Gender classification and manifold learning on functional brain networks

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How to compare brain networks?

Richiardi and Ng (2013)
Brain networks as SPD matrices

• Brain networks derived from correlation analysis of fMRI data can be characterized by symmetric positive semi-definite matrices

• Sparse estimators impose simple models and provide good fit to the data (GLASSO algorithm)
Recovering connectivity structure

Original connectivity network

Sparse connectivity network $\alpha = 0.2$
Riemannian manifolds

- Covariances do not conform to Euclidean geometry but rather form a Riemannian manifold.
- In the manifold setting, a SPD matrix can be represented as an element in a vector space.
- Convenient computations with eigenvalue decomposition.

\[ P = U \, \text{diag} (\sigma_1, \ldots, \sigma_n) \, U^T \]

\[ \expm(P) = U \, \text{diag} (\exp(\sigma_1), \ldots, \exp(\sigma_n)) \, U^T \]

\[ \logm(P) = U \, \text{diag} (\log(\sigma_1), \ldots, \log(\sigma_n)) \, U^T \]
Log-Riemannian manifold

\[ \log_p : M \rightarrow T_p(M) \]

\[ \exp_p : T_p(M) \rightarrow M \]
Dimensionality reduction

• Keep PCs that explain 98% of the variance in training set
Dataset

- HCP data
- 2 rfMRI sessions (30min each)
- 100 subjects (46 male, 54 female)
- Pre-processed fMRI data
- Normalized timeseries to 0 mean and standard deviation 1

- How are the nodes defined?
  - Each node corresponds to a ROI from a parcellation scheme
- What is the representative timeseries?
  - Region average timeseries
- How are the edge weights defined?
  - Pearson’s correlation coefficient
- Subject-level analysis
Anatomical Parcellations

- Desikan-Killiany atlas
  \textit{(Desikan et al., NeuroImage 2006)}
  - 35 gyral based regions of interest
  - Based on MRI scans of 40 subjects

- Destrieux atlas
  \textit{(Fischl et al., Cerebral Cortex 2004)}
  - 75 regions of interest per hemisphere
  - Based on probabilistic information of a manually annotated training set
Functional Parcellations

- Three-layer \textit{(Arslan and Rueckert, MICCAI 2015)}
  - Three layer parcellation framework, each targeting a specific problem
- Normalized cuts \textit{(Craddock et al., HBM 2012)}
  - Spatially constrained spectral clustering approach for group clustering
- Joint spectral decomposition \textit{(Arslan et al., IPMI 2015)}
  - Generating group-wise and single-subject parcellations from a joint graphical model
- Region growing \textit{(Blumensath, NeuroImage 2013)}
  - Region growing technique followed by hierarchical clustering
Framework evaluation

- Two different sets of networks based on the two different fMRI sessions
- Check whether networks from the subject lie closer to each other in Riemannian rather than Euclidean space

<table>
<thead>
<tr>
<th>Parcellation method</th>
<th>Number of parcels (per hemisphere)</th>
<th>Euclidean setting</th>
<th>Riemannian setting</th>
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</table>
Gender classification (Riemannian space)

Gender classification accuracy for 20-fold cross validation

Classification accuracy

# parcels per hemisphere

- JOINT
- 3LAYER
- RGHC
- NCUT
- Random
- Desikan-Killiany
- Destrieux

- 35 parcels
- 50 parcels
- 75 parcels
- 100 parcels
- 150 parcels
Conclusions

• Riemannian framework picks up networks generated from the same subject more accurately than Euclidean setting
• Functional parcellations (and especially the 3LAYER one) outperform the anatomical parcellations in the same task
• Random parcellations perform equivalently well due to more evenly sized parcels
• Differences between the two genders are not significant, but still better than Euclidean setting
• More parcels do not guarantee higher discriminative power
• Framework limited by correspondence between network nodes
Thank you