Whole brain effective connectivity from fMRI data

Some subtitle

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Whole brain connectivity

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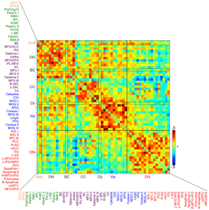
- Connectivity between ROIs

Functional Connectivity (FC)



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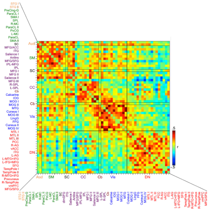

- Pearson correlation between ROIs

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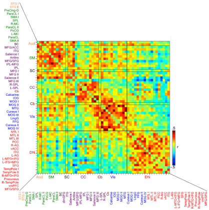

- Pearson correlation between ROIs
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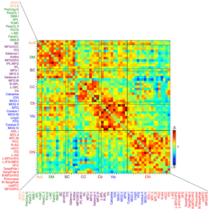

- Pearson correlation between ROIs
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- Symmetric: no directionality of interactions

Effective Connectivity (EC)

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- Network model

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Outline

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- Estimation of model parameters

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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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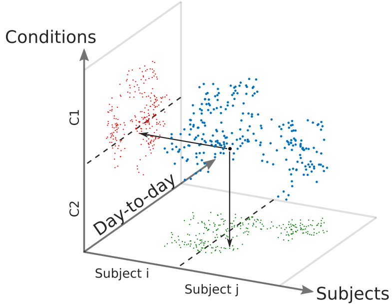
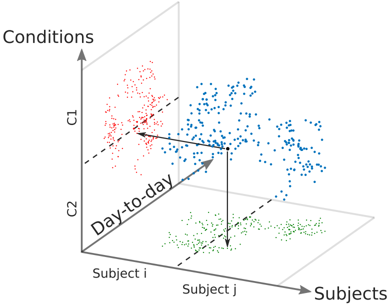


Characterization of whole brain networks underlying "mental" states

- 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

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    - impact of training set size

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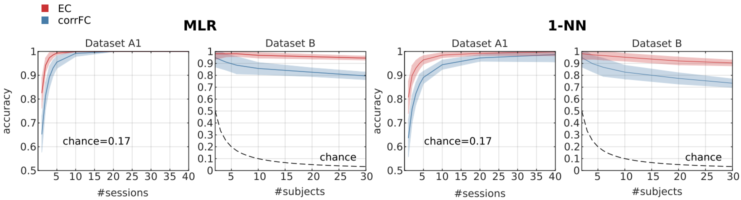
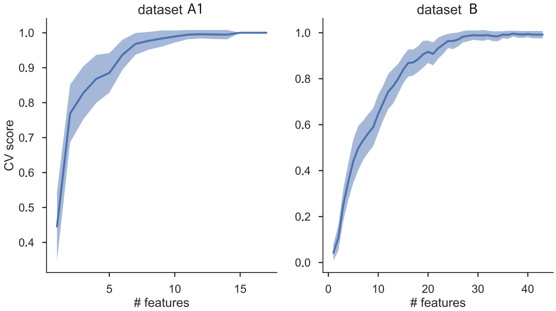
- $C_k = \sigma(\sum_j^N \beta_{jk} x_j)$
- allows to estimate the most relevant features for the classification
- Recursive feature elimination:
  - recursively remove feature $i = \arg\min_j \sum_k \beta_{jk}$
  - survival time reflects relevance of each link

Subjects classification



Subjects classification

Classification accuracy using subsets of links according to RFE ranking



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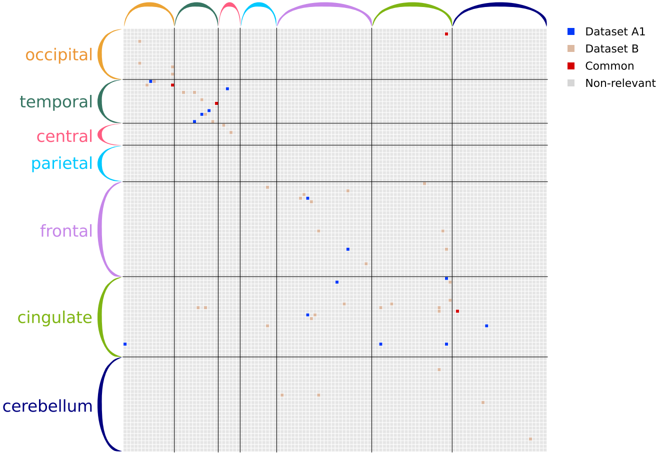
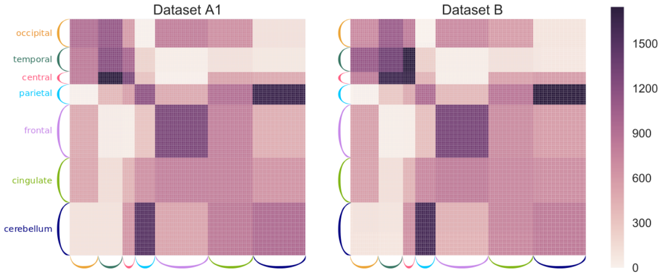


Adjacency matrix

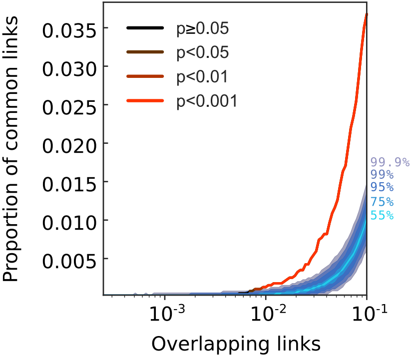
Subjects classification

Average ranking by subsystem



Subjects classification

Number of overlapping links is much higher than expected by chance



Condition classification

resting VS movie viewing

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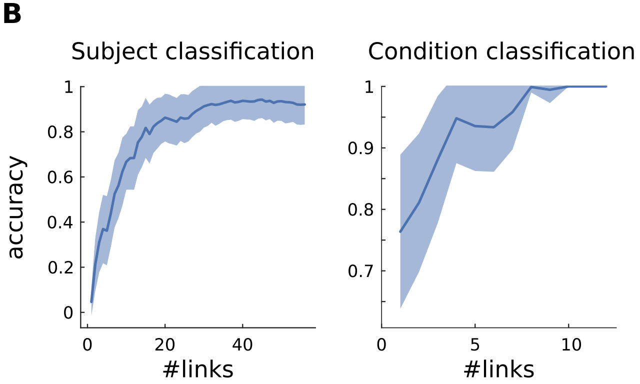

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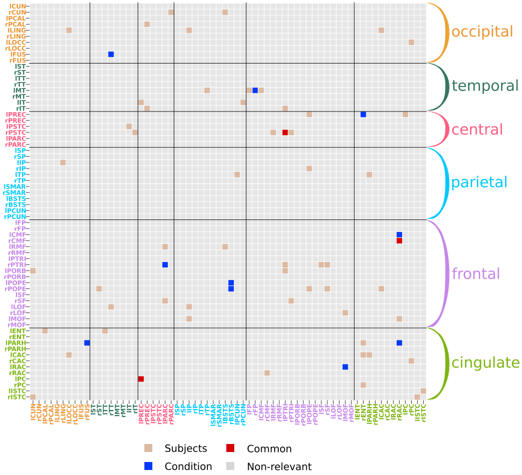
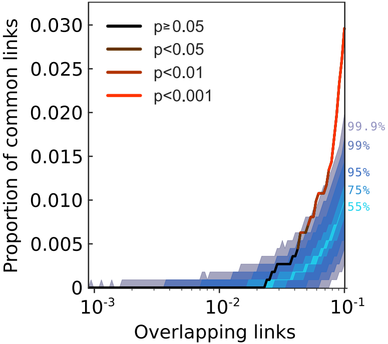


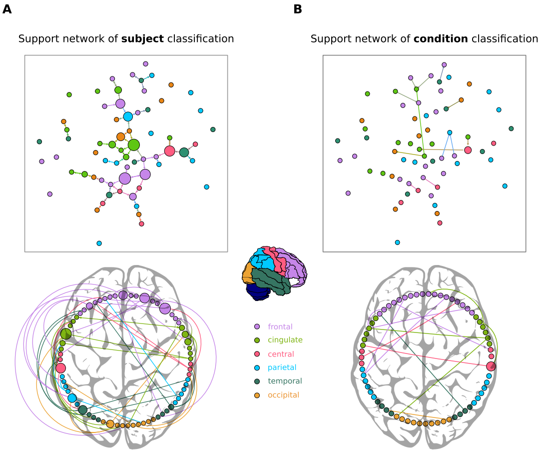
Condition classification

Number of overlapping links is similar to that expected by chance



Condition classification

Subjects and conditions networks



Summary (ad interim)

-

Estimation of parameters in the MOU model

Estimation of parameters

- Lyapunov optimization (Gilson et al. PLoS Comp Biol 2015)
- minimize $V = \sum_{m,n}(\mathbf{Q}^0_{mn} - \hat{\mathbf{Q}}^0_{mn})^2 + \sum_{m,n}(\mathbf{Q}^\tau_{mn} - \hat{\mathbf{Q}}^\tau_{mn})^2$

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Bayesian estimation of parameters

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- Model comparison

Bayesian estimation of parameters

- MAP estimate with uniform prior ($\equiv$ MLE): Tizio et al. 2017
- $x(t')|x(t) \sim \mathcal{N}(x(t)expm(-\lambda(t'-t)), \frac{\sigma^2}{2\lambda}(1 - expm(-2\lambda(t'-t)))$
- $x(t) \sim \mathcal{N}(0, \frac{\sigma^2}{2\lambda}$
- $P(X|\lambda, \sigma^2) = \prod_n^{N-1} P(x_{n+1}|x_n, \lambda, \sigma^2) P(x_n|\lambda, \sigma^2)$
- $P(\lambda, \sigma^2|X) = \frac{P(X|\lambda,\sigma^2)P(\lambda,\sigma)}{P(X)}$
- $C^* = logm[(\mathbf{Q^0})^{-1}\mathbf{Q^1}]$

MAP estimate for large scale networks

MAP estimate for small time samples

Influence of weight values

True and predicted weights

Summary

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Matthieu Gilson

Ana Sanjuan

Simone Kuhn

Dante Mantini

Gustavo Deco

John Cunningham

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