Deciphering brain activity under natural vision

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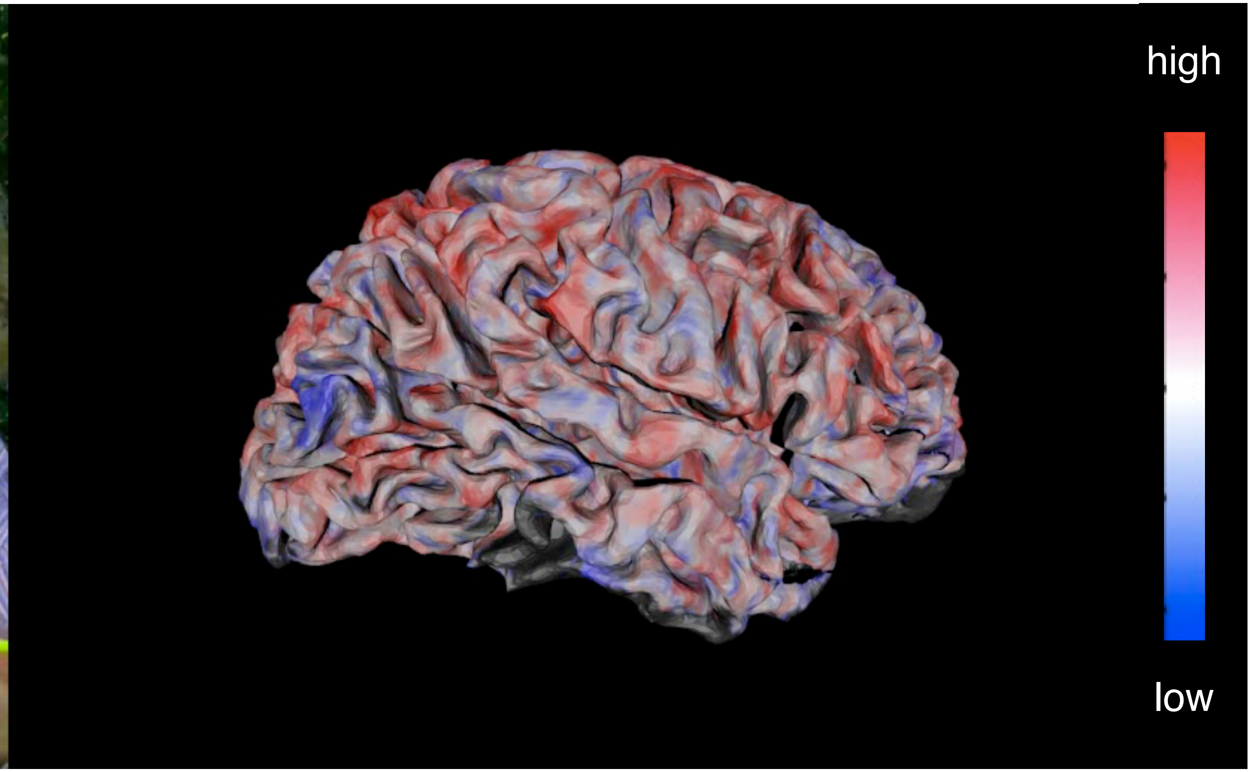
Our visual experience is like watching a movie: vivid, dynamic, and rich

Modeling and decoding human brain

Natural experience
(e.g., movie stimuli)

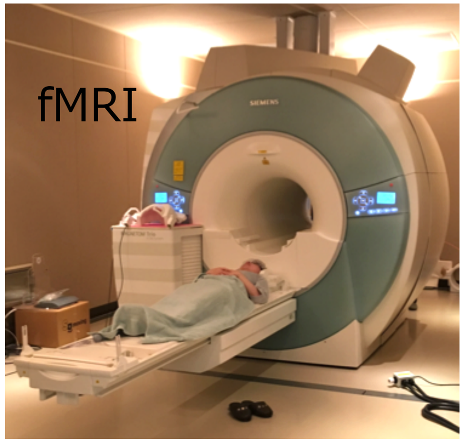
Brain activity



Artbeats HD

We aim to understand how the brain works under natural (visual) experiences. To this aim, we:

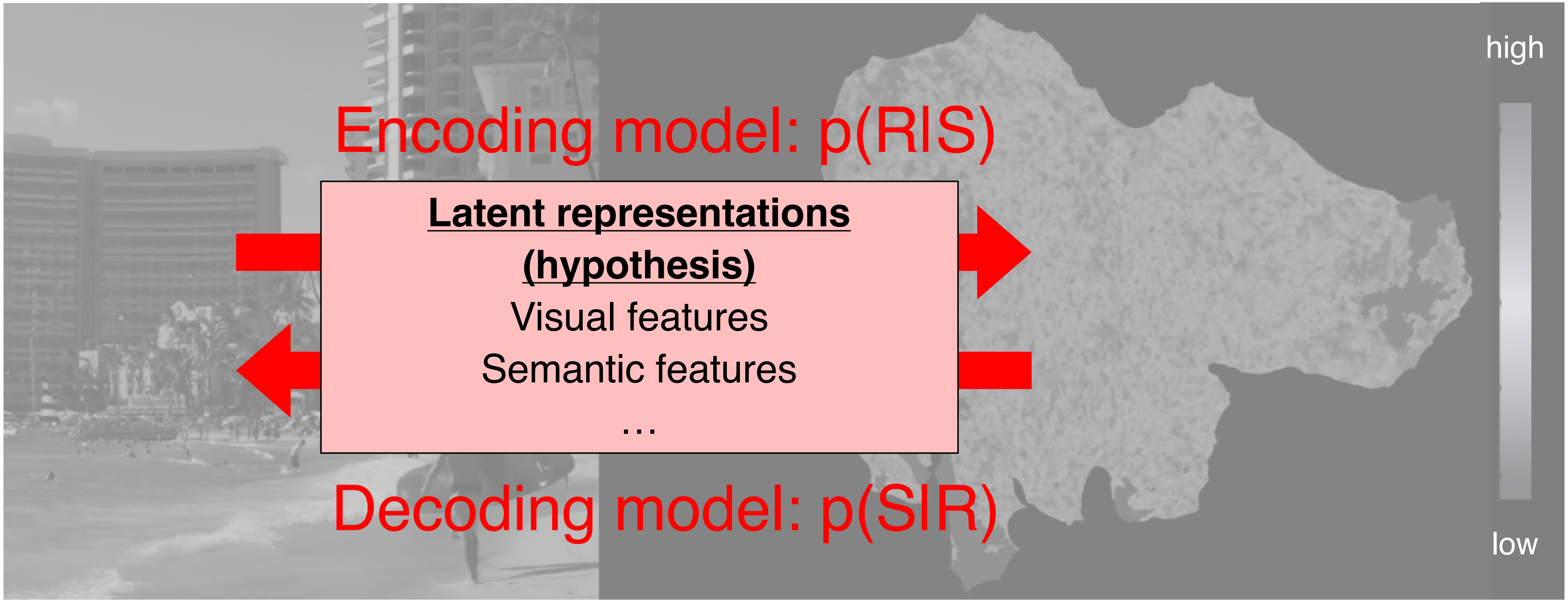
- record hours of movie-evoked brain activity using fMRI
- build predictive models that explain the relationship between experience and brain activity



Modeling and decoding human brain

Natural experience
(e.g., movie stimuli)

Brain activity



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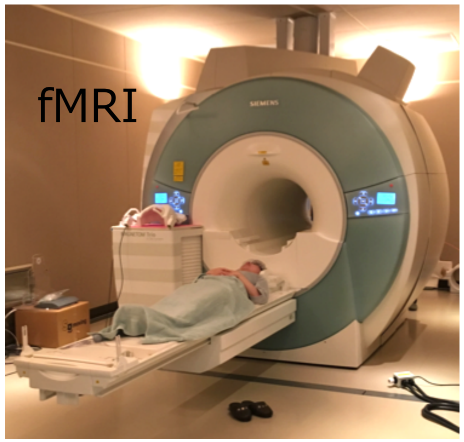
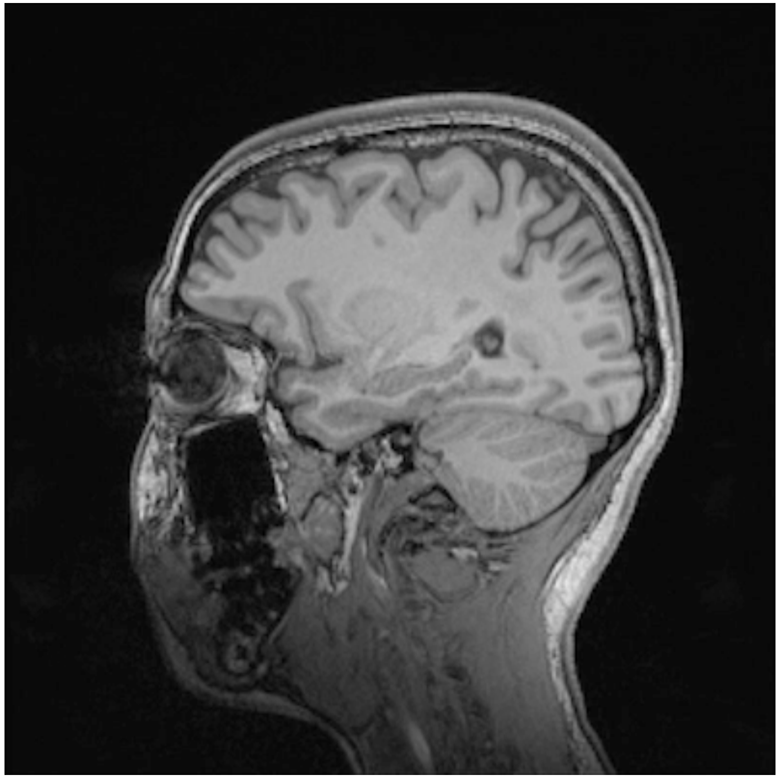
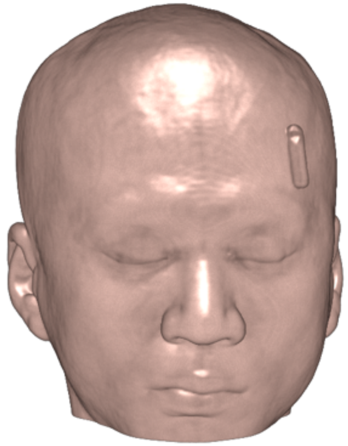


Magnetic Resonance Imaging (MRI): scan the structure



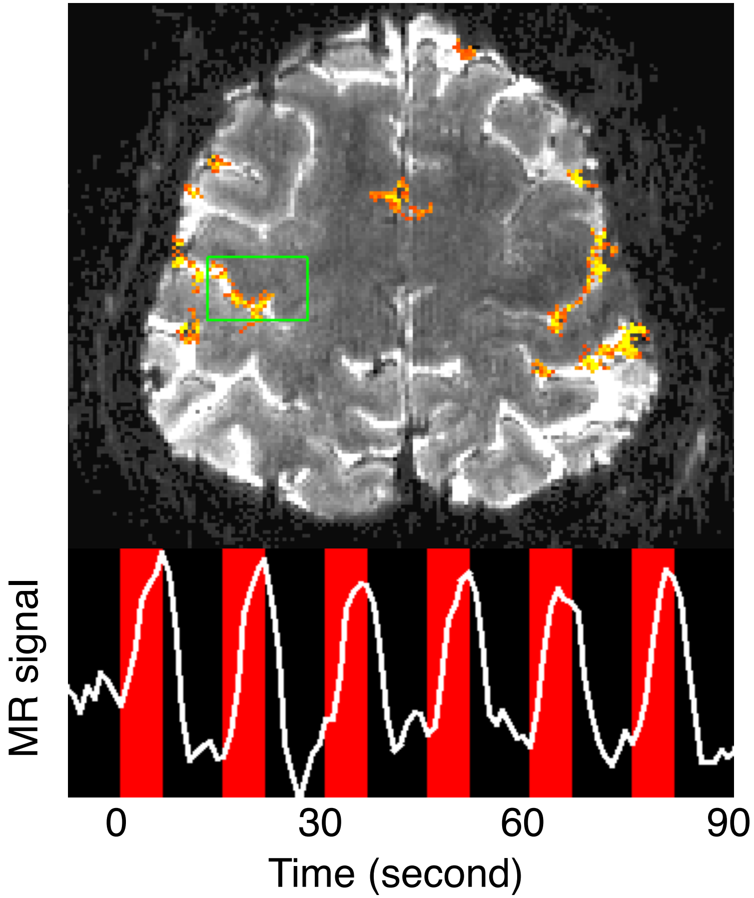


\+ Vitamin bar

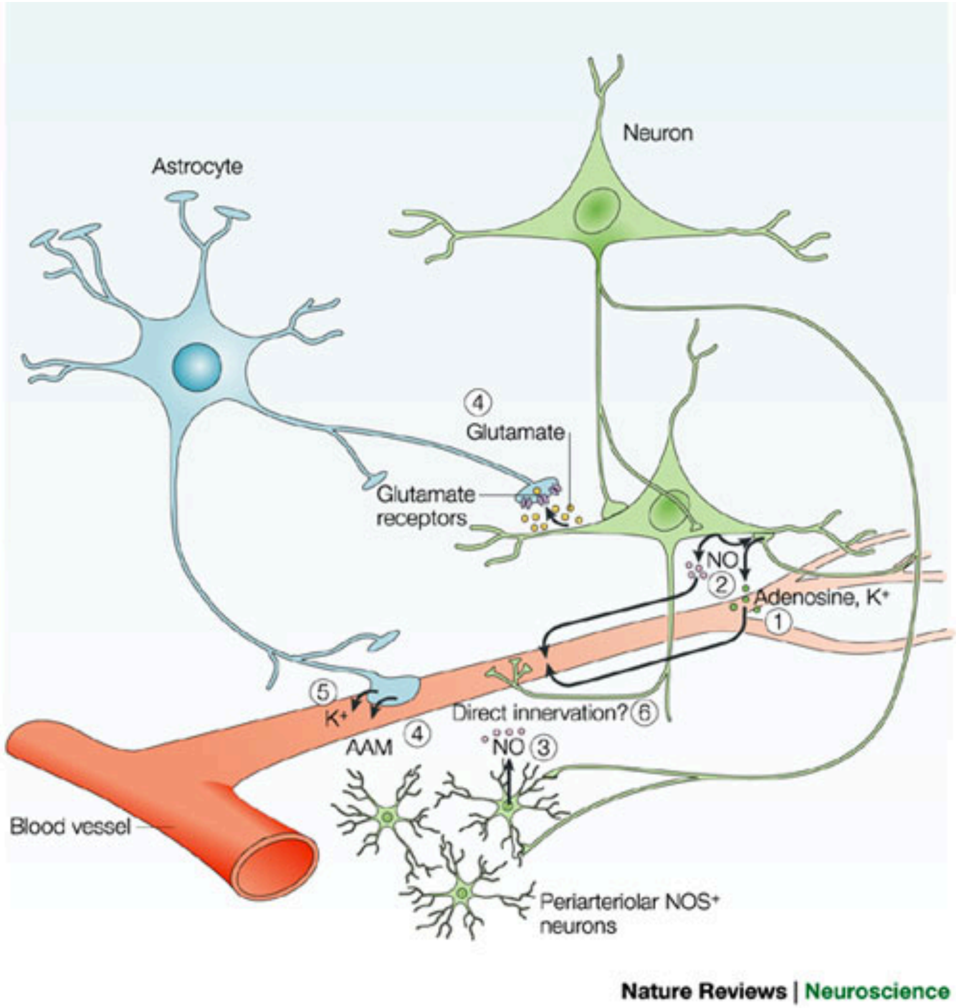
\+ Orthodontics
(Dental bridge)

Typical scan parameters:
- Resolution: 1 mm cube (voxel)
- 208 sagittal slices
- 6 minutes/scan
- 1 scan volume/person

Functional MRI (fMRI): scan brain activity



Finger tap - Nothing

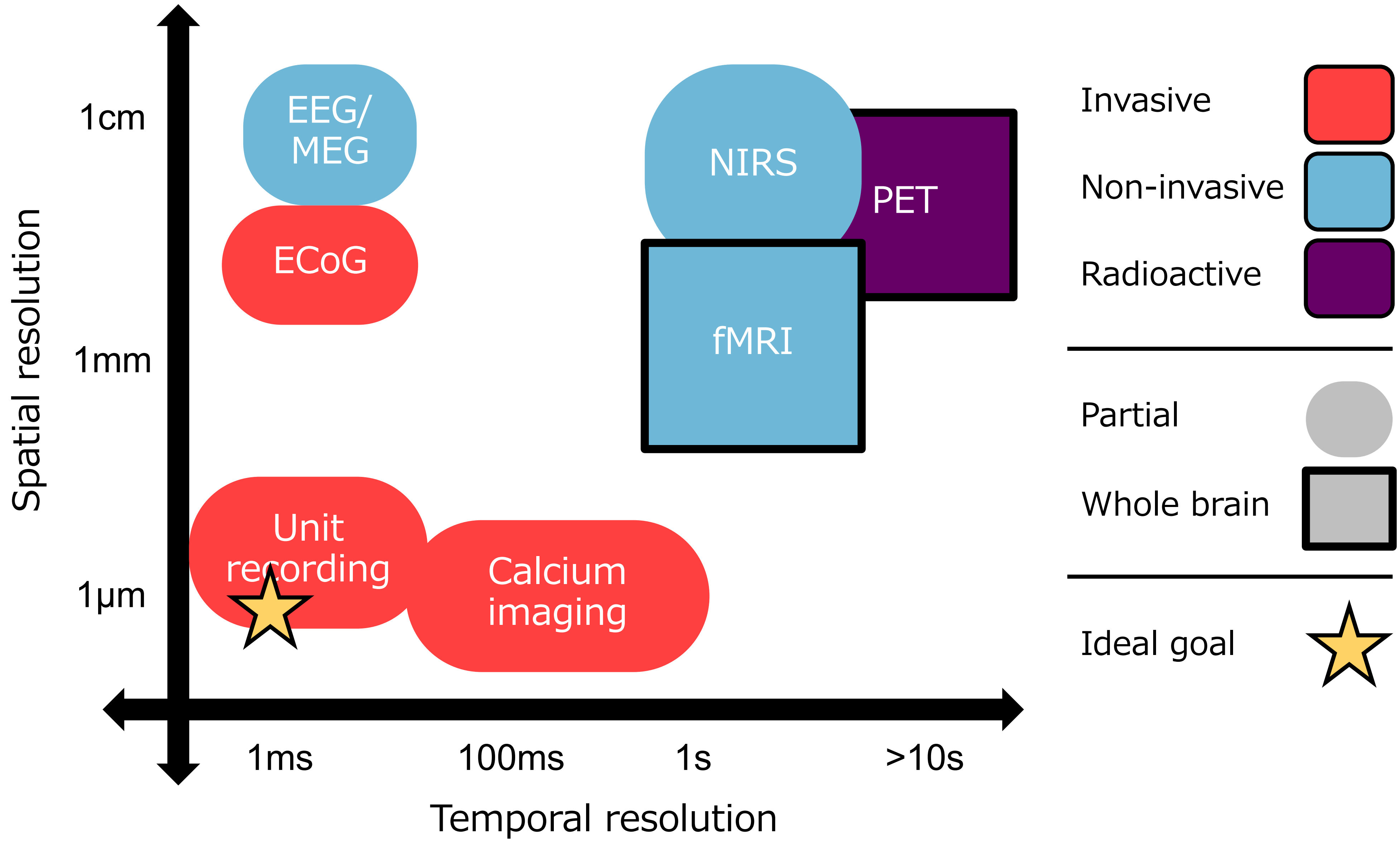


Typical scan parameters:
- Resolution: 2-3 mm cube
- 1-2 seconds/scan
- many scans during tasks

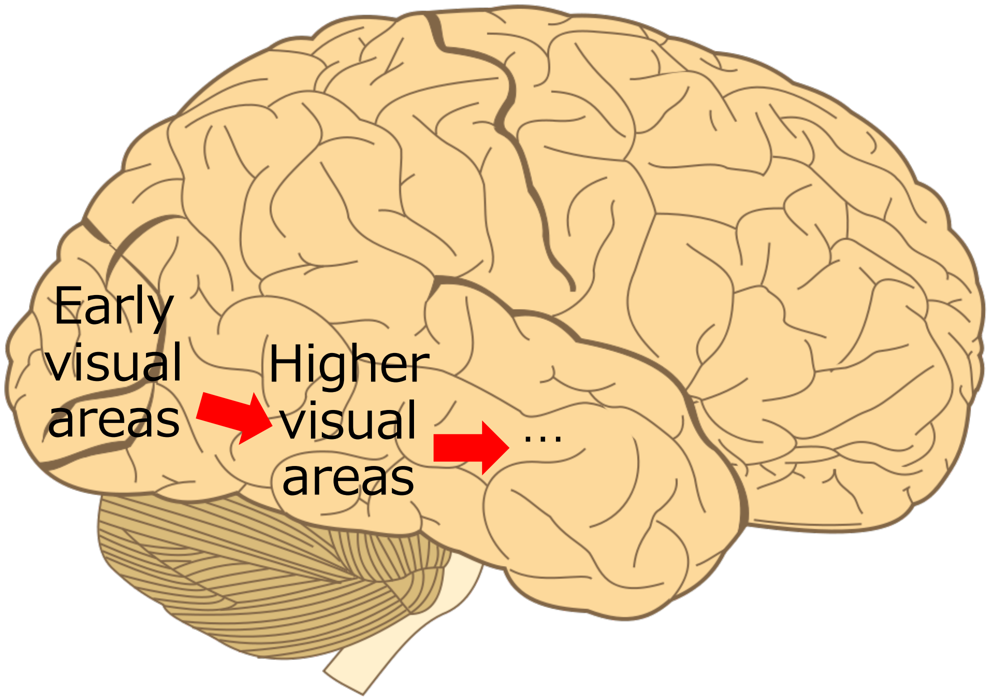
D'Esposito et al., 2003

fMRI experiment B-roll

Variety of measurement methods (no single ultimate method, yet)



Hierarchical visual processing in the human cortex



- Posterior to Anterior
- Concrete to Abstract
- Objective to Subjective

DIVIDE AND CONQUER

Revealing quantitative representation at each stage

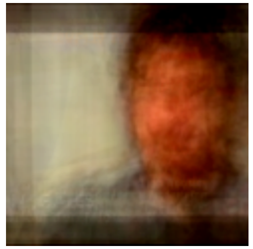
↓

Better understanding on how the brain sees/structures the world

Early visual areas		Higher visual areas		…
Image property (motion, color,…)	→	Semantics (object, impression,…)	→	…

Talk summary

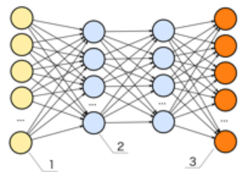
1. Visual spatiotemporal representation



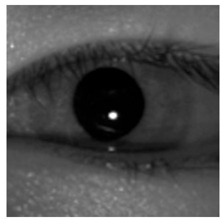
2. Visual category representation

3. Language model representation

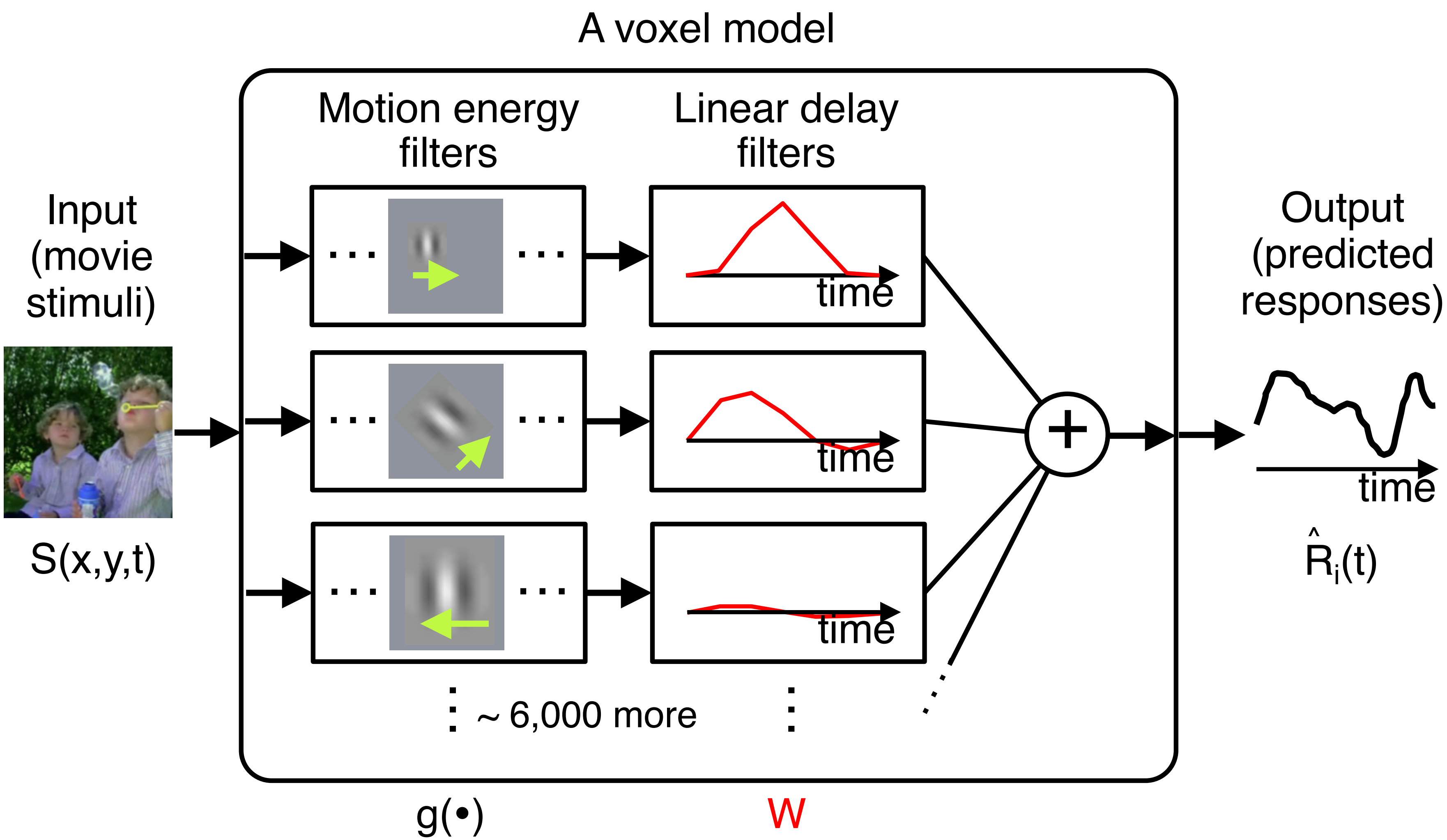
4. Using “AI” to decode brain



5. Eye movement-invariant representation



Motion-energy encoding model

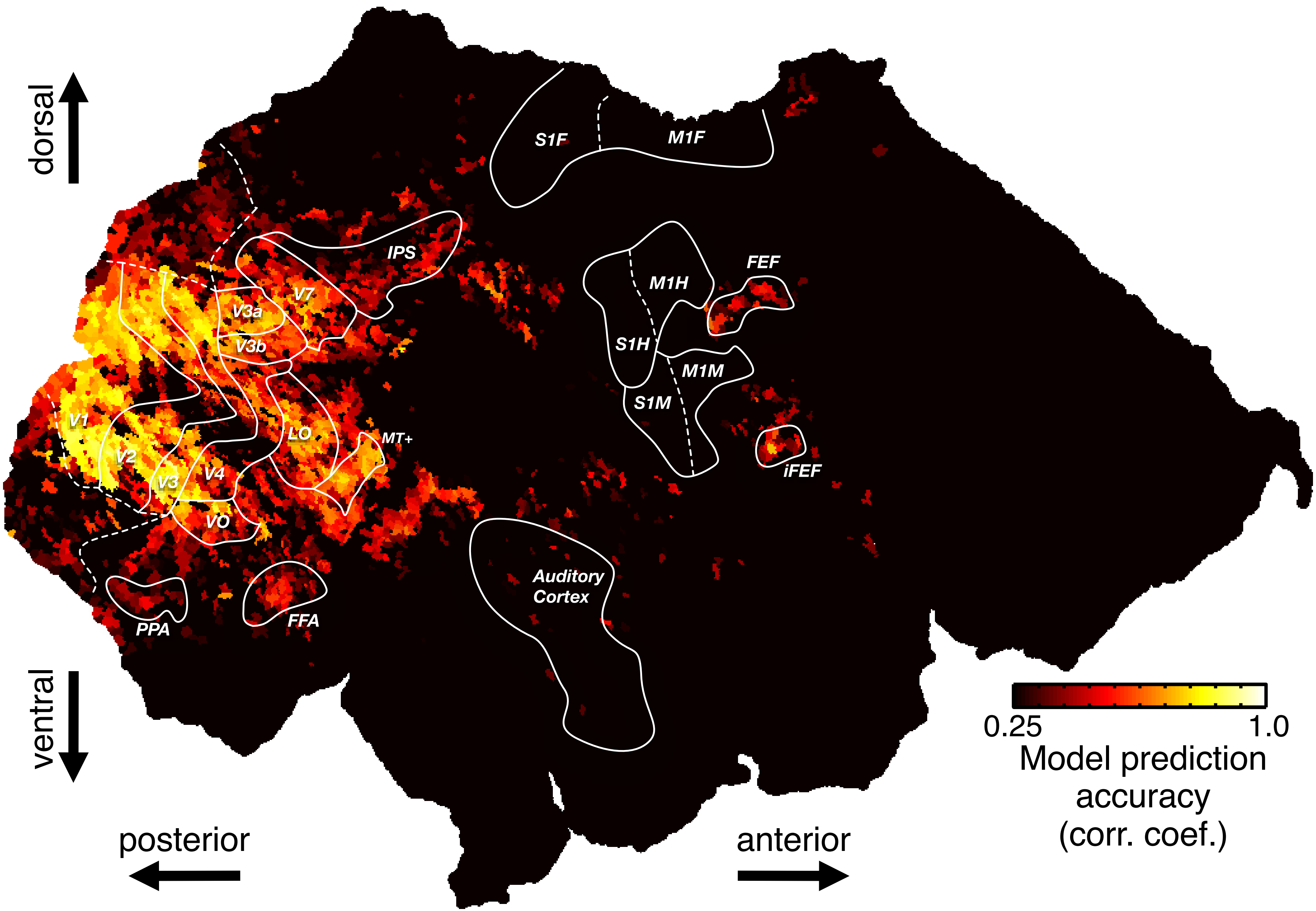


Model: $g(S)W = \hat{R}$

Objective: $\underset{W}{\text{minimize}}\ (g(S)W - R)^2 + \lambda |W|_1$

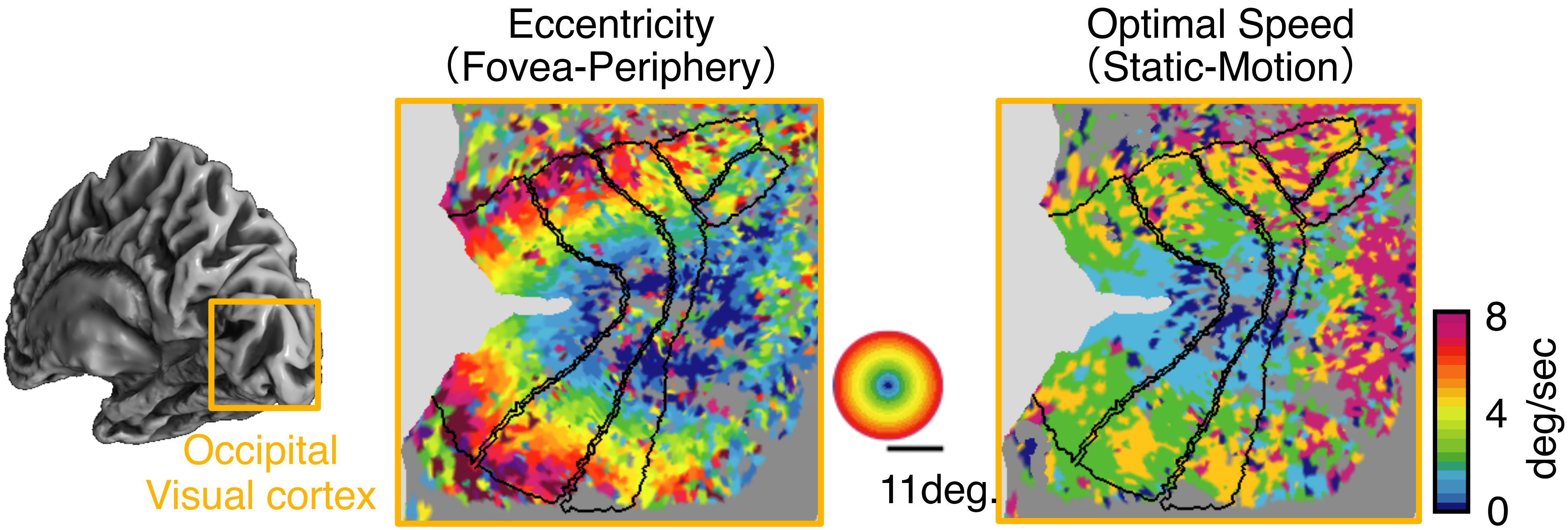
Nishimoto et al., 2011 *Current Biology*

The motion-energy model explains the early visual areas in humans



The model recovers spatiotemporal representations

Functional maps of visual information



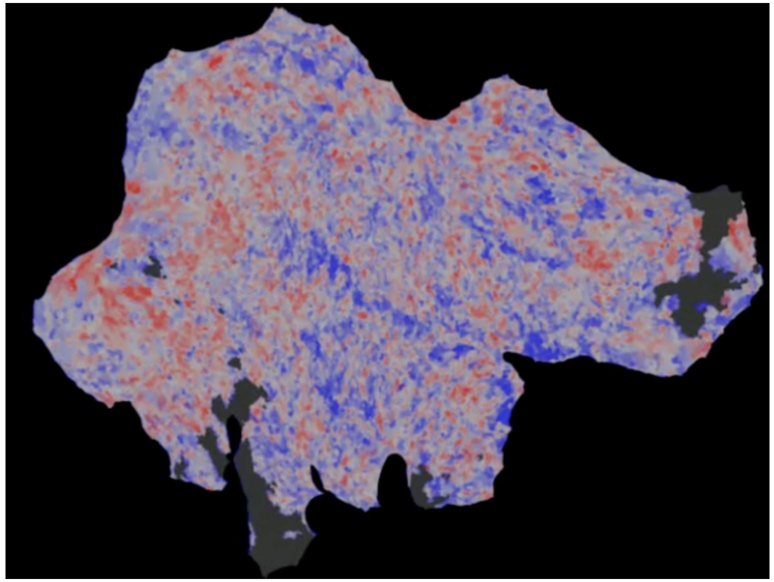
Nishimoto et al. 2011 *Current Biology*

- The occipital cortex contains retinotopic and speed maps
- The optimal speed depends on eccentricity
- …can we do the opposite?

Bayesian decoding using encoding model

Stimuli (S)

Brain activity (R)



Encoding model

$p(R|S)$

Decoding model

$$p(S|R) \propto p(R|S)p(S)$$

Encoding model

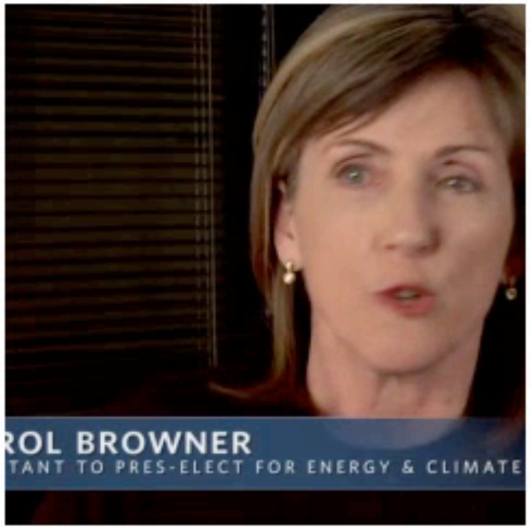
$MVN(g(S)W,\Sigma)$

Movie prior

(18 million seconds of natural video database)

Decoding perceptual experiences from brain activity

Experience



Decoded experience from brain activity

Nishimoto et al., 2011 *Current Biology*

- A general approach for perception and imagination

  e.g., Imagination-aided Google Image Search (Naselaris et al., 2015)

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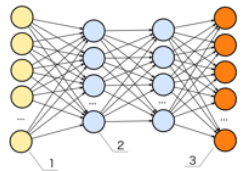

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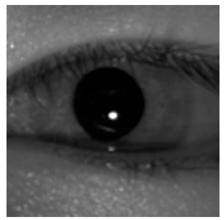
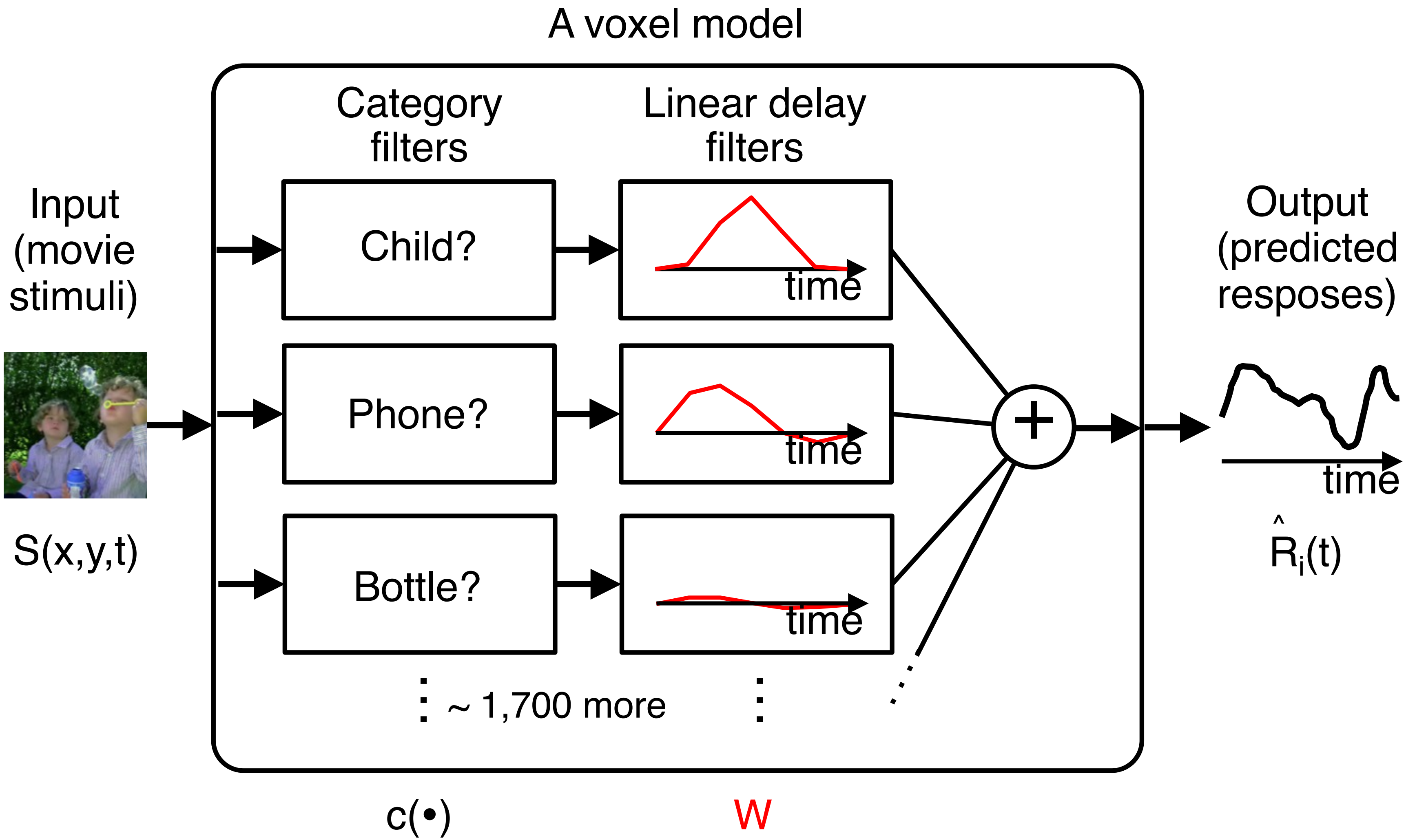
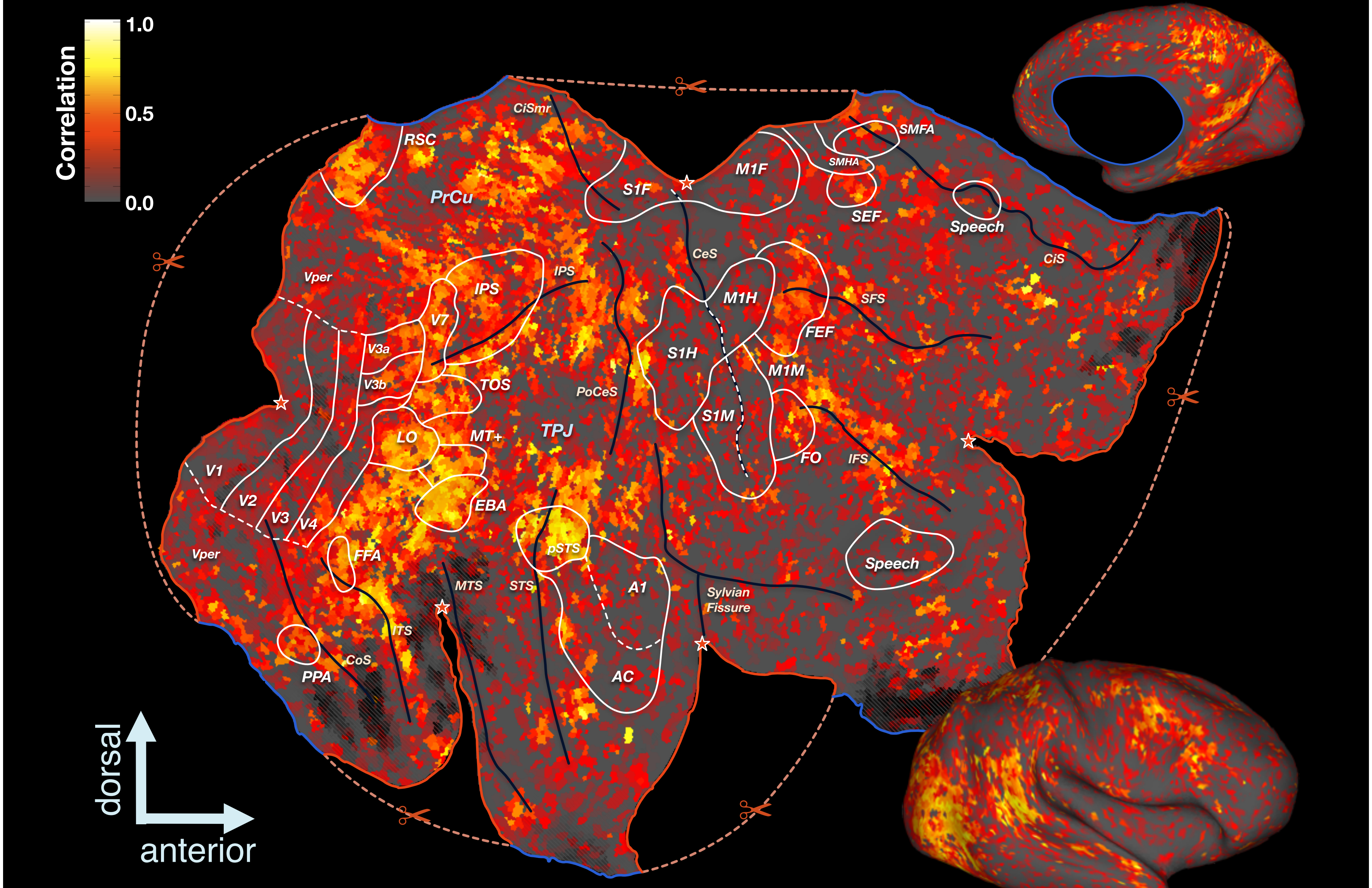


The category encoding model



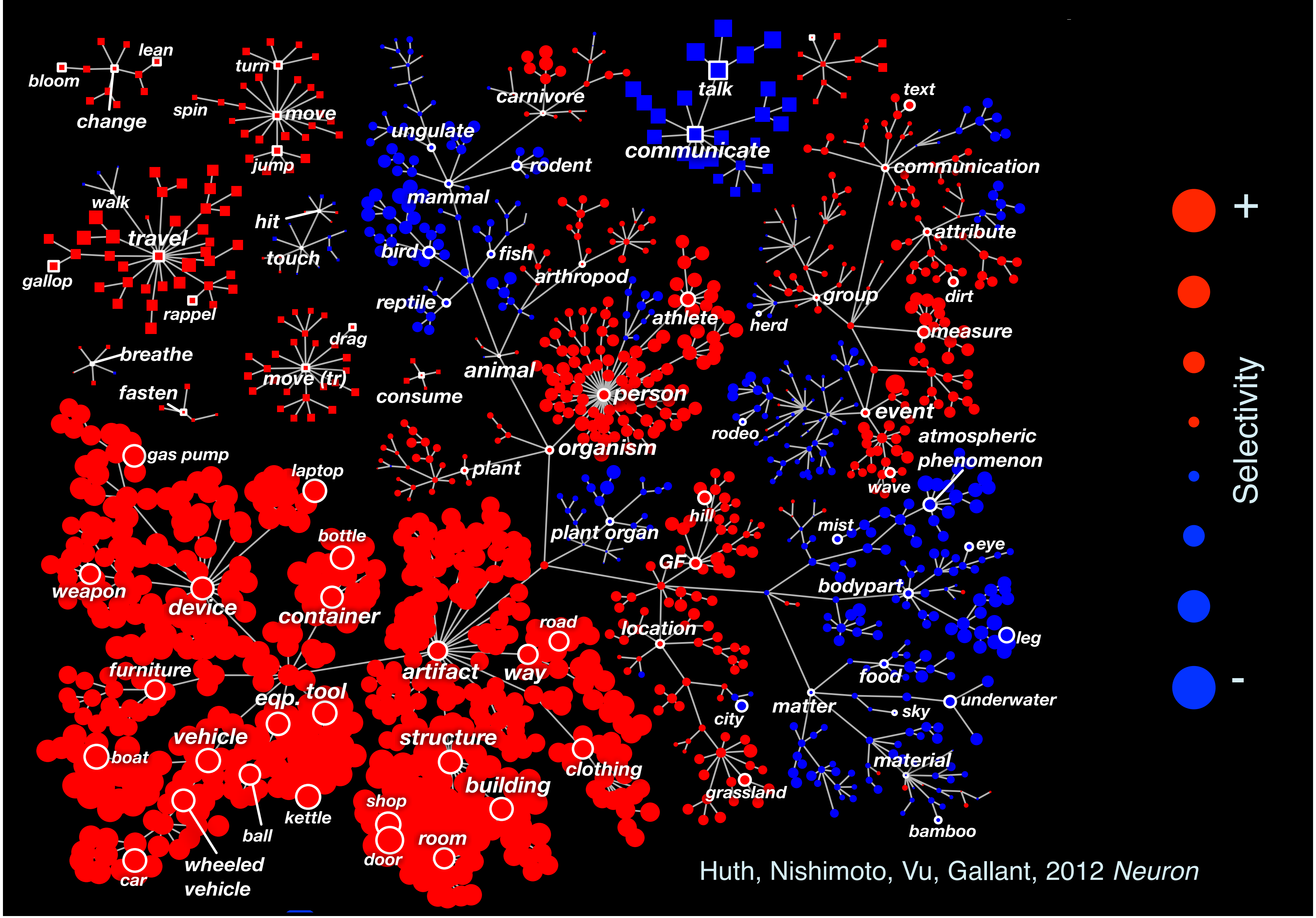
Huth, Nishimoto, Vu, Gallant, 2012 *Neuron*

The category model explains higher-order visual areas



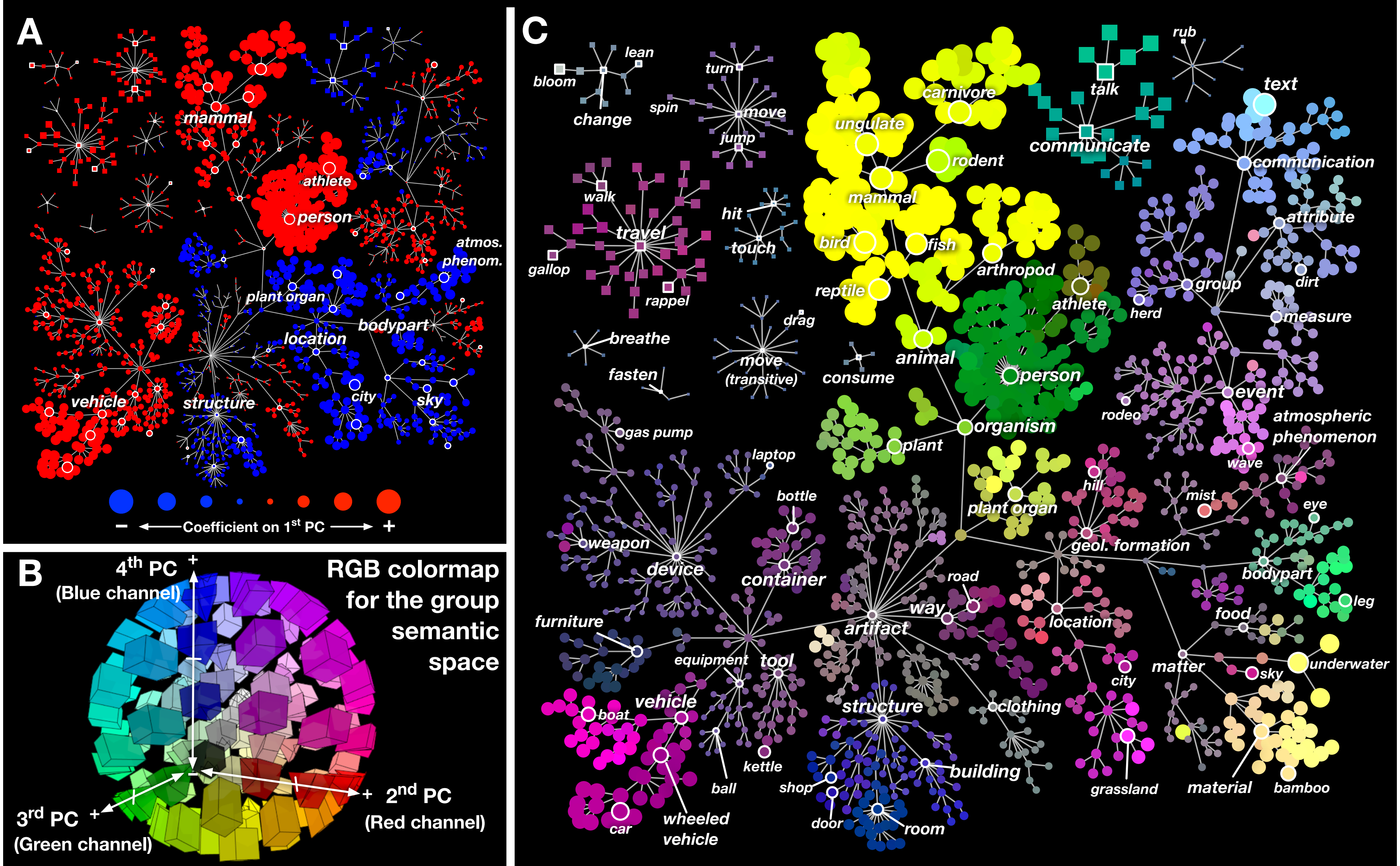
Huth, Nishimoto, Vu, Gallant, 2012 *Neuron*

The model recovers voxel-wise category selectivity



Huth, Nishimoto, Vu, Gallant, 2012 *Neuron*

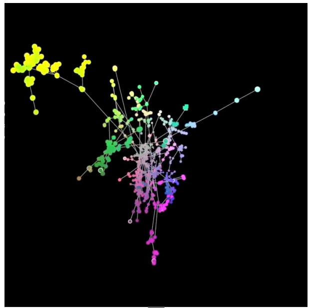
The model recovers principal semantic components



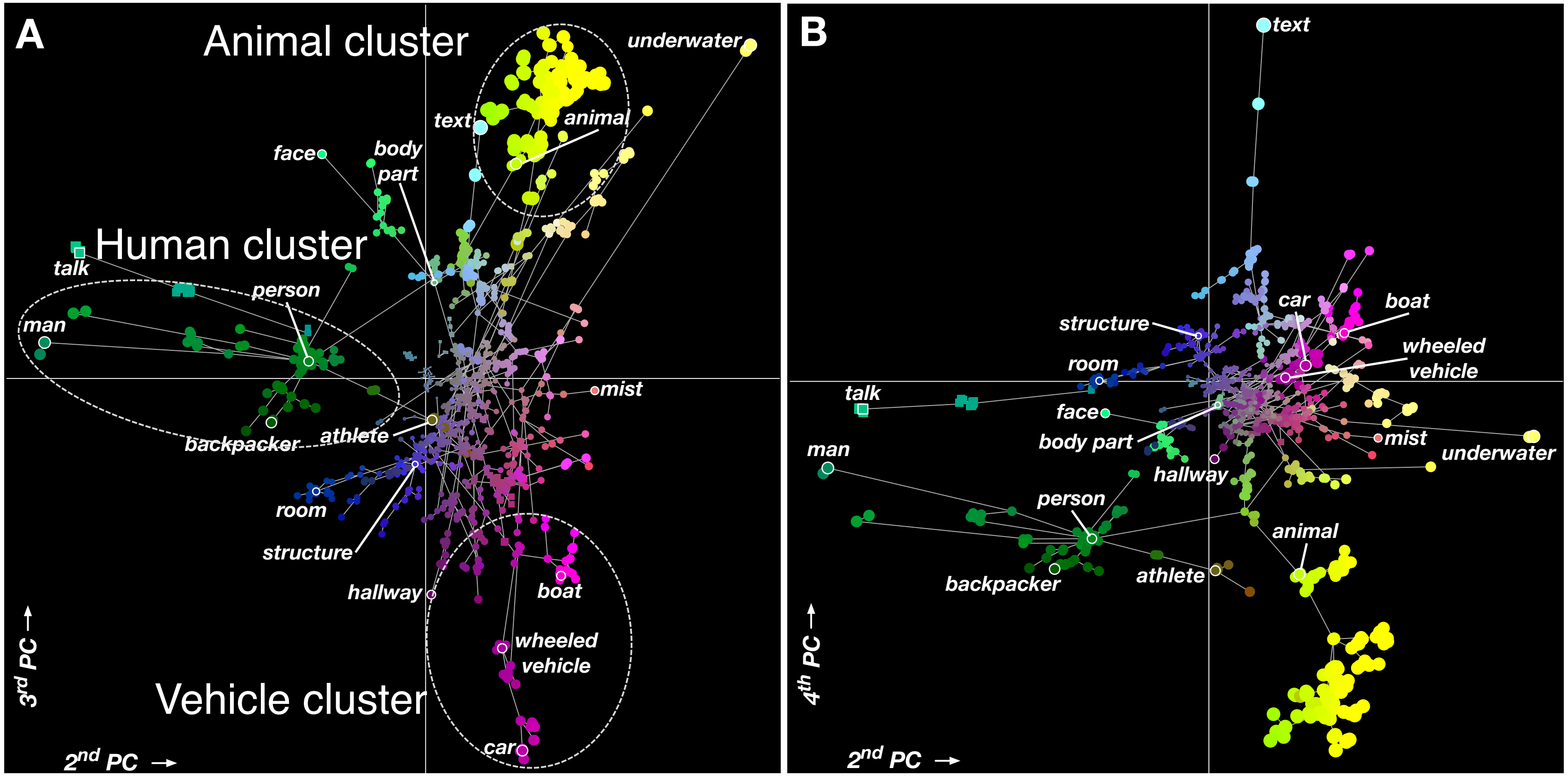
Huth, Nishimoto, Vu, Gallant, 2012 *Neuron*

Structures of the semantic space in humans

Semantic space



2D projections



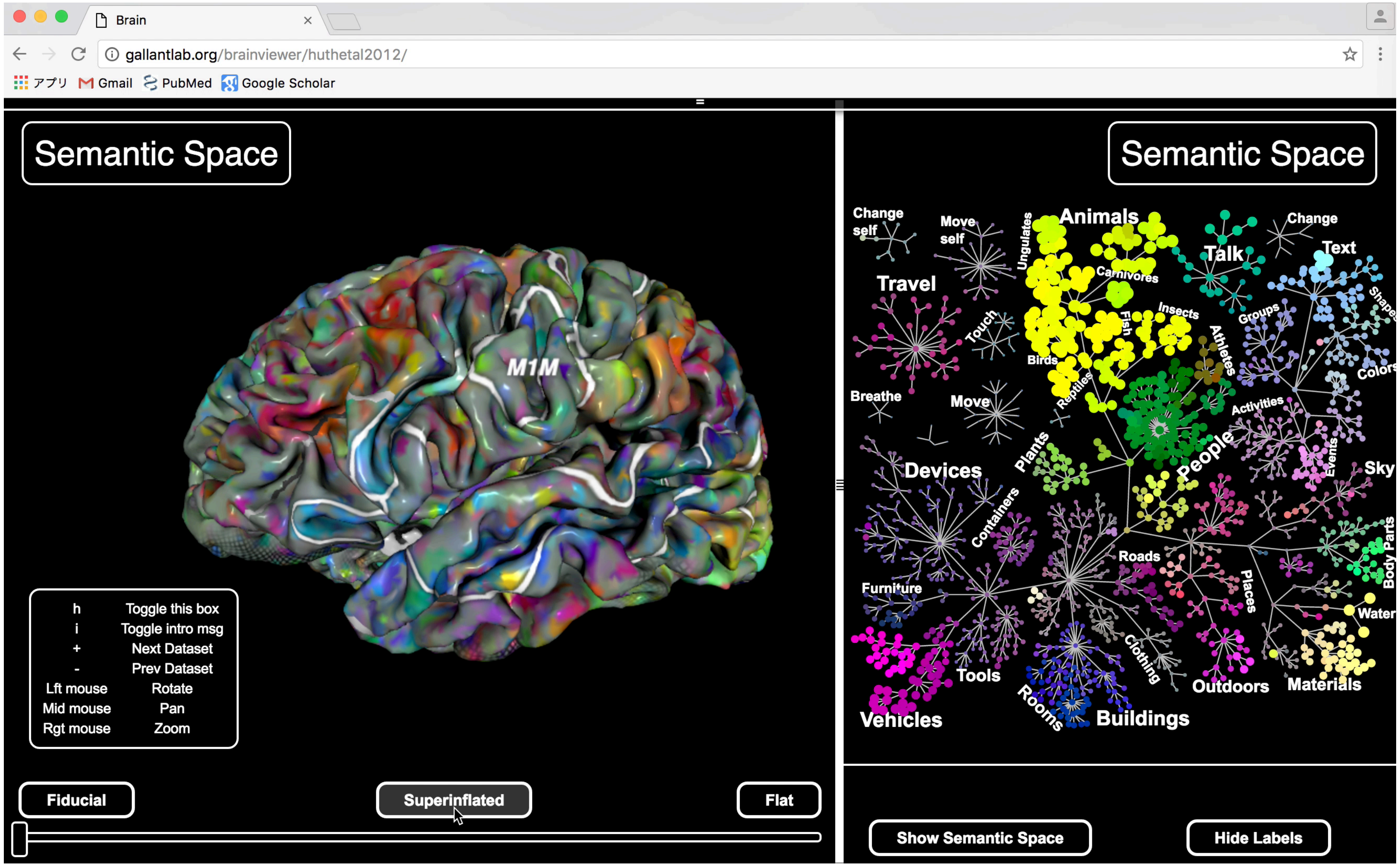
Huth, Nishimoto, Vu, Gallant, 2012 *Neuron*
Çukur, Nishimoto, Huth, Gallant, 2013 *Nature Neuroscience*
Çukur, Huth, Nishimoto, Gallant, 2016 *J. Neuroscience*

- Quantifying an embedding space of categories (man, mist, text, …) in the human brain
- Application: data-driven retrieval of human common sense for building brain-like AI

  e.g. performance improvement in machine learning tasks using brain data

  (Ruan et al., 2016 *EMNLP* ; Fong et al., 2017 arXiv)

Pycortex: an interactive surface visualizer for fMRI



Google search: Brain Viewer

GitHub: pycortex

Gao et al., 2015 *Front. Neuroinform.*

Example of decoding using the category model

Presented movie

Decoding of perceived categories from brain activity

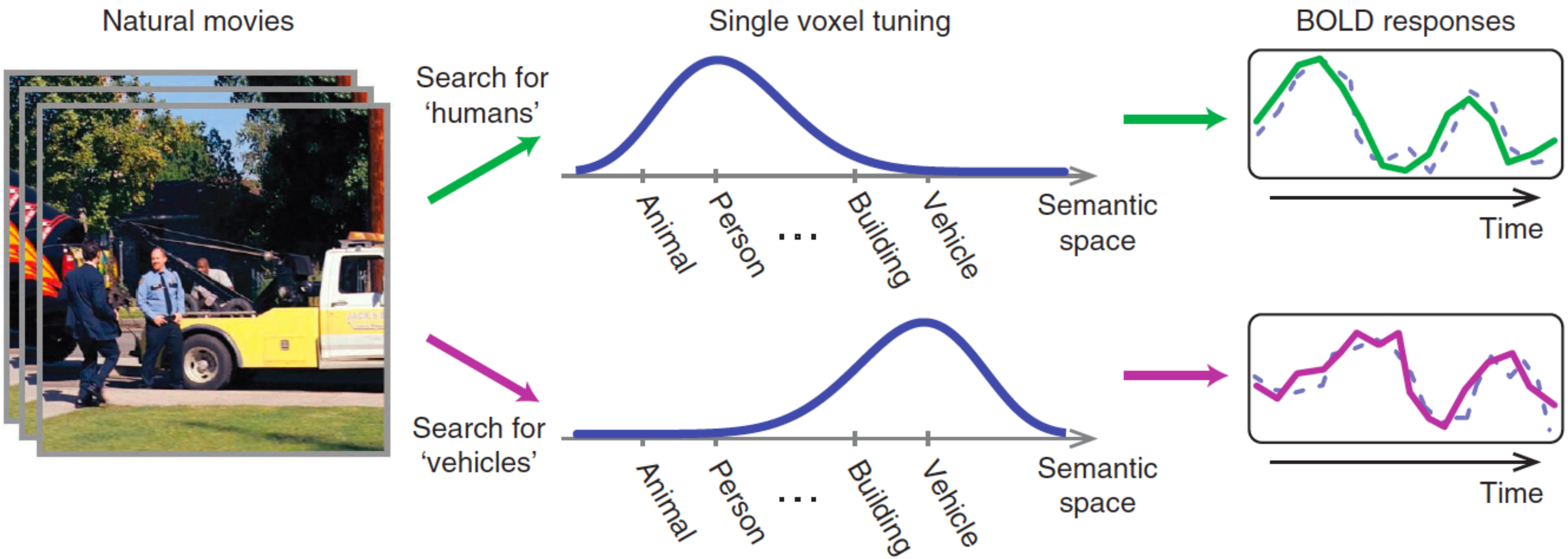
Huth et al., 2012 *Cosyne*; Huth et al., 2016 Front. Syst. Neurosci.

- Application: Decoding of "dream" contents (Horikawa et al., 2013 *Science*)

Can attention alter the semantic space?

- Attention alters (low-level) feature representation.
- What about higher-order (category) representation under natural vision?

Categorical attention experiment

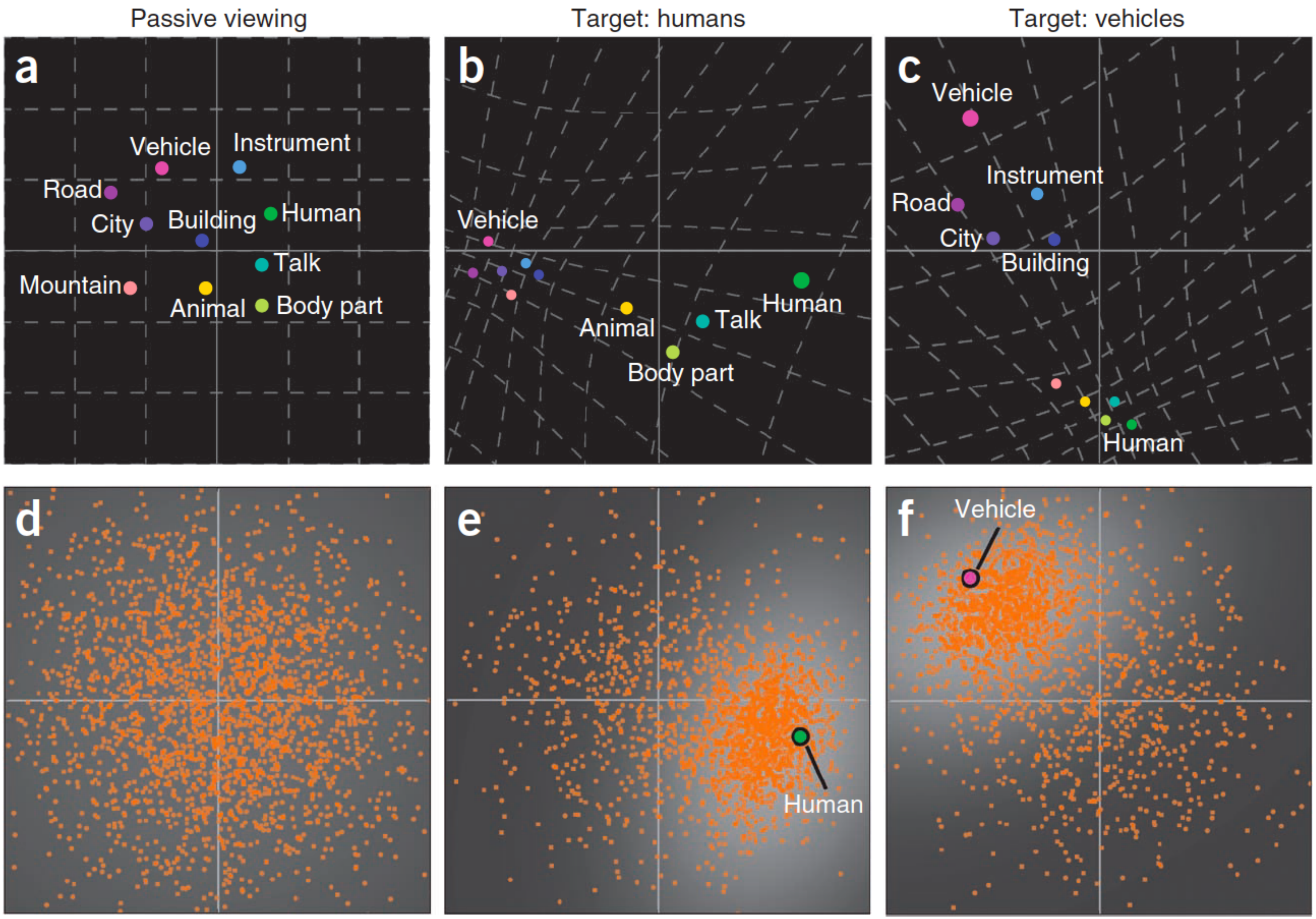


Çukur, Nishimoto, Huth, Gallant, 2013 *Nature Neuroscience*

- Recording: measuring whole-brain activity evoked by natural movies
- Subject task: searching for "humans" or "vehicles"

  fixating at the center of the screen

Matched filter hypothesis: attention warps the semantic space



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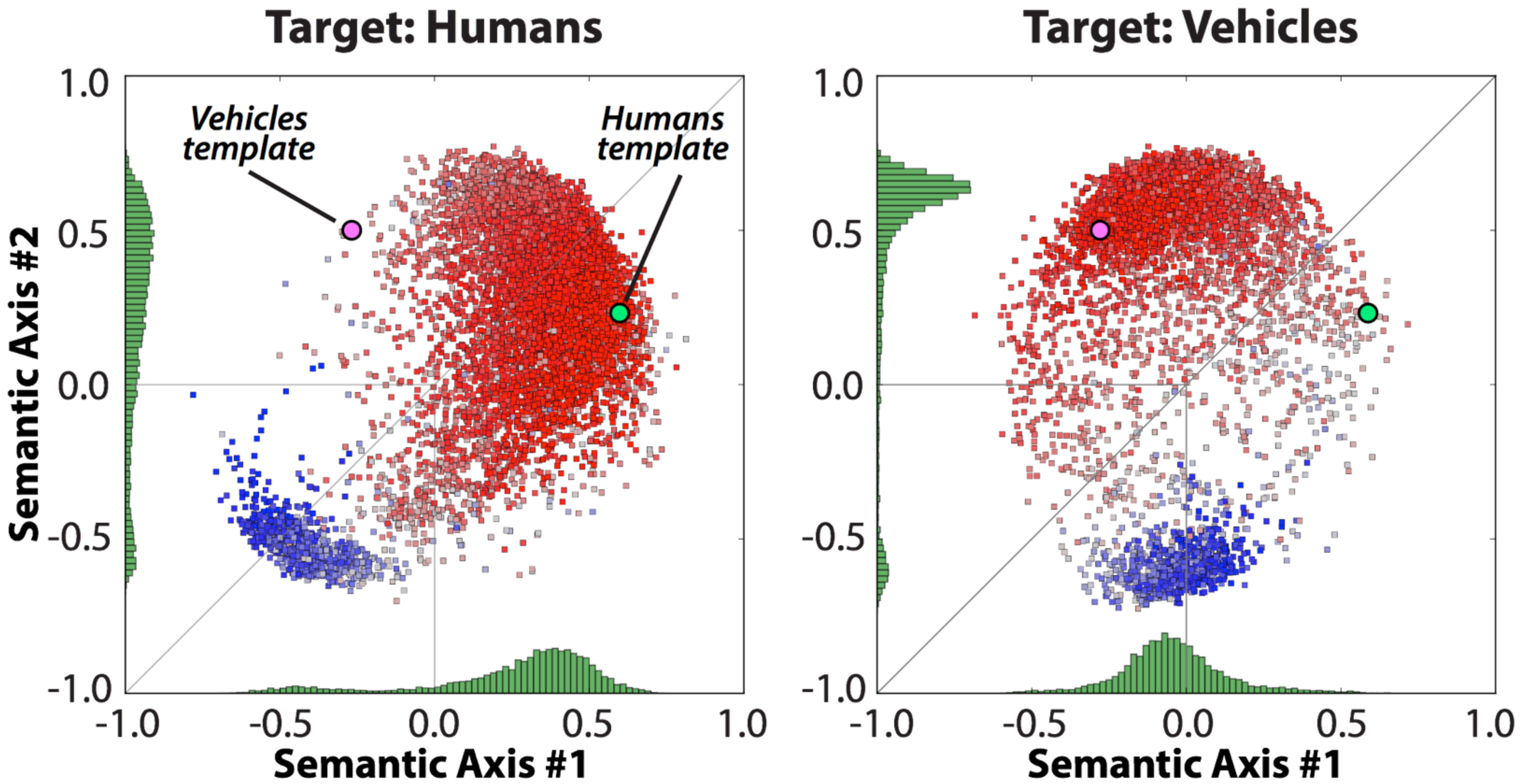
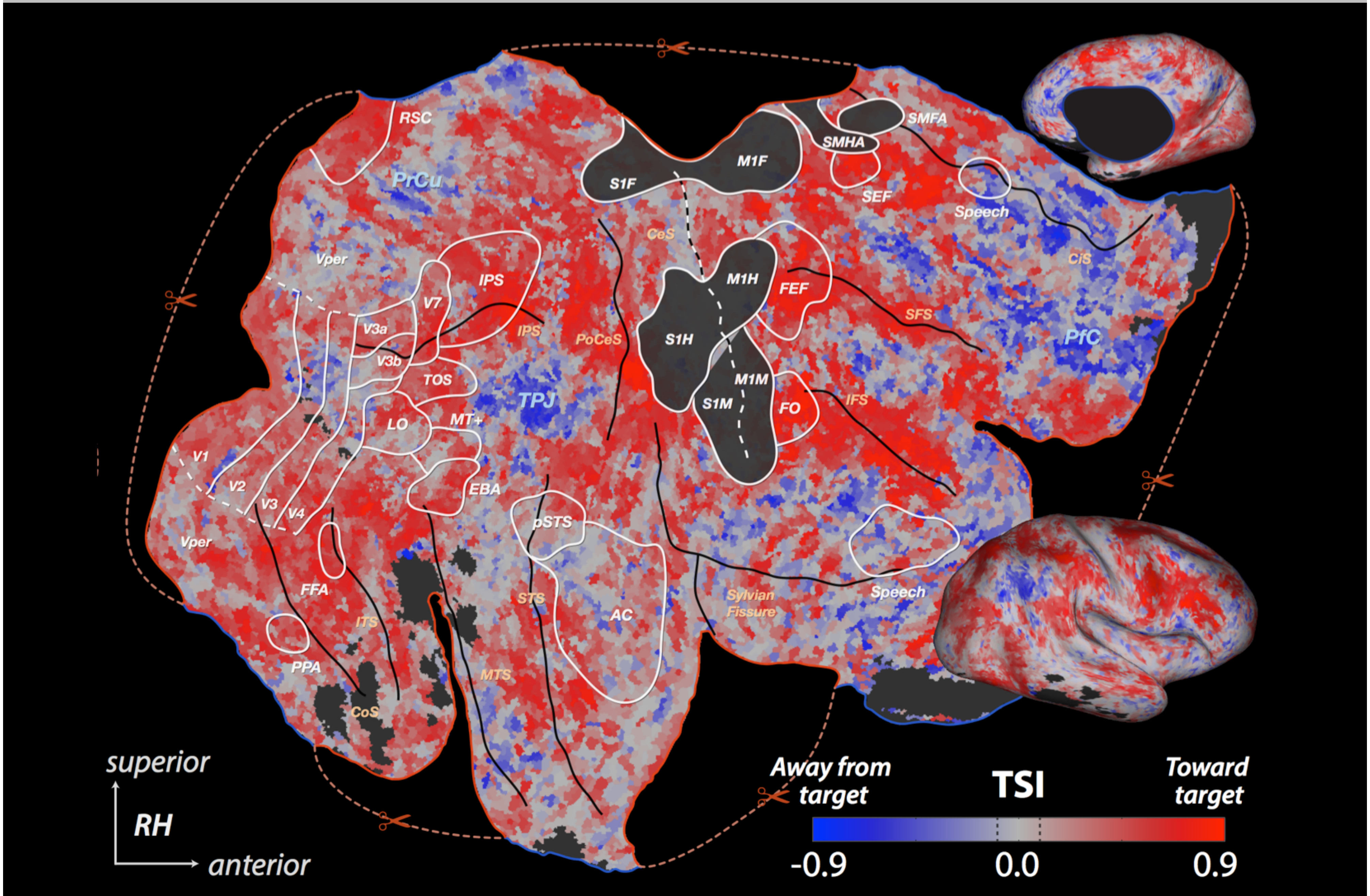
Category attention shifts semantic tuning



Çukur, Nishimoto, Huth, Gallant, 2013 *Nature Neuroscience*

Widespread shifts of category representation



Çukur, Nishimoto, Huth, Gallant, 2013 *Nature Neuroscience*