Is Neural Conceptual Space Spherical?
Intrinsic Properties vs. Artifacts in Multidimensional Scaling

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Introduction

- How does the brain organize and represent all its vast knowledge about concepts and categories?
- We investigated the neural structure of conceptual space by using three publically available datasets that all sample from a high number of visually presented concepts.
- To examine the shape and structure of the representational space, we used multidimensional scaling (MDS), a dimensionality reduction technique commonly applied to both visualize and inspect the underlying structure of a dataset.
- Across measurement scales (fMRI and single-cell recordings) and species (human vs. non-human primates), the derived representational manifolds were spherical in shape (e.g. Fig.1&2).
- However, MDS of random data (containing near equal dissimilarities) will also lead to spherical solutions in a 3D space (Borg & Groenen, 2003).

Research Question

Are the spherical manifolds observed in the experimental neural data an artifact due to noise (or randomness) or are they an intrinsic property of conceptual space?

Experimental Data Description

Dataset 1: Kiani Data (Kiani et al., 2007): 1084 visual object representations of single cell recording from monkey inferior temporal cortex.
Dataset 2: Kriegeskorte Data (Kriegeskorte et al., 2008): 92 visual object representations of human and monkey inferior temporal cortex, based on a subsample of 96 objects from the Kiani dataset. The human data was acquired via fMRI scanning.
Dataset 3: BOLD5000 (Chang et al., 2019): Human MRI activation responses to 5000 visual images from five different ROIs (early visual cortex (EV), lateral occipital cortex (LOC), parahippocampal place area (PPA), retrosplineal complex (RSC), occipital place area (OPA)).

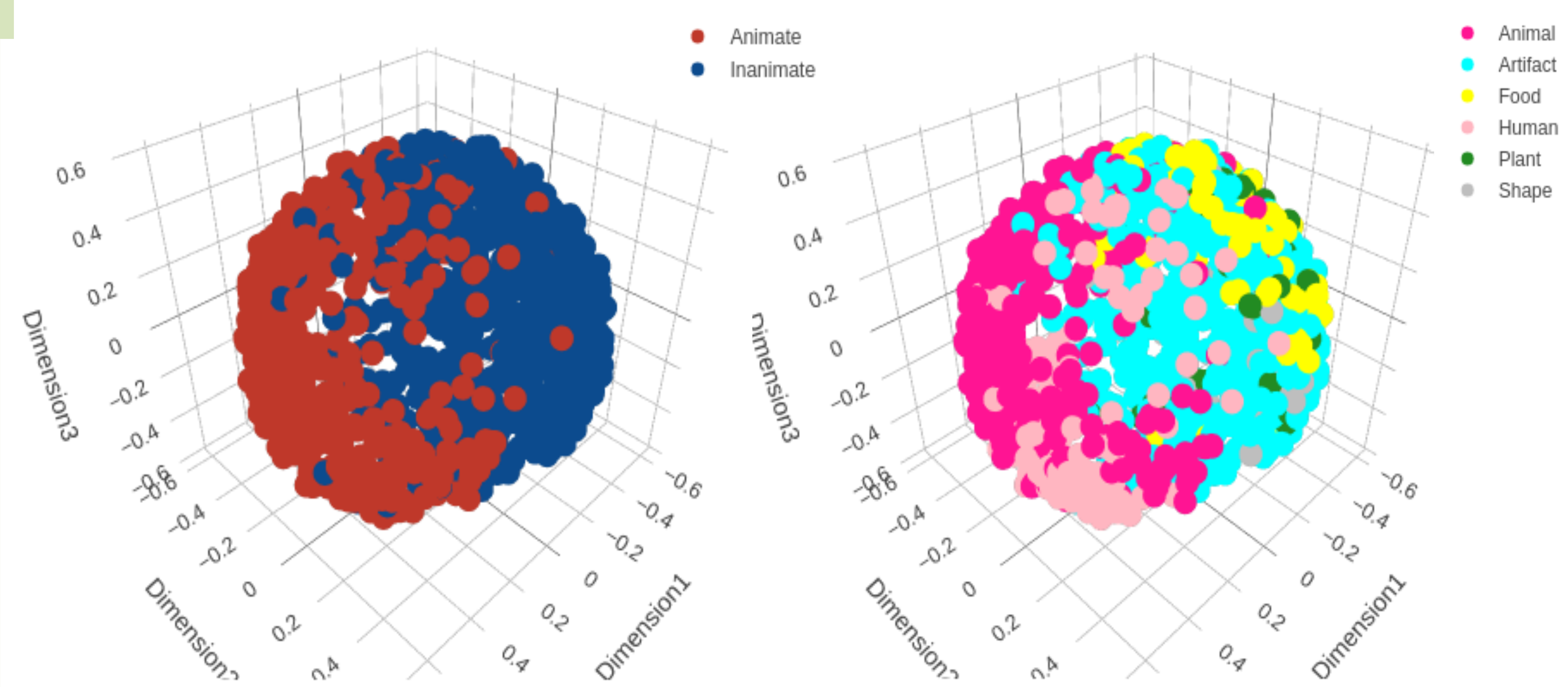

Figure 1. 3D color-coded plot of the Kiani data showing clustering of the different subcategories.

What Is Causing Spherical Manifolds in MDS?

Proposition1: *Datasets with large number of items scale into spheres.*
- No, distances of 1000 European cities do not scale into a sphere, but reproduce a map of Europe.

Proposition2: *Data of only specific distributions scale into spheres.*
- No, all data sampled from a random Gaussian, lognormal, negative binomial, exponential, Poisson, gamma, or uniform variable create spherical manifolds when scaled in 3D.

Proposition3: *Data that is random should violate the third metric axiom – the triangle inequality. Only data that violates the triangle inequality scales into a sphere.*
- No, all distributions sampled from a random variable produce spheres, whether they violate the triangle inequality or not. All three experimental datasets satisfy the triangle inequality.

> **The Triangle Inequality**: $d(A,B) \leq d(A,C) + d(B,C)$
> The distance between concepts A and C cannot be further than the sum of their distances to any other object B.

Proposition4: *The distance metric used influences the shape of the resultant MDS solution.*
- Yes. Correlation distance produces a hollow sphere, while Euclidean, Manhattan, Canberra, Minkowski, and cosine distances produce a filled sphere.

Proposition5: *The data does not contain any structure.*
- No, all three neural datasets contain meaningful categorical clustering (e.g.: see Fig.1)

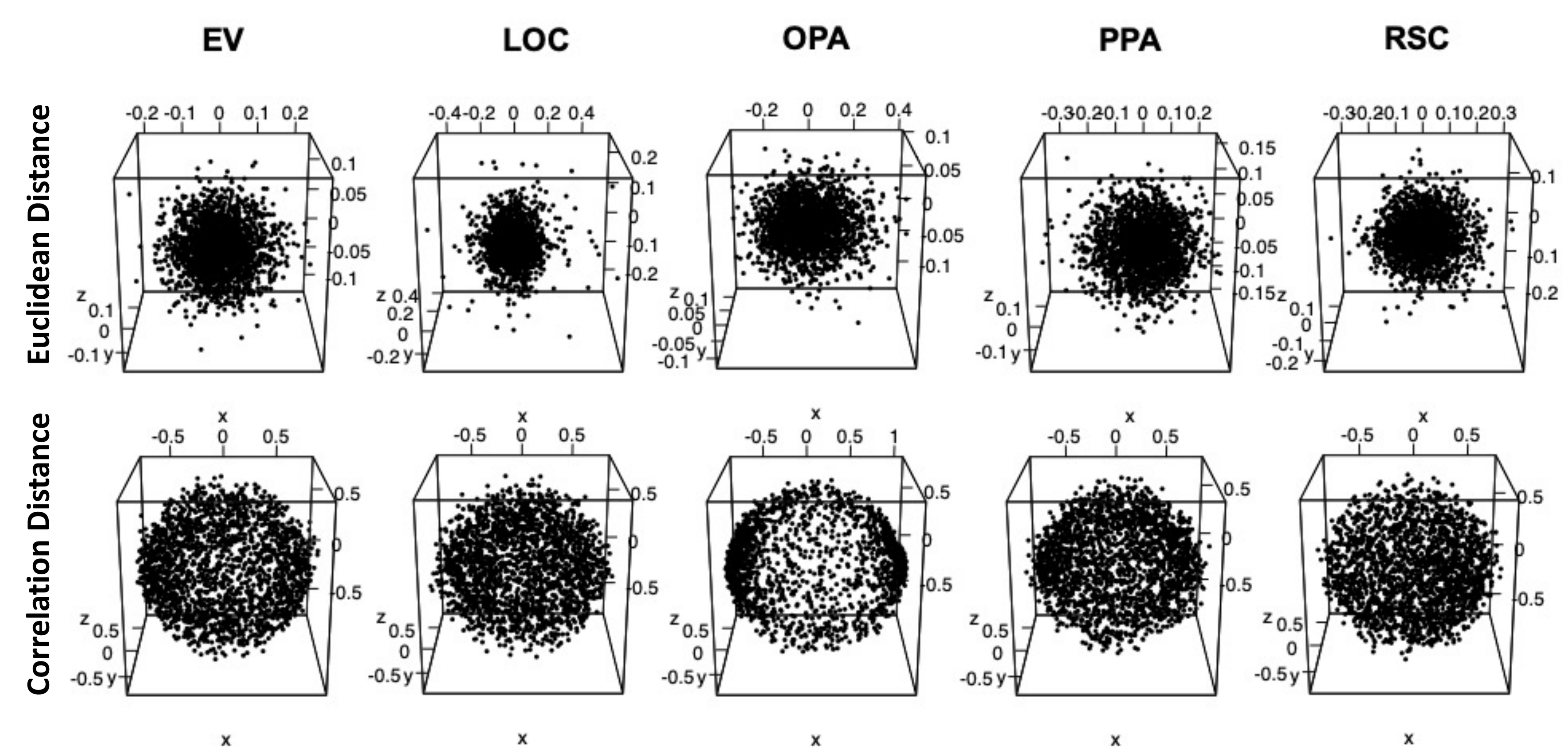

Figure 2. 3D MDS configurations for CSI3 of the BOLD5000 data from the left hemisphere of the five different ROIs. The top panel shows 3D MDS solutions using Euclidean distance, while the bottom panel used correlation distance.

$1/f^{\alpha}$ Spherical Simulation

- To examine the relationship between the amount of structure in the data and the shape of the scaled manifold, we systematically varied the structure in a series of simulations away from randomness by manipulating the data's power spectrum.
- Using an inverse Fourier transform, we generated spatial data on a grid of 500x500 and incrementally increased the exponent in steps of 0.2 from white noise (f^0) to pink noise (f^1), to Brownian noise (f^2), and to 3.6.
- We show that spherical manifolds break down between pink ($1/f^1$) and Brownian noise ($1/f^2$) (see Fig.2).

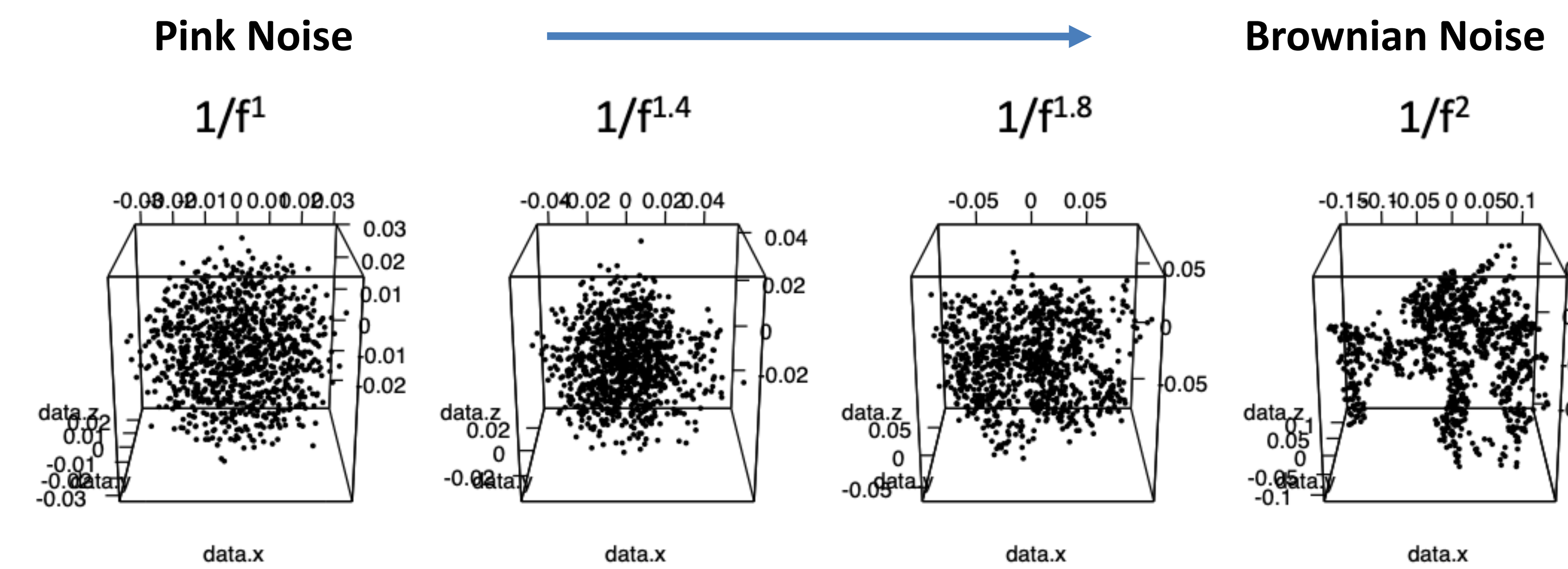

Figure 3. 3D MDS solutions showing the decomposition of the spherical structure from pink to Brownian noise.

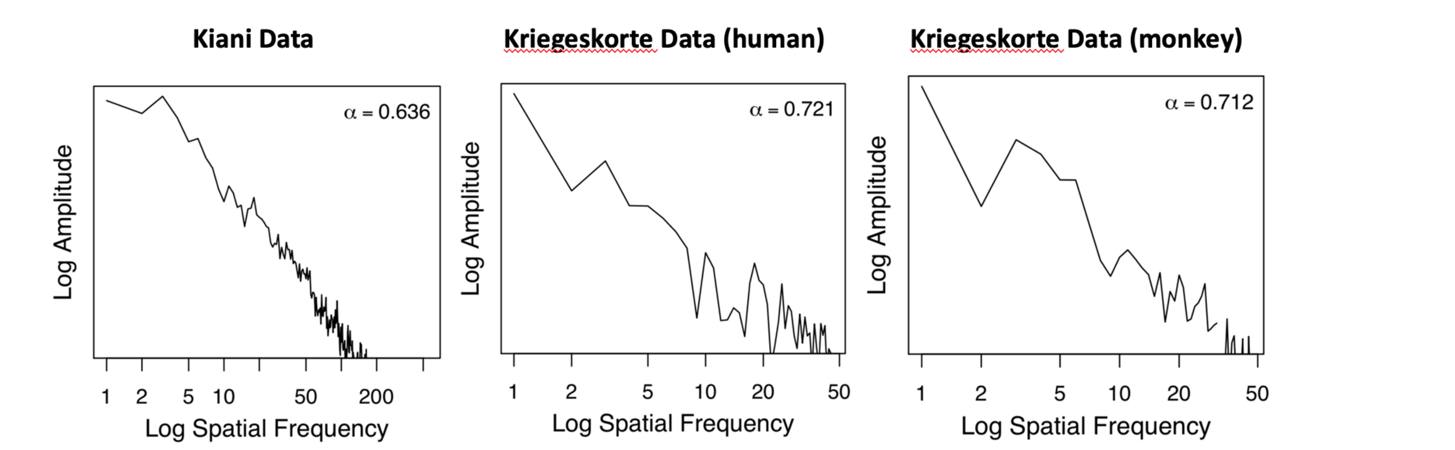

Figure 4. Spectral density analysis of the Kiani and Kriegeskorte data revealing frequency spectra closer to pink noise.

Discussion

- Both random and non-random data can produce spherical manifolds. Four features distinguish artifact from meaningful shape: the type of spherical shape, the triangle inequality, the data's categorical structure, and its frequency spectrum.
- The particular **type of spherical shape** is an artifact caused by the distance metric applied. Correlation distance leads to an empty shell-like spherical structure (i.e. Fig.2, bottom panel), while all other tested distance metrics lead to a filled sphere (Fig.2, top panel).
- All experimental data satisfy the **triangle inequality**, which might be a necessary but not sufficient criterion.
- The Kiani and Kriegeskorte datasets exhibit meaningful **category clustering** (e.g. Fig.1), but the BOLD5000 dataset does not.
- **Power spectra** of both white and pink noise can produce spherical manifolds. A phase shift occurs at the boundary between pink (α=1) and Brownian noise (α=2). The frequency spectrum of the Kiani and Kriegeskorte data lie close to pink noise (mean α=0.69; Fig.4), which has been argued to be a characteristic signature of complexity (Gilden, Thornton, & Mallon, 1995) and a common occurrence in human cognition (Wagenmakers, Farrel, & Ratcliff, 2004; Kello et al., 2008). However, the BOLD5000 data consists of a frequency spectrum closer to white noise (mean α = 0.16).
- The triangle inequality and power spectra might be related to the homogeneity of the category structure. This needs to be tested further.

Conclusions

Our results show that the spherical manifolds observed in the experimental datasets is an intrinsic property of the conceptual space and not an artifact of the MDS model. Thus, we cannot rule out that neural concept space is spherical.

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