Exploring the Enigma of Neural Dynamics Through A Scattering-Transform Mixer Landscape for Riemannian Manifold

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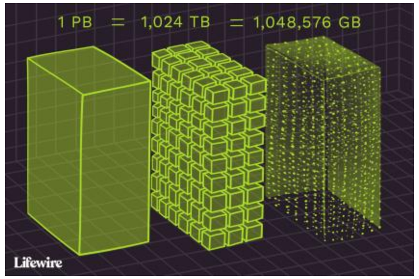
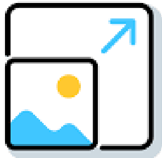
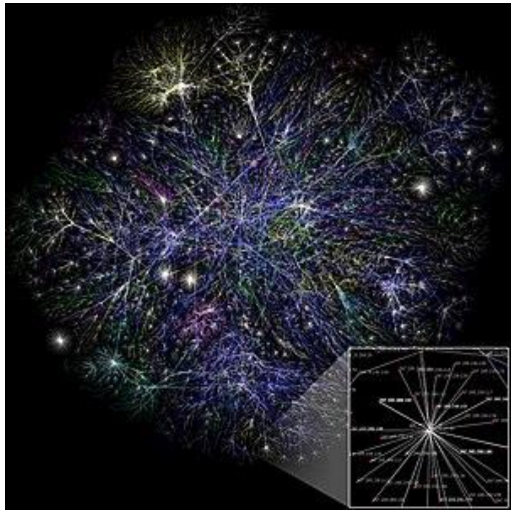


Variety





High-dimension

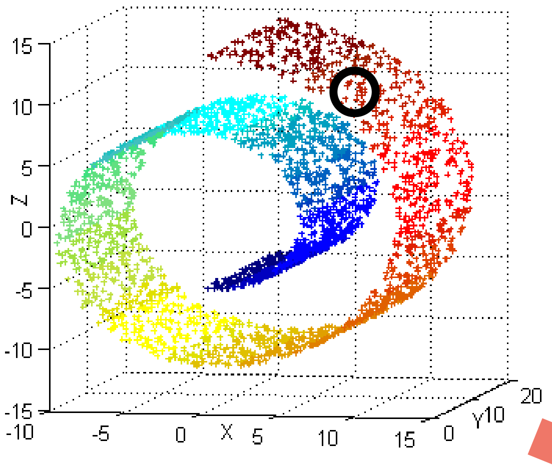
↓

- Info. Redundancy
- Dimensionality Curse
- Vis. Extract. Cluster…

↓

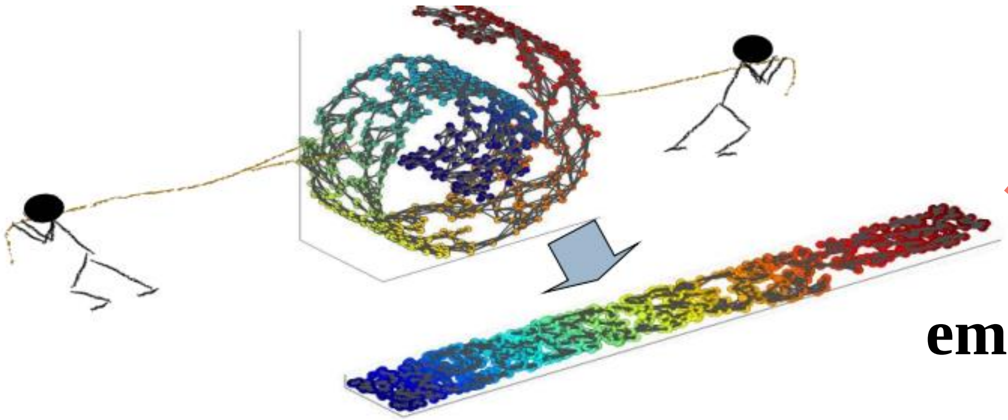
Characterize?

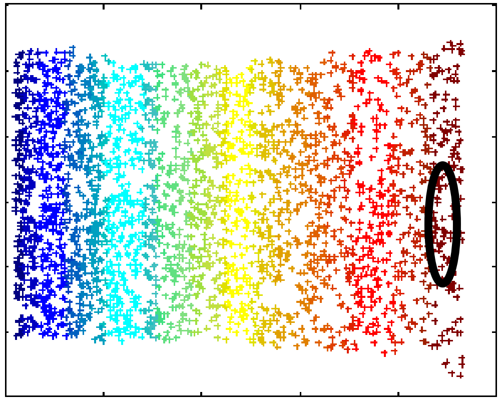
Introduction



Nonlinear dimensionality reduction

geometric topology remains





data / observation space

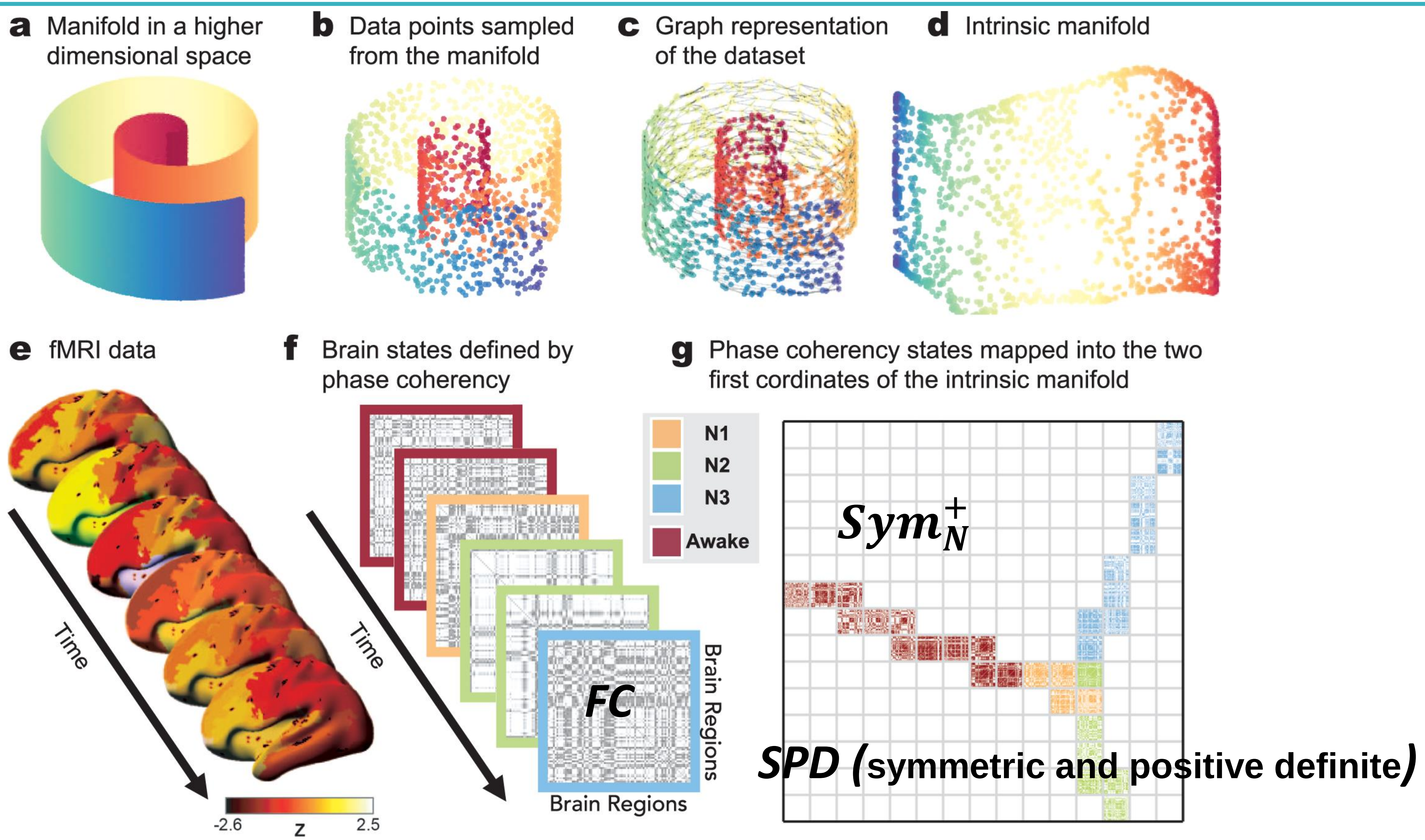
embedding / coordinate space

Manifold learning

Manifold learning may be a natural way of behavior in human cognition.

《The manifold ways of perception》 2000，Seung et al., Science

Motivation

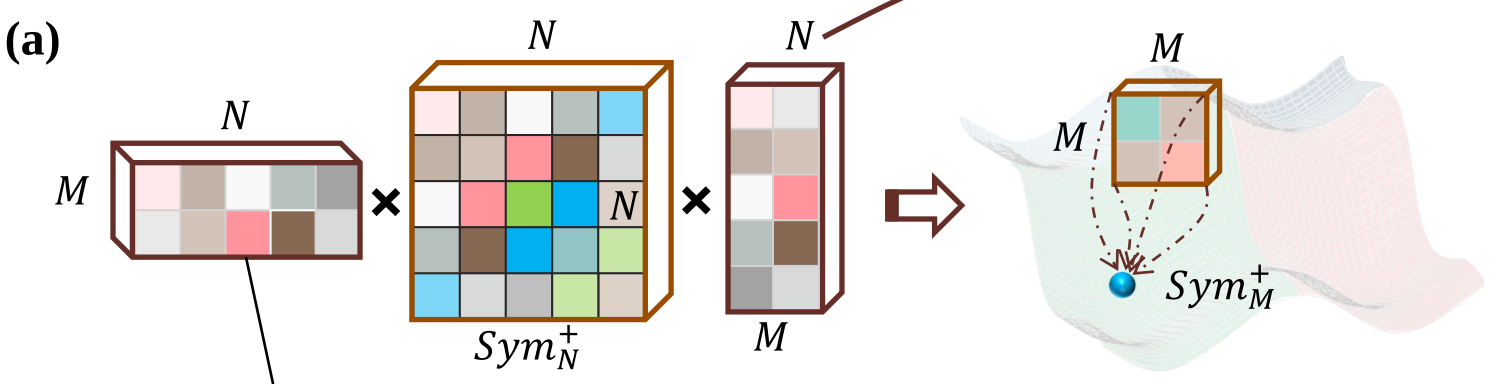


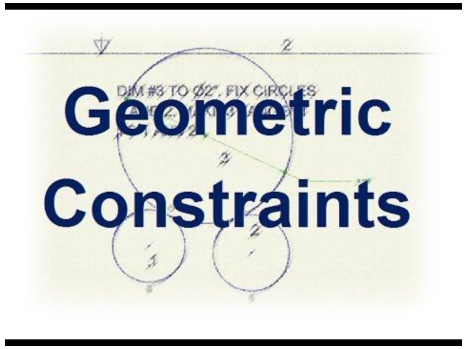
a Manifold in a higher dimensional space
b Data points sampled from the manifold
c Graph representation of the dataset
d Intrinsic manifold
e fMRI data
Time
-2.6
z
2.5
f Brain states defined by phase coherency
Time
FC
Brain Regions
Brain Regions
N1
N2
N3
Awake
g Phase coherency states mapped into the two first cordinates of the intrinsic manifold
Sym_N^+
SPD (symmetric and positive definite)

Motivation

SPDNet

original high-dimensional matrix





mapping

Intrinsic low-dimensional matrix

$$Y = \Psi X \Psi^T$$

No constraint on the mapping functions

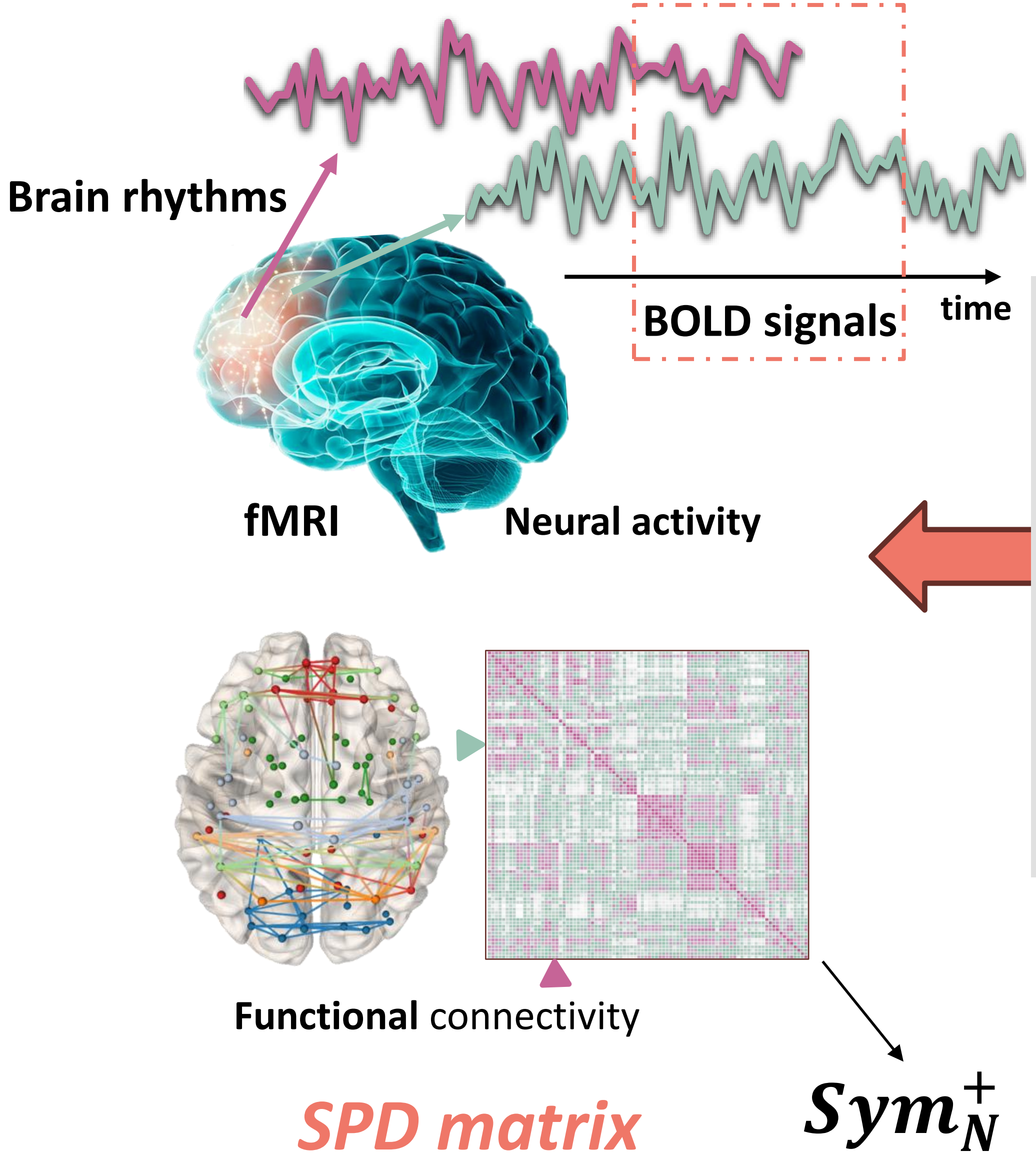
(1) the learned mapping functions **lack explainability**,

(2) such deep model may **demand a relatively large volume of training data**,

(3) adapting a **pre-trained model to a new dataset** may pose challenges.

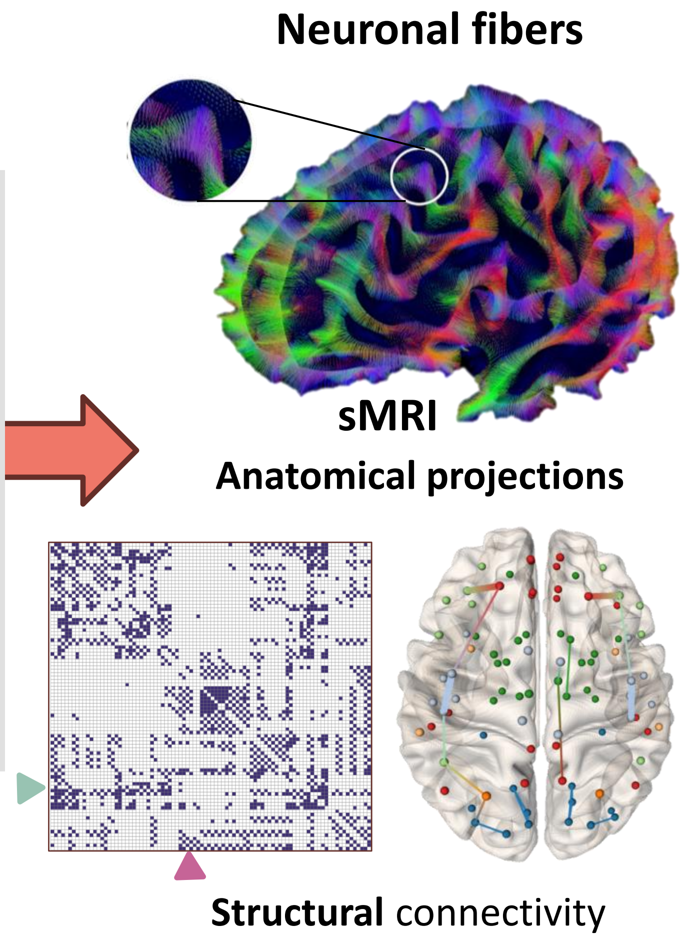
independently

Motivation



How does the **structural foundation** of the brain shape its **dynamic functional** activities?

How does the **coupling between SC and FC** contribute to the emergence of cognition and behavior?



Preliminaries

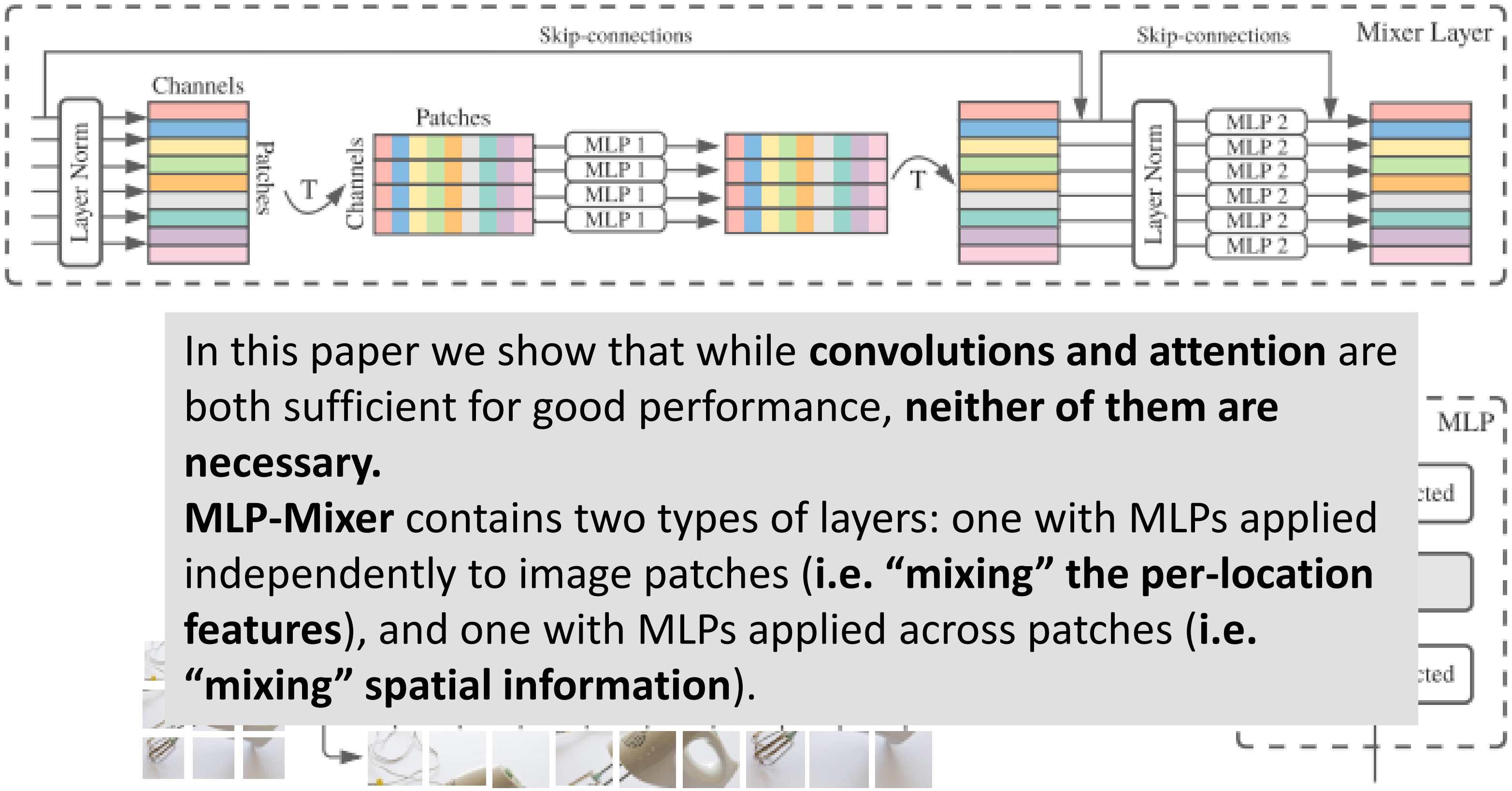
Canonic

$\mathbf{X}_l =$

$\mathbf{X}_{l-1}$

$\mathbf{\Psi}_l \in$

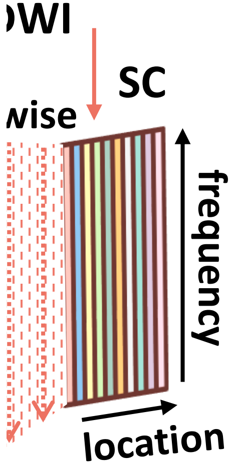
$\mathbf{X}_l \in$



In this paper we show that while **convolutions and attention** are both sufficient for good performance, **neither of them are necessary.**

MLP-Mixer contains two types of layers: one with MLPs applied independently to image patches (**i.e. "mixing" the per-location features**), and one with MLPs applied across patches (**i.e. "mixing" spatial information**).

Figure 1: MLP-Mixer consists of per-patch linear embeddings, Mixer layers, and a classifier head. Mixer layers contain one token-mixing MLP and one channel-mixing MLP, each consisting of two fully-connected layers and a GELU nonlinearity. Other components include: skip-connections, dropout, and layer norm on the channels.



$\mathcal{L} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^{\top}$

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contex

velet)

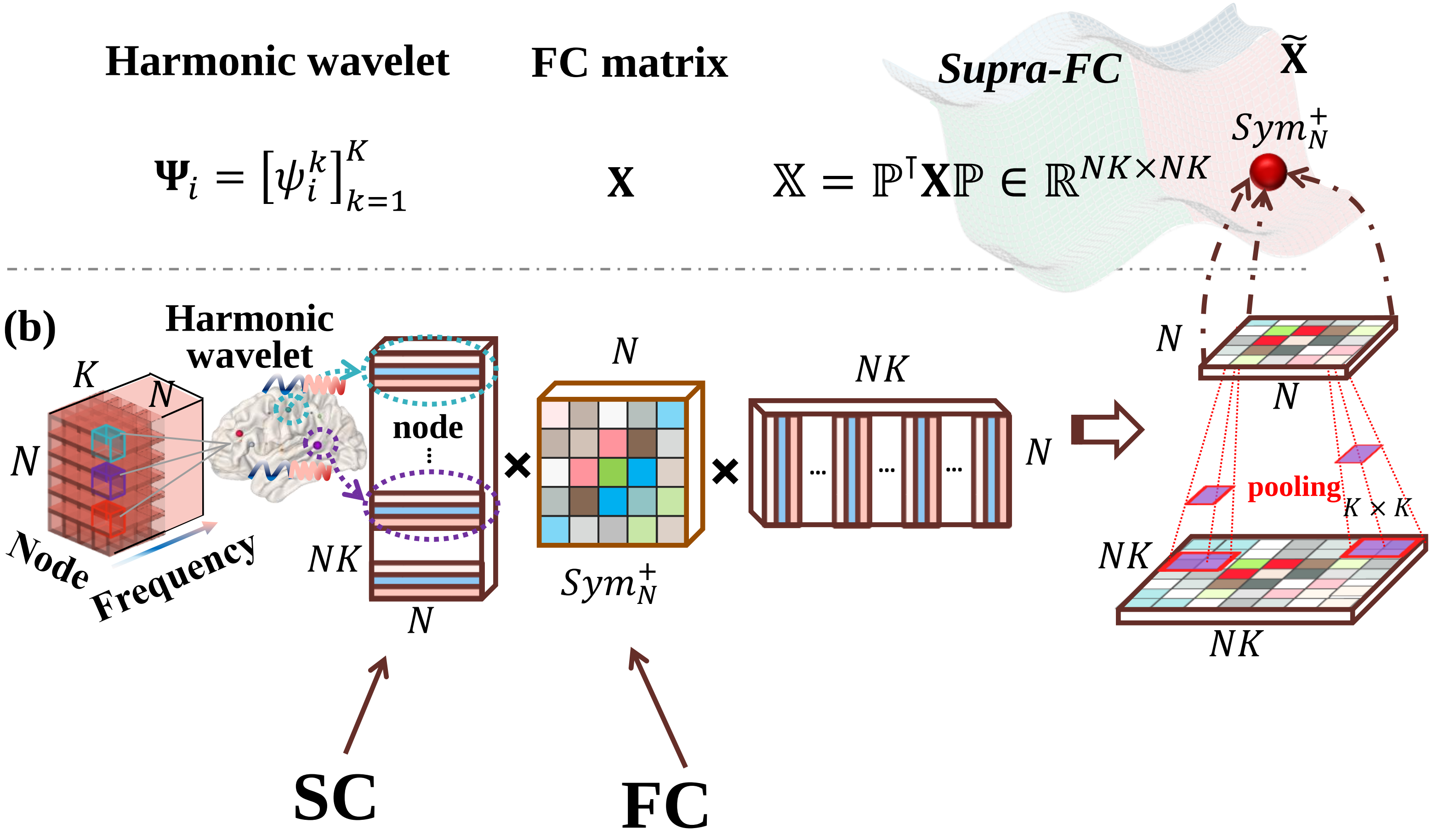
ons:

frequency and location.

Methods

New Mapping Function on Riemannian Manifold Constrained by Graph Scattering Transforms

$$\tilde{\mathbb{X}} = \begin{bmatrix} max(\mathbb{X}_{11}) & max(\mathbb{X}_{12}) & \cdots & max(\mathbb{X}_{1N}) \\ max(\mathbb{X}_{21}) & max(\mathbb{X}_{22}) & \cdots & max(\mathbb{X}_{2N}) \\ \vdots & \vdots & \ddots & \vdots \\ max(\mathbb{X}_{N1}) & max(\mathbb{X}_{N2}) & \cdots & max(\mathbb{X}_{NN}) \end{bmatrix}$$



We seek to use the pooling operation to **regain the SPD property** while reducing the dimensionality.

The ***MLP-Mixer*** architecture of positive mapping $\mathbb{P}^{\intercal}\mathbf{X}\mathbb{P}$ on **Riemannian manifold** can be formulated as:

$$\begin{cases} \mathbb{X}_{l+1} = \sigma_{row}\{\mathrm{LN}[\sigma_{column}(\mathrm{LN}(\mathbb{P}^{\intercal}\tilde{X}_l))\mathbb{P}]\} \\ \tilde{X}_{l+1} = \text{max-pooling}(\mathbb{X}_{l+1}) \\ \tilde{X}_{l+1} = \frac{1}{2}(\tilde{X}_{l+1} + (\tilde{X}_{l+1})^{\intercal}) \end{cases}$$

Methods

DeepHoloBrain: A Proof-of-Concept Approach to Explore the Enigma of Neural Dynamics Through the Insight of Deep Model

Scattering Transforms:

Stepping Stone between Deep Learning and SC-FC Couplings.

FC matrix $\mathbf{X}$ encodes pairwise correlations between two time course of neural activities

$\mathbf{X} = \mathbf{H}\mathbf{H}^{\intercal}$

$h_i = [h_i(1), h_i(2) \ldots h_i(T)]$

Harmonic wavelets $\mathbb{P}$ we apply harmonic wavelets on FC matrix $\mathbf{X}$

Augmented time course matrix $\boldsymbol{Z}$

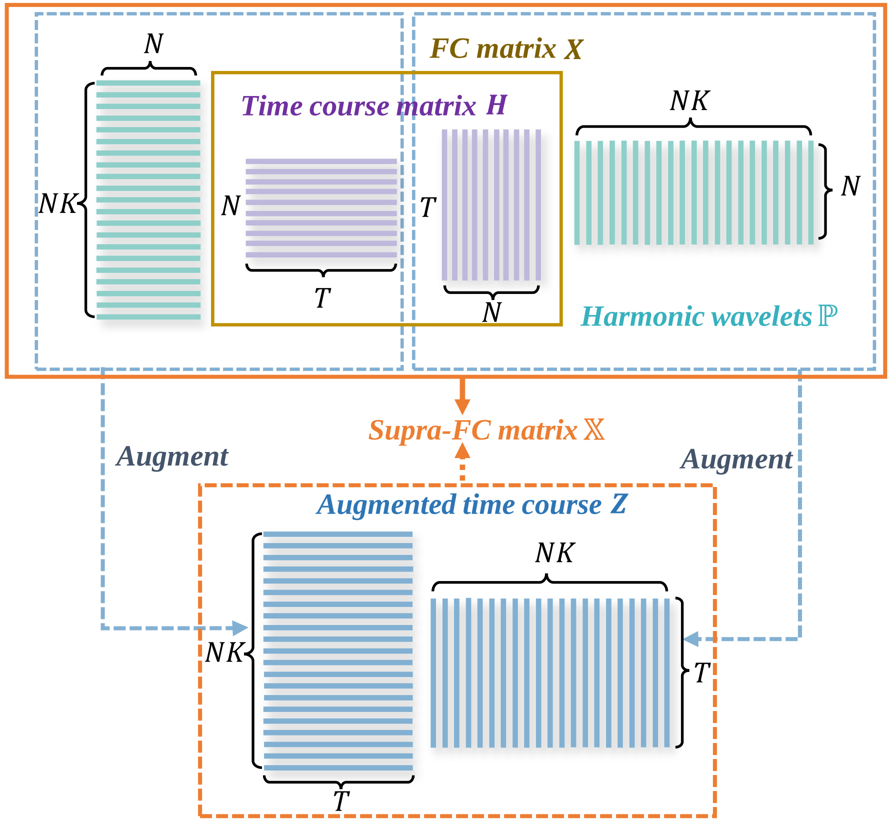
We study each column in $\mathbf{H}$, which is the whole-brain snapshot of neural activities $h^t \in \mathbb{R}^N$ at time t

We first apply harmonic wavelets $\mathbb{P}$ to each snapshot h^t, yielding an augmented time course matrix

$Z = \mathbb{P}\boldsymbol{H} \in \mathbb{R}^{NK \times T}$

Supra-FC matrix $\mathbb{X} = \mathbf{Z}\mathbf{Z}^{\intercal}$

After that, the inner project of $\boldsymbol{Z}$ and $\boldsymbol{Z}^{\intercal}$ results in the *Supra-FC matrix* $\mathbb{X}$



$\mathbb{X} = \mathbf{Z}\mathbf{Z}^{\intercal}$

records **interference patterns** generated by two SC-modulated neural activity signals.

Neuroscience Insights.

The **oscillation patterns** of each harmonic wavelet ψ_i^k, **constrained by the local topology of structural connectome**, characterize the **frequency-specific neural activities** supported by the underlying neural circuit.

The inner project $\langle \psi_i^k, h^t \rangle$ over time essentially allows us to **modulate the observed neural activity signals with the pre-define bandpass filters**, which gives rise to **coupled neural oscillations** at distinct frequencies.

Results

Table 1. Results on brain task recognition for HCP-Aging dataset.

METHODS	ACCURACY	RECALL	F1-SCORE
SPDNET	0.984± 0.003	0.975± 0.004	0.978± 0.004
CDL	0.976± 0.003	0.962± 0.005	0.966± 0.005
LEML	0.961± 0.022	0.903± 0.039	0.929± 0.036
SPDML	0.944± 0.015	0.908± 0.027	0.920±0.019
AIM	0.952± 0.014	0.9114± 0.016	0.929±0.015
RSR	0.966± 0.005	0.944± 0.010	0.951 ±0.008
DEEPO2P	0.977± 0.004	0.963± 0.006	0.969± 0.005
OURS	**0.995± 0.003***	**0.989± 0.003***	**0.993± 0.003***

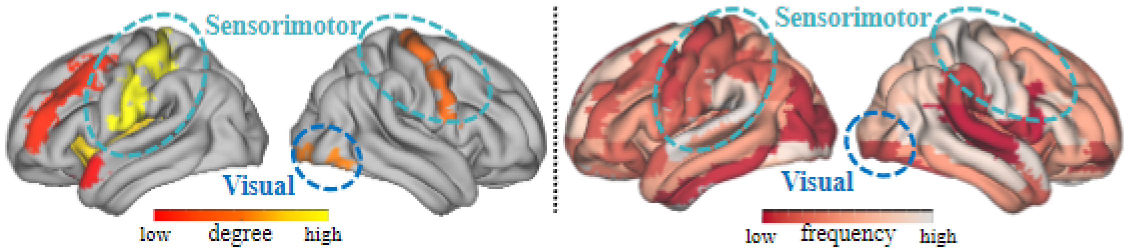


Figure 4. Left: Uncovered anatomical regions (using node-wise attention) for task VISMOTOR and task FACENAME, respectively. Right: Oscillation patterns underlying the more relevant harmonic frequencies for VISMOTOR and FACENAME tasks, revealing task-specific wavelet dynamics.

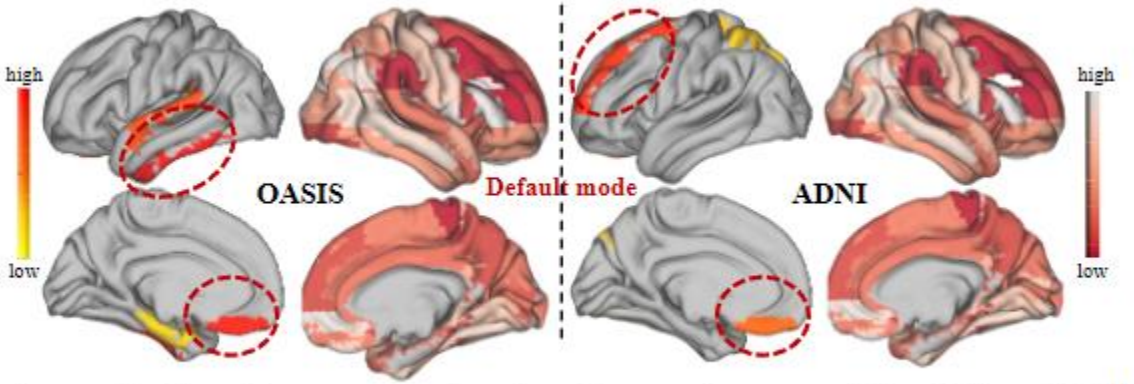


Figure 5. Consistency evaluation for region-specific (1^{st} and 3^{rd} columns) and frequency-specific (2^{nd} and 4^{th} columns) attentions learned from OASIS (left) and ADNI (right).

METHODS	ACCURACY	RECALL	F1-SCORE
SPDNET	0.871± 0.018	0.593± 0.017	0.613± 0.024
CDL	0.827± 0.623	0.570± 0.062	0.581 ±0.047
LEML	0.796± 0.193	0.624± 0.045	0.632± 0.117
SPDML	0.786± 0.148	0.739± 0.038	0.697±0.091
AIM	0.816± 0.098	0.540± 0.043	0.539±0.072
RSR	0.840± 0.020	0.690± 0.020	0.689 ±0.028
DEEPO2P	0.857 ± 0.019	0.684± 0.02	0.675± 0.021
OURS	**0.885±0.017***	**0.740± 0.045***	**0.6974± 0.041***
SPDNET	0.800±0.085	0.670± 0.067	0.627± 0.090
CDL	0.710±0.095	0.500± 0.018	0.415±0.064
LEML	0.704±0.095	0.523±0.019	0.474±0.065
SPDML	0.672± 0.079	0.543± 0.037	0.529± 0.055
AIM	0.708± 0.089	0.500± 0.000	0.413± 0.032
RSR	0.740± 0.106	0.610± 0.059	0.608± 0.080
DEEPO2P	0.760± 0.089	0.614± 0.068	0.625±0.082
OURS	**0.820± 0.071***	**0.625± 0.049***	**0.647±0.079***

Results

Generality as A Pre-trained Model.

One of the critical challenges of deploying computer-assisted diagnosis in clinical routine is **the limited sample size**, especially for disease cohorts

We **pre-train** a regression model based on Montreal Cognitive Assessment (MoCA) score on HCP-A data, and **fine-tune** a classification mode on ADNI data.

	ACCURACY	RECALL	F1-SCORE	PRECISION
SPDNET+	0.7120	0.7120	0.6632	0.7409
CDL+	0.6640	0.5253	0.5168	0.5397
LEML+	0.6080	0.5501	0.5466	0.5462
SPDML+	0.5880	0.5803	0.5581	0.5671
AIM+	0.6160	0.5356	0.5356	0.5356
RSR+	0.6880	0.6880	0.8690	0.4716
DEEPO2P+	0.6960	0.6880	0.5971	0.7369
OURS+	**0.7400***	**0.6103***	**0.6081***	**0.7892***

Thank you!

Q&A