Canonical Dimensions of Vision

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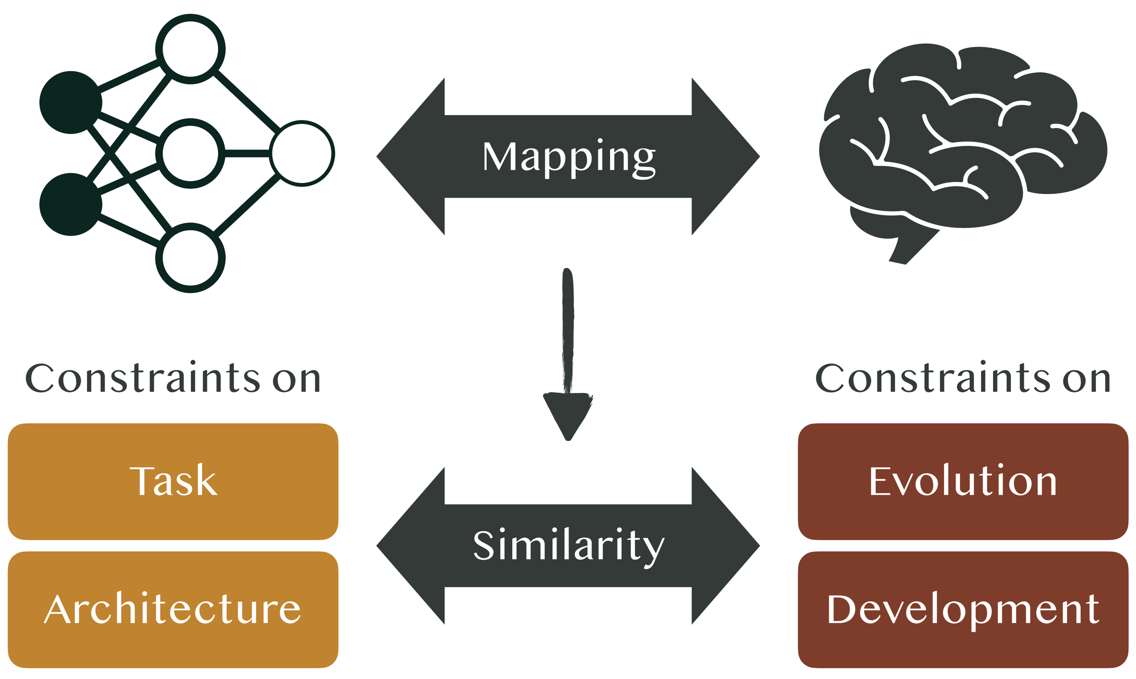
Motivation

Neuroscientists attributed representational similarity between human brain and deep neural network (DNN) to similarities in the optimization constraints on these systems[1,2].



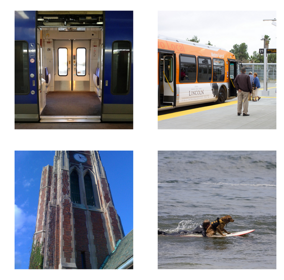
However, studies showed that recent DNNs of different designs do not yield significant variation in brain similarity[3,4,5].

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

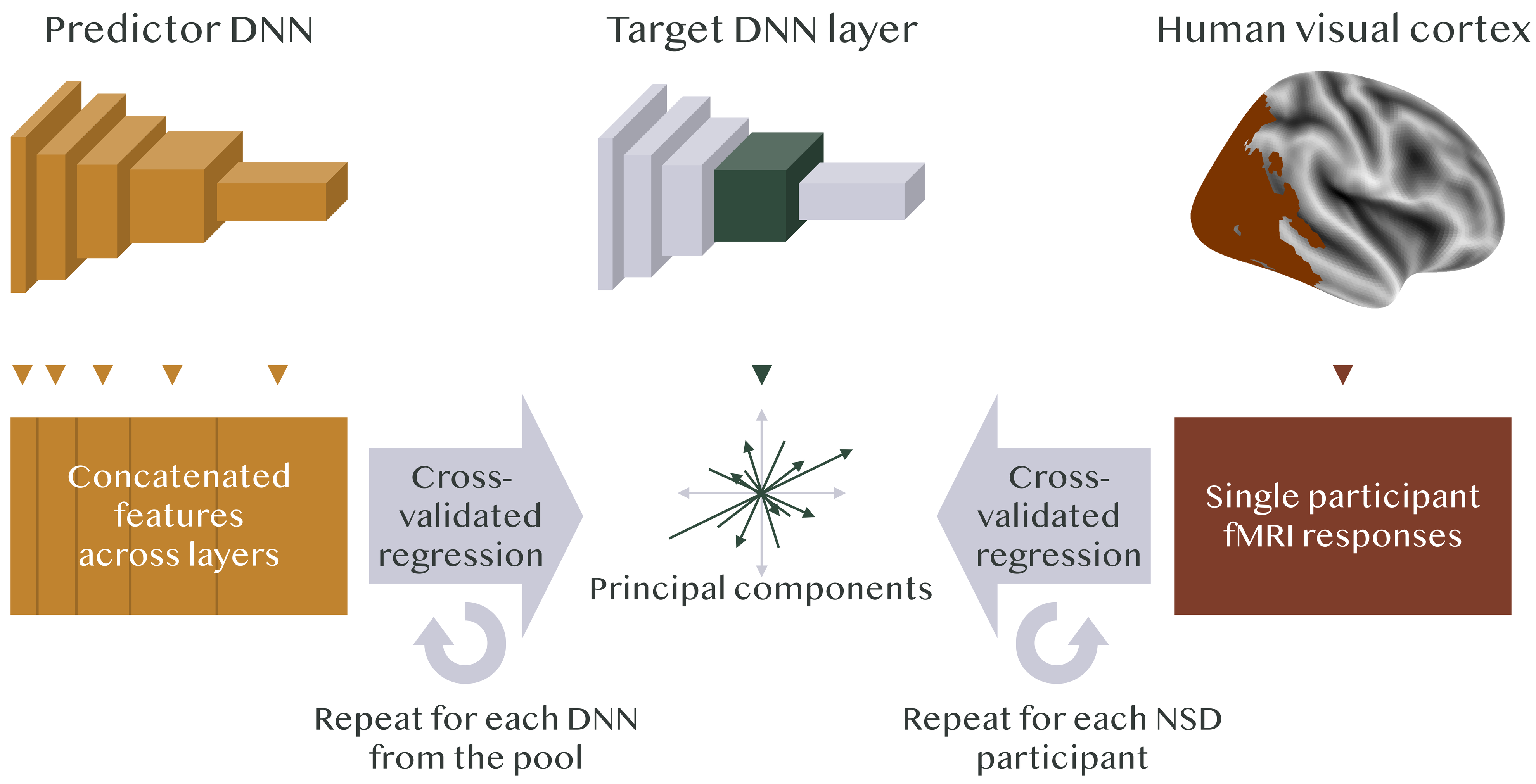
Are these canonical dimensions also encoded in human visual cortex?

Methods

Stimuli and neural data



fMRI responses of 8 participants to 872 color natural scene images from the Natural Scenes Dataset[6] (NSD)



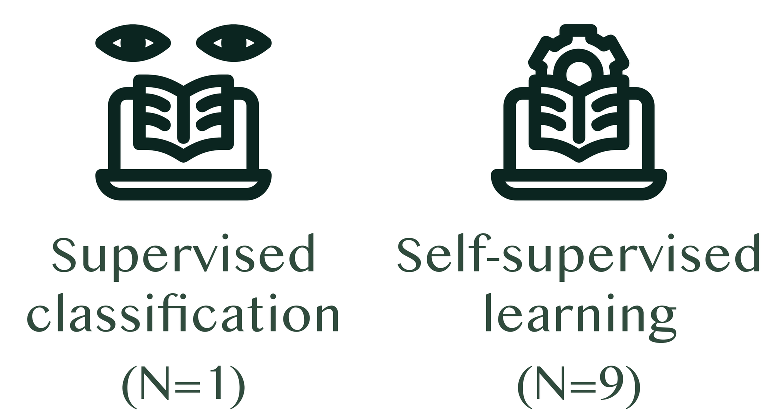
Canonical strength = average prediction accuracy across DNN predictors

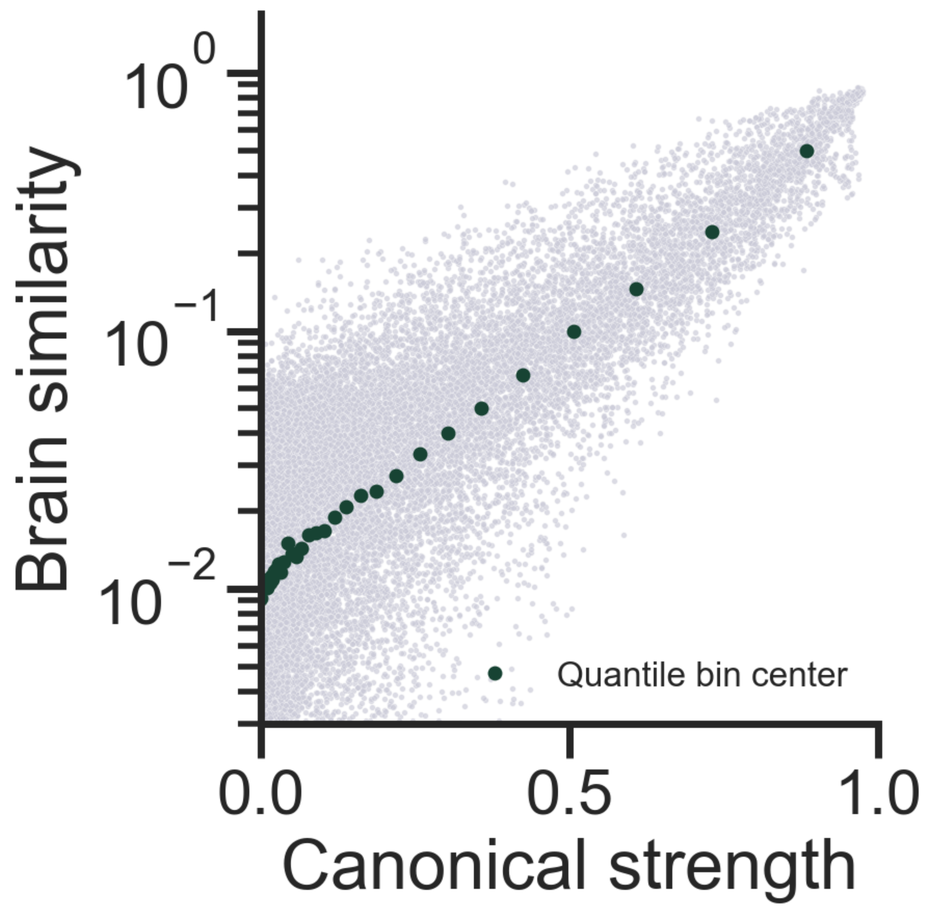
Brain similarity = average prediction accuracy across NSD participant predictors

Results & Discussion

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

- DISTINCT tasks
- Same architecture (Resnet-50[7])
- Same training data (ImageNet[8])
- 106,889 features

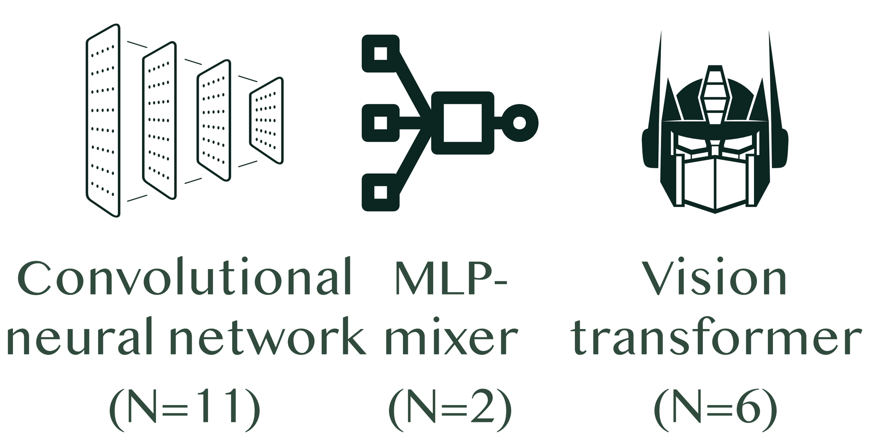


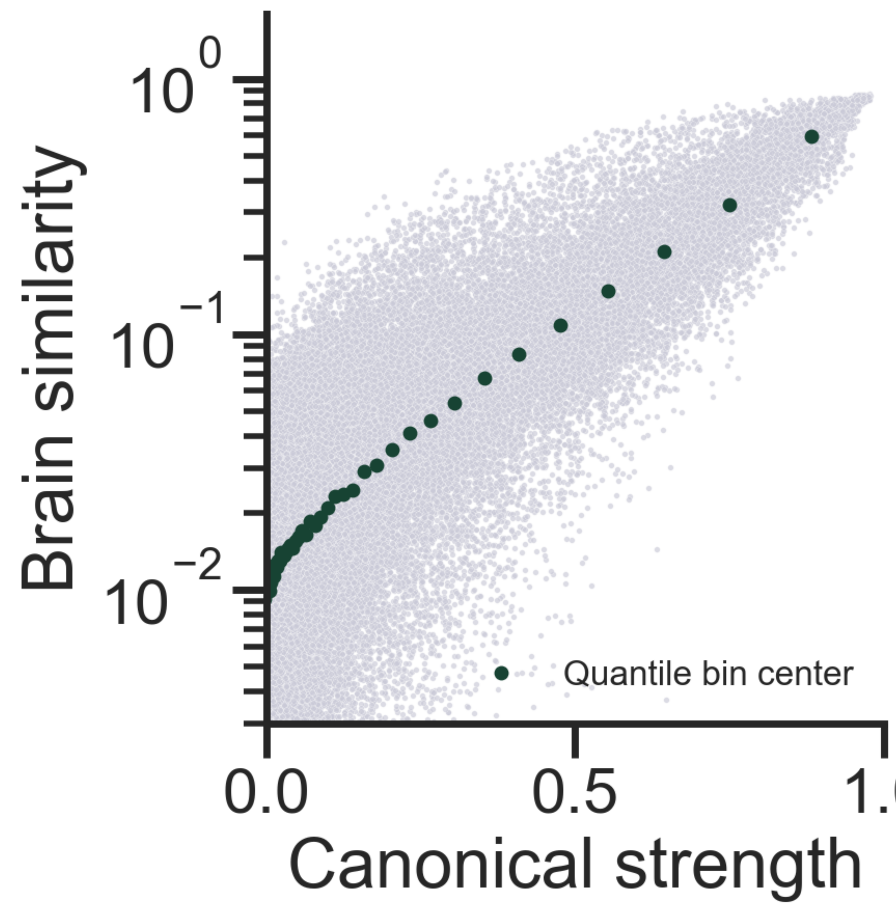


DNNs learn canonical dimensions independent to training tasks.

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

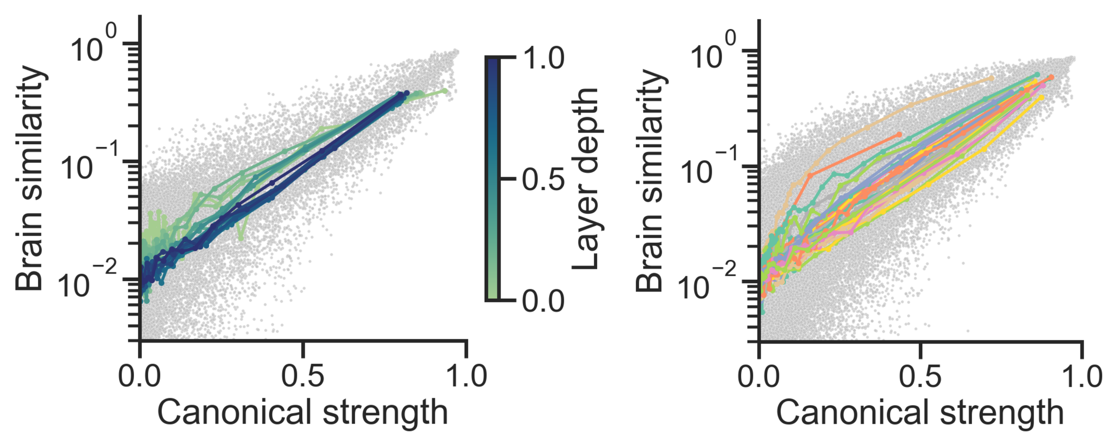
- DISTINCT architectures
- Same task (object classification)
- Same training data (ImageNet[8])
- 217,879 features





DNNs learn canonical dimensions independent to architectures.

3 Is the effect confounded by specific layer depth or models?



Consistent effect across all layers and models.

4 What are the most canonical features?

Takeaway:

- Biologically relevant visual features are generically learnable and are independent to constraints on task or architecture.
- There are unifying statistical principles across biological and artificial visual system which drives the learning and extraction of the canonical dimensions.

References

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