

Integration of Network Topological Features and Graph Fourier Transform for fMRI Data Analysis

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Final Project for the M.Sc. Course «Signal Processing for Big Data»
Elective Course for the Ph.D. Programme in Data Science

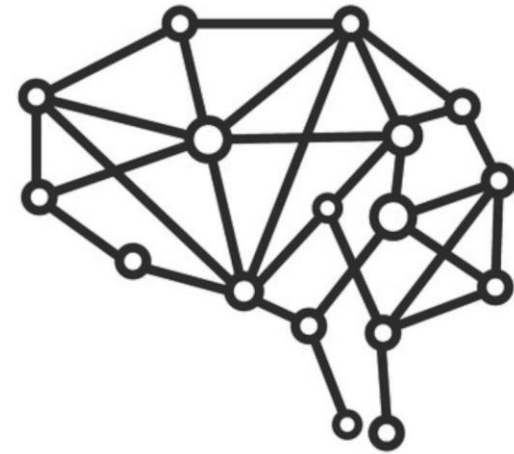
Prof. Sergio Barbarossa

Prof. Paolo Di Lorenzo

Context & Motivations

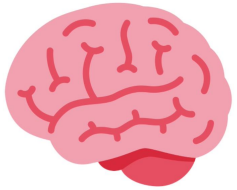
Brain Network

Modeling the human brain as a network is an emerging approach in neuroscience.



Brain Network

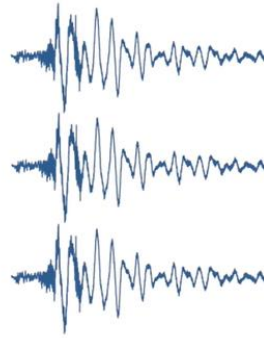
Brain



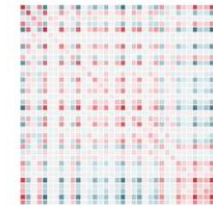
fMRI



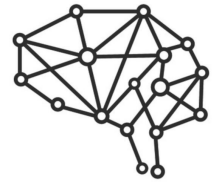
Signals



*Correlation
Matrix*



Network



The Challenge

Given the fMRI scans of patients belonging to 2 different groups, has been proved that the brain network approach can reveal meaningful patterns that help in discriminating the 2 groups.

Can Graph Signal Processing improve this methodologies?

The Answer

YES!

Wang et al. (ISBI 2018) proposed a classification model that exploit features either from the vertex domain and from the frequency domain, getting better results!

Problem Statement

Problem Statement

Input

We are given in input the fMRI scans of patients belonging either to the group A, or to the group B.

Each fMRI scan record the BOLD level, that is the measurement of the release of oxygen by blood, that has been proved to be associated to a functional activation of a specific brain region. Scans are opportunely pre-processed in order to remove noise and correct possible movements of the patient.

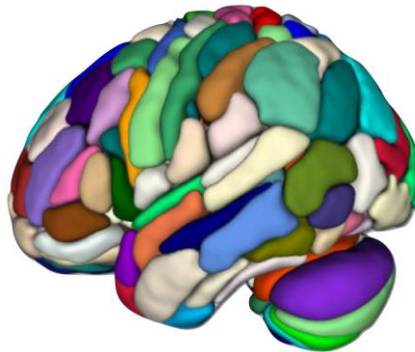


Problem Statement

Input

Then, in order to reduce complexity, it is applied the AAL parcellation. A brain parcellation is a map of the region of the brains, whose aim is to aggregate the high number of signals obtained from the fMRI scan.

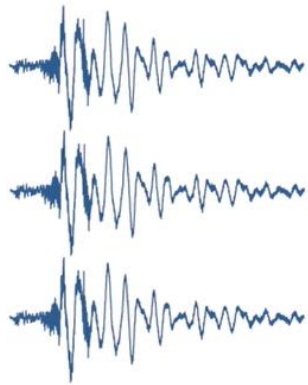
In particular the AAL parcellation contains 116 regions. Hence, the final result of a single fMRI scan is a $116 \times T$ matrix, where T is the period of the scan.



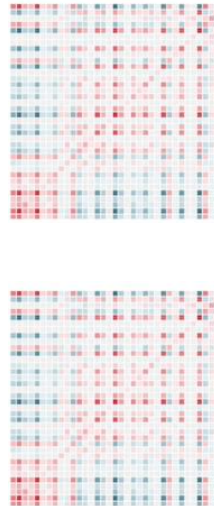
Algorithmic Solution

GSP Track

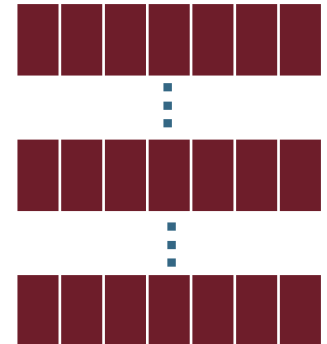
fMRI Scan



Summary Adj.
Matrices



GFT



GSP Track

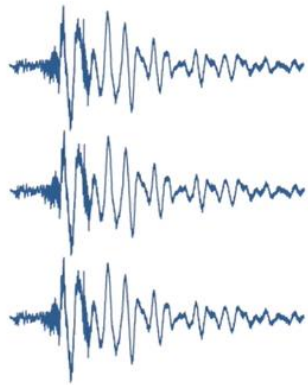
- From the fMRI scan, we compute a **summary adjacency matrix** for each group. In order to do so, we apply an RBF kernel to the matrix $116 \times (TN)$, composed by all the fMRI scans of the N patients of a single group concatenated.
- Each weight in the summary adjacency matrix represent the geodesic distance on the manifold of brain regions with nearby neighbors.

GSP Track

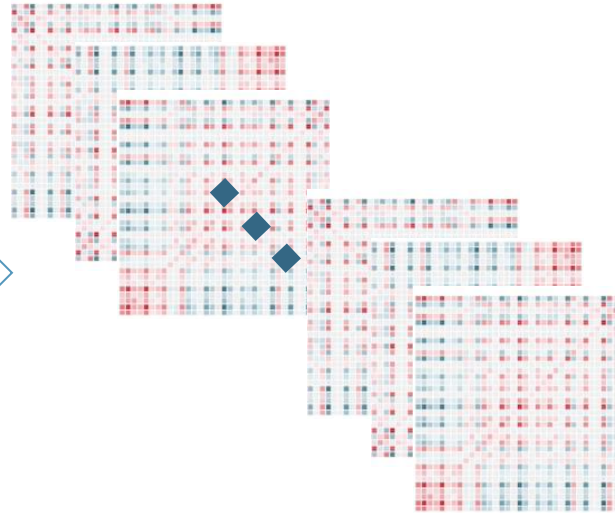
- We consider the fMRI scan as a time-varying graph signal coming from the summary adjacency matrix. Following the approach proposed by Munoz-Barona et al., we summarize the time-varying graph signal to a static graph signal, averaging the signal for each vertex.
- Finally we apply a low-pass filter and compute the GFT for each signal.
- We remind that the GFT of a graph signal is an expansion of the signal in terms of the eigenvector of the Laplacian of the graph.

BN Track

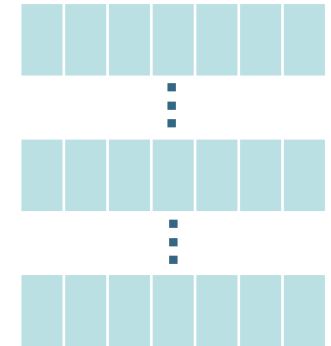
fMRI Scan



Brain Networks



Topological
Network
Features



BN Track

- We build the brain network according the pipeline explained previously.
- We apply a thresholding strategy, widely adopted in literature, to remove noise. In particular we opt for trimming all the edges whose weight below the 80th percentile.

BN Track

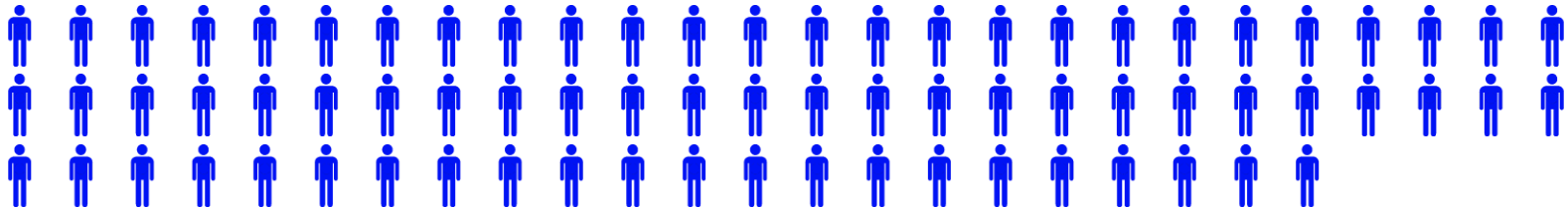
- From those network, we compute for each vertex the following metrics:
- ***Degree***: number of connections a single vertex has in the network.
- ***Betweenness Centrality***: measure of centrality of the vertex, based on the number of shortest paths that goes through itself.
- ***Clustering Coefficient***: measure of segregation, quantified by the number of triangles around the node.

Experimental Results

Dataset

166 Individuals – ABIDE Dataset (<http://preprocessed-connectomes-project.org/abide/>)

74 $Age < 10$



92 $Age \in [20,30]$



Classification Experiment

We employed an SVM model, with a Recursive Feature Elimination pipeline that reduce complexity, and 10-fold cross-validation. We repeated the pipeline 5 times, and reported average of specific metrics.

We trained different models according different combinations of the four type of features available, i.e.:

- Graph Fourier Transform (GFT)
- Degree (DG)
- Betweenness Centrality (BC)
- Clustering Coefficient (CC)

Classification Experiment

Features	Accuracy	Sensitivity	Specificity
GFT+DG+BC+CC	0.82 \pm 0.05	0.83 \pm 0.05	0.87 \pm 0.07
GFT+DG+BC	0.81 \pm 0.07	0.86 \pm 0.09	0.79 \pm 0.12
GFT+DG+CC	0.77 \pm 0.05	0.77 \pm 0.11	0.81 \pm 0.09
GFT+BC+CC	0.69 \pm 0.05	0.93 \pm 0.08	0.67 \pm 0.05
GFT	0.58 \pm 0.08	0.96 \pm 0.04	0.59 \pm 0.06
DG	0.74 \pm 0.06	0.78 \pm 0.08	0.73 \pm 0.12
BC	0.58 \pm 0.09	0.97 \pm 0.02	0.56 \pm 0.09
CC	0.69 \pm 0.07	0.9 \pm 0.07	0.69 \pm 0.12

Alternative Classification Experiment

Maintaining the same setup, we supposed to have limited information about the fMRI data, thus we employed a sampling+reconstruction strategy.

We supposed to have a restricted version of the data, containing the **80% of the nodes' signal**.

We opted for the **alternating projection method** to reconstruct the signal.

We repeated the same classification procedure.

Classification Experiment

Features	Original Signals (Accuracy)	Reconstructed Signals (Accuracy)
GFT+DG+BC+CC	0.82 ± 0.05	0.77 ± 0.09
GFT+DG+BC	0.81 ± 0.07	0.74 ± 0.1
GFT+DG+CC	0.77 ± 0.05	0.74 ± 0.06
GFT+BC+CC	0.69 ± 0.05	0.64 ± 0.09
GFT	0.58 ± 0.08	0.52 ± 0.07

Conclusions

- Employing GSP to in a fMRI classification task proved to be useful when combined with topological features of the underlying brain network.
- Such methodologies proved to be consistent even in a scenario of reduced availability of data, providing a tiny increase of performance.

Future Work

- Such methodology can be easily extended to other case studies relative to human brain (e.g.: control vs condition paradigm)

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