Choice of Metric and the Effect of Scan Length for Reliability in Resting-State fMRI

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ABSTRACT

Resting-state fMRI (rs-fMRI) studies are often used to study functional connectivity, i.e., the communication between R distinct regions when no specific task is being performed. Such data are often presented as R x R covariance matrices, each of which can be regarded as being a point on a manifold. We discuss measures of reliability for such data that are based on metrics that respect the manifold structure of the space. Applying these concepts, we explore aspects of design and data collection for such studies including region selection, scan length, and time interval between scans. We illustrate these concepts through application to rs-fMRI data from the Midnight Scanning Club dataset.

Keywords: resting-state fMRI; correlation matrices; object-valued data, Riemannian metric

Clarifying and Extending Permutation Tests on Brain Map Correspondence Through Mixed-Effects Modeling

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ABSTRACT

Permutation-based methods such as the spin test, BrainSMASH, and the SPICE test are widely used to assess correspondence between spatially distributed brain maps while accounting for their spatial autocorrelation. However, these methods define and evaluate correspondence in fundamentally different ways, making their results difficult to compare or interpret jointly. We address these limitations by introducing a two-factor mixed-effects modeling framework that decomposes brain map variability into inter-subject and spatial components. This formulation characterizes distinct sources of variability in brain maps and reveals how different permutation tests target correspondence related to the different components. Within this framework, we further show the analytical expressions of the null distributions of the spin test, BrainSMASH, and SPICE in terms of model parameters. This unified framework clarifies the fundamental distinctions among permutation tests, reveals their implicit assumptions, and provides a principled way to compare and interpet their results across diverse correspondence scenarios. Beyond clarifying existing methods, the modeling framework naturally motivates a bootstrap-based inference method for jointly quantifying multiple compositions of correspondence. Using simulations and empirical analyses of structural (cortical thickness vs. sulcal depth) and functional (language vs. motor contrast) brain maps, we demonstrate that the bootstrap-based method offers competitive type I error control, much higher statistical power, and richer insights into the compositions and sources of variations that give rise to brain map correspondence.

Keywords: Brain map correspondence; Mixed-effects models; Permutation tests; Bootstrap

Threshold Spatial Attention Transformer for Efficient Image Generation

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ABTRACT

We propose the threshold spatial attention transformer (TSAT), a novel model for efficient and high-quality image generation, with a focus on medical imaging applications. Existing models such as Generative Adversarial Networks (GANs) and Diffusion Probabilistic Models (DDPMs) often face challenges related to data efficiency, computational demands, and reliance on extensive labeled datasets. The proposed TSAT model addresses these limitations through a block-wise feature sampling mechanism integrated with special transformer architectures. Using an encoder-decoder framework, the mode effectively reduces the token dimensionality while preserving essential spatial and contextual information, enabling accurate image reconstruction and synthesis. Key innovations include low-rank approximation, spatial attention kernels, and nested thresholding techniques, which collectively improve computational efficiency. TSAT supports both supervised and semi-supervised training paradigms, demonstrating flexibility across different dataset sizes and labeling conditions. Numeric experiments on state-of-the-art computer vision datasets and the fMRI activation maps in the Human Brain Connectome (HCP) study highlight the superior performance of the TSAT, while requiring significantly smaller training sample size.

Keywords: Generative model, Neuroimaging, Deep neural networks