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Predicting the Existence of Dyslexia in Children Using fMRI

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Motivation

Why detect Dyslexia using fMRI?

- Current diagnosis lacks objective criteria.
- Reading disorder is common to many psychiatric and neurological conditions, among them Dyslexia and ADHD. Accurate diagnosis is crucial for proper treatment.
- fMRI provides accurate and consistent results for brain function, and has the potential to discriminate between reading disorders.

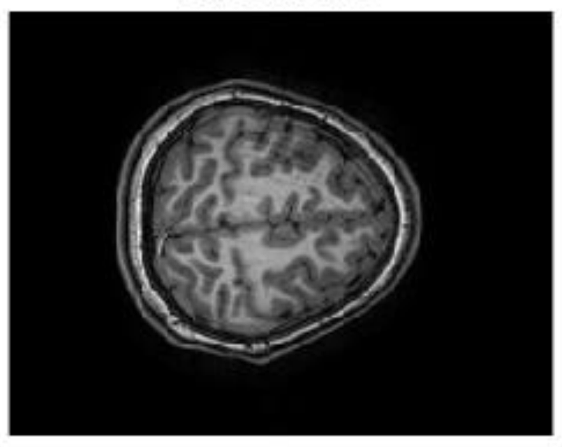
Goals

- Find active brain networks using non-linear algorithms in different patient groups, as basis for identifying differences in brain connectivity.

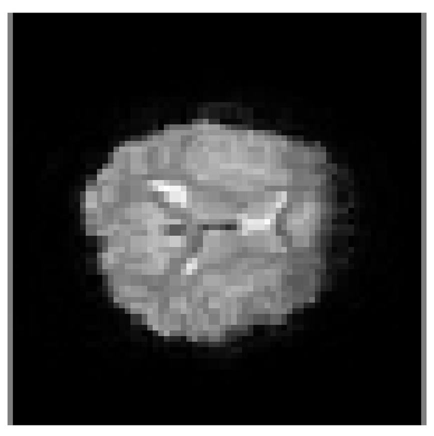
Functional MRI

- fMRI is a neuroimaging technique used to map active brain areas responsible for performed tasks (such as thought, speech, movement, and sensation).
- By measuring blood oxygen level dependent (BOLD) signal changes, fMRI detects active regions of the brain.
- Increasing attention has been paid to how different parts of the brain connect, interact and coordinate with each other to perform a certain kind of cognitive function.

Structural image
slice 200/256



Functional image
slice 15/37, time point 90/180



Our Baseline: Independent Component Analysis

- Assume that the signals are a linear combination of independent components:

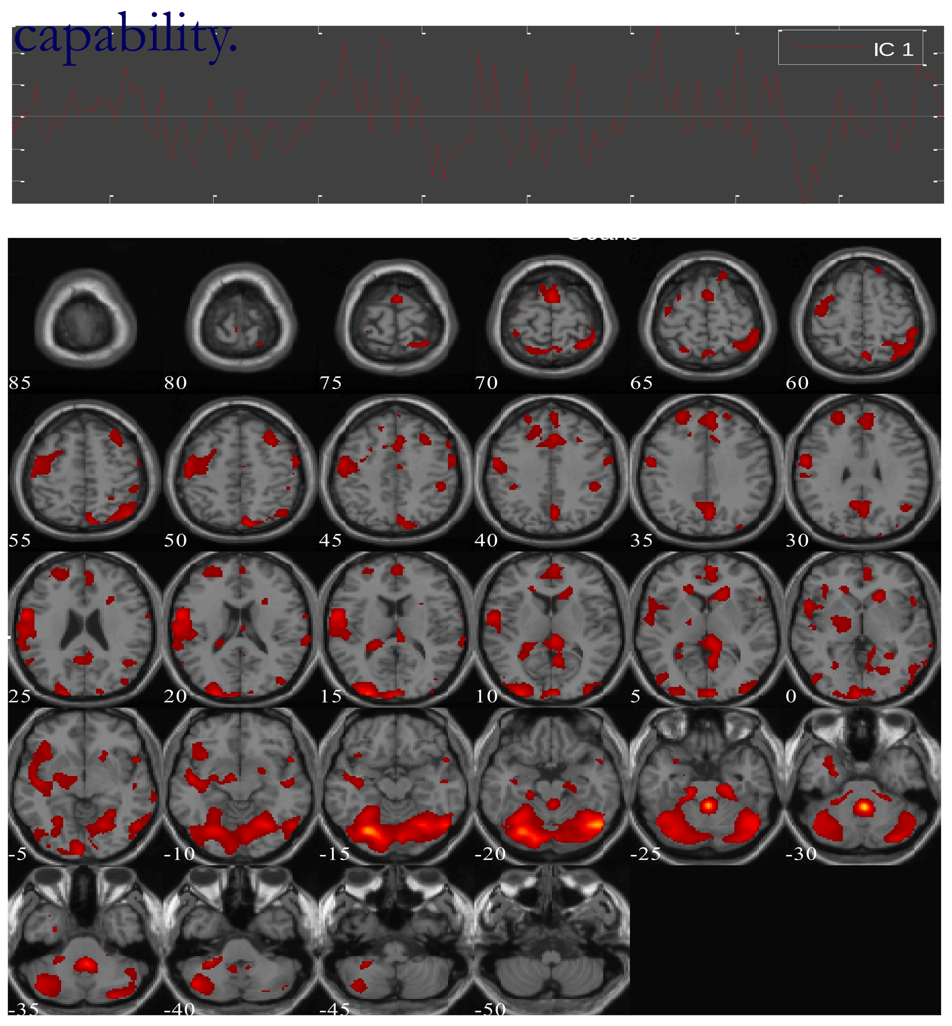
$$\vec{x} = A\vec{s} \qquad s.t \quad P(s_1 \cdots s_n) = \prod_{1}^{n} P(s_j)$$

- ICA finds the independent components $\vec{s}$ and the mixing matrix A
- This is done by maximizing independence measures (kurtosis, negentropy, etc.)

ICA is the leading tool to analyze functional brain activity

Baseline Results

- According to above workflow, we have extracted an independent component, presumably corresponding to a brain network.
- This result will be used to compare future advance to present state capability.



Non Linear Algorithms

Linear algorithms are based on the assumption of linear data mixing. Contrary to the extensive use of linear algorithms like ICA and PCA in the processing of fMRI data, this assumption may not be accurate for brain activity. Studies have observed nonlinearity in resting state fMRI BOLD signals.

For this reason we turned to test nonlinear dimensionality reduction techniques as an alternative to conventional linear clustering algorithms.

Laplacian Eigenmaps

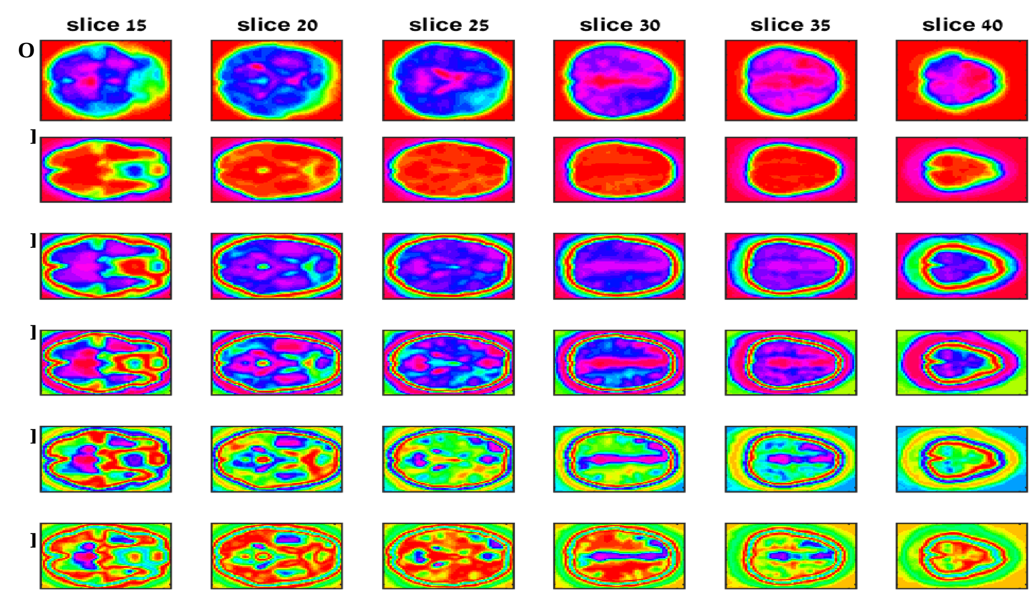
A manifold learning technique that preserves locality in the embedding from high to low dimensional space.

It emphasizes the natural clusters in the data and so it can be helpful for clustering, and indeed it has a strong relation to spectral clustering.

The algorithm:

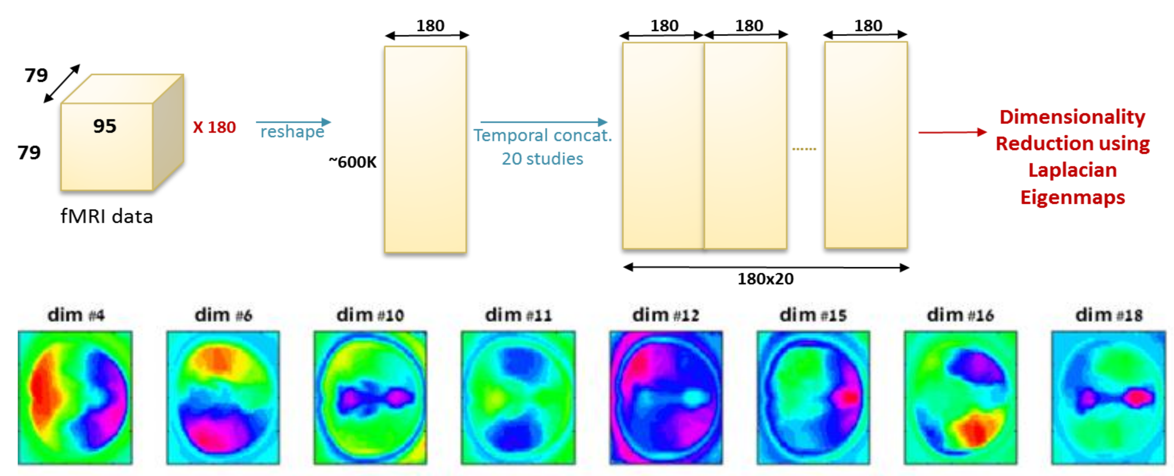
1. Construct a distance graph
2. Apply weights $W_{ij} = exp(-\frac{\|x_i - x_j\|^2}{\sigma^2})$
3. Compute $D = diag(sum(W))$ and $L = D - W$
4. Solve the generalized eigenvector problem $Ly = \lambda Dy$

Single Subject Processing – Too noisy

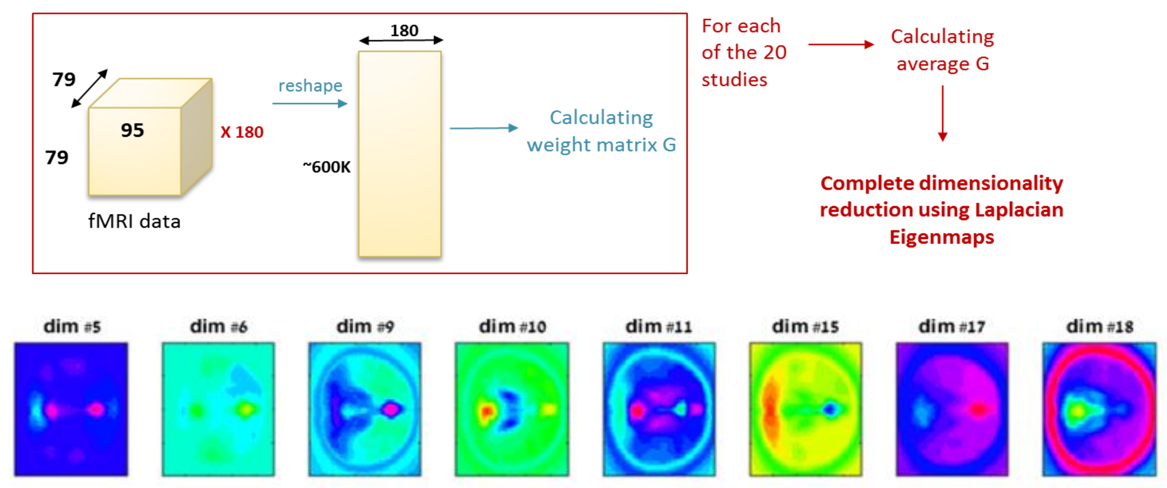


Group Analysis – 2 Approaches

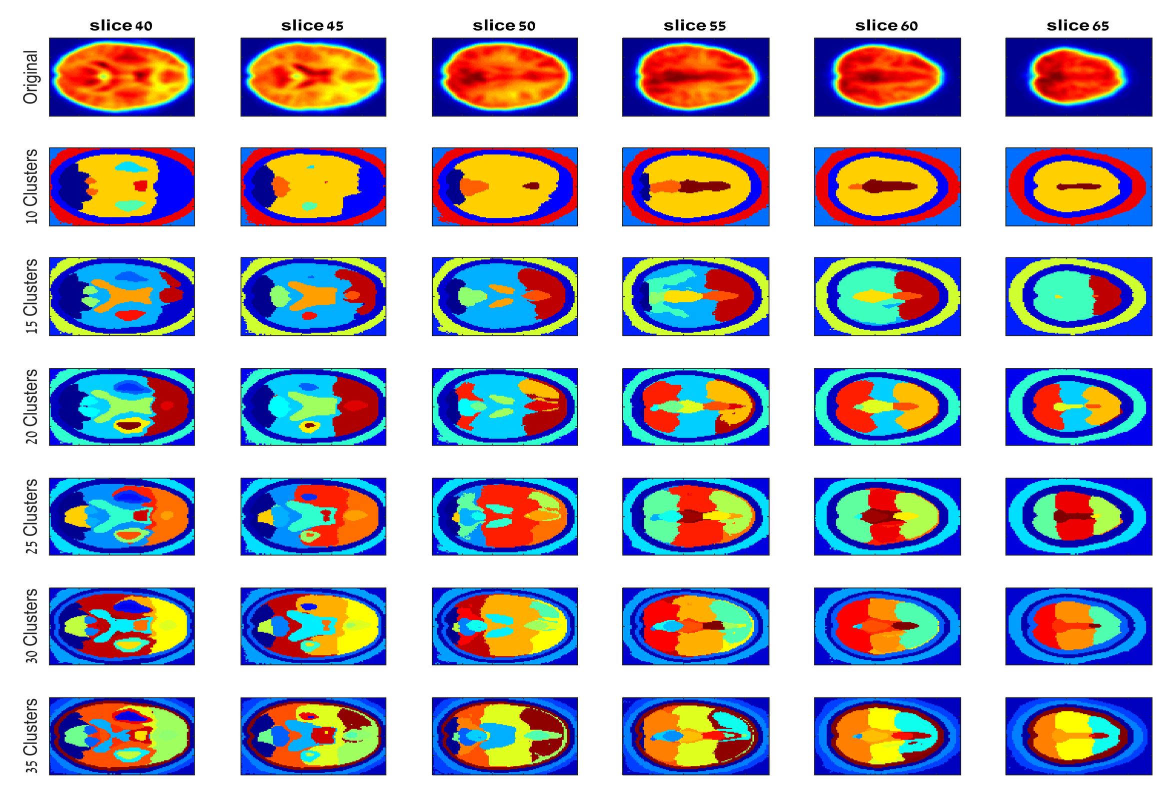
1. Temporal Concatenation



2. Mean Weight Matrix



Mean Weight Matrix: with clustering



Summary

- In this project, we implemented and investigated new unexplored methods for the processing and analysis of fMRI data. Our principal focus was using Laplacian Eigenmaps, a manifold learning technique, in order to analyze and extract significant information from time courses of resting state fMRI scans.
- The results presented demonstrate a clear potential of the proposed methodology for the clinical diagnosis of brain disorders.
- Although the results provided cannot aid in the discrimination between healthy and diagnosed subjects by themselves, they can lay the foundation for additional processing and analysis steps that could fulfil this objective.