Problem

Given a collection of pairs (X, y) of data X and labels y construct the decision rule $f : X \rightarrow R$. In our case $y \in \{0, 1\}$ is a binary response variable labeling patients belonging to eigher Depression/ No Depression (D/No D), or Depression/Control (D/C) groups of the dataset provided by Solovyov Scientific and Practical Centre for Neuropsychiatry and Skoltech Biomedical Initiative program. The dataset includes 1.5T resting-state functional MRI (rs-fMRI) of the four groups: 25 healthy controls, 25 patients with depression, 25 patients with epilepsy and 25 patients with both depression and epilepsy.

Input data

$X \in R$ 117×117 representing pairwise correlations between time series measuring hemodynamic response of 117 brain regions obtained from raw rs-fMRI data. The number and locations of brain regions of interest was decisevely selected by applying AAL brain atlas to raw 4D (3D + time) rs-fMRI data. Time series have length k equals 130, which corresponds to measuring HRF with a rate of 4 Hz during 9 minutes.

Data processing

I model rs-fMRI multivariate time series as a graph. For each X undirected, weighted graph G(X) is constructed by associating vertices V of the graph with matrix columns (rows), and edges of the graph E from vertex X_i to X_j with the weight w of the edge computed from the value of X_{ij} mapping correlations from interval $[-1, 1]$ to measures of similarity from interval $[0, 1]$ where 1 is complete similarity and 0 is complete dissimilarity. Mapping is done either in injective ($w = \arccos(X_{ij})$) or non-injective manner ($w = 1 - |X_{ij}|$). This graph is fully connected in general. Clique complex K(G(X)) is constructed from the graph, (for simplicity we will further denote it K(X)) by associating every k-clique of the graph G(X) with (k-1)-simplex in the complex K(X).

Classification

Persistence diagram is not a vector, but a multiset of intervals of arbitrary length, so it could not be directly used as a feature to the machine learning algorithms. The solutions are 1) measuring distances between diagrams by means of optimal transport with W_2 and W_∞ (bottleneck) metrics, 2) defining kernels between diagrams – Persistence Scale Space (PSS) kernel, Persistence Weighted Gaussian (PWG) kernel , Sliced Wasserstein (SW) kernel, Persistence Fisher (PF) kernel

Experiments

Results obtained for:

- Pearson correlation matrix

(D/C) accuracy: 0.75