High-dimensional latent structure in visual cortex representations

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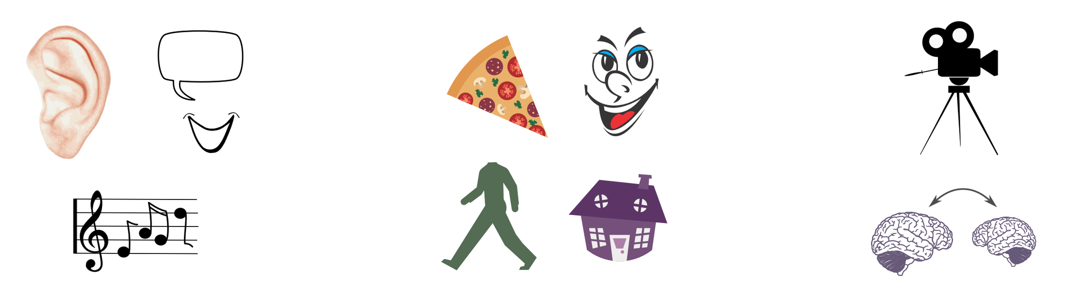
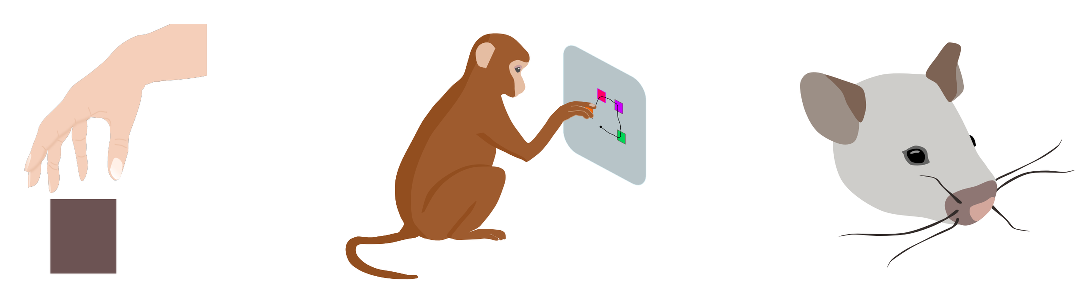
Motivation

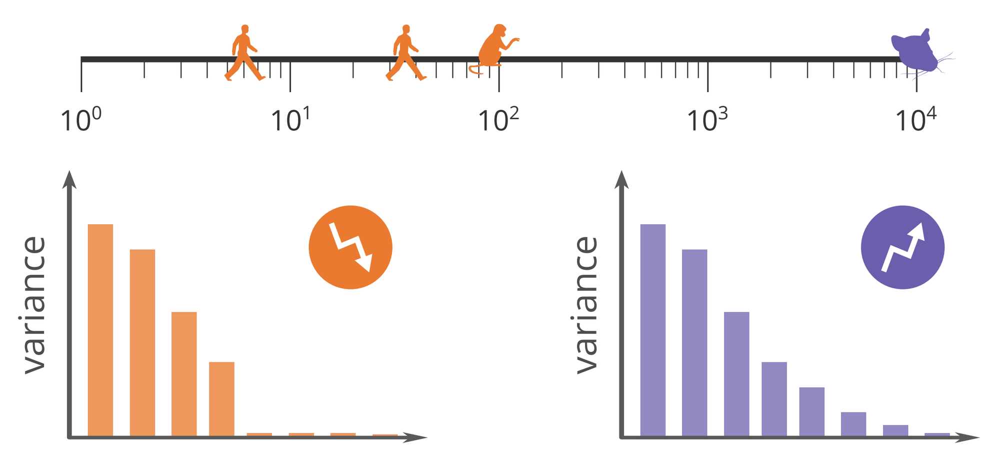
Studies of the **human brain** often find **low-dimensional** latent representations ...



... but recent work has detected much ***higher*-dimensional** signal



Estimates of visual cortex dimensionality vary *widely*[1-4]



Interpret the few latent dimensions!

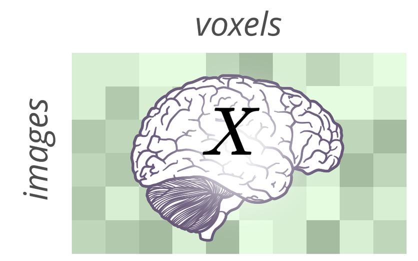
Focus on overall statistical properties!

How many **visual dimensions** can we detect with **large-scale fMRI**?

Methods

The large-scale **natural scenes fMRI dataset**[8] lets us study the high-dimensional regime

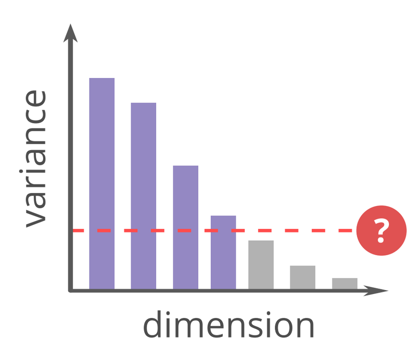
~1,000 images seen by all 8 participants



regions of interest

1. general visually responsive region
2. V1, V2, V3, hV4

Q How to *robustly* estimate the **dimensionality** of a system?



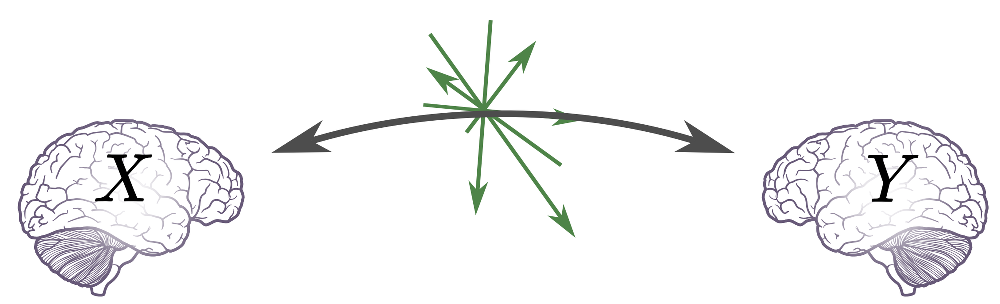
Incorrect assumption

high variance → signal

low variance → noise

No obvious discontinuity!

A Investigate its *cross-validated* **covariance spectrum**



Which dimensions are *reliable* across images and brains?

extracts stimulus-related signal

$$X_{\text{train}}^\top Y_{\text{train}} = U \Sigma V^\top$$

$$\Sigma_{\text{test}} = (X_{\text{test}} U)^\top (Y_{\text{test}} V)$$

generalizes to pairs of systems

Σ_{CV} **cross-validated singular values** reveal the latent dimensionality

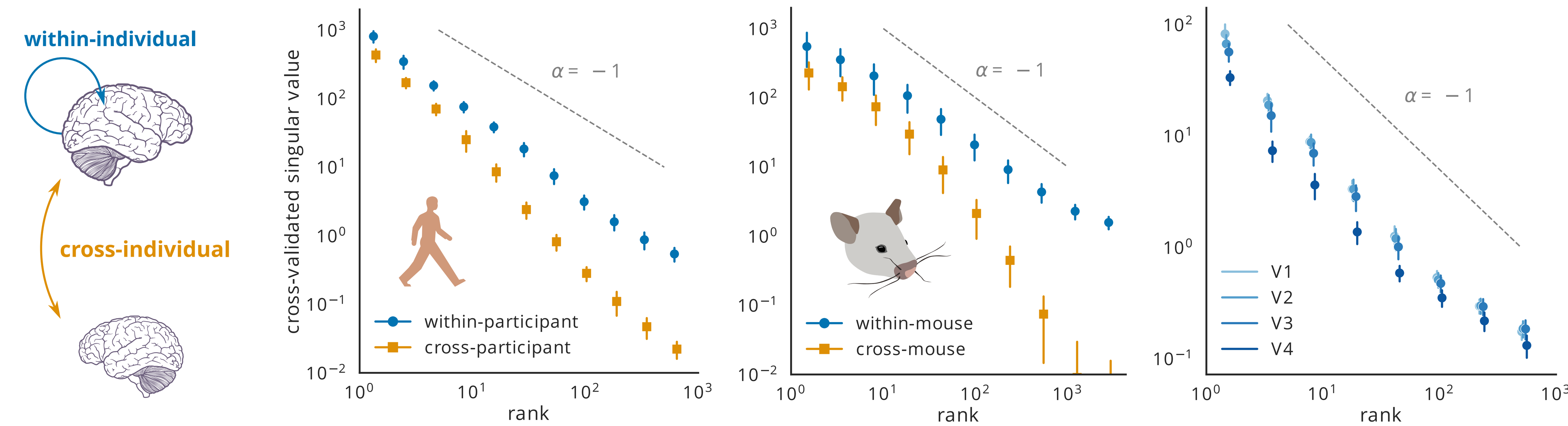
Results & Discussion

1 Visual cortex representations have power-law covariance spectra

Both within- and cross-individual spectra obey a power-law distribution over three orders of magnitude! Even low-variance dimensions contain stimulus-related signal, as seen in the tails of the spectra. The signal hasn't decayed completely — with more images, we expect even higher dimensionality.

$$\Sigma_{\text{CV}} \sim (\text{rank})^\alpha$$

$$\alpha \approx -1$$



2 Idiosyncratic representations in high-rank subspace

Cross-individual spectra decay faster than within-individual spectra, suggesting that high-rank dimensions are represented differently across participants. Both human and mouse data exhibit a qualitatively similar pattern.

3 Universal power law index of −1

Within-individual spectra decay with a slope close to −1 throughout visual cortex, which has been proposed as an upper bound for smooth representational manifolds.[4]

Visual cortex representations have **high-dimensional latent structure** described by **power-law covariance spectra** with **index -1**

Why are high-dimensional representations useful?

- **rich feature space** with **efficient linear readouts**[10]
- **better transfer learning** in neural network models[9]

How should we study cortical representations?

- **dimensionality reduction** with arbitary thresholds
- **cross-validated methods** to separate **signal** from noise

A new perspective on high-dimensional population codes

- α **constrains smoothness** of representational manifolds[4]
- **improves performance** in artifical neural networks[11]

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2 **Lehky et al. (2014).** *Dimensionality of Object Representations in Monkey Inferotemporal Cortex.* Neural Computation, 26(10), 2135–2162.

3 **Khosla et al. (2022).** *A highly selective response to food in human visual cortex revealed by hypothesis-free voxel decomposition.* Current Biology, 32(19), 4159-4171.e9.

4 **Stringer et al. (2019).** *High-dimensional geometry of population responses in visual cortex.* Nature 571, 361–365.

5 **Norman-Haignere et al. (2015).** *Distinct Cortical Pathways for Music and Speech Revealed by Hypothesis-Free Voxel Decomposition.* Neuron 88, 1281–1296.

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7 **Yan et al. (2020).** *Unexpected complexity of everyday manual behaviors.* Nature Communications 11, 3564.

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9 **Elmoznino & Bonner (2022).** *High-performing neural network models of visual cortex benefit from high latent dimensionality.* bioRxiv preprint.

10 **Fusi et al. (2016).** *Why neurons mix: high dimensionality for higher cognition.* Current Opinion in Neurobiology, 37, 66–74.

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