Whole brain effective connectivity from fMRI data

Andrea Insabato

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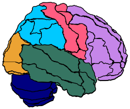
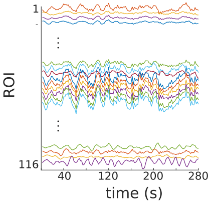
Universitat Pompeu Fabra Barcelona
CBC Center for Brain and Cognition
Columbia University The Italian Academy for Advanced Studies in America
Columbia University

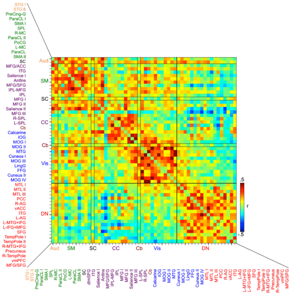
Whole brain connectivity



- Whole brain is divided in ROIs (parcellation)
- Average activity in each ROI
- Connectivity between ROIs



Functional Connectivity (FC)



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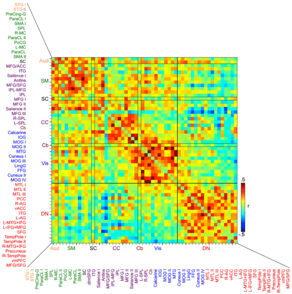

- Pearson correlation between ROIs

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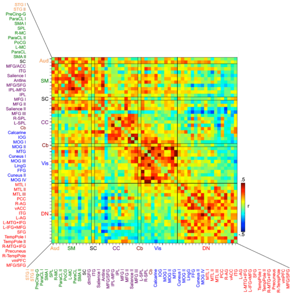

- Pearson correlation between ROIs
- Dense

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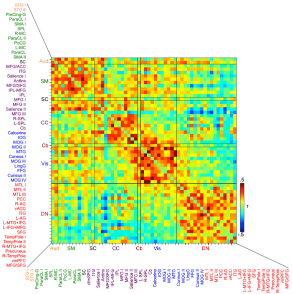
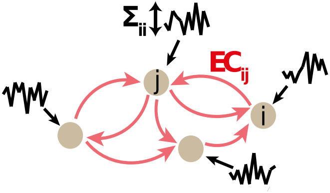


- Pearson correlation between ROIs
- Dense
- Symmetric: no directionality of interactions

Effective Connectivity (EC)



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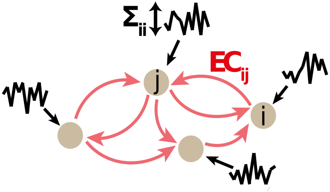
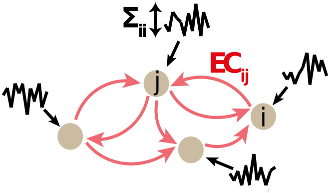


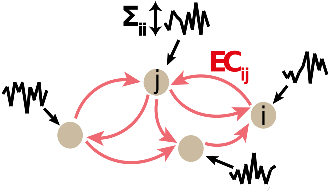
- Network model

Effective Connectivity (EC)



- Network model
- Sparse

Effective Connectivity (EC)



- Network model
- Sparse
- Asymmetric: directionality of interactions

Outline

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- Network model

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- EC based subject and condition identification

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- Estimation of model parameters

Network model

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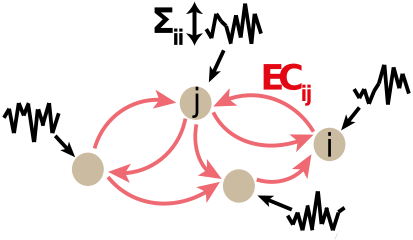
- $dx_i(t) = [-\frac{x_i(t)}{\tau_i} + \sum_{j \neq i} C_{ij} x_j + \eta_i]dt + dB_i; \qquad dB_i \sim \mathcal{N}(0, \sigma_i^2)$



Estimation of parameters postponed. . .

Characterization of whole brain networks underlying "mental" states

Characterization of whole brain networks underlying watching a movie

Characterization of whole brain networks underlying remembering

Characterization of whole brain networks underlying calculating

Characterization of whole brain networks underlying pathological states (dementia, autism, depression, etc.)

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- Separate different sources of varibility

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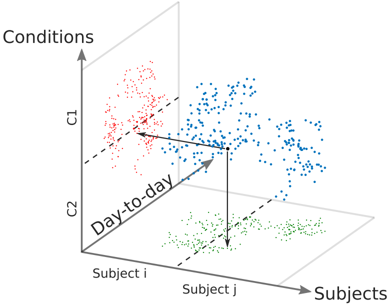
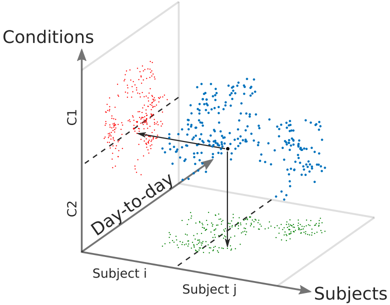


Characterization of whole brain networks underlying "mental" states

- Separate different sources of varibility
  - classify subjects
  - classify conditions
  - extract networks underlying each classification



Datasets

Dataset name	Acquisition	Number of subjects	Sessions per subject	Session duration
Dataset A1	Day2day project	6	40-50	5 minutes
Dataset B	CoRR	30	10	10 minutes
Dataset C	Gilson et al. 2017, Mantini et al. 2012	19	3 resting; 2 movie	10 minutes

Subjects classification

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  - **Test-retest** dataset (10-50 sessions per subject):
    - accurate assessment of test accuracy
    - impact of training set size

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- $C_k = softmax(\sum_j^N \beta_{jk} x_j)$

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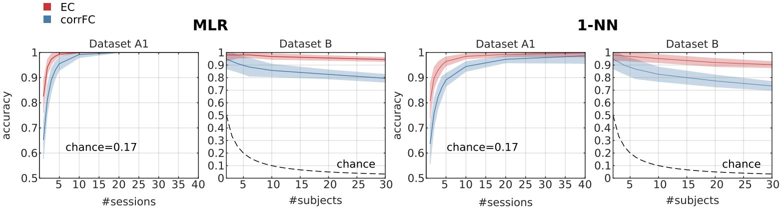
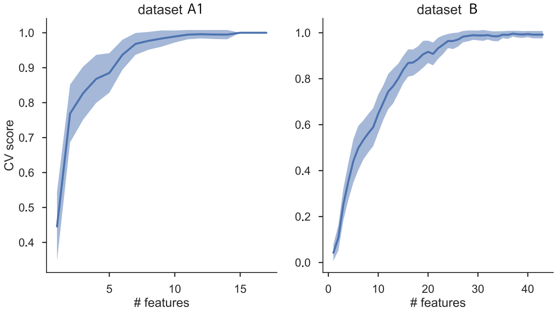
- $C_k = softmax(\sum_j^N \beta_{jk} x_j)$
- allows to estimate the most relevant features for the classification
- Recursive feature elimination:
  - recursively remove feature $i = \arg\min_j \sum_k \beta_{jk}$
  - survival time reflects relevance of each link

Subjects classification



Subjects classification

Classification accuracy using subsets of links according to RFE ranking



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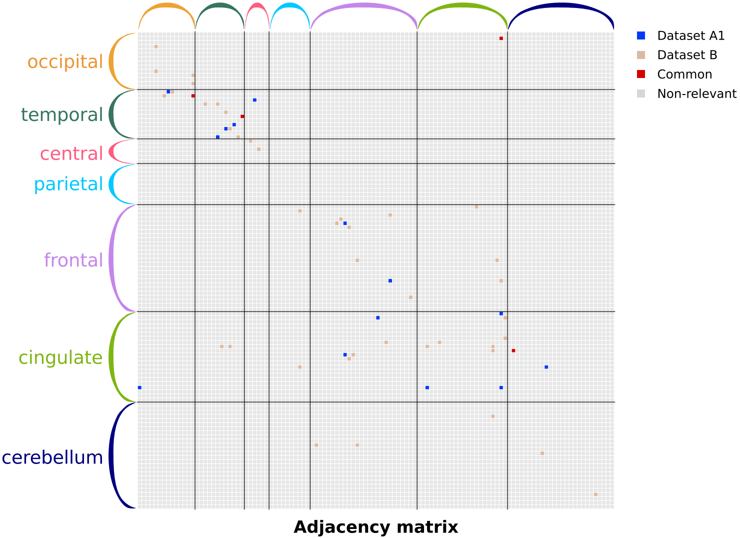
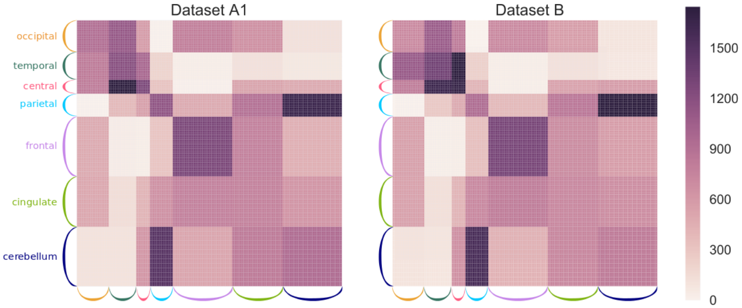


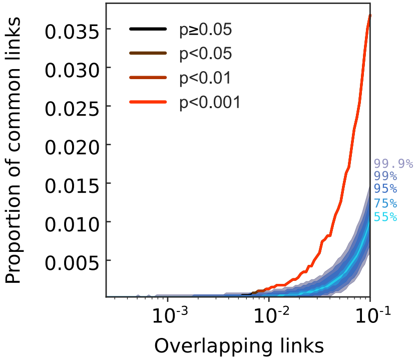
Subjects classification

Average RFE ranking by subsystem



Subjects classification

Number of overlapping links is much higher than expected by chance



Condition classification

Dataset C: resting $\Leftrightarrow$ movie viewing

Condition classification

Dataset C: resting ⇔ movie viewing

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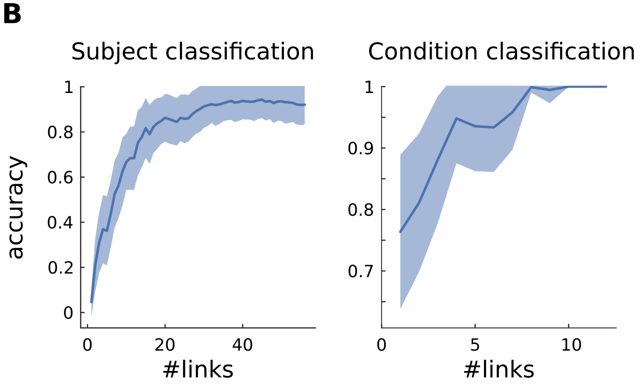
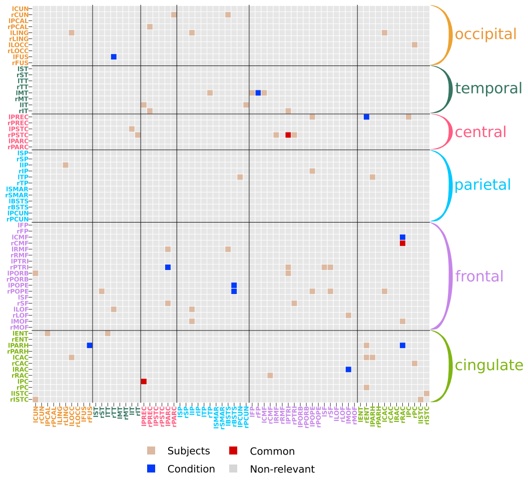
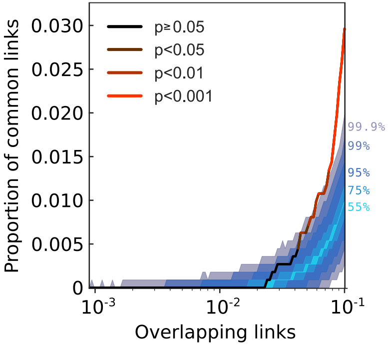


Condition classification



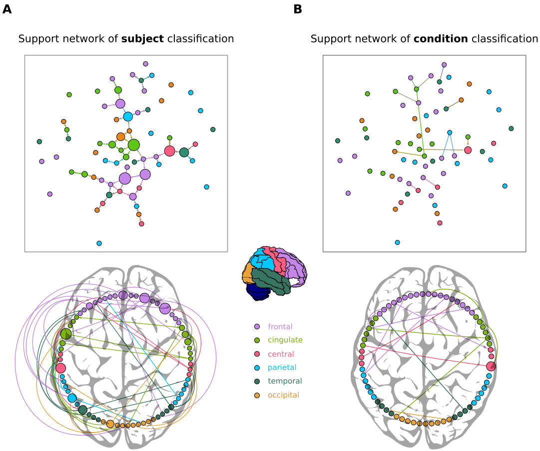
Condition classification

Number of overlapping links is similar to that expected by chance



Condition classification

Subjects and conditions networks



Summary (ad interim)

- MOU model estimates whole brain connectivity
- Classification of subjects identity based on estimated connectivity achieves very high accuracy with few recording sessions per subject
- Effective connectivity is more reliable than correlation-based functional connectivity
- Classification of behavioral conditions and subjects identity on the same dataset achieves very high accuracy
- Subjects and condition specific networks show very different properties

Estimation of parameters in the MOU model

Estimation of parameters

- $dx_i(t) = [-\frac{x_i(t)}{\tau_i} + \sum_{j \neq i} C_{ij} x_j] dt + dB_i$

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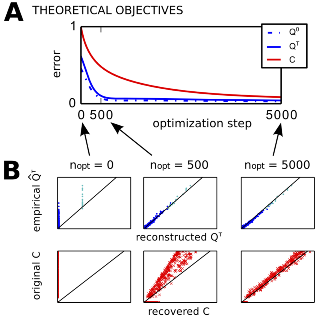
- $dx_i(t) = [-\frac{x_i(t)}{\tau_i} + \sum_{j \neq i} C_{ij} x_j] dt + dB_i$
- Lyapunov optimization (Gilson et al. PLoS Comp Biol 2015)
- minimize $V = \sum_{m,n} (\mathbf{Q}^0_{mn} - \hat{\mathbf{Q}}^0_{mn})^2 + \sum_{m,n} (\mathbf{Q}^\tau_{mn} - \hat{\mathbf{Q}}^\tau_{mn})^2$



Bayesian estimation of parameters

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- Model comparison

MAP estimate with uniform prior

Singh et al. arXiv 2017

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$$x(t')|x(t) \sim \mathcal{N}(x(t)expm(-\boldsymbol{\lambda}\Delta t), \mathbf{Q}^0 - expm(-\boldsymbol{\lambda}\Delta t)\mathbf{Q}^0 expm(-\boldsymbol{\lambda}\Delta t)^T)$$

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$$\boldsymbol{\lambda}_{ij} = \delta_{ij}/\tau_i + C_{ij}; \qquad \Delta t = t' - t$$

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x(t) $\sim \mathcal{N}(0, \mathbf{Q}^0)$

P(X| $\boldsymbol{\lambda}, \mathbf{Q}^0) = \prod_n^{N-1} P(x_{n+1}|x_n, \boldsymbol{\lambda}, \mathbf{Q}^0) P(x_n|\boldsymbol{\lambda}, \mathbf{Q}^0)$

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$\mathrm{P}(\boldsymbol{\lambda},\ \mathrm{Q}^0|X) = \frac{P(X|\boldsymbol{\lambda},\mathbf{Q}^0)P(\boldsymbol{\lambda},\mathbf{Q}^0)}{P(X)}$

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P($\boldsymbol{\lambda}$, Q$^0|X) = \frac{P(X|\boldsymbol{\lambda},\mathbf{Q}^0)P(\boldsymbol{\lambda},\mathbf{Q}^0)}{P(X)}$

$\boldsymbol{\lambda}^* = -logm(\sum_{n=1}^{N-1} x_{n+1}x_n^T(\sum_{n=1}^{N-1} x_n x_n^T)^{-1})/\Delta t$

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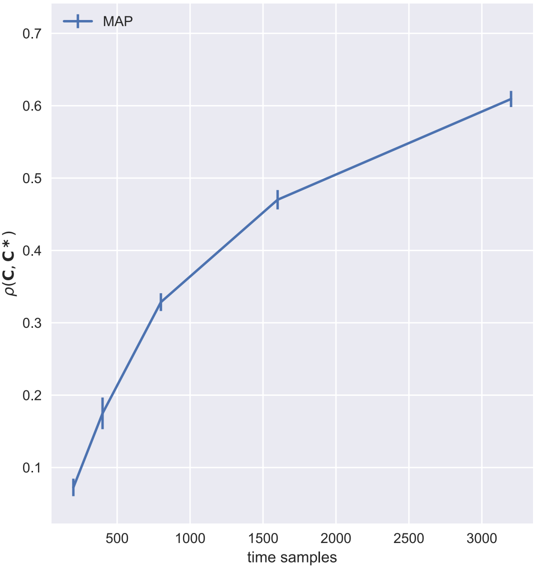
C$^*_{ij} = \boldsymbol{\lambda}^*_{ij} \qquad \text{for } i \neq j$

Synthetic data

- Simulated data from MOU
- N=50 nodes
- Connection probability: 0.2
- Uniform distribution of weights

MAP estimate for small time samples



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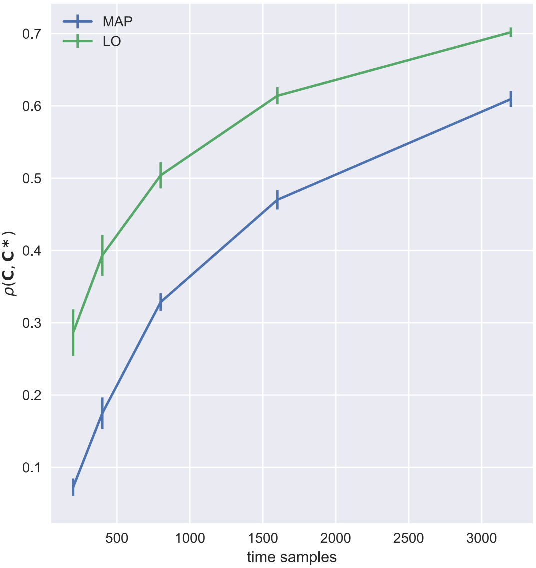
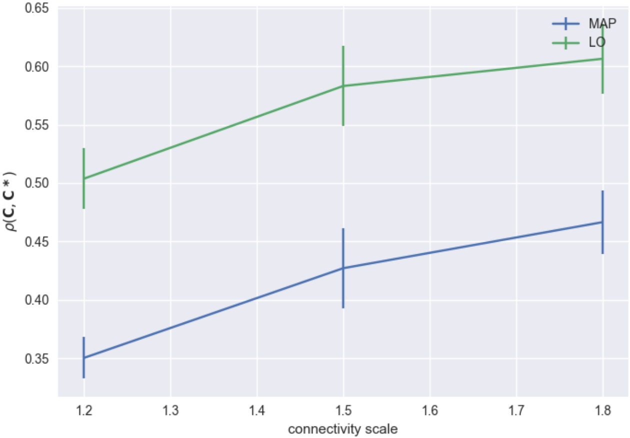
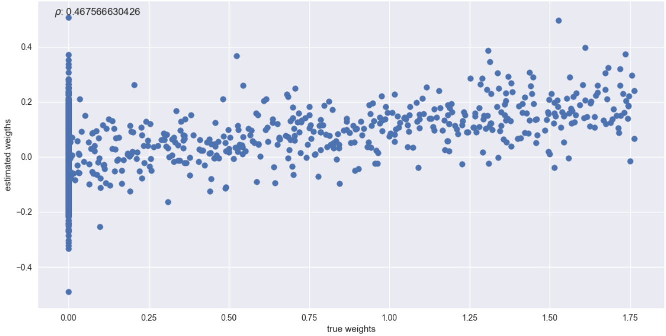


Influence of weight values



True and predicted weights



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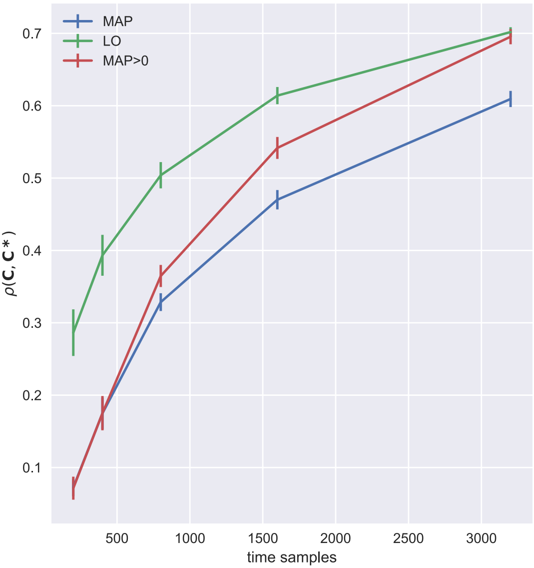

Next steps

- Sparse network prior
- . . . ?

Acknowledgments

Vicente Pallares

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John Cunningham

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