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fMRI advanced:

Independent Component Analysis

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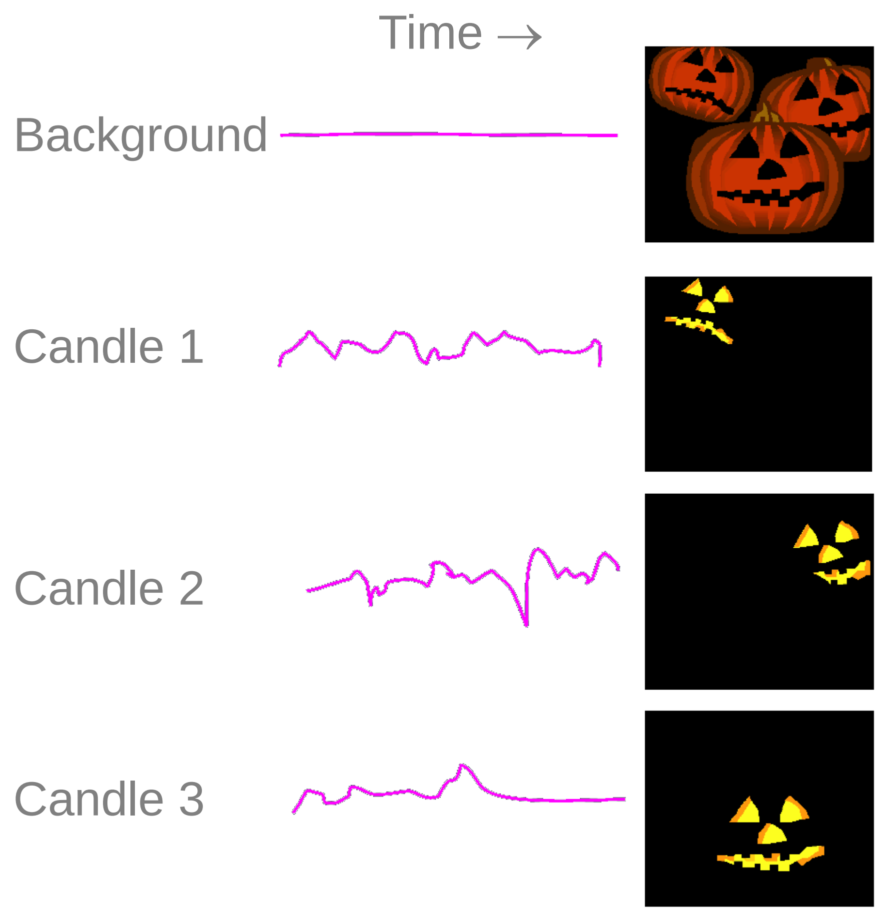
Introduction

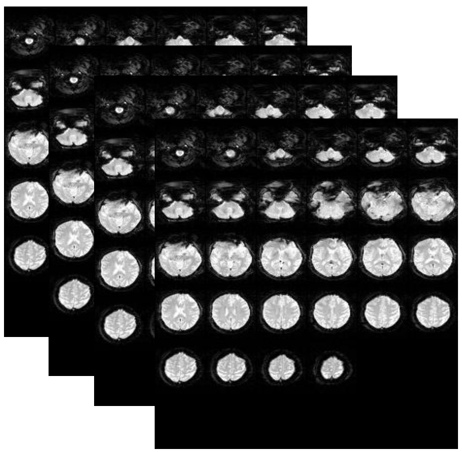
- Independent Component Analysis (ICA)
  - A multidimensional statistical method
  - Allows extraction unknown sources (Blind Source Separ.)
- No need for apriori information about data
  - Useful on Resting-State data
  - Avoid low sensitivity due inaccurate model
  - Avoid multiple statistical testing (as for single dim. methods)
- Limitations
  - Need to estimate # of sources
  - Sources must not have a Gaussian distribution (with exception of one) and be statistically independent (spatial and temporal domain)
  - Direct interpretation problematic

ICA illustration example

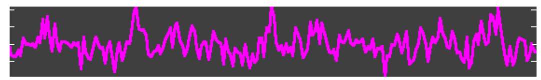
(Calhoun V.D.: Group ICA of FMRI: Introduction and Review of Current Work)

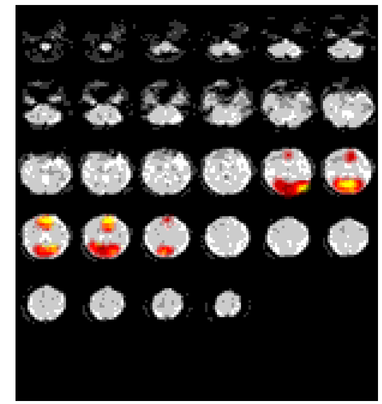


ICA on fMRI data

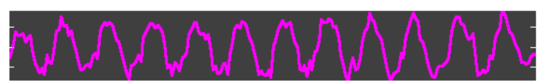


Component 1
default mode network

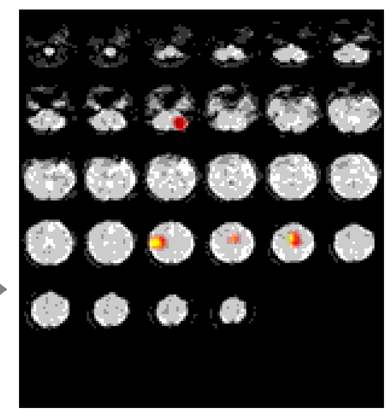




Component 2
Activity in motor cortex

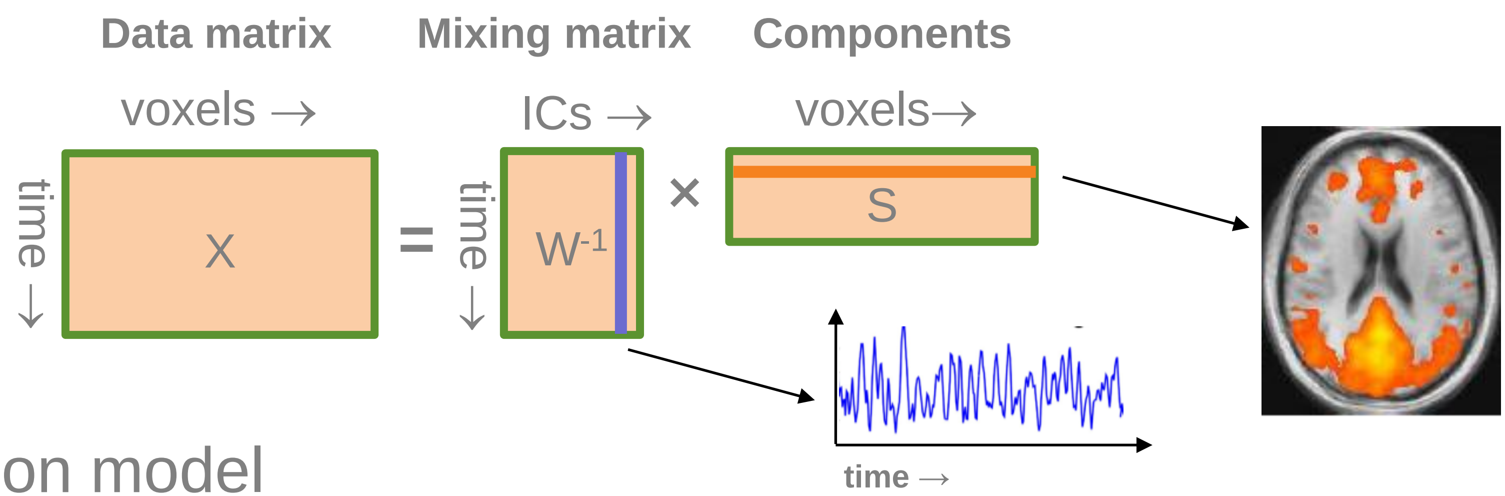


time →



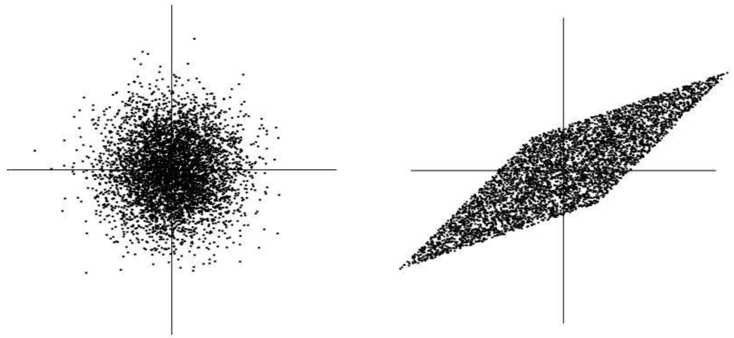
ICA principle

- ICA model - spatial ICA (sICA)
  - **$X = A \cdot S = W^{-1} \cdot S$**
  - Data matrix (X) is decomposed into linear combination of spatially independent sources (S) of variability
  - <u>Assumption that brain activity sources are not overlapping</u>



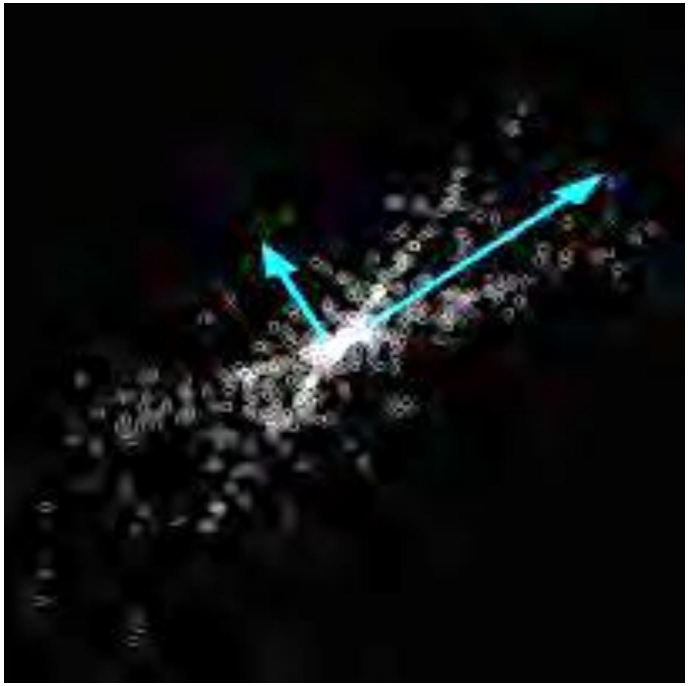
- Inversion model
  - $S = W \cdot X$
  - Estimation of demixing matrix (W) in order to maximize statistical independence of sources (rows of matrix S)

ICA principle

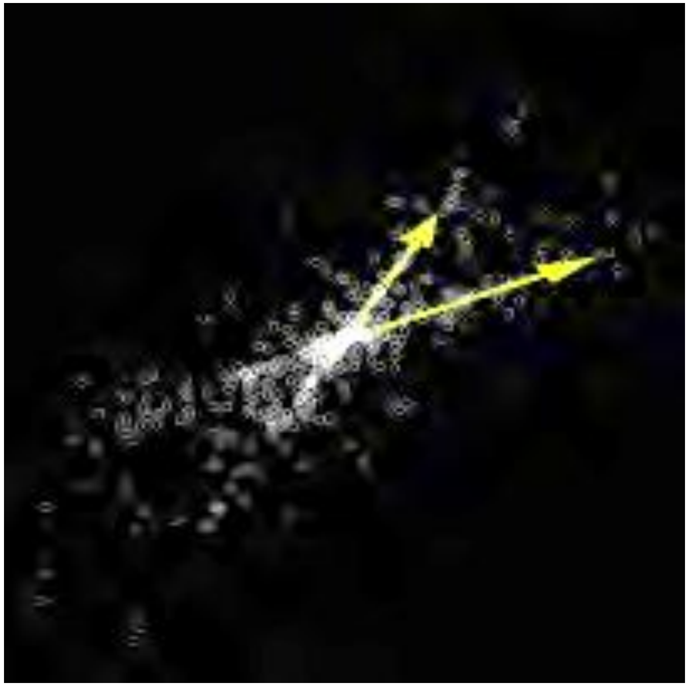


- ICA model
  - $\mathbf{X = A \cdot S = W^{-1} \cdot S}$
- Due ambiguity of right side of the equation
  - We cannot determine order of sources (contrast to PCA)
  - We cannot determine sign
  - Output component's variance is set to 1
- Noise-free model
  - All sources of variability in data are separated into ICs, i.e. brain networks, task-related activity, and also noise, such as movement artifacts, etc.
- Mixing matrix limitations
  - (maximum rank, square)
  - # of components has to be <= # of observations (= timepoints in fMRI)

ICA vs. PCA



PCA finds directions
of maximal variance
(using second order statistics)



ICA finds directions
which maximize independence
(using higher order statistics)

ICA model calculation

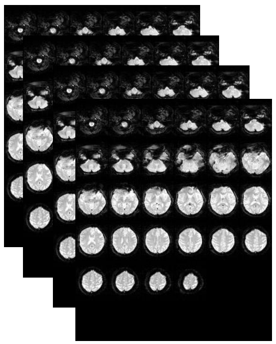
- Estimation of demixing matrix (W)
  - Iterative process

- 1.step – initialization of W (random)
- 2.step – maximization of statistical independence between components (rows of S) according to selected criterion
  - Minimization of Mutual Information
  - Maximization of non-Gaussianity (negentropy)
- Repeat until convergence condition met

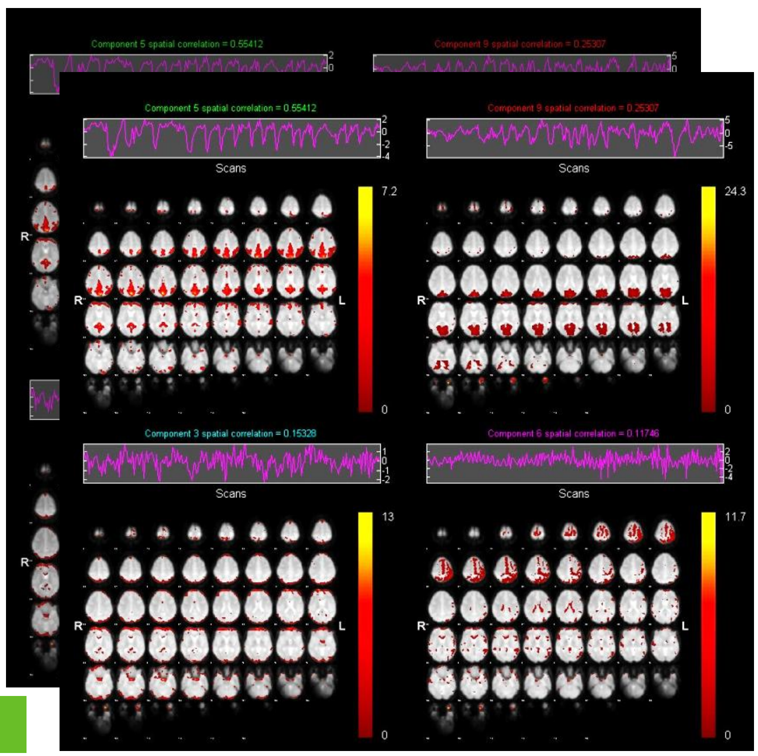
- Many algorithms available
  - Infomax, FastICA, JADE, Amuse, etc.

ICA processing pipeline

Measured data (realigned, normalized and smoothed)



→ Estimating # of components → PCA reduction → ICA calculation



Postprocessing:
- Sorting components
- Selection of interesting components
- Univariate statistical testing
- Interpretation

Estimating # of components/sources

- Each process should be represented by one component

a) Possible to set threshold based on contained variability (PCA)
b) Analytical tool, such as Minimum Description Length (MDL)
    - Information theoretic criterion based on data compression
c) Arbitrary number, usually 15 to 100 ICs for fMRI data

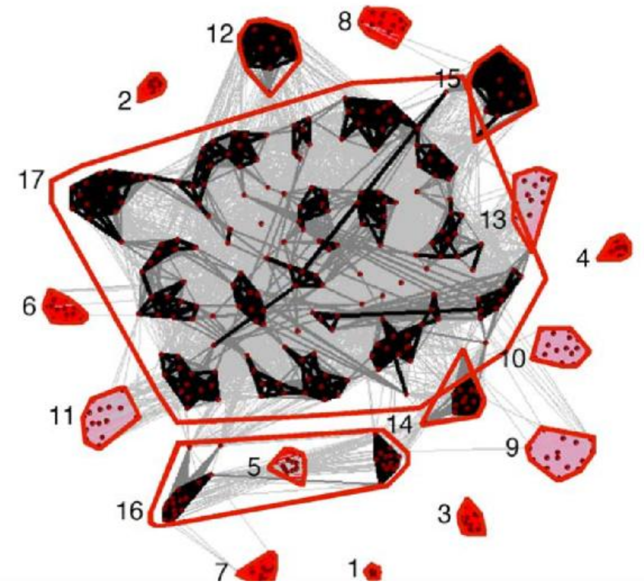
- Too many components
    - Meaningful ICs (such as brain networks) split up,
    - Increasing computational workload and time
- Too few components
    - Merging different sources (overlapping activity)

ICASSO
(J.Himberg, 2003)

- Repeating ICA calculation using
  - Bootstrapping
  - Different initial conditions (mixing matrix)
  - (Both of above)

- Projecting results to multidimensional space
  - Resulting ICs as cluster centroids
  - Cluster size corresponds to stability and reliability of ICA estimates
  - Noise ICs are usually unstable

- When increasing # of components, the stability decreases quickly



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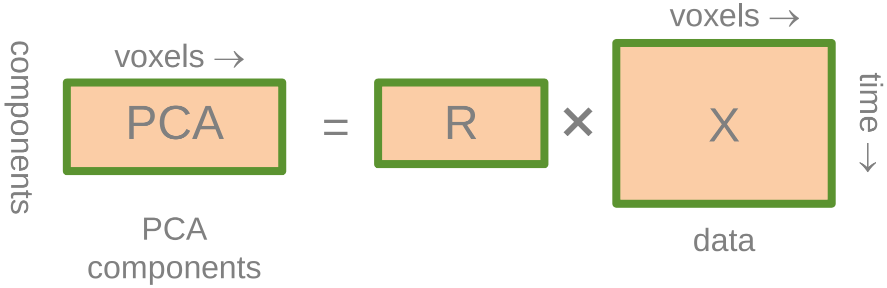
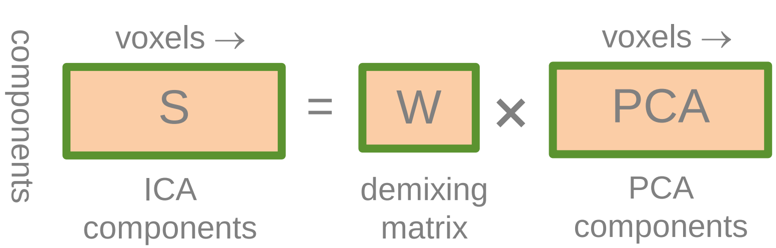
Data reduction using PCA

- Principal Component Analysis (PCA)
  - Reducing dimensionality while preserving maximum variability
  - Whitening (decorrelation) facilitates ICA calculation
  - Useful for group ICA



PCA reduction

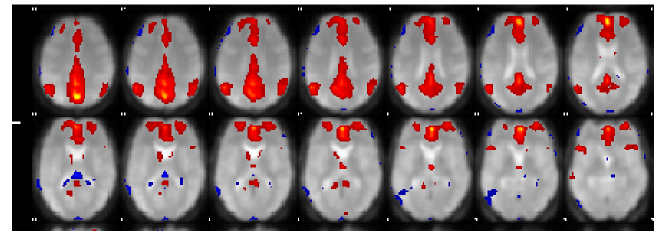
- Matrix R can be found analytically using eigenvectors and eigenvalues of matrix $X*X^T$

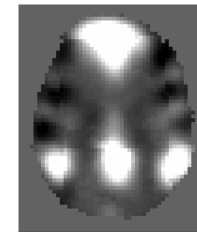


ICA inversion model

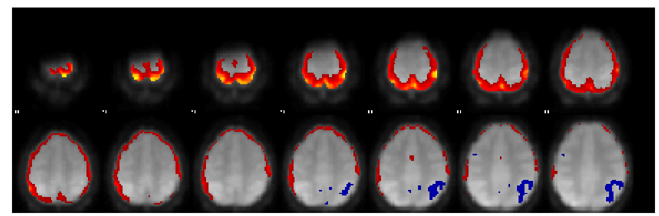
Postprocessing ICs

- Sorting based on spatial distribution
  - Similarity to well-known mask (Default Mode Network, etc.)

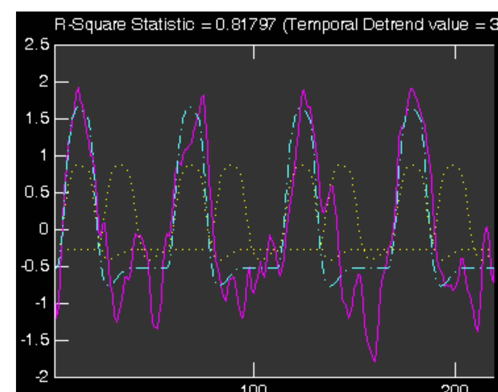




  - Expert evaluation: for example movement artifacts represented as corona shapes on the edges

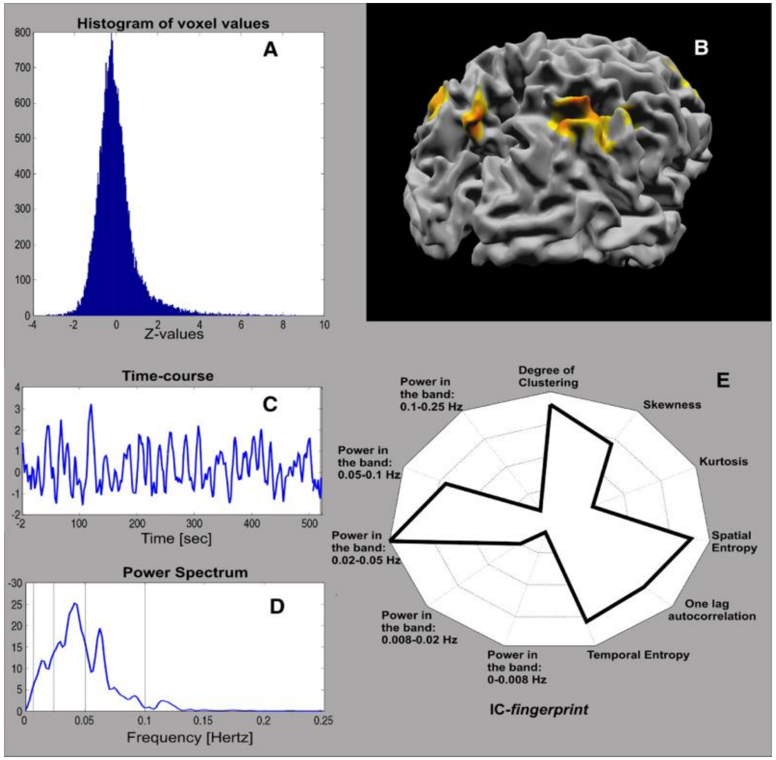


- Sorting based on timecourse parameters (in freq.domain too)
  - Low frequency components ≈ Resting State Networks
  - High freq. components ≈ noise, large vessels artifacts
  - Task-related components based on correlation with stim.timecourse



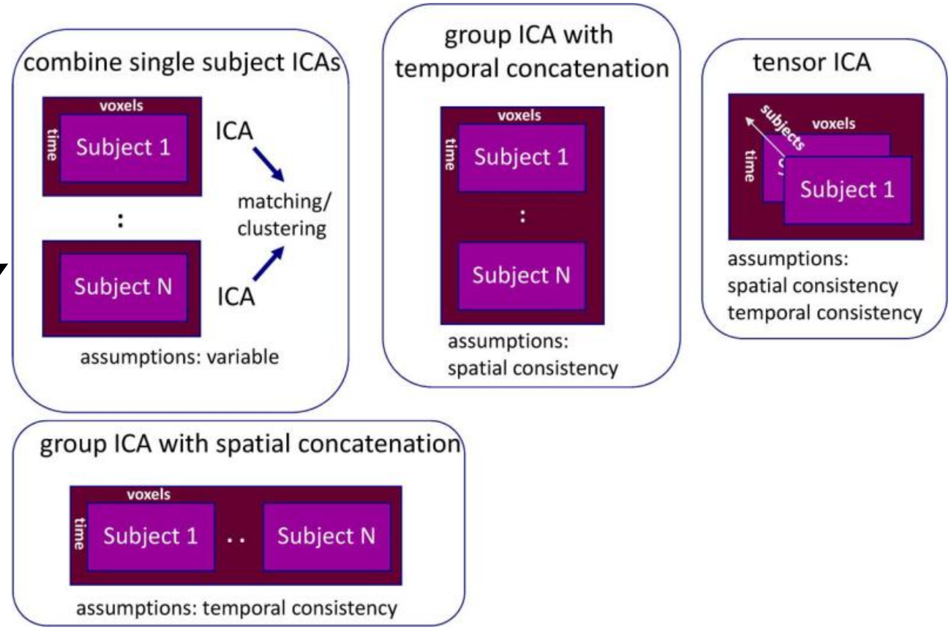
Postprocessing ICs

- Semi-automated IC-fingerprint classificator (F.DeMartino, 2007)
  - Description using 11 measures based both on spatial and temporal parameters (kurtosis,skewness, entropy, one-lag autocorrelation, etc.)
  - Components representing same process have similar „fingerprint“ in parametric space
  - SVM-classificator
  - 6 classes
    - BOLD (both task and non-task)
    - Motion artifacts
    - EPI susceptibility artifacts
    - Vessels and other noise artifacts
  - Need to expert-labelled data
  - Robust results (multiple datasets)
    - About 90% sensitivity for BOLD

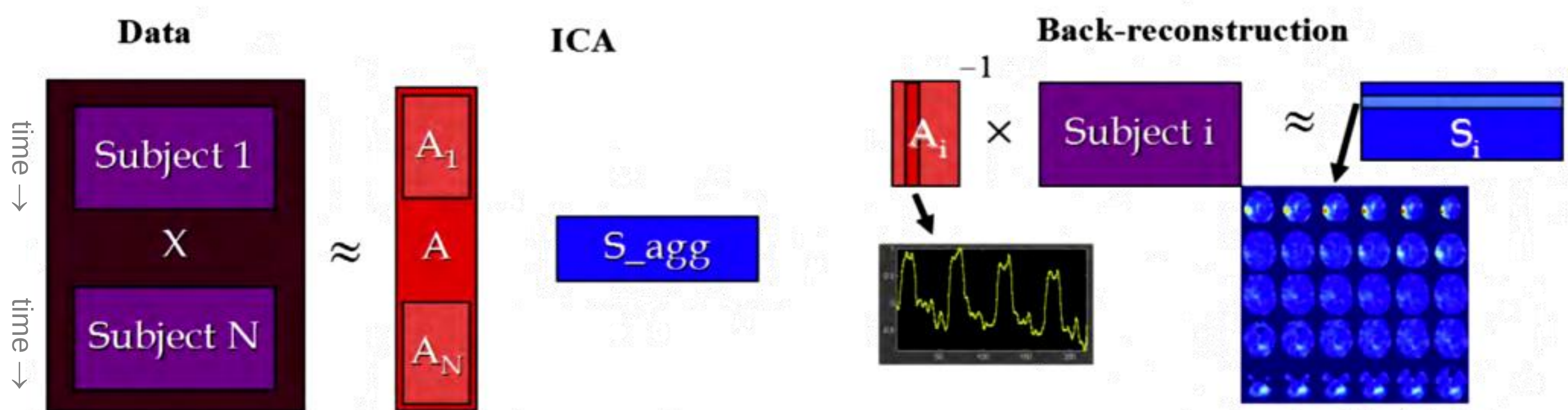


Group ICA

- Group level inference
- Many possible approaches



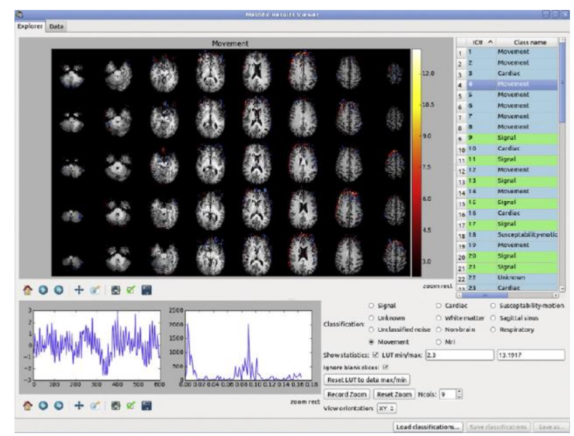
- Temporal concatenation
  - $\mathbf{Y = A \cdot S_{agg}}$ (aggregated comp.)
  - Back reconstruction of individual ICs for all subjects by separation of mixing matrix or dual regression
  - Resulting ICs can be tested for significance (among group) using voxel-by-voxel based T-test, calculation of mean spatial map and time course



Brief overview of software tools

- fMRI data toolboxes that allows ICA
  - GIFT or ICATB (http://mialab.mrn.org/software/gift)
  - MELODIC (part of FSL) (www.fmrib.ox.ac.uk/fsl)
  - BrainVoyager
  - etc.

- fMRI data denoising
  - FIX (http://fsl.fmrib.ox.ac.uk/fsl/fslwiki/FIX)
    - uses 180 features (both spatial and temporal)
    - automated classificator
    - very high (95%) overall accuracy



  - Principle: zeroing noise IC’s and reconstruction of data

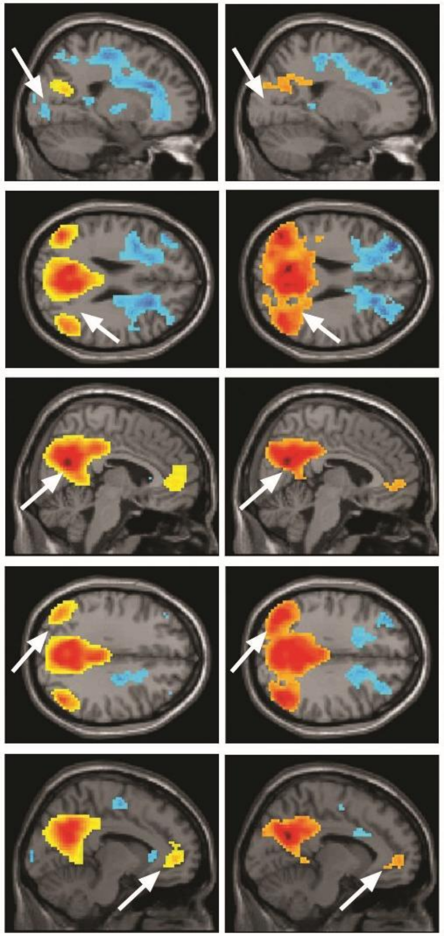
Practical example – prof.Rektorova's study

- 300scan/15min resting state
  - Healthy control group
  - Patients with Alzheimer Disease (AD)

- ICA performed for both groups
- DMN component for each subject selected using comparison with mask
- Statistical testing between groups

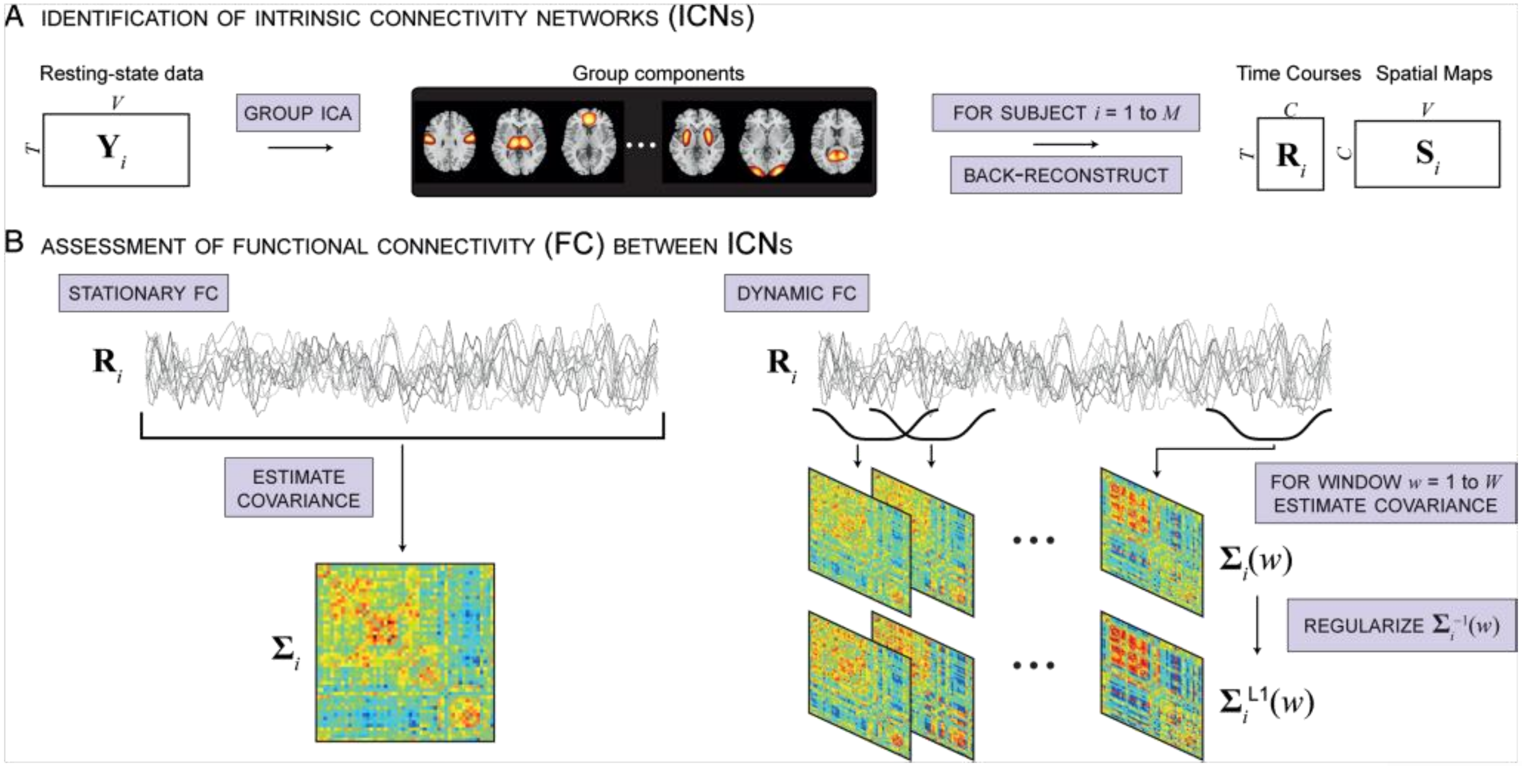
- (arrows points out significant differences)

Healthy controls | AD Patients



ICA in context of functional connectivity
(E.A.Allen, 2012)

- ICA components can be seen as functional networks
- Brain regions represented in one IC shares similar BOLD activity pattern => similar metabolism, neural activity => they are functionally connected
- Investigating connectivity or causality based on comparing IC's timecourses



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