

# Distributed representations of behaviorally-relevant object dimensions in the human brain

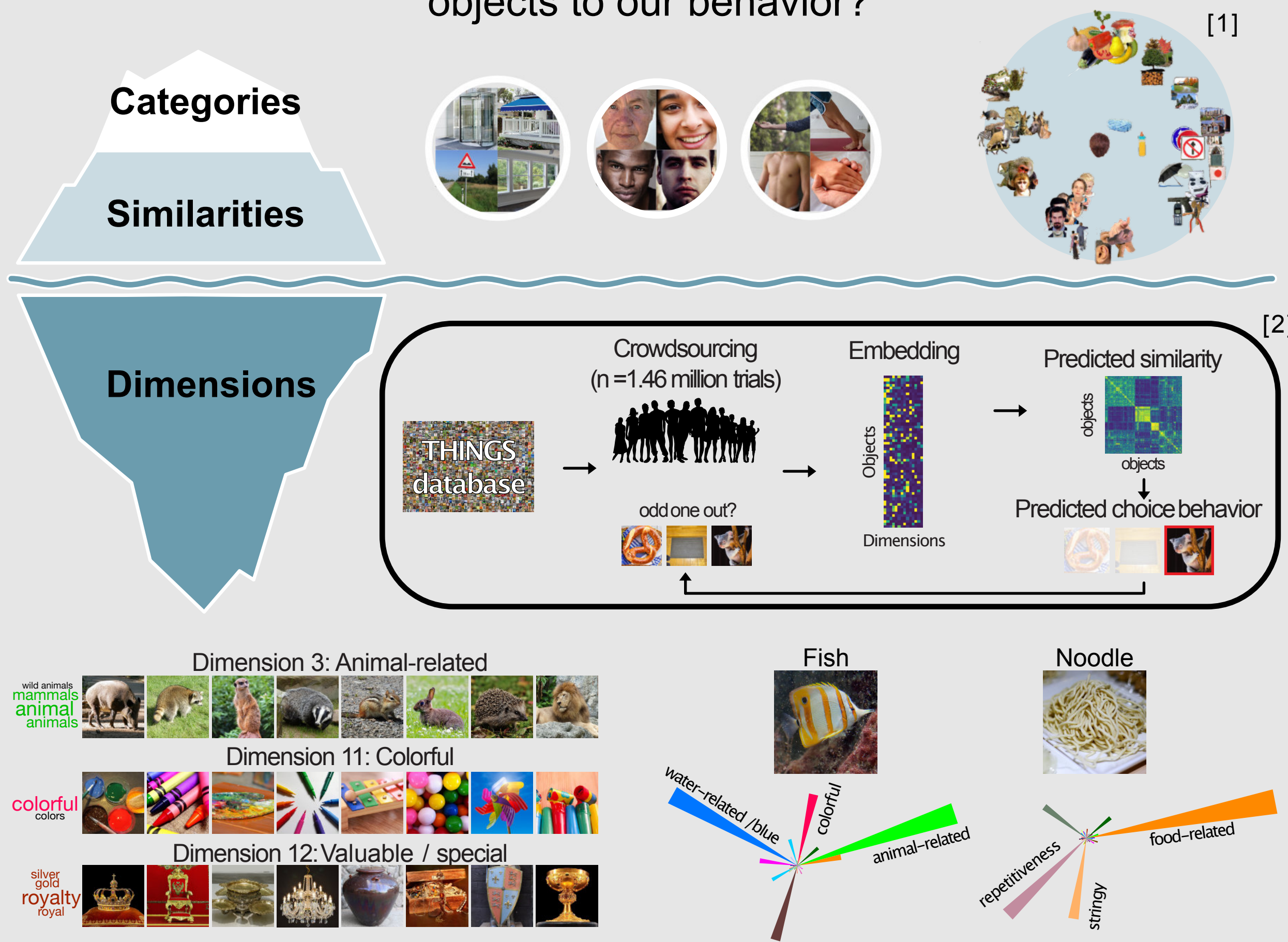
## Background

How does the human brain represent the relevance of every-day objects to our behavior?

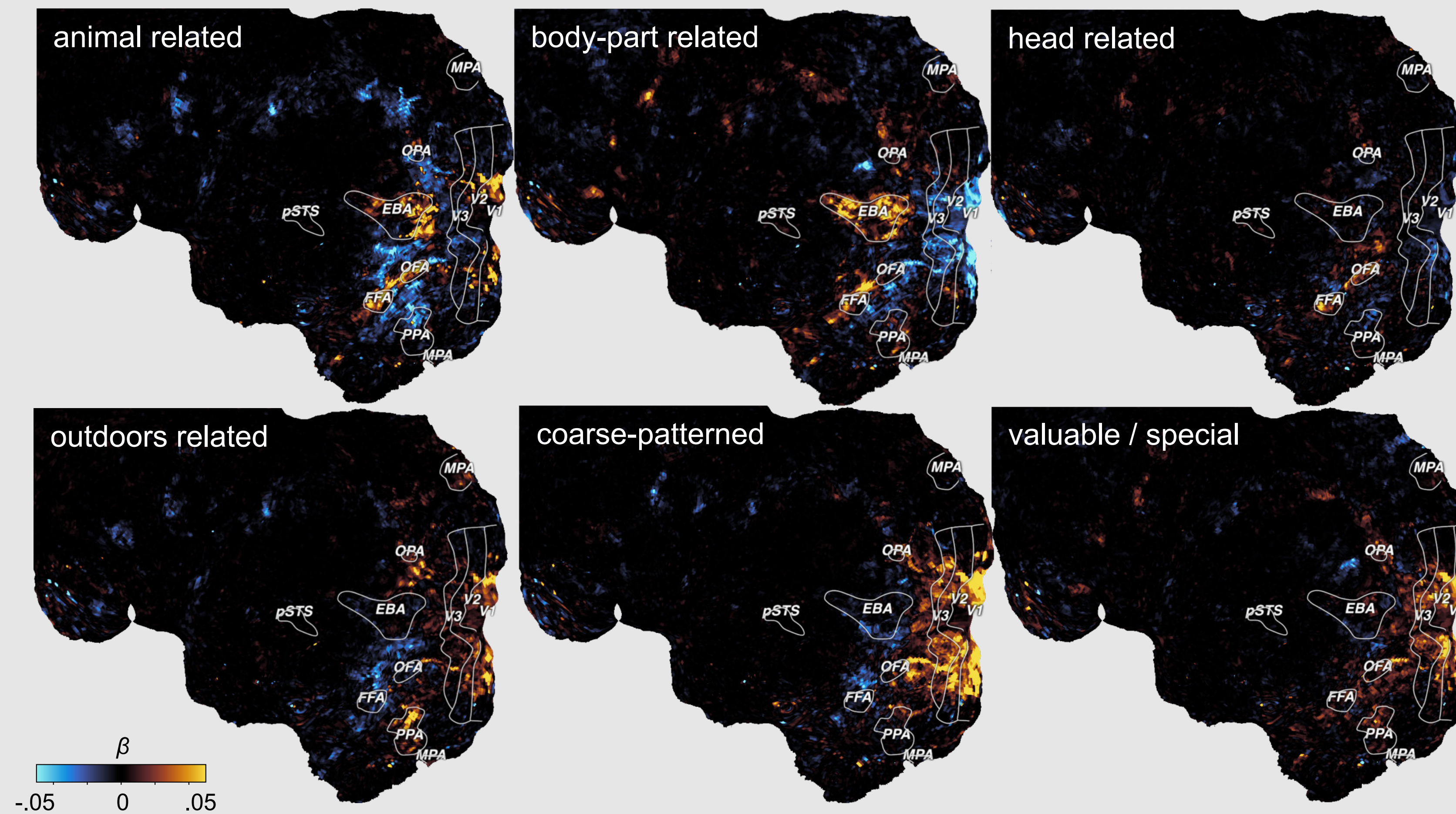
Categories

Similarities

Dimensions

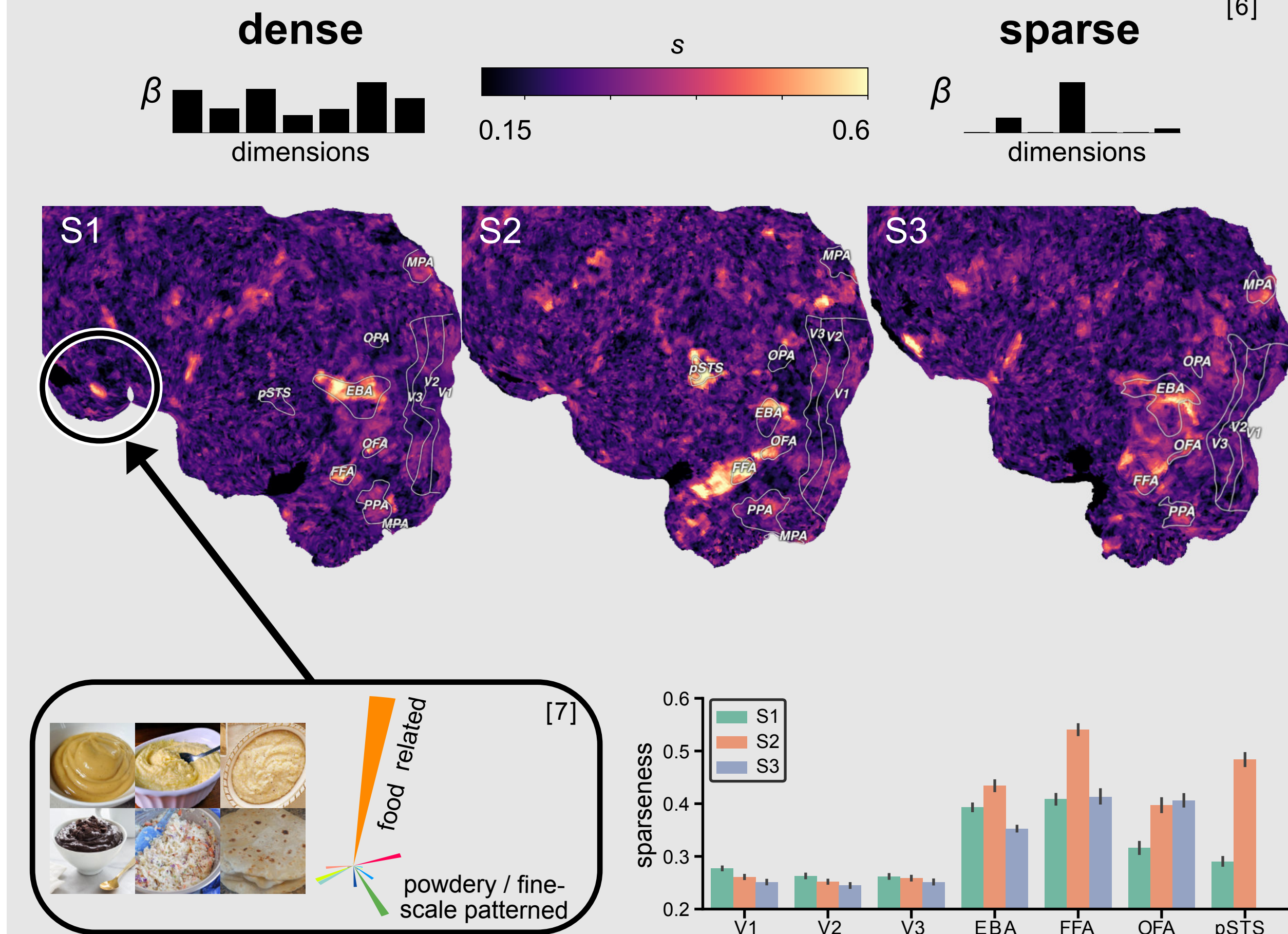


## What's the functional topography of object dimensions?



► Highly distributed, covering early visual as well as category-selective areas

## Is category-selectivity a special case?

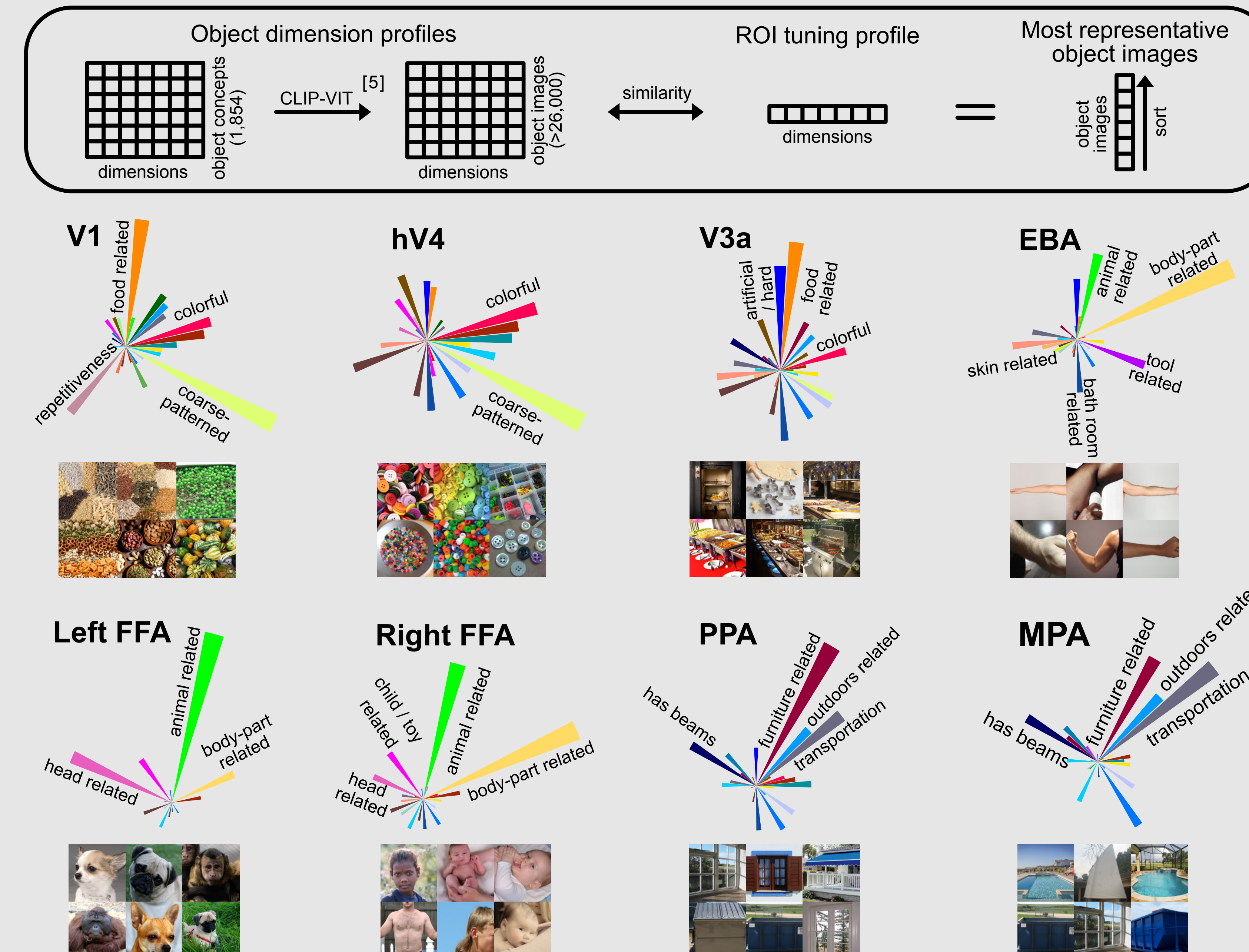


► **Category-selective regions** are characterized by a **sparse representation** of behaviorally-relevant object dimensions.  
► Sparse clusters point to functionally selective regions.

## Methods

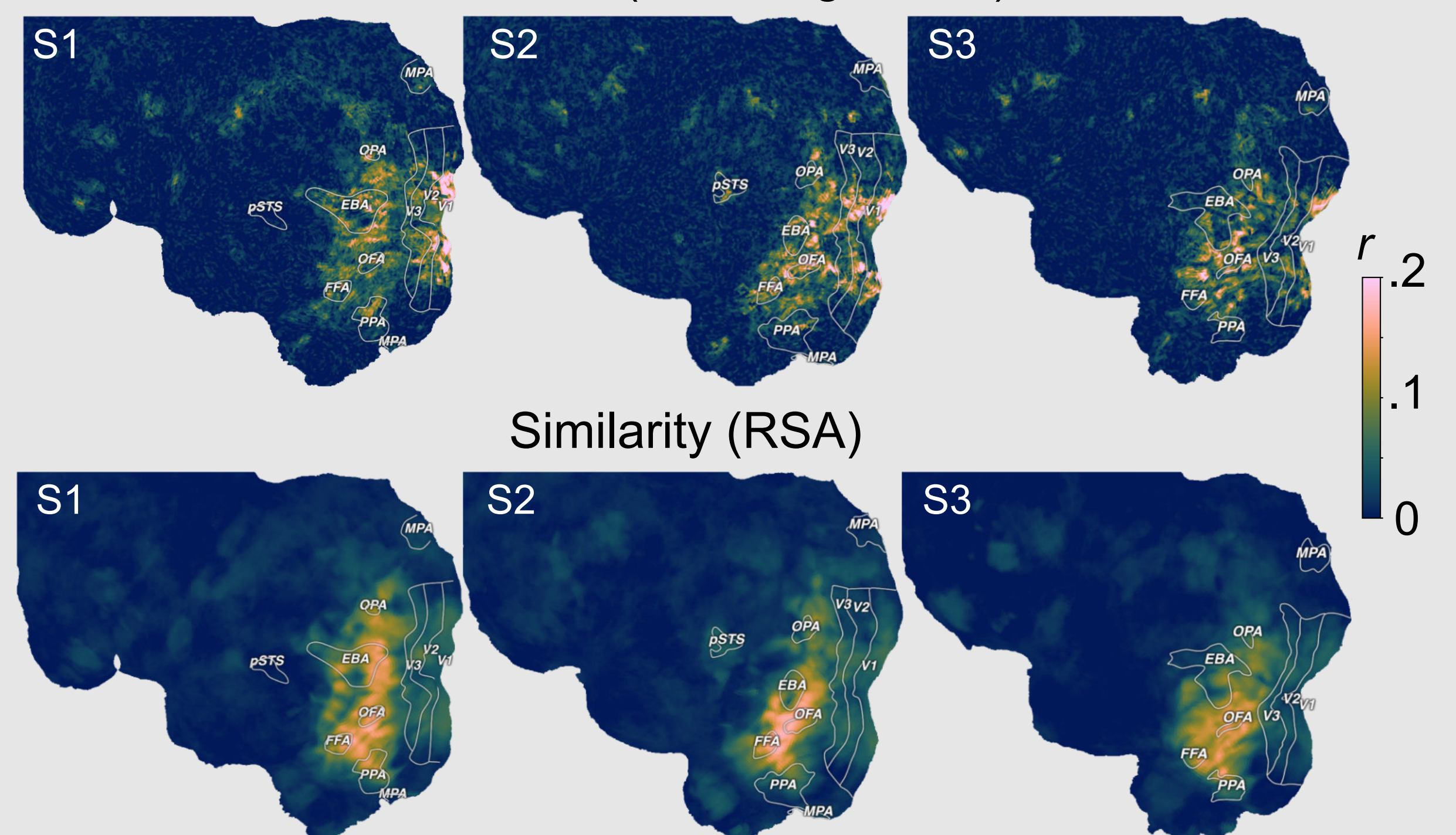
- **fMRI voxel-wise encoding model**
- Model: **49 behaviorally relevant object dimensions**
- 3 Participants, 8,740 unique images of 720 objects
- 3 Tesla fMRI, 2mm, 1.5 s TR, 12 sessions

## How are visual brain regions tuned towards object dimensions?



## Where are object dimensions represented?

Dimensions (encoding model)



► Dimensions predict activity **throughout the visual system**.  
► Similarity is primarily linked to activity in higher-level visual cortex.

## Conclusions

- Behaviorally-relevant object dimensions can reveal **more fine-grained** cortical representations than similarity and categories.
- The behavioral relevance of objects is not confined to higher visual regions but **represented more globally**.
- Multidimensional approach **captures representation** in visual brain regions and can identify most representative images.
- **Category-selectivity** may be a special case of **sparse tuning** towards behaviorally-relevant object dimensions.
- Object dimensions can provide **interpretable** description of behavioral relevance of the different processing stages in the visual system.

## References

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- [2] Hebart et al., *Nature Human Behavior* (2020)
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- [4] Magri & Konkle, *Conference on Cognitive Computational Neuroscience* (2019)
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- [7] Simmons et al., *Cerebral Cortex* (2005)