Attention alters animal and action representation in highly-distributed, functionally-defined cortical parcels

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Introduction

Attention reduces the complexity of information processing by selectively prioritizing task-relevant representational content. Electrophysiological work suggests that attention improves behavioral performance by reducing interneuronal correlation at the population level[1]. In order to interface with high-level semantic representations encoded in distributed neural populations, we expect attention to operate in a distributed fashion as well.

Hypothesis: Attention selectively sculpts representational geometry to enhance the categoricity of distributed semantic representations for downstream readout.

Design and preprocessing

12 right-handed participants (7 female)

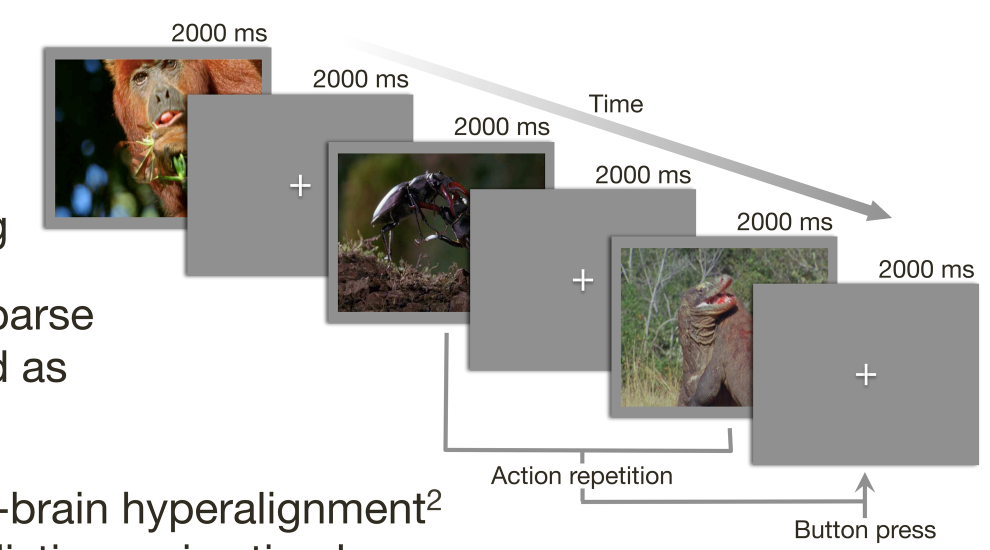
Stimuli: 2 s naturalistic video clips of behaving animals

Rapid event-related design: 2 s video clip + 2 s fixation

5 animal types: birds, insects, primates, reptiles, ungulates
4 action types: eating, fighting, running, swimming
20 conditions: 5 (animal type) x 4 (action type) fully crossed design

Attention task: 1-back repetition detection requiring participants to attend to either animal *taxonomy* or *behavior*

Preprocessing:
Despiking
Slice timing correction
4 mm spatial smoothing

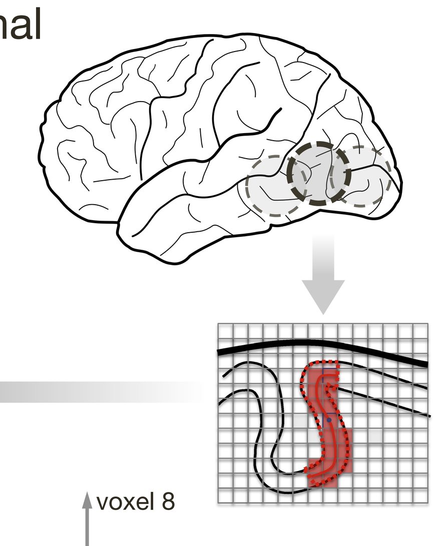


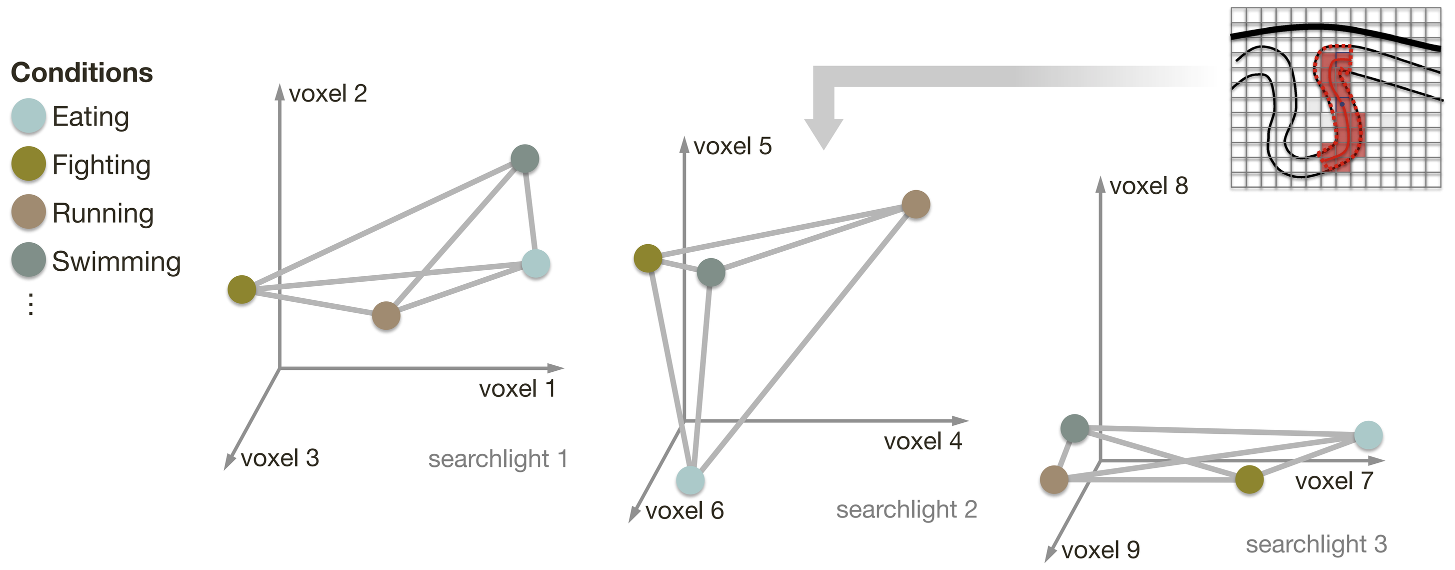
GLM: canonical HRF, sparse button presses included as nuisance regressors

Hyperalignment: Whole-brain hyperalignment[2] based on 1 hr naturalistic movie stimulus: *Life* documentary, narrated by David Attenborough

Representational similarity analysis

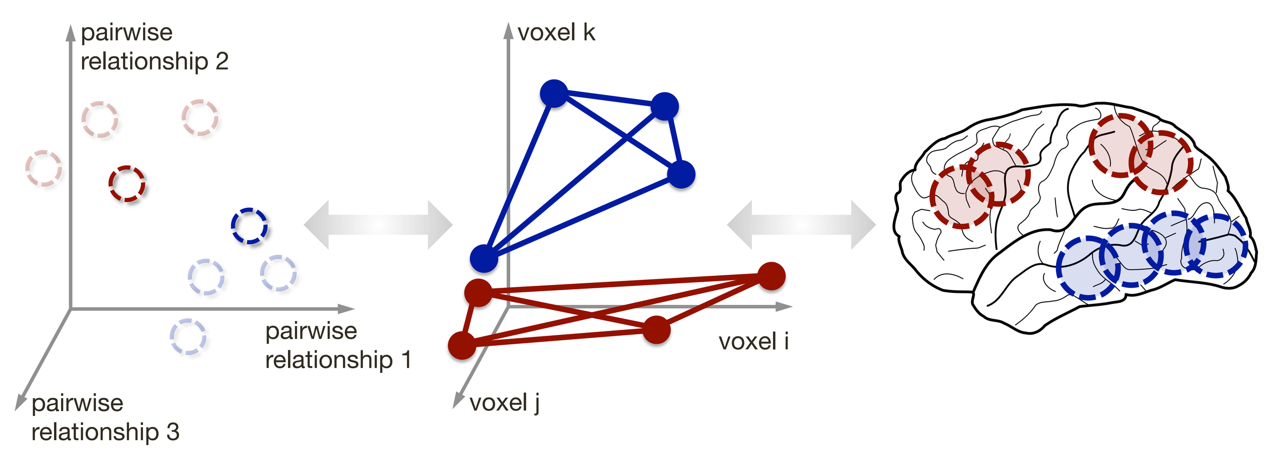
For each surface-based searchlight[3], representational dissimilarity matrices (RDMs) were constructed by computing the pairwise correlation distances between the 20 conditions[4]. Local representational geometries were characterized across the cortical surface.

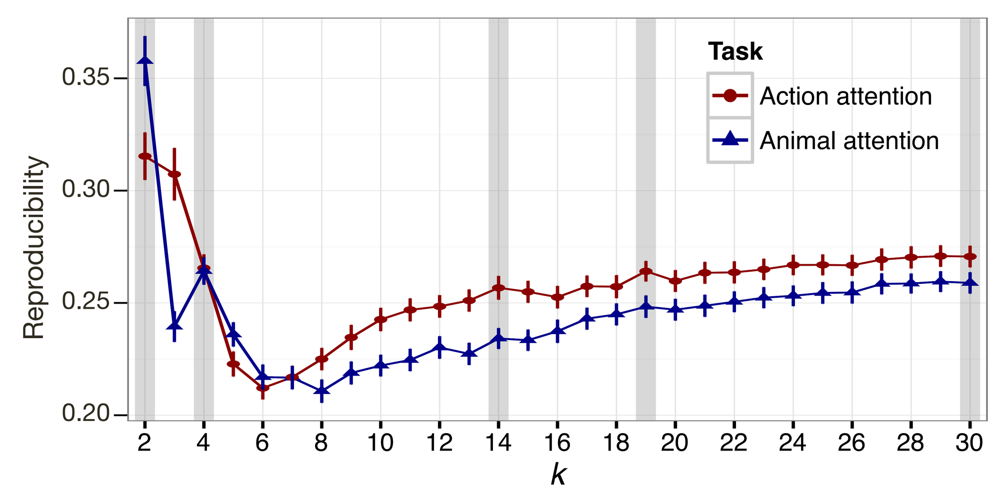




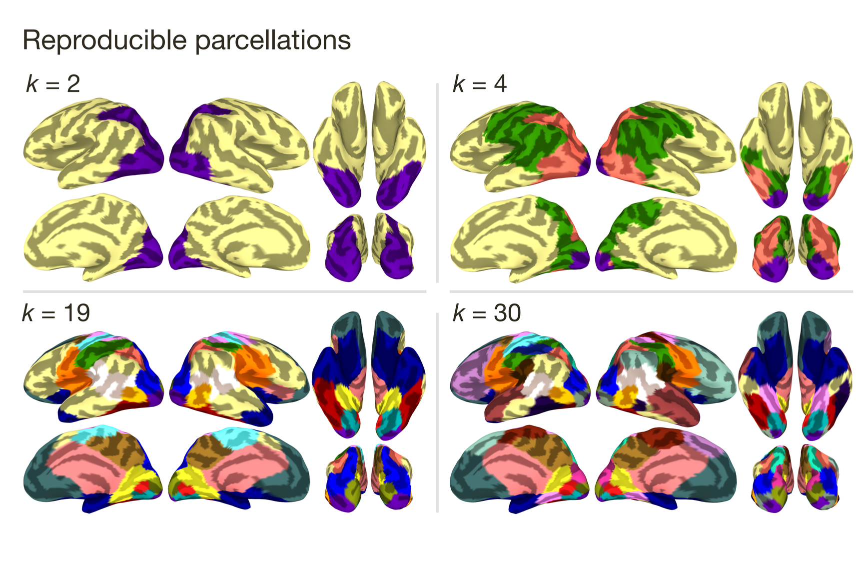
Functional parcellation based on representational geometry

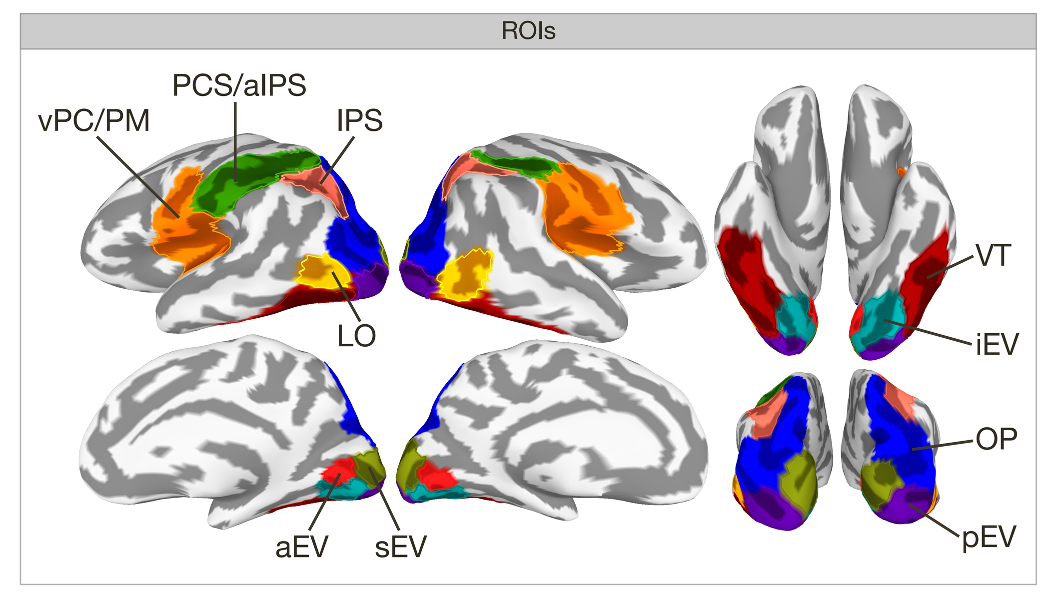
Surface-based searchlights were clustered according to their representational geometries using Gaussian mixture models with tied covariance. The resulting clusters can then be projected back to the cortical surface.





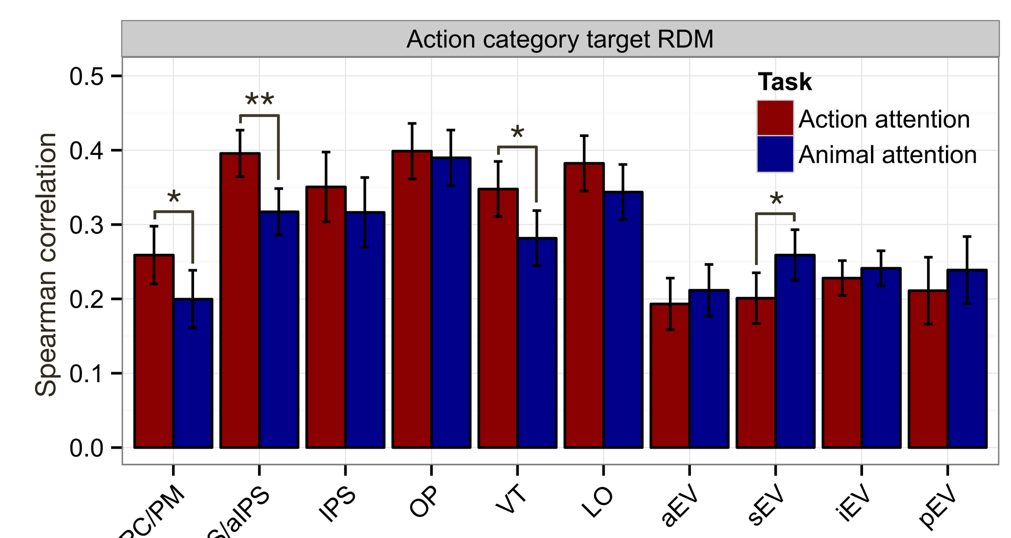
Parcellation reproducibility[5] was estimated at numbers of parcels from $k = 2$ to 30 using split-half cross-validation across participants (100 partitions). Parcellations at local peaks in reproducibility capture well-documented functional boundaries. Ten regions of interest (ROIs) were selected from the parcellation at $k = 19$.

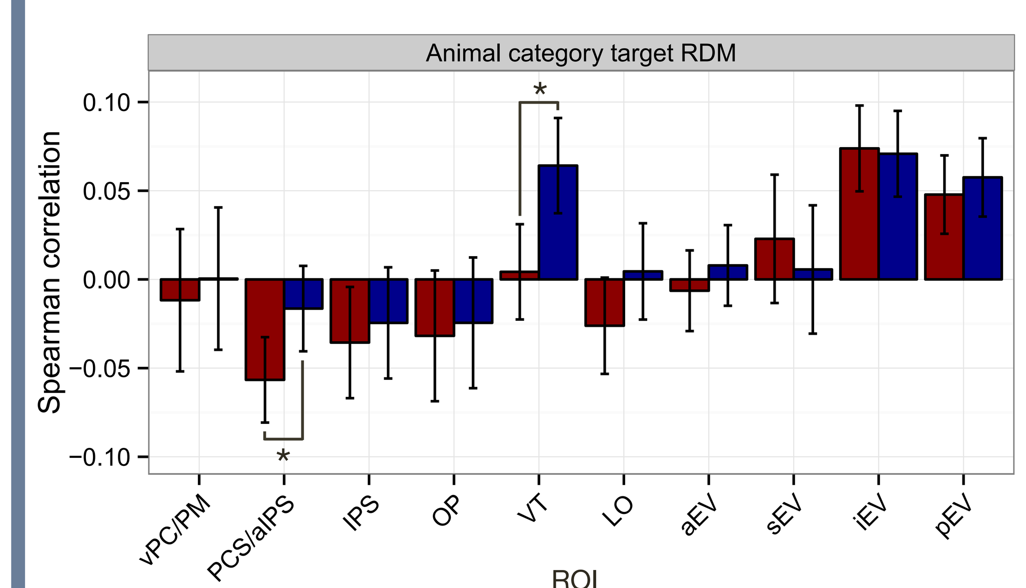


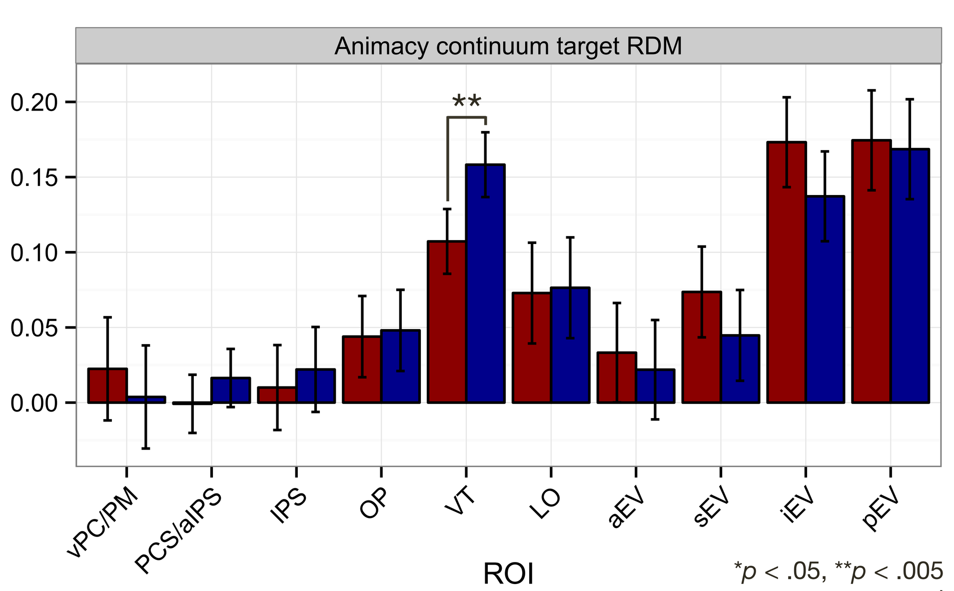


Attention alters representational geometry

Neural RDMs were computed across all voxels participating in each ROI (mean = 2,011 voxels, SD = 1,035). Attentional differences in Spearman correlation between neural RDMs and target RDMs were assessed for 10 ROIs. Target RDMs were constructed based on the experimental design: action category target RDM, animal category target RDM, and animacy continuum target RDM.

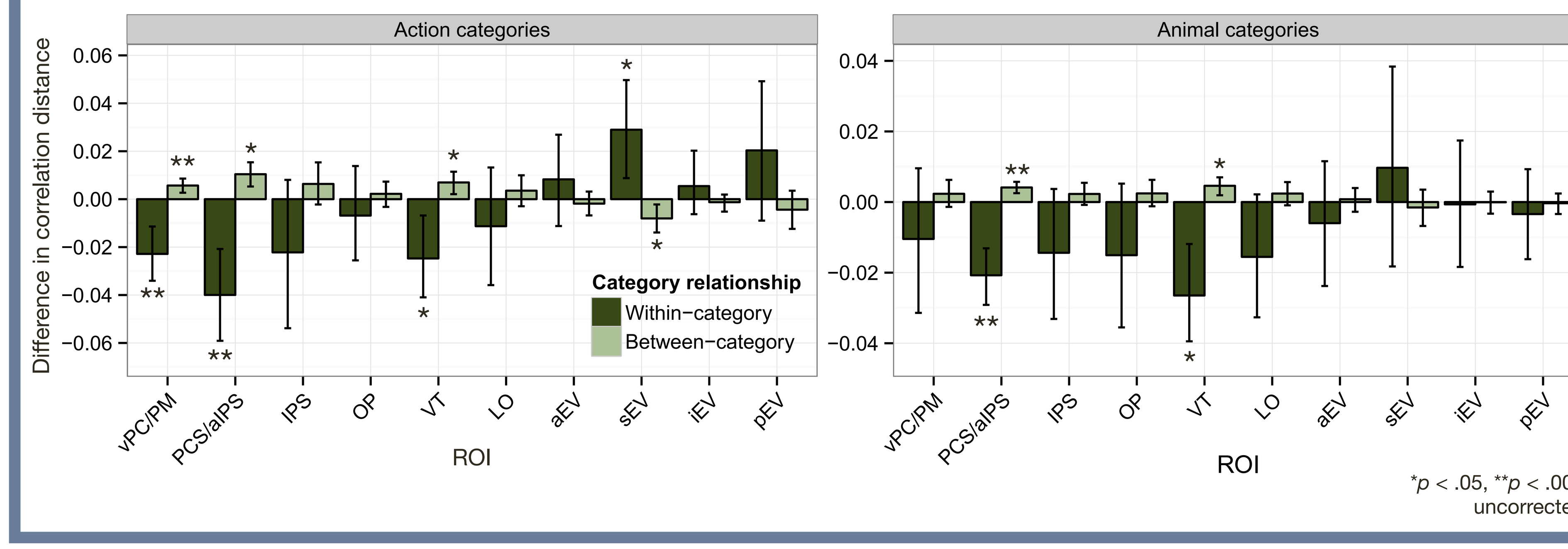






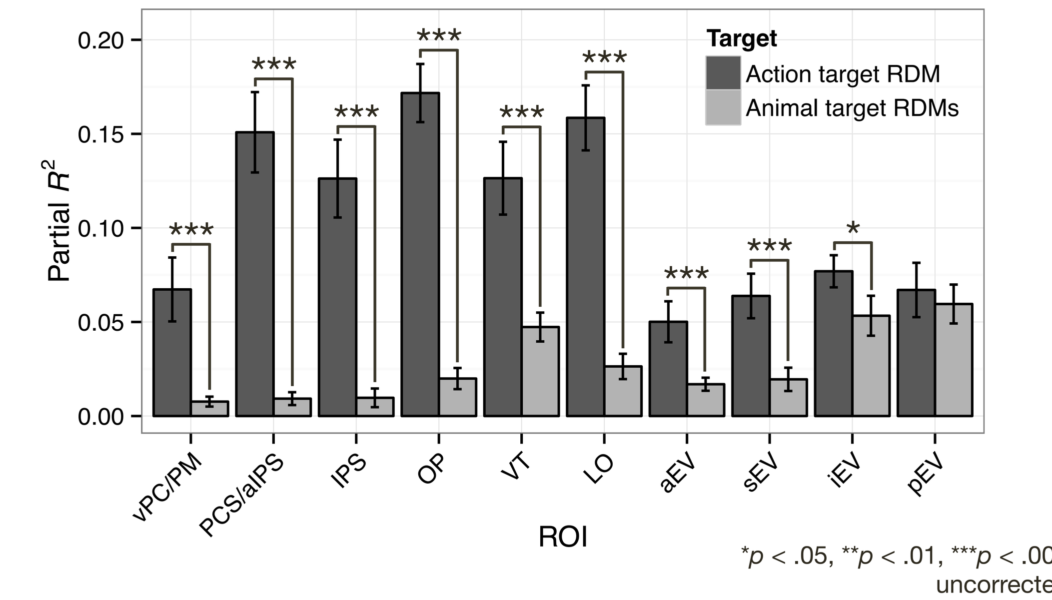
Attention enhances categoricity

Differences in within- and between-category correlation distances as a function of attentional allocation. Attention reshapes representational geometry by both compressing within-category distances and expanding between-category distances.



Primacy of action representation

Models of representational geometry were compared using AIC and partial R^2 for both the action category target RDM and the combined animal category and animacy continuum target RDMs. The animal behavior model fit the observed neural representational geometry better than the animal taxonomy model in most ROIs.



Conclusions

Attending to different semantic channels of a complex stimulus selectively reshapes the geometry of distributed representation in late-stage perceptual and somatomotor areas.

Functional ROIs characterized by consistent representational geometries can be identified using unsupervised learning algorithms.

Attention operates across highly-distributed neural populations so as to increase the discriminability of task-relevant representations and collapse task-irrelevant representations.

Attention enhances the categoricity of representation by both decreasing within-category representational distances and increasing between-category distances.

Animal behavior was represented more robustly than animal taxonomy throughout cortex, including in the ventral visual pathway.

Effectively, attention increases how explicitly task-relevant information is represented, facilitating downstream readout and behavior[6].

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