Large-scale functional-connectivity graphical models for individual subjects using population prior

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Network inference

Gaussian Graphical models

- Generative model of the signal
- Interaction between regions estimated by partial correlation
- Amounts to covariance estimation

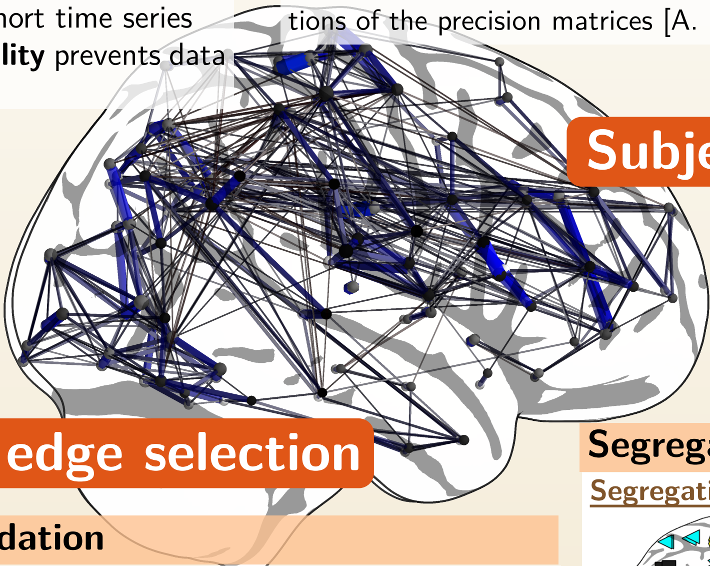
An estimation problem

- Many brain regions, short time series
- **Inter-subject variability** prevents data accumulation

ℓ_{21} penalization for inverse covariance

$$\left(\hat{\mathbf{K}}^{(s)}_{\ell_{21}}\right)_{s=1..S} = \underset{\mathbf{K}^{(s)}\succ 0}{\operatorname{argmin}} \sum_{s=1}^{S} \left(\operatorname{tr}(\mathbf{K}^{(s)}\,\hat{\Sigma}^{(s)}_{\text{sample}}) - \log\det \mathbf{K}^{(s)}\right) + \lambda \sum_{i\neq j} \|\mathbf{K}^{(\cdot)}_{ij}\|_2$$

- **Joint sparsity**: pattern shared in population (similar to group-lasso) $\sum_{i\neq j} \|\mathbf{K}^{(\cdot)}_{ij}\|_2 = \sum_{i\neq j} \sqrt{\sum_{s=1}^{S} (\mathbf{K}^{(s)}_{ij})^2}$
- Convex optimization with cyclical coordinate descent on Choleski decompositions of the precision matrices [A. Rothman, 2008]



Subject-level edge values

Atlas used: poster 335

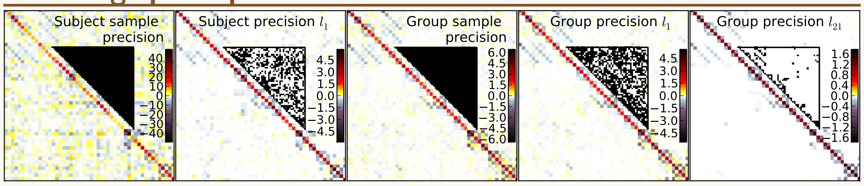
Group-level edge selection

Experimental validation

Use a full-brain atlas to extract time-series

- Probabilistic atlas of anatomical structures (poster 335)
- 137 cortical and sub-cortical regions

Resulting sparse precision matrices



Cross validation results

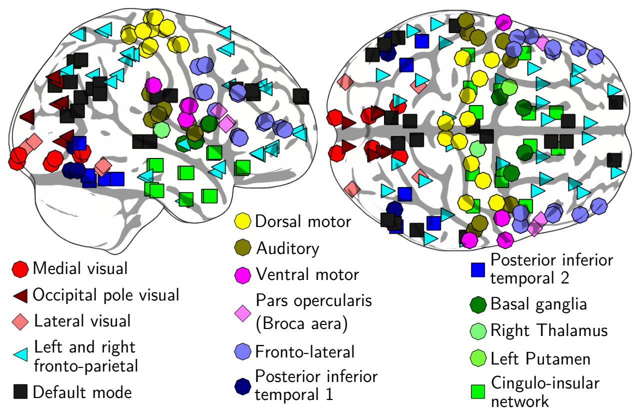
Comparison with other covariance estimation method:

- LW = Ledoit-Wolf: non-sparse shrinkage
- ℓ_1 = Normal sparse inverse covariance

	Using subject data				Uniform group model				
	MLE	LW	ℓ_2	ℓ_1	MLE	LW	ℓ_2	ℓ_1	ℓ_{21}
Generalization score	-57.1	33.1	38.8	43.0	40.6	41.5	41.6	41.8	45.6
Filling factor	100%	100%	100%	45%	100%	100%	100%	60%	8%
Communities	6	5	5	9	9	8	7	9	16
Modularity	.07	.07	.12	.25	.23	.23	.18	.32	.60

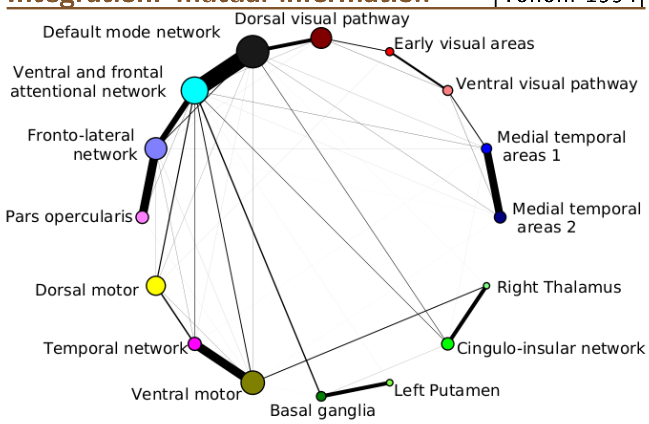
Segregation into functional networks

Segregation: graph communities [Bullmore, 2009]



- **Modularity**: partitioning the graph in functional *communities* to maximize the ratio of connections inside/across clusters
- Graph cut algorithm similar to normalized cuts
- Communities of sparse (ℓ_{21}) graphs separate functional networks

Integration: mutual information [Tononi 1994]



Reference:

G. Varoquaux *et al.*, Brain covariance selection: better individual functional connectivity models using population prior, Adv. NIPS 2010

http://books.nips.cc/nips23.html