# Gender classification and manifold learning on functional brain networks

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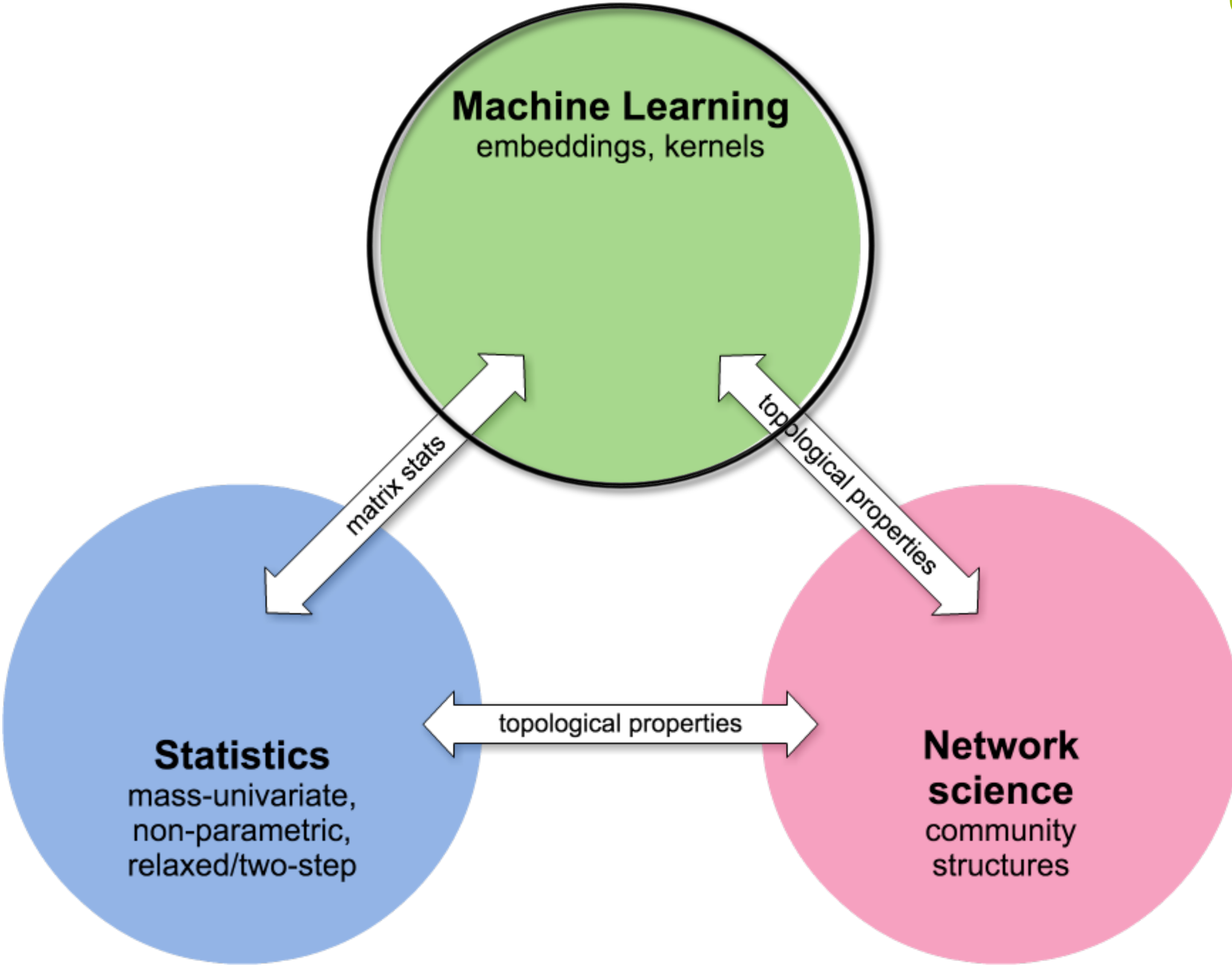
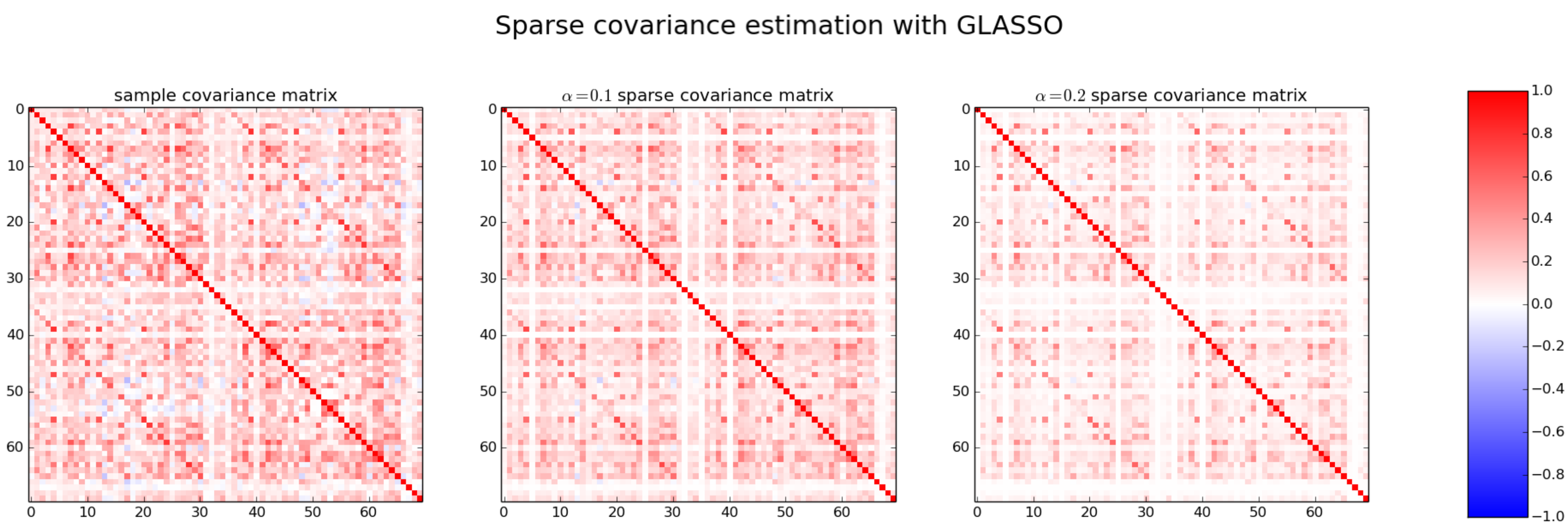
# How to compare brain networks?



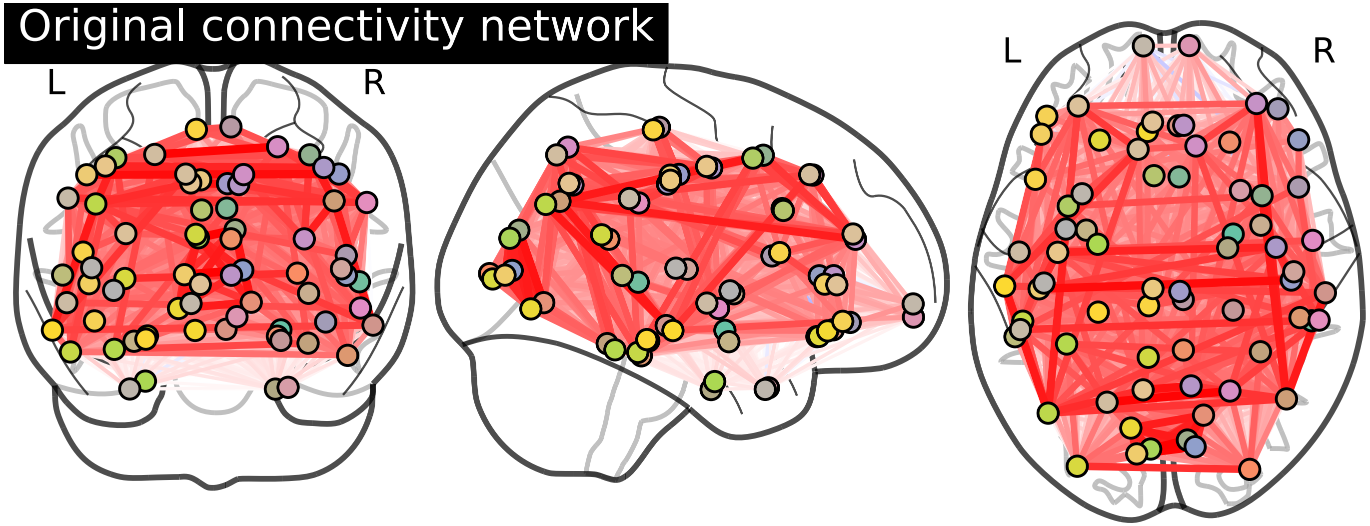

Richiardi and Ng (2013)

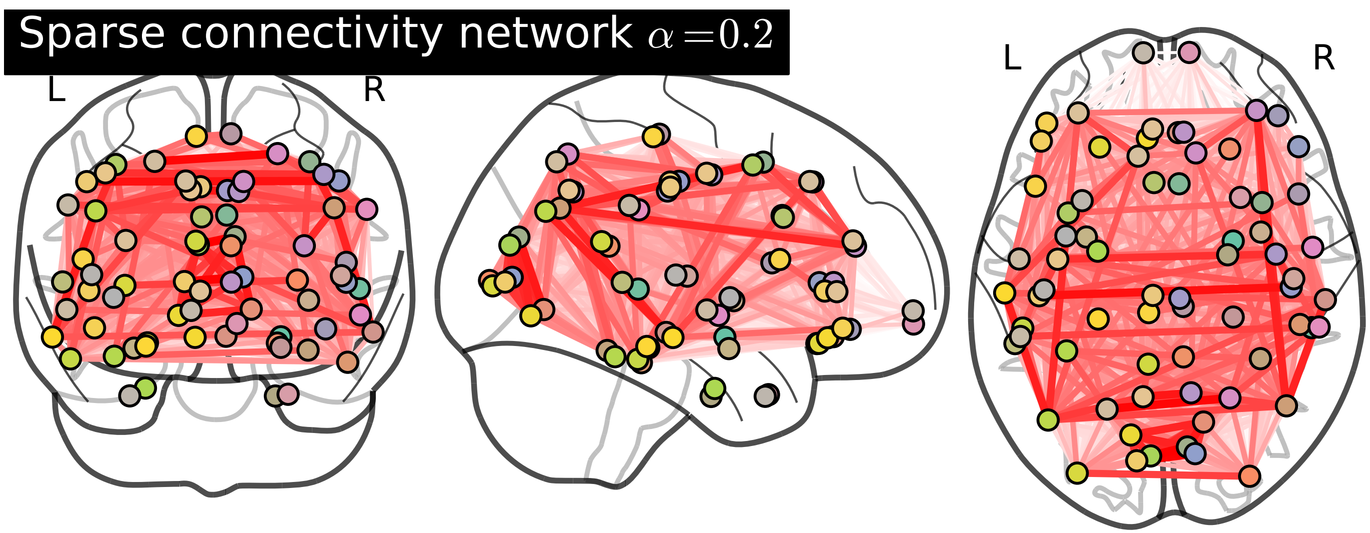
# Brain networks as SPD matrices

- 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



# Riemannian manifolds

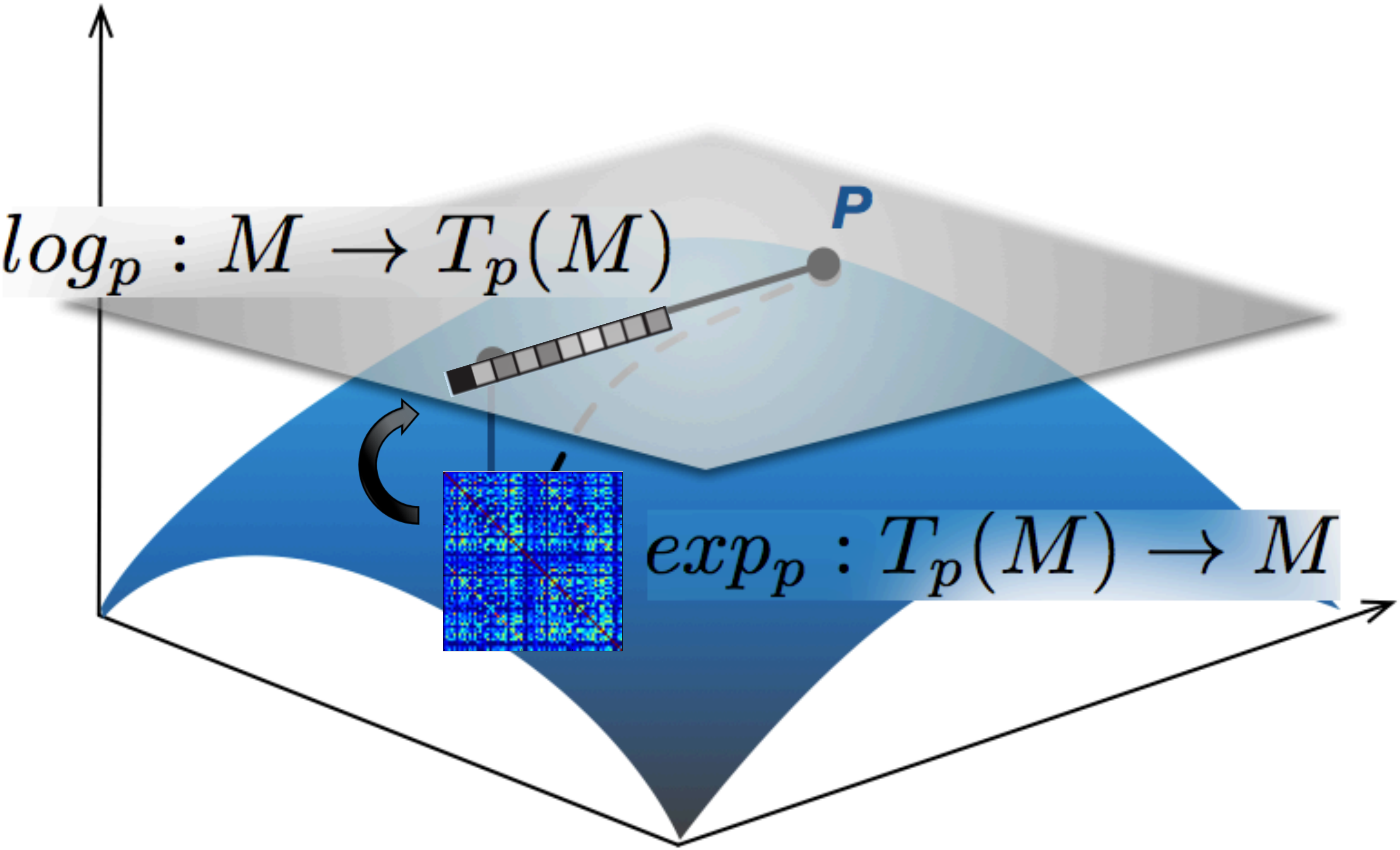
- Covariances do not conform to Euclidean geometry but rather form a Riemannian manifold
- In the manifold setting, a SPD matrix can be represented as an element in a vector space
- Convenient computations with eigenvalue decomposition

$$\mathbf{P} = \mathbf{U} \operatorname{diag}(\sigma_1, \ldots, \sigma_n) \mathbf{U}^T$$

$$\operatorname{expm}(\mathbf{P}) = \mathbf{U} \operatorname{diag}(\exp(\sigma_1), \ldots, \exp(\sigma_n)) \; \mathbf{U}^T$$

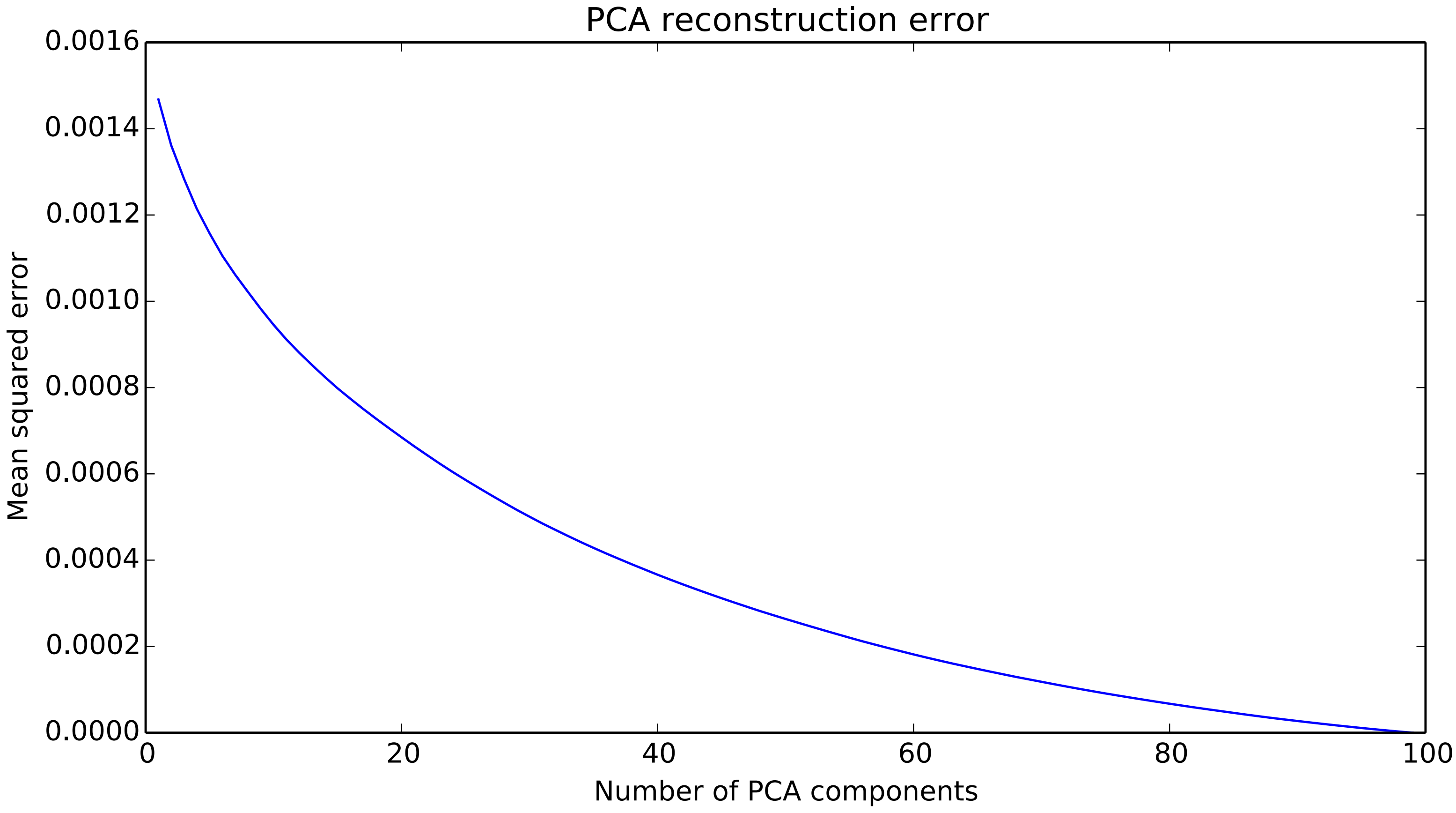
$$\operatorname{logm}(\mathbf{P}) = \mathbf{U} \operatorname{diag}(\log(\sigma_1), \ldots, \log(\sigma_n)) \; \mathbf{U}^T$$

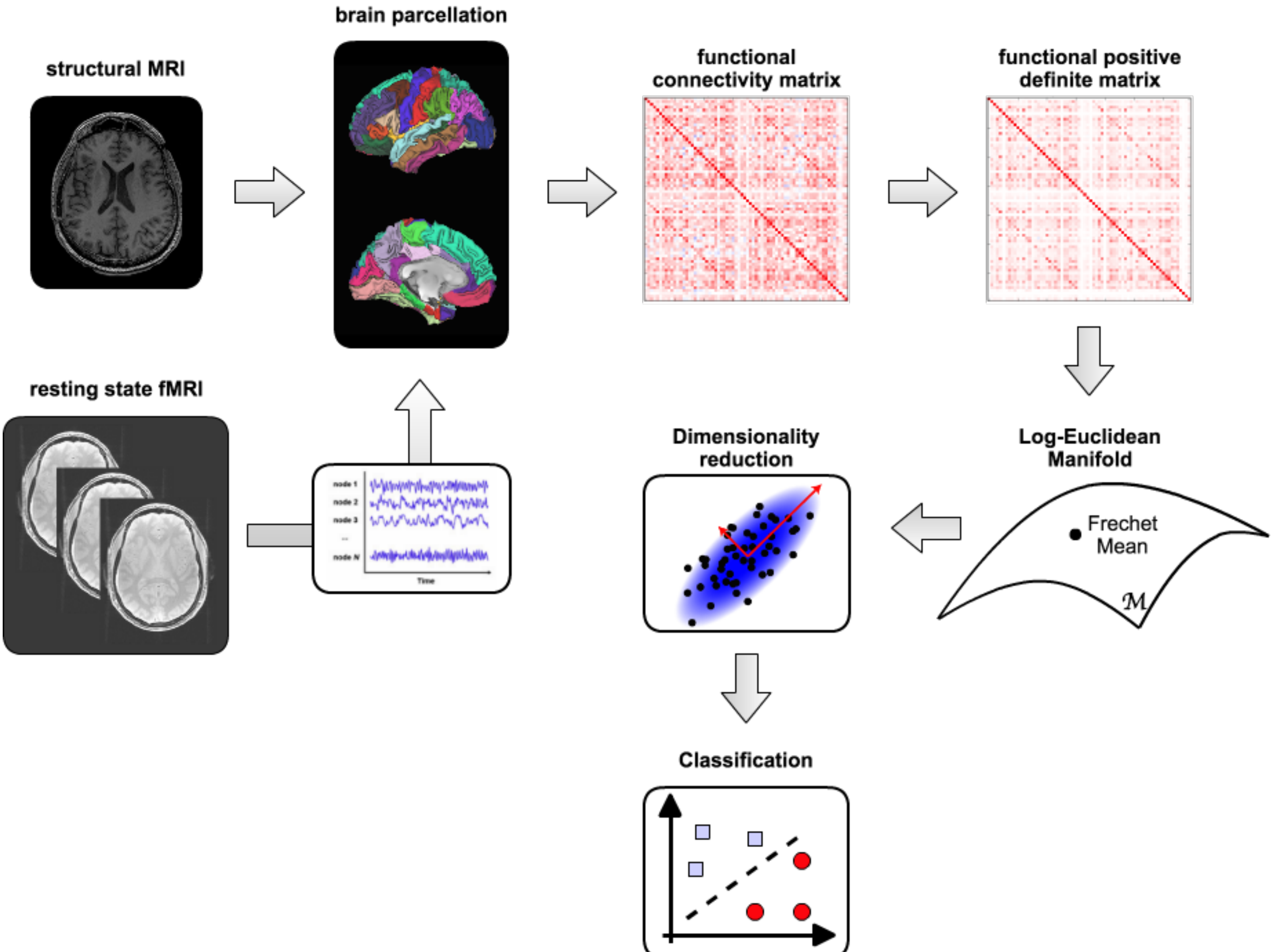
# Log-Riemannian manifold



# Dimensionality reduction

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




structural MRI
brain parcellation
functional
connectivity matrix
functional positive
definite matrix
resting state fMRI
node 1
node 2
node 3
node N
Time
Dimensionality
reduction
Log-Euclidean
Manifold
Frechet
Mean
$\mathcal{M}$
Classification

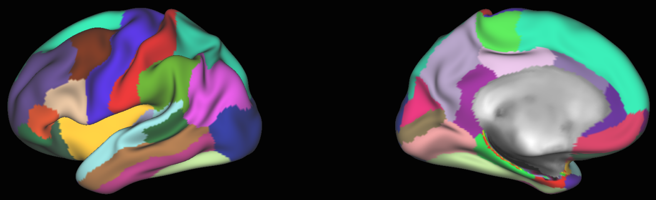
# Dataset

- 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

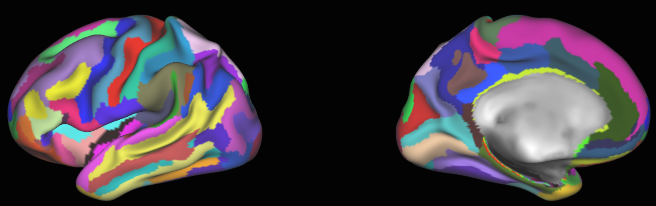
- How are the nodes defined?
  - Each node corresponds to a ROI from a parcellation scheme
- What is the representative timeseries?
  - Region average timeseries
- How are the edge weights defined?
  - Pearson's correlation coefficient
- Subject-level analysis

# Anatomical Parcellations

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

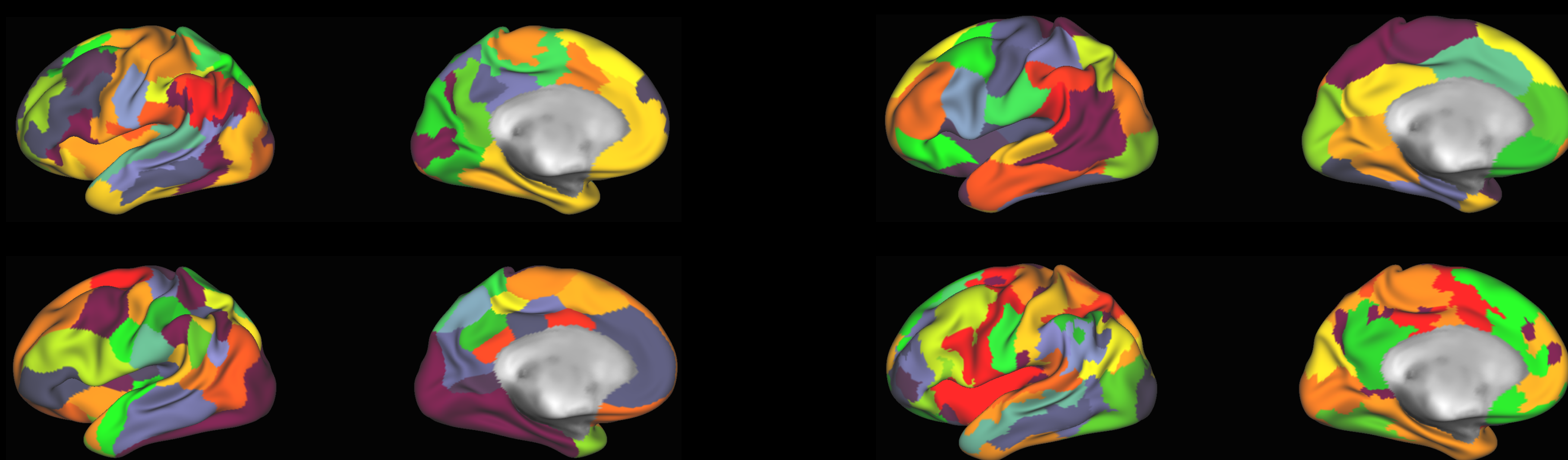


- Destrieux atlas
  (*Fischl et al., Cerebral Cortex 2004*)
- 75 regions of interest per hemisphere
- Based on probabilistic information of
  a manually annonated training set



# Functional Parcellations

- Three-layer (*Arslan and Rueckert, MICCAI 2015)*
  - Three layer parcellation framework, each targeting a specific problem
- Normalized cuts (*Craddock et al., HBM 2012)*
  - Spatially constrained spectral clustering approach for group clustering
- Joint spectral decomposition (*Arslan et al., IPMI 2015*)
  - Generating group-wise and single-subject parcellations from a joint graphical model
- Region growing (*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

| Parcellation method | Number of parcels (per hemisphere) | Euclidean setting | Riemannian setting |
|---|---|---|---|
| *DESIKAN-KILLIANY* | 35 | 0.54 | 0.85 |
| *DESTRIEUX* | 75 | 0.70 | 0.94 |
| *3-LAYER* | 30 | 0.99 | 1.00 |
| | 35 | 1.00 | 1.00 |
| | 50 | 1.00 | 1.00 |
| | 100 | 1.00 | 1.00 |
| *NCUT* | 50 | 0.95 | 1.00 |
| *RG-HC* | 50 | 0.98 | 1.00 |
| | 100 | 0.97 | 1.00 |
| *RANDOM* | 35 | 0.95 | 1.00 |
| | 50 | 0.95 | 1.00 |
| | 100 | 0.97 | 1.00 |

# Gender classification (Riemannian space)

# 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