A GENERATIVE-DISCRIMINATIVE BASIS LEARNING FRAMEWORK TO PREDICT AUTISM SPECTRUM DISORDER SEVERITY

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ABSTRACT

We propose a matrix factorisation technique that decomposes the resting state fMRI (rs-fMRI) correlation matrices for ASD patients into a sparse set of representative subnetworks, as modelled by rank one outer products and combined using patient-specific non-negative coefficients. We extend the prior work of [1] by predicting the clinical severity of every patient as a weighted linear combination of the coefficients.

Index Terms— Matrix Factorisation, Basis Learning

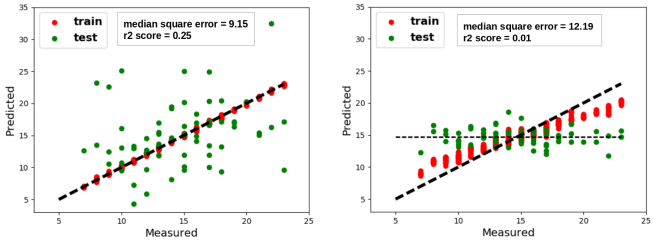
1. BASIS LEARNING FOR CONNECTOMICS

Resting state fMRI allows us to quanify the intrinsic communication patterns in the brain. The goal of our work is to learn a relationship between these neural patterns and an observed behavioural trait such as clinical severity. Our model balances a generative representation of group level effects while simultaneously explaining patient variability across the cohort.

Correlation matrices $\Gamma_n \in \mathcal{R}^{P\times P}$ for each patient are calculated from the average time courses of P predefined atlas regions. The severity scores $\{y_n\}$ for N patients are stacked into a vector $Y \in \mathcal{R}^N$. The basis subnetworks $\{b_i\}$, common to the set of patients, are concatenated into the basis matrix B. Columns of $C \in \mathcal{R}^{K\times N}$ are the patient-wise network coefficients for the K networks in B. The coefficients $\{c_n\}$ are further weigthed by $W \in \mathcal{R}^K$ to estimate a severity score.

$$\underset{B,C,W}{\arg\min} \sum_n ||\Gamma_n - B\mathbf{diag}(c_n)B^T||_F^2 + \lambda||C^TW - Y||_2^2$$

We impose an ℓ_1 sparsity penalty on the columns of B, while quadratic regularisers are added for C and W. A non-negativity constraint $c_{k,n} \geq 0$ over the network coefficients is included. This joint optimisation problem over $\{B,C,W\}$ is solved by an alternating minimisation strategy whereby, gradient descent is performed over B, C is updated using N quadratic solvers, and the closed form solution for W is computed sequentially at every iteration until global convergence.



(a) Proposed model (b) Baseline

Fig. 1. Performance of Autism Diagnostic Observation Schedule (ADOS) score prediction by a) Our model ($K = 8$) b) kernel PCA (rbf kernel, $\beta = 0.01$) and Random Forest Regression on the correlation features. Results are obtained via ten fold cross validation.

2. RESULTS

Rs-fMRI scans for 66 ASD patients were collected and preprocessed using the pipeline in [2]. Average time courses are extracted using the Automated Anatomical Labelling (AAL) atlas. As a baseline, we present the prediction results using kernel PCA for dimensionality reduction of the rsfMRI correlations and Random Forest regression to learn the clinical severity. Baseline predictions on the held out data track the mean severity of the population (black line in Fig.1(b)). In contrast, our method identifies meaningful co-activation patterns in the brain through a learnt basis; these coefficients intelligently map to the behavioural data viewpoint.

3. REFERENCES

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