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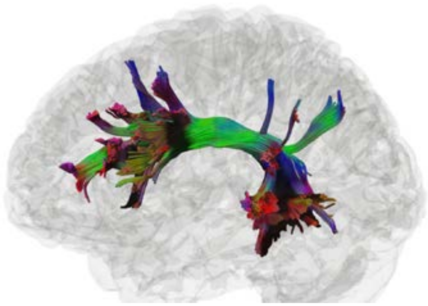
Functional Connectivity

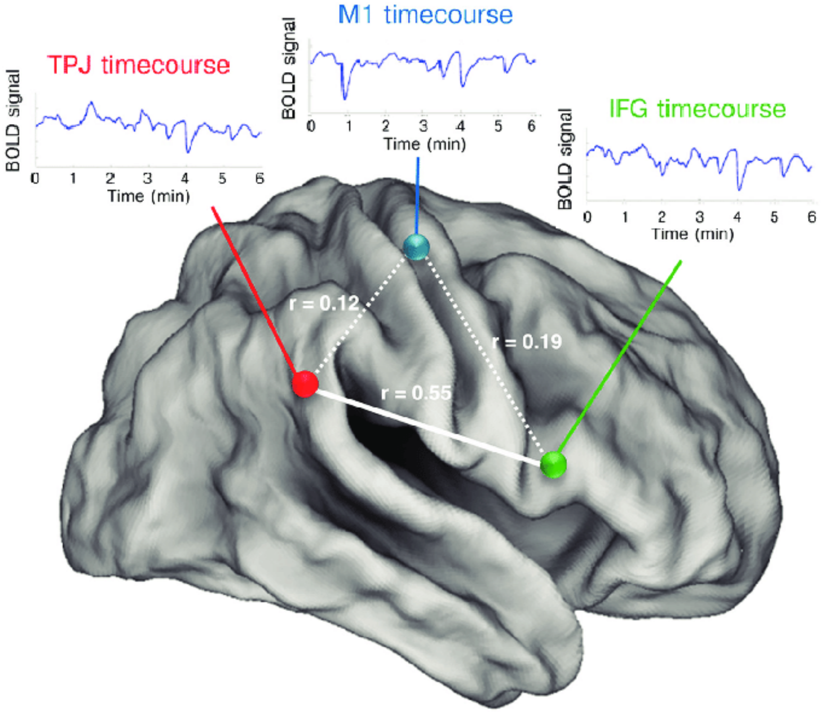
Petar Raykov

Types of Connectivity

1. Structural / Anatomical Connectivity (Tractography from DWI)



2. Functional Connectivity (statistical dependence across Regions)



3. Effective Connectivity
(direct/directed; state dependent changes in connectivity)

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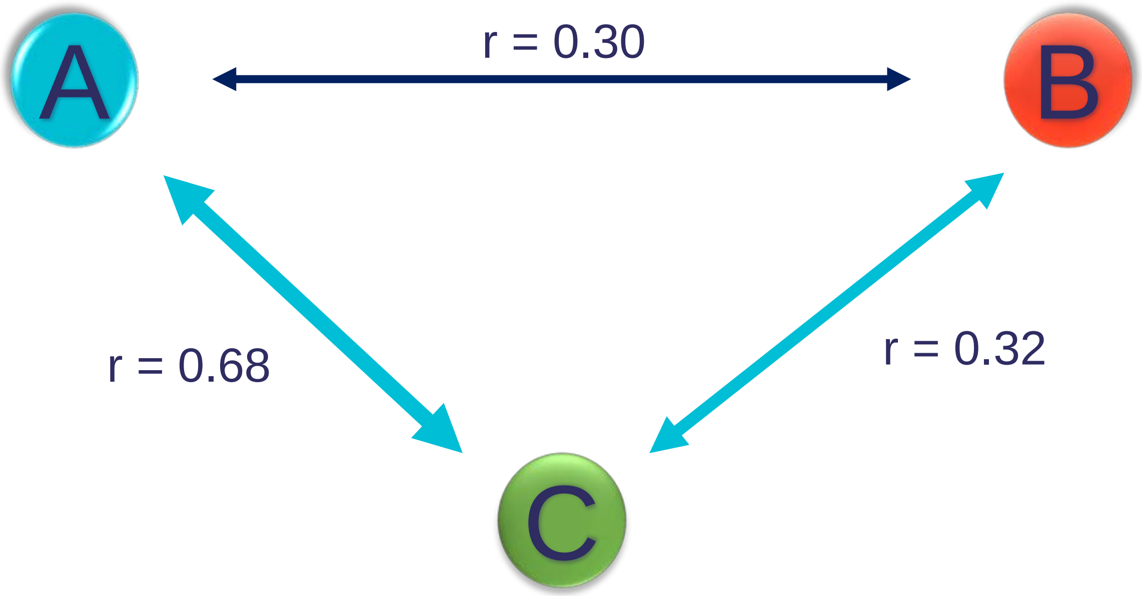
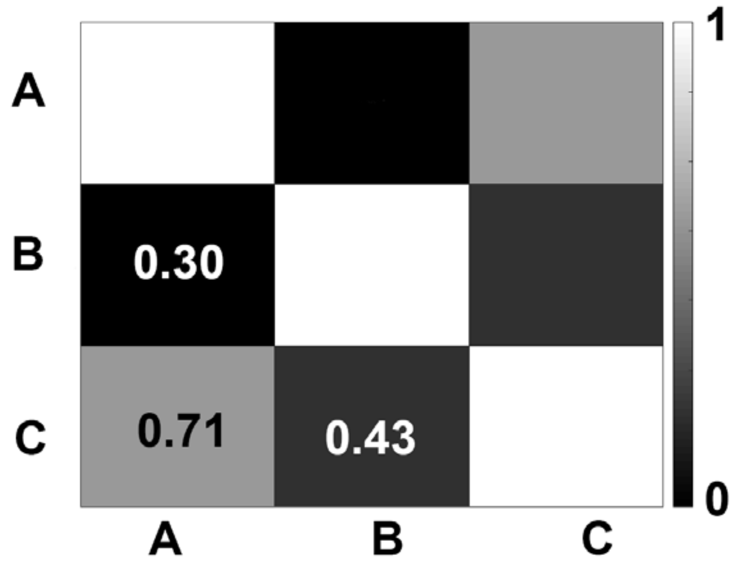
Why Connectivity?

- Localisation vs Connectivity
- Understand how groups of regions relate to cognition
- Clinical / Cognitive Biomarkers
- Effects of Genes
- Individual differences
- Little experimental setup

Functional Connectivity vs Effective Connectivity





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Measure of Connectivity

- Pearson Correlation - Indirect
- Partial Correlation (Inverted Covariance Matrix) – direct, number of time-points and regions an important consideration;
- Directed Connections (e.g., Granger Causality, Dynamic Causal modelling)
- Multivariate Connectivity (Basti et al., 2020) (https://doi.org/10.1016/j.neuroimage.2020.117179)
- Effective Connectivity (Task based changes in connectivity)

Overview Functional Connectivity

Useful when no clear task model (e.g., resting state).

Popular examples:

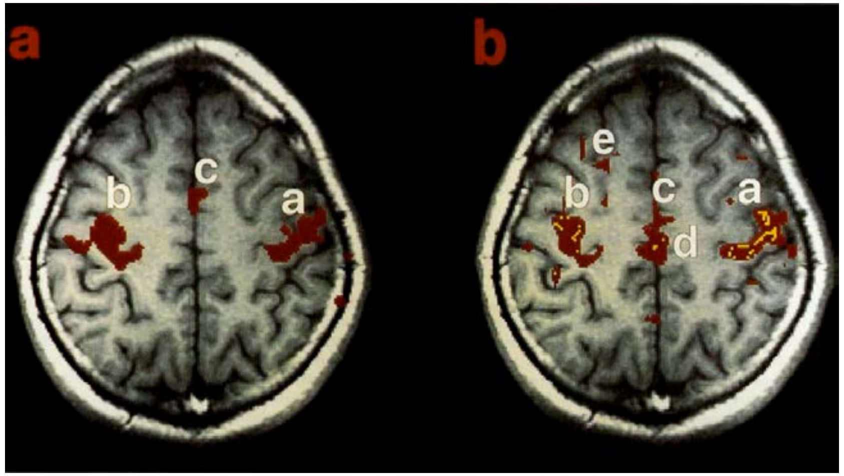
- Seed-to-voxel, seed-to-seed correlations
- Multivariate decomposition methods such as ICA
- Graph-theory summaries – covered in separate talk

Seed-Based FC

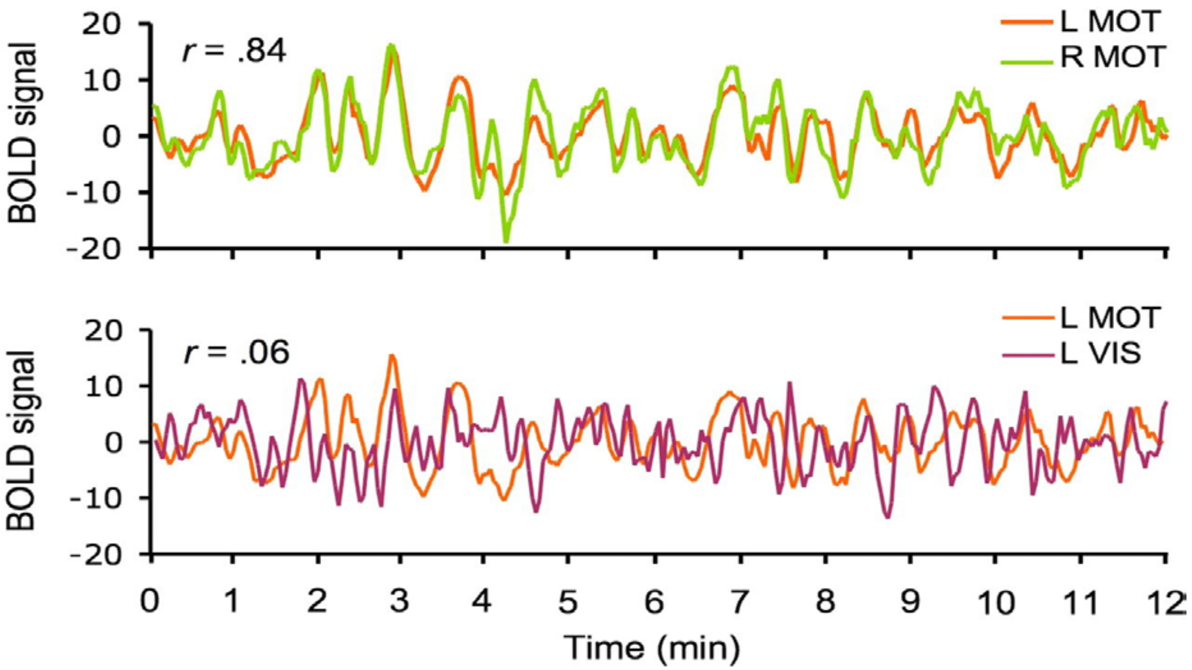
- Extract time course from a brain region

  Often average, but can be SVD.

- Correlate seed time-course with every voxel in the brain
- Group Analysis
- Correction for multiple-tests



Biswal et al., 1995



Van Dijk et al., 2010

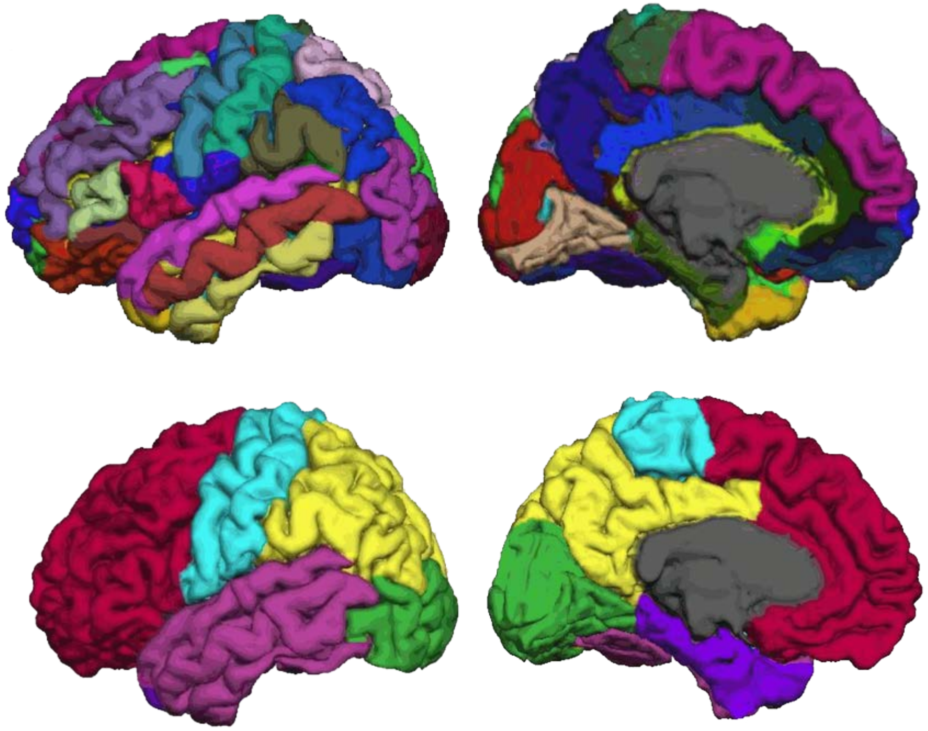
Occurs at task and rest
Useful for identifying networks

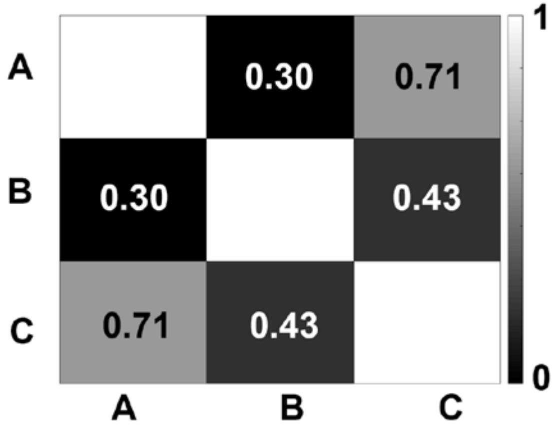
Note resulting network is very dependent on choice of seed.

ROI-to-ROI FC

- Choose a Brain Parcellation (or ROIs).
- Calculate connectivity for pairs of ROIs
- Perform Group analysis:

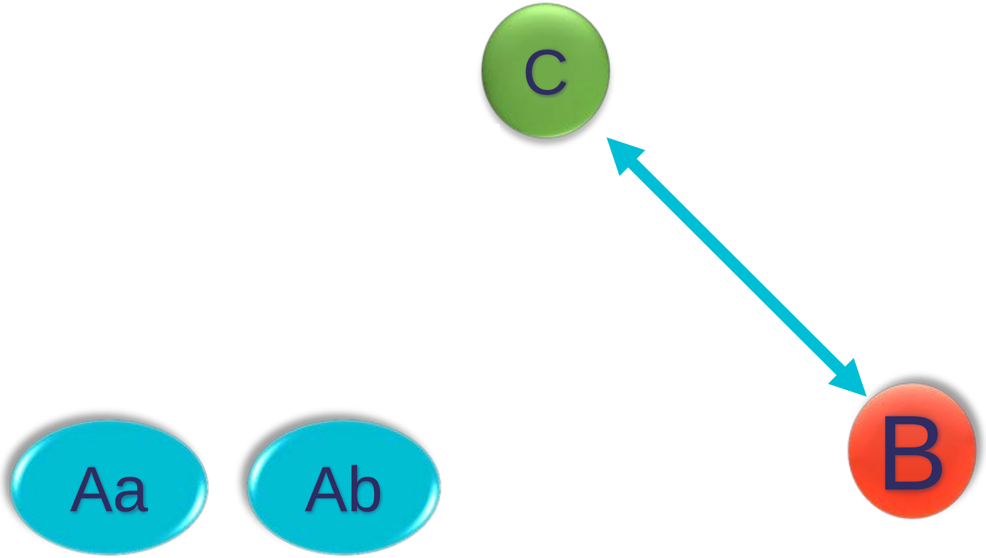
1. Mass Univariate
2. Multivariate





Choosing Atlas

- Number of Regions – e.g., 1000 regions with 100 time-points
  - Resting / Functional / Anatomical
    - Data Driven
  - Lateralisation (partial correlation)

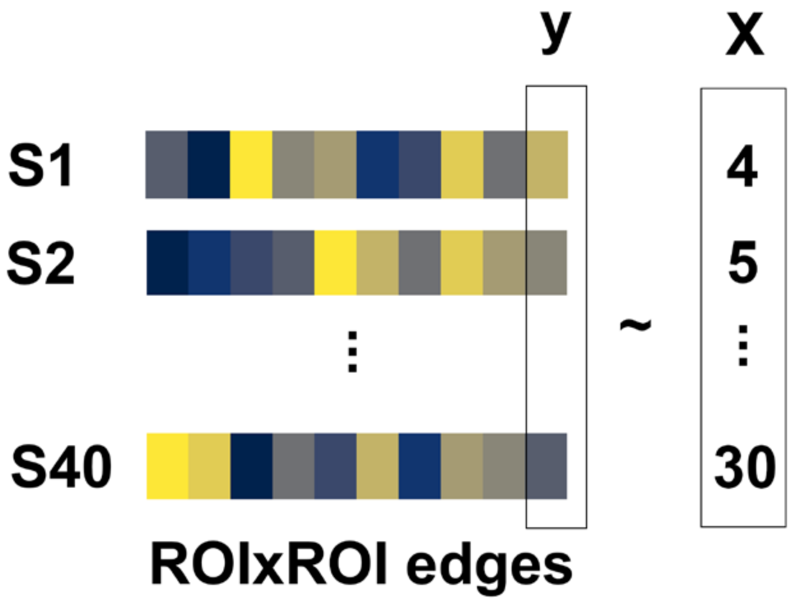


Mass Univariate

We take the off-diagonal elements of the connectivity matrix

We fit a GLM to each edge independently

Perform multiple comparisons correction



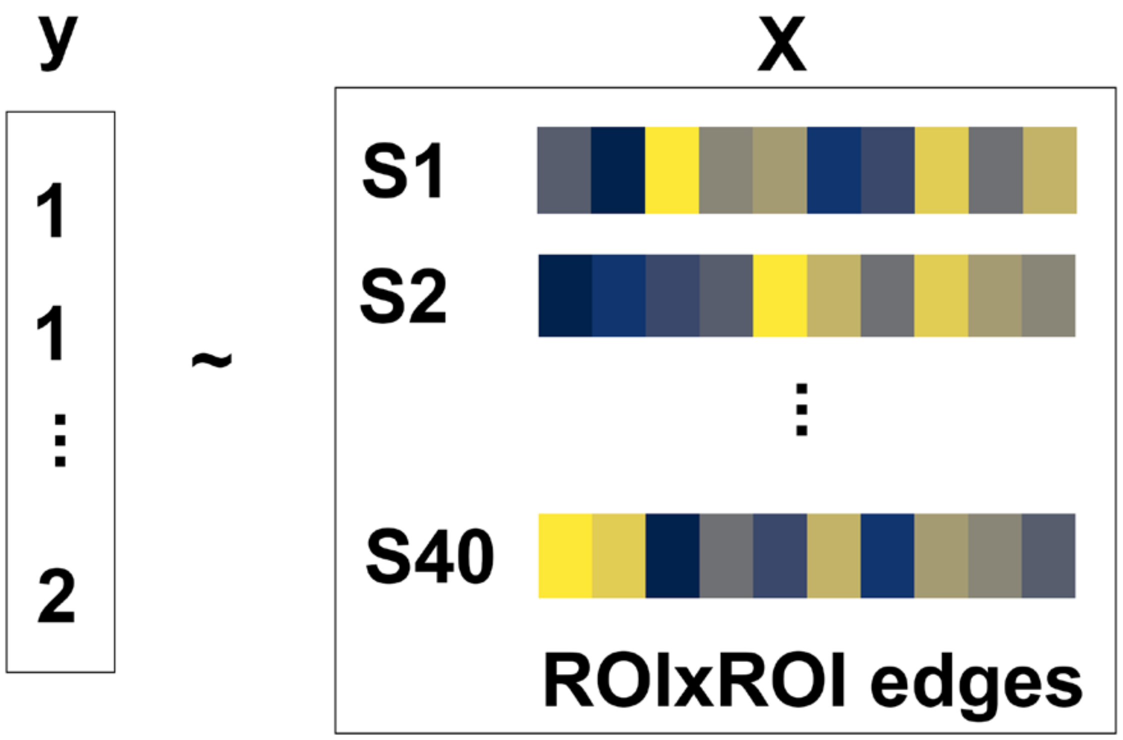
Multivariate

Unlike mass univariate this takes covariation in edge connectivity into account

Use all edges to predict characteristics in participants

- Classification (e.g., patients vs controls)
- Regression (e.g., brain age)

Is there information in the connectivity matrix that can help identify patients?



Preprocessing

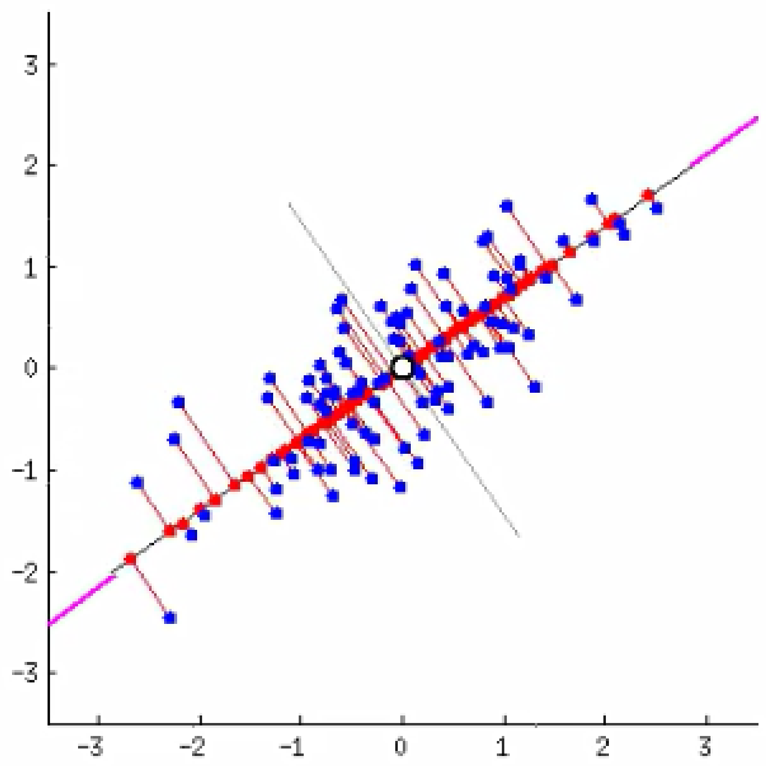
- Low pass filtering (0.1 Hz) or band-pass filtering?
- Covary WM/CSF/Global Signal
- “Scrubbing” (Delete volumes with high motion), but ignores temporal autocorrelation
- Regress out motion parameters, including derivatives, second-order expansions to help reduce spin-history effects
- Spikes – separate regressors for high motion TRs

Physiological Artefacts

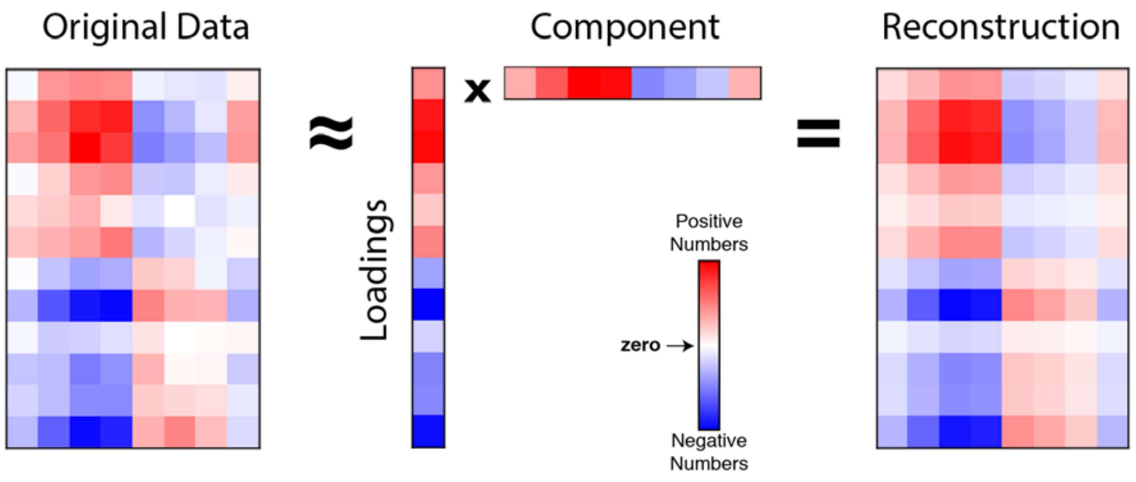
- High-pass filter e.g., to 0.01Hz (since many biorhythms aliased to lower frequency)
- Record and adjust for physiological signals (e.g., cardiac, respiratory) RETROICOR – e.g., (Kasper 2017)
- Use mean or first few principal components of signal of CSF/WM (aCompCorr, outputted in fmriprep)
- Perform Global Signal Regression – Murphy & Fox (2017) https://doi.org/10.1016/j.neuroimage.2016.11.052

1. CONN (Matlab/SPM) / Rik's rsfMRI_GLM function (https://github.com/MRC-CBU/riksneurotools/blob/master/Conn/rsfMRI_GLM.m)
2. FSL (FSLNets) & Nilearn
3. See XCP-D, works on fMRIprep outputs

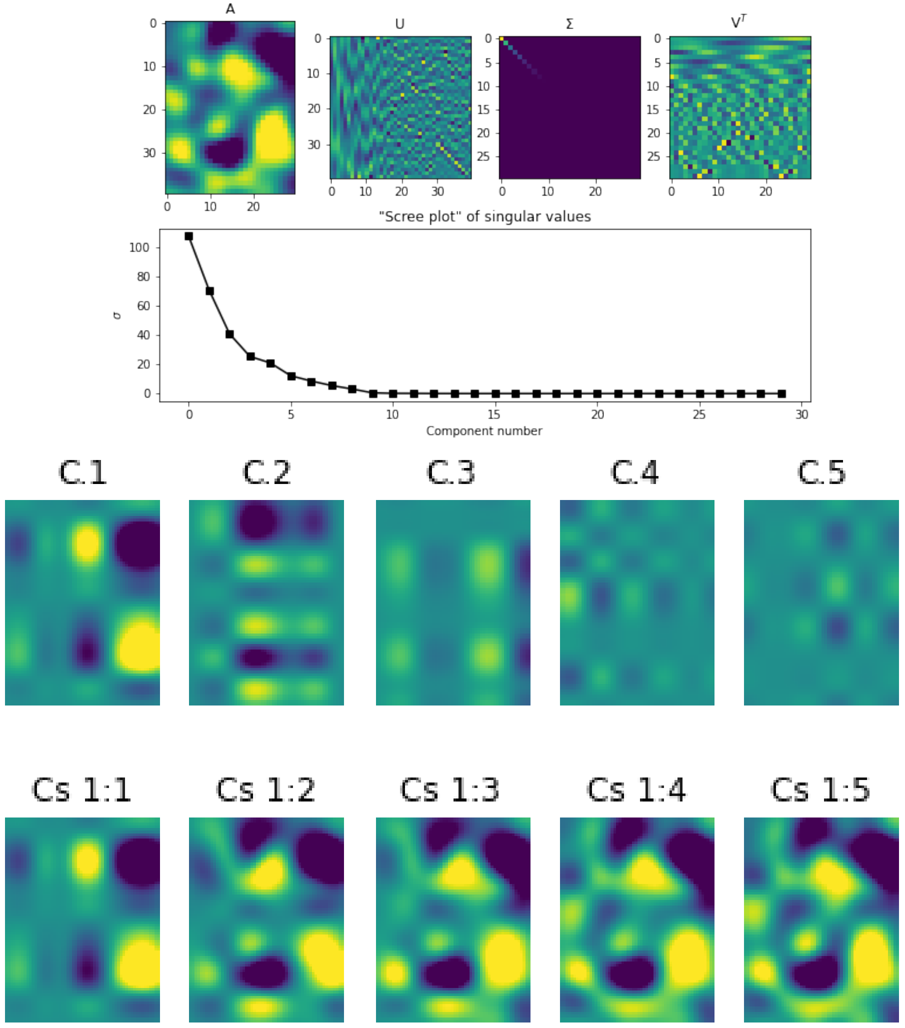
Matrix Factorization Methods



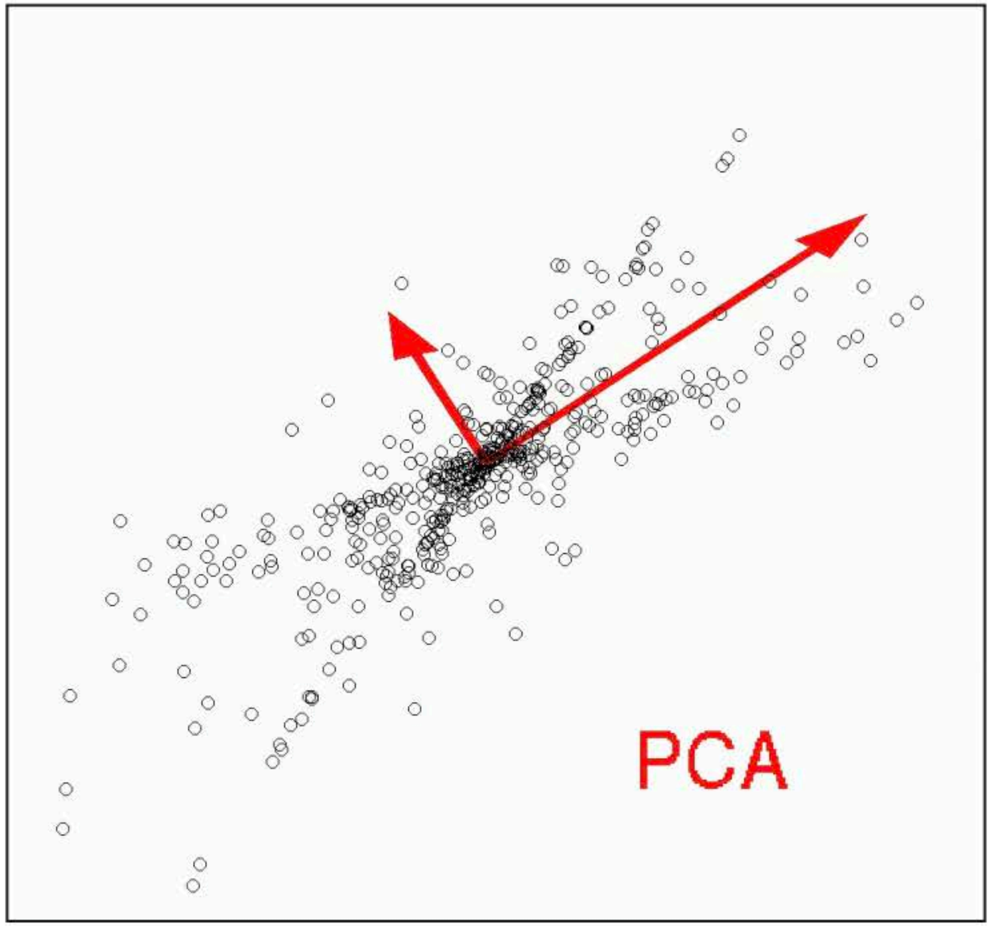
Matrix Factorization Methods

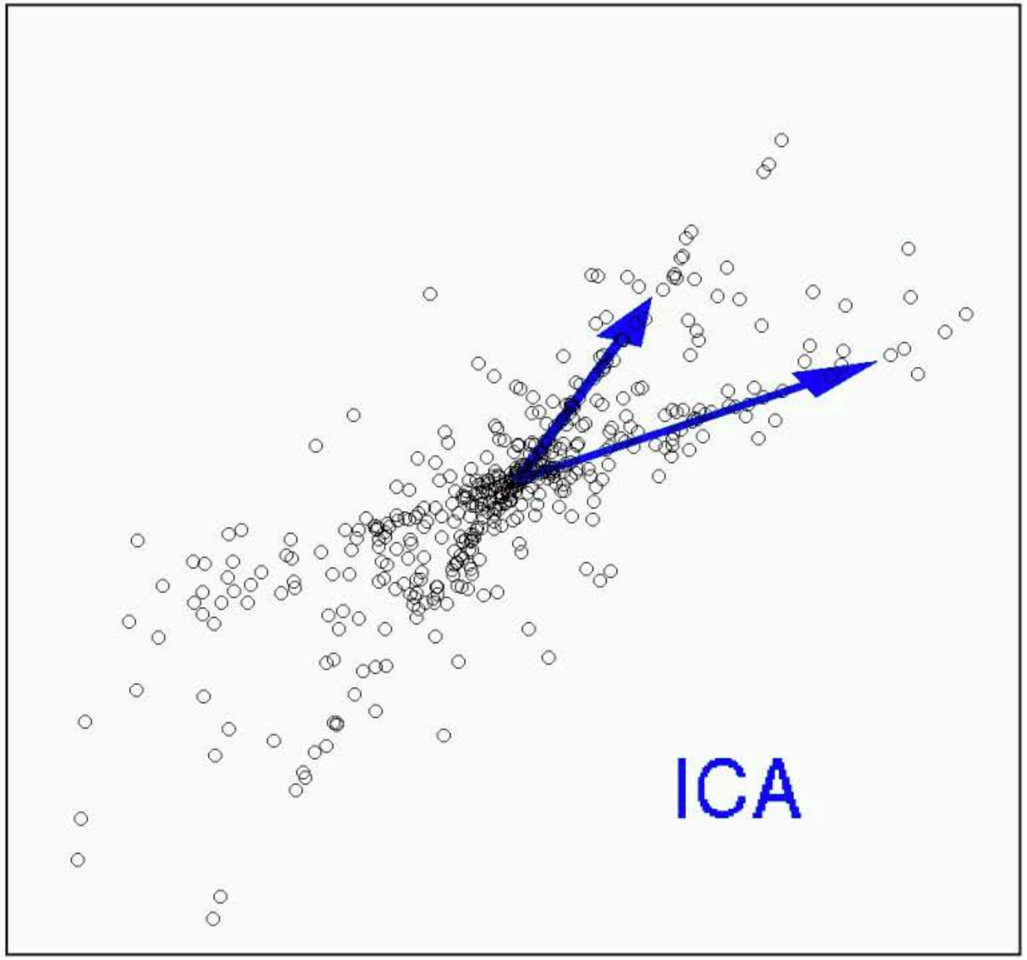


https://alexhwilliams.info/itsneuronalblog/2016/03/27/pca/

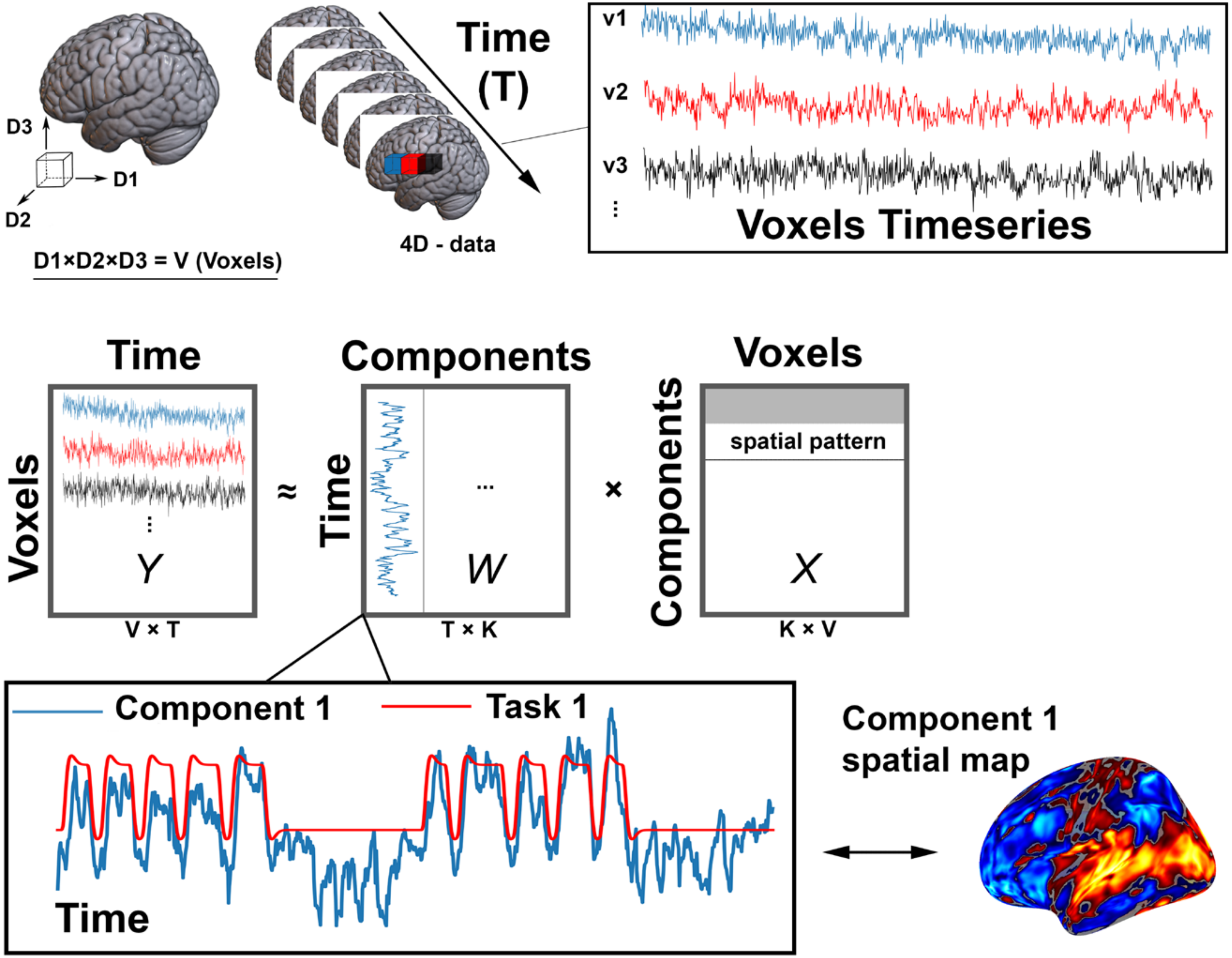


SVD, PCA, ICA, FA etc.





Factorization Methods (PCA/ICA)

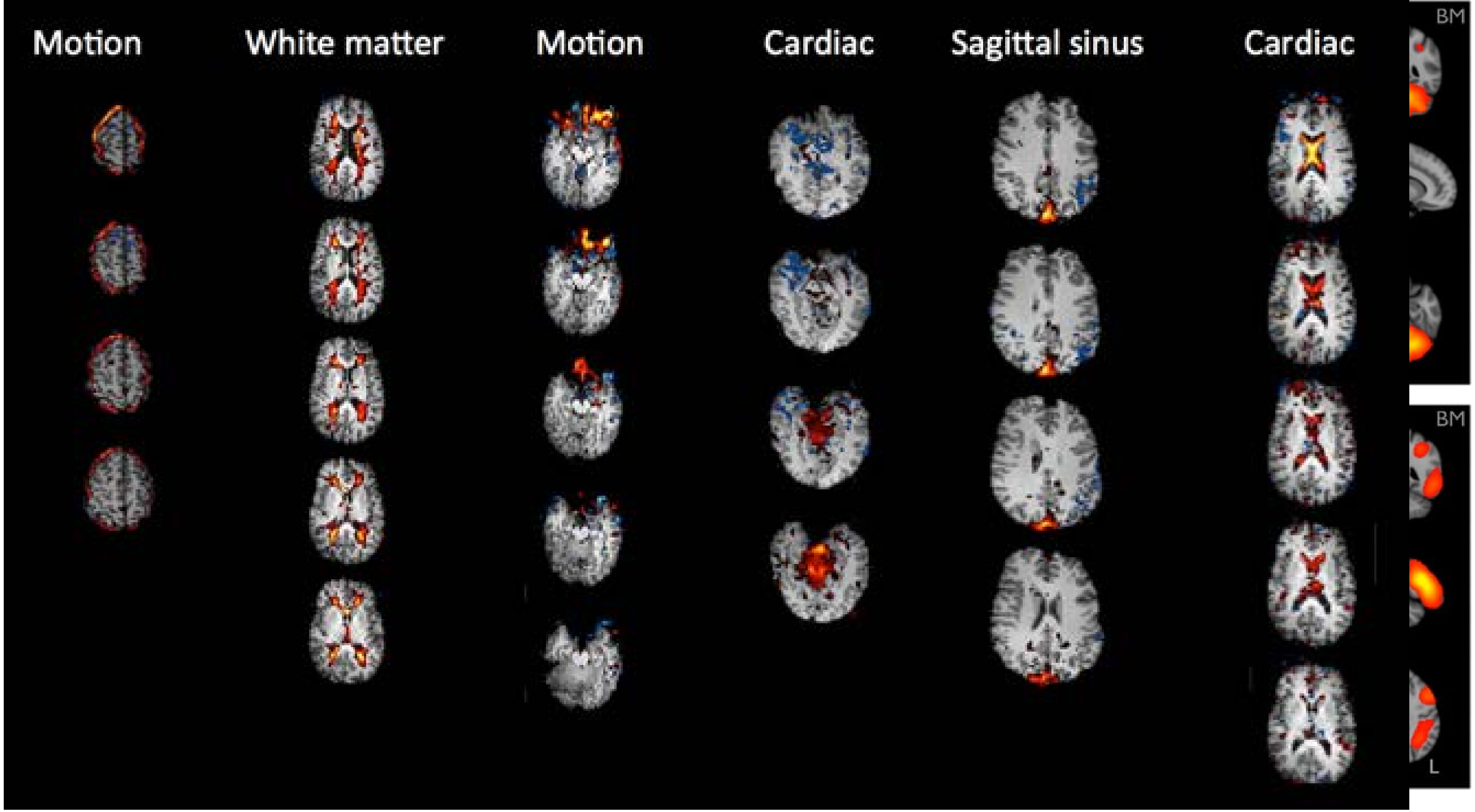


SVD, PCA vs ICA

- PCA (Eigen decomposition) is SVD of a covariance matrix, assuming uncorrelated (orthogonal components) – e.g., spatial patterns across voxels

- ICA assumes components are *independent* (either across space or time, but mostly used as spatial in fMRI). Has been shown to be effective in (re)producing characteristic resting-state networks and cleaning signal from noise. see Shlens (2014); Beckman et al., (2004)

- Other decomposition and clustering techniques



ICA-AROMA (also in fMRIPrep), FIX (FSL)

SVD, PCA vs ICA

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- ICA assumes components are *independent* (either across space or time, but mostly used as spatial in fMRI). Has been shown to be effective in (re)producing characteristic resting-state networks and cleaning signal from noise.
- Other decomposition and clustering techniques
- Group ICA (MELODIC in FSL) Concatenate subjects in time or Tensor ICA; Dual regression
- GIFT Matlab toolbox
- Nilearn

Overview

Pre-processing

FC (seed-based, ROI based, ICA based)

Full vs Partial Correlations

FC vs Effective Connectivity

Thank you

https://www.surveymonkey.com/r/K3C6BPK

Acknowledgements