Uncovering High-Dimensional Visual Neural Structures: A Topological Approach to Representational Similarity Analysis

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01 Introduction

Understanding brain function across regions requires robust analytical techniques that can bridge brain-activity measurement, behavioral data, and computational modeling. Traditional approaches, such as **Representational Similarity Analysis (RSA)**, have proven effective in investigating visual neural activity by constructing **Representational Dissimilarity Matrices (RDMs)**[1]. However, RSA's reliance on linear similarity metrics can obscure deeper, high-dimensional structures in neural data **(Fig. 1)**.

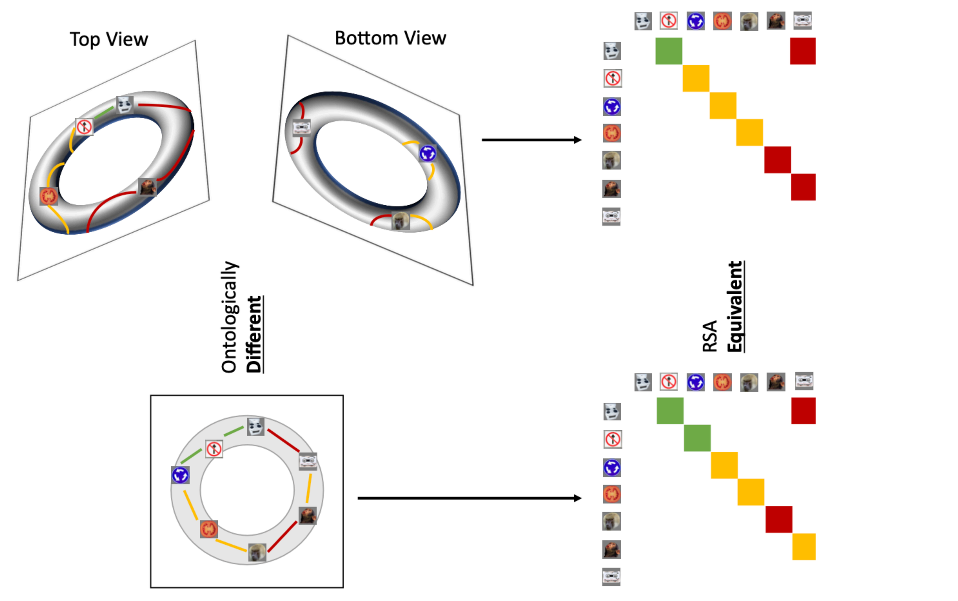

Fig. 1 | Sampled representations from a torus (rat's grid cells), projected onto an annulus, and the resulting two RDMs. The two RDMs would be considered equivalent by RSA, despite distinct topological spaces[2].

02 Objective

To overcome these limitations, Brown and Farivar proposed **Representational Topology Analysis**[2]. Building on this framework, I performed RTA to the neural data of the first subject involved in the natural scene dataset (NSD) experiment to uncover higher dimensional features.

REPRESENTATIONAL TOPOLOGY ANALYSIS (RTA)

A powerful alternative to RSA, leverages Topological Data Analysis (TDA) and **Persistent Diagrams (PDs)** with machine learning and statistical inference. It captures topological features such as clusters, loops, and voids within neural representations.

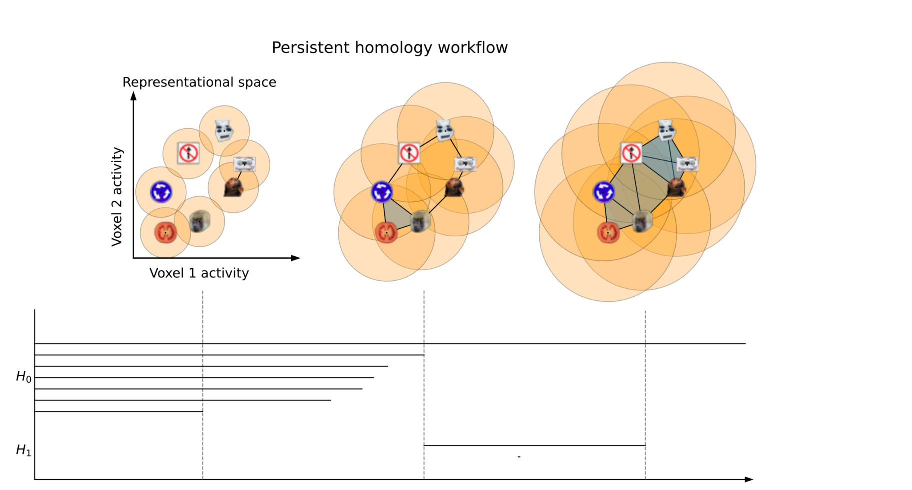

Fig. 2 | A linkage radius ϵ is increased from 0. Data points are connected when their distance is at most ϵ, forming Vietoris-Rips complexes[2].

03 Methodology

Data Collection from NSD Experiment

This study utilized the **Natural Scenes Dataset (NSD)**, a publicly available dataset that includes high-resolution (1.8-mm) whole-brain 7T functional magnetic resonance imaging (fMRI) data from eight carefully screened human participants. Each subject viewed approximately 9,000–10,000 unique natural scene images over the course of 30–40 scan sessions distributed across one year. Across all participants, NSD encompasses responses to 70,566 distinct natural scene images, making it an order of magnitude larger than similar fMRI datasets. Detailed information about NSD experiment design is shown in Figure 3.

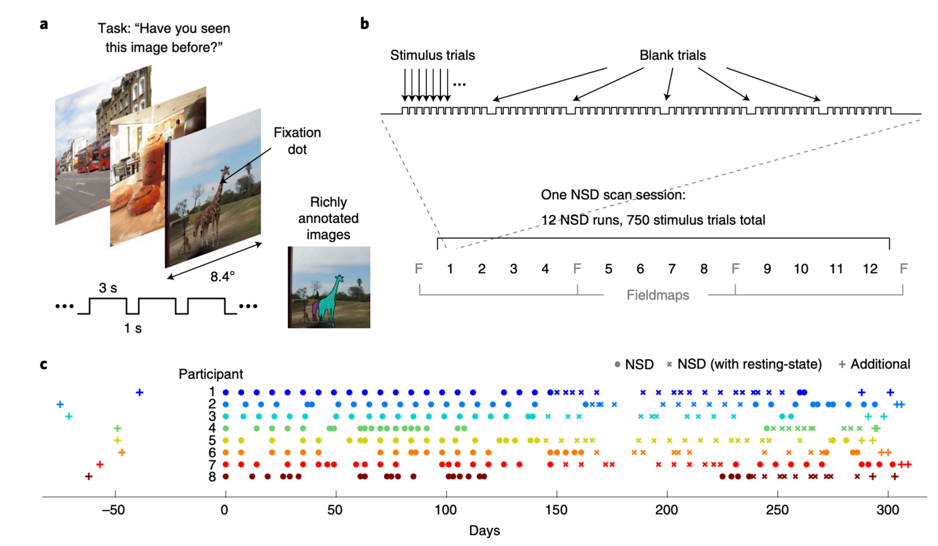

Fig. 3 | Design of the NSD experiment[3]**. a,** Trial design **b,** Run and session design. **c,** Timeline of 7T fMRI scan sessions.

Representational Similarity Analysis (RSA)

First, we obtained surface-based fMRI beta values from the first session of the participant 1 in NSD. Each vertex (node) in the cortical surface space represented an **activation pattern** across different conditions (750 image stimuli). We assign each vertex to a specific region of interest (ROI) based on HCP_MMP1.mgz atlas[4]. This allowed us to map each of the 163,842 cortical nodes to one of 180 predefined brain regions and produce a table (163,842 x 750) for RDM calculation. Seven ROIs in early and late visual areas are being examined closely: **Primary Visual Cortex (V1), Second Visual Area (V2), Third Visual Area (V3), Fourth Visual Area (V4), Eighth Visual Area (V8), Area Lateral Occipital 2 (Lo2), and Posterior-Infero-Temporal Complex (PIT).**

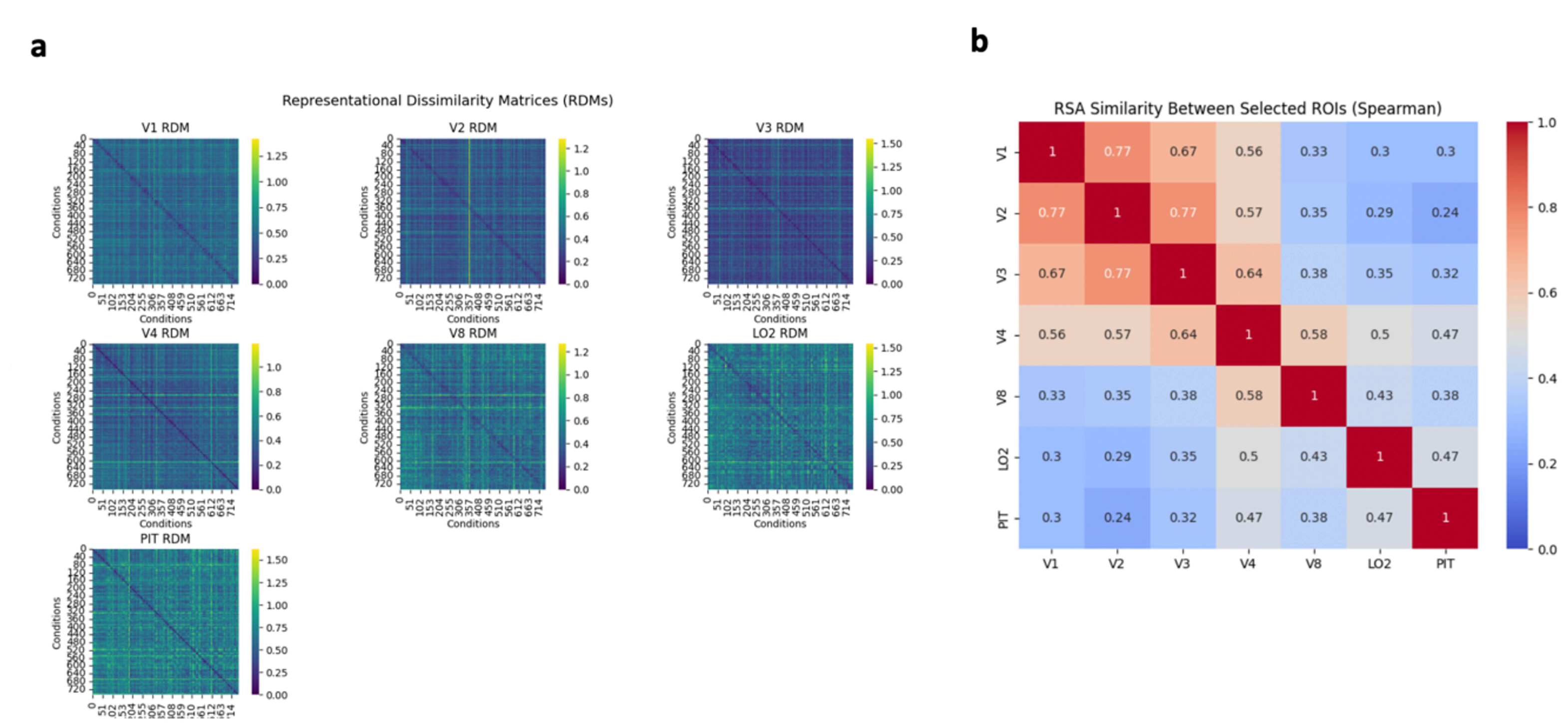

Fig. 4 | Representational Similarity Analysis (RSA). a, representational dissimilarity matrices (RDM) of seven selected region of interests b, second-order isomorphism of RDMs calculated using Spearman correlation distance

Representational Topology Analysis (RTA)

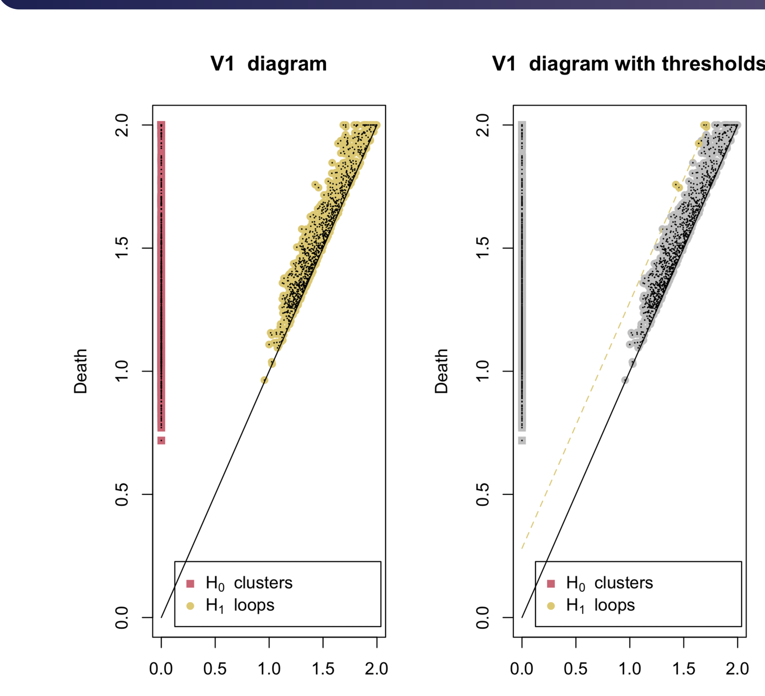

Fig. 5 | Persistent Diagram (PD) of RDM of V1. This plot shows that six significant H1 features are found.

To uncover higher-order structural patterns in fMRI data, we applied RTA on RDMs to detect topological features such as loops (1-dimensional homology) that might reflect meaningful stimulus relationships in the brain's representational space.

Each region's RDM was subjected to the **bootstrap_persistence_thresholds function (from TDApplied**[5]**)** to identify statistically significant persistent features. This method involves repeated random sampling of the RDM to generate a **null distribution** of persistence diagrams, allowing for empirical p-value estimation. In this study, we are only considering two dimensions (maxdim = 1) and keeping features in the top 2.5% of the null distribution (thresh = 2). **(Fig. 5)**

Due to the random nature of bootstrapping, results varied slightly between runs. However, stable trend emerged in V1, consistently yielding 4 to 6 significant H1 features.

04 Analysis

Vietoris-Rips (VR) Graph Construction and Visualization

Having detected significant H1 (loops) features, we now arrive at the most exciting part – mapping actual NSD images underlying each feature to visualize topological patterns.

For each detected feature, we extracted the underlying trials from **subsetted_representatives** output of bootstrapping method. In the NSD experiments, image stimuli are presented and repeated in a specific pattern. We matched each trial to the image stimulus via a trial-to-nsdID mapping. This allowed visual inspection of the actual stimuli contributing to each topological feature **(Fig. 6)**.

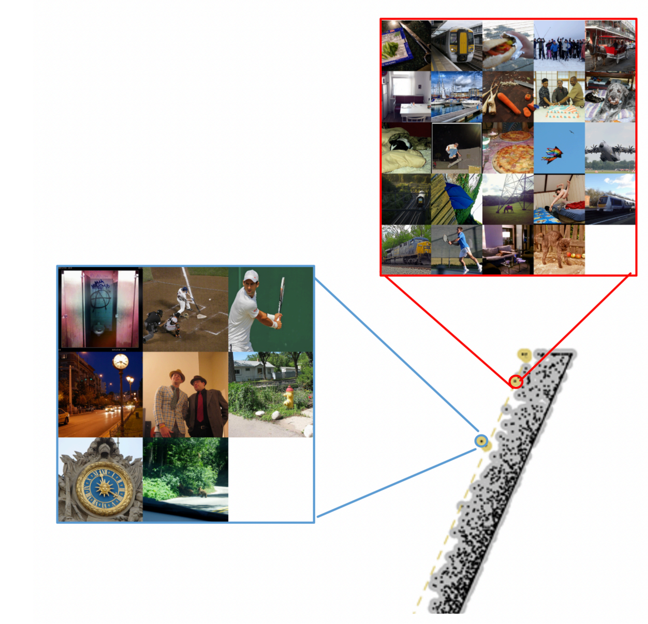

Fig. 6 | Trial-to-nsdID mapping. This plot zooms in two significant H1 features (out of six) of V1. Their underlying trials and corresponding NSD images are displayed.

Vietoris-Rips (VR) Graph Construction and Visualization

In the VR graph of the primary visual cortex (V1), Feature 1 was distinctly separated from the rest **(Fig. 7)**. Upon visual inspection of the NSD images associated with this feature, it turns out that the majority of these images contains distinct vertical lines. Given that V1 neurons are highly sensitive to line orientation, especially vertical and diagonal edges, this cluster might suggest a shared activation pattern for vertical lines across V1's early visual detectors.

In contrast, the VR graph of the third visual area (V3) clustered animal-related stimuli more tightly than in earlier visual areas like V1 or V2. This emerging structure suggests a potential transition from low-level visual representations (e.g., edges, textures, symmetry) toward mid-level or even proto-semantic groupings. Although V3 is still considered part of early visual cortex, it is associated with the processing of global shapes and motion, and hence may begin to reflect more integrated representations of visual scenes.

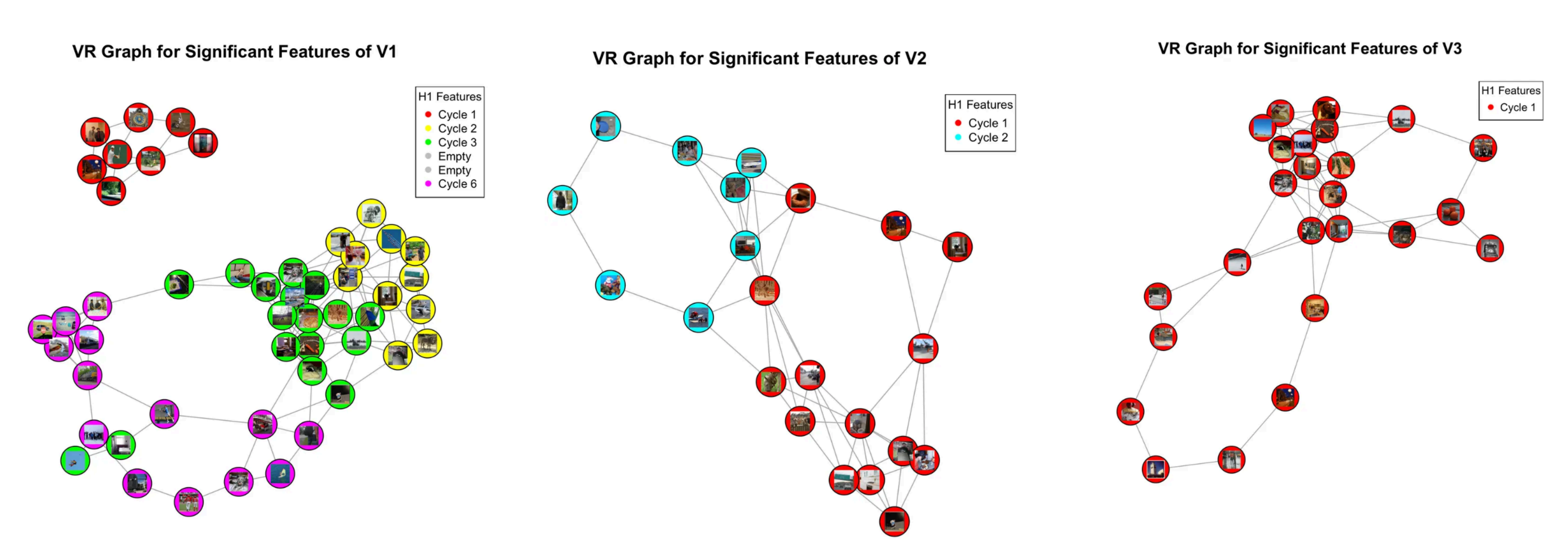

Fig. 7 | Vietoris-Rips (VR) Graph for significant features in V1 to V3 and corresponding PDs. Some cycles have empty nodes and are not real topological feature with valid representative cycles.

However, in higher-order regions—including V4, V8, LO2, and PIT— no statistically significant topological features were consistently detected. Note that the current analysis is solely based on a single session from a single participant in the NSD experiment, which limited our ability to capture variability and abstract coding in higher-order visual areas. Future analysis can incorporate multiple sessions and participants to extend these preliminary findings in both early and late visual areas.

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