2-056

Cue-invariant Geometric Structure of the Population Codes in Macaque V1 and V2

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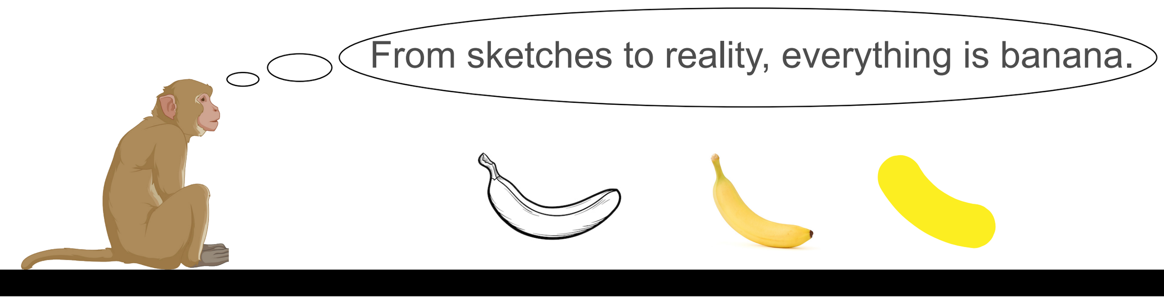
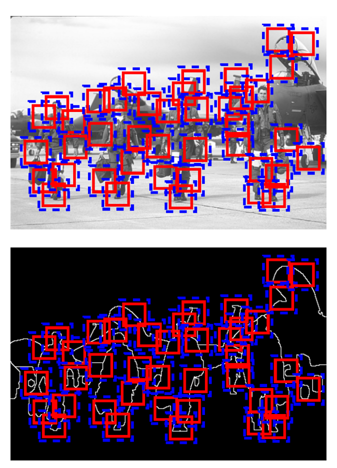
Introduction

- Humans have a remarkable ability to recognize objects and natural scenes whether depicted in photographs, cartoons, or just line drawings (a.k.a. visual cues).
- Our study revealed that the geometric structure of the population code could support the formation of a cue-invariant representation of abstract surface boundary concepts.
- This geometric structure is evident in macaque V1 and V2, as well as in models of the ventral visual stream, suggesting a shared computational mechanism for cue-invariant representation.



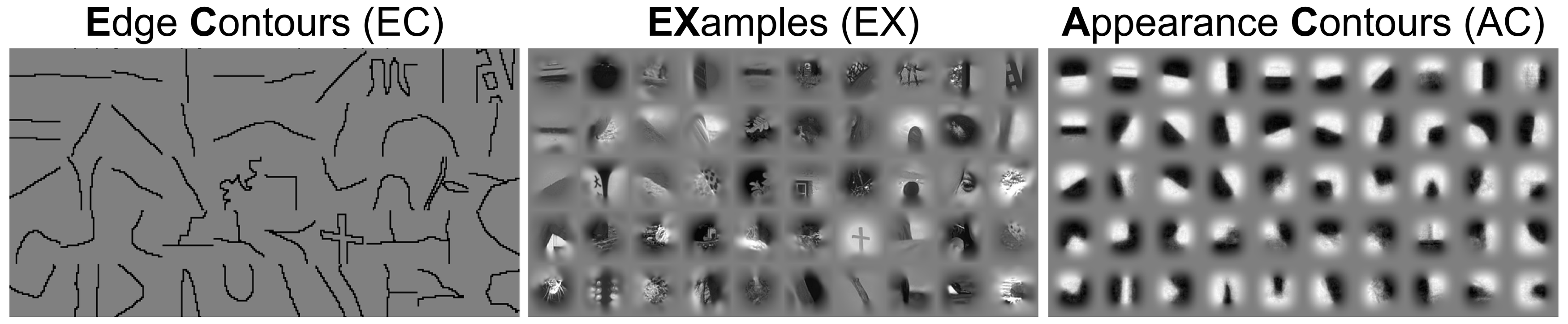
Visual stimuli



- **Extraction of local surface boundary patches**: 5818 patches were extracted from the Berkeley Segmentation Dataset using human-labeled contours.
- **Clustering boundary concepts**: We computed pairwise shape distances between segmented boundary patches using the Hausdorff metric, then clustered the patches with affinity propagation.
- **Defining stimulus sets**: 50 cluster centers were selected as the **Edge Contours** stimuli. The corresponding original patches formed the **Example** stimuli. **Appearance Contour** stimuli were derived from the first principal component of each cluster's patches.

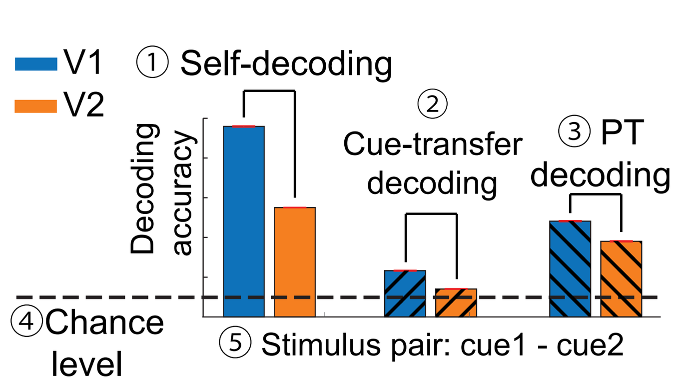
50 visual stimuli rendered in 3 cue types

Edge **C**ontours (EC) | **EX**amples (EX) | **A**ppearance **C**ontours (AC)



Sketch-like object boundary concepts | Original natural scene patches | Resembled the mean luminance structure

Making sense of this bar jungle



①: An upper bound of accuracy was obtained by decoding held-out trials of the **same** cue.

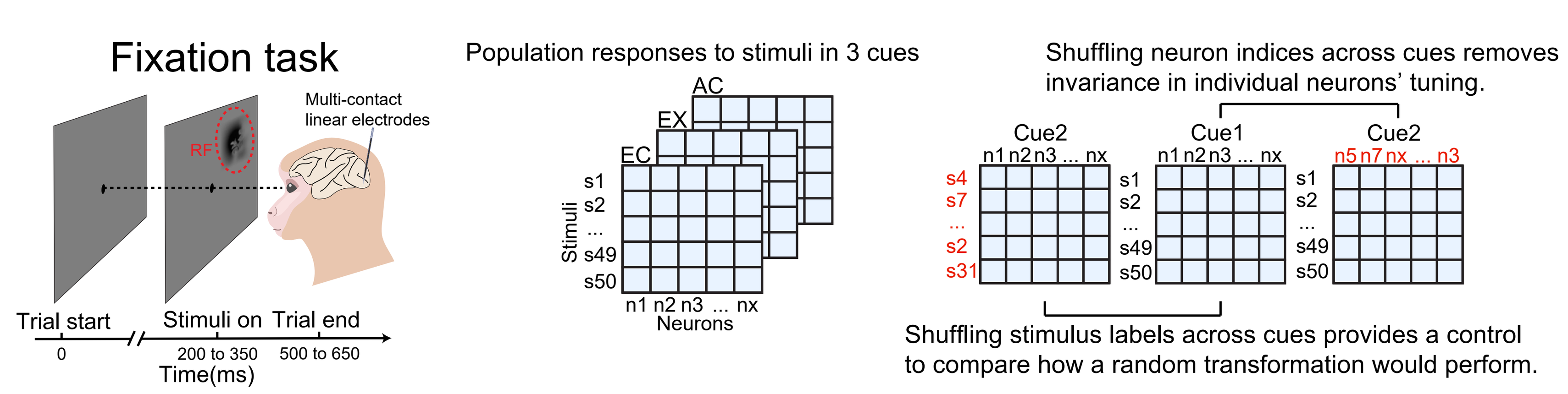
②: Cue-transfer (non-PT) decoding: An SVM was trained on neural responses to stimuli rendered in one cue, then tested on the same stimuli in a different cue.

③: PT decoding: cue-transfer decoding after the population code of one cue underwent **P**rocrustes **T**ransformation (rotation, scaling, and translation) to match the population code of another cue.

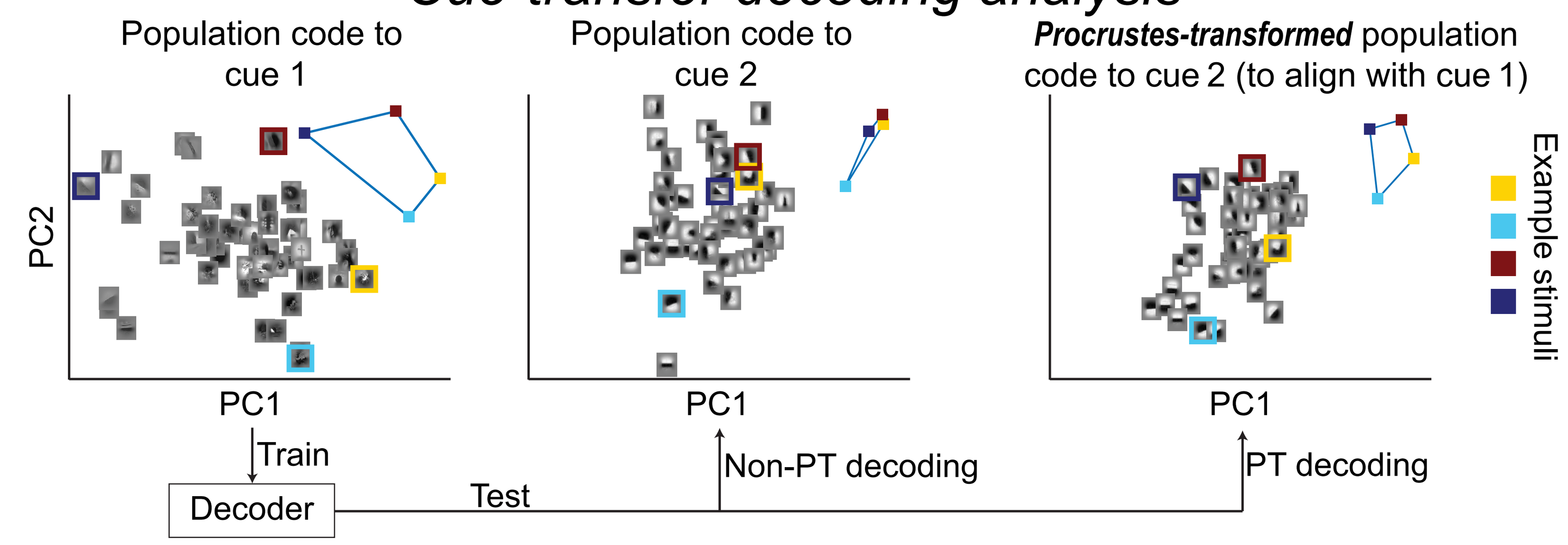
④: A theoretical chance level of 2%.

⑤: The average decoding performance of **reciprocal** cue pairs (e.g., AC-EC and EC-AC).

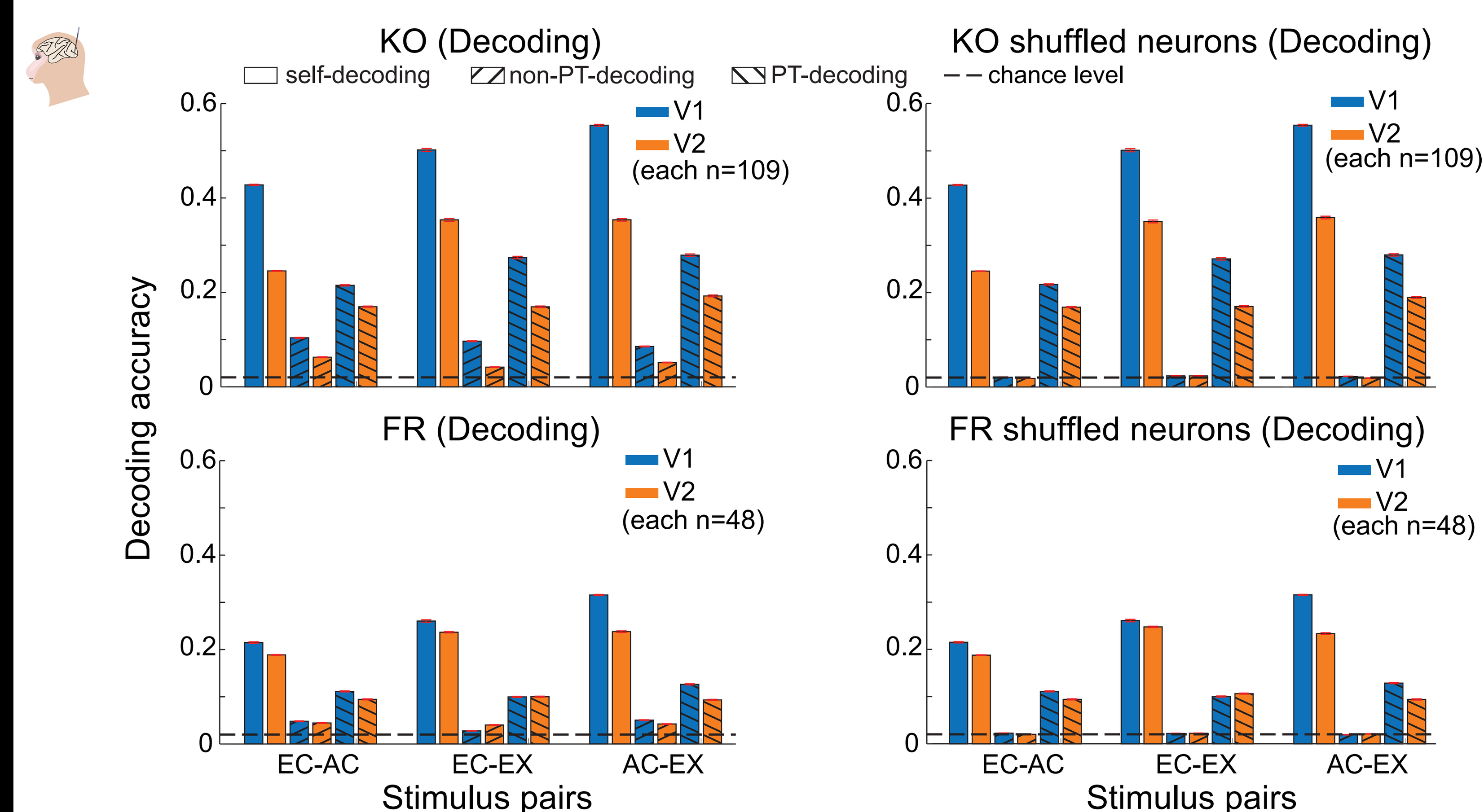
Experimental setup



Cue-transfer decoding analysis

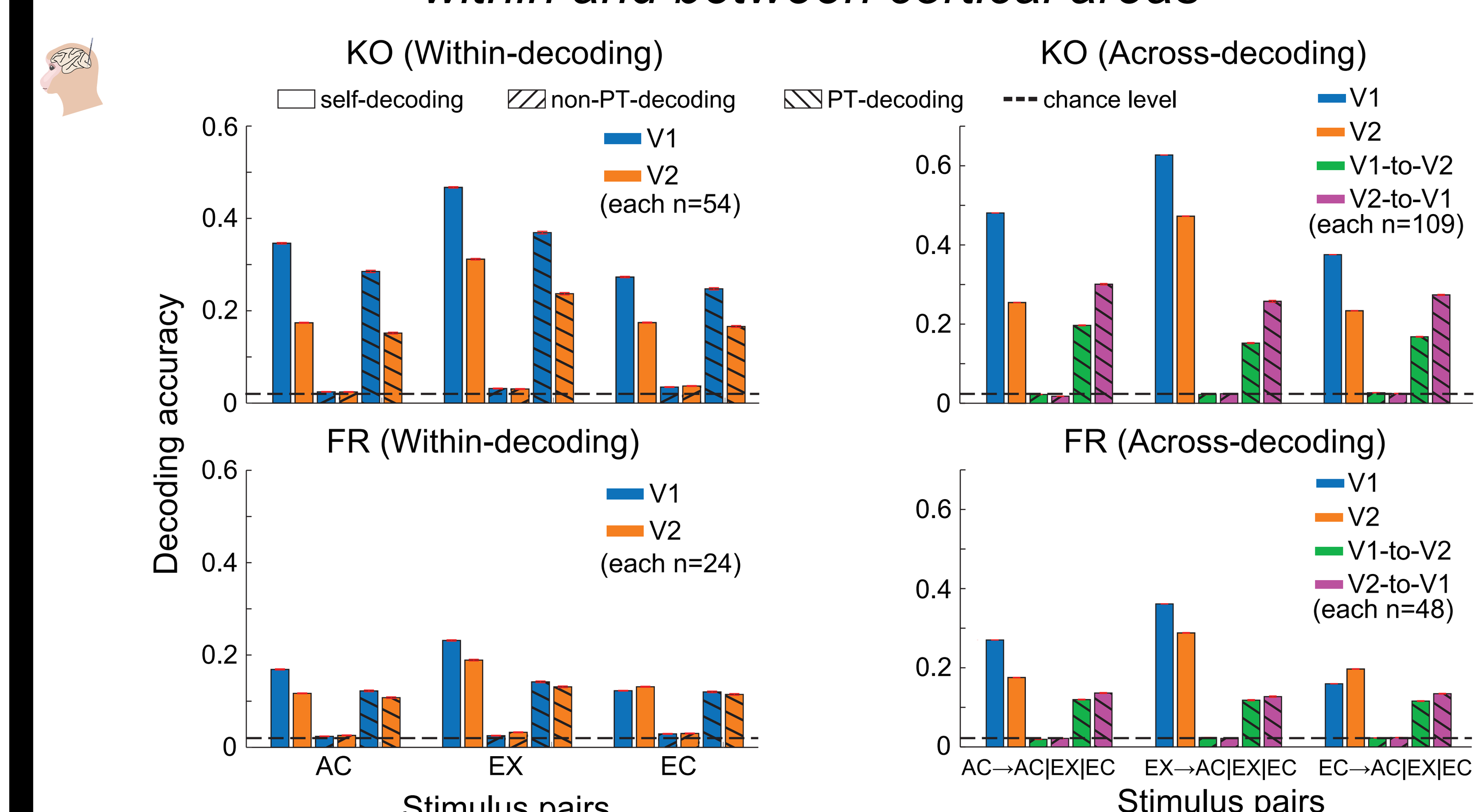


Cue-transfer decodability in V1 and V2 population codes



- PT significantly improved cue-transfer decoding in both V1 and V2.
- V1 showed higher PT decoding and self-decoding accuracy than V2, suggesting a more discriminative population code for boundary concepts.
- V2's cue-invariant geometric structure remains but degraded relative to V1, possibly due to a trade-off with other invariances (translation, rotation) developing along the ventral stream.
- Shuffling neuron indices did not affect PT decoding, showing that cue-invariant geometry is independent of individual neurons' tuning invariance.

Cue-transfer decodability across subpopulations within and between cortical areas

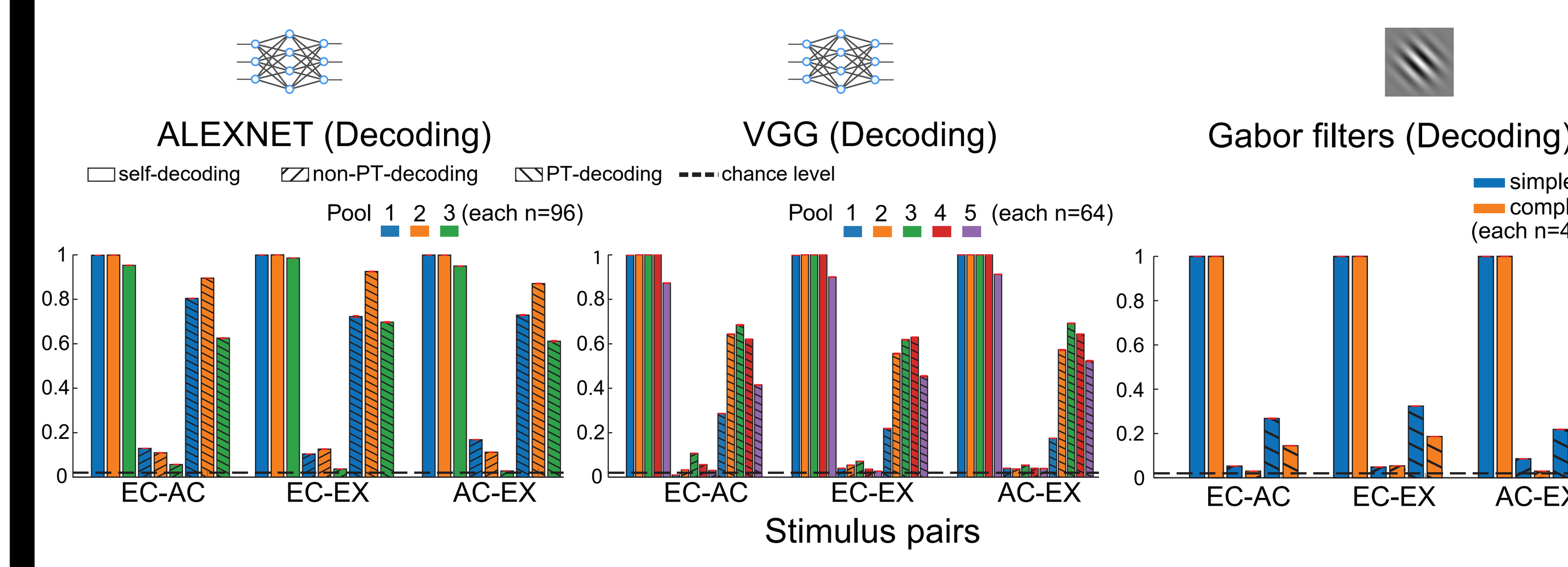


- Cue-invariant geometric structure is preserved across populations of neurons within (left panels), and across V1 and V2 (right panels).
- In all cases, PT significantly improved cue-transfer decoding, whereas non-PT decoding remained at chance due to tuning differences between distinct neurons.

Conclusion

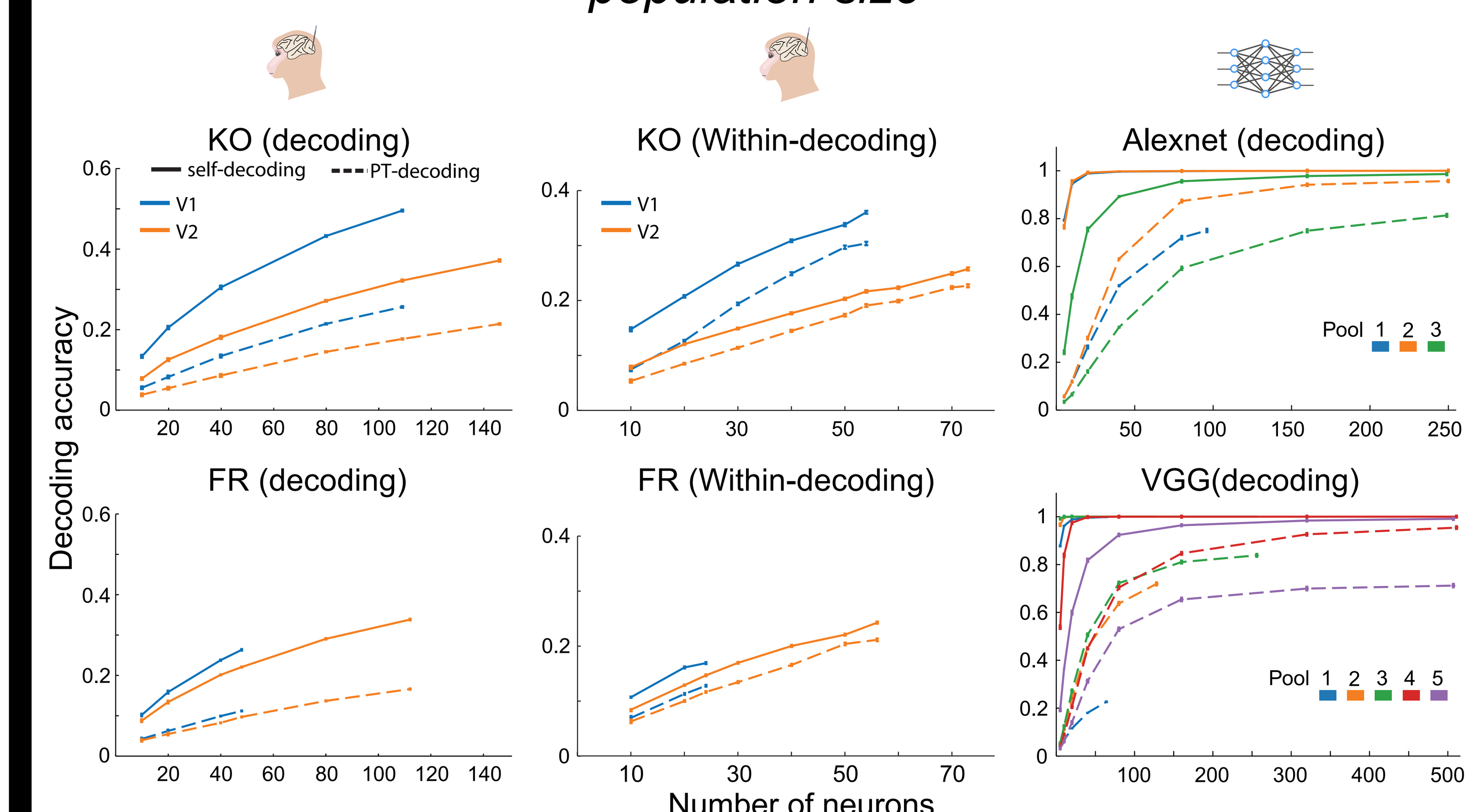
1. We found evidence of cue-invariant geometric structures (a) in V1 and V2 population codes, (b) across subpopulations within and between cortical areas, and (c) in models of the ventral visual stream.
2. We concluded that V1, V2, and models of the ventral visual stream can leverage the geometric structure of their population codes, using simple downstream mechanisms to build cue-invariant representations of abstract visual concepts.
3. Cue-invariance of visual concepts might depend more on the geometric structure of the population code than on individual neurons' tuning invariance.

Cue-transfer decodability in models of the ventral visual stream



- Intermediate layers of AlexNet and VGG show high PT cue-transfer decoding accuracies.
- Gabor filters have lower PT decoding accuracy, suggesting simpler feature representations capture fewer cue-invariant properties.
- Similar to the neural data, the geometric structure of the population codes in models of the ventral visual stream could also support cue-invariant representations of abstract visual concepts.

Higher cue-transfer decoding accuracy with increased population size



- In both neuronal and ANN data, PT cue-transfer decoding accuracy improved with more neurons, independent of the decoding scenario.
- The cue-invariant geometric structure becomes more stable as the population size increases.

References

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