Unsupervised machine learning for analysis of EEG and MEG at rest

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*with*

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Abstract

- Resting-state networks in the brain
- Improving ICA of resting EEG/MEG
  - Applying ICA on time-frequency decompositions
  - Spatial version of independent component analysis (ICA)
- Testing components: Are they just random effects?
  - Intersubject consistency provides an plausible null hypothesis
- Causal analysis / effective connectivity
  - Structural equation models better estimated using non-Gaussianity
The brain at rest

- The subject’s brain is being measured while
  - the subject has no task
  - the subject receives no stimulation
- Measurements by
  - functional magnetic resonance imaging (fMRI)
  - electroencephalography (EEG)
  - magnetoencephalography (MEG)
- Why is this data so interesting?
  - Not dependent on subjective choices in experimental design (e.g. stimulation protocol, task)
  - Not much analysis has been done so far
  - Completely new viewpoint: rich internal dynamics
Is anything happening in the brain at rest?

- Some brain areas are actually more active at rest
- “Default-mode network(s)” in PET and fMRI (Raichle 2001)
- Brain activity is “intrinsic” instead of just responses to stimulation
- How to analyse resting state in more detail?

(Raichle, 2010 based on Shulman et al 1997)
Independent component analysis (ICA)

- Supervised methods cannot be used: no “teaching signal”
- Assume a linear mixing model

\[ x_i = \sum_j a_{ij} s_j \]  

where \( x_i \) are observed variables, and \( s_j \) latent variables.

- ICA finds both \( a_{ij} \) and \( s_j \) by maximising sparsity of the \( s_j \).
- Sparsity = probability density has heavy tails and peak at zero:

![Graphs comparing Gaussian and sparse distributions](image)
ICA finds resting-state networks in fMRI

- a) Medial and
- b) lateral visual areas,
- c) Auditory system,
- d) Sensory-motor system,
- e) Default-mode network,
- f) Executive control,
- g) Dorsal visual stream

(Beckmann et al, 2005)
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Very similar results obtained if subject watching a movie!
How about EEG and MEG?

- EEG and MEG are measurements of electrical activity in the brain
  - Very high temporal accuracy (millisecond scale)
  - Not so high spatial accuracy (less than in fMRI)
- Typically characterized by oscillations, e.g. at around 10 Hz
- Up to 306 time series (signals), $10^4 \ldots 10^5$ time points.
- Information very different from fMRI
Different sparsities of EEG/MEG data

- ICA finds components by maximizing sparsity, but sparsity of what?
  Depends on preprocessing and representation
- Assume we do wavelet or short-time Fourier transform
- We have different sparsities:
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For example: Joint sparsity in time and frequency allows separation of even Gaussian sources (NeuroImage, 2010).
Spatial sparsity (spatial ICA)

- Images observed at different time points are linear sums of “source images”

\[
\begin{align*}
\text{Image 1} &= a_{11} + a_{12} + \ldots + a_{1n} \\
\text{Image 2} &= a_{21} \\
\vdots \\
\text{Image n} &= a_{n1}
\end{align*}
\]

- Reverses the roles of observations and variables
- Maximizes spatial sparsity alone
- Almost always used in fMRI
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Spatial ICA in MEG

- Spatial ICA possible for MEG by projecting data on the cortex
- We combine this with short-time Fourier transforms
- Maximizes sparsity spatially and spectrally
- **No** assumption on temporal independence

(Ramkumar et al, Human Brain Mapping, in press. Here, not resting data but with “naturalistic stimulation”)
Testing ICs: motivation

- ICA algorithms give a fixed number of components and do not tell which ones are reliable (statistically significant)
- How do we know that an estimated component is not just a random effect?
- Algorithmic artifacts also possible (local minima)
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We develop a statistical test based on inter-subject consistency:

- Do ICA separately on several subjects
- A component is significant if it appears in two or more subjects in a sufficiently similar form
- We formulate a rigorous null hypothesis to quantify this idea (NeuroImage, in press)
Testing ICs: results

One IC

Distribution over channels

Modulation by stimulation

Fourier spectrum

#8

Frequency (Hz)

Another IC

Distribution over channels

Modulation by stimulation

Fourier spectrum

#3

Frequency (Hz)
Causal analysis: Introduction

- Model connections between the measured variables
- Two fundamental approaches
  - If time-resolution of measurements fast enough, we can use autoregressive modelling (Granger causality)
  - Otherwise, we need structural equation models
- If measured variables are raw EEG/MEG, we should first localize sources
- After blind source separation, sources are uncorrelated
  ⇒ More meaningful to model dependencies of envelopes (amplitudes, variances)
Structural equation models

- How does an externally imposed change in one variable affect the others?

\[ x_i = \sum_{j \neq i} b_{ij} x_j + e_i \]

- Difficult to estimate, not simple regression
  - Classic methods fail in general
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- Can be estimated if (Shimizu et al., JMLR, 2005)
  1. the \( e_i(t) \) are mutually independent
  2. the \( e_i(t) \) are non-Gaussian, e.g. sparse
  3. the \( b_{ij} \) are acyclic: There is an ordering of \( x_i \) where effects are all “forward”
Simple measures of causal direction

- The very simplest case: choose between regression models
  \[ y = \rho x + d \]  
  \[ x = \rho y + e \]  
  where \( d \) is independent of \( x \), and symmetrically

- If data is Gaussian we can estimate \( \rho = E\{xy\} \)

**BUT:** Both models have same likelihood!

- For non-Gaussian data, approximate log-likelihood ratio as
  \[ R = \rho E\{xg(y) - g(x)y\} \]  
  where \( g \) is a nonlinearity similar to those used in ICA:
  \( g(u) = u^3 \) or \( g(u) = -\tanh(u) \) (ACML2010).

- Choose direction based on sign of \( R \)!
Sample of results on MEG

Black: positive influence, red: negative influence.
Green: manually drawn grouping.
Here, using GARCH model (Zhang and Hyvärinen, UAI2010)
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- activity not directly related to stimulation
- responses when stimulation too complex
Discussion

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- We present two stages of analysis
  - Finding sources by different variants of ICA
    - Spatial ICA, time-frequency decompositions, etc.
  - Analyzing their effective connectivity:
    - Non-Gaussian versions of SEM
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