# Resting-State fMRI:

## ICA and Dual Regression

FSL Course 2026

24 June, Bordeaux, France

# Resting state fMRI and ICA

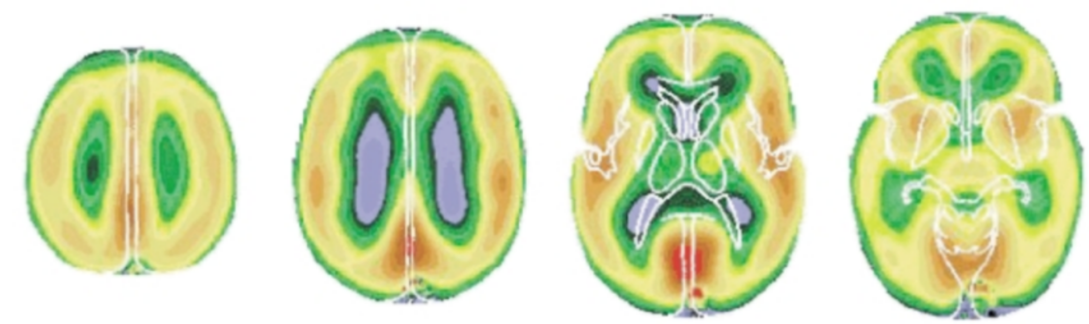
- Introduction to resting state
- Independent Component Analysis
- Single-subject ICA
- Multi-subject ICA
- Dual regression

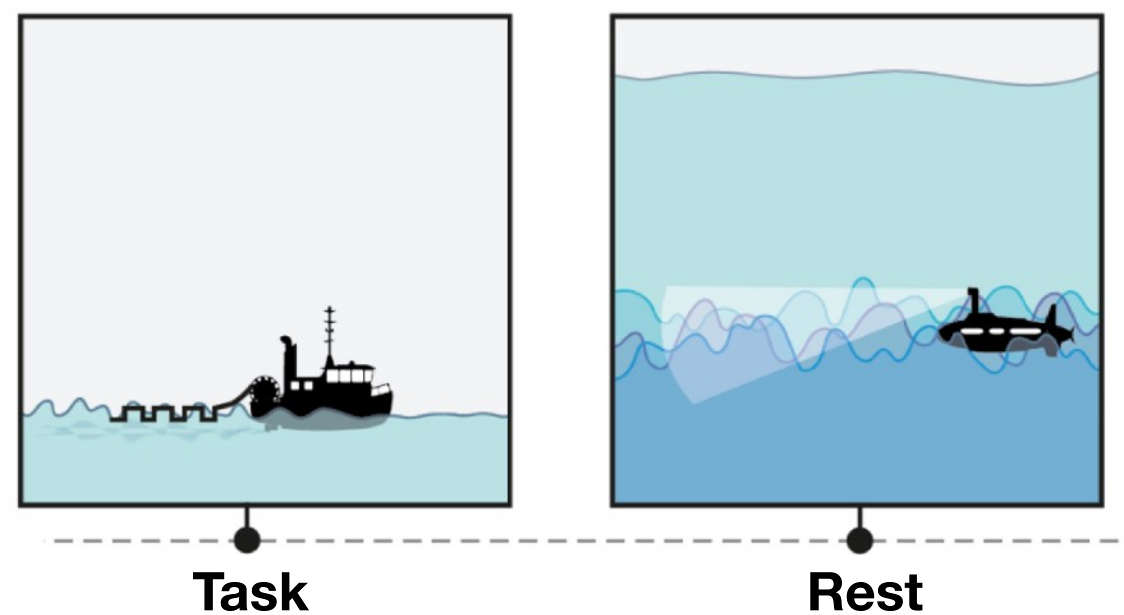
# Why resting state fMRI?

# Energy consumption in the brain

- Brain < 2% body weight but consumes ~20% of total energy
- Estimated 60-80% of this energy used to support communication between cells
- fMRI provides a window to brain activity
- Task-evoked activity accounts for ~1%

**Oxygen consumption**



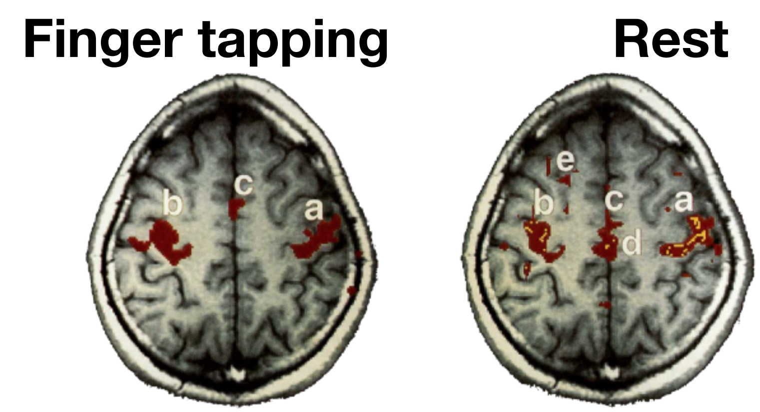



*Finn 2021*

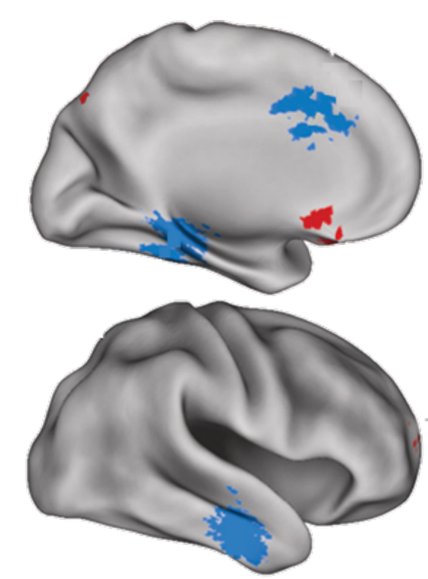
**Resting state -> intrinsic functional brain organisation**

# Why study the brain at rest?

- Understand the inherent functional organisation of the brain
- Clinical/cognitive biomarker
- Pragmatic benefits: can be done in any population, with relatively little setup and expertise required
- Localisation vs connectivity




*Biswal et al (1995)*



*Sheline et al (2010)*

# Overview of Resting State Analysis

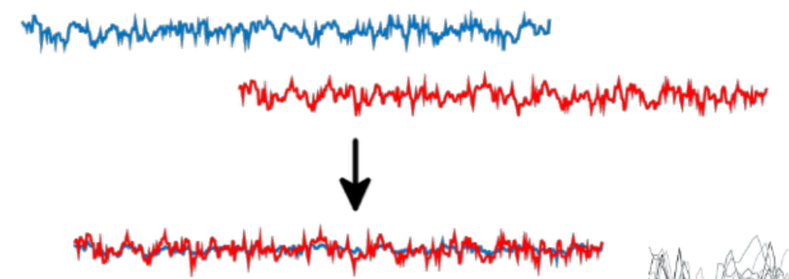
# Principles of resting state analysis

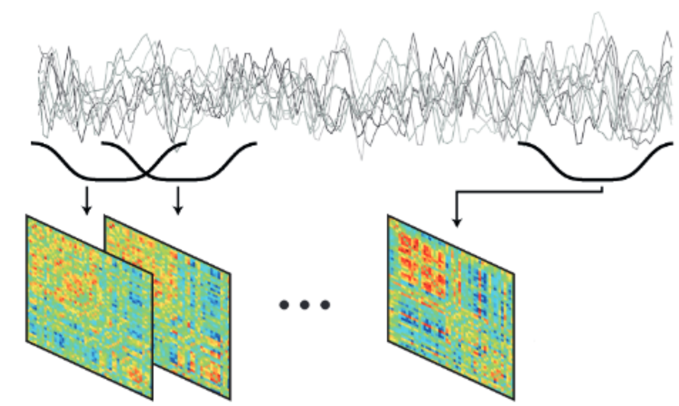
- Many different methods available for analysis
- All have one assumption in common:
    - The definition of functional connectivity is based on a statistical dependency between timeseries
- Differences between methods lie in the way these similarities are estimated and/or represented

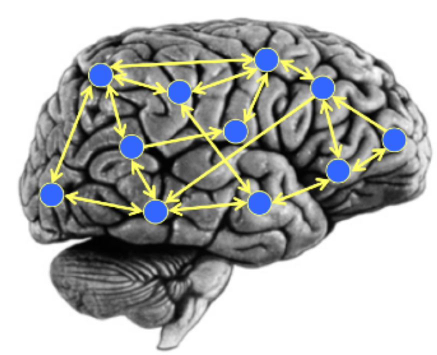
**If two brain regions show similarities in their BOLD timeseries, they are functionally connected**

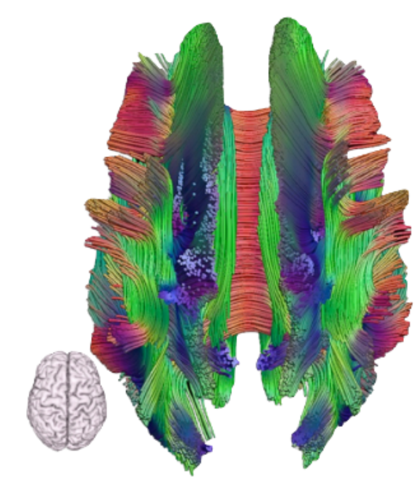
# Types of connectivity

- Functional connectivity
    - Statistical dependency
- Dynamic connectivity
    - Changes in functional connectivity over time
- Effective connectivity
    - Directional influence
- Anatomical (structural) connectivity
    - Presence of a white matter tract

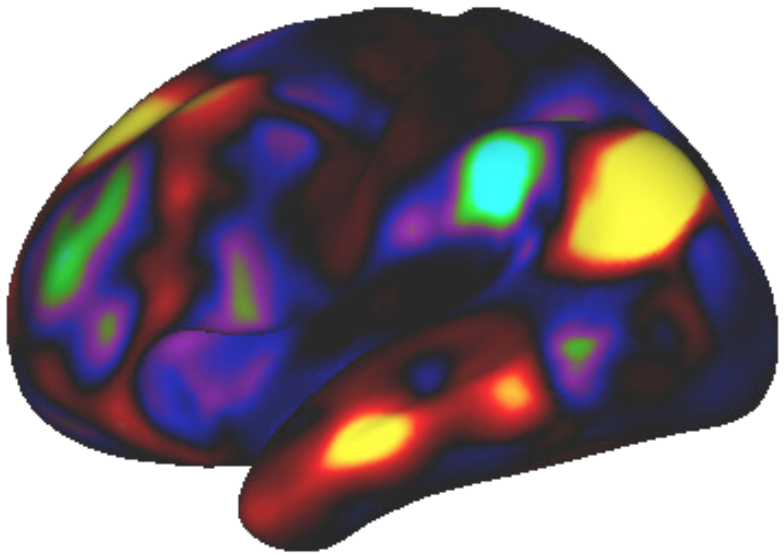




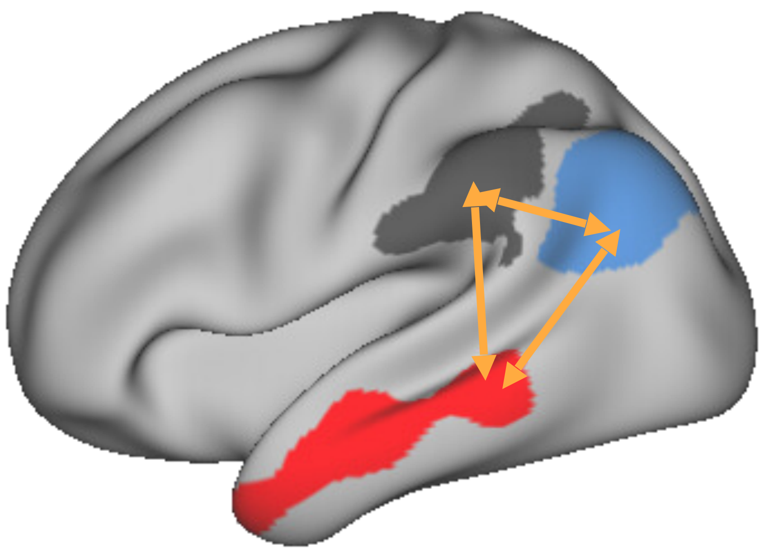




# Two broad categories of resting state connectivity methods



**Voxel-based methods**



**Node-based methods**

# Overview of resting state methods

***Voxel-based methods***

- Seed-based correlation analysis
  - SCA
- Independent component analysis
  - ICA
- Amplitude of low frequency fluctuations
- Regional homogeneity

***Node-based methods***

- Network modelling analysis
  - FSLNets
- Graph theory analysis
  - Such as degree, hub, path length
- Dynamic causal modelling
- Non-stationary methods

# Overview of resting state methods

***<u>Voxel-based methods</u>***

- Seed-based correlation analysis
  - SCA
- Independent component analysis
  - ICA -> this afternoon
- Amplitude of low frequency fluctuations
- Regional homogeneity

***<u>Node-based methods</u>***

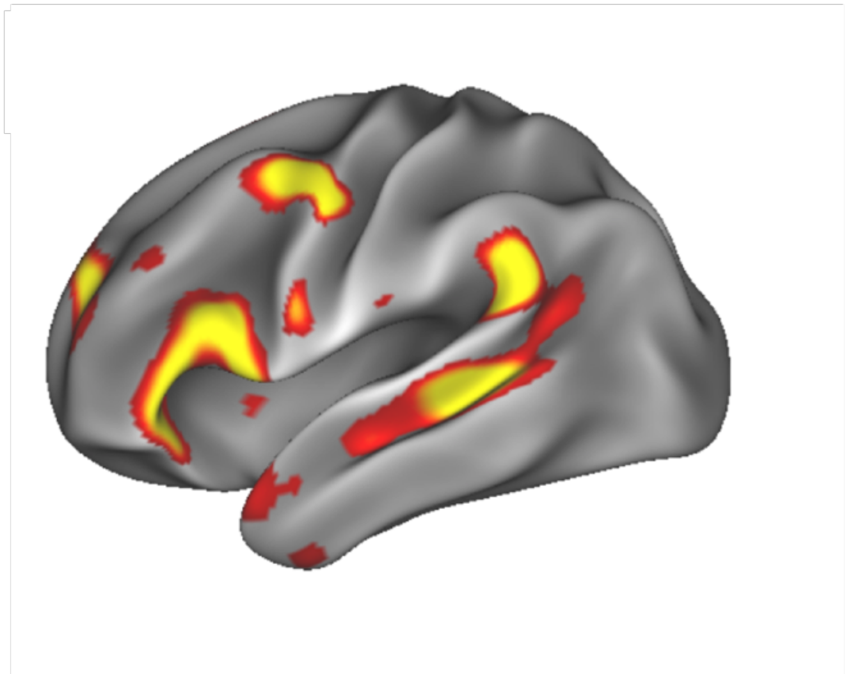
- Network modelling analysis
  - FSLNets -> tomorrow morning
- Graph theory analysis
  - Such as degree, hub, path length
- Dynamic causal modelling
- Non-stationary methods

# Resting state fMRI and ICA

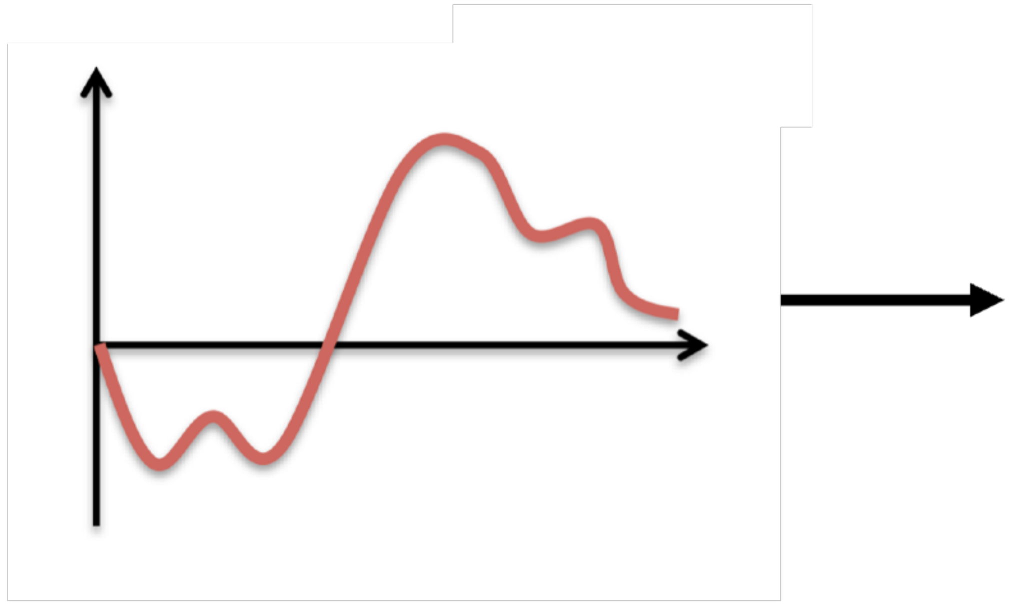
- Introduction to resting state
- Independent Component Analysis
- Single-subject ICA
- Multi-subject ICA
- Dual regression

# Resting state functional components

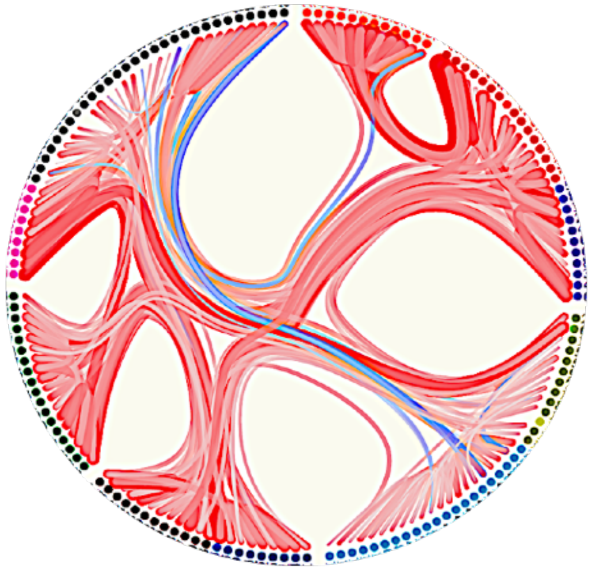
Spatial Maps or Configuration



Time Courses



Network Modelling



- Each component -> a set of brain regions that work in synchrony
- Timecourses can then be used for network modelling

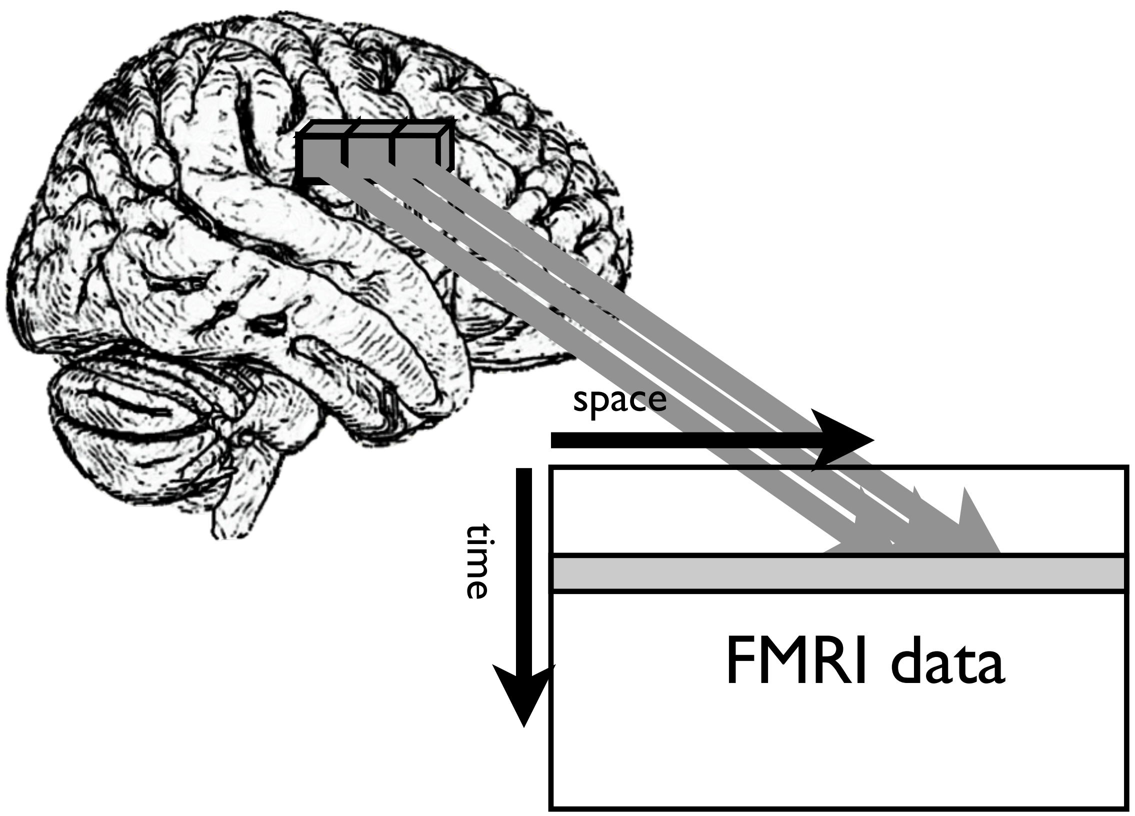
# MELODIC: ICA tool in FSL

# Melodic

multivariate linear decomposition:

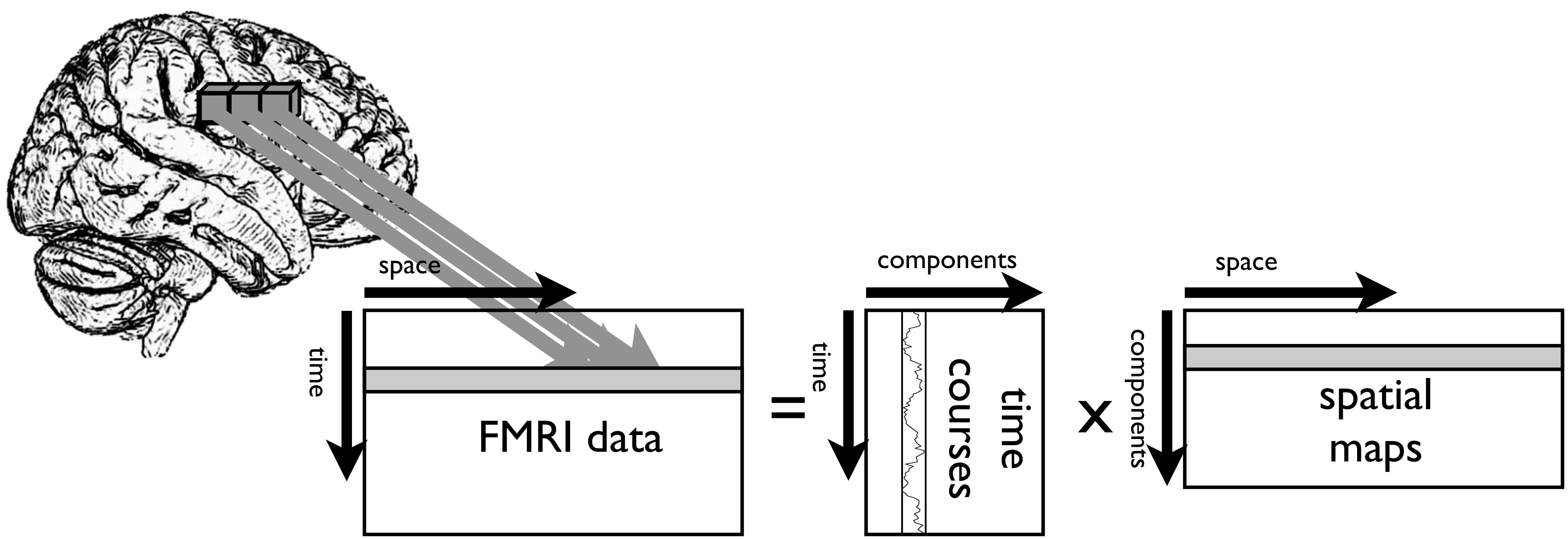
# Melodic

multivariate linear decomposition:



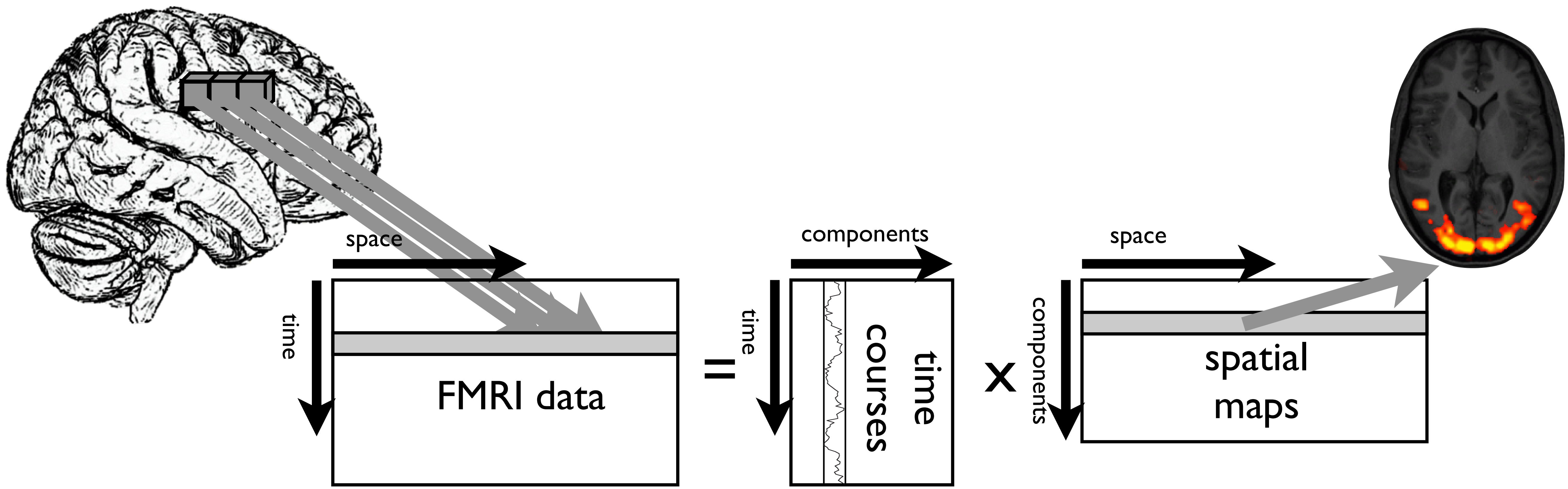
# Melodic

multivariate linear decomposition:



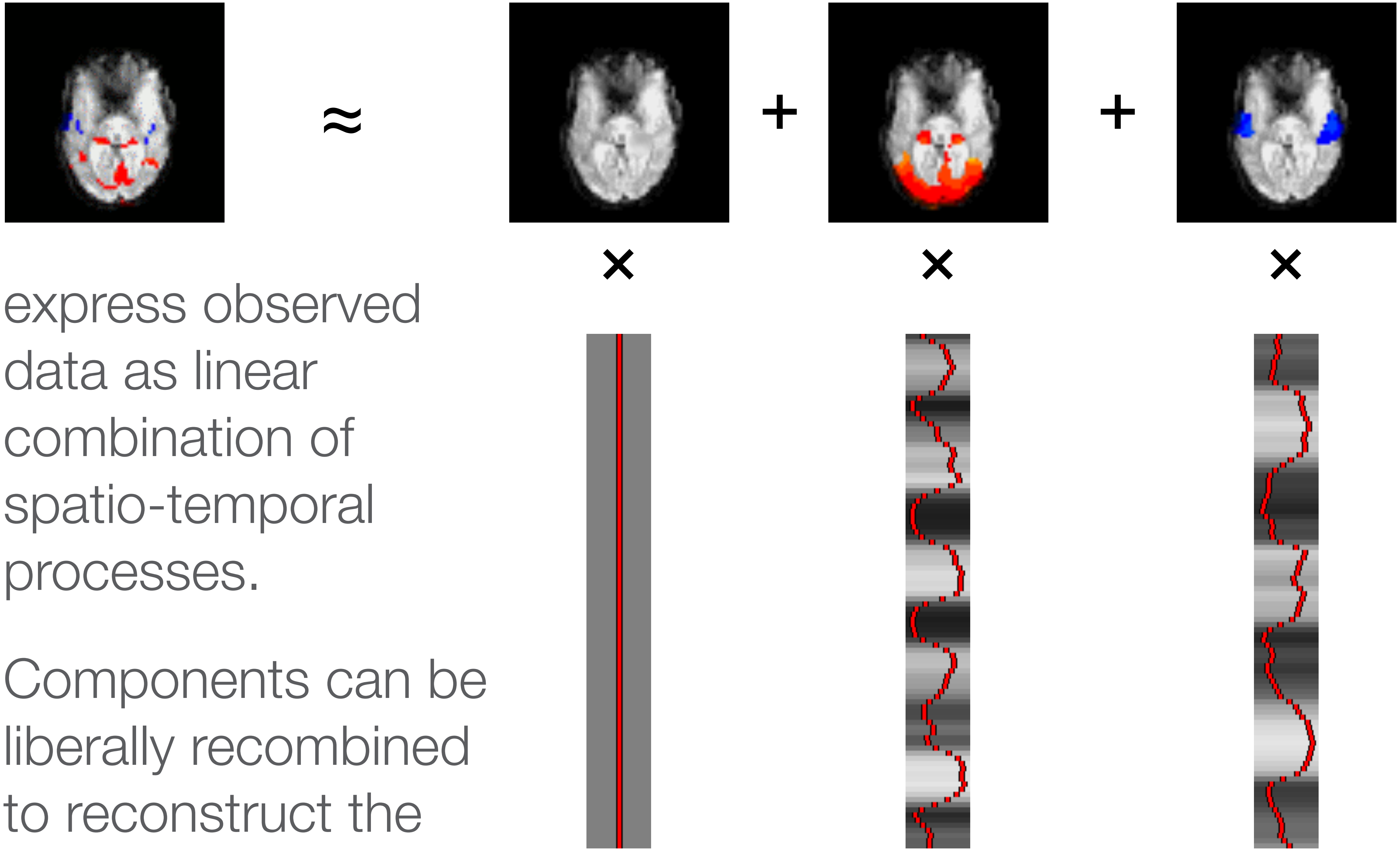
# Melodic

multivariate linear decomposition:




Data is represented as a 2D matrix and decomposed into components

# What are components?




- express observed data as linear combination of spatio-temporal processes.
- Components can be liberally recombined to reconstruct the original data.

# Some characteristics of MELODIC

- Multivariate voxel-based approach
- Exploratory “model-free” method to find interesting structure in the data
- Gives “spatially independent” components
- “Avoiding overfitting” through automatic model order selection
- “Thresholding" to remove background from main signal

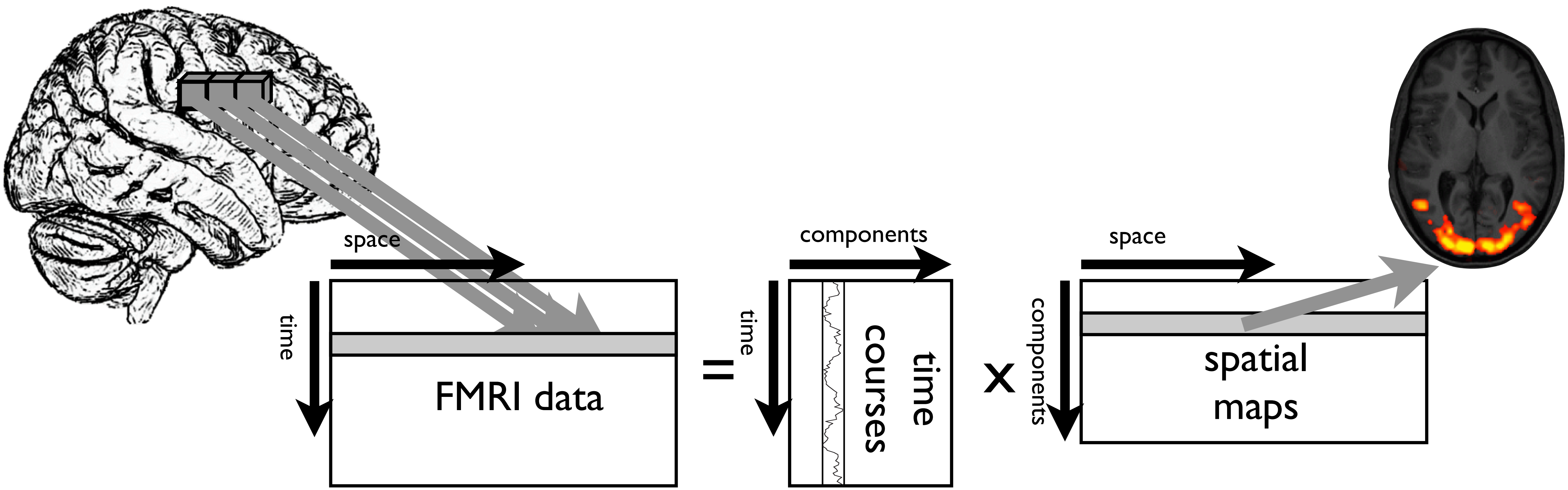
# Some characteristics of MELODIC

- Multivariate voxel-based approach
- Exploratory “model-free” method to find interesting structure in the data
- Gives “spatially independent” components
- “Avoiding overfitting” through automatic model order selection
- “Background suppression" to remove background from main signal

# ICA vs GLM:
# Exploratory vs Confirmatory

# Melodic

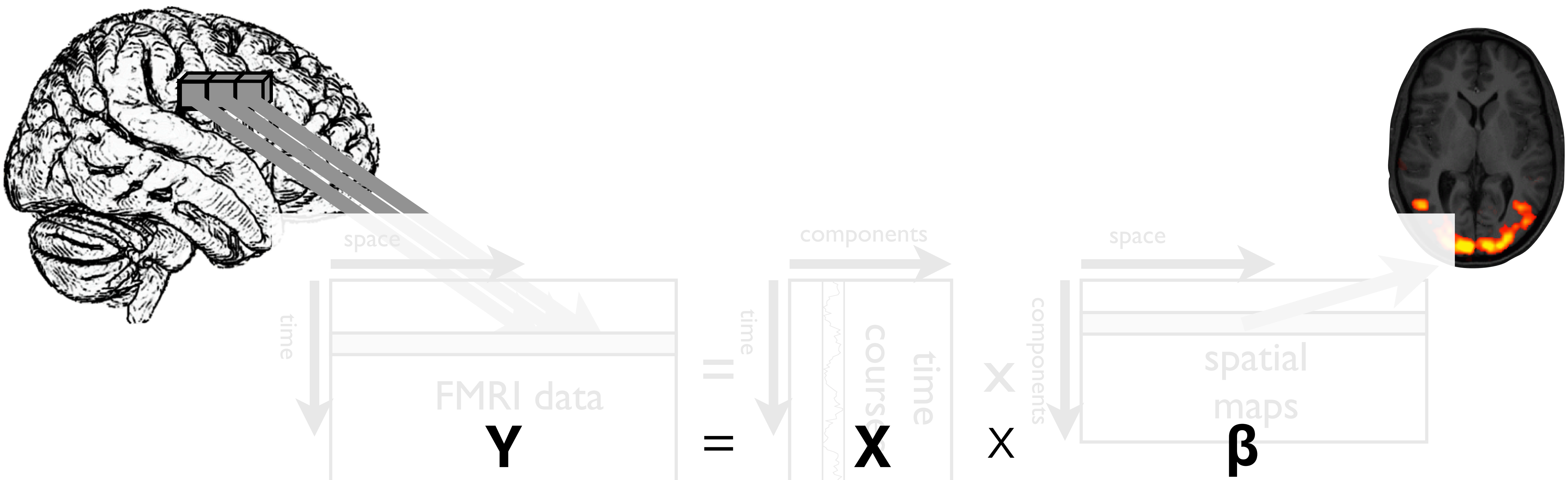
multivariate linear decomposition:




Data is represented as a 2D matrix and decomposed into components

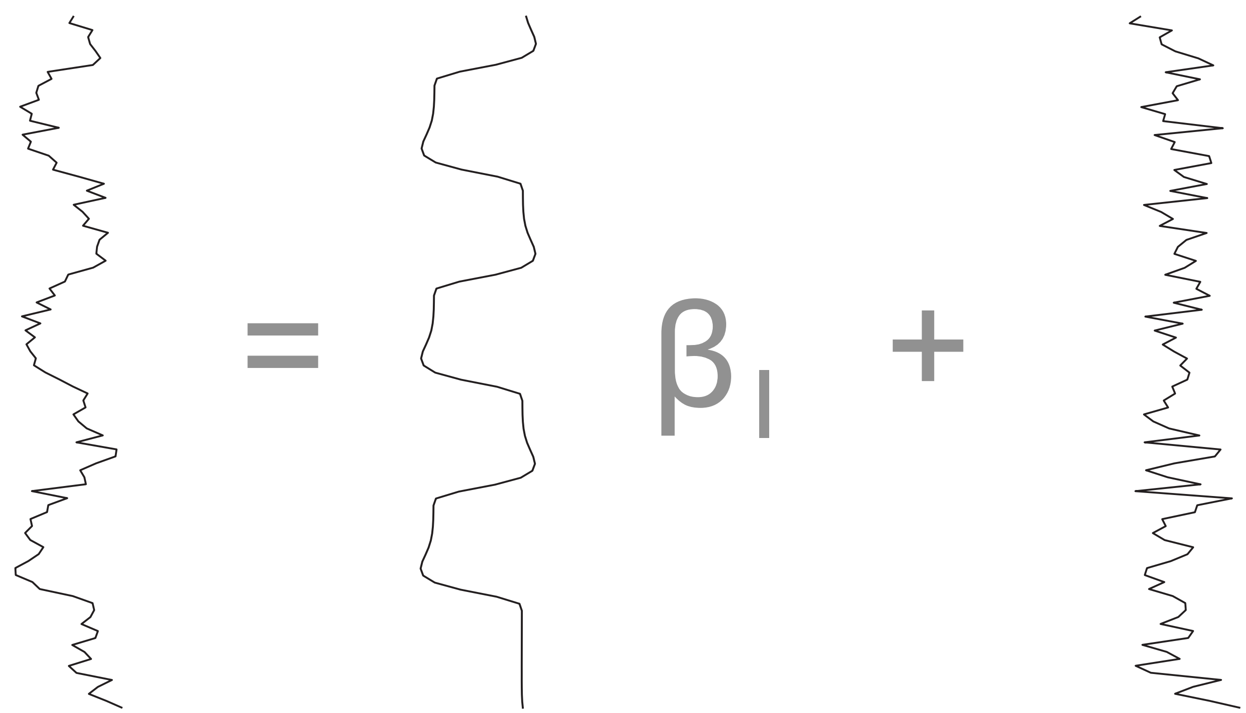
# Melodic

multivariate linear decomposition:




Data is represented as a 2D matrix and decomposed into components

# Model-based (GLM) analysis




- Model each measured time-series as a linear combination of signal and noise
- We know the expected response -> use that to define the design matrix

# Resting state = Model-free?


Resting state timeseries are unconstrained -> no design matrix

# Task: Confirmatory vs Rest: Exploratory

## Confirmatory

- "How well does my model fit to the data?"

Problem → Data →

| Model → Analysis |
|---|

→ Results

- results depend on the model

## Exploratory

- "Is there anything interesting in the data?"

Problem → Data →

| Analysis → Model |
|---|

→ Results

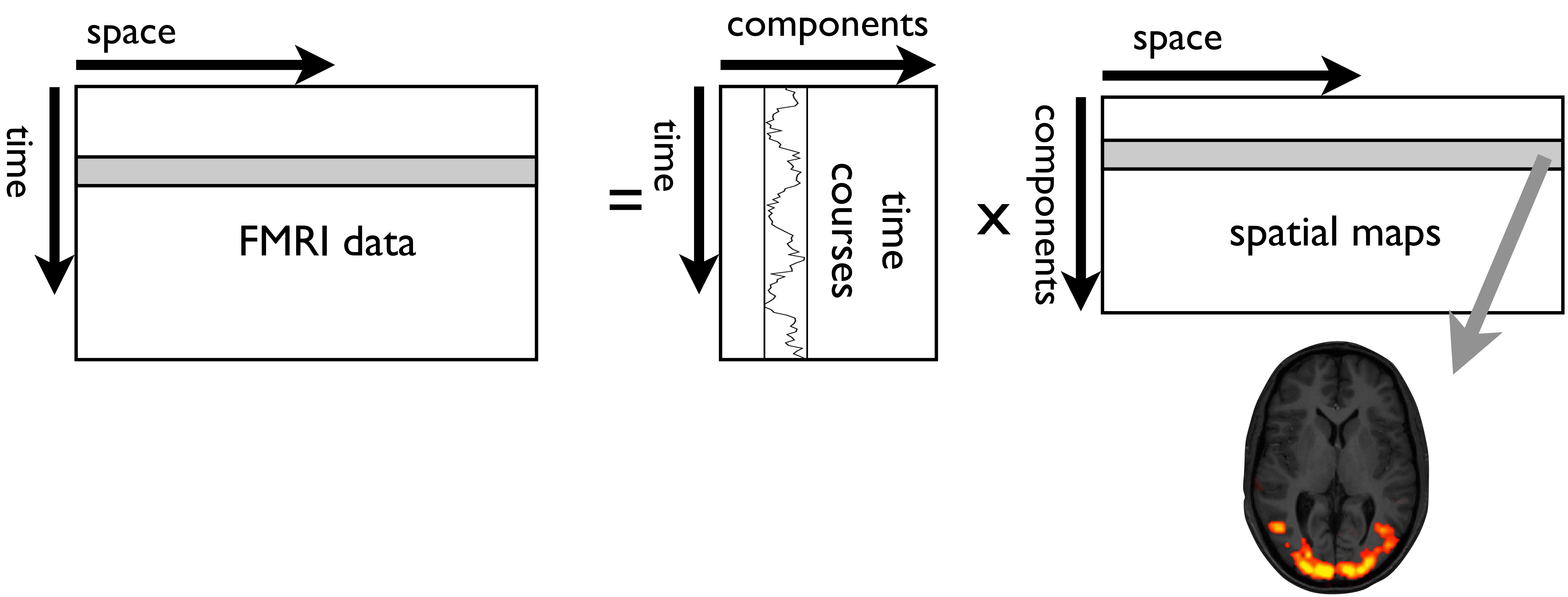
- can give unexpected results

# Some characteristics of MELODIC

- Multivariate voxel-based approach
- Exploratory “model-free” method to find interesting structure in the data
- Gives “spatially independent” components
- “Avoiding overfitting” through automatic model order selection
- “Background suppression" to remove background from main signal

# Spatially independent components

# Spatial ICA for FMRI



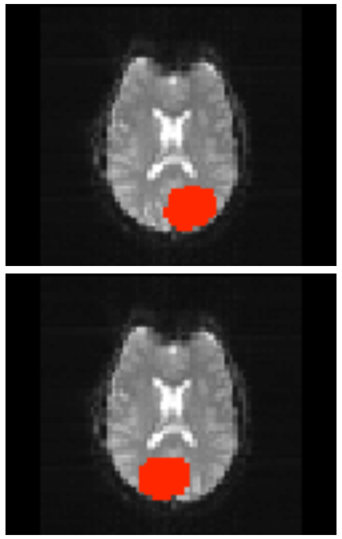

– data is decomposed into a set of spatially independent maps and a set of time-courses

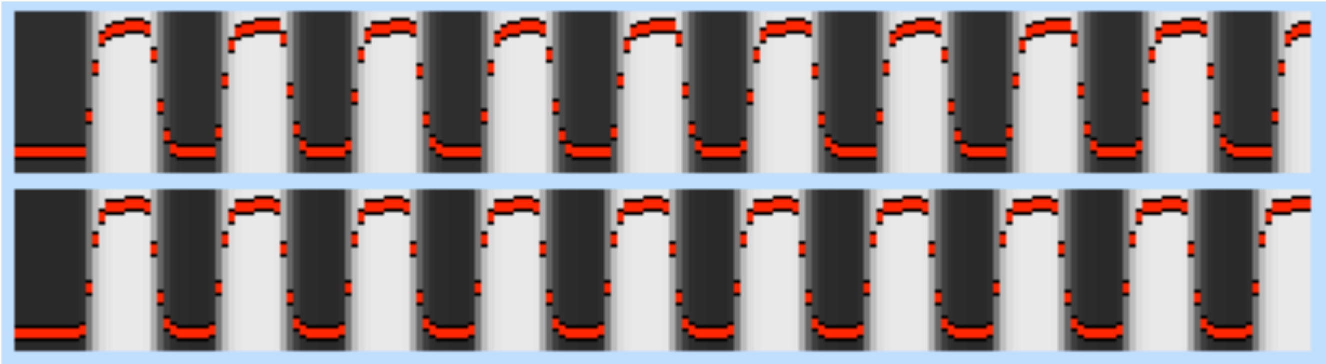
*McKeown et al.*
*HBM 1998*

# PCA vs. ICA ?

Simulated Data

(2 components, slightly different timecourses)

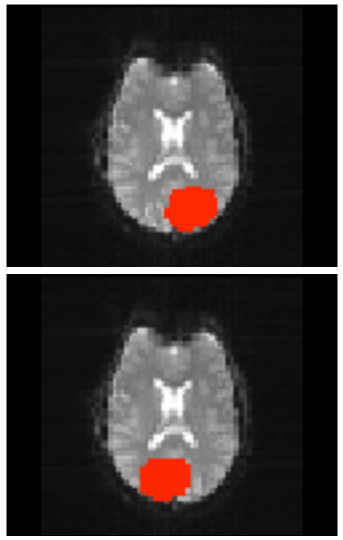


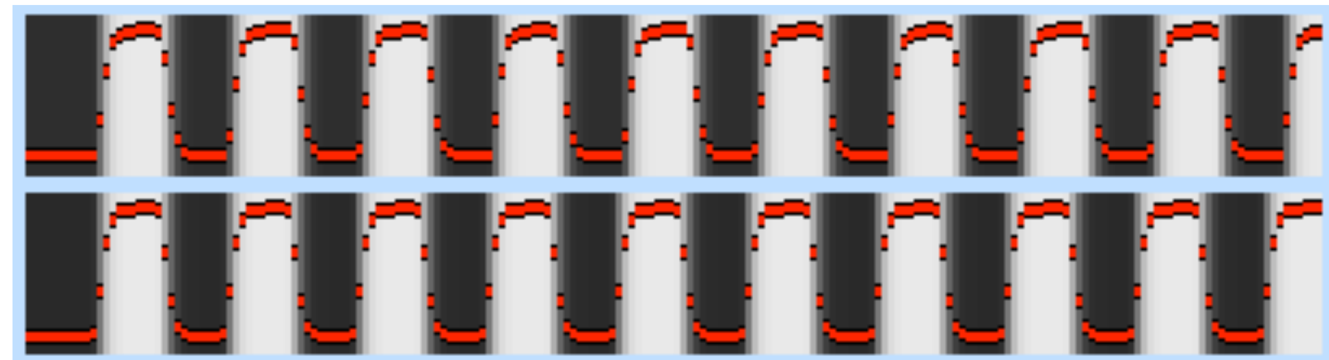


# PCA vs. ICA ?

Simulated Data

(2 components, slightly different timecourses)

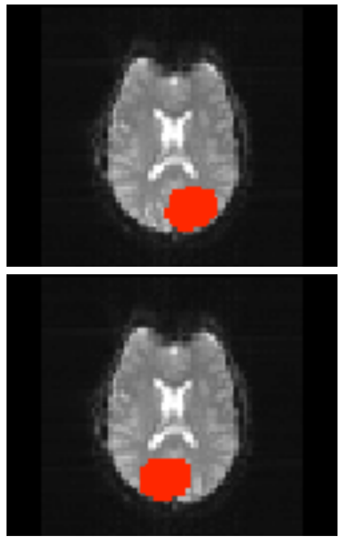


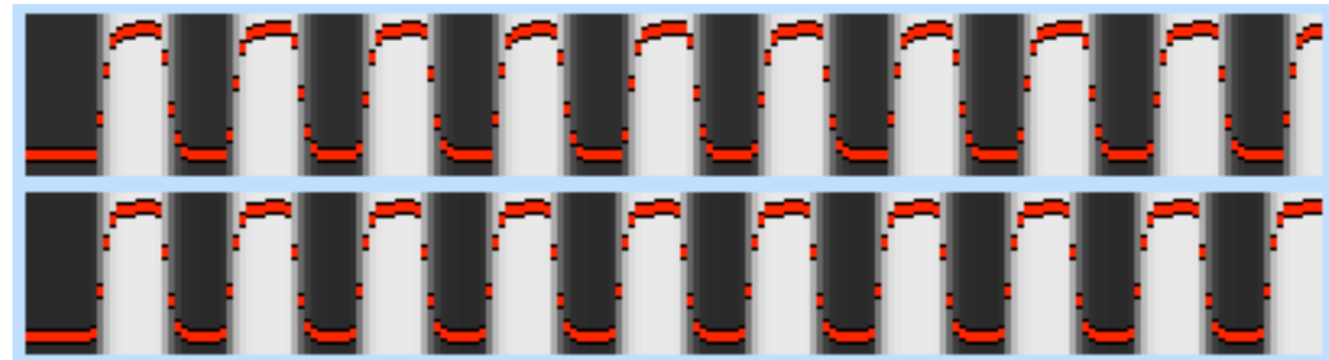


# PCA vs. ICA ?

## Simulated Data

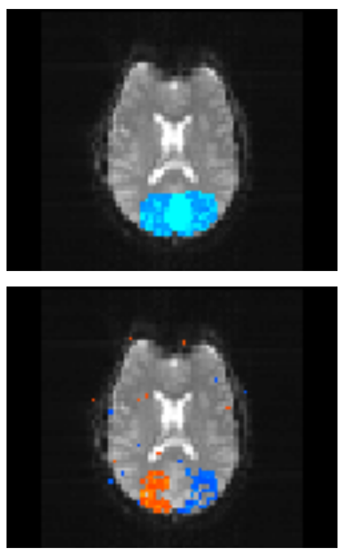
(2 components, slightly different timecourses)

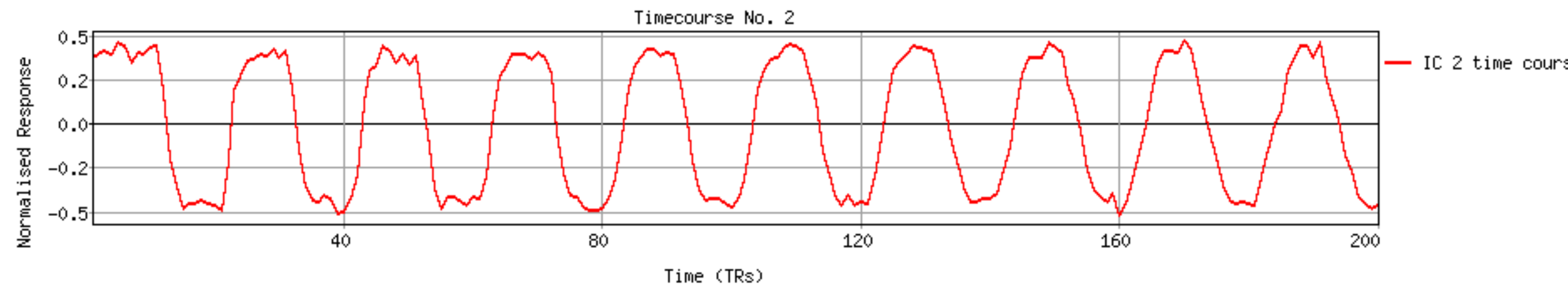


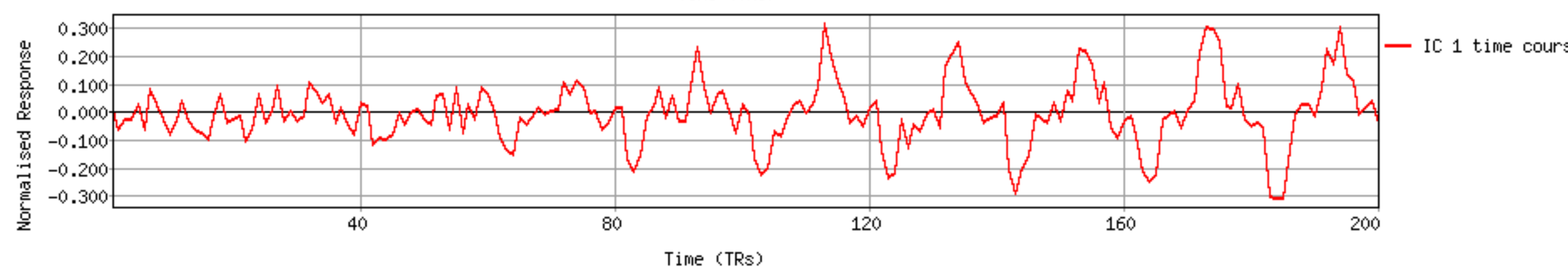


## PCA

- Timecourses orthogonal
- Spatial maps and timecourses "wrong"

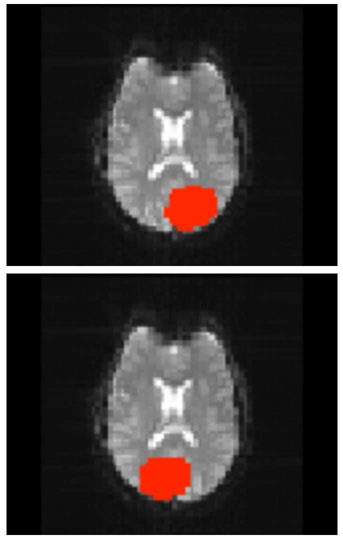


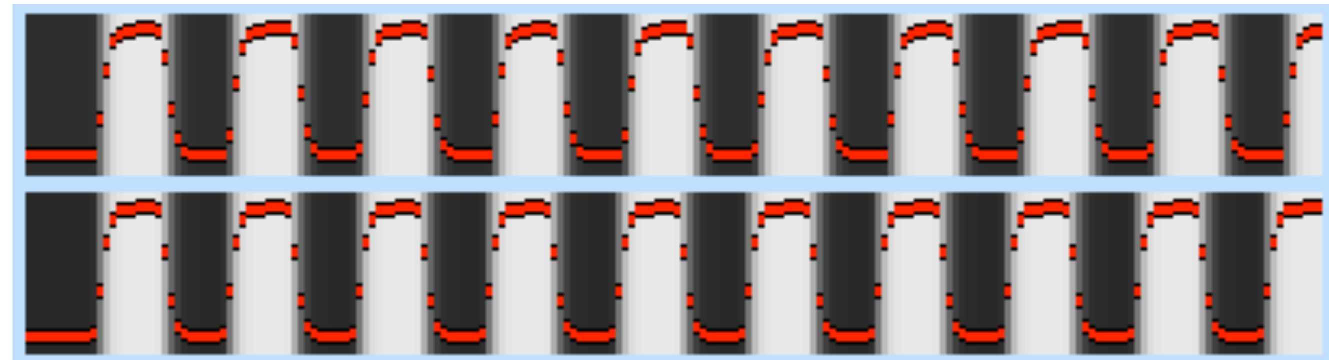


## Simulated Data

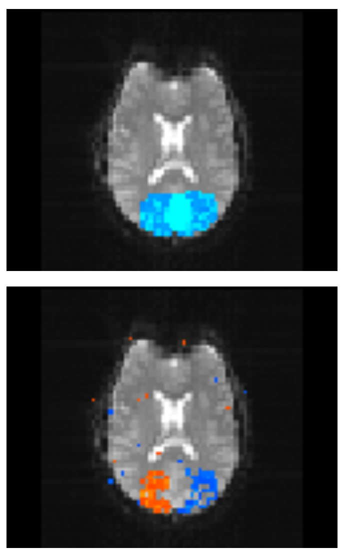
(2 components, slightly different timecourses)

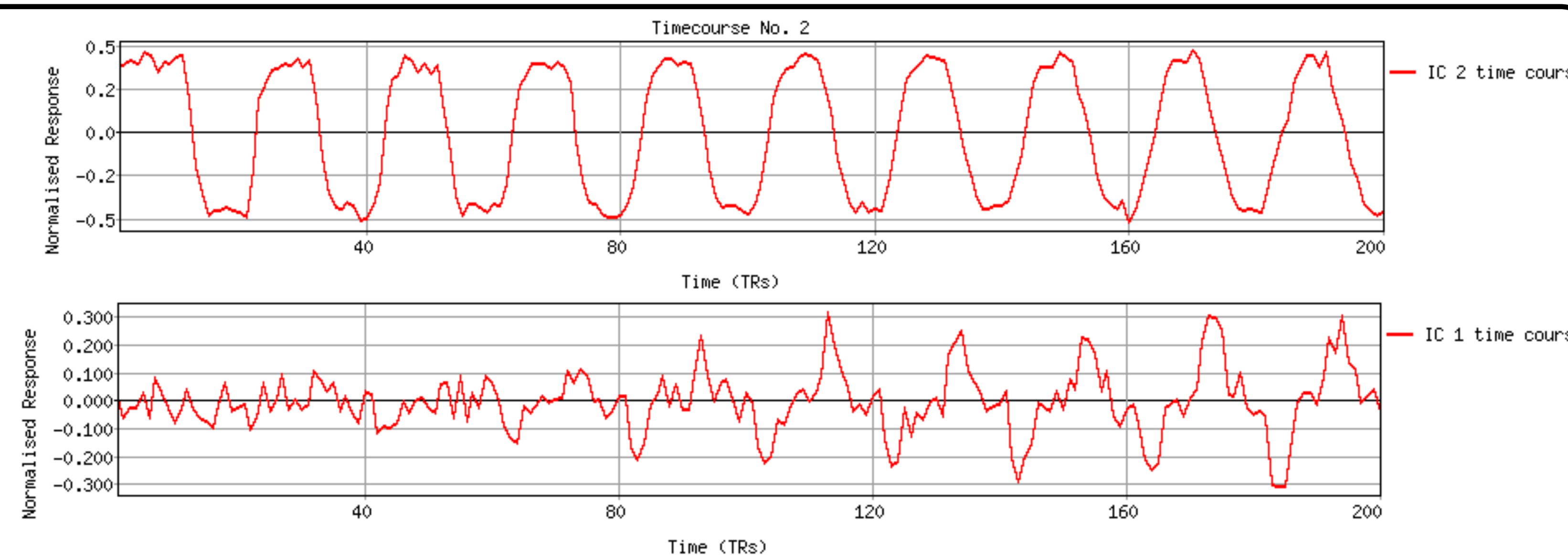




## PCA

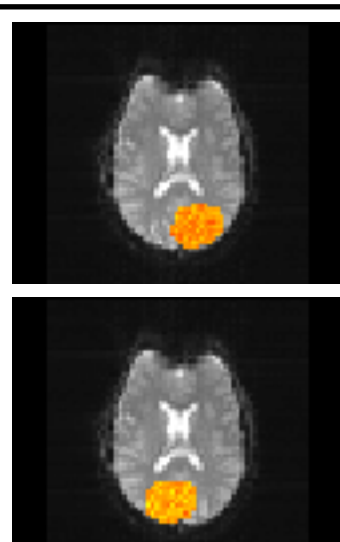
- Timecourses orthogonal
- Spatial maps and timecourses “wrong”

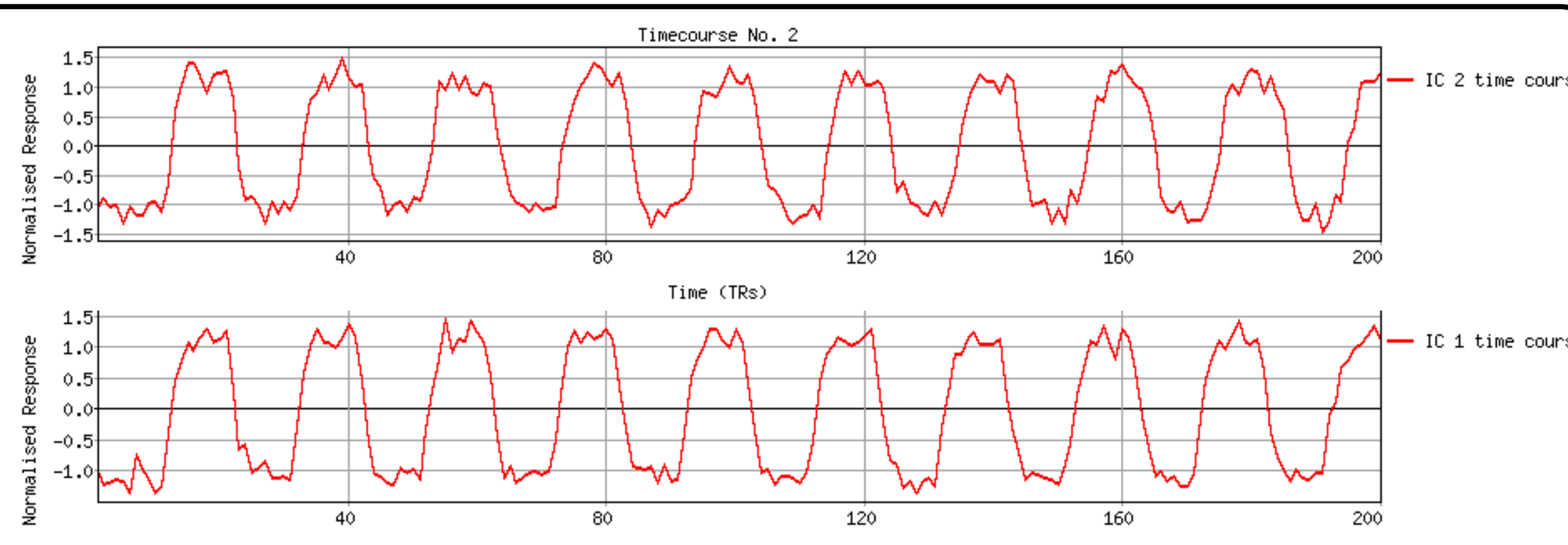





## ICA

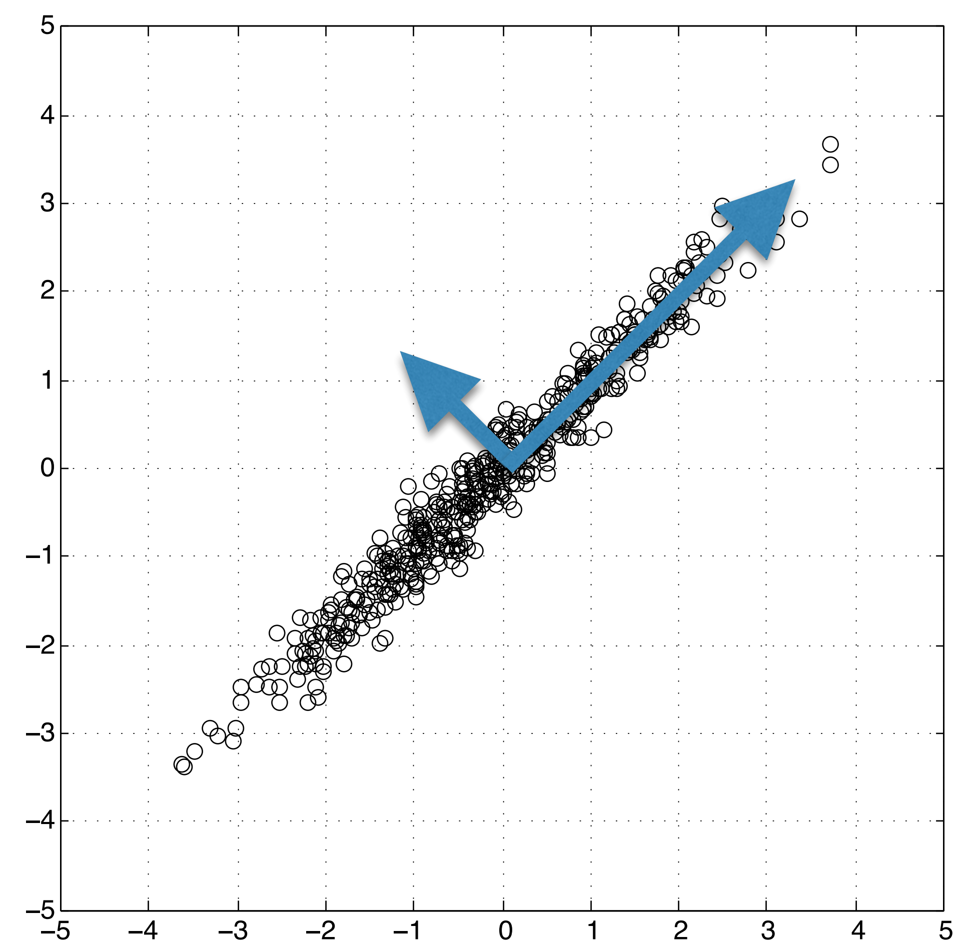
- Timecourses non-co-linear
- Spatial maps and timecourses “right”





# PCA vs. ICA

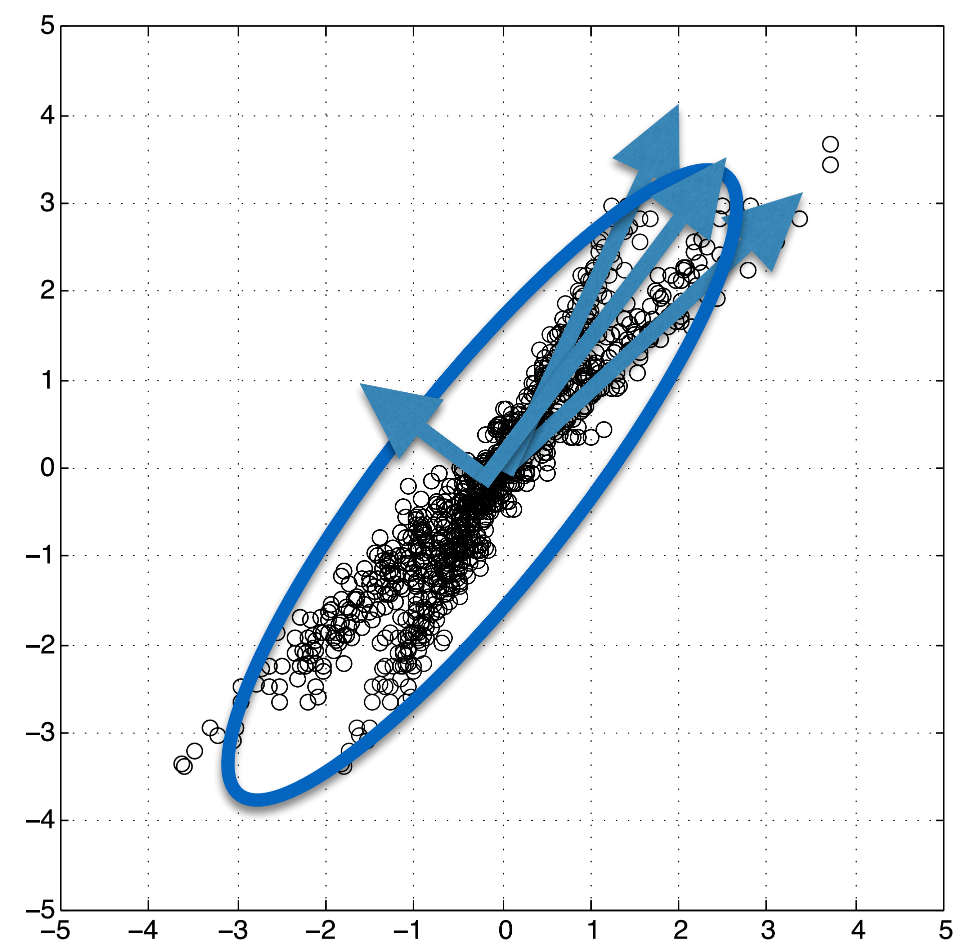
- PCA finds projections of maximum amount of variance in Gaussian data (uses 2nd order statistics only)




Gaussian data

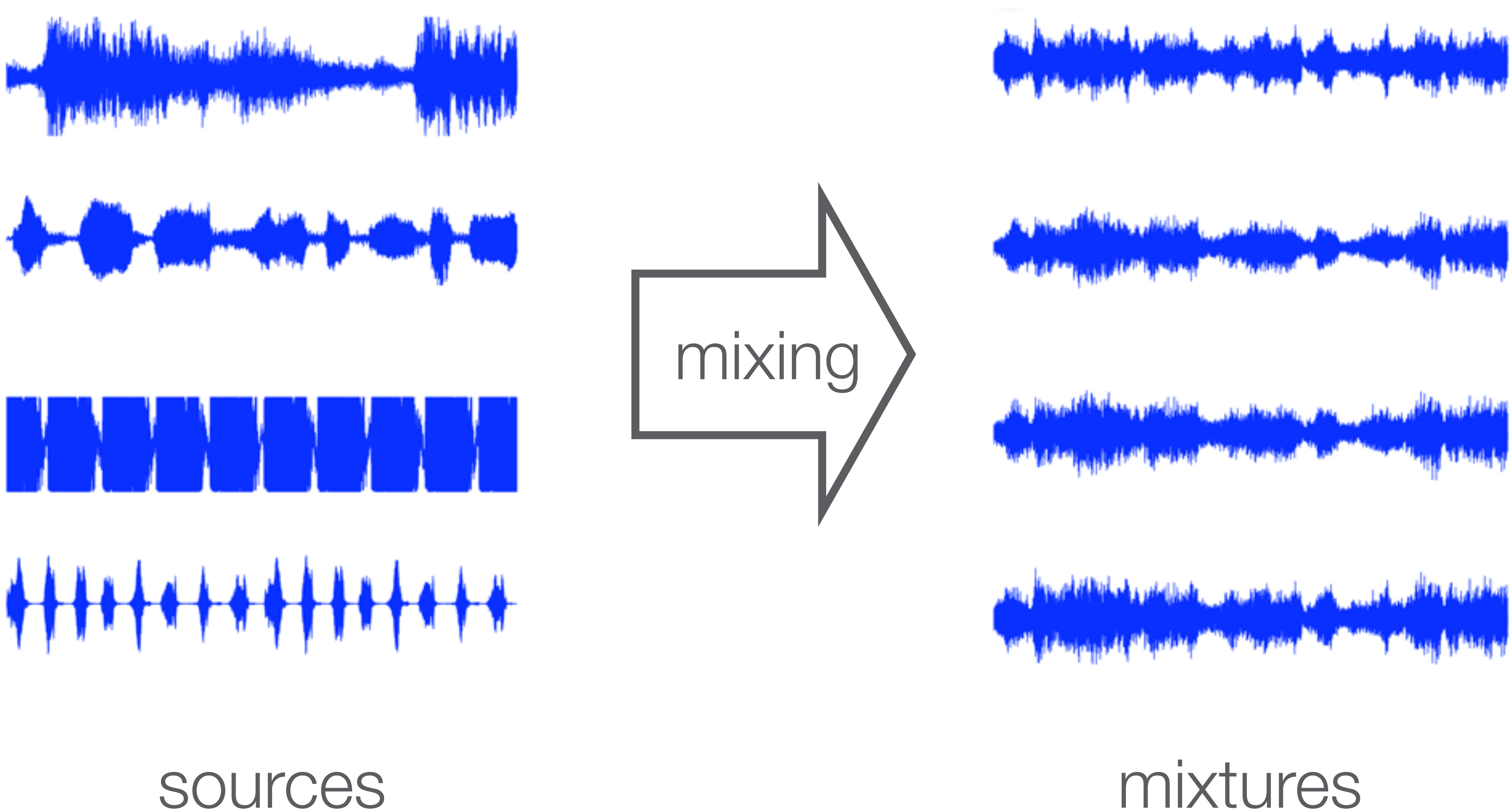
# PCA vs. ICA

- PCA finds projections of maximum amount of variance in Gaussian data (uses 2nd order statistics only)
- Independent Component Analysis (ICA) finds projections of maximal independence in non-Gaussian data (using higher-order statistics)

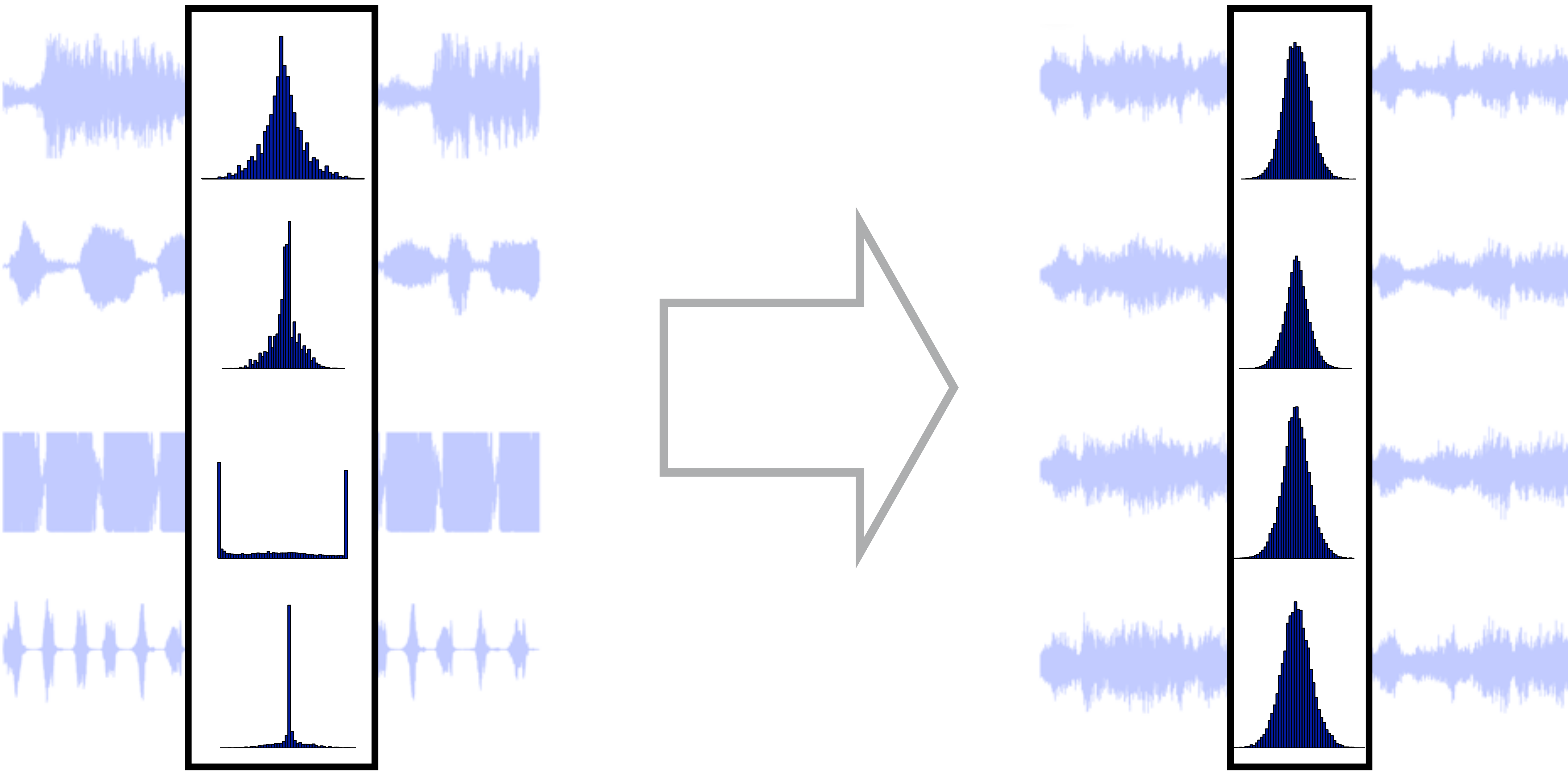



non-Gaussian data

# Non-Gaussianity



# Non-Gaussianity



# ICA estimation

- Random mixing results in more Gaussian-shaped PDFs (Central Limit Theorem)
- ICA turns this around:

  if we estimate components with less Gaussian distributions this is unlikely to be a random result

  ➡ measure non-Gaussianity

Hyvärinen & Oja 1997

# ICA estimation

- Need to find an unmixing matrix such that: a) maximises independence between components and b) maximises non-Gaussianity of components
- Therefore, we need a contrast (objective/cost) function to drive the unmixing which measures statistical independence and an optimisation technique:
  - gradient descent & kurtosis or cumulants (Jade)
  - gradient descent & maximum entropy (Infomax)
  - fixed point iteration & neg-entropy (FastICA)

# Some characteristics of MELODIC

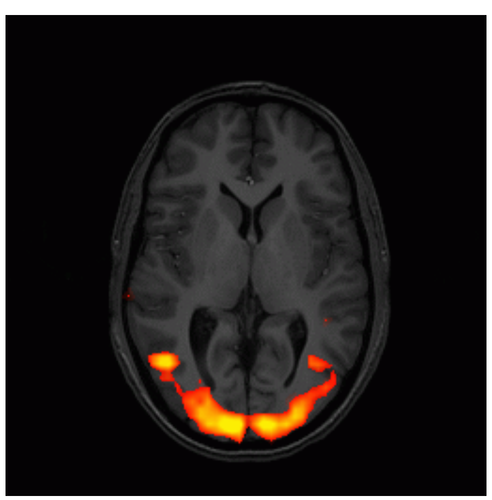
- Multivariate voxel-based approach
- Exploratory “model-free” method to find interesting structure in the data
- Gives “spatially independent” components
- “Avoiding overfitting” through automatic model order selection
- “Background suppression" to remove background from main signal

# Managing overfitting:
# Automatic model order selection

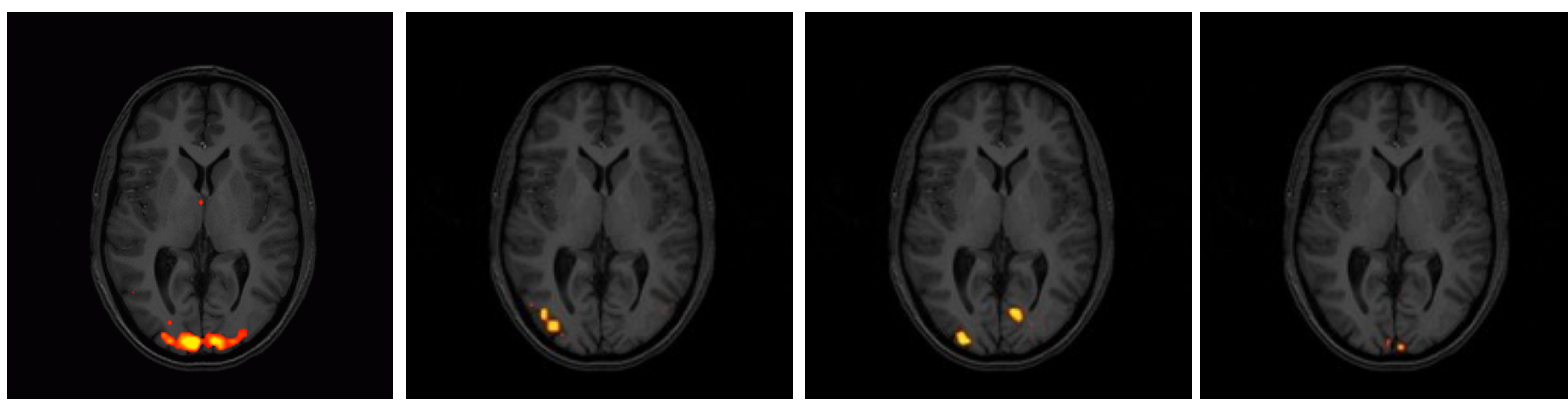
# The ‘overfitting’ problem

Fitting an unsupervised model to noisy observations:

- No control over signal vs. noise (non-interpretable results)



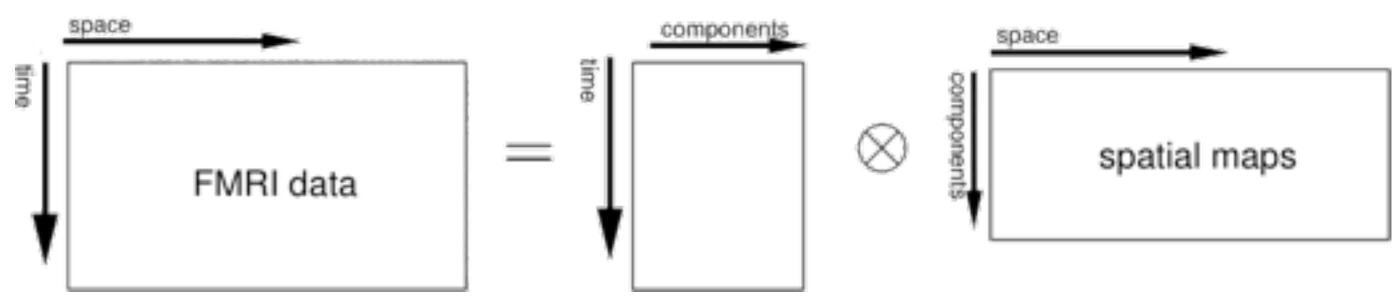
**GLM analysis**



**standard ICA (unconstrained)**

# Probabilistic ICA model in MELODIC

statistical “latent variables” model: we observe linear mixtures of hidden sources in the presence of Gaussian noise




+ noise

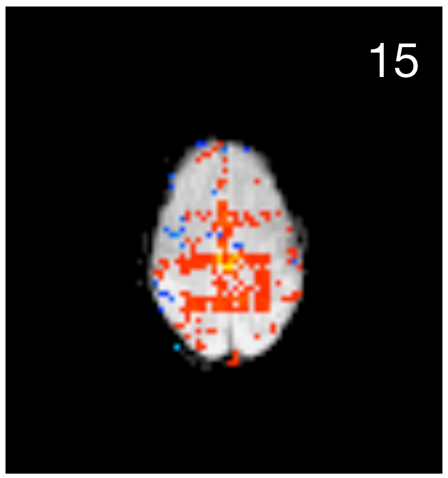
$$\mathbf{Y} = \mathbf{X} \quad \boldsymbol{\beta} + \mathbf{E}$$

Issues:

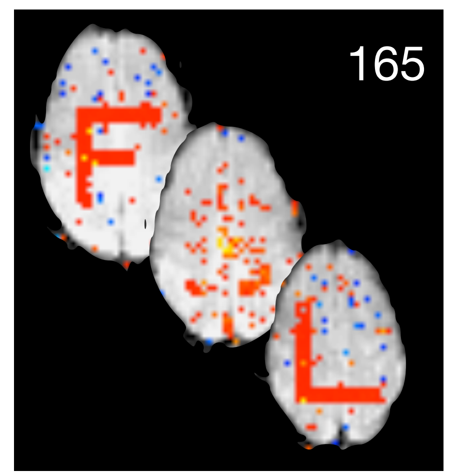
- Model Order Selection: how many components?

# Model Order Selection

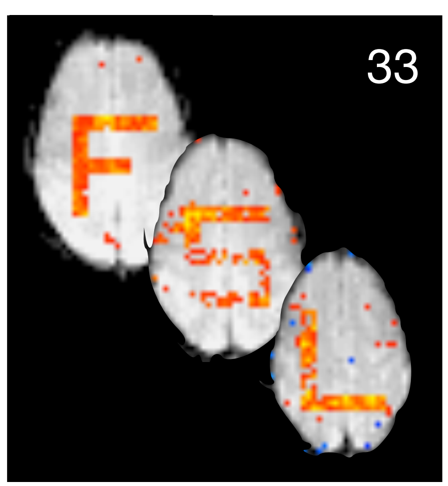
## ‘How many components’?




*under-fitting*: the amount of explained data variance is insufficient to obtain good estimates of the signals

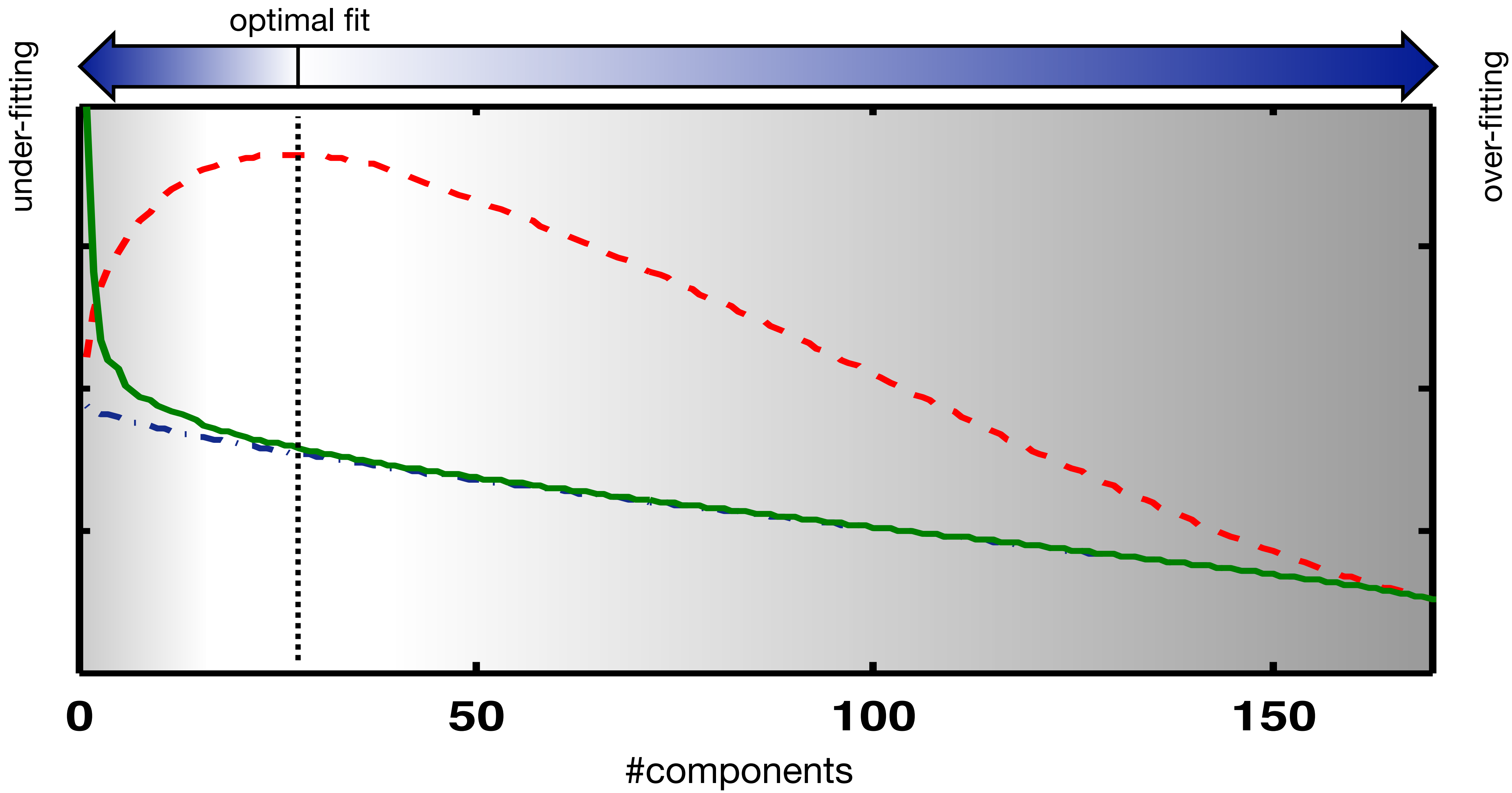



*over-fitting*: the inclusion of too many components leads to fragmentation of signal across multiple component maps, reducing the ability to identify the signals of interest




*optimal fitting*: the amount of explained data variance is sufficient to obtain good estimates of the signals while preventing further splits into spurious components

# Model Order Selection

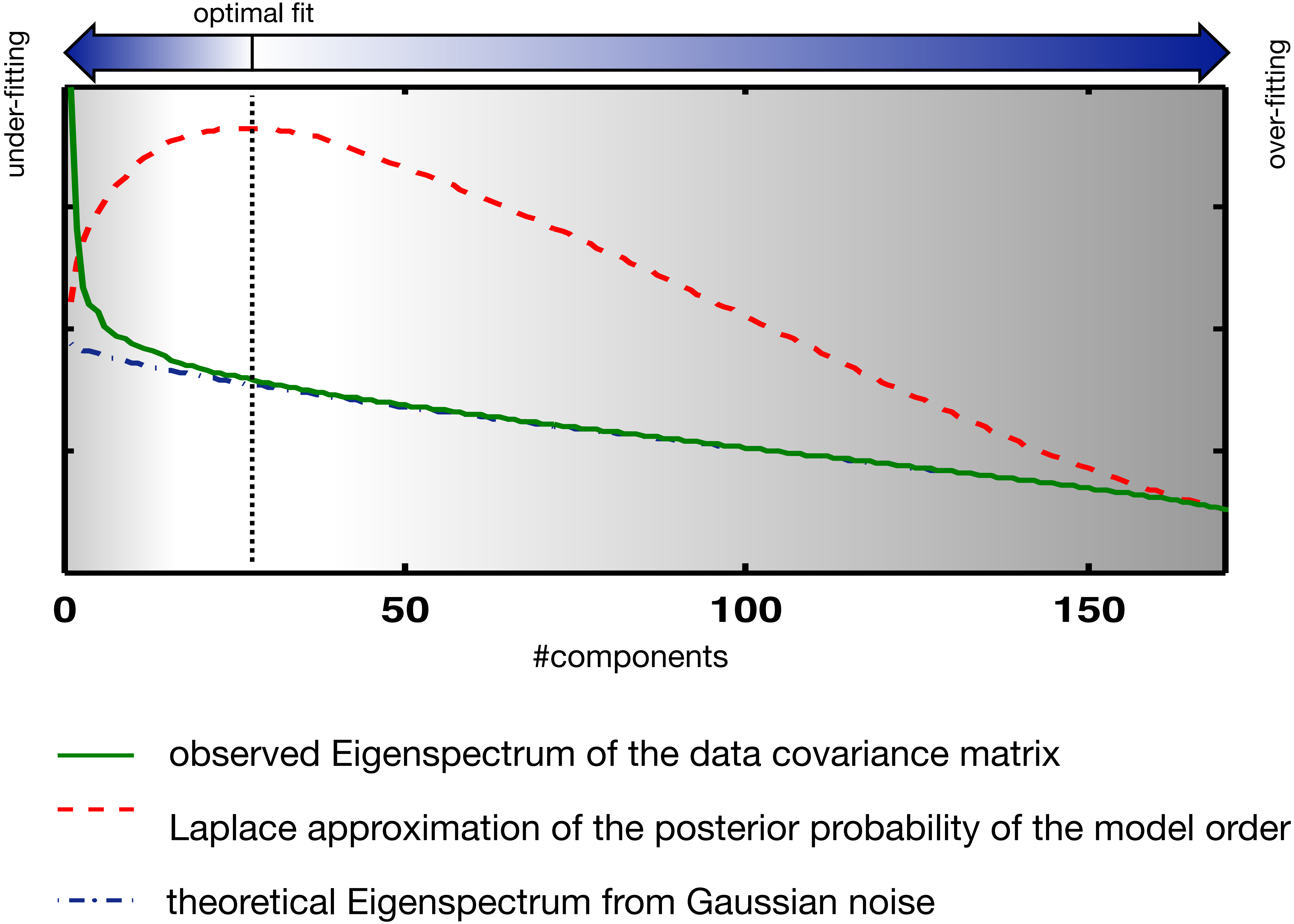



observed Eigenspectrum of the data covariance matrix

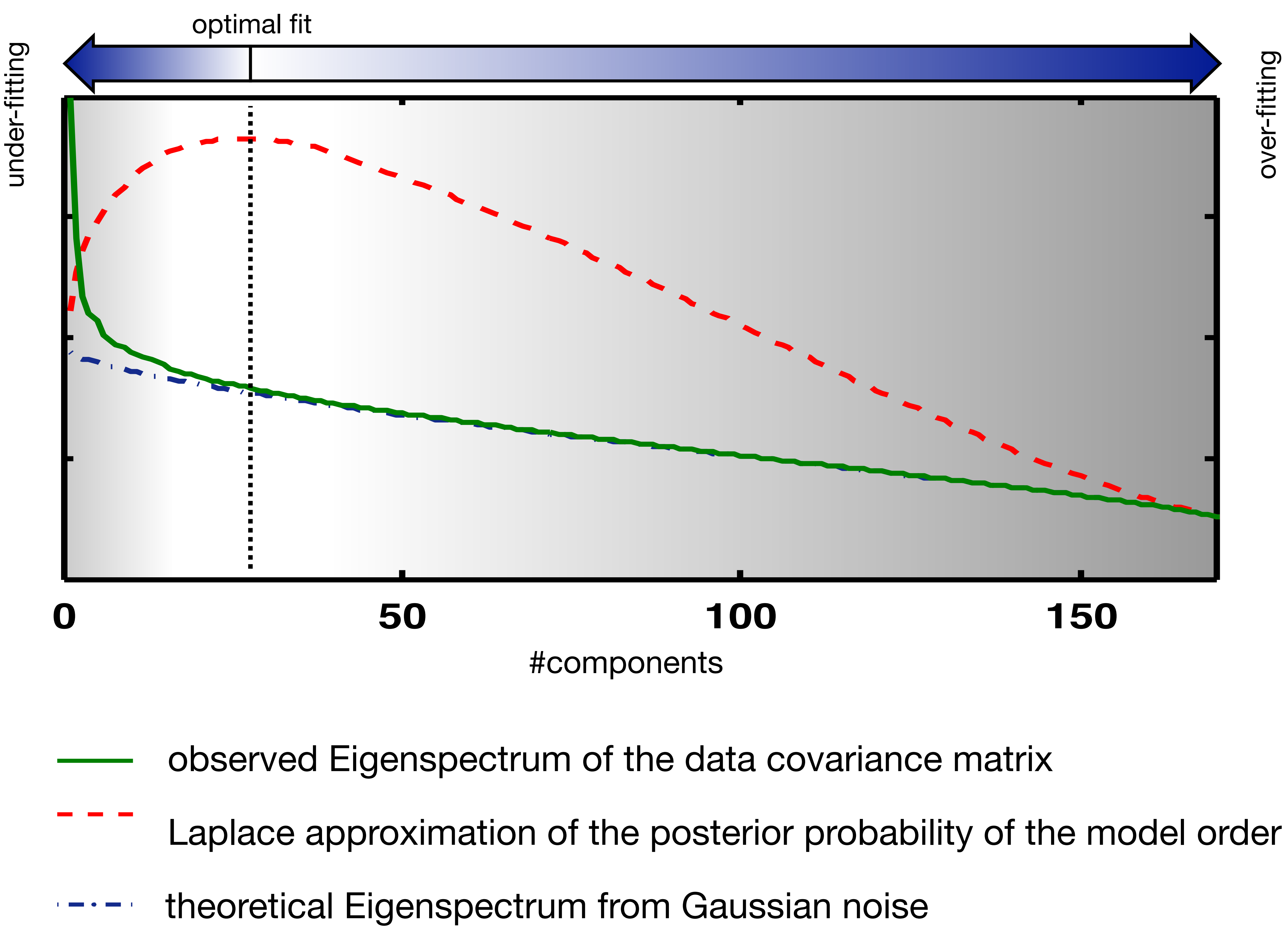
Laplace approximation of the posterior probability of the model order

theoretical Eigenspectrum from Gaussian noise

# Model Order Selection



# Model Order Selection

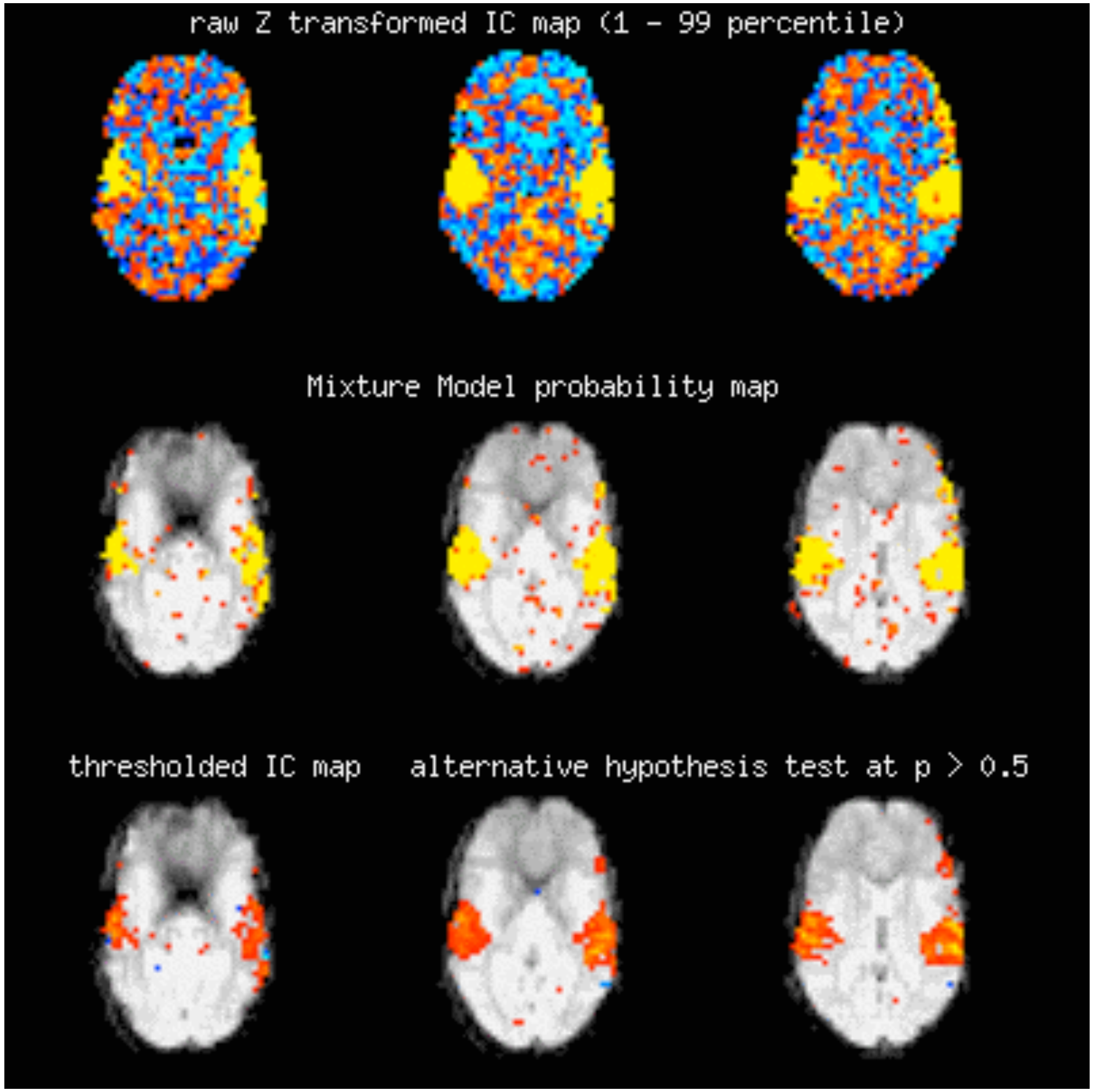


# Some characteristics of MELODIC

- Multivariate voxel-based approach
- Exploratory “model-free” method to find interesting structure in the data
- Gives “spatially independent” components
- “Avoiding overfitting” through automatic model order selection
- “Background suppression" to remove background from main signal

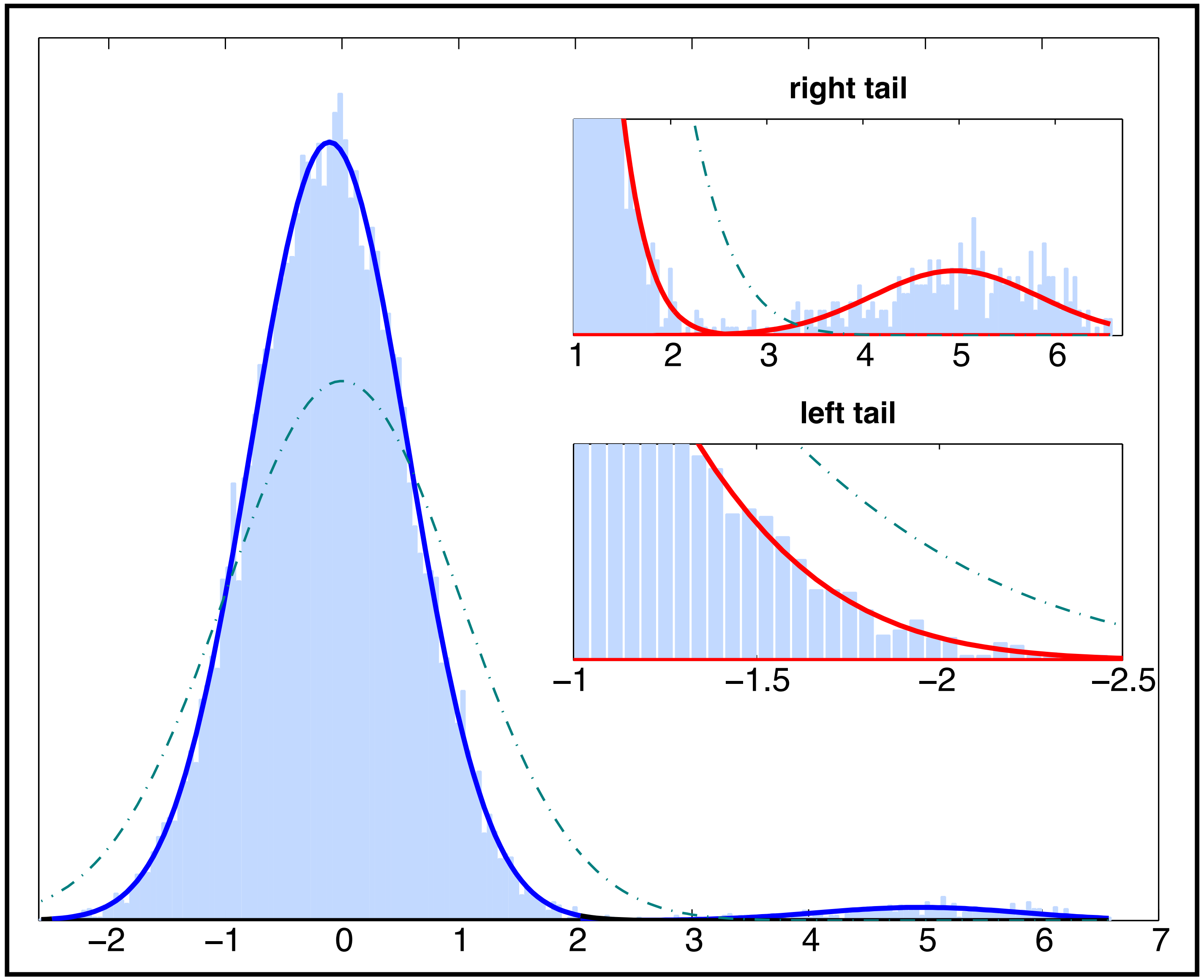
# Background suppression

# Background suppression

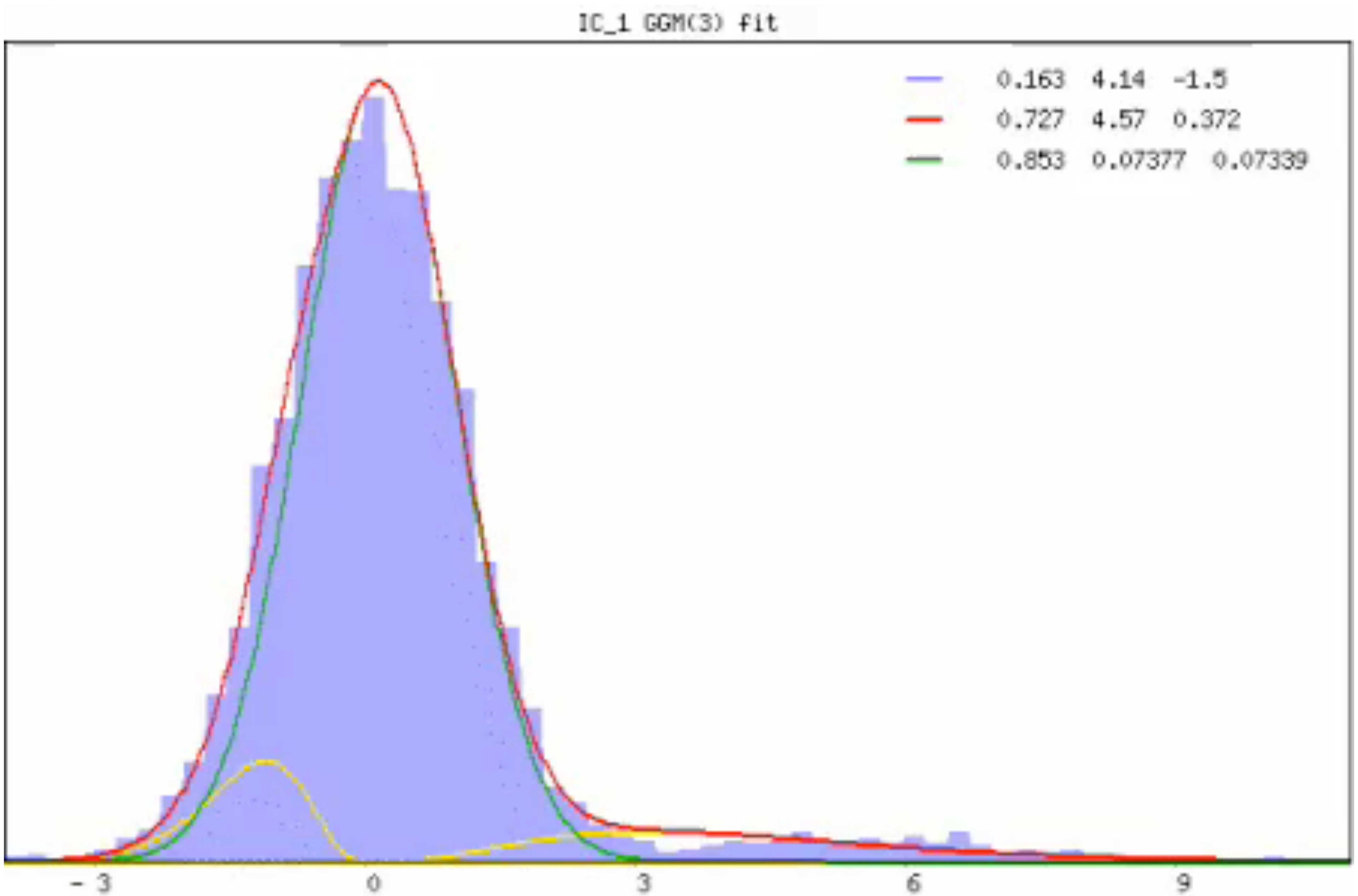


# Background suppression

- data is assumed to be a linear combination of signals and noise
- the distribution of the estimated spatial maps is a mixture distribution!



# Background suppression




- use Gaussian/Gamma mixture model fitted to the histogram of intensity values (using EM)

# Summary of part 1

- Resting state allows us to study the intrinsic organisation of the brain
- Resting state analysis focuses on connectivity and estimates functional components (resting state networks, RSN)
- Each RSN is characterised with a spatial map and a time course
- ICA can be used to characterise these RSNs
- MELODIC is FSL's ICA tool
  - Model-free, spatial independence, non-Gaussianity, model order selection, background suppression via mixture modelling

# Resting-State fMRI:
## ICA and Dual Regression

FSL Course 2026

24 June, Bordeaux, France

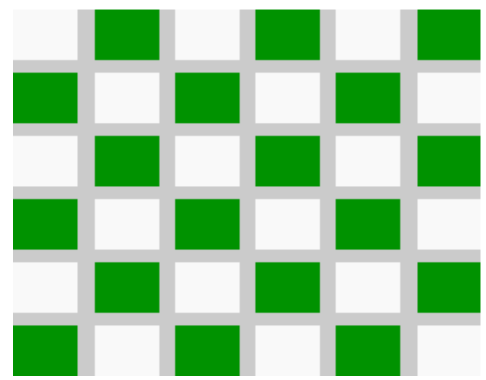
# Resting state fMRI and ICA

- Introduction to resting state
- Independent Component Analysis
- Single-subject ICA
- Multi-subject ICA
- Dual regression

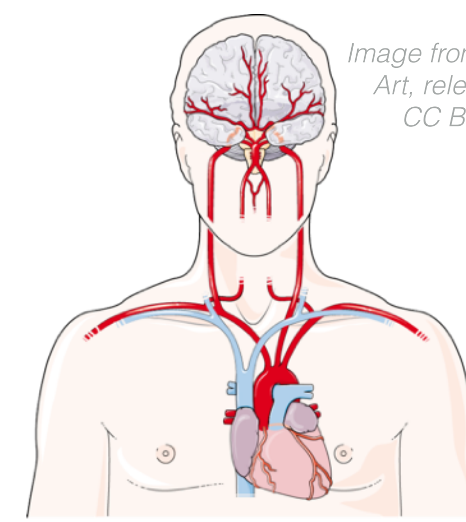
The goal of single subject ICA is artefact detection

# FMRI inferential path

Experiment



Physiology



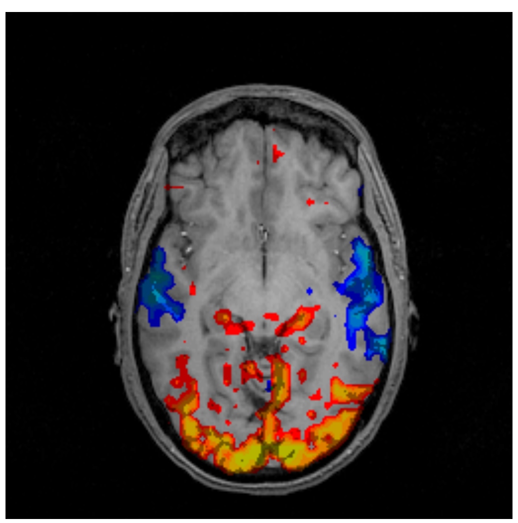


MR Physics



Analysis

Interpretation of final results



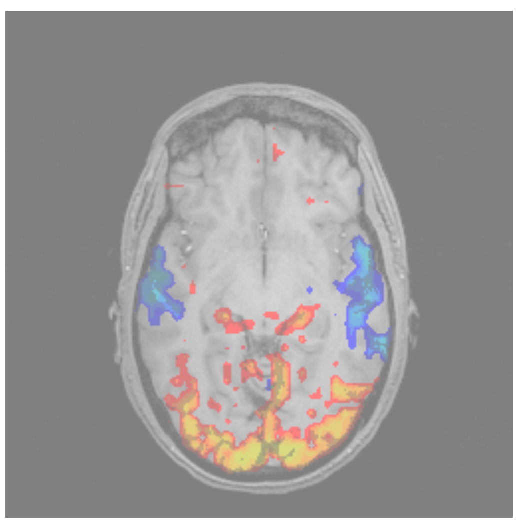
# Variability in FMRI

suboptimal event timing,
inefficient design, etc.

secondary activation, ill-defined baseline, resting-fluctuations etc.

MR noise,
field inhomogeneity,
MR artefacts etc.

filtering & sampling artefacts, design misspecification, stats & thresholding issues etc.

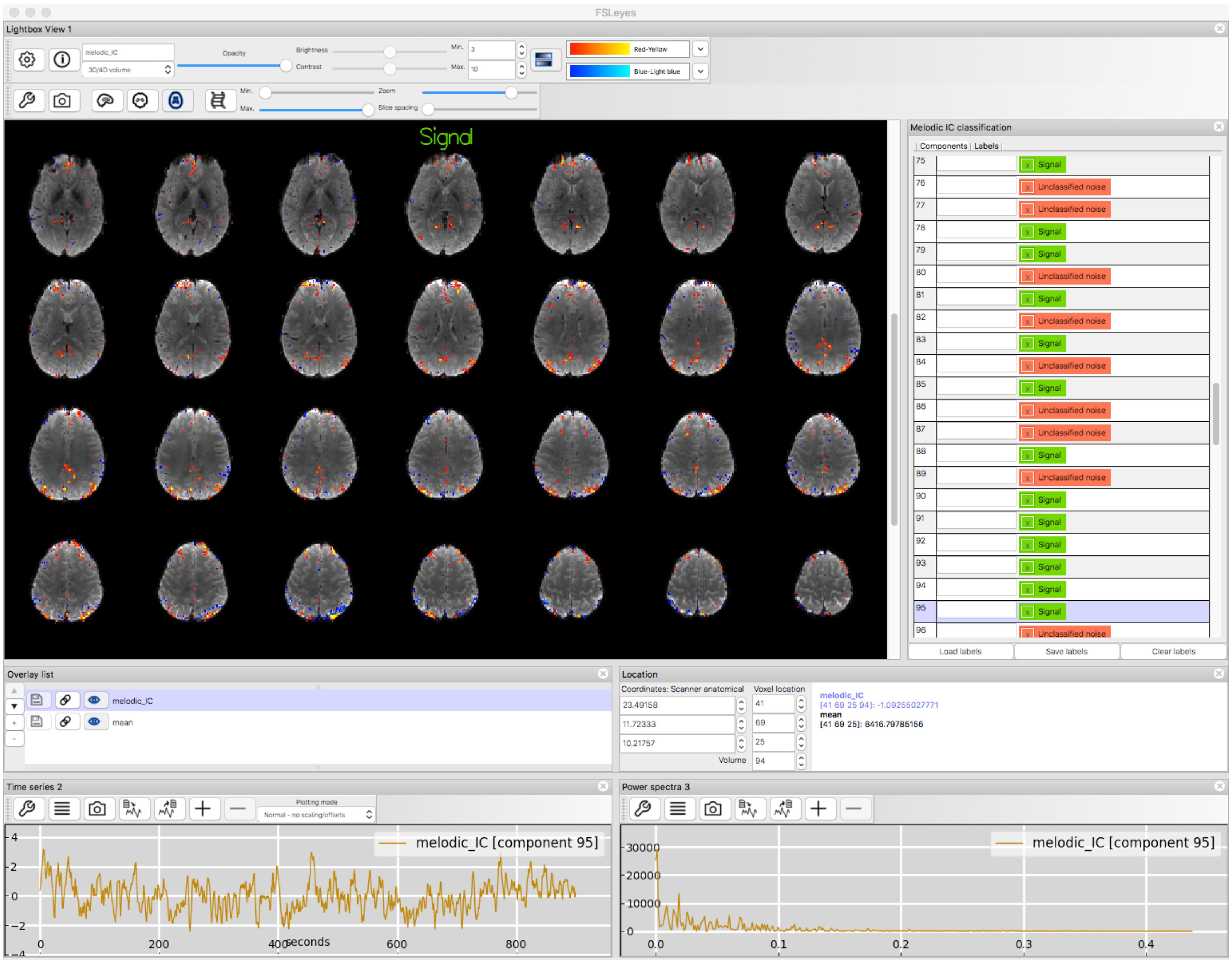


# Artefact detection

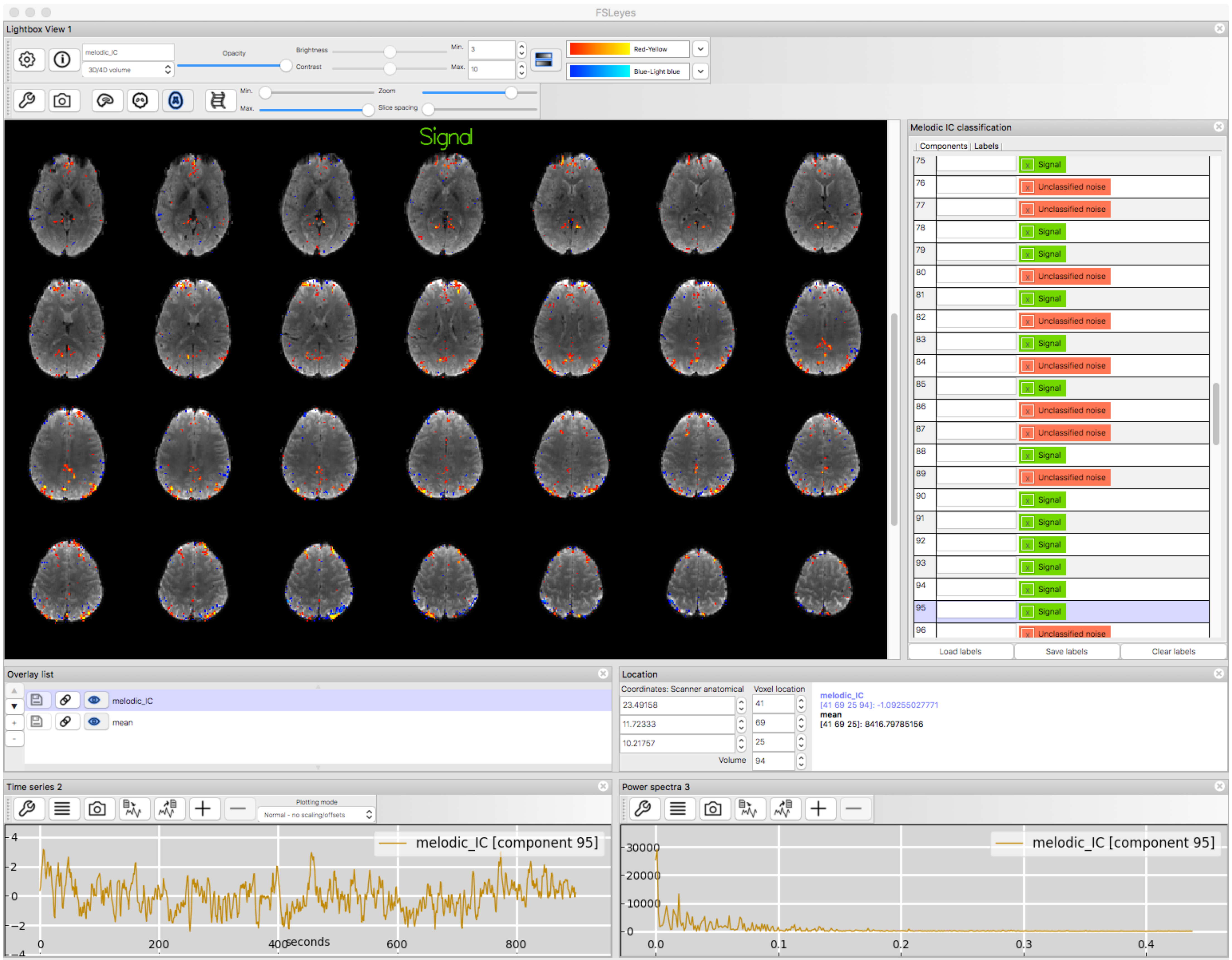
- Resting state FMRI data contain a variety of source processes
- Some of these sources are interesting signals and others are artefacts such as motion, cardiac pulsation, respiration
- Artifactual sources typically have unknown spatial and temporal extent and cannot easily be modelled accurately
- Good news: they are spatiotemporally distinct from true signals in the brain
- Therefore, ICA which is an exploratory tool which requires minimal knowledge of spatiotemporal characteristics of components can be used to identify artefacts, a.k.a, **Structured noise**.
- This is done at **single-subject level.**

# Manual labelling of ICA components as signal vs artefact

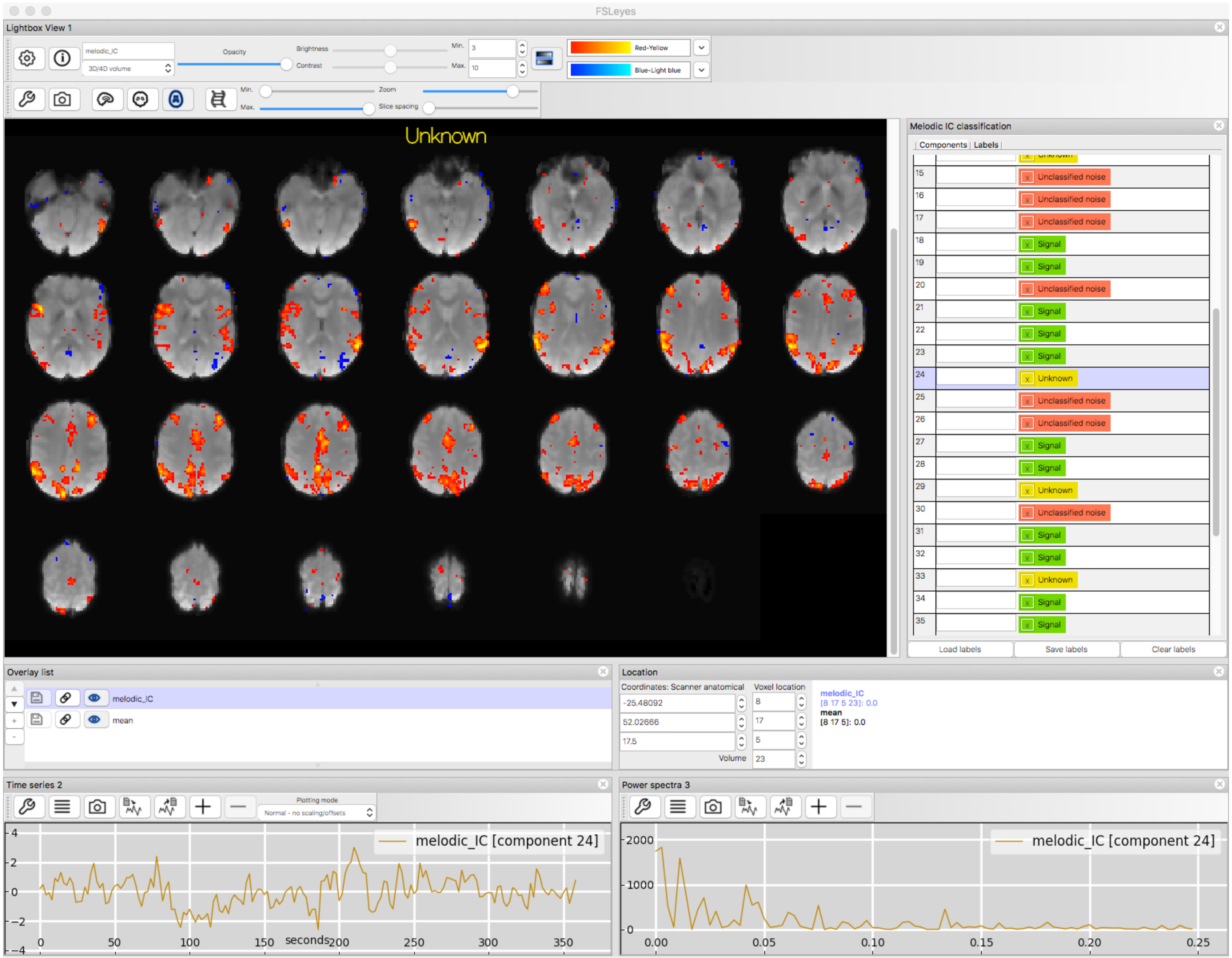
# FSLeyes Melodic Mode



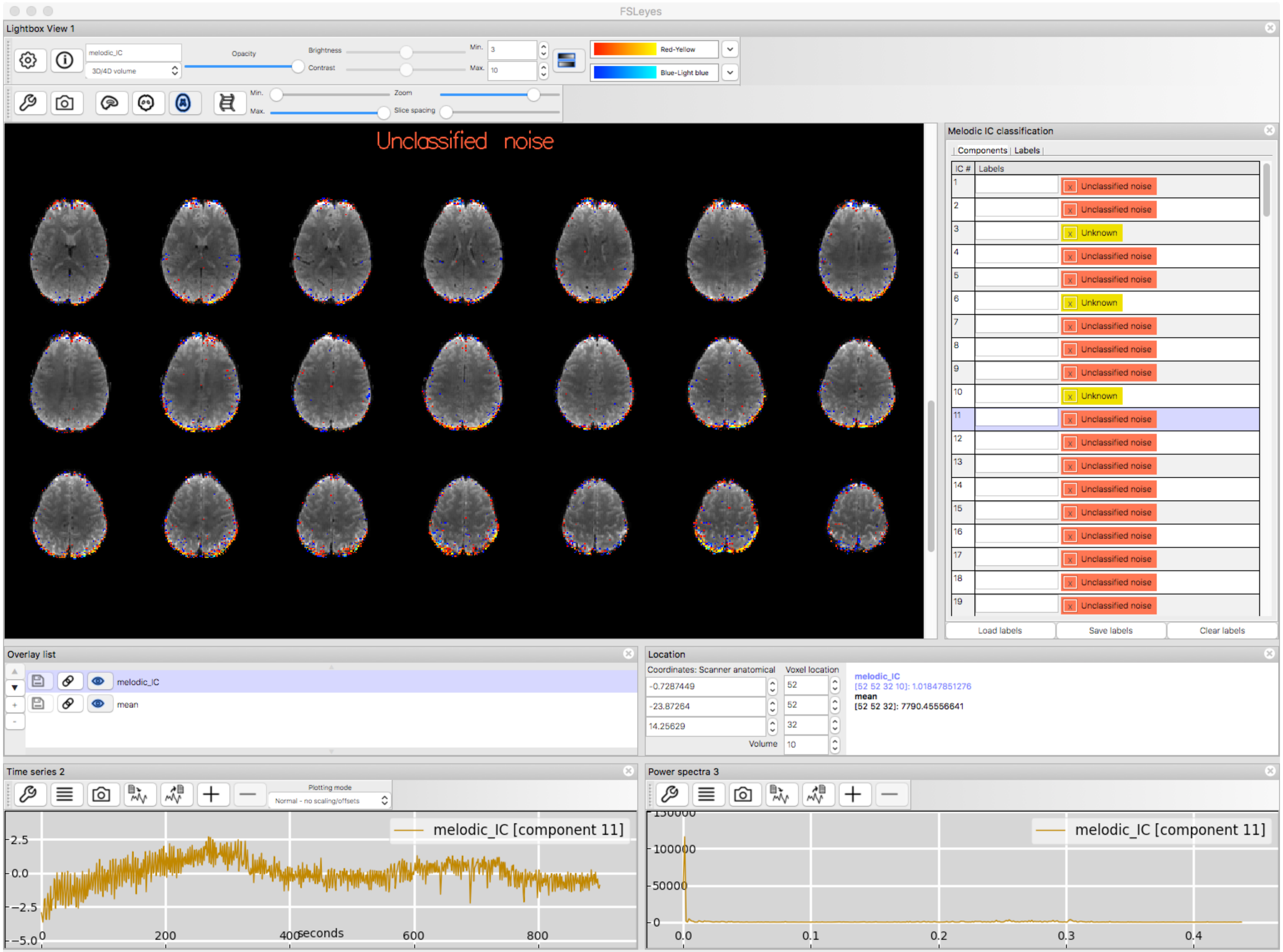
# signal


FSLeyes
Lightbox View 1
melodic_IC
3D/4D volume
Opacity
Brightness
Contrast
Min.
Max.
Red-Yellow
Blue-Light blue
Zoom
Slice spacing
Signal
Melodic IC classification
Components
Labels
75 Signal
76 Unclassified noise
77 Unclassified noise
78 Signal
79 Signal
80 Unclassified noise
81 Signal
82 Unclassified noise
83 Signal
84 Unclassified noise
85 Signal
86 Unclassified noise
87 Unclassified noise
88 Signal
89 Unclassified noise
90 Signal
91 Signal
92 Signal
93 Signal
94 Signal
95 Signal
96 Unclassified noise
Load labels
Save labels
Clear labels
Overlay list
melodic_IC
mean
Location
Coordinates: Scanner anatomical
Voxel location
23.49158
11.72333
10.21757
41
69
25
Volume
94
melodic_IC
[41 69 25 94]: -1.09255027771
mean
[41 69 25]: 8416.79785156
Time series 2
Plotting mode
Normal - no scaling/offsets
melodic_IC [component 95]
seconds
Power spectra 3
melodic_IC [component 95]

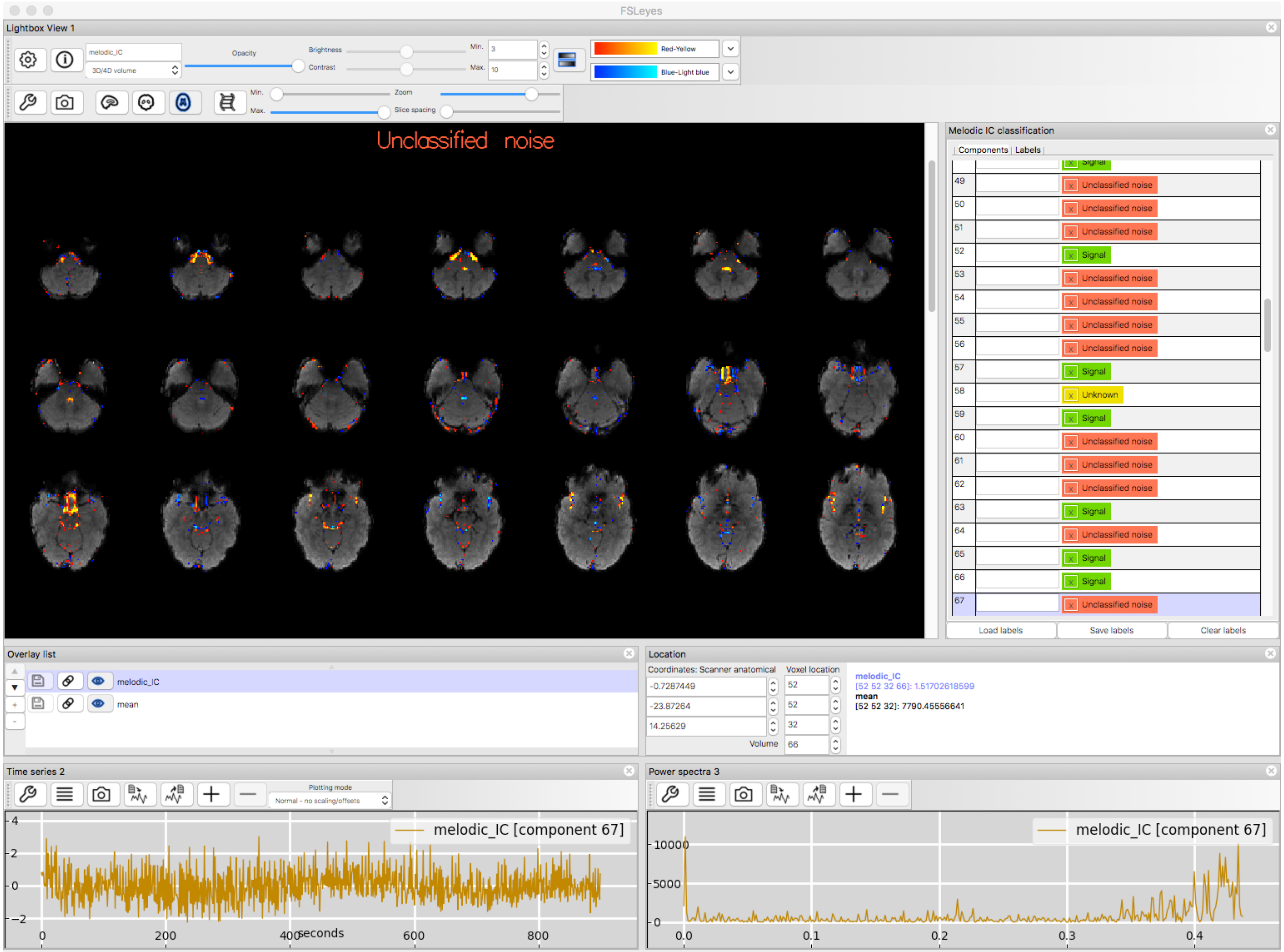
# effects of scan parameters



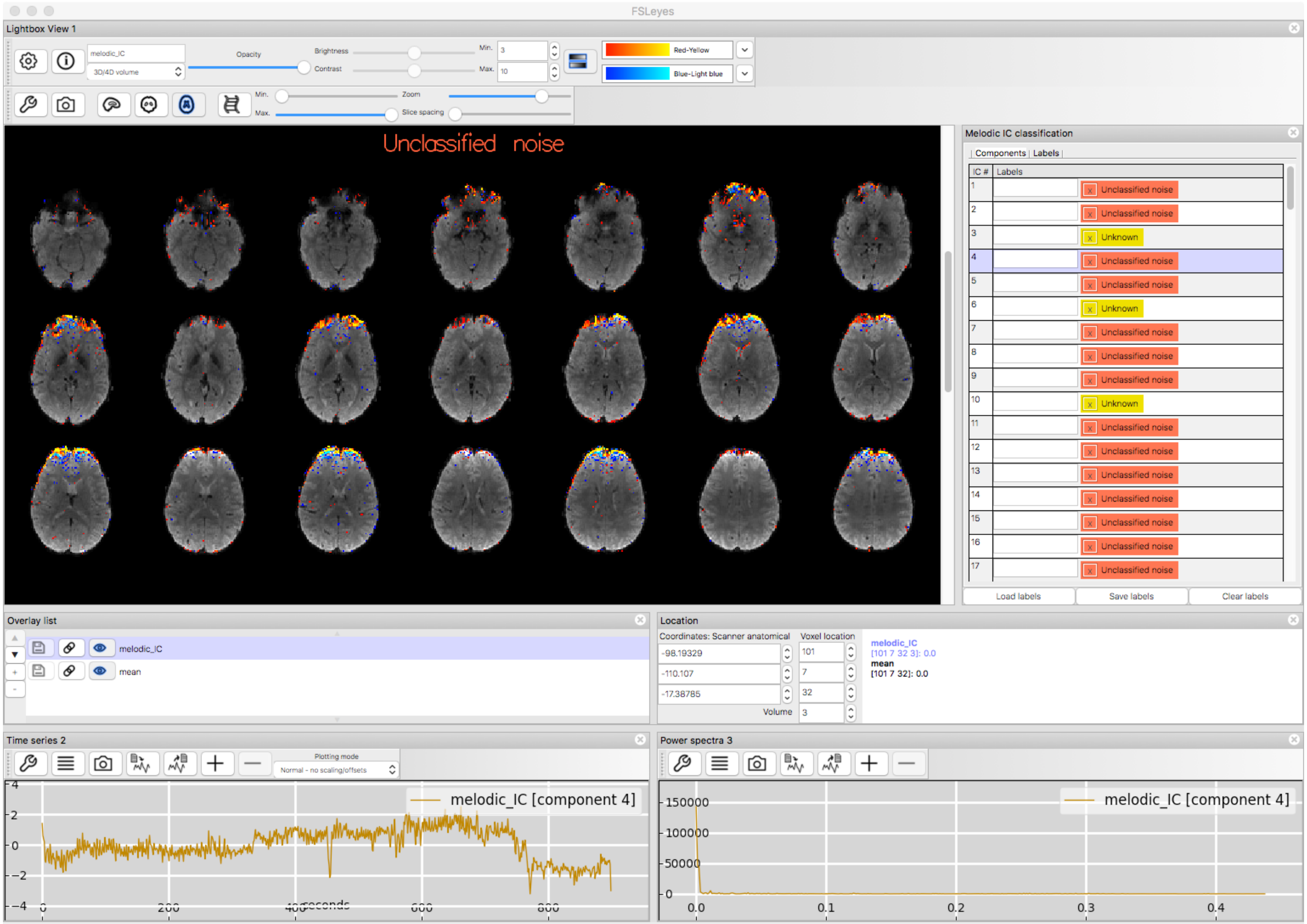
# motion


FSLeyes
Lightbox View 1
Unclassified noise
Melodic IC classification
Components | Labels
Load labels
Save labels
Clear labels
Overlay list
melodic_IC
mean
Location
Time series 2
melodic_IC [component 11]
seconds
Power spectra 3
melodic_IC [component 11]

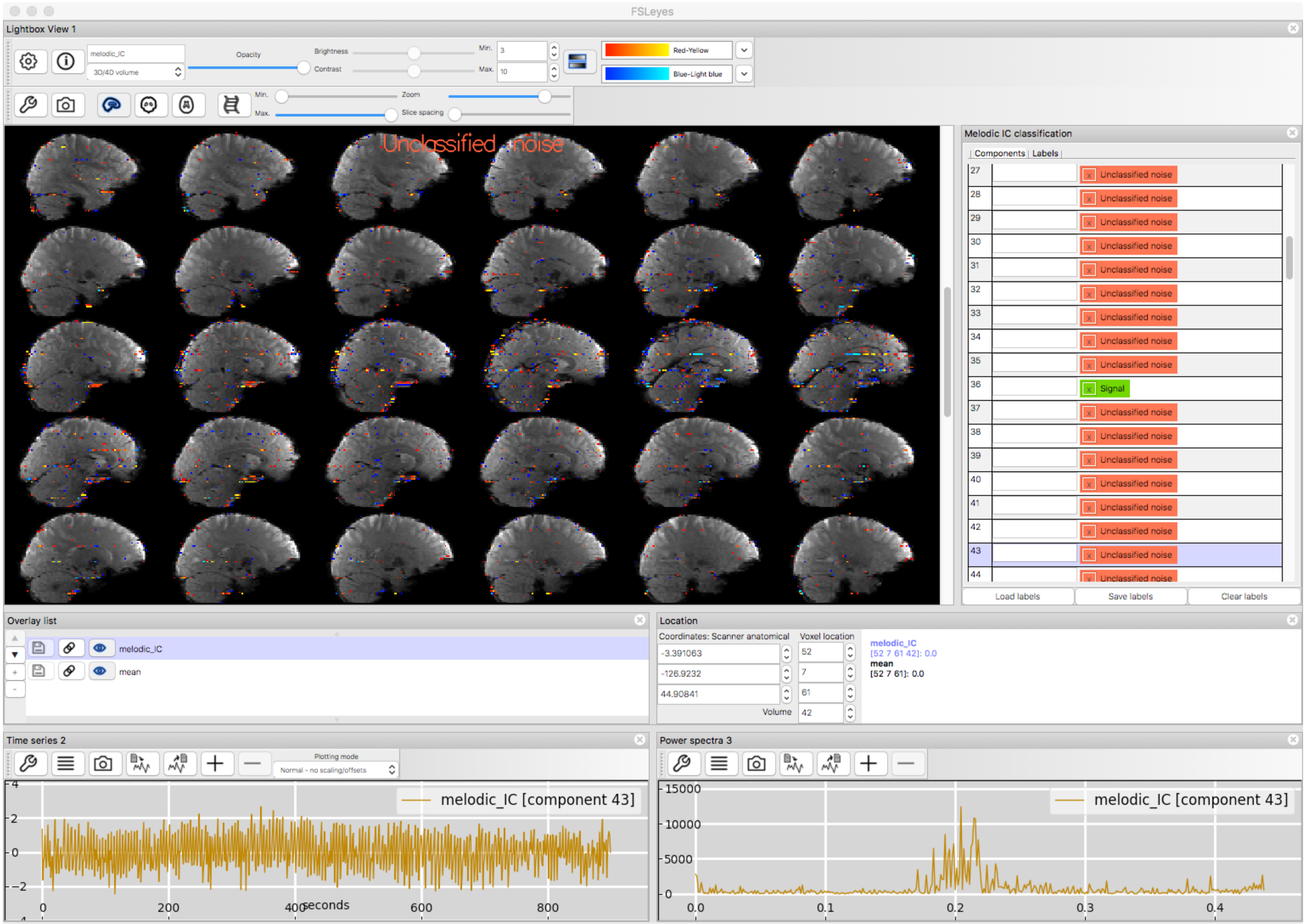
# cardiac


FSLeyes
Lightbox View 1
Unclassified noise
Melodic IC classification
Components | Labels
49 Unclassified noise
50 Unclassified noise
51 Unclassified noise
52 Signal
53 Unclassified noise
54 Unclassified noise
55 Unclassified noise
56 Unclassified noise
57 Signal
58 Unknown
59 Signal
60 Unclassified noise
61 Unclassified noise
62 Unclassified noise
63 Signal
64 Unclassified noise
65 Signal
66 Signal
67 Unclassified noise
Load labels
Save labels
Clear labels
Overlay list
melodic_IC
mean
Location
melodic_IC
[52 52 32 66]: 1.51702618599
mean
[52 52 32]: 7790.45556641
Time series 2
melodic_IC [component 67]
seconds
Power spectra 3
melodic_IC [component 67]

# susceptibility motion

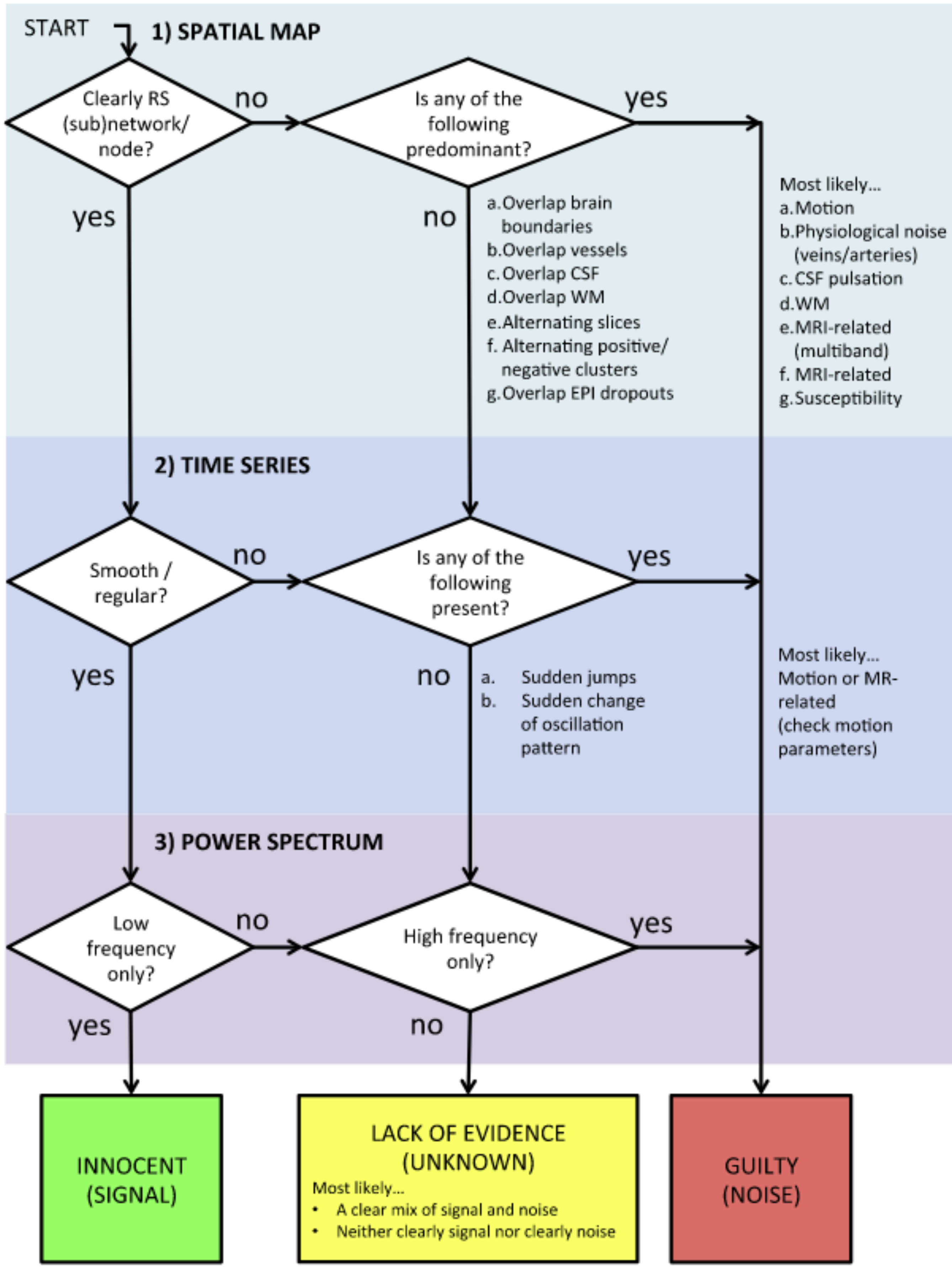


# multiband



FSLeyes
Lightbox View 1
melodic_IC
3D/4D volume
Opacity
Brightness
Contrast
Min.
Max.
3
10
Red-Yellow
Blue-Light blue
Zoom
Slice spacing
Unclassified noise
Melodic IC classification
Components | Labels
27 Unclassified noise
28 Unclassified noise
29 Unclassified noise
30 Unclassified noise
31 Unclassified noise
32 Unclassified noise
33 Unclassified noise
34 Unclassified noise
35 Unclassified noise
36 Signal
37 Unclassified noise
38 Unclassified noise
39 Unclassified noise
40 Unclassified noise
41 Unclassified noise
42 Unclassified noise
43 Unclassified noise
44 Unclassified noise
Load labels
Save labels
Clear labels
Overlay list
melodic_IC
mean
Location
Coordinates: Scanner anatomical
Voxel location
-3.391063
-126.9232
44.90841
52
7
61
Volume
42
melodic_IC
[52 7 61 42]: 0.0
mean
[52 7 61]: 0.0
Time series 2
Plotting mode
Normal - no scaling/offsets
melodic_IC [component 43]
seconds
Power spectra 3
melodic_IC [component 43]

# manual classification

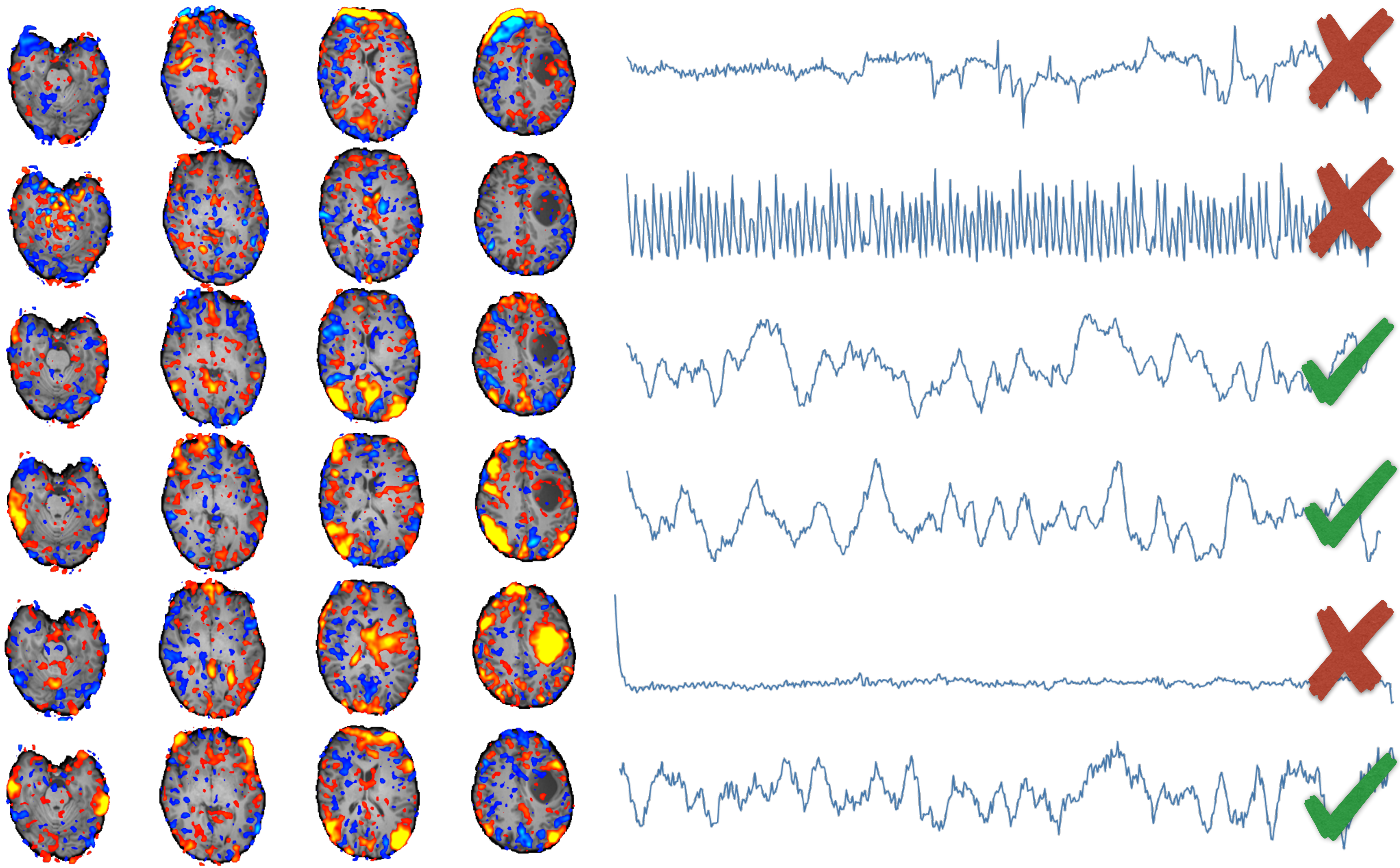



Griffanti et al (2016).

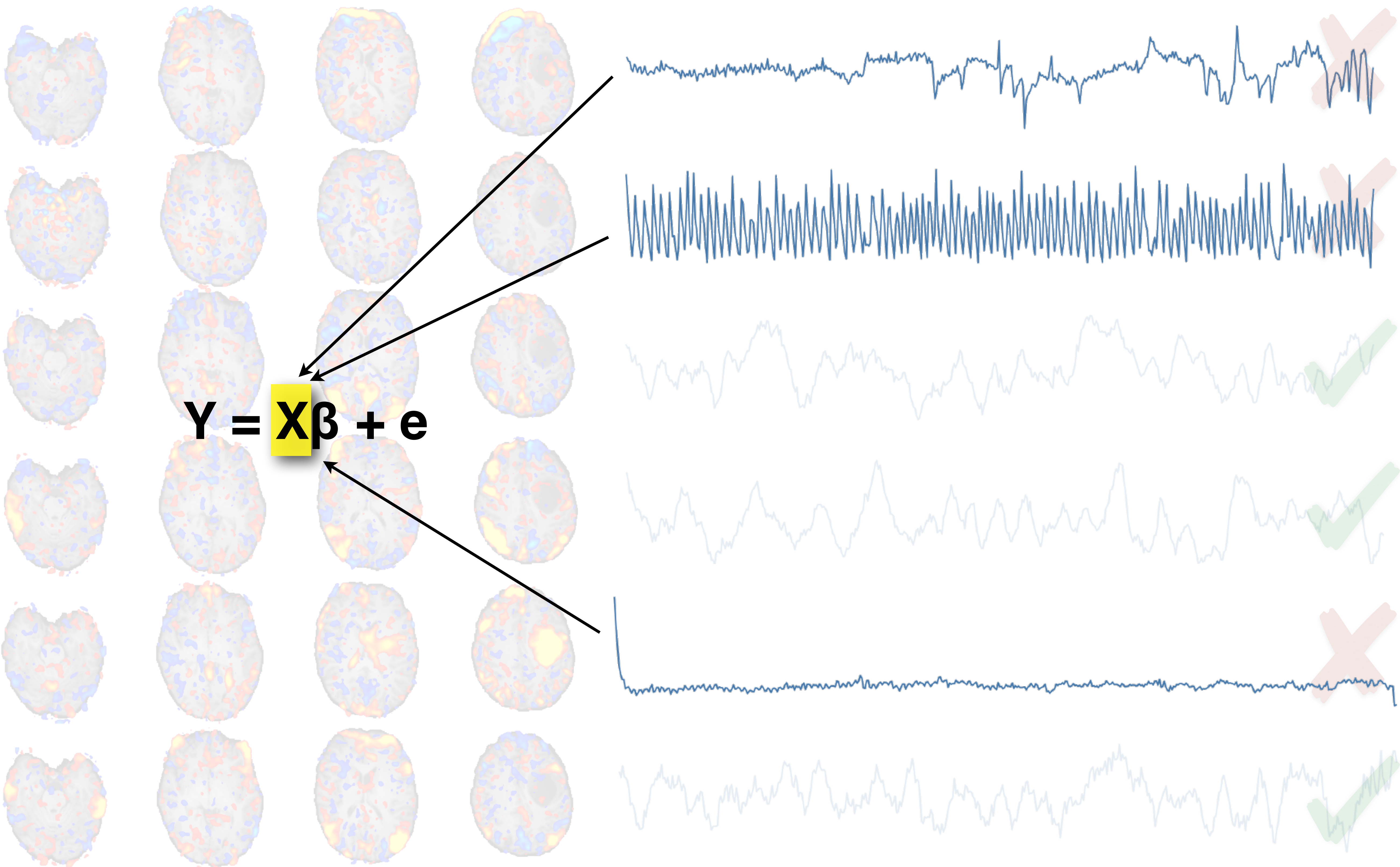
https://doi.org/10.1016/j.neuroimage.2016.12.036

# Removing artefacts

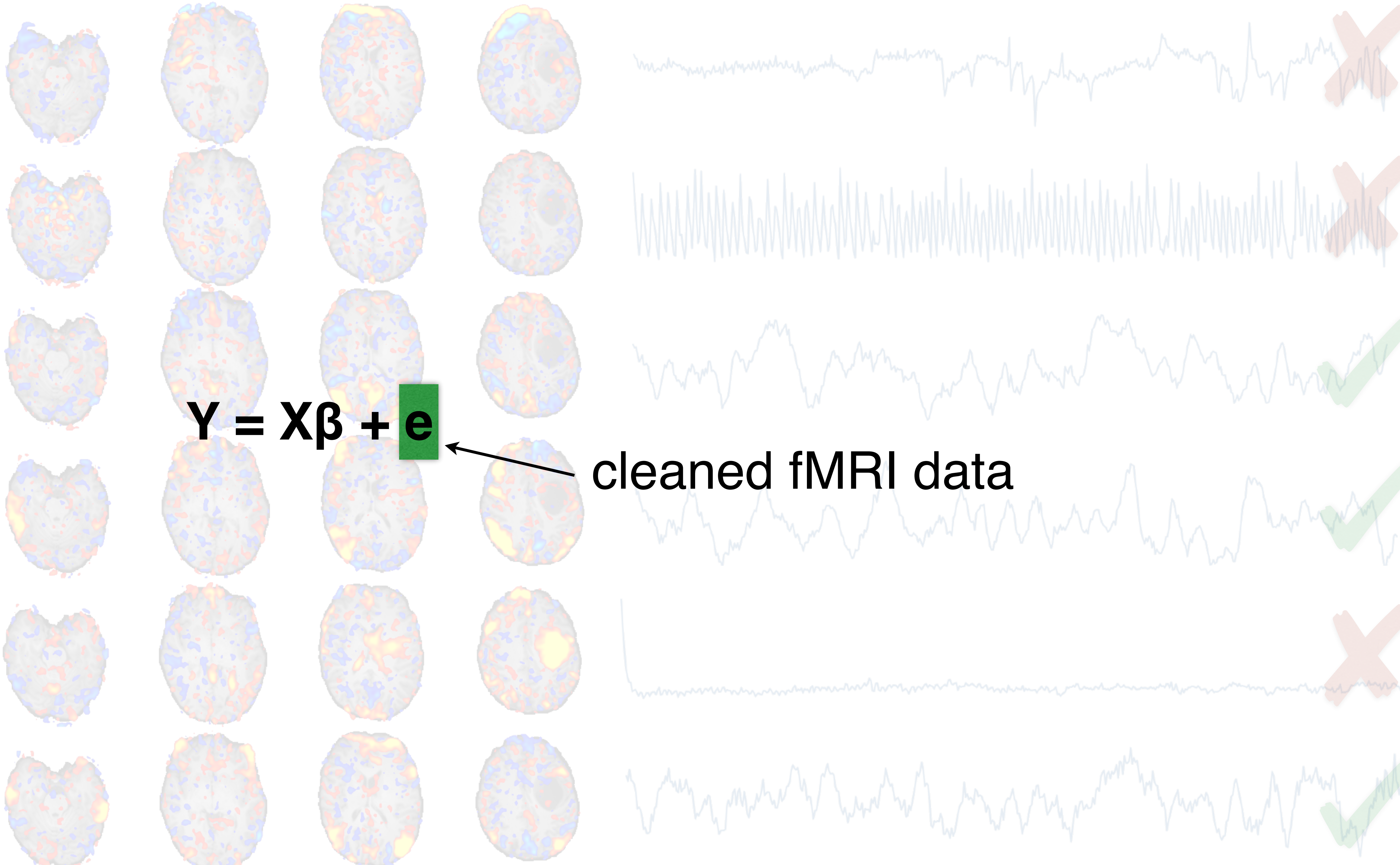
# ICA-based denoising



# ICA-based denoising



# ICA-based denoising

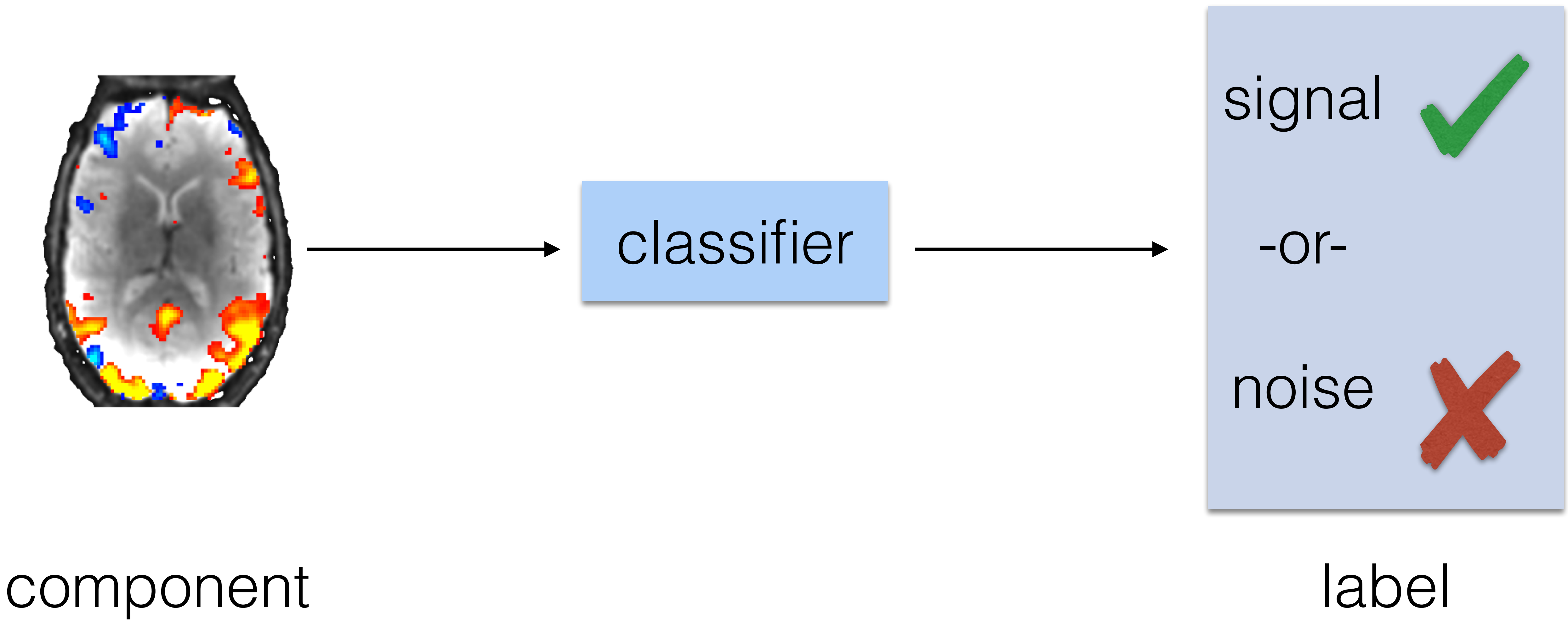


$$Y = X\beta + e$$

cleaned fMRI data

# Semi-automatic artefact detection

# Semi-automatic classification



# semi-automatic classification

- FIX (https://fsl.fmrib.ox.ac.uk/fsl/docs/#/resting_state/fix)
  - Classifier with many features
  - Requires manually labelled training data
  - 99% accuracy on high-quality data
- The latest version is reimplemented in Python and installed as part of FSL, unlike previous MATLAB/R version that needed separate installation.

# semi-automatic classification

- FIX (https://fsl.fmrib.ox.ac.uk/fsl/docs/#/resting_state/fix)
  - Classifier with many features
  - Requires manually labelled training data
  - 99% accuracy on high-quality data
- ICA-AROMA (github.com/rhr-pruim/ICA-AROMA)
  - Simple classifier with only 4 features
  - No training data required
  - Mainly designed for motion artefacts

# Resting state fMRI and ICA

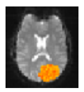
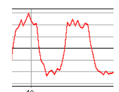
- Introduction to resting state
- Independent Component Analysis
- Single-subject ICA
- Multi-subject ICA
- Dual regression

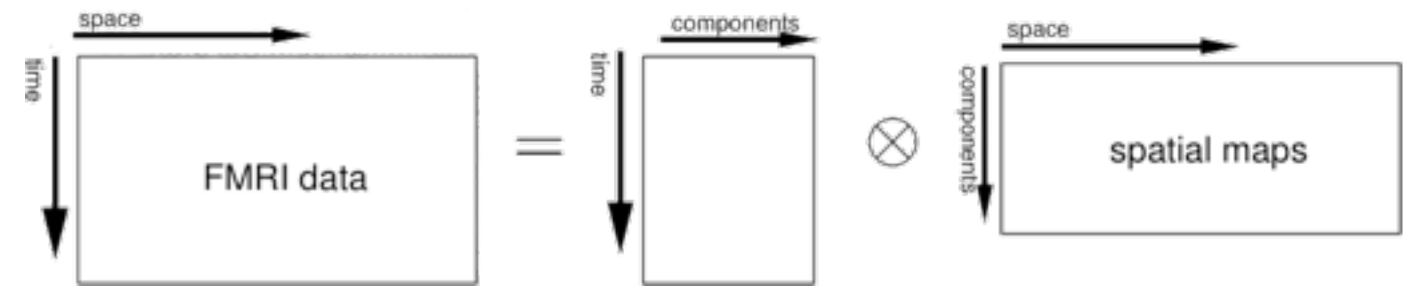
The goal of multi subject ICA is to characterise Resting State Networks (RSNs)

# Different ICA models

## Single-Session ICA

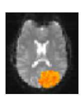
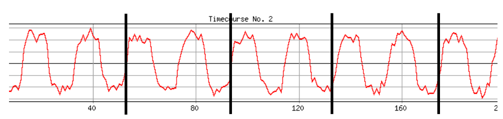
each ICA component comprises:

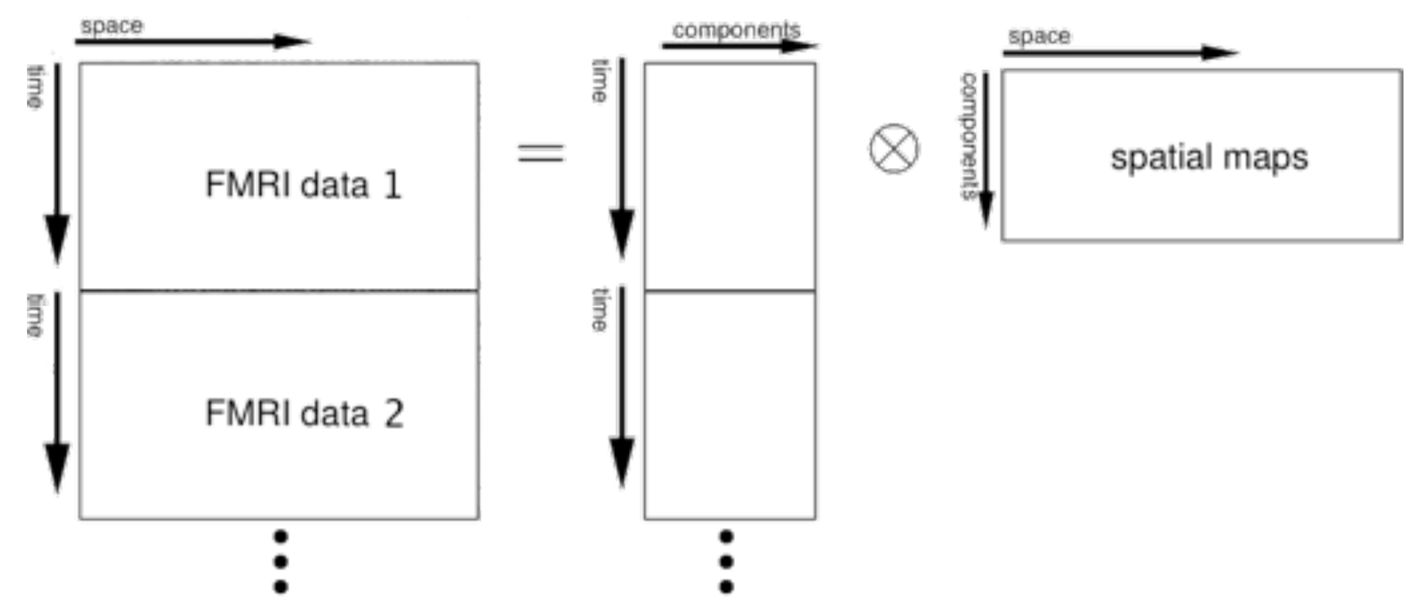
 spatial map & timecourse 



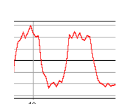

## Multi-Session or Multi-Subject ICA: **Concatenation approach**

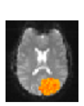
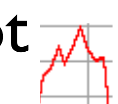
each ICA component comprises:

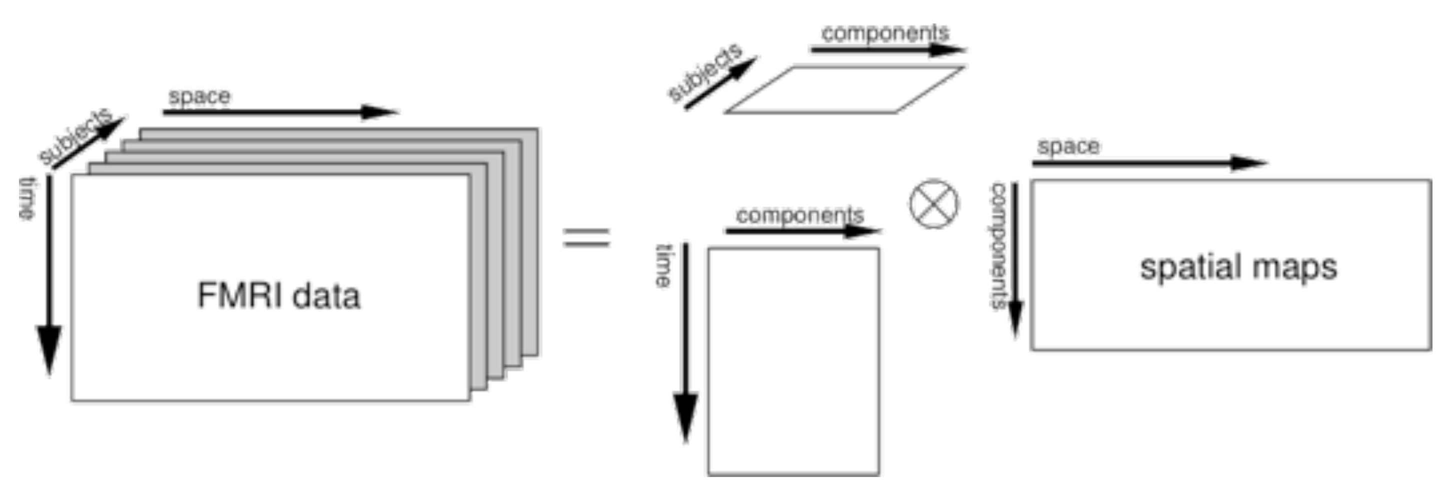
 spatial map & timecourse
(that can be split up into subject-specific chunks) 




## Multi-Session or Multi-Subject ICA: **Tensor-ICA approach**

each ICA component comprises: 

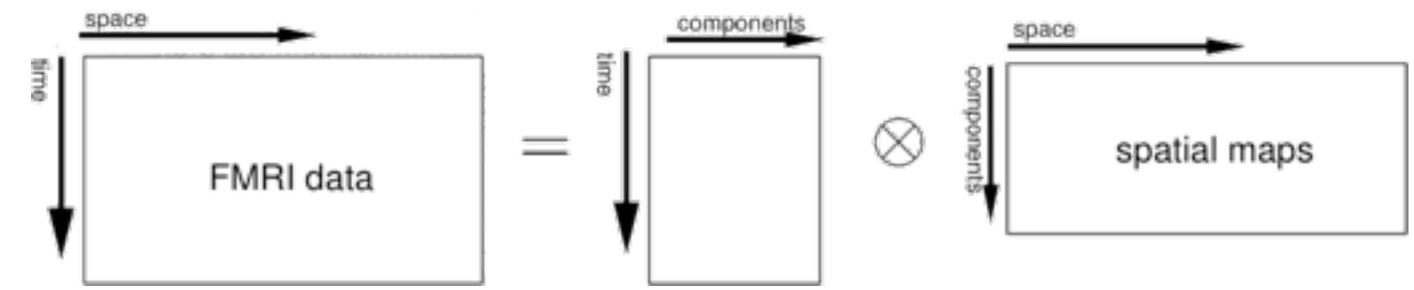
 spatial map, session-long-timecourse & subject-strength plot 



# Different ICA models

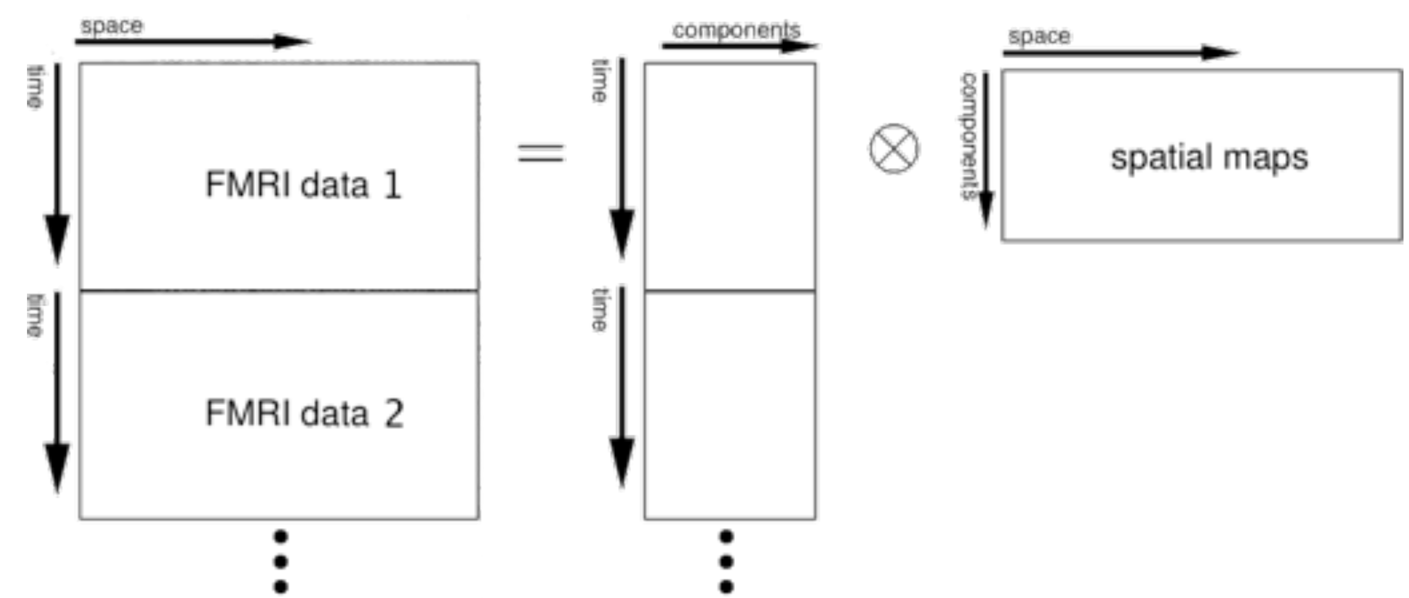
**Single-Session ICA**

each ICA component comprises:
spatial map & timecourse



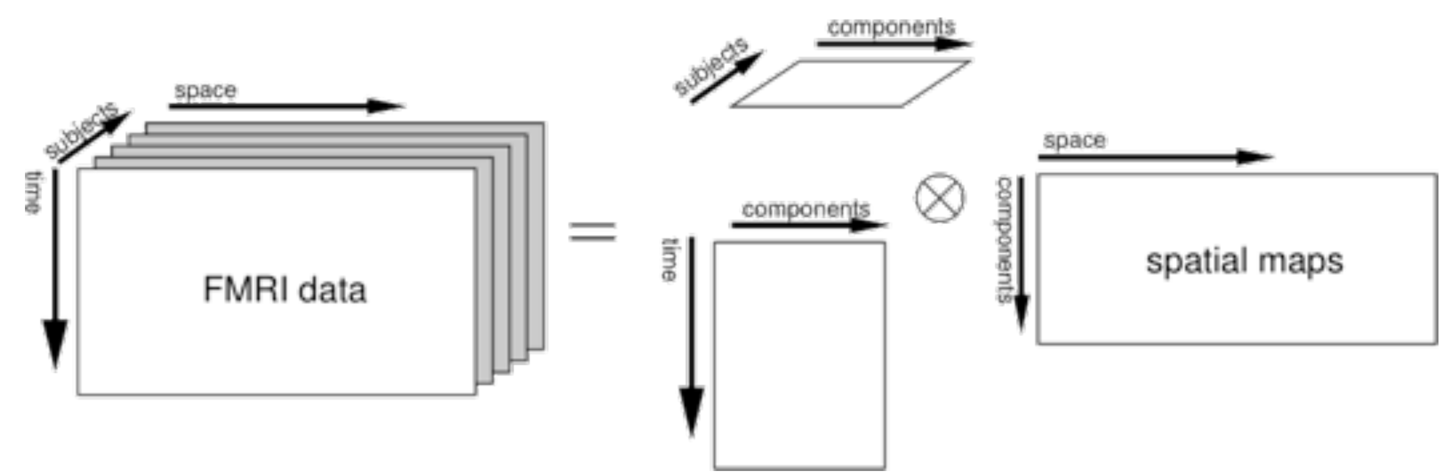

Multi-Session or Multi-Subject ICA:
**Concatenation approach**

good when:
each subject has DIFFERENT timeseries
e.g. resting-state FMRI



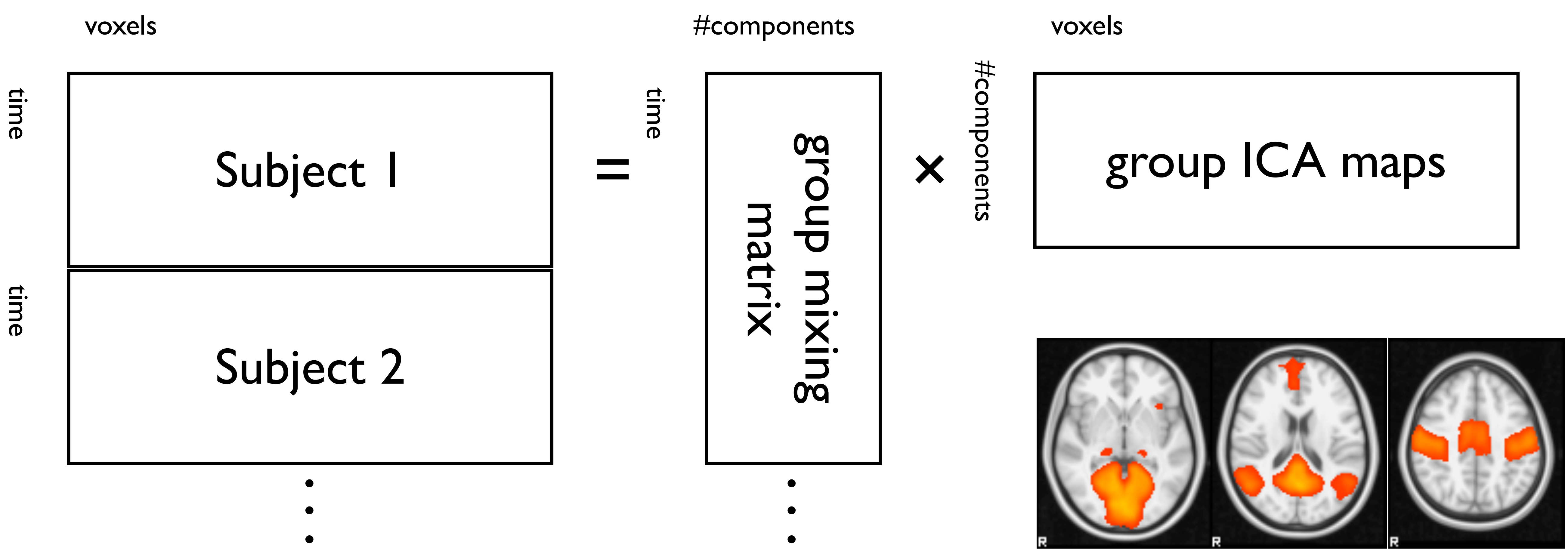

Multi-Session or Multi-Subject ICA:
**Tensor-ICA approach**

good when:
each subject has SAME timeseries
e.g. activation FMRI



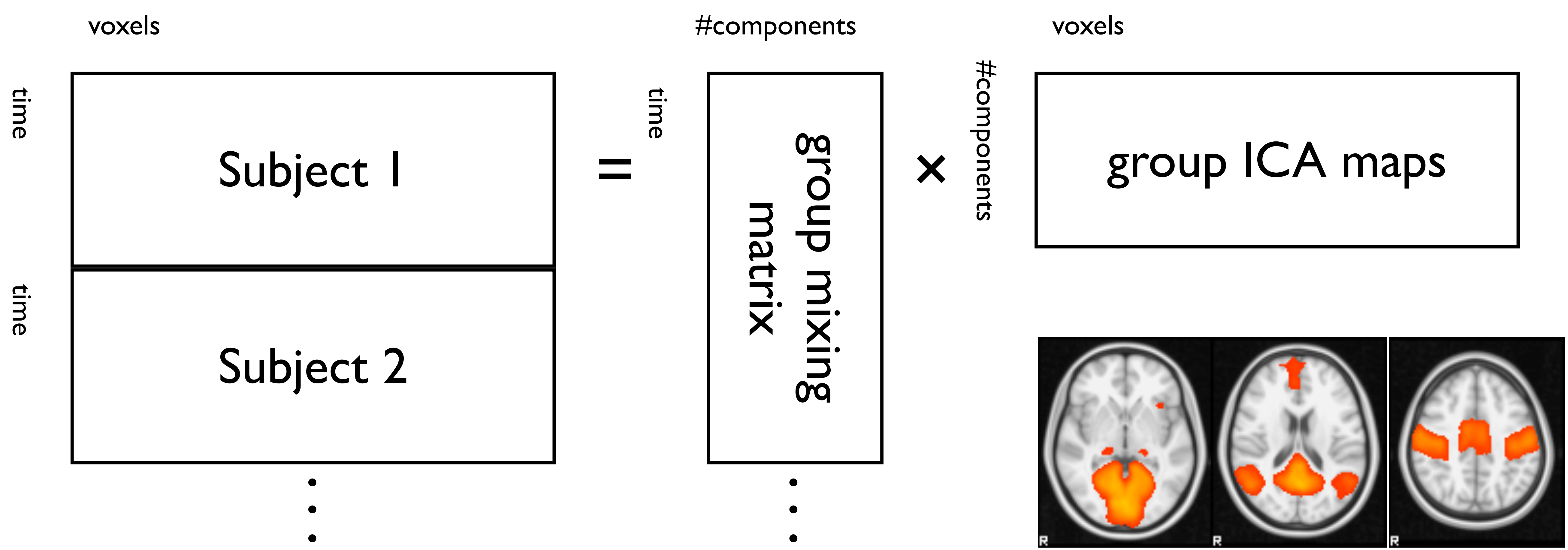
# Concatenated ICA

- Concatenate all subjects' data temporally
- Then run ICA
- More appropriate than tensor ICA (for RSNs)



# Concatenated ICA

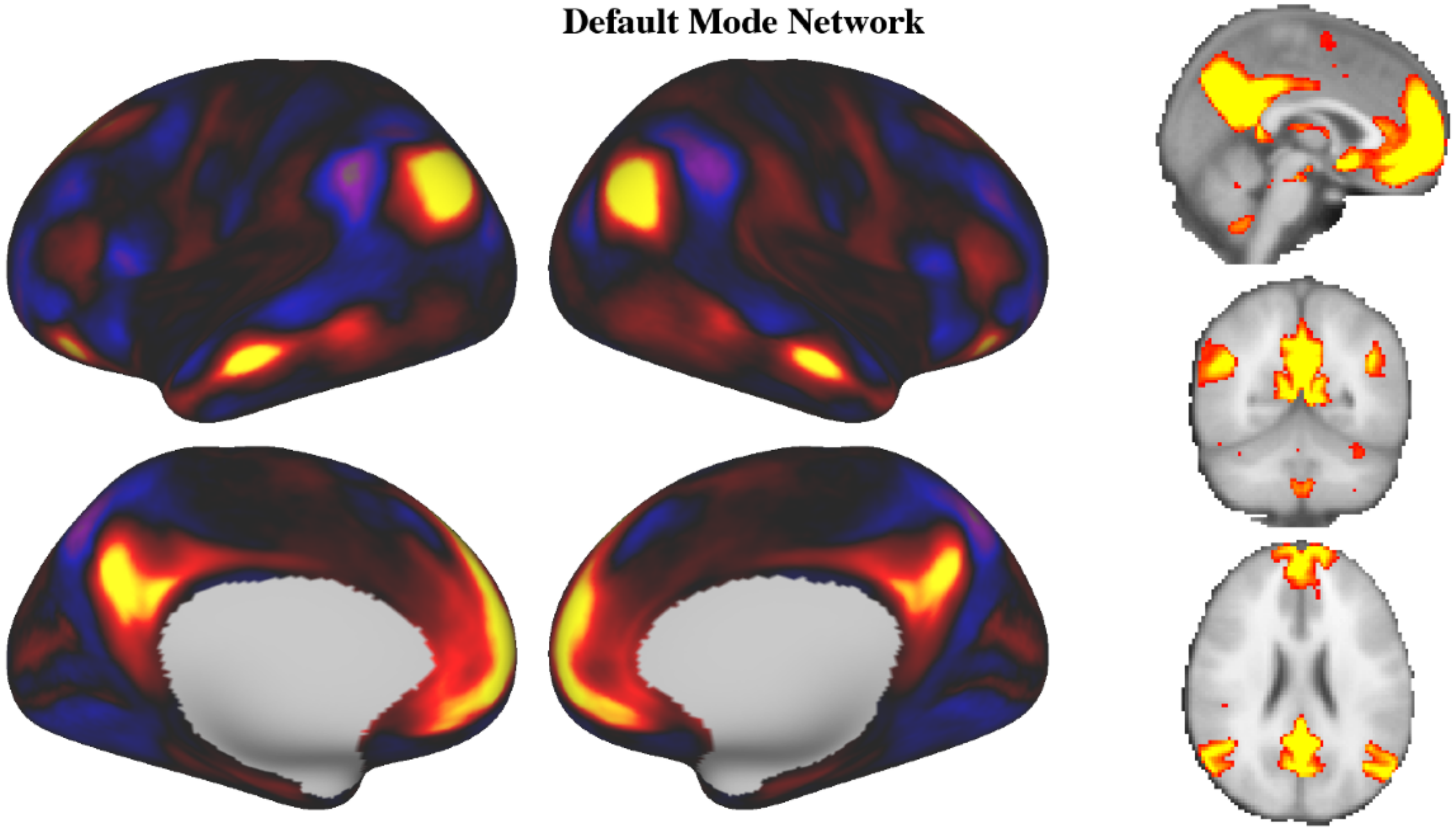
- Data sets must be registered to a common space (anatomical alignment)
- Memory optimisation trick (called MIGP)

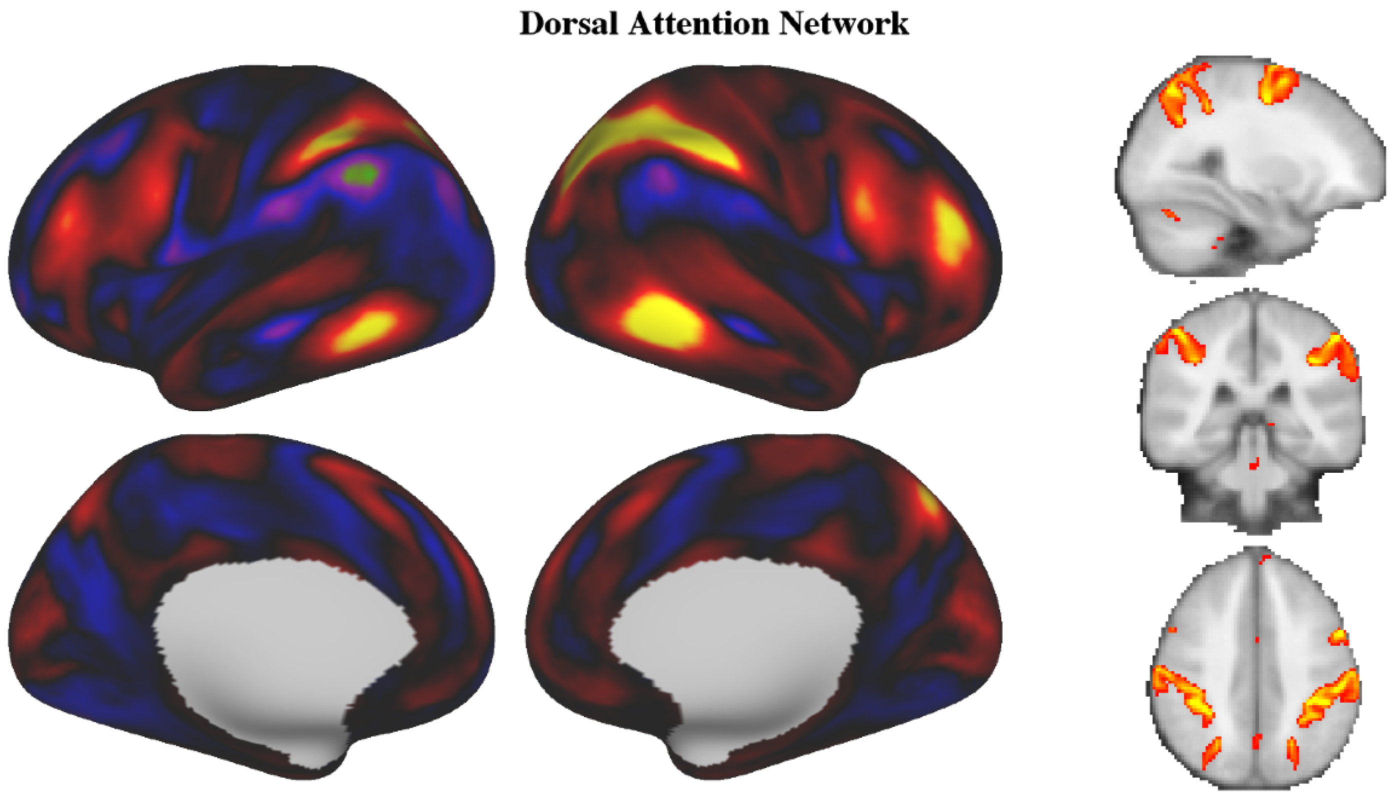


# Resting state multi-subject ICA

- Why not just run ICA on each subject separately?
  - Correspondence problem (eg RSNs across subjects)
  - Different splittings sometimes caused by small changes in the data (naughty ICA!)
- Instead - start with a "group-average" ICA
  - But then need to relate group maps back to the individual subjects

# Resting state networks

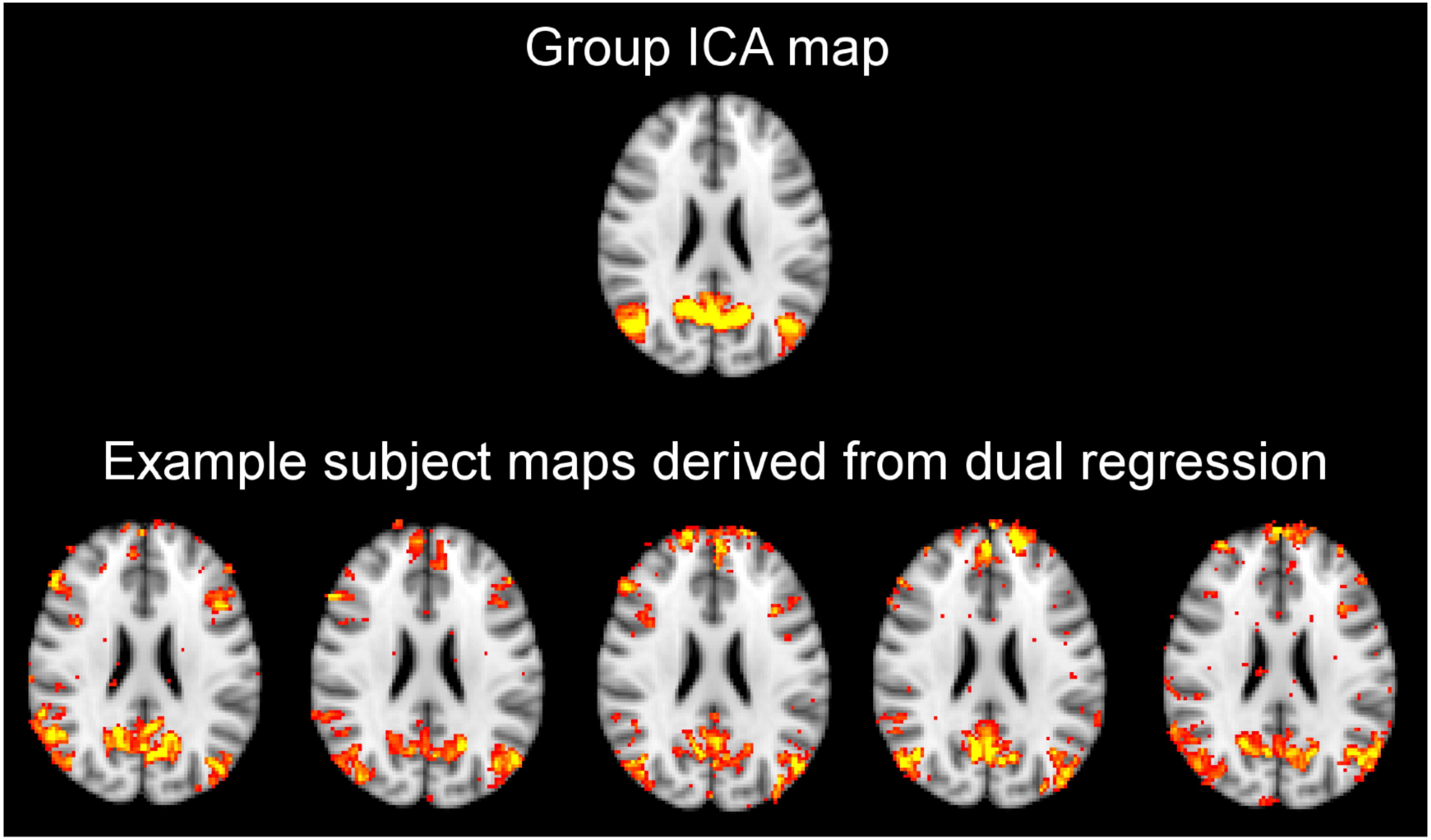


# Resting state fMRI and ICA

- Introduction to resting state
- Independent Component Analysis
- Single-subject ICA
- Multi-subject ICA
- Dual regression

# Resting state multi-subject ICA

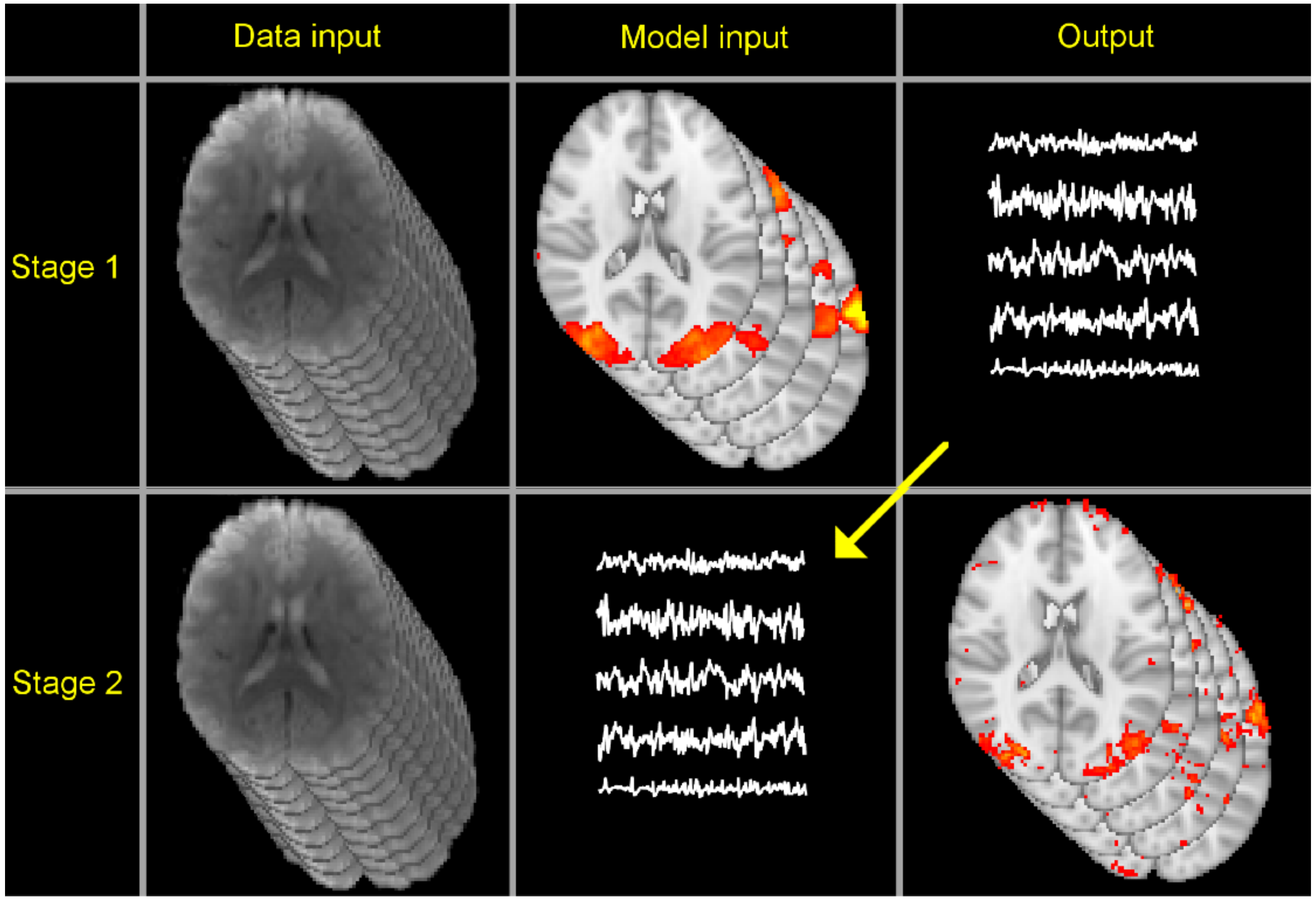


# Dual Regression

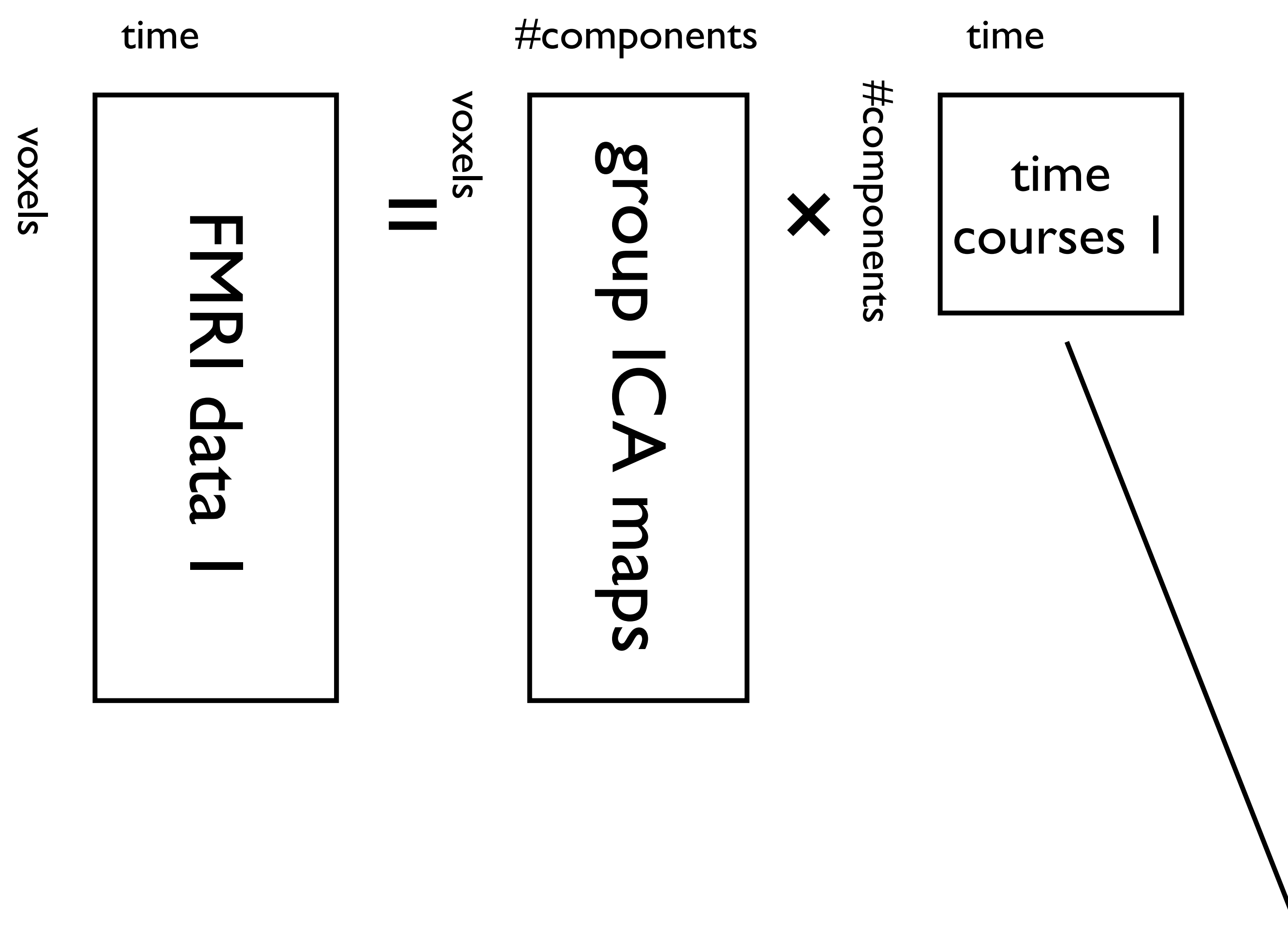
Two steps that both involve multiple regression:

1. Extract subject timeseries

2. Extract subject maps

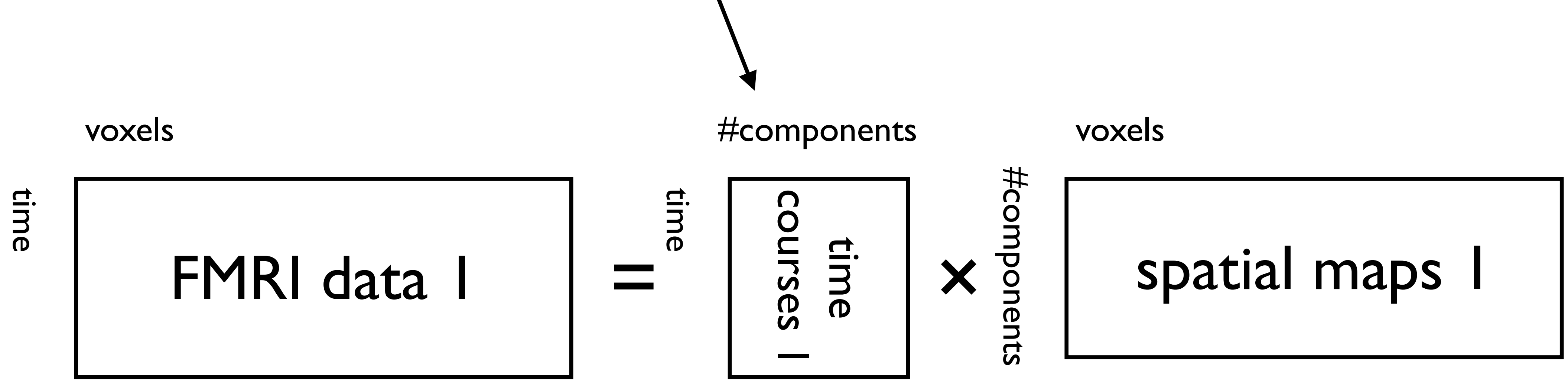


# Dual Regression

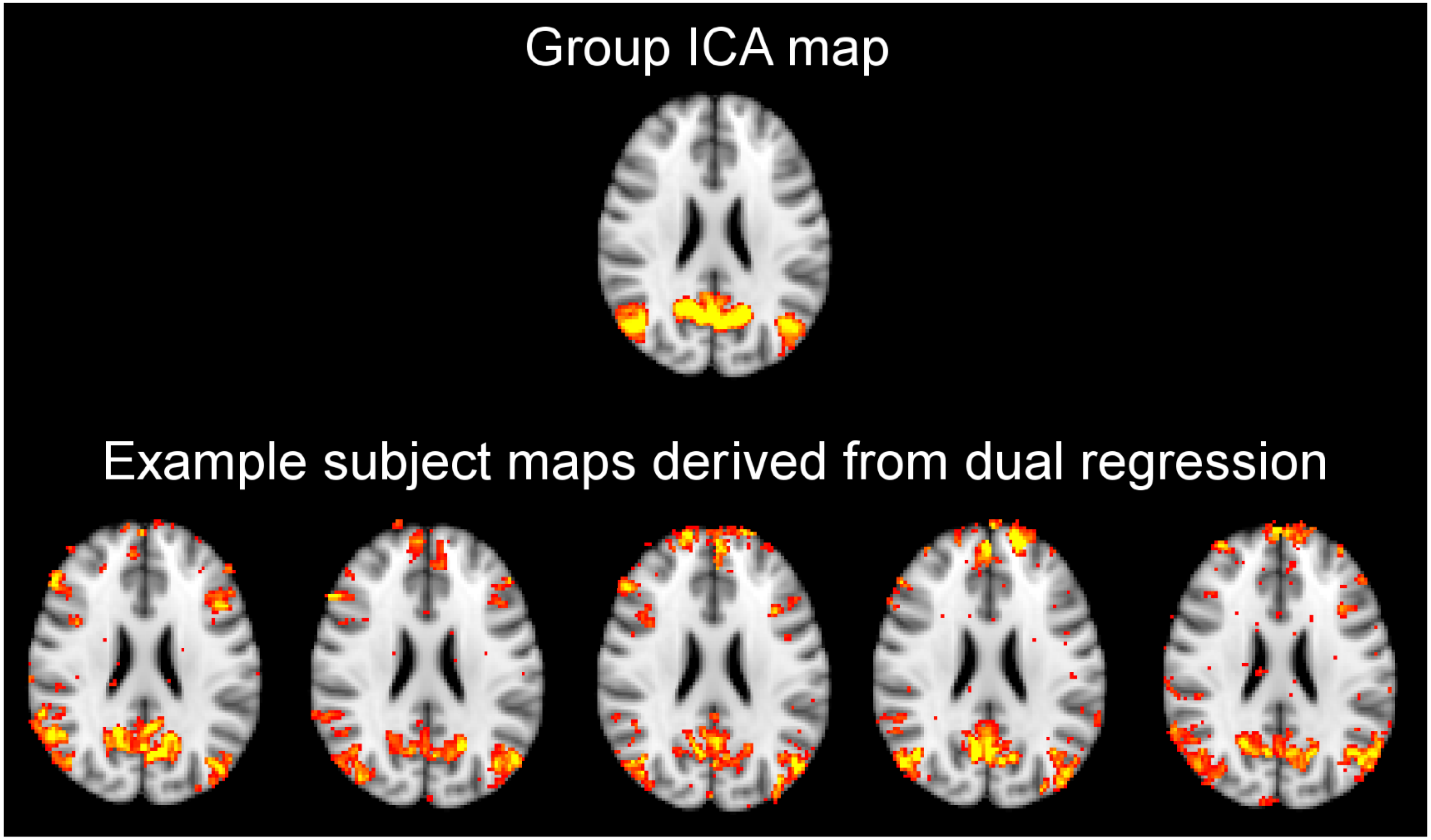



1. Regress group maps into each subject's 4D data to find subject-specific timecourses

2. Regress these timecourses back into the 4D data to find subject-specific spatial maps



# Dual Regression



# Running dual_regression

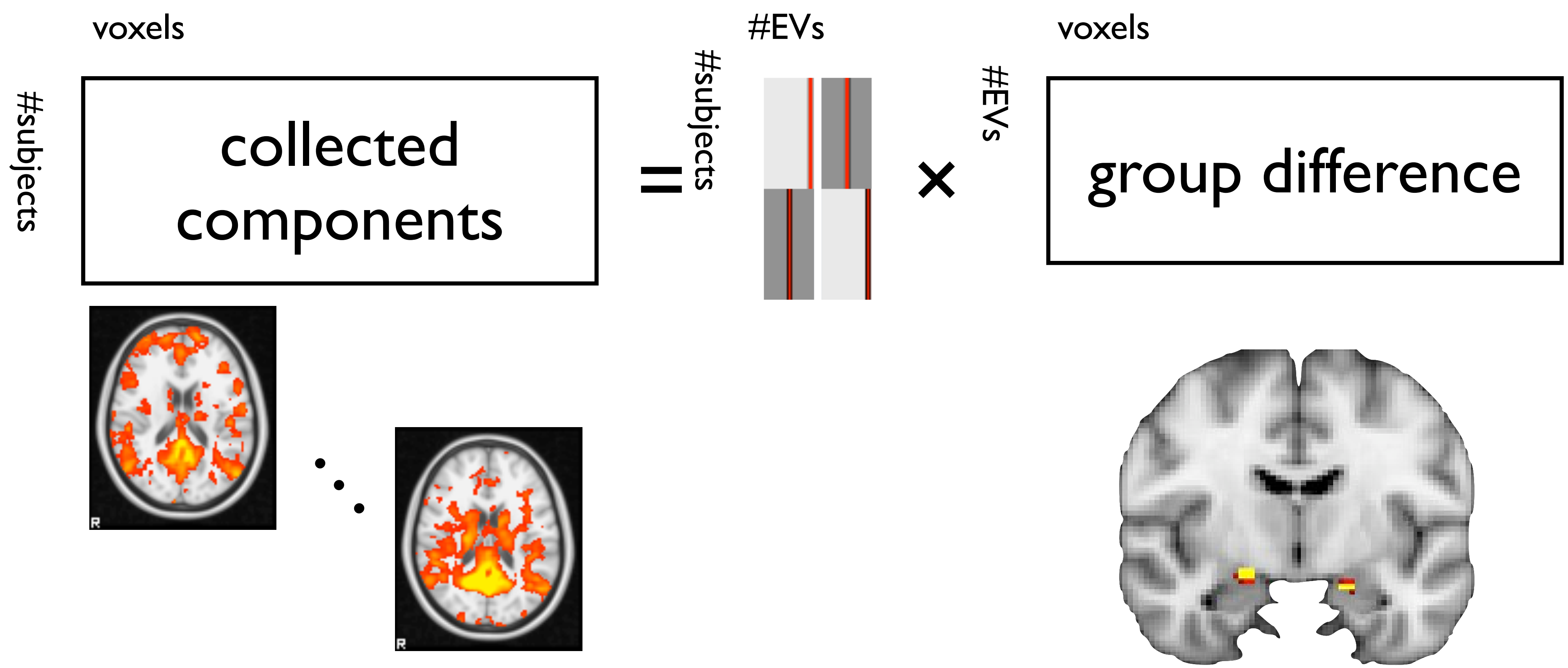
beckmann — bash — bash — 142×23

```
[islay:~] dual_regression.sh

dual_regression v0.5 (beta)

***NOTE*** ORDER OF COMMAND-LINE ARGUMENTS IS DIFFERENT FROM PREVIOUS VERSION

Usage: dual_regression <group_IC_maps> <des_norm> <design.mat> <design.con> <n_perm> <output_directory> <input1> <input2> <input3> .........
e.g.   dual_regression groupICA.gica/groupmelodic.ica/melodic_IC 1 design.mat design.con 500 grot `cat groupICA.gica/.filelist`

<group_IC_maps_4D>            4D image containing spatial IC maps (melodic_IC) from the whole-group ICA analysis
<des_norm>                    0 or 1 (1 is recommended). Whether to variance-normalise the timecourses used as the stage-2 regressors
<design.mat>                  Design matrix for final cross-subject modelling with randomise
<design.con>                  Design contrasts for final cross-subject modelling with randomise
<n_perm>                      Number of permutations for randomise; set to 1 for just raw tstat output, set to 0 to not run randomise at all.
<output_directory>            This directory will be created to hold all output and logfiles
<input1> <input2> ...         List all subjects' preprocessed, standard-space 4D datasets

<design.mat> <design.con>     can be replaced with just
-1                            for group-mean (one-group t-test) modelling.
If you need to add other randomise option then just edit the line after "EDIT HERE" below

[islay:~]
```

- FSL command line tool, combining:
    - DR to create subject-wise estimates (stage 1 + stage 2)
    - Group comparison using randomise (stage 3)

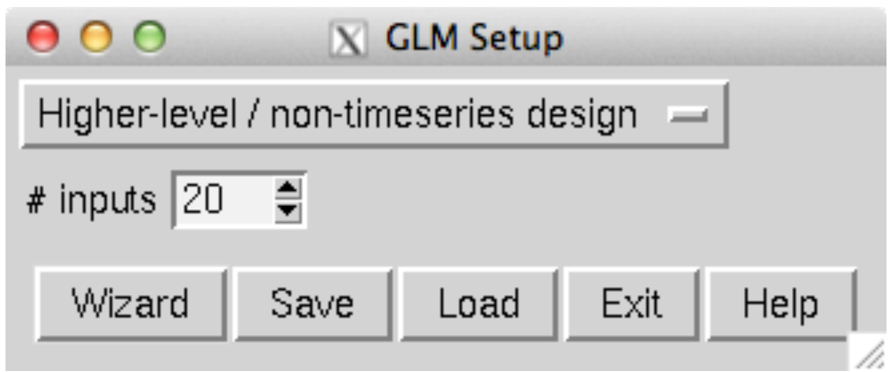
# Group comparison

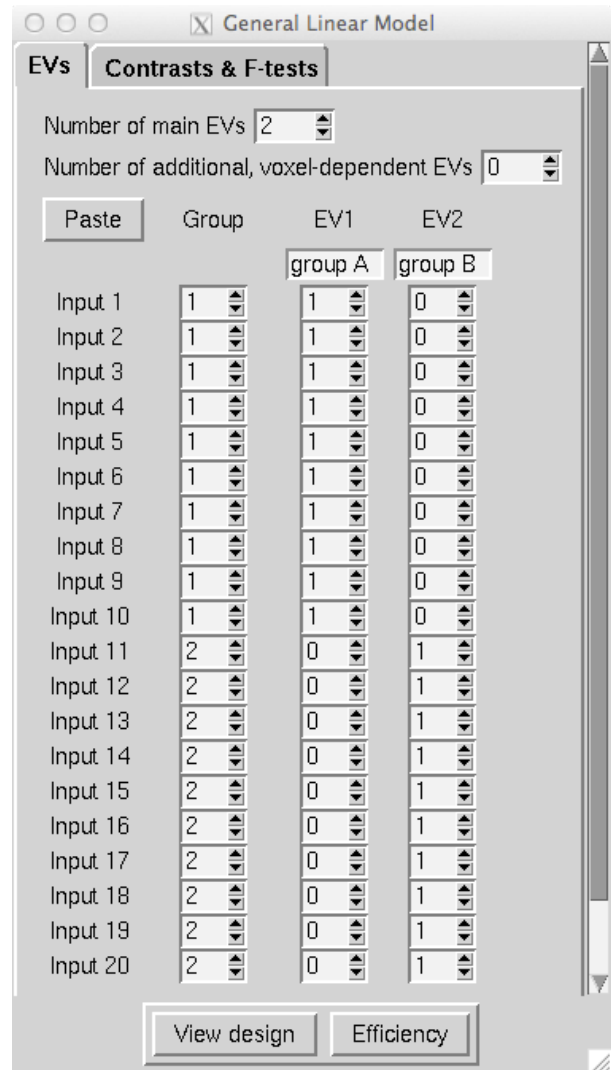
- Collect maps and perform voxel-wise test (e.g. randomisation test on GLM)

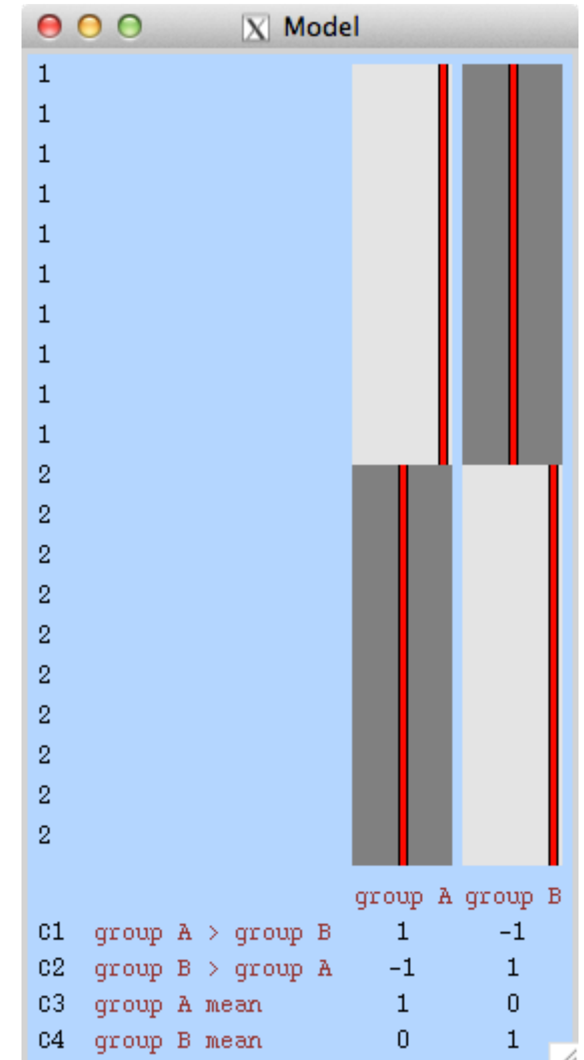



- Can now do voxelwise testing across subjects, separately for each original group ICA map
- Can choose to look at strength-and-shape differences

# Group analysis on maps



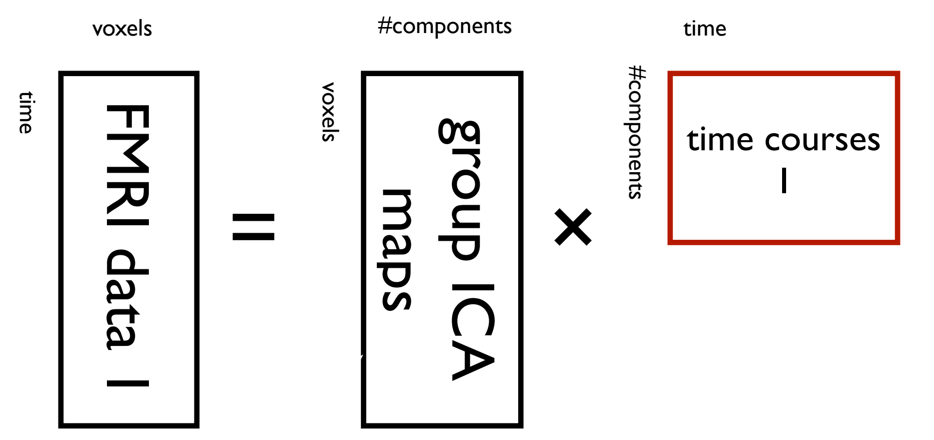




- can use the Glm tool (Glm_gui on mac) to create GLM design and contrast matrices

# Dual regression outputs

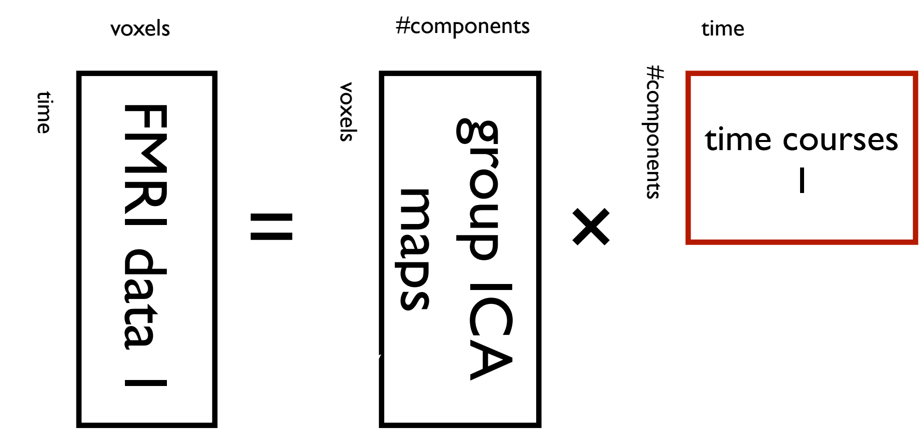
- dr_stage1_subject[#SUB].txt - the timeseries outputs of stage 1 of the dual-regression.

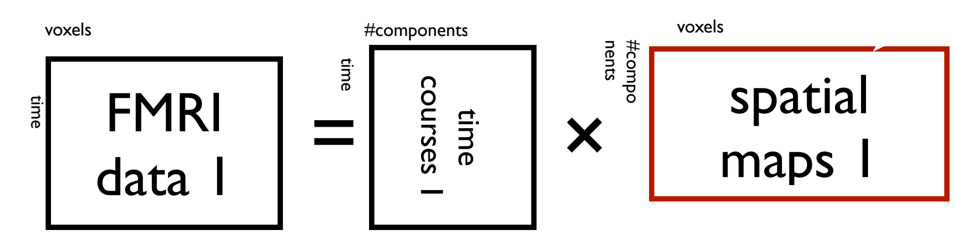


# Dual regression outputs

- dr_stage1_subject[#SUB].txt - the timeseries outputs of stage 1 of the dual-regression.

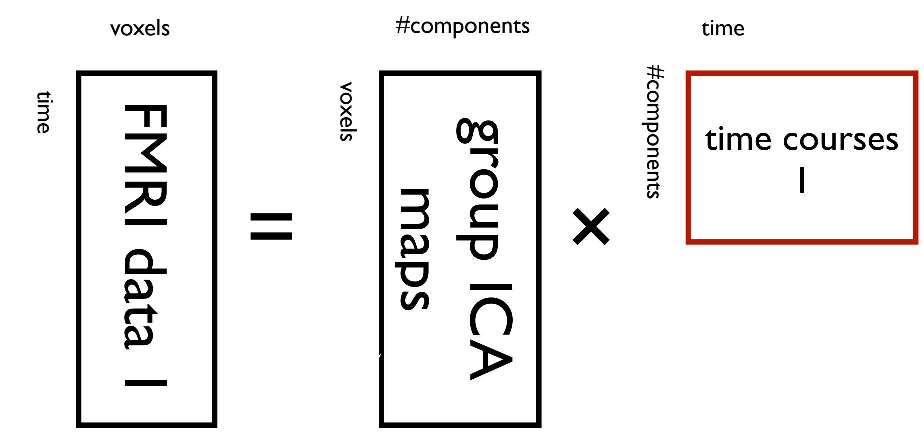
- dr_stage2_subject[#SUB].nii.gz - the spatial maps outputs of stage 2 of the dual-regression.



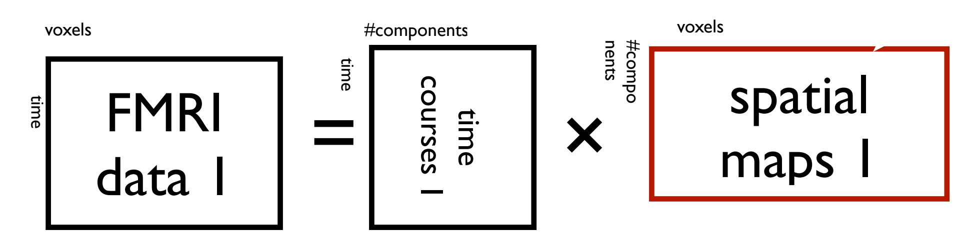
# Dual regression outputs

- dr_stage1_subject[#SUB].txt - the timeseries outputs of stage 1 of the dual-regression.



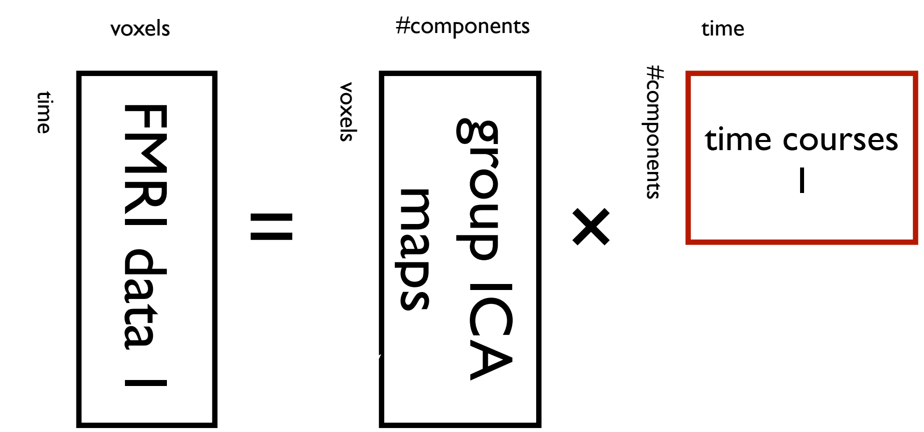

- dr_stage2_subject[#SUB].nii.gz - the spatial maps outputs of stage 2 of the dual-regression.

- dr_stage2_ic[#ICA].nii.gz - the re-organised parameter estimate images

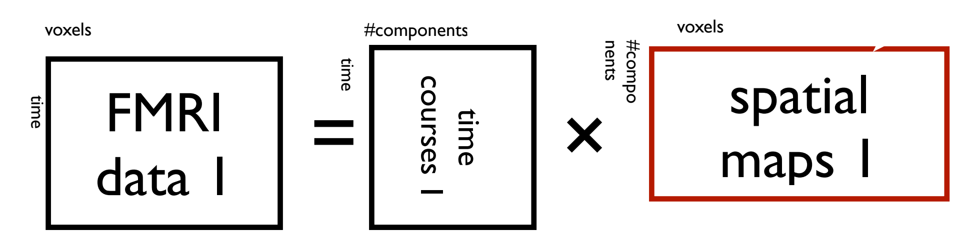


# Dual regression outputs

- dr_stage1_subject[#SUB].txt - the timeseries outputs of stage 1 of the dual-regression.



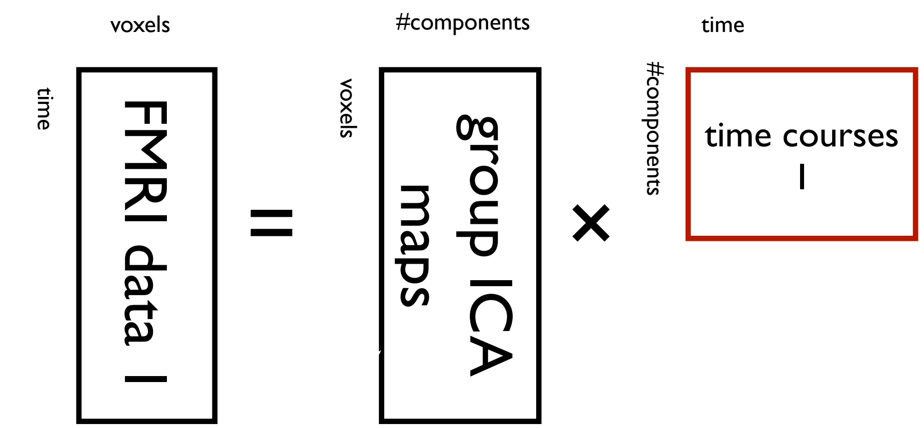

- dr_stage2_subject[#SUB].nii.gz - the spatial maps outputs of stage 2 of the dual-regression.




- dr_stage3_ic[#ICA]_tstat[#CON].nii.gz - the output from randomise

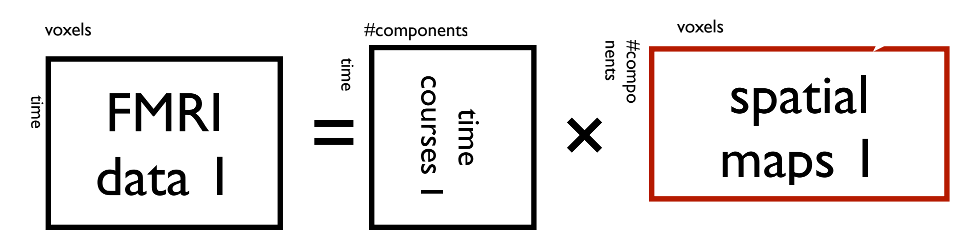
# Dual regression outputs

- dr_stage1_subject[#SUB].txt - the timeseries outputs of stage 1 of the dual-regression.




- dr_stage2_subject[#SUB].nii.gz - the spatial maps outputs of stage 2 of the dual-regression.

- dr_stage2_ic[#ICA].nii.gz - the re-organised parameter estimate images

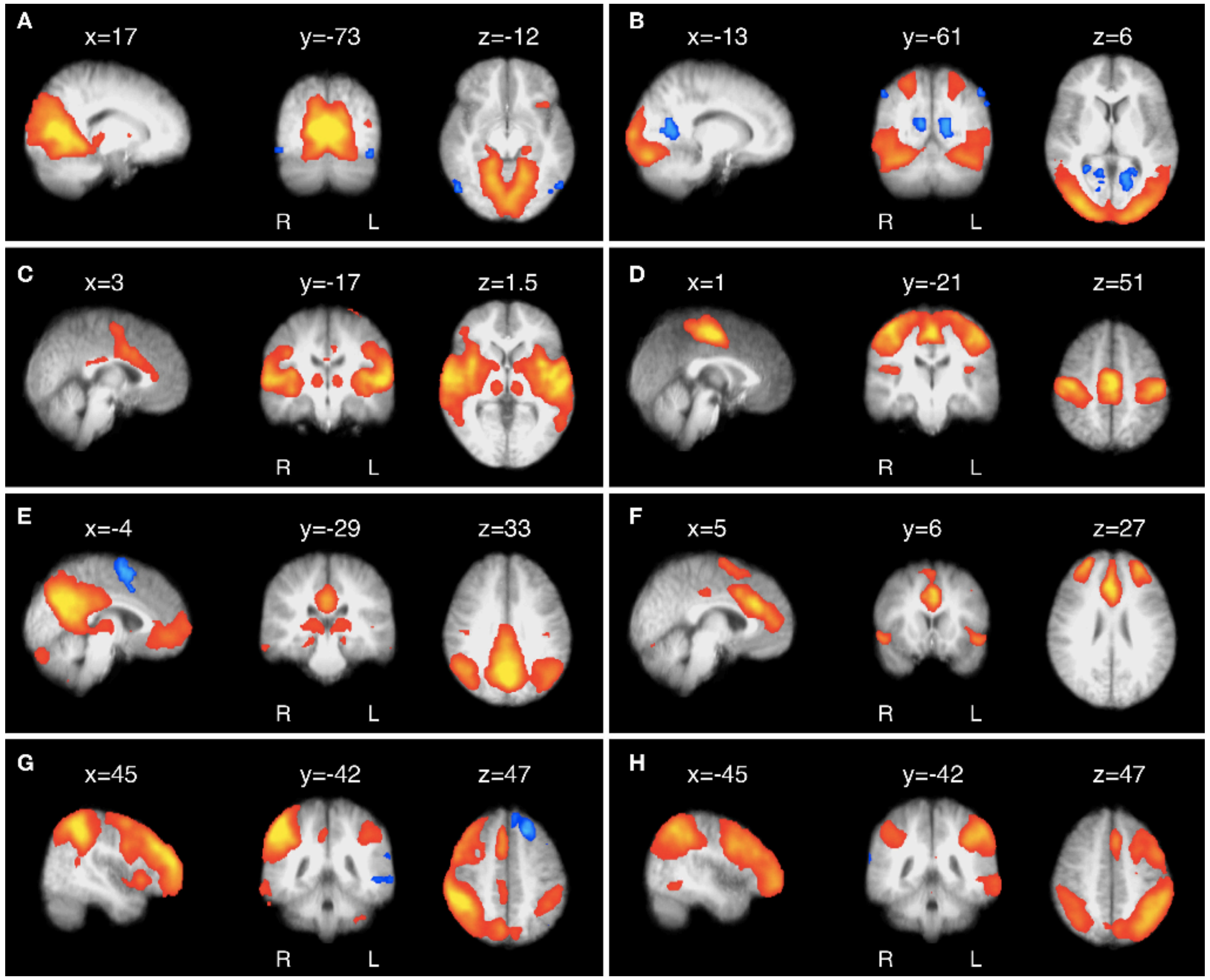



- dr_stage3_ic[#ICA]_tstat[#CON].nii.gz - the output from randomise

(corrected for multiple comparisons across voxels but not across #components!!)

# Group template maps

- Generate from the data using ICA
  - use all data to get unbiased templates

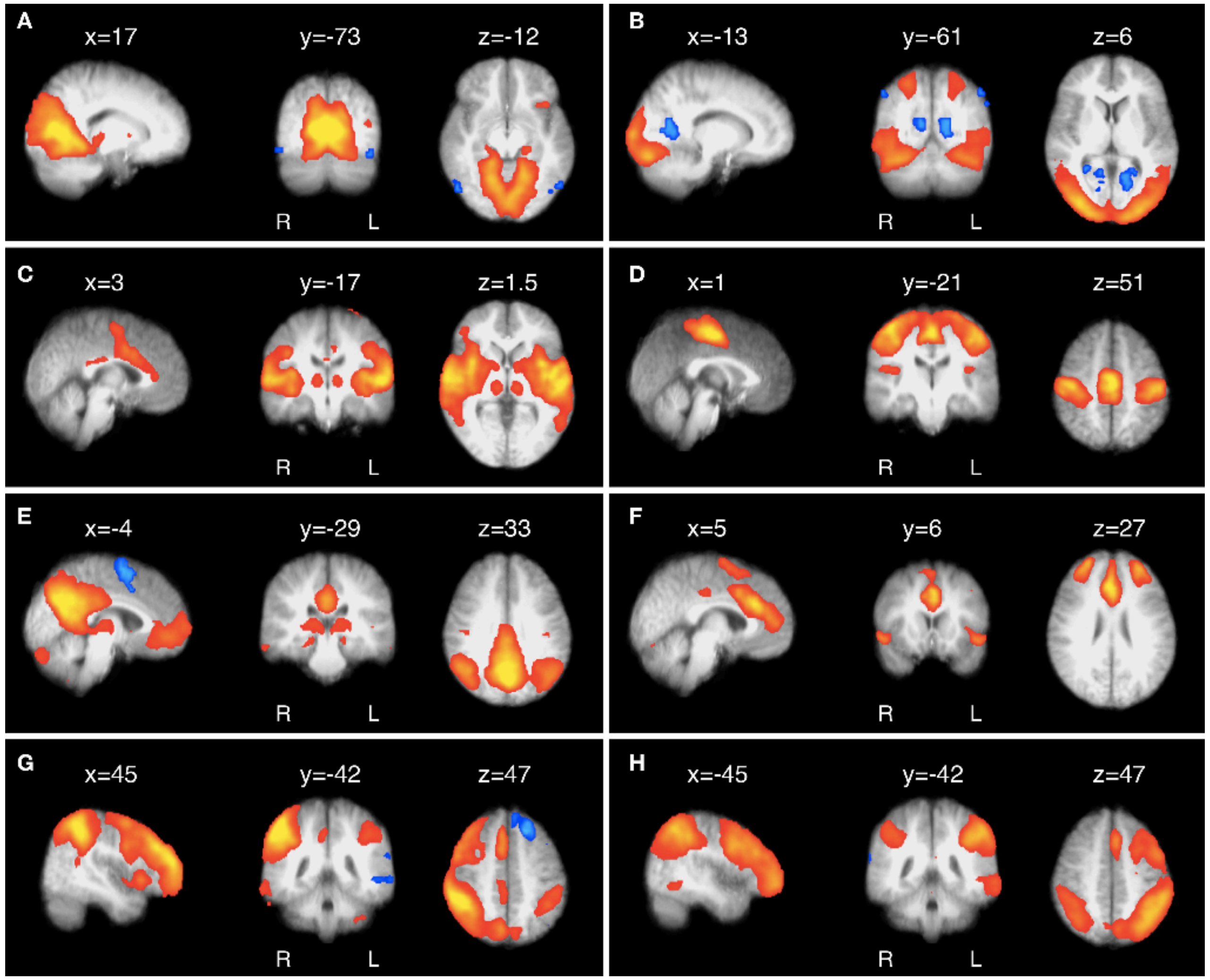



template RSNs

https://www.fmrib.ox.ac.uk/datasets/royalsoc8/

# Group template maps

- Generate from the data using ICA
  - use all data to get unbiased templates
  - use independent control group
    - will not model signals and artefacts

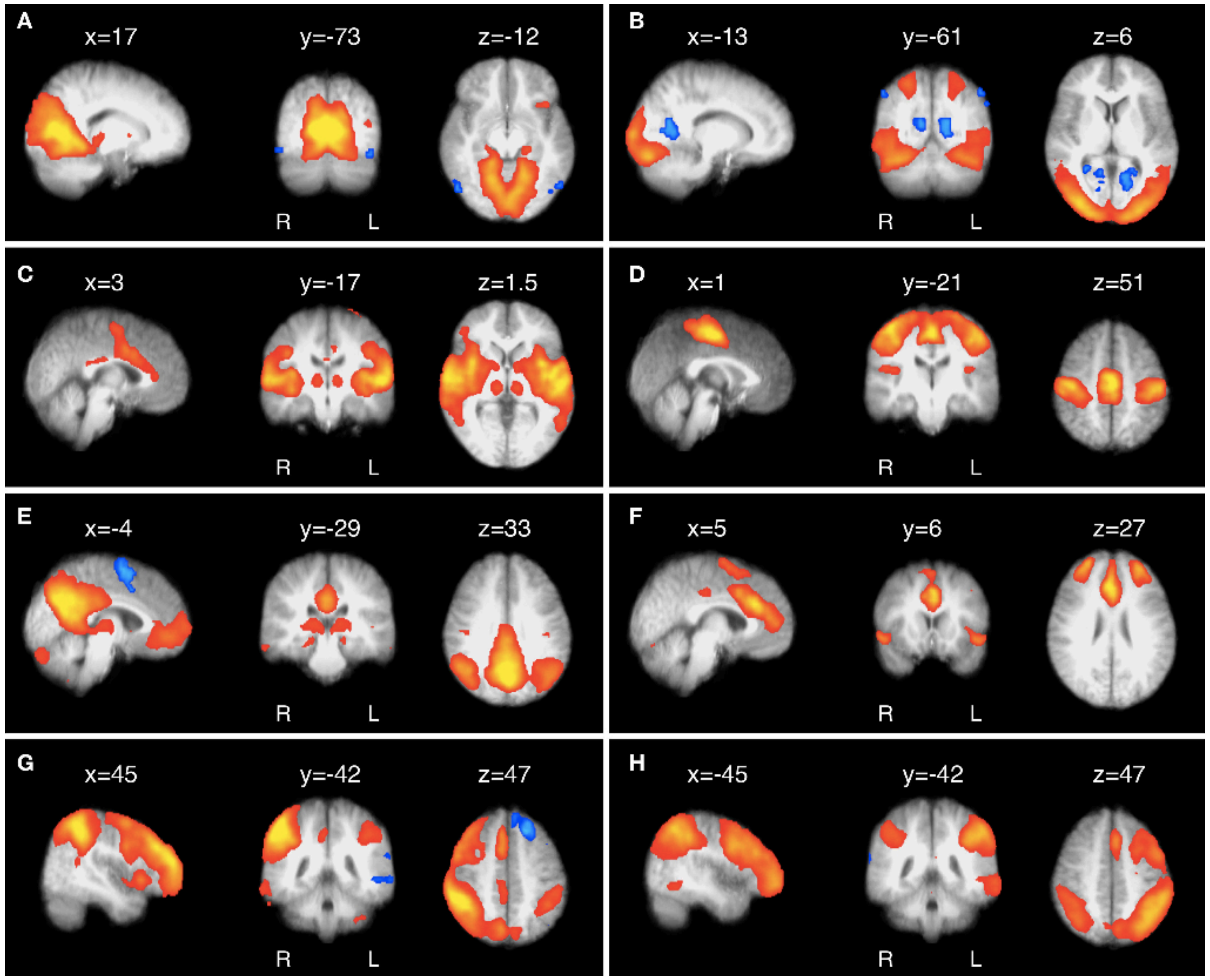



template RSNs

https://www.fmrib.ox.ac.uk/datasets/royalsoc8/

# Group template maps

- Generate from the data using ICA
  - use all data to get unbiased templates
  - use independent control group
    - will not model signals and artefacts
- use existing template




template RSNs

https://www.fmrib.ox.ac.uk/datasets/royalsoc8/

# Summary of part 2

- MELODIC ICA is applied to resting state fMRI for two main purposes: artefact detection, resting state network characterisation
- Artefact detection is done using single subject ICA
    - Artefact components can be classified manually or using FIX/AROMA
    - We then use GLM to regress out the artefacts and clean up the fMRI
- RSN estimation is done using group-level ICA
    - We use concatenation technique
    - This will give consensus RSNs which we then project onto subject fMRI using dual regression
    - Subject specific RSNs obtained from dual regression can be used for statistical comparisons (and input to FSLNets -> we will learn about this tomorrow)

Thank you!

# Resting state fMRI and ICA

Available from:

- Oxford University Press
- Amazon