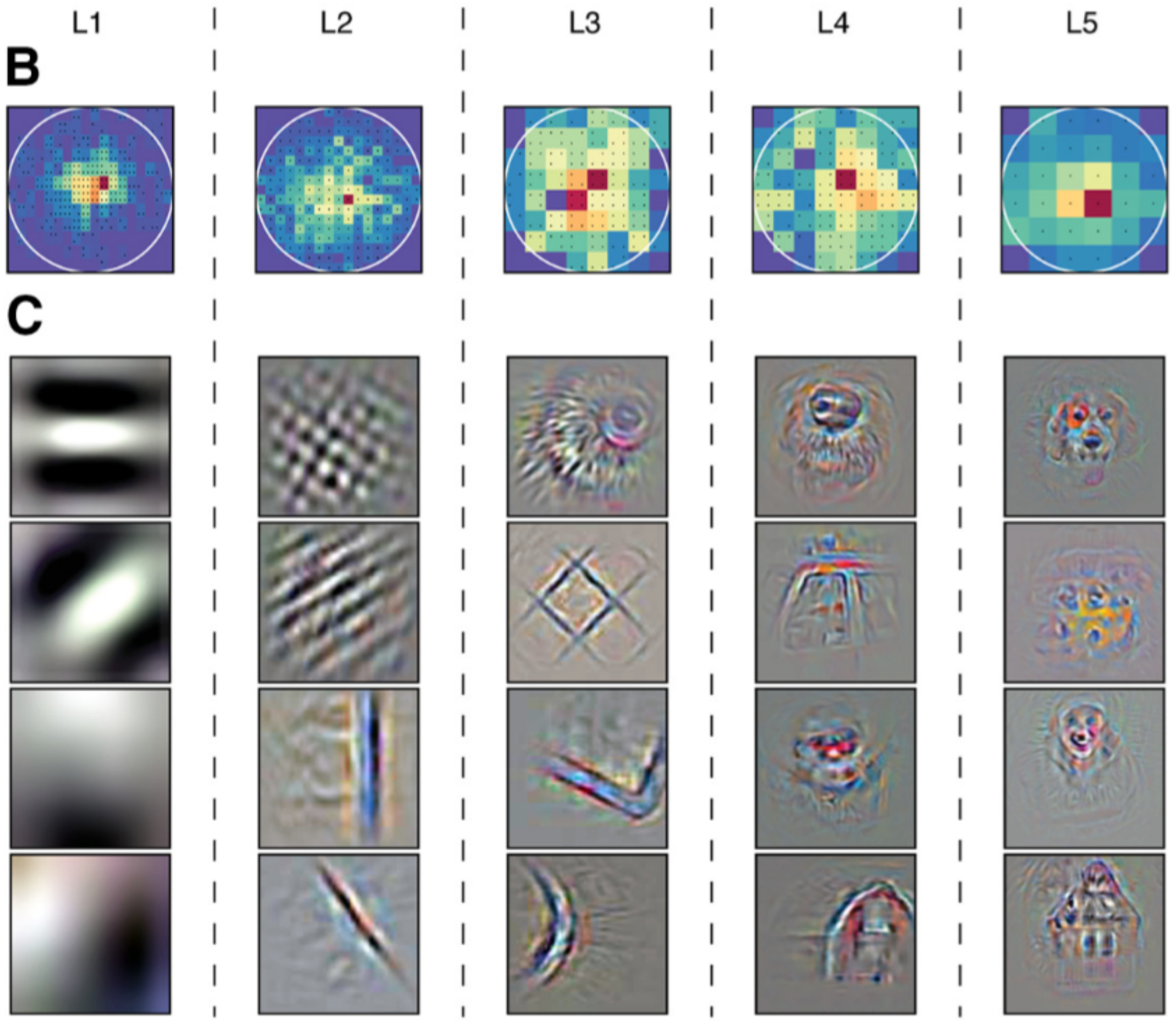
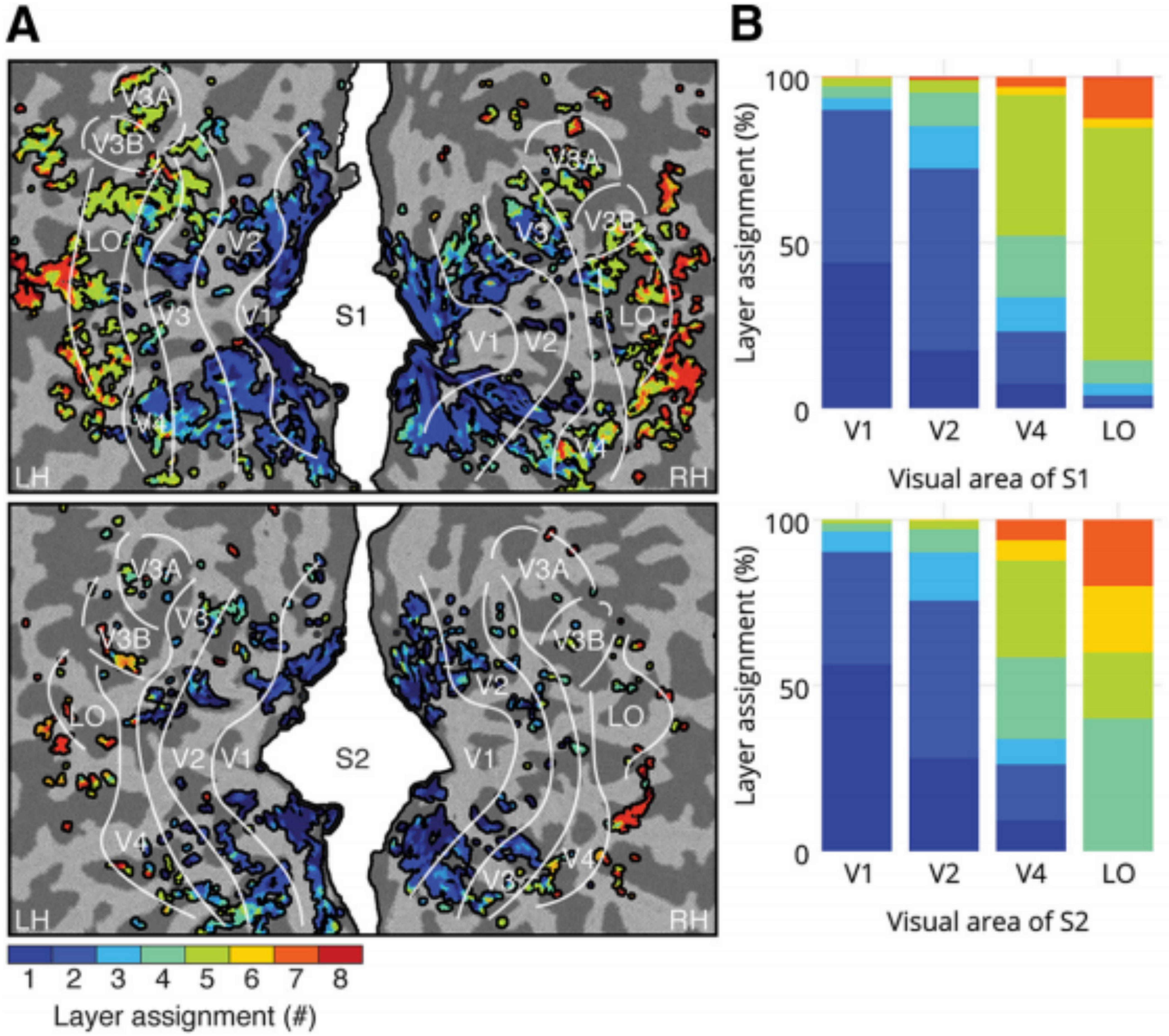


Estimate a huge amount of parameters, using ***penalised regression***

Kay et al, 2008

Neural Networks as encoding model





Güçlü U, van Gerven MAJ. 2015

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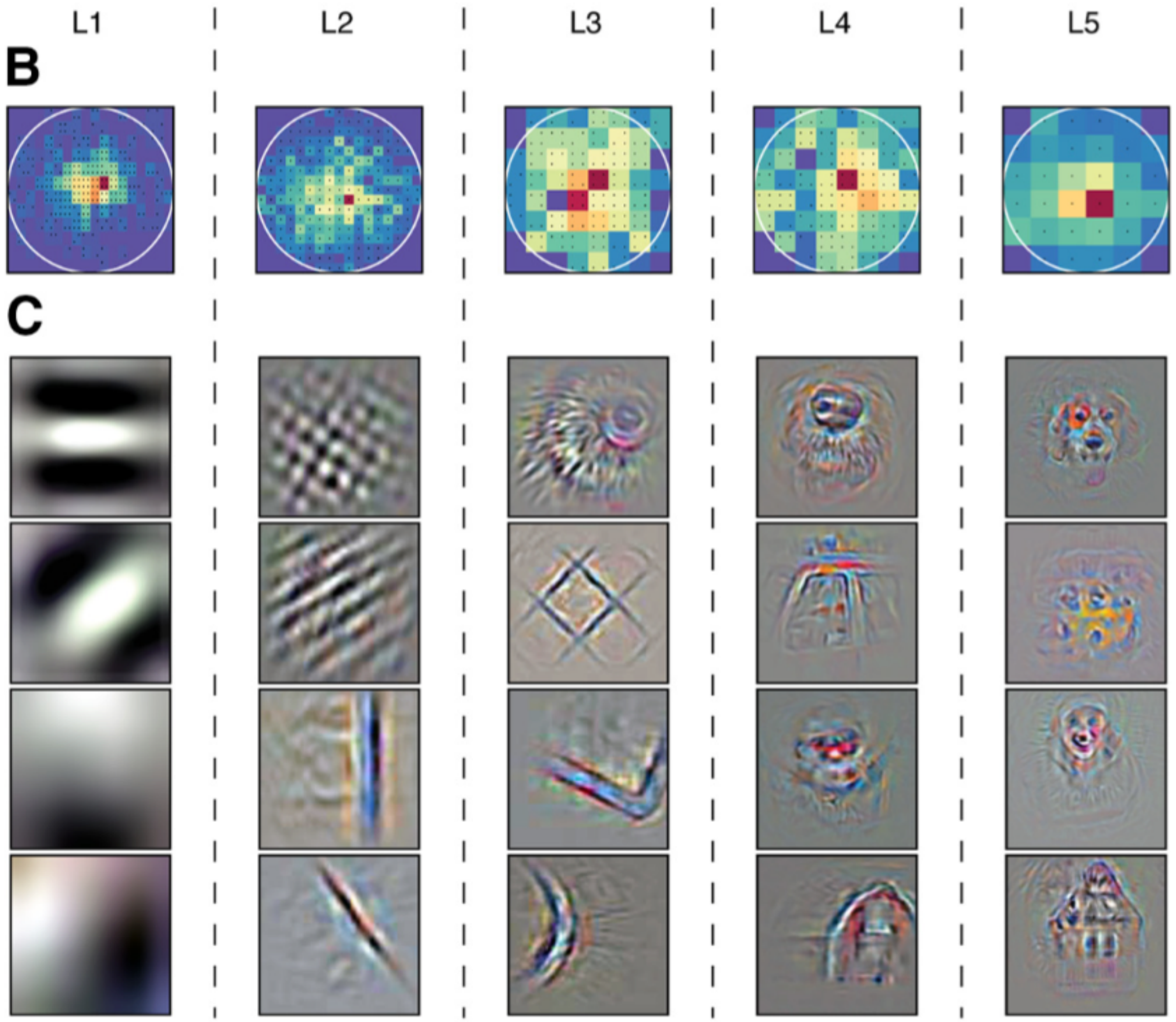

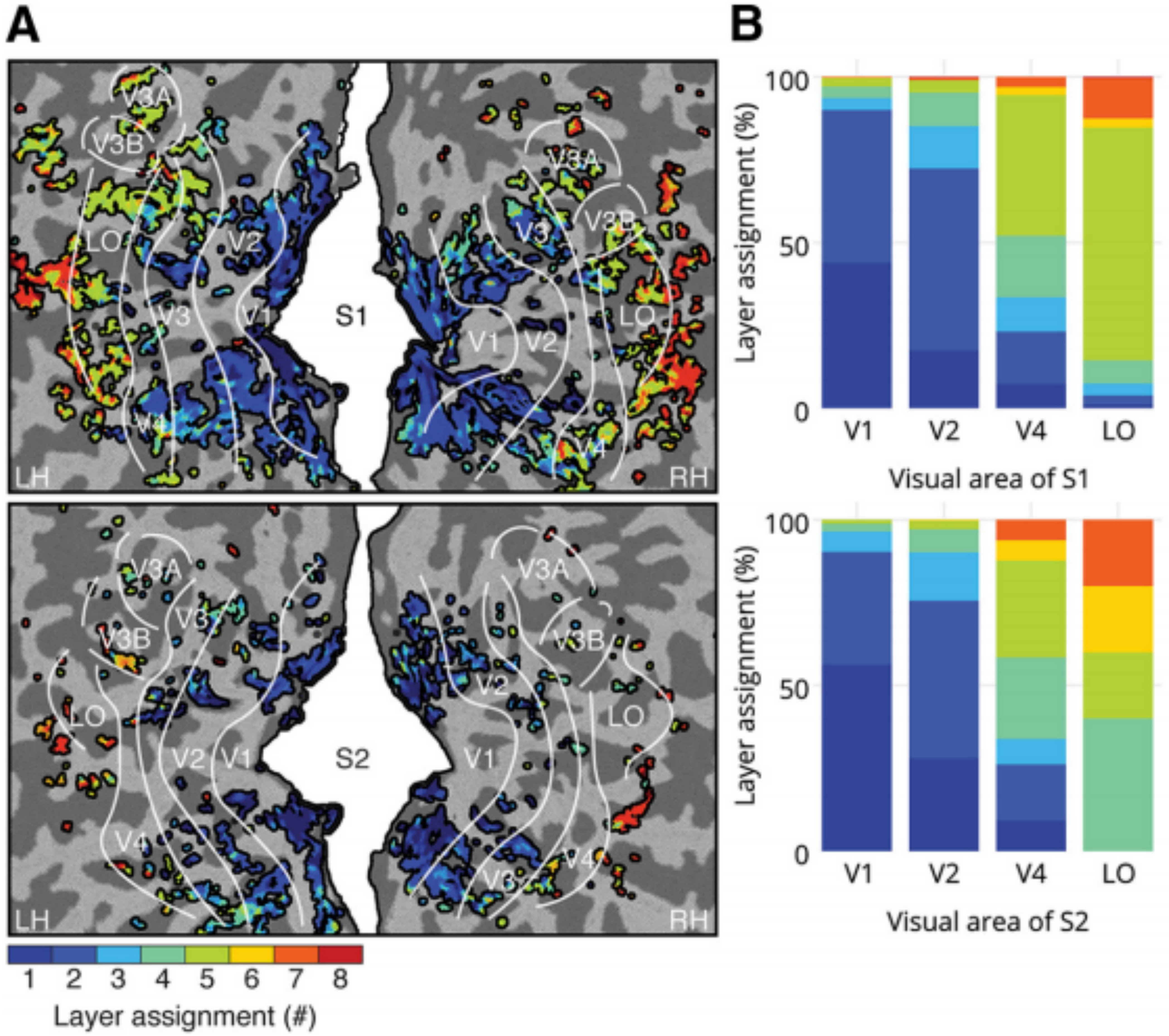

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Estimate a huge amount of parameters, using ***penalised regression***

Penalised Regression

Ordinary Least Squares

Only stable when # regressors < # timepoints
(when X is *full rank*)

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

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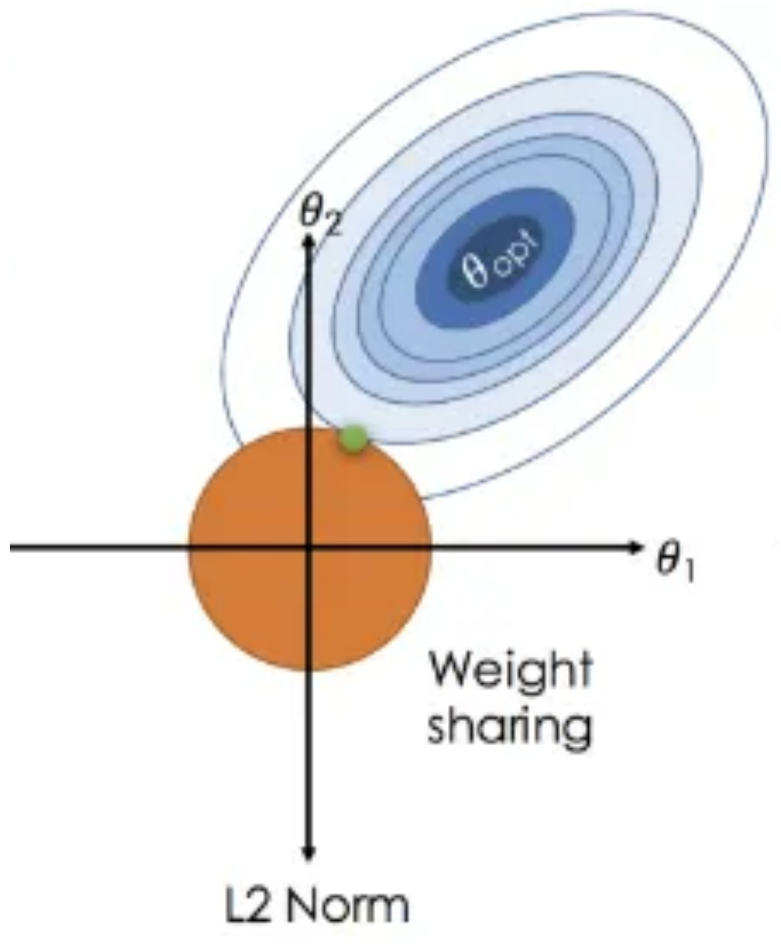

'Penalises' β weight values, forcing them towards 0

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With $\lambda = 0$, we have OLS.
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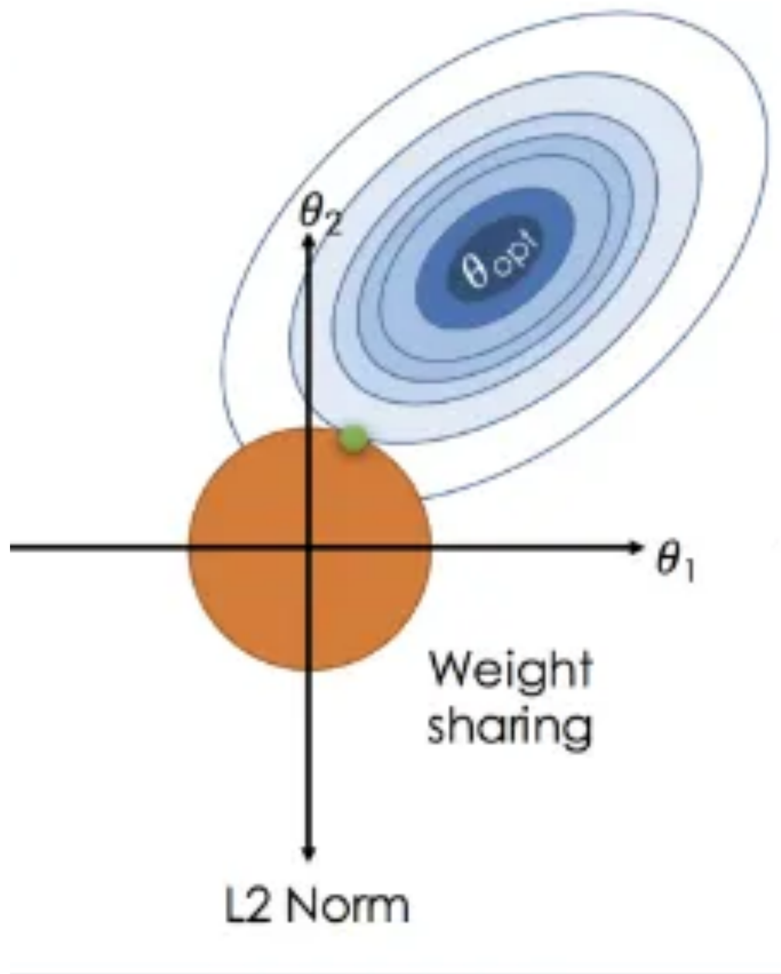

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Need to cross-validate to find λ

Recap: how to fit encoding models?

Two ways:

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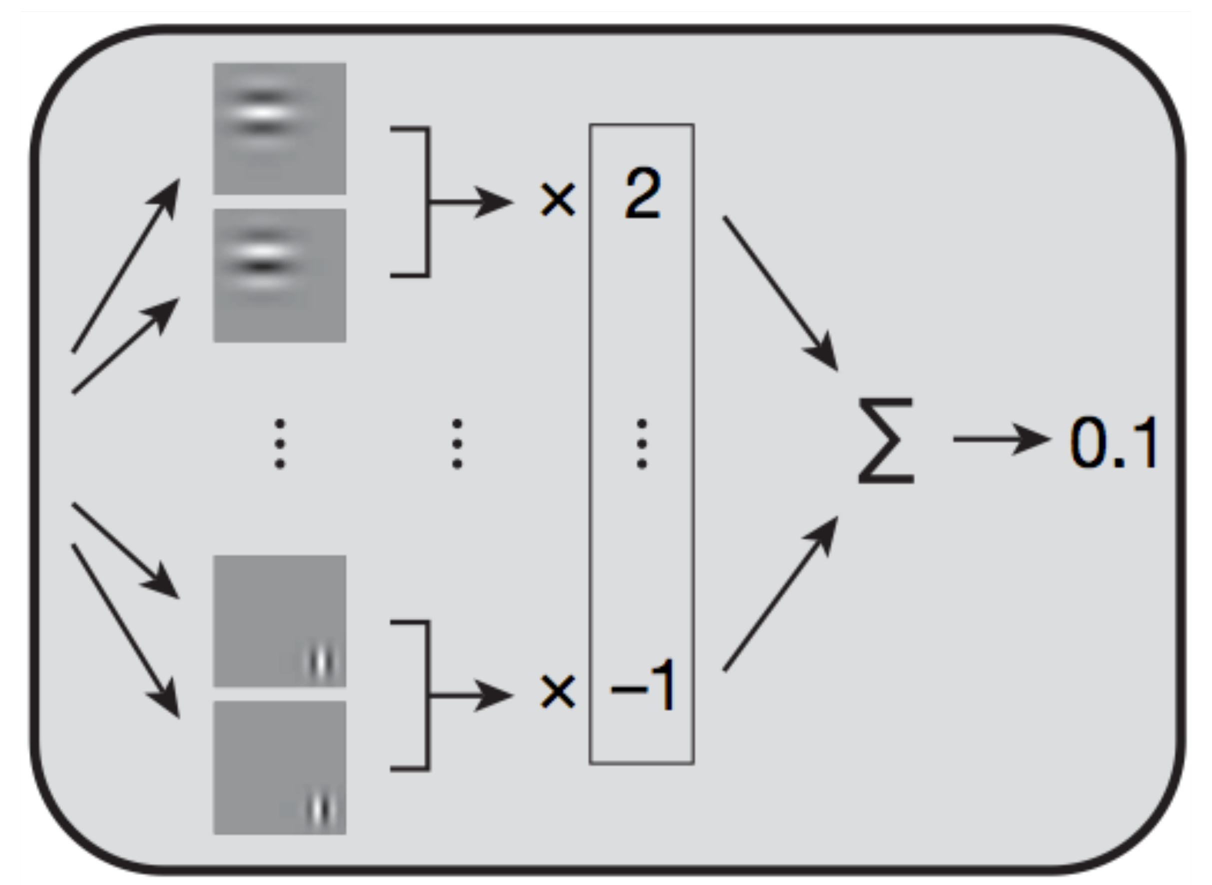
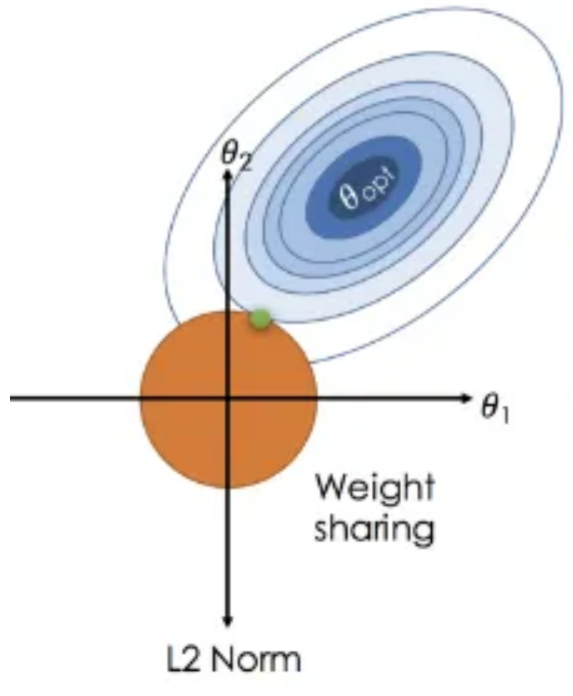
1. **Linear (Penalised) regression, with a very large design matrix**

   More data-driven, less constrained

2048 regressors



Receptive-field model for one voxel



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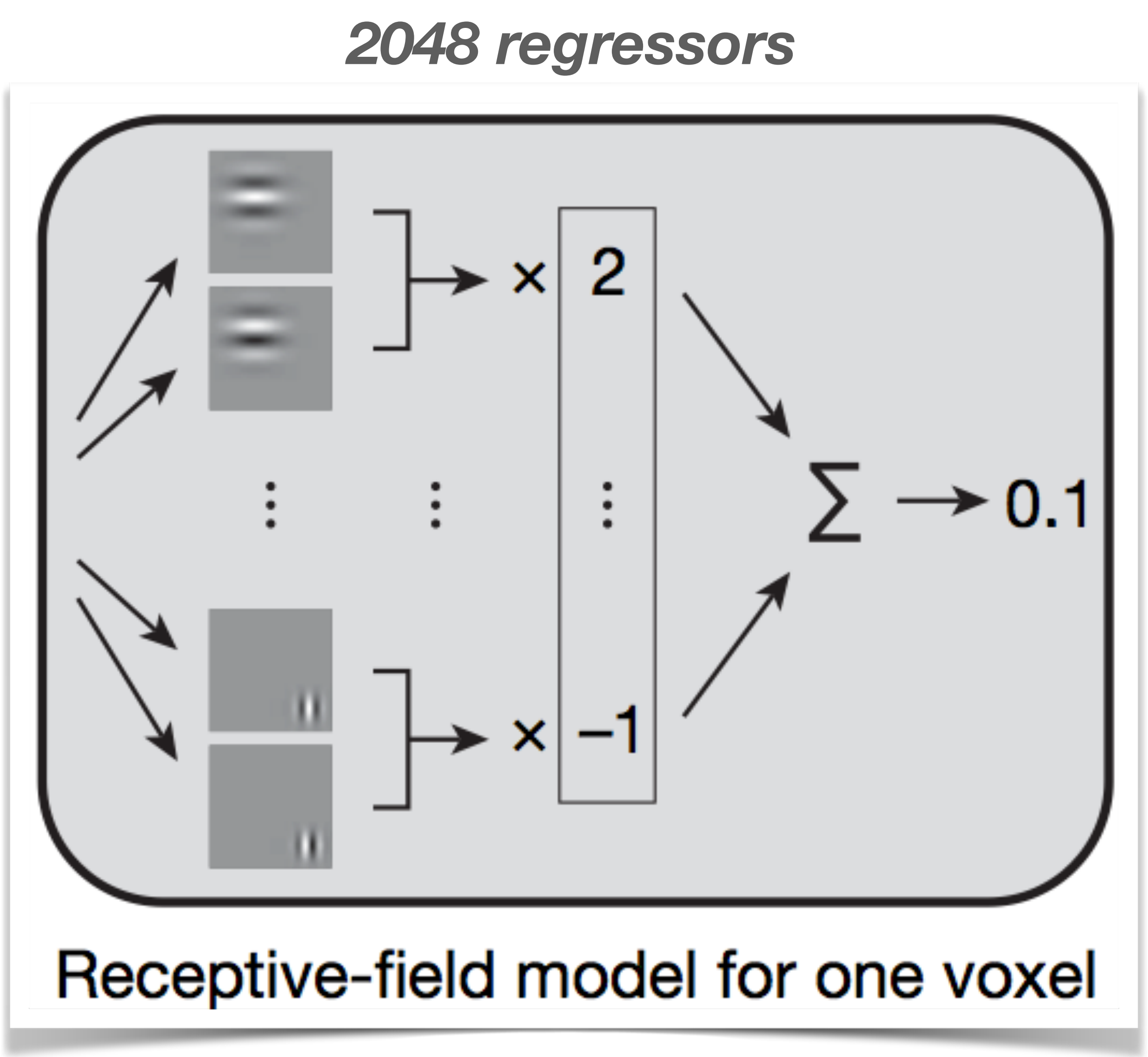

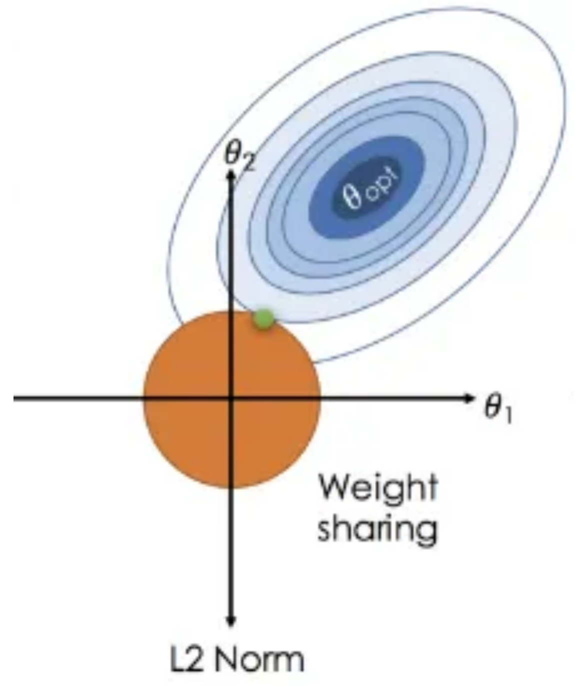

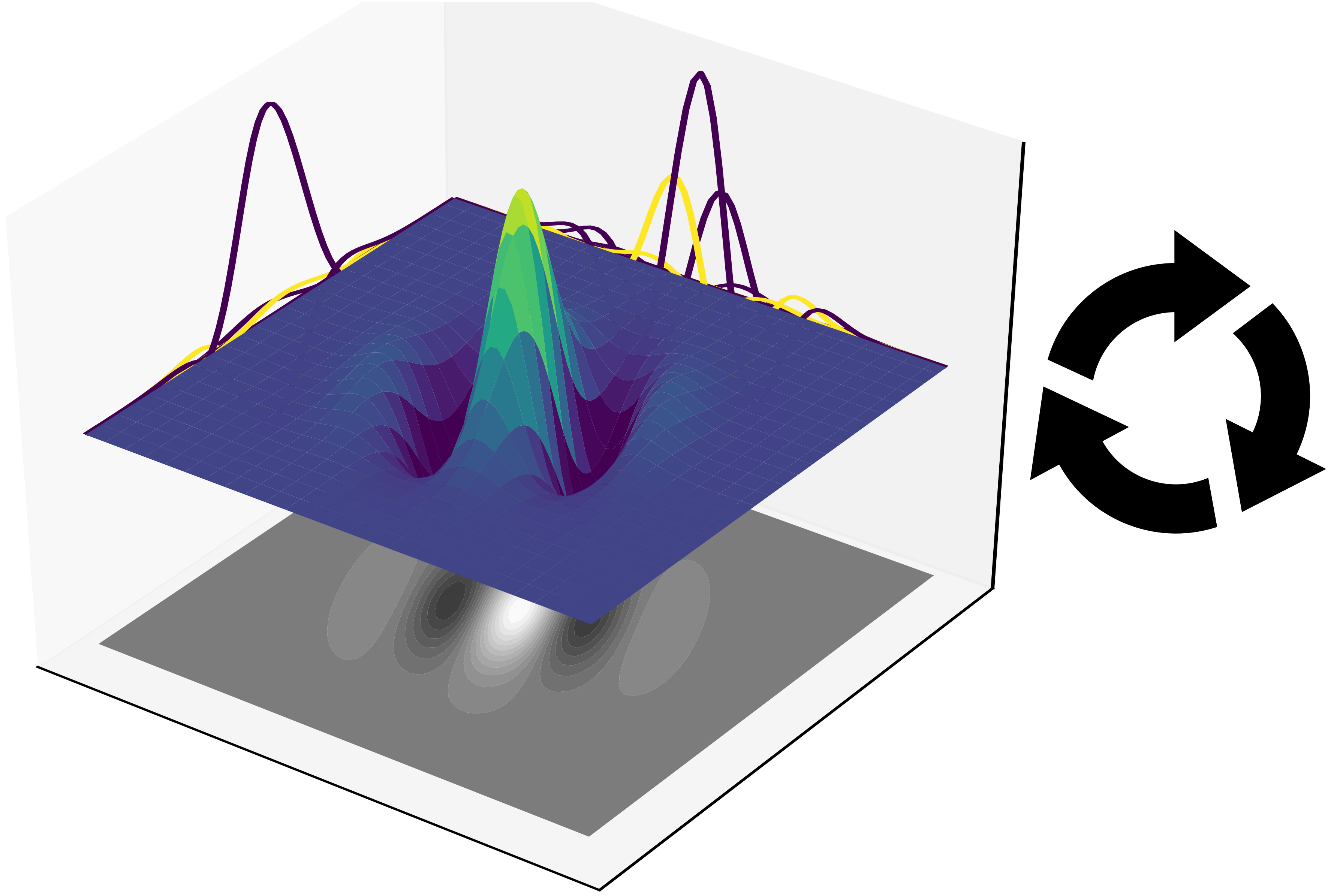

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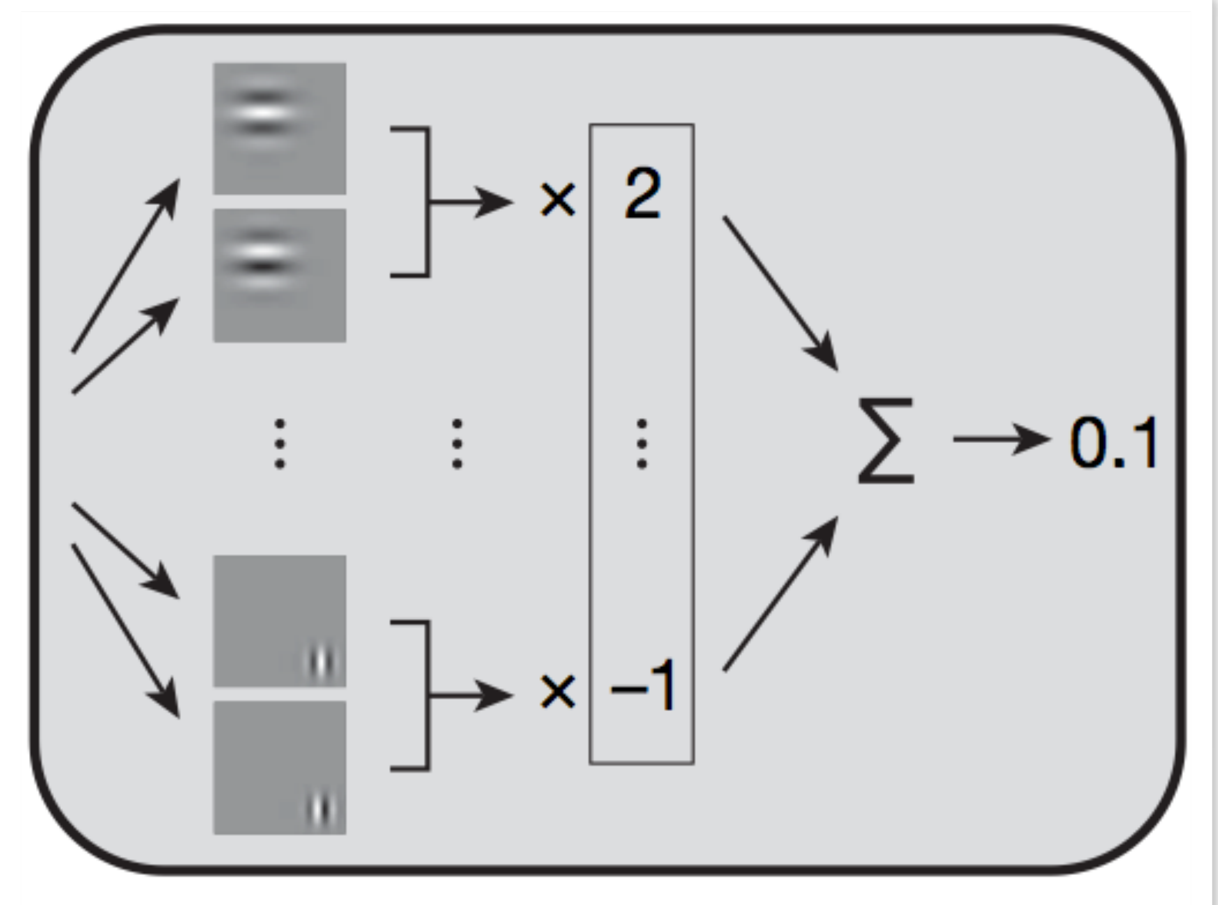

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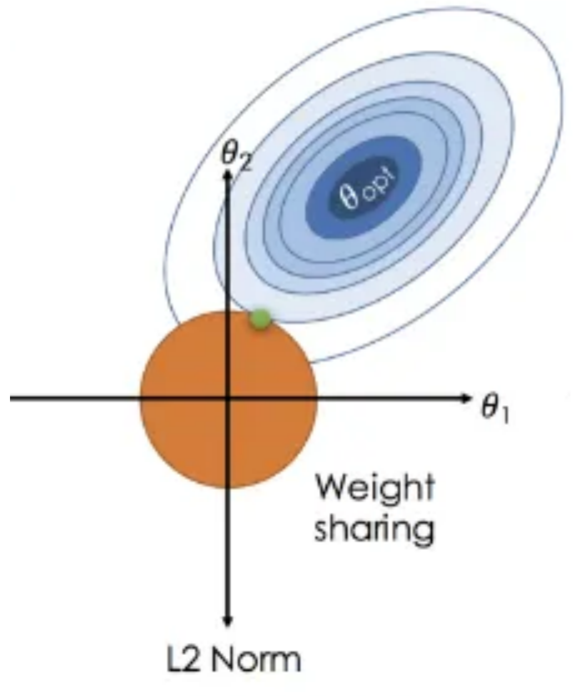
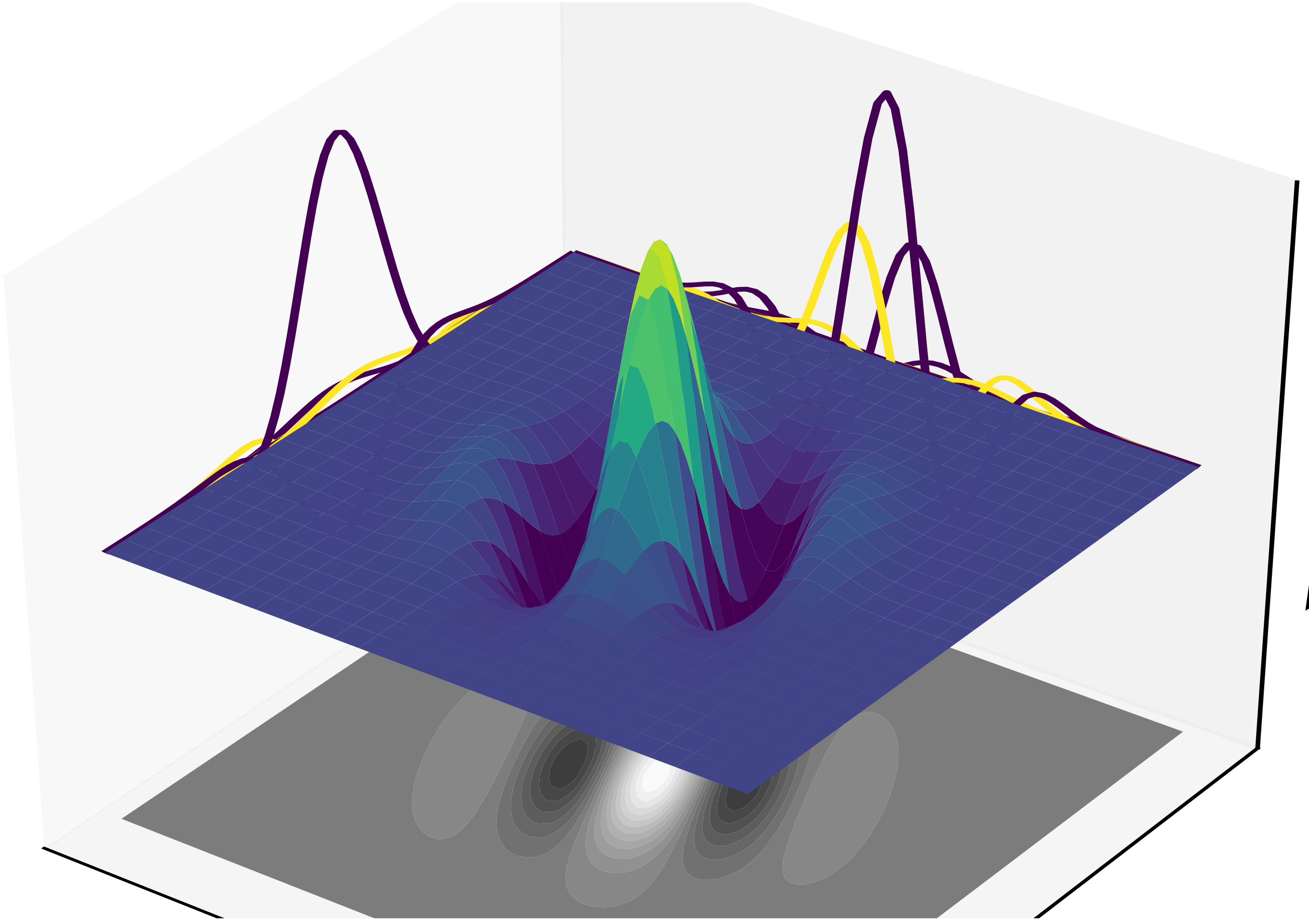
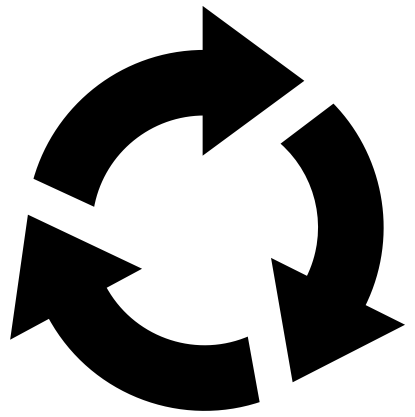


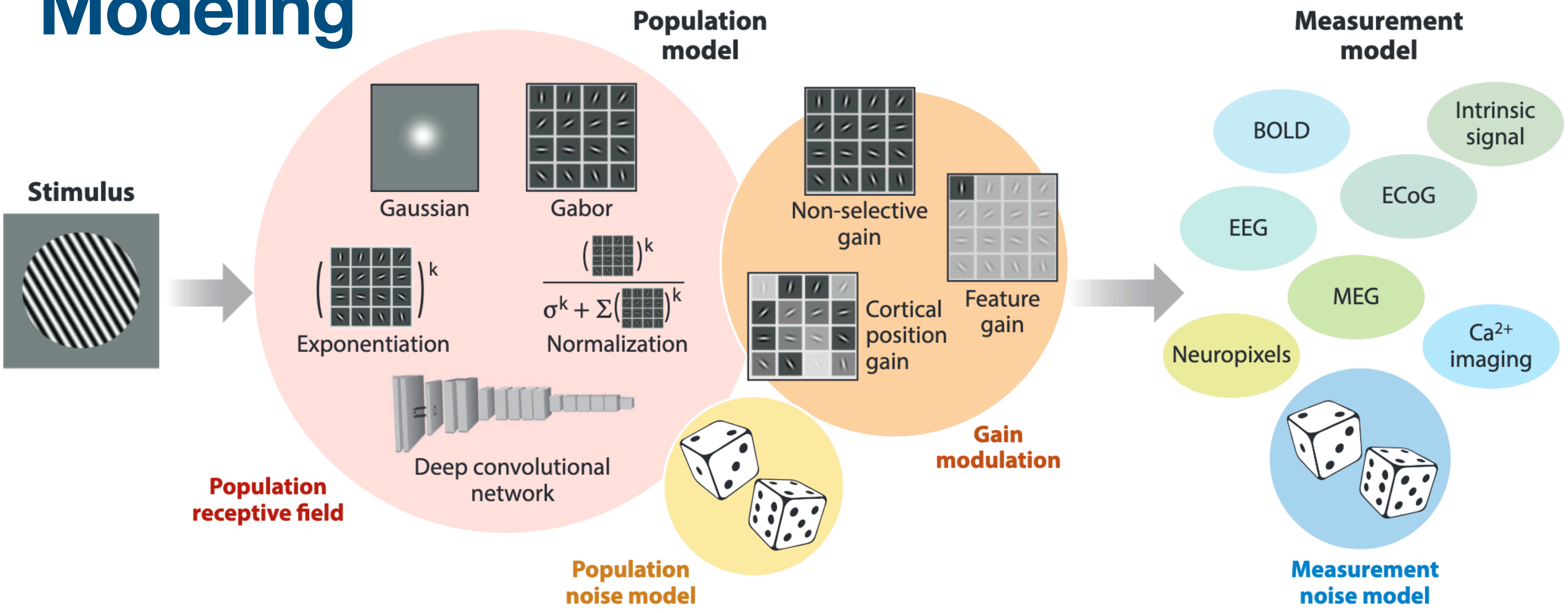




7 parameters

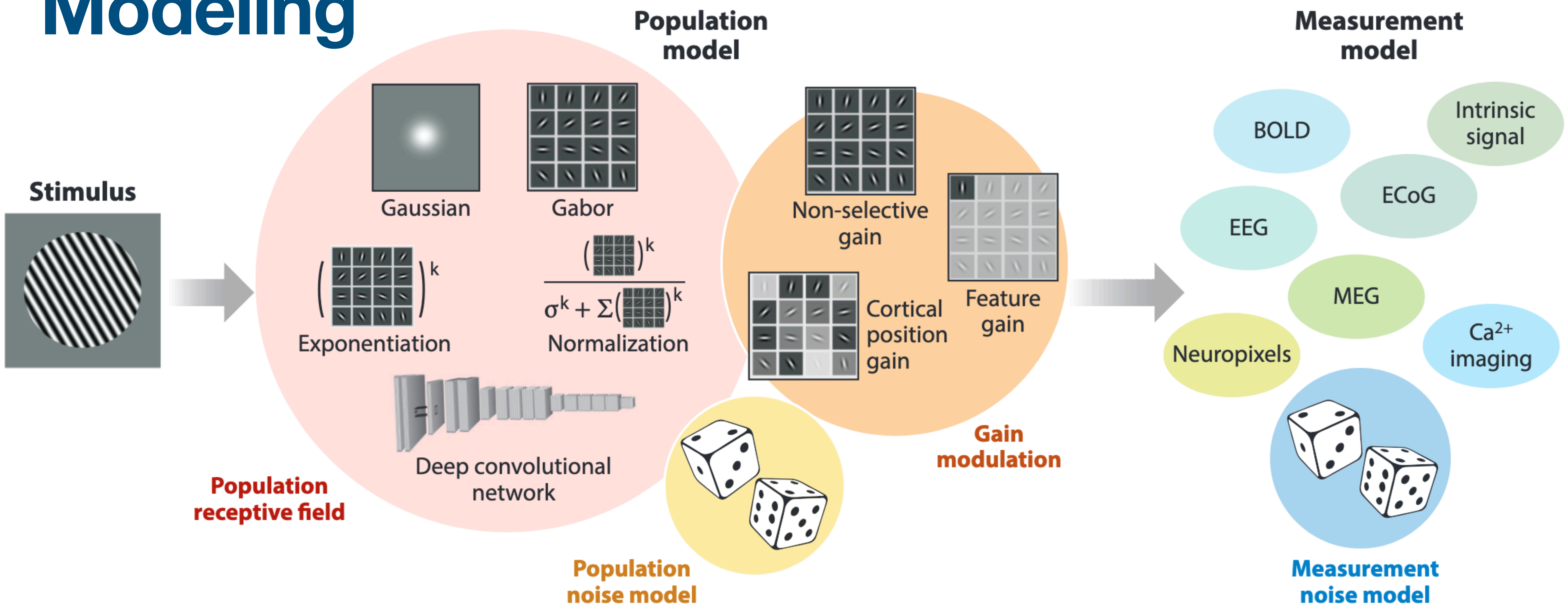
$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda} + \psi\right)$$

Modeling



From Gardner & Merriam, 2022

Modeling



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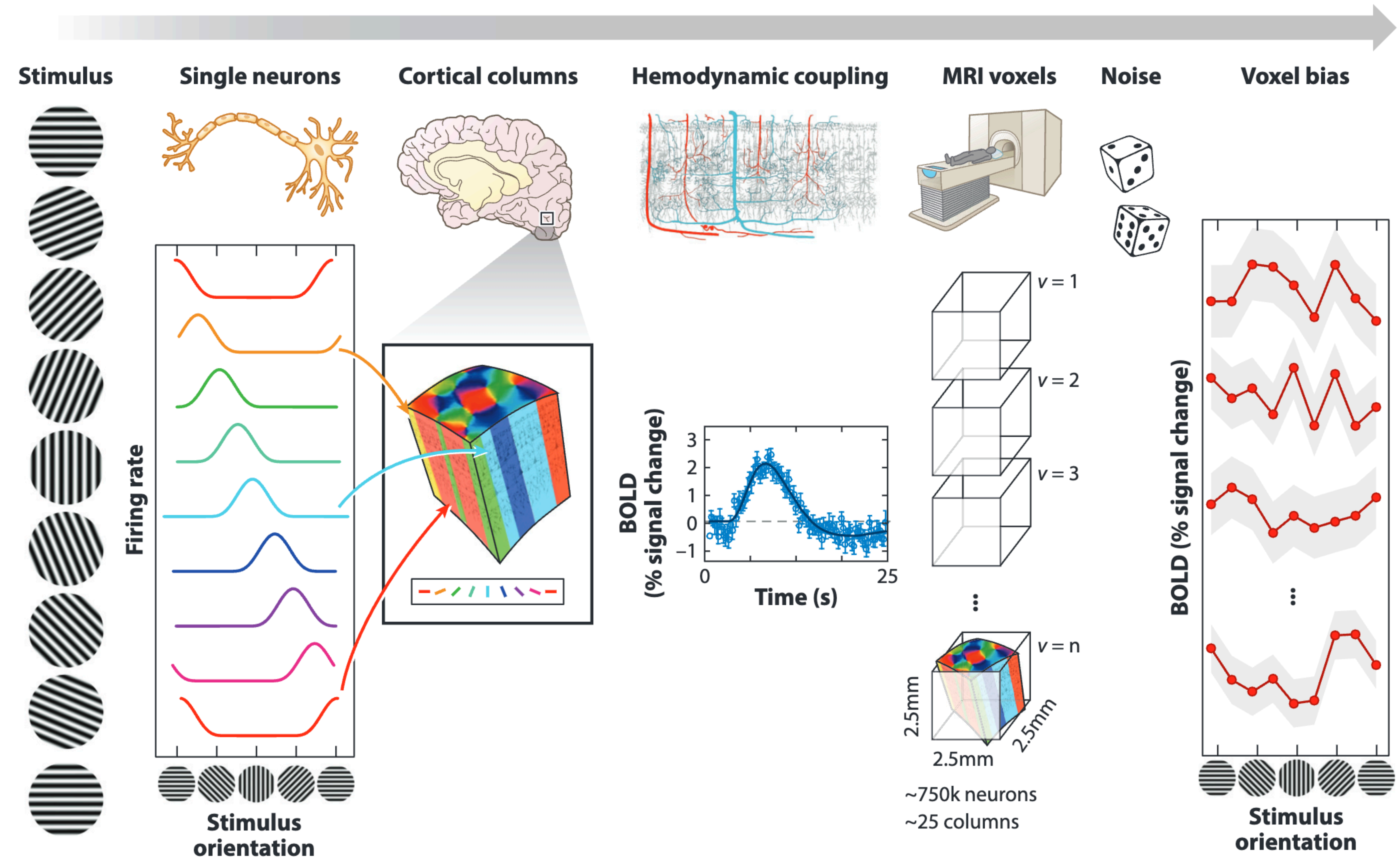

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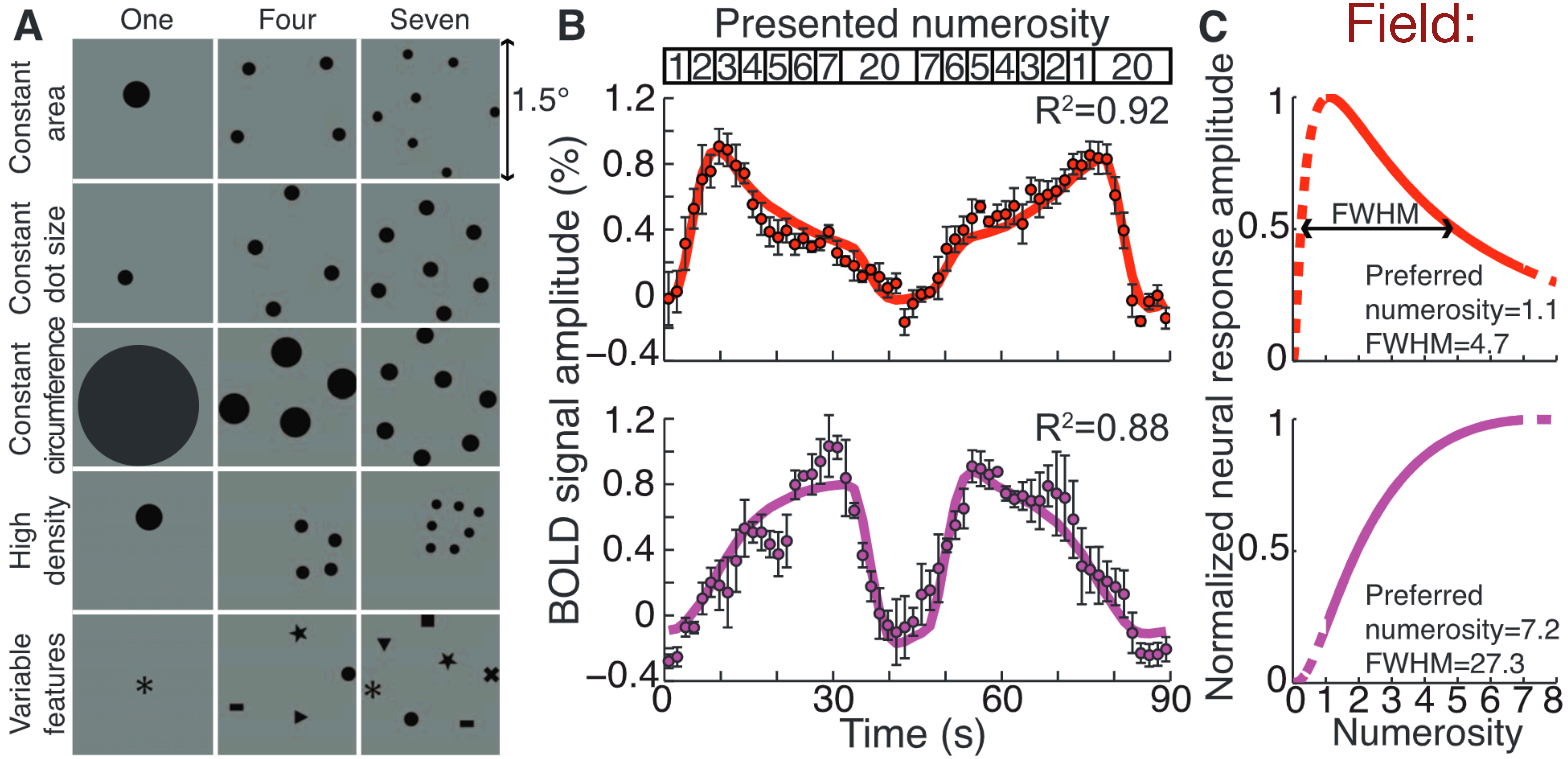
Does it have to be visual?

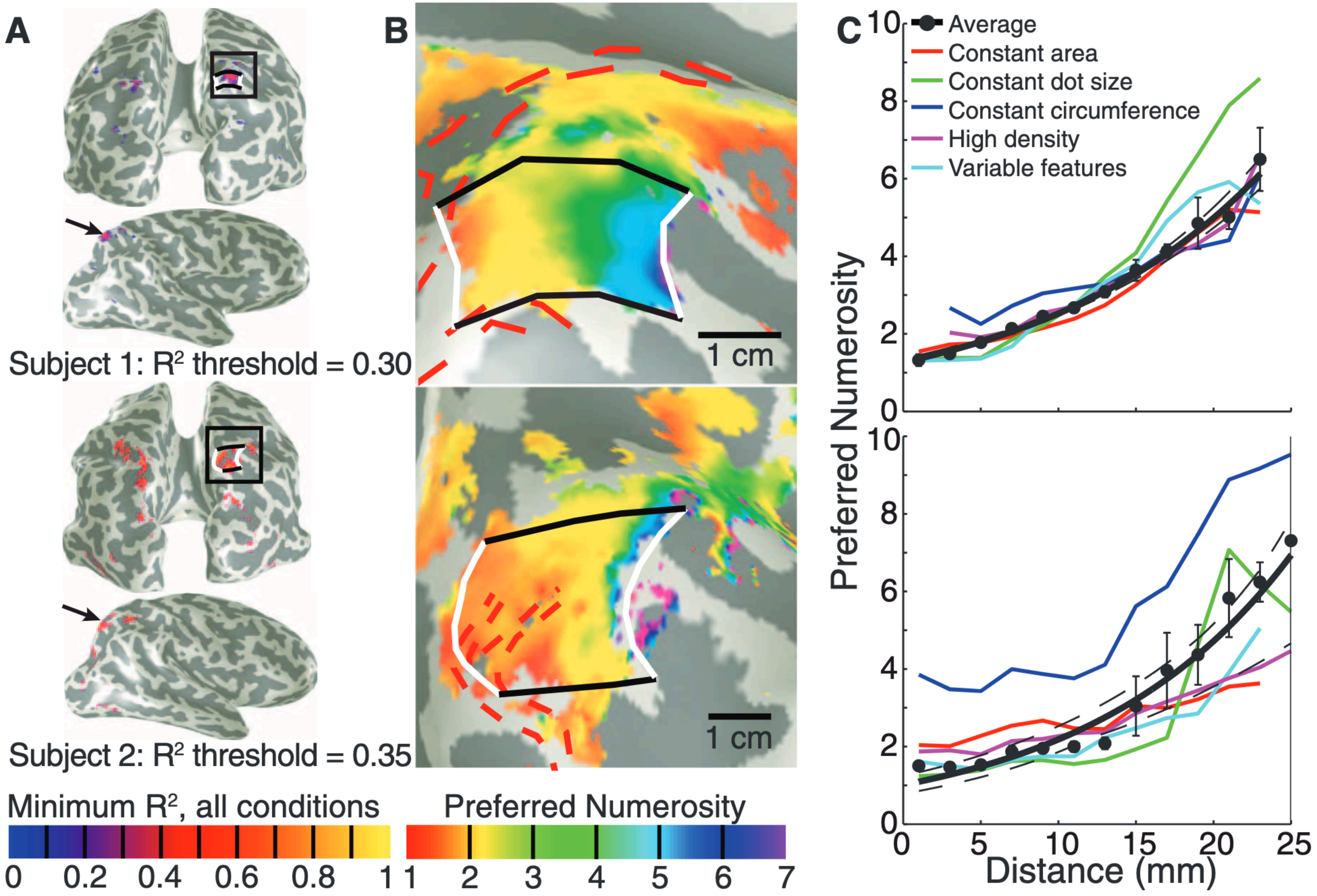
But more…

Also more abstract dimensions are represented using receptive fields, found using fMRI

Receptive Field:



These receptive fields are layed out on maps…



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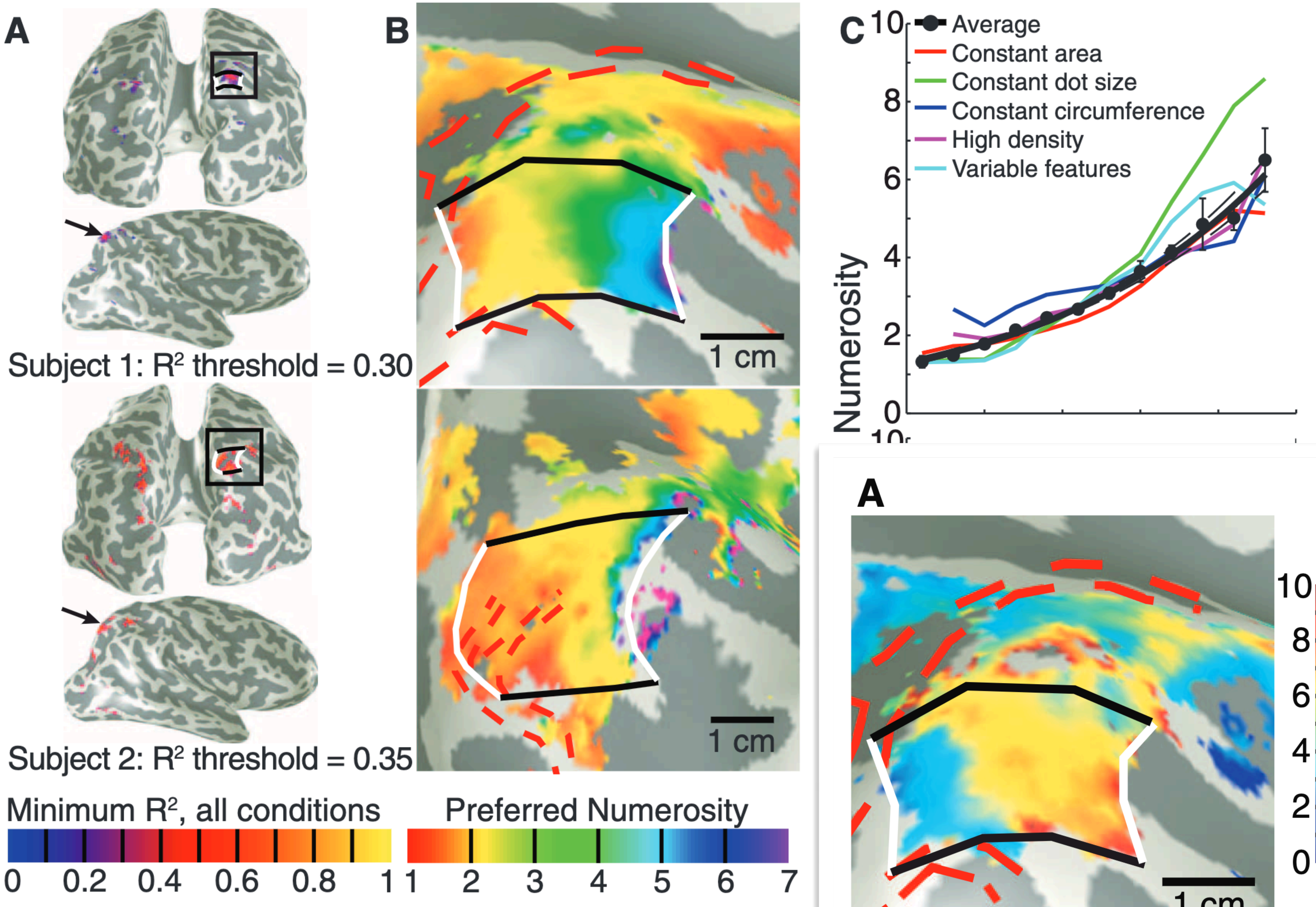

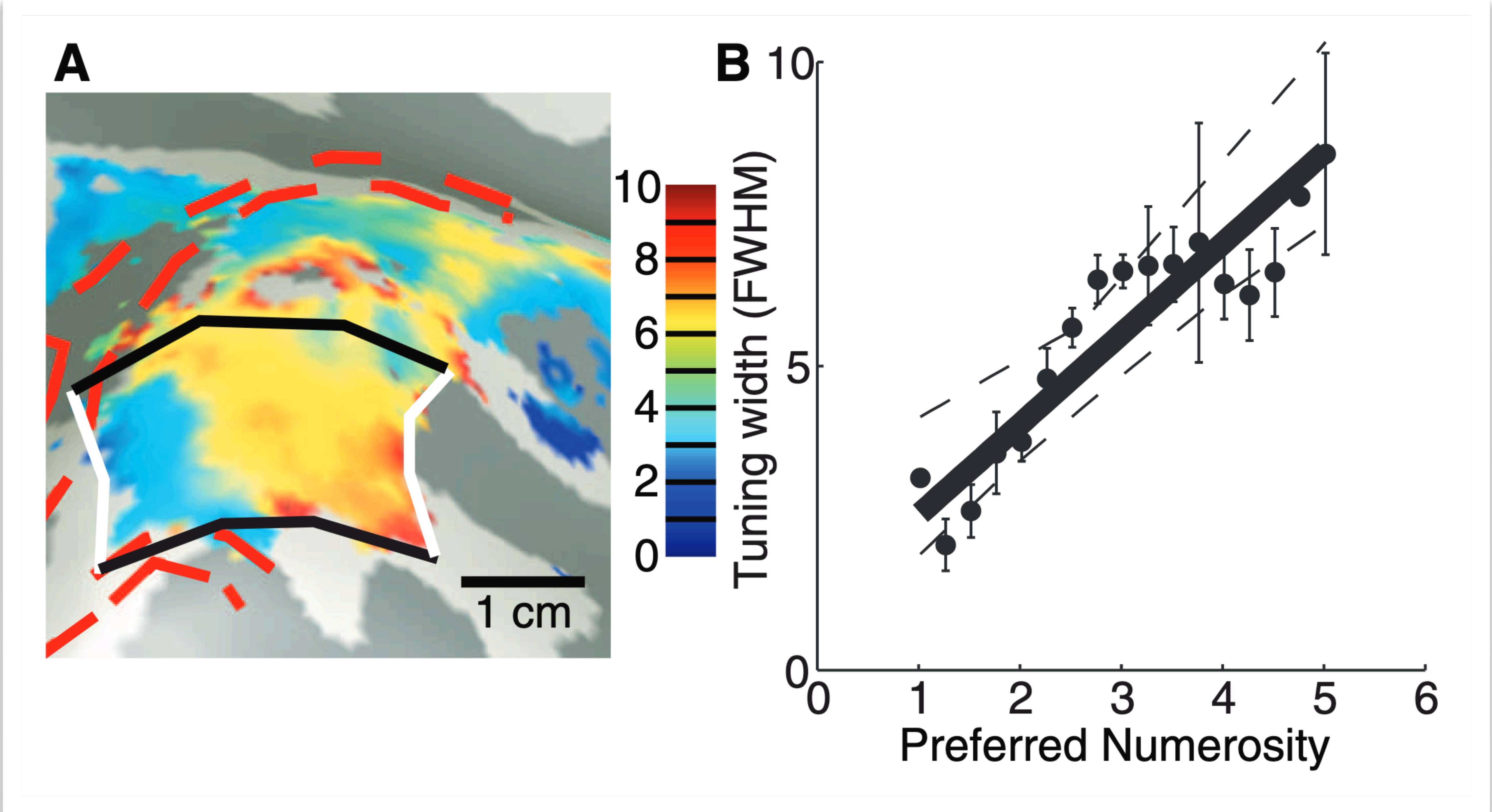

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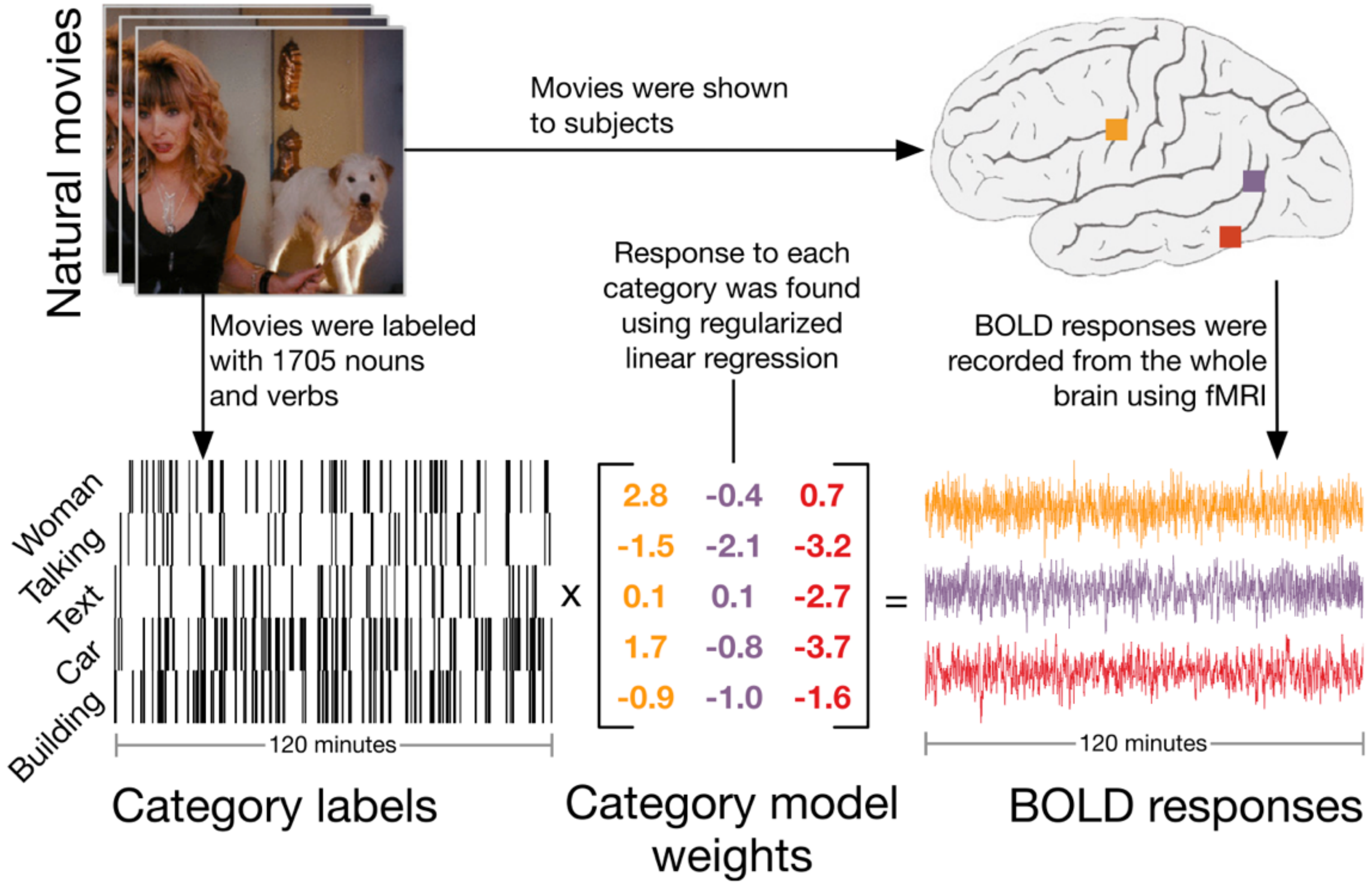

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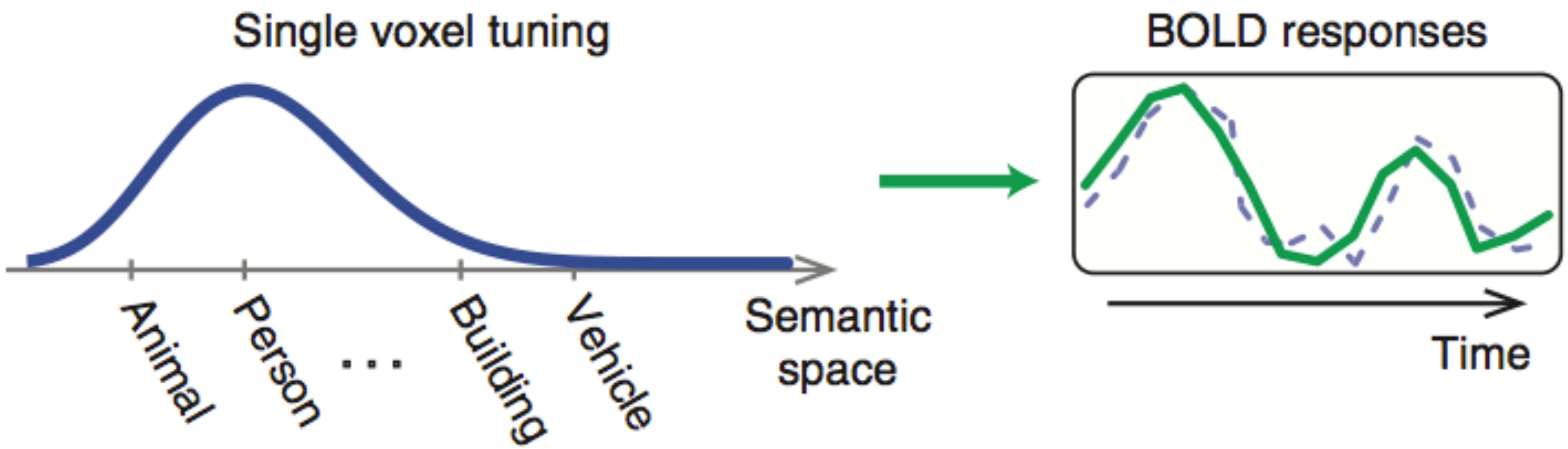
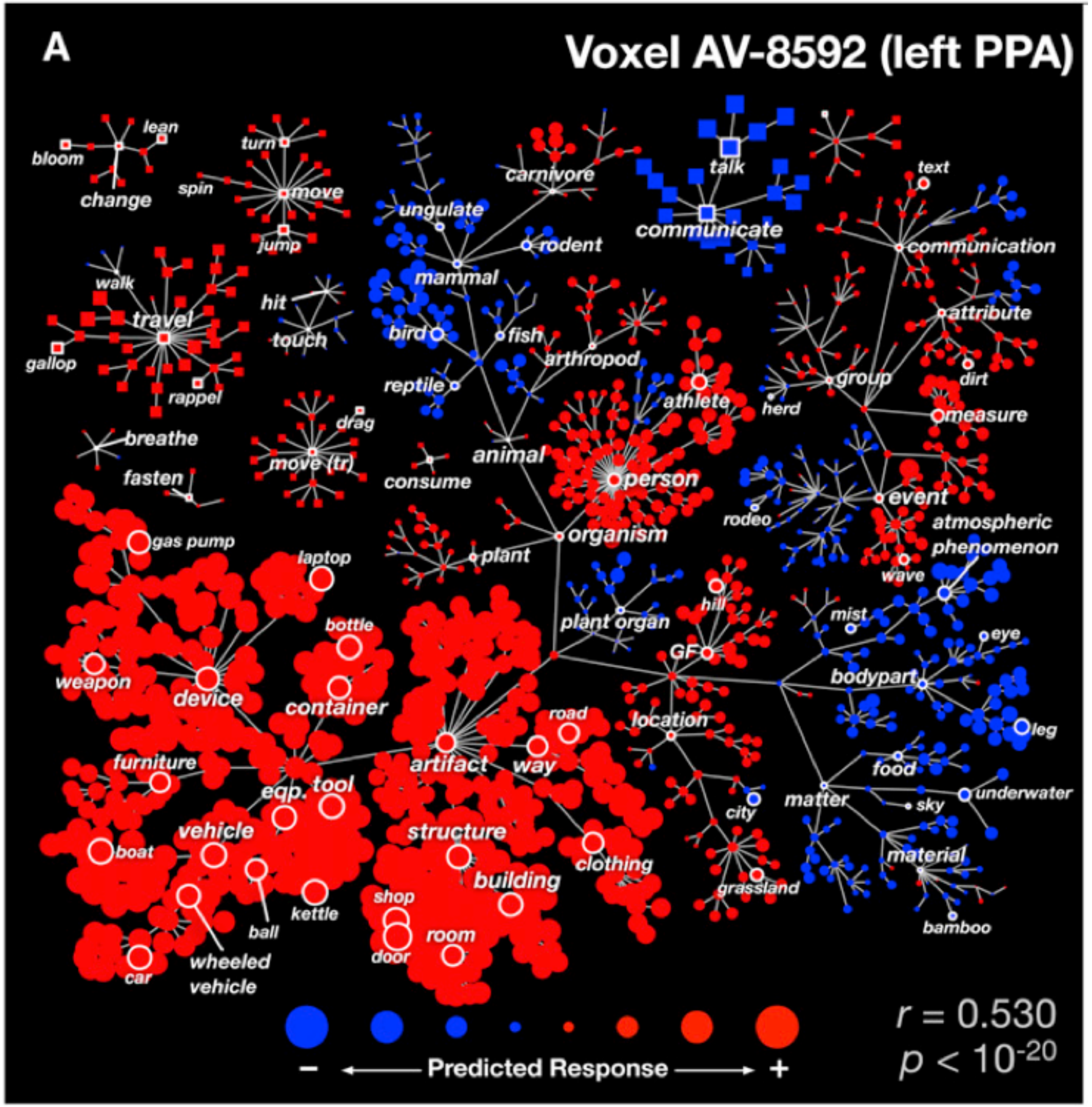


Single-voxel
tuning curve
in a
semantic space



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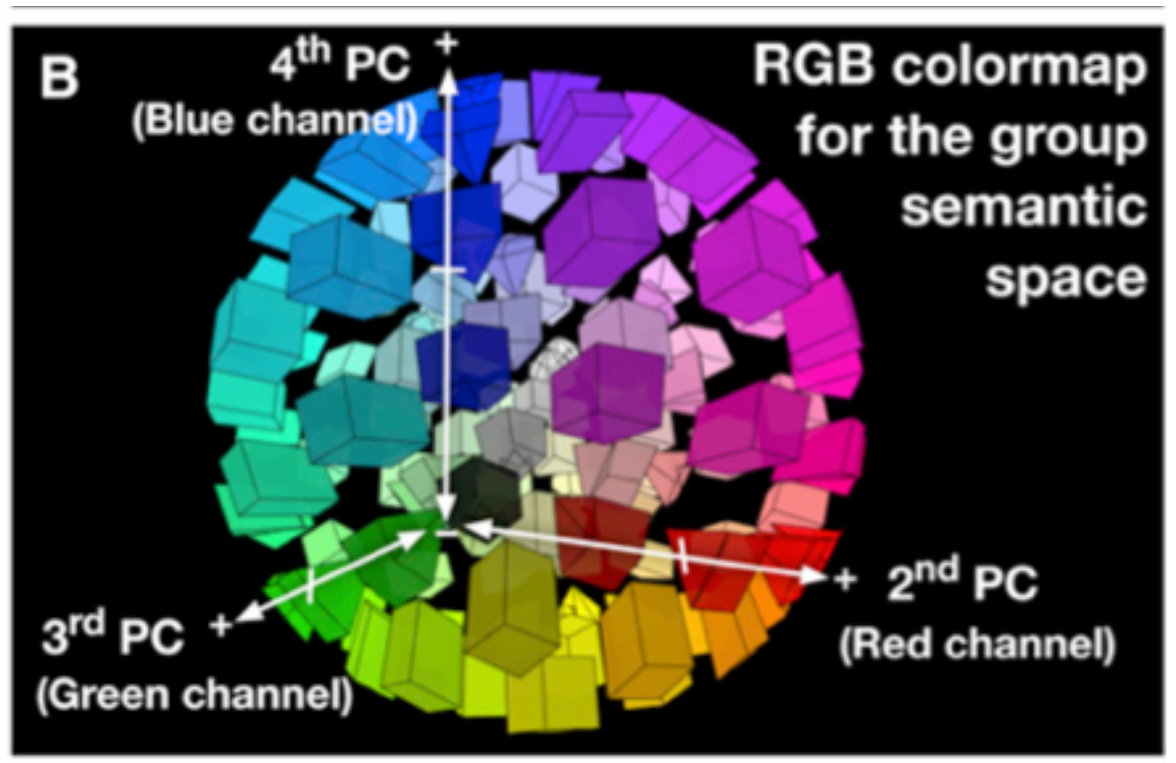

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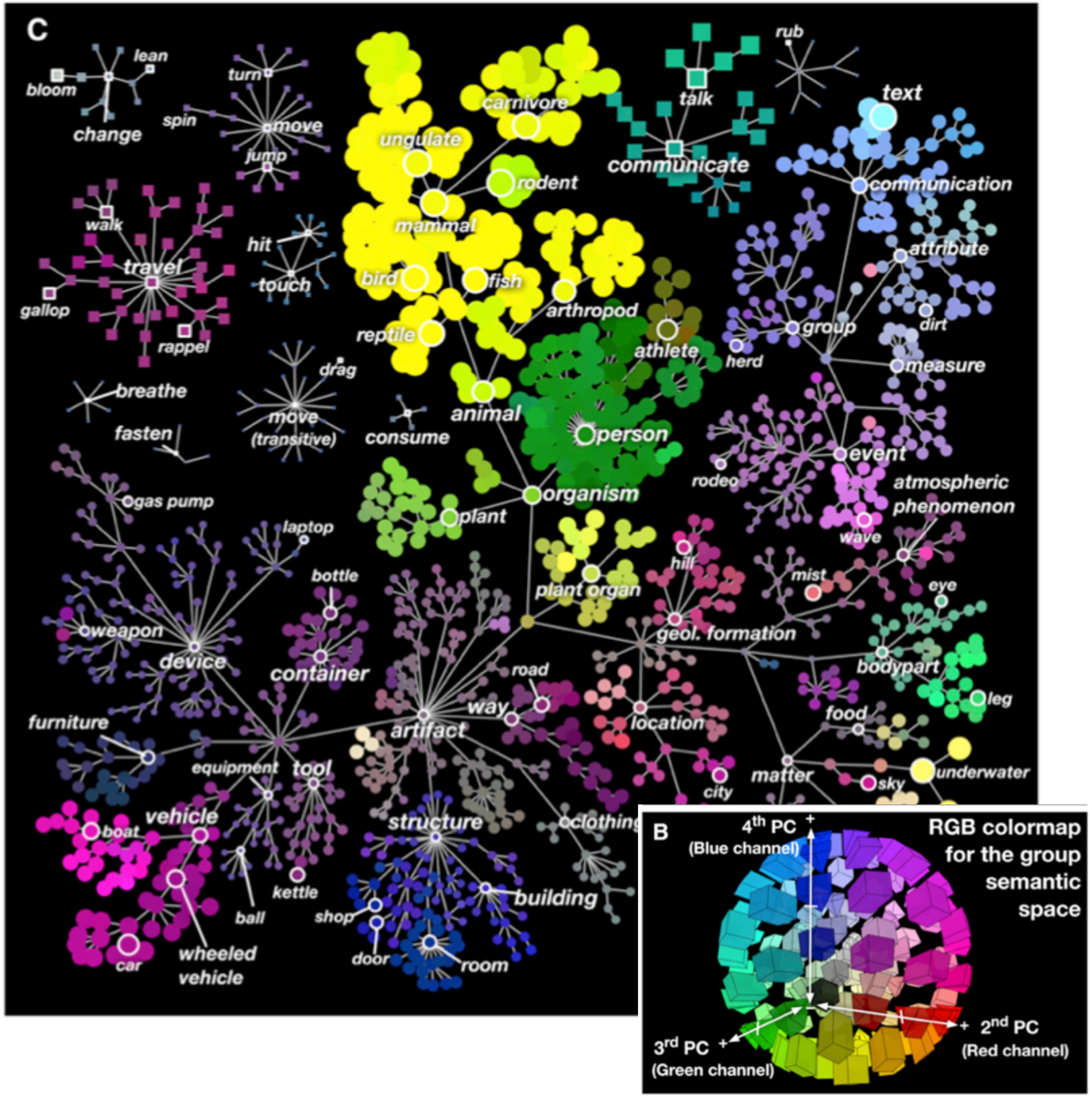
- Projecting onto semantic structure:



roll
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move
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information
tree
herb
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mustache
cloud
machine
rock
appliance
object
piece
causal_agent
glass
medium
point
face
leg
cabinet
art
conduit
fluid
gas
implement
picture
game_equipment
structure
field
building
shop
motor vehicle
car
S4
S3a
S3b
S1
S2
V2
V1
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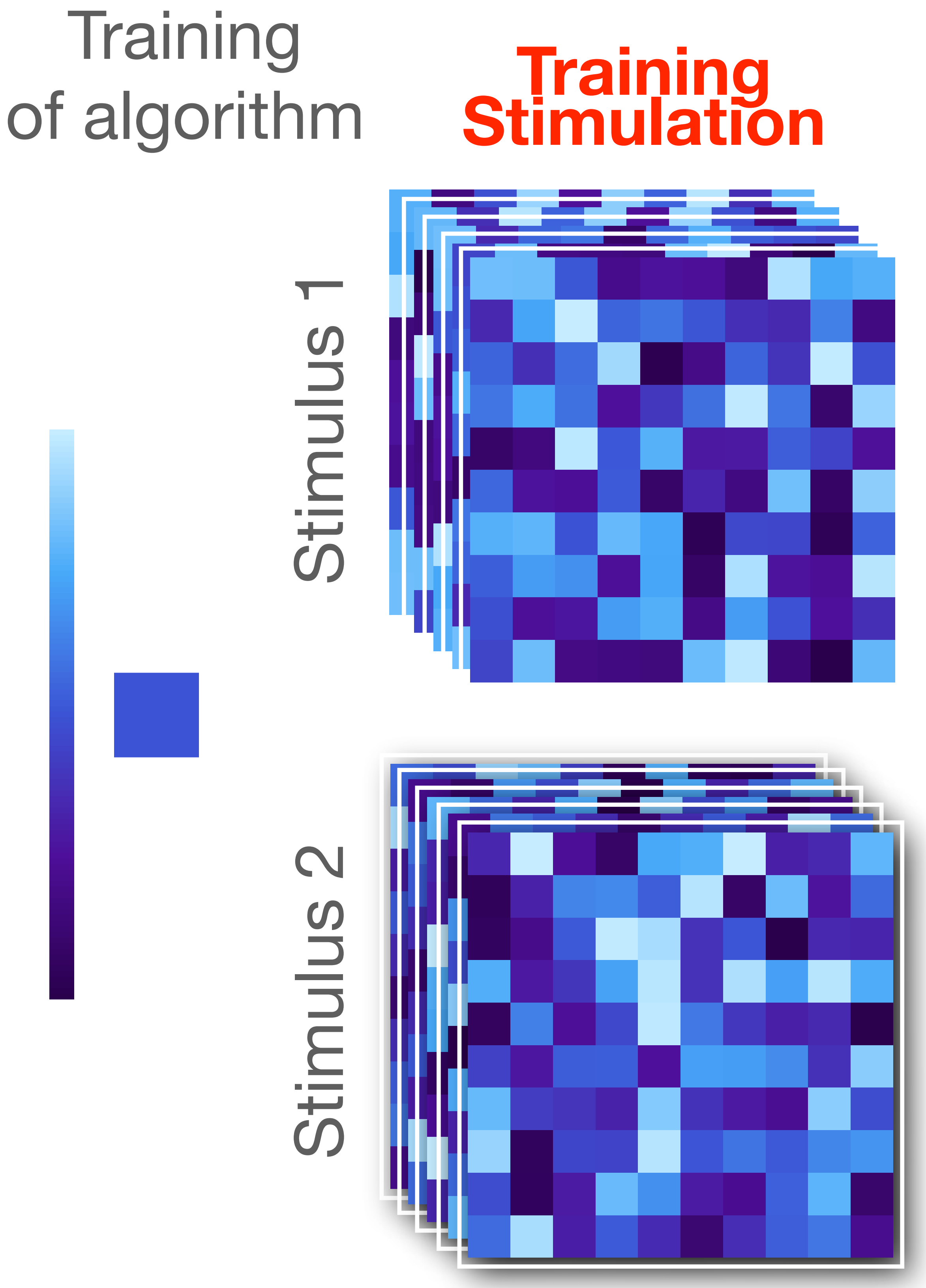
Not mean signal intensity, but the **pattern** of activity in a certain region of interest is used to classify what the brain state is.



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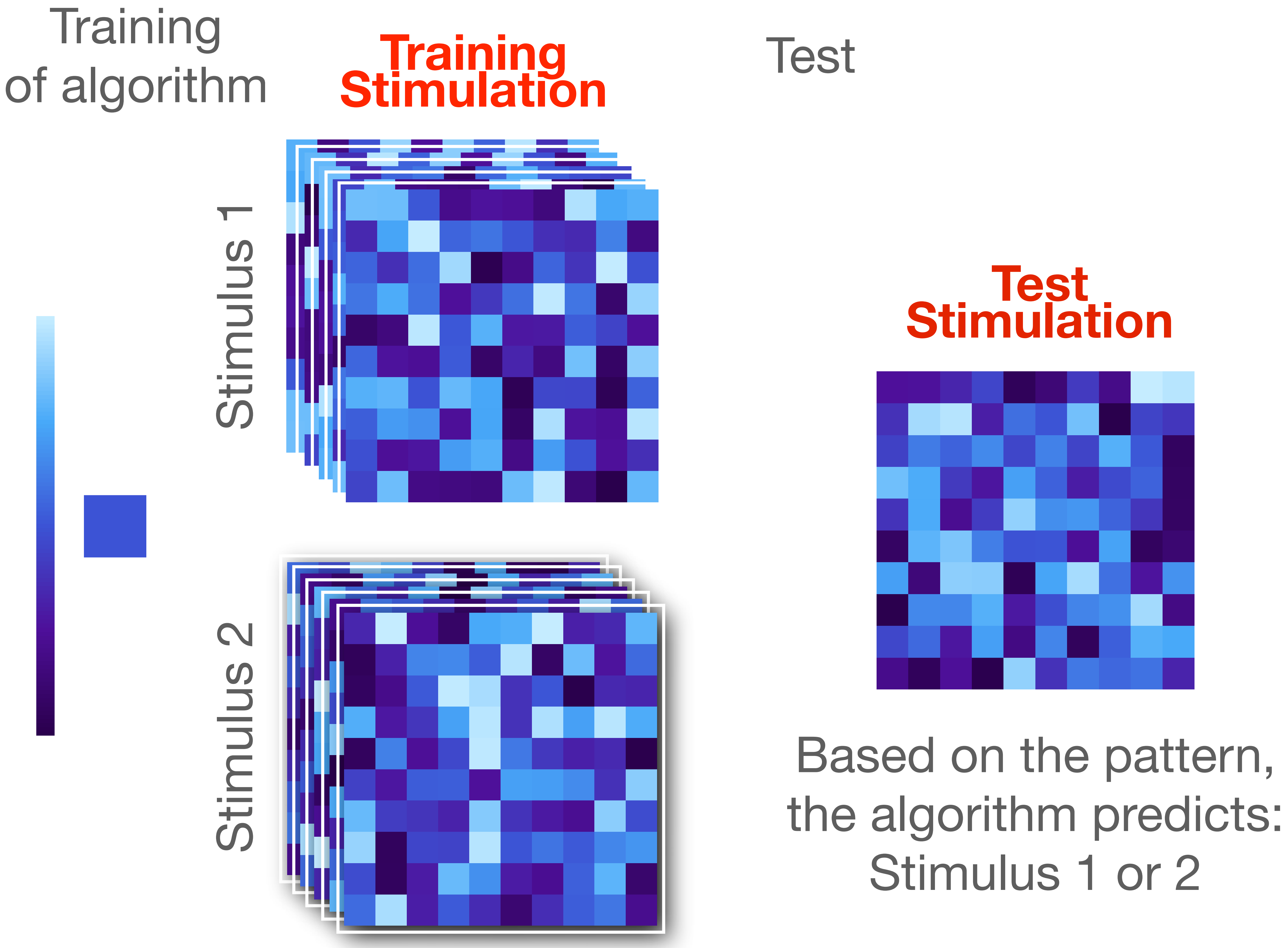

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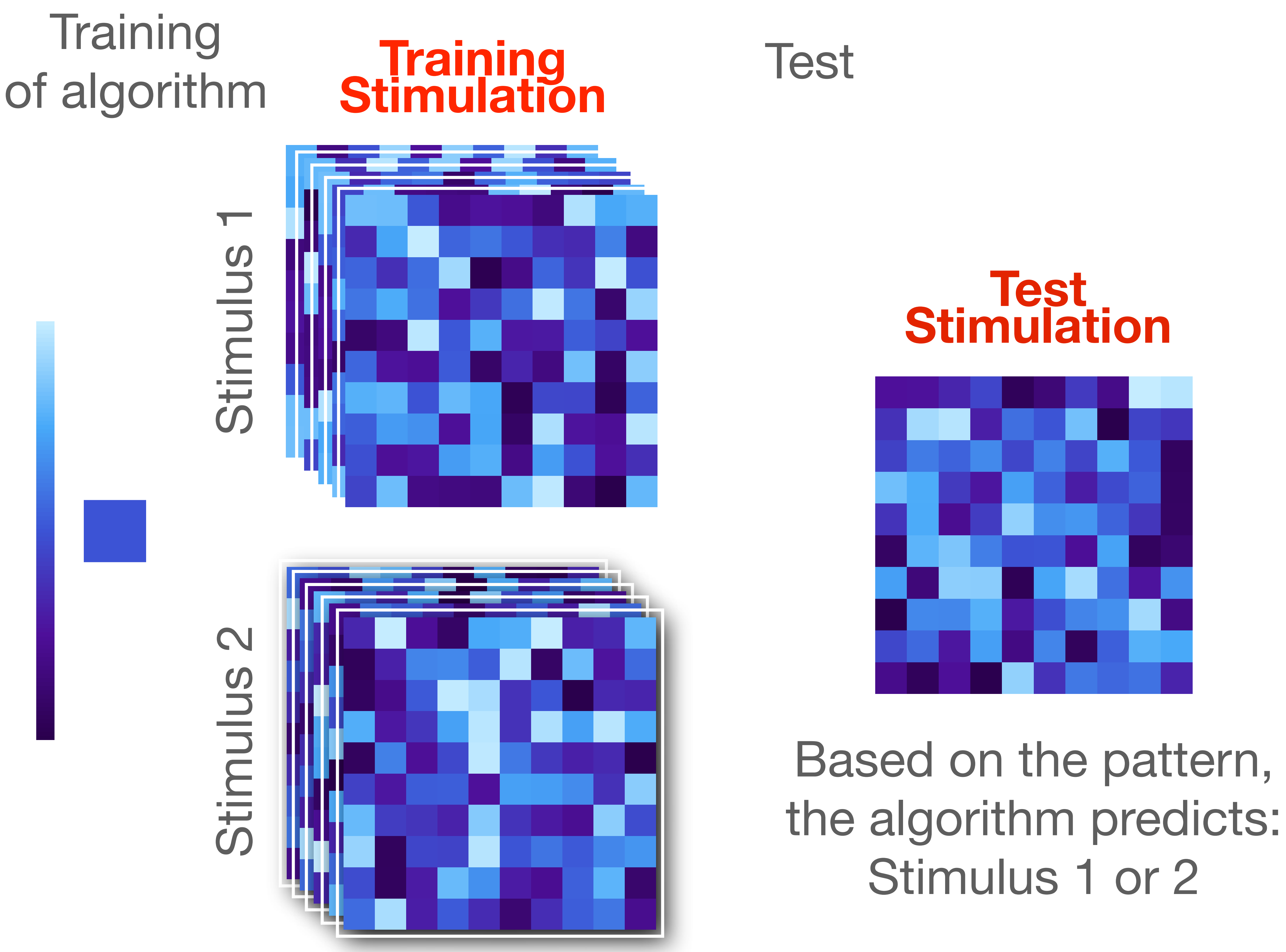

Performance of algorithm expressed as accuracy: percentage correct

Gauge on information content in a specific region of interest

Decoding

Decoding

Picking up on the feature space ***is left to the machine-learning algorithm****, and with sophisticated algorithms it is* ***difficult to understand*** *what structure the algorithm is basing its judgments on.*

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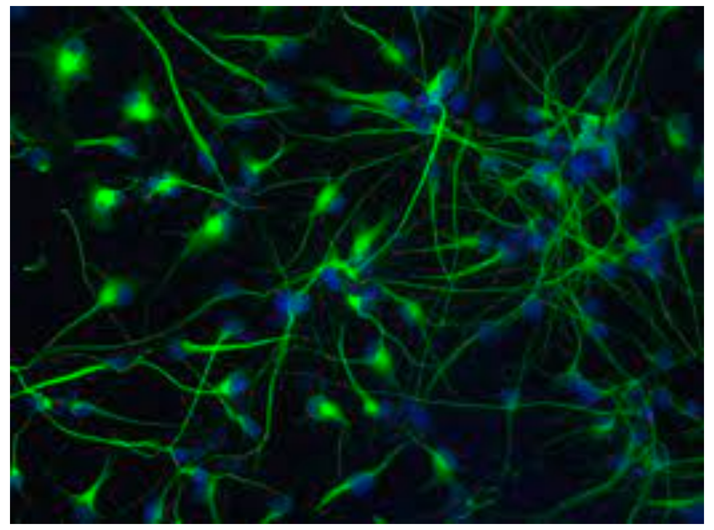
We don’t know, because the information-processing and measurement mechanism remains implicit.

Encoding



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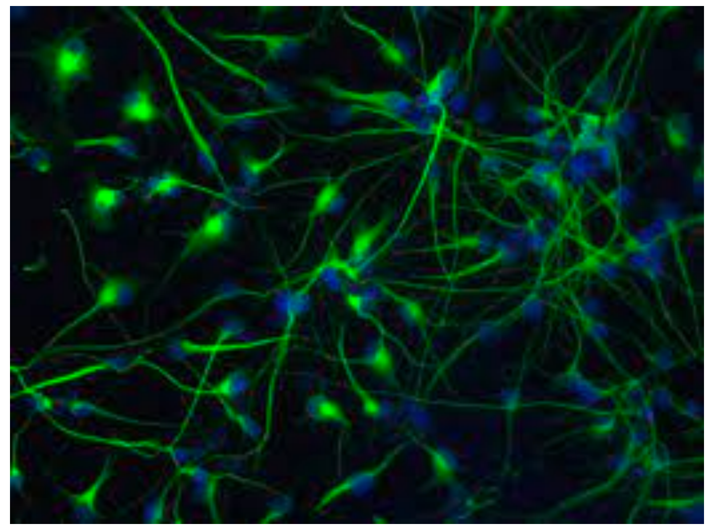
*If we can find what a neuron/sensor/voxel responds to, we will have a model of how this unit encodes information: **an encoding model***



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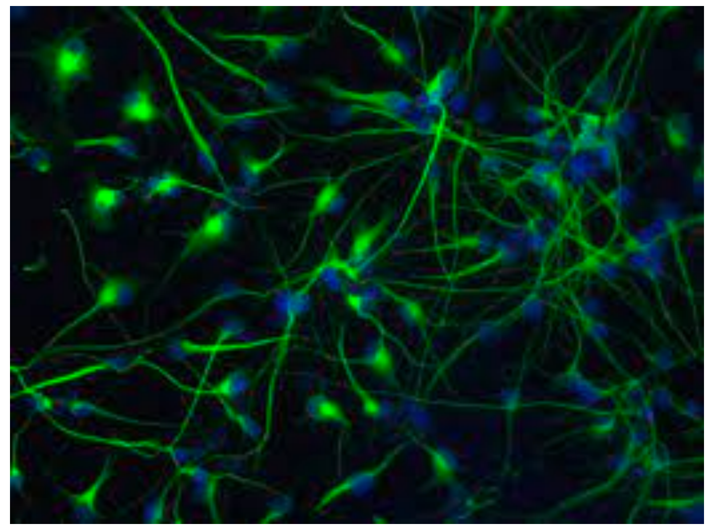

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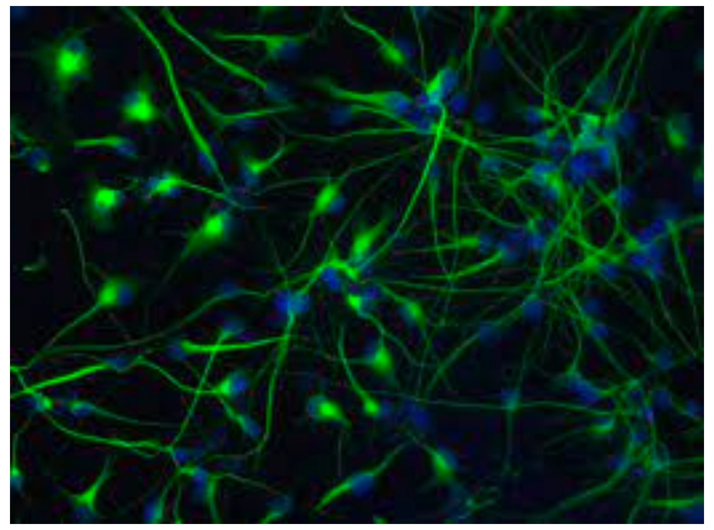

Once we know this, we can reverse this process, and see for a whole group of neurons/sensors/voxels, what their pattern of activations tells us about conditions, stimuli, etc. - ***encoding-model based decoding***

Bayesian decoding from an encoding model

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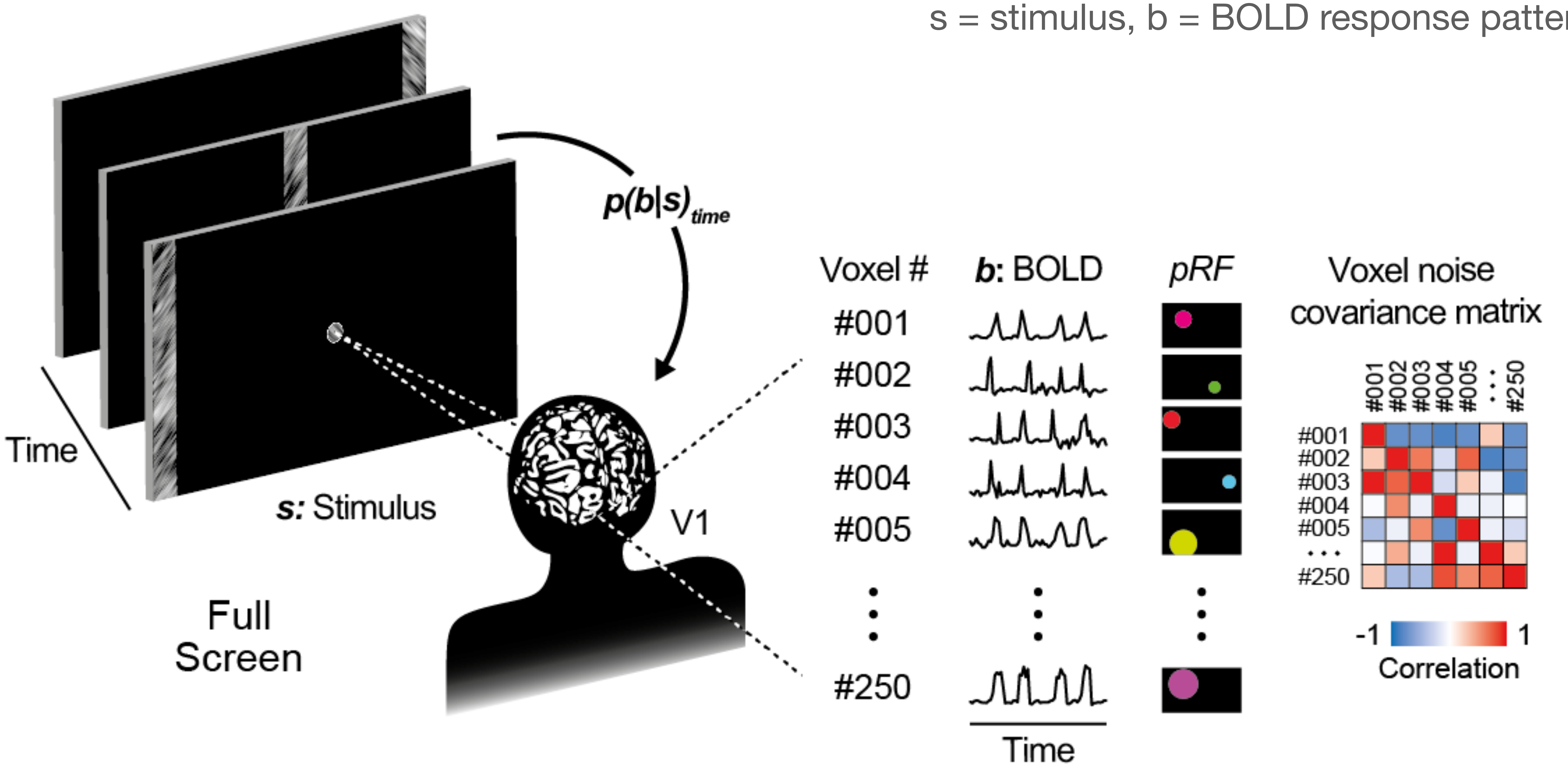

Bayesian decoding from an encoding model

What we want to know, the probability of a stimulus
given a BOLD response pattern
DECODING

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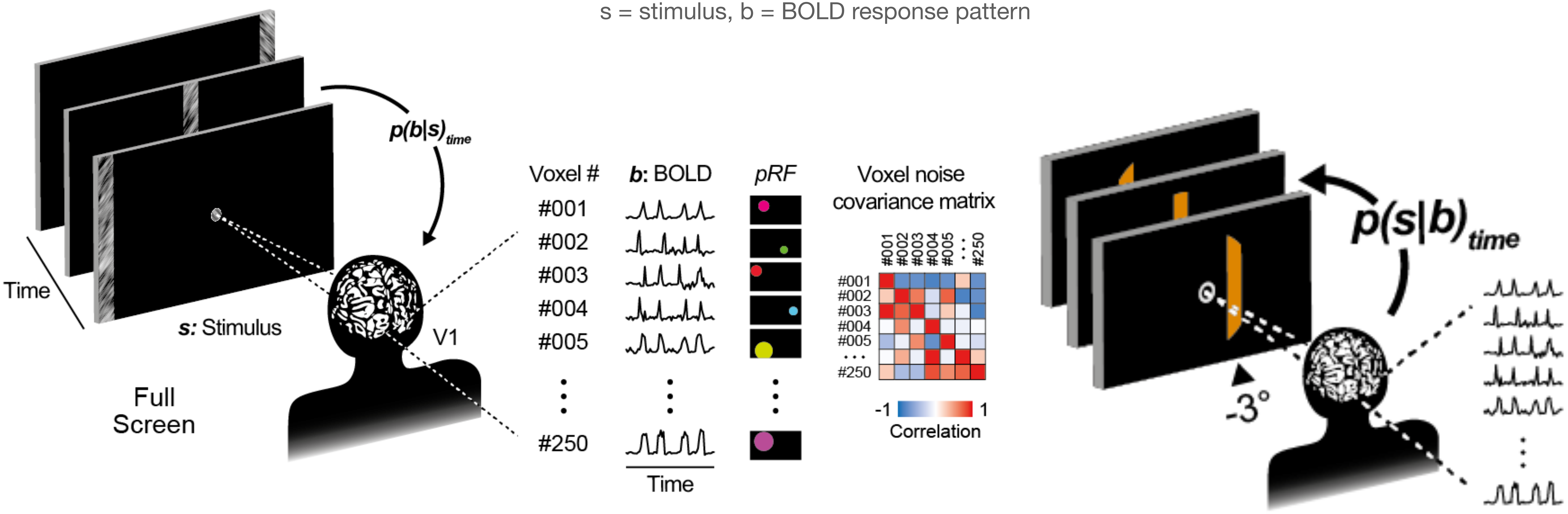

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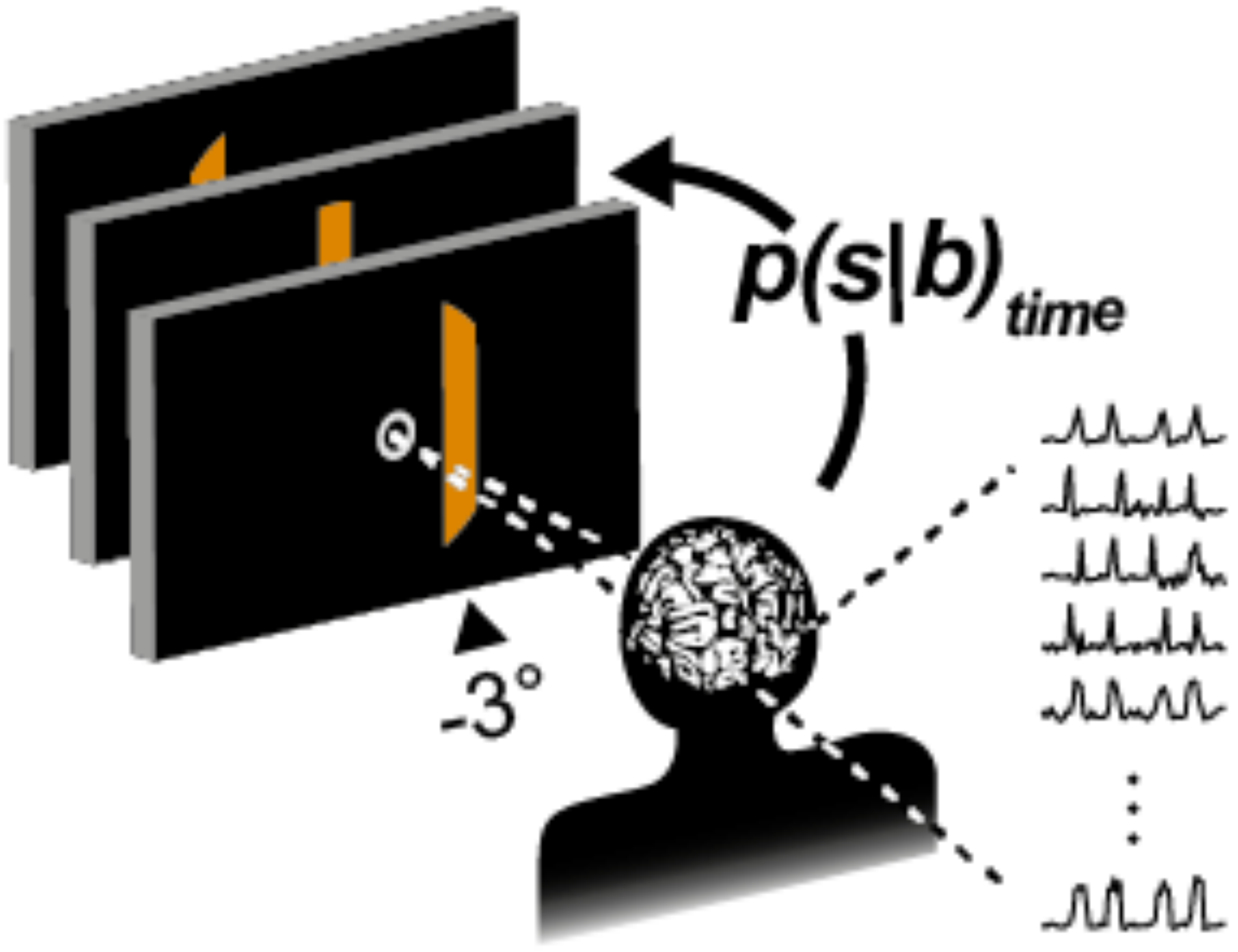
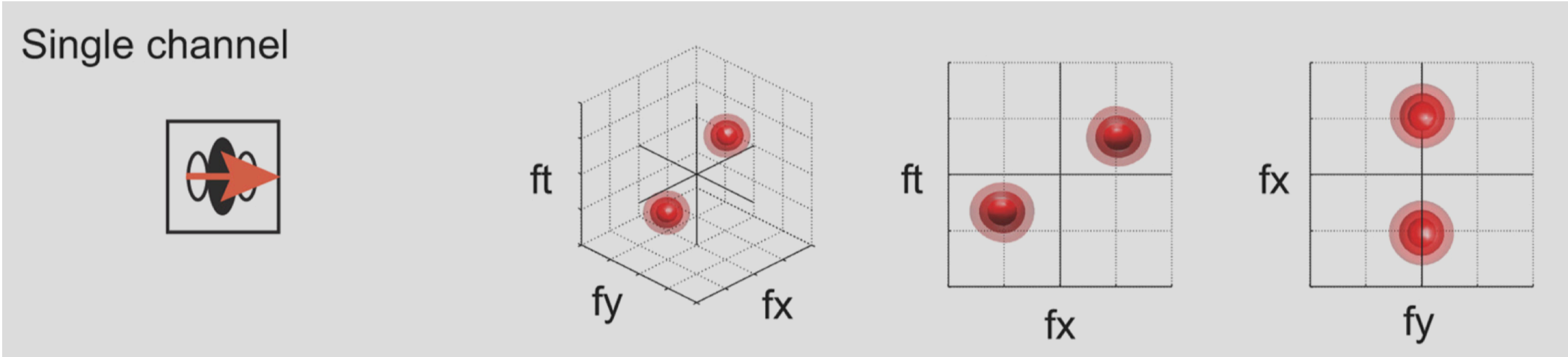
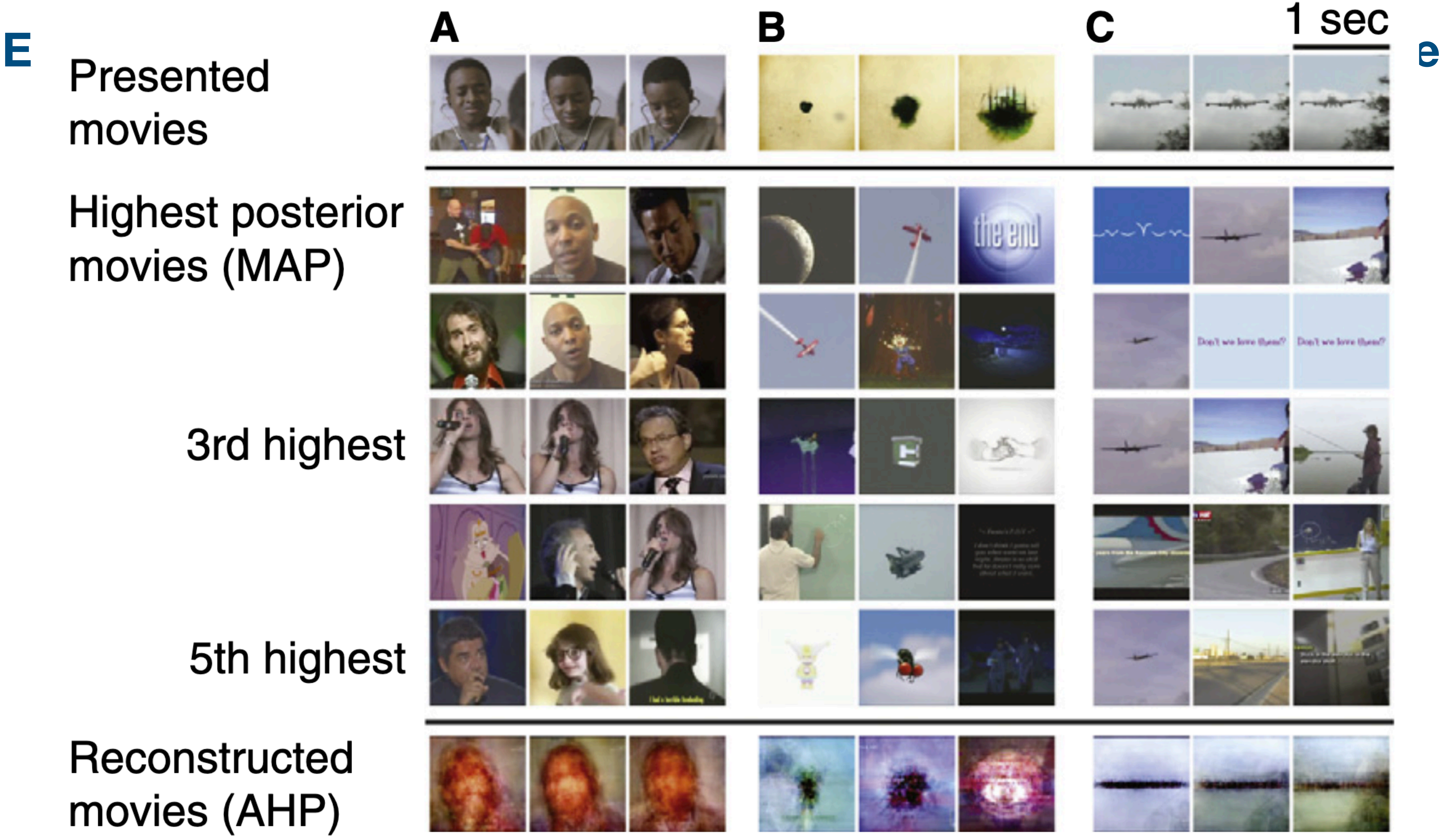


Extend this to movies: Add spatiotemporal receptive field structure




E
A
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C
1 sec
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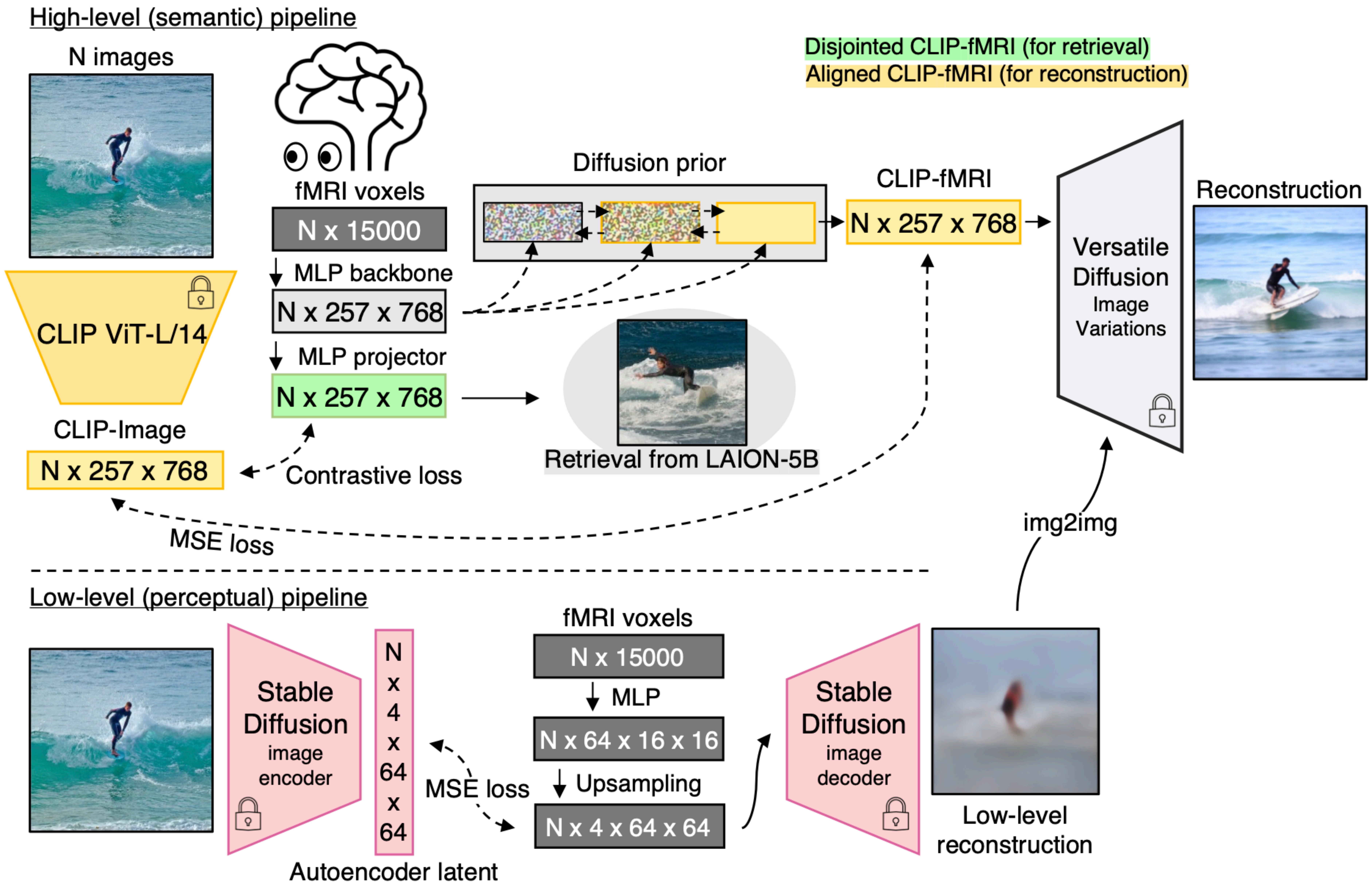
Presented movies
Highest posterior movies (MAP)
3rd highest
5th highest
Reconstructed movies (AHP)

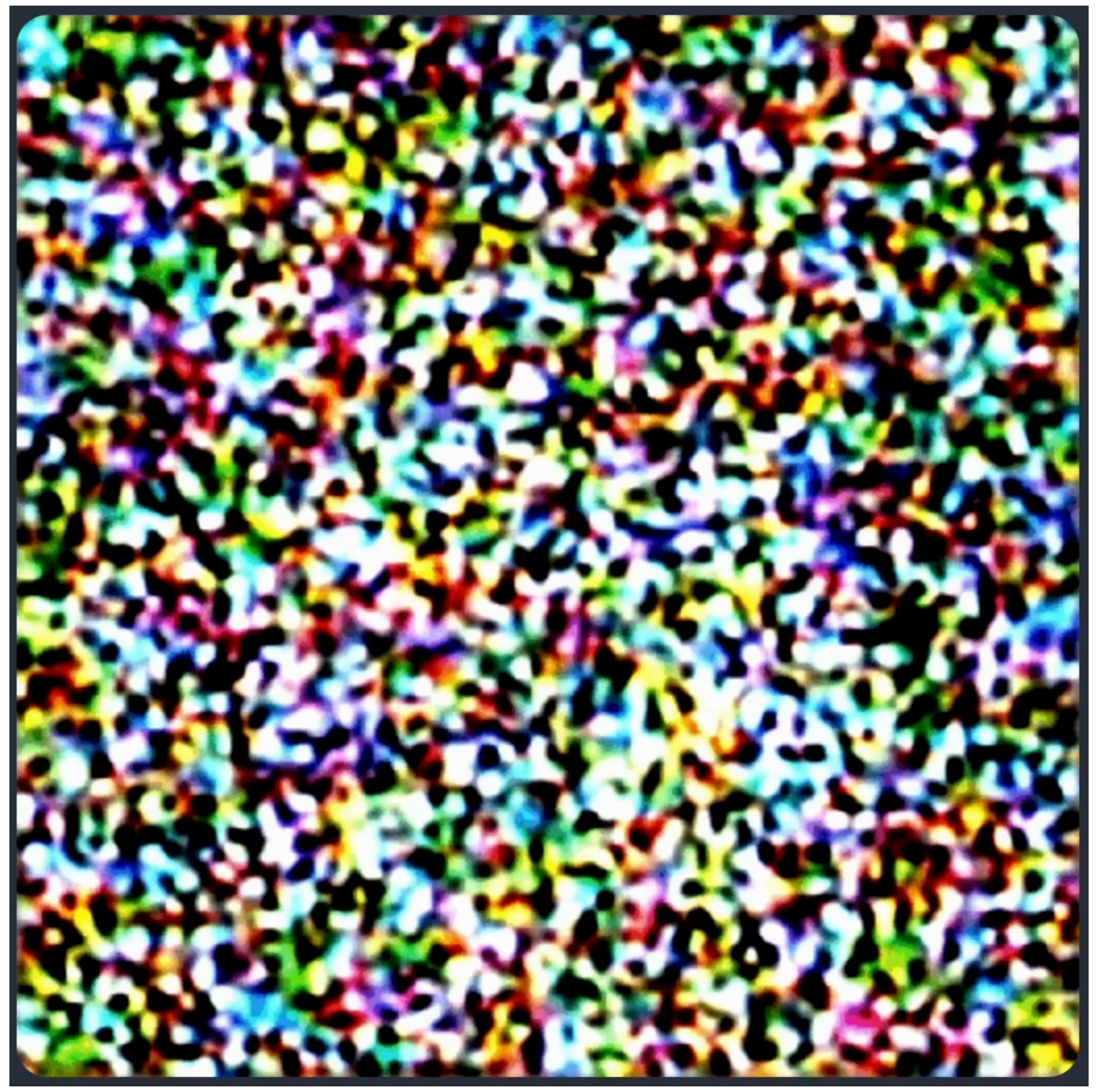
Presented clip

Clip reconstructed from brain activity

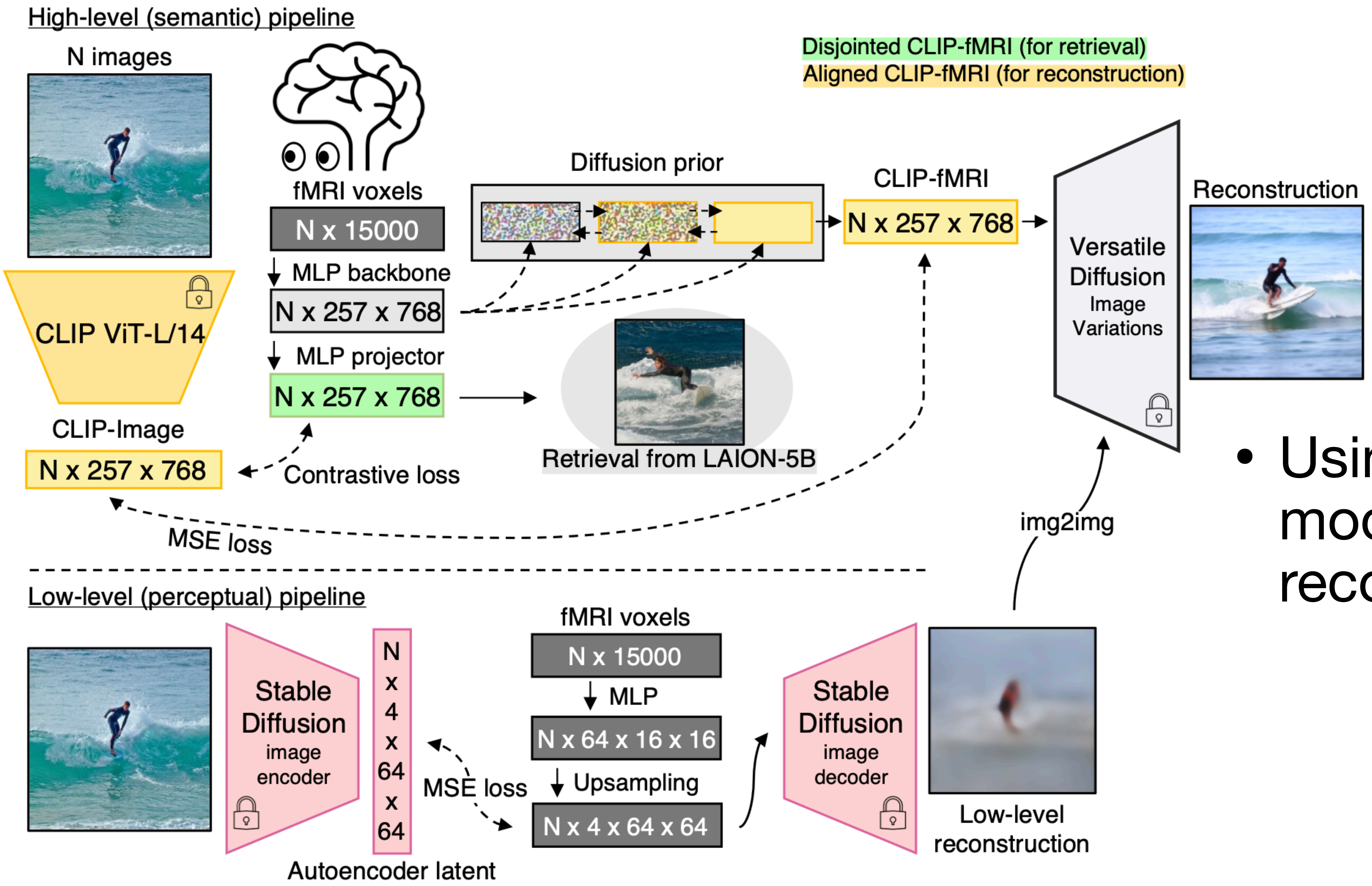
Stimulus reconstruction using AI

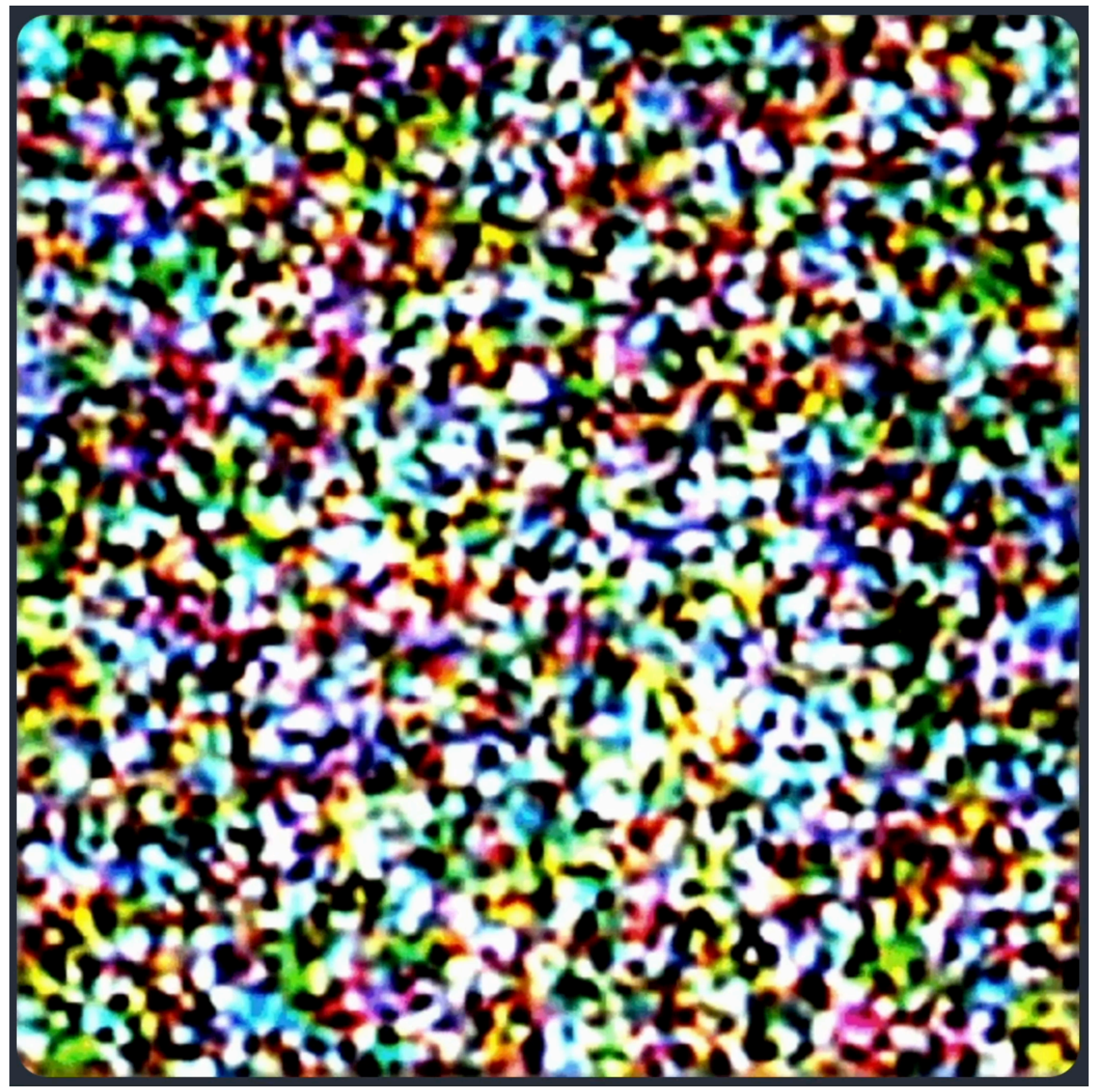
Stimulus reconstruction using AI





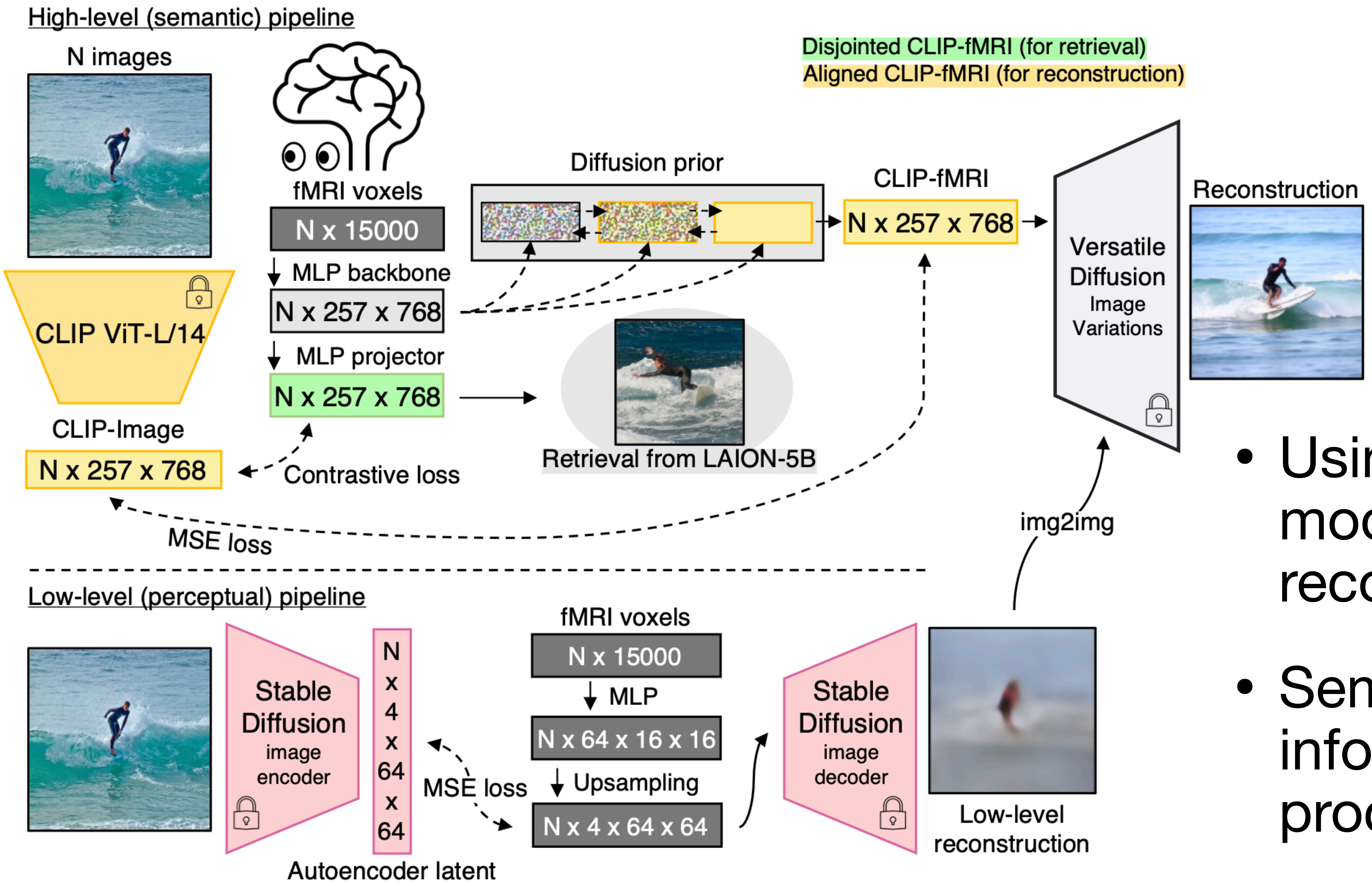
Stimulus reconstruction using AI

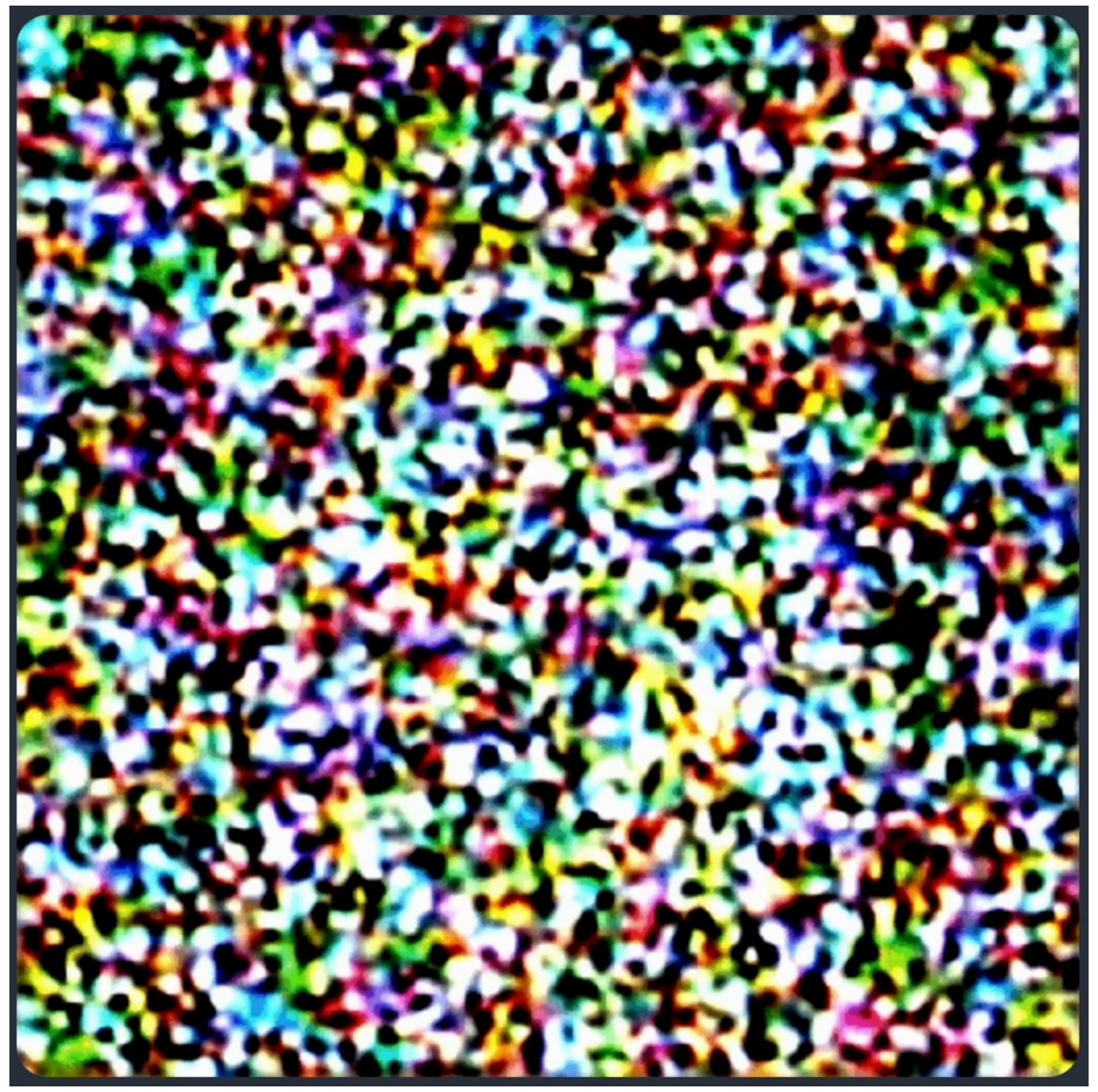




- Using diffusion models for reconstruction

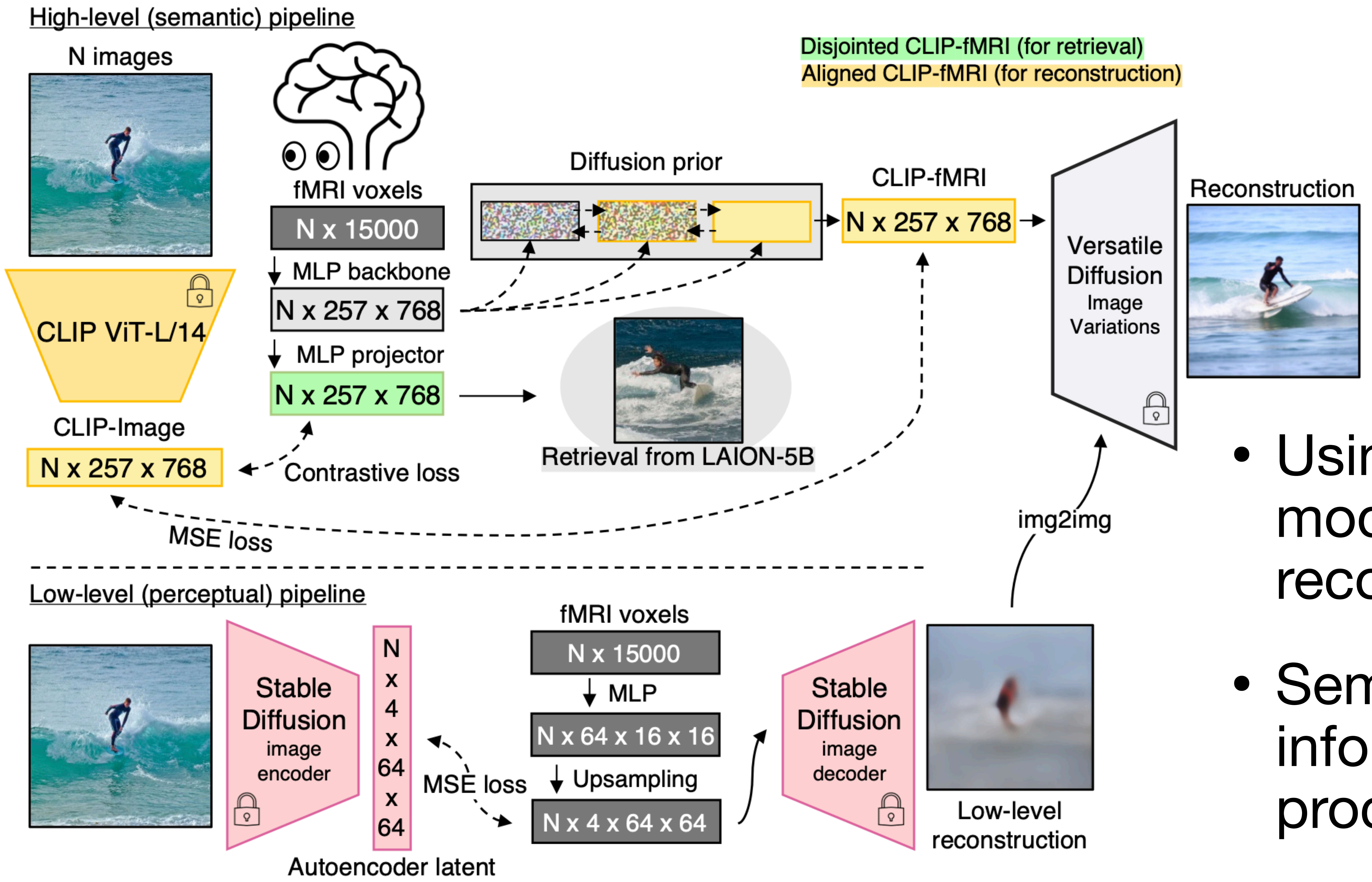
Stimulus reconstruction using AI

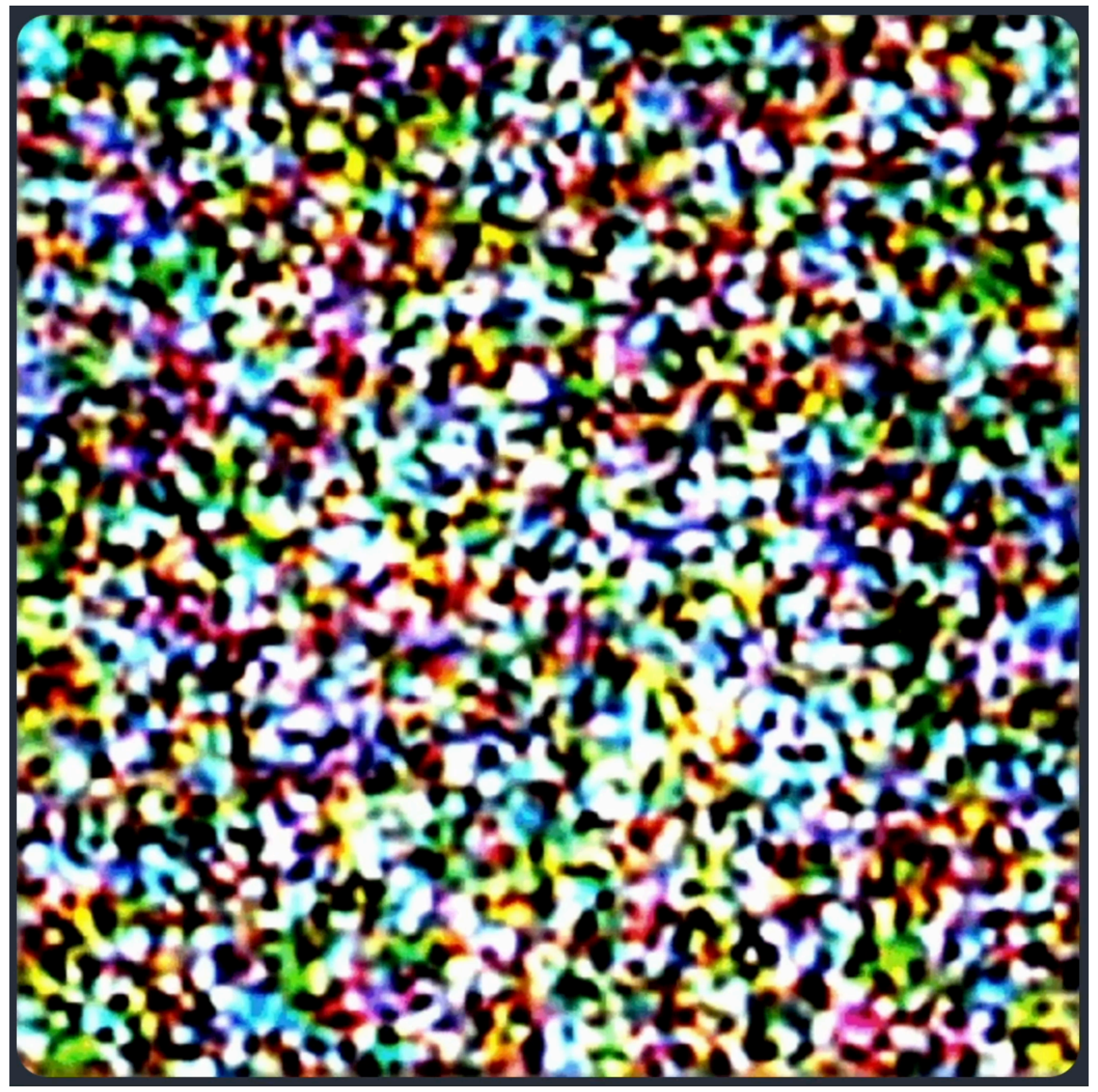




- Using diffusion models for reconstruction
- Semantic & Visual information processing streams

Stimulus reconstruction using AI





- Using diffusion models for reconstruction
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Take-away points

- Encoding/pRF models make neuron-voxel relationships explicit, and leverage the receptive field analogy
- Encoding/pRF models are explicit models of information processing:
    - ***Powerful!***
    - ***Hard!***
- Decoding based on single-voxel encoding model fits makes the patterns of MV**P**A explicit
    - ***Powerful!***
    - ***Hard!***