Canonical Dimensions of Vision

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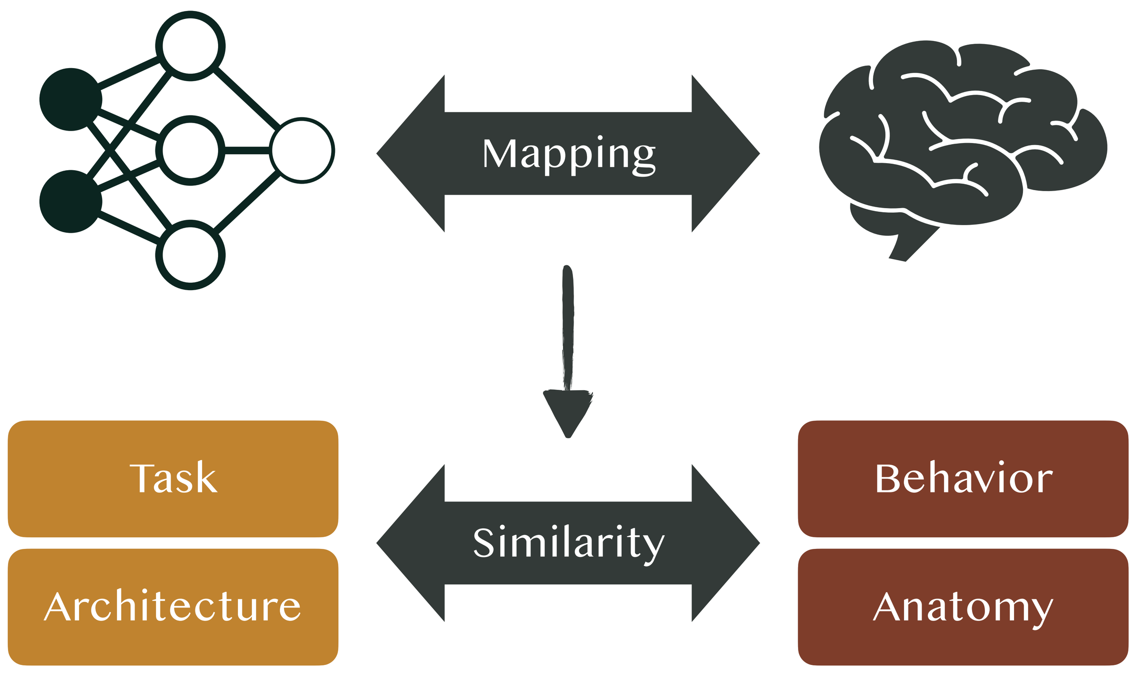
Website Poster Tutorial

Motivation

Representational similarities between deep neural networks (DNN) and brains have been attributed to shared optimization constraints[1,2].



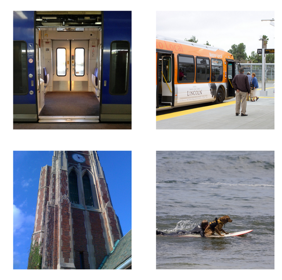
However, DNNs with widely varied designs are all surprisingly similar to the brain[3,4,5].

Do DNNs learn constraint-independent, "canonical" features?

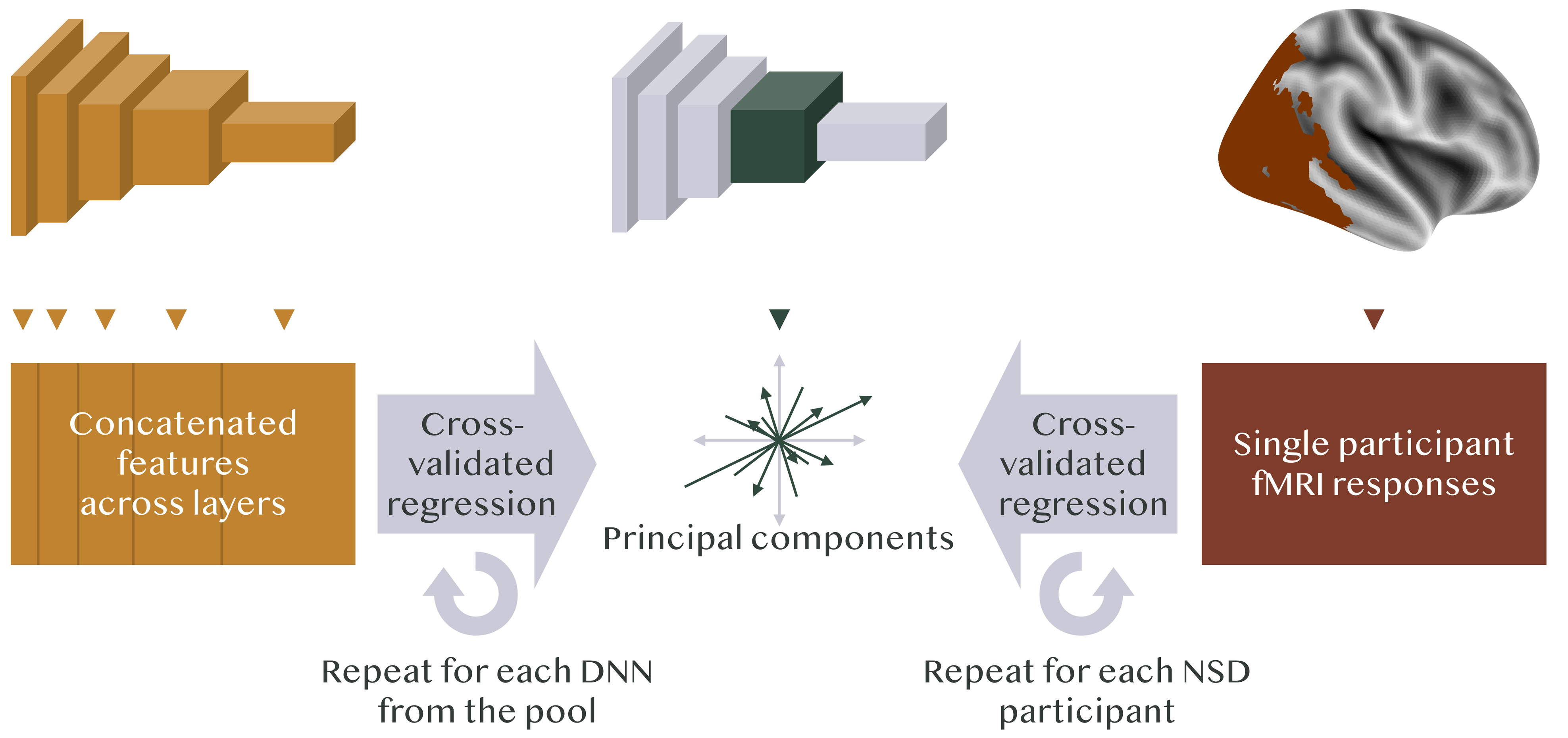
Are these canonical dimensions also encoded in human visual cortex?

Methods

Stimuli and neural data



Natural Scenes Dataset[6] (NSD)
fMRI responses of 8 participants to 872 natural scenes



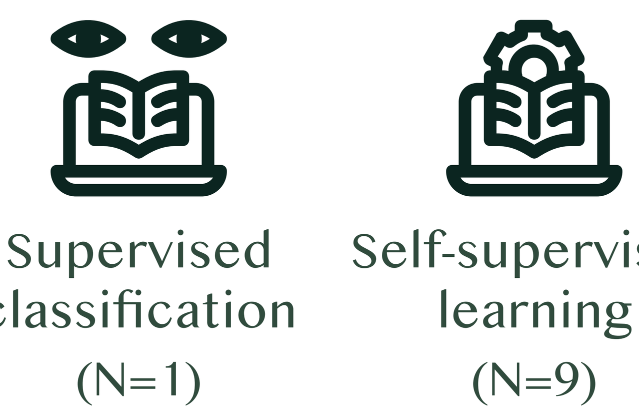
Canonical strength = average prediction accuracy across DNN predictors

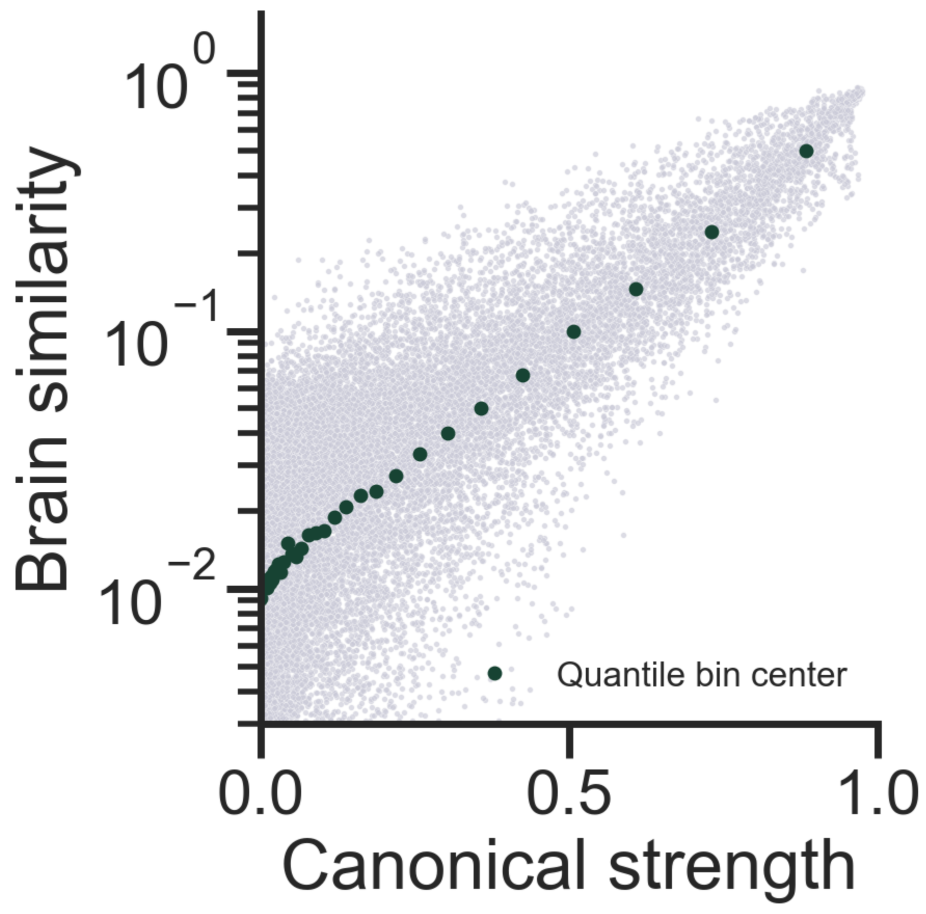
Brain similarity = average prediction accuracy across NSD participant predictors

Results & Discussion

1 Are biological-relevant visual features constrained by **training tasks**?

- DISTINCT tasks
- Same architecture (ResNet)
- Same training data (ImageNet)
- 106,889 features

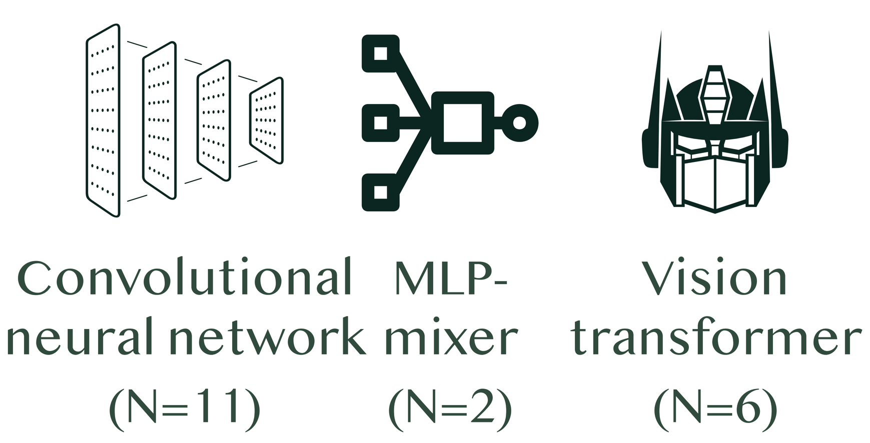


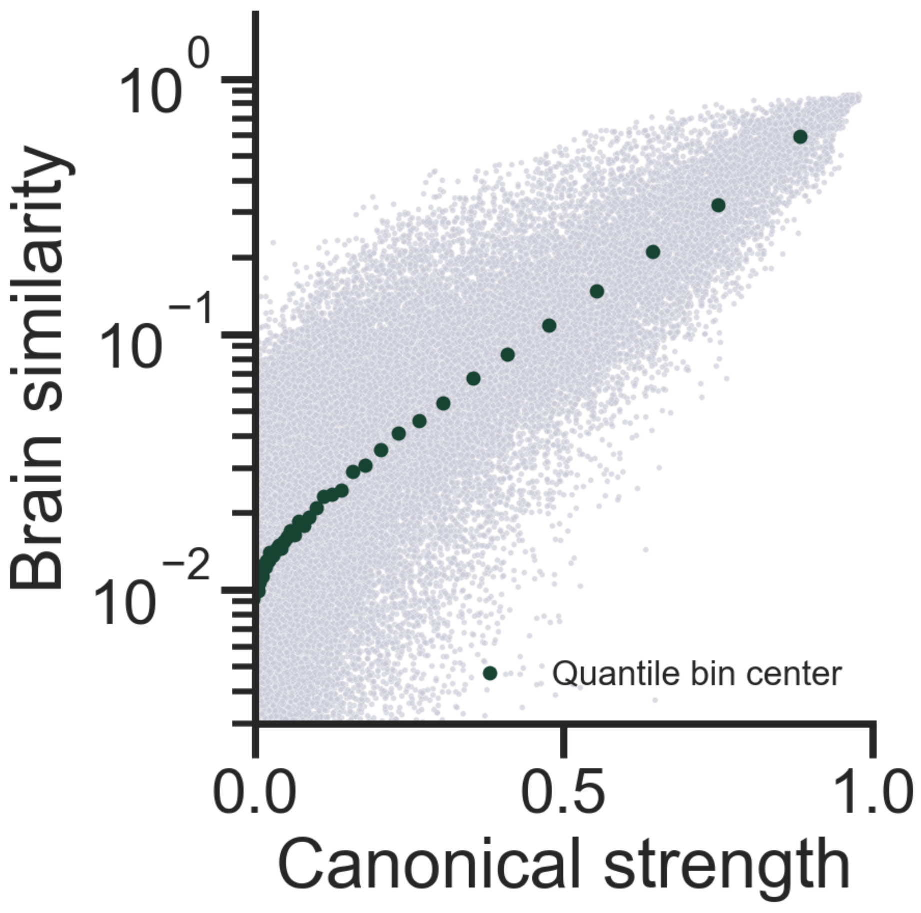


DNNs learn canonical dimensions independent of training tasks.

2 Are biological-relevant visual features constrained by **architectures**?

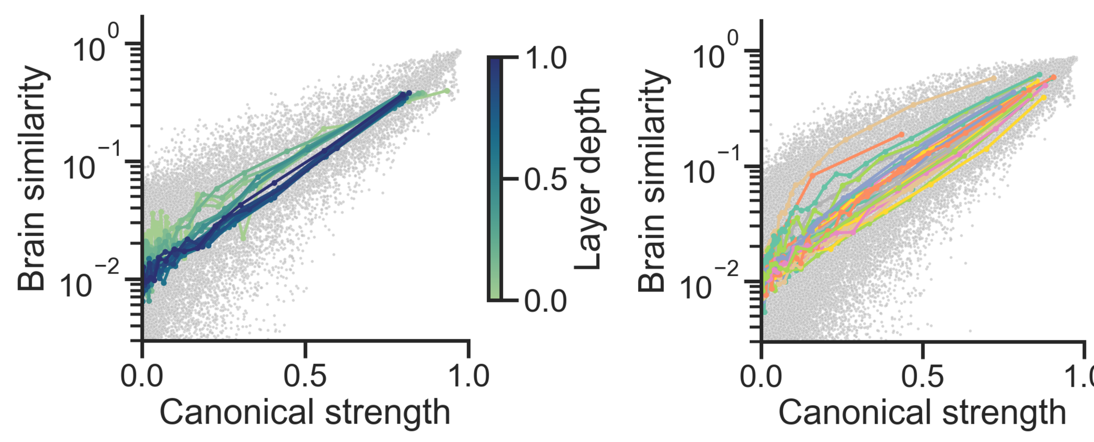
- DISTINCT architectures
- Same task (object classification)
- Same training data (ImageNet)
- 217,879 features





DNNs learn canonical dimensions independent of architectures.

3 Are these effects driven by specific layers or models?



Consistent across layers and models

4 What images strongly activate the canonical dimensions?

Takeaway

- Biologically relevant visual features are generically learnable and are largely independent of constraints on task or architecture.
- Suggests that core statistical principles across biological and artificial vision give rise to canonical representational dimensions.

References

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