

Single-trial EEG analysis workshop

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Single-trial EEG analysis workshop

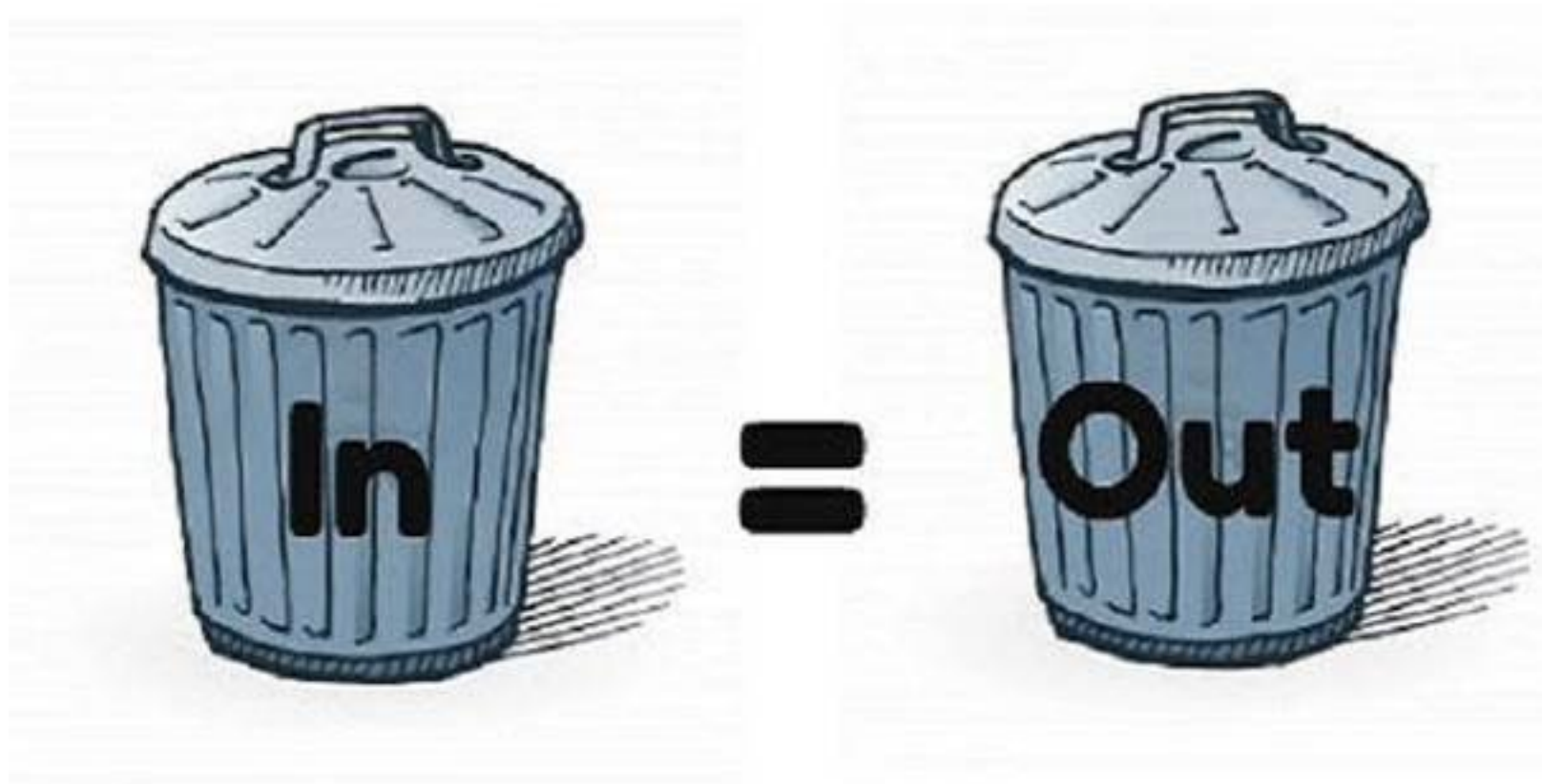
Session 2

Preprocessing

Intro to Independent Component Analysis

Preprocessing & artifacts

THE MOST IMPORTANT THING TO KNOW ABOUT EEG PREPROCESSING



Preprocessing & artifacts

THE MOST IMPORTANT THING TO KNOW ABOUT EEG PREPROCESSING

- How to obtain ***clean data***
 - Keep electrode ***impedance*** / resistance low
 - Remove ***external sources*** of artifacts
 - Turn off phones
 - Turn of unnecessary electronic devices
 - Brief ***participant*** to not produce unnecessary artifacts
 - Jaw clenching
 - Gum chewing
 - ...
 - (Use ***copper chamber*** to avoid line noise artifacts)

Types of Artifacts

Endogenous vs. Exogenous [physiological vs. non-physiological]

Endogenous

- Eye-movements
 - Blinks
 - Saccades
 - ...
- Electromyogram
 - Jaw clenching
 - Neck muscles
- Sweat
- Cardiac
- (Alpha)



Exogenous

- Electrode artifacts
- Lead movement
- Salt bridge
- Line noise
- Phone

Types of artifacts

Stereotypical vs. non-stereotypical

- From an analysis perspective, a more classification of artifacts than physiological vs. non-physiological is “***stereotypical***” vs. “***non-stereotypical***”

Stereotypical artifacts

- Ongoing / recurrent through all (or most) of the dataset
- Look (roughly) the same every time they occur
- Examples
 - Blinks
 - Saccades
 - Some electrode artifacts
 - Line Noise

Non-stereotypical artifacts

- Only occur intermittently
- Look unique every time they occur
- Examples
 - EMG artifacts
 - Sweat artifacts
 - Some electrode artifacts

Types of artifacts

Stereotypical vs. non-stereotypical artifacts

- ***Non-stereotypical artifacts***

- Mostly call for ***removal of time-segments*** of data (i.e., delete all channel data for a given time range from the dataset)

- ***Stereotypical artifacts***

- Can often be removed from the data ***without discarding actual time segments***
- Many methods exists depending on the artifact
 - Channel removal (and interpolation) for electrode artifacts
 - Regression methods for eye-blink removal (e.g., Gratton et al., 1983)
 - Notch filtering for line noise artifact
- Can very easily addressed using ***Independent Component Analysis***

Preprocessing

A typical EEG preprocessing pipeline

- ***Frequency-domain restriction***
 - Done via filtering
 - No differences between regular filtering (e.g., for a classic ERP study) and single-trials
- ***Artifact rejection***
 - Removing time periods with artifacts (deleting them from the data)
 - Non-stereotypic artifacts only
 - Mostly done to retain the maximum of available data dimensions for ICA
- ***Artifact correction***
 - Done via Independent Component Analysis
 - Data segments are retained, but artifacts are calculated out of the data
 - Part of the preprocessing (*but also helpful later to increase SNR for single-trial analyses*)

Preprocessing step 1

Frequency-domain restriction via filtering

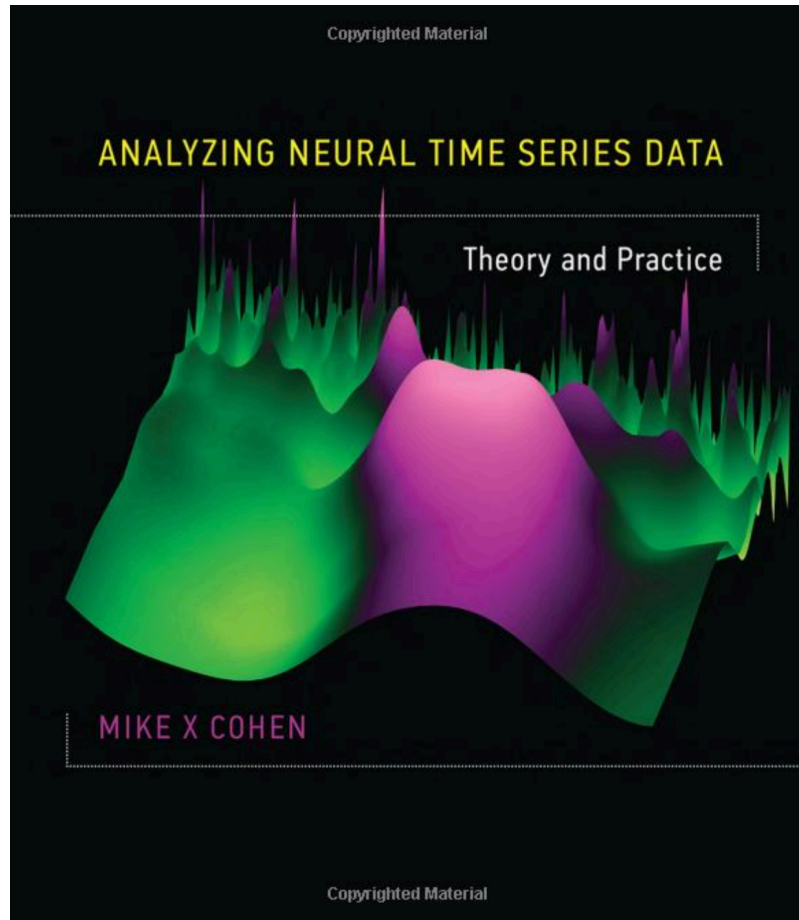
Filtering

Overview

- **(Temporal) filtering** refers to the removal of selected frequencies from the overall EEG signal
- For the majority of purposes, the scalp EEG signal only **contains meaningful information** between around .1 Hz and ~60Hz
- Many **artifacts** have frequency properties that are above (or below) that band
- Therefore, the most commonly used primary artifact removal technique is filtering to **restrict the frequency information** present in the recording
 - **High-pass filters** let high frequencies past -> remove low frequencies
 - **Low-pass filters** let low frequencies past -> remove high frequencies
- Filtering is usually already done on the **hardware side**
 - **Recording frequencies** are restricted to a band of e.g., .01 Hz – Nyquist freq
 - If no low-pass cut off is provided, the **sampling rate** provides an implicit low-pass filter

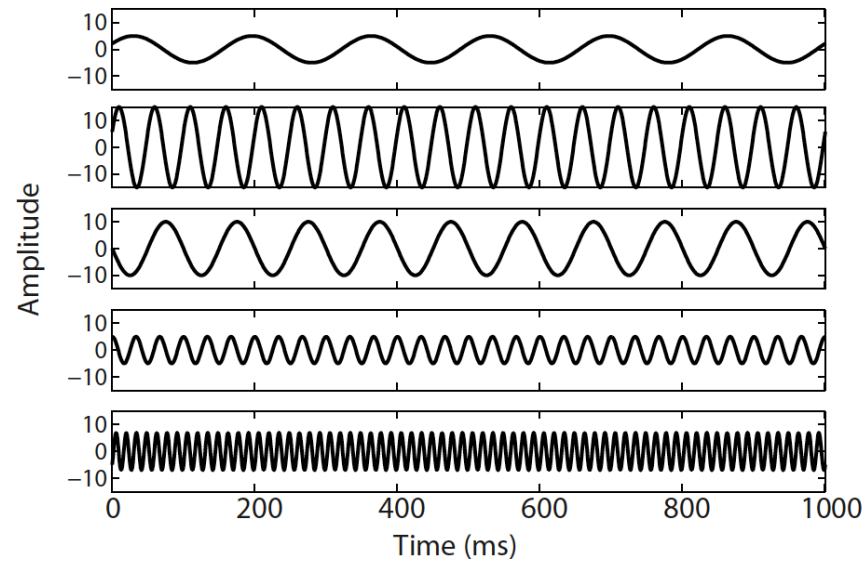
Filtering

Understanding the EEG signal as a frequency composition

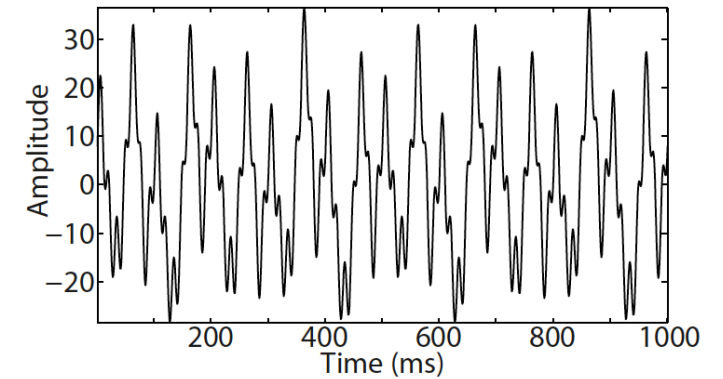


ISBN: 978-0262019873

A) Individual sine waves



B) Sum of sine waves

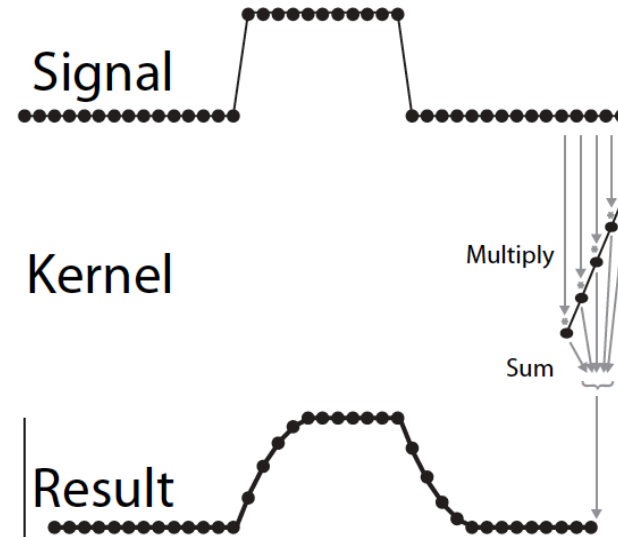
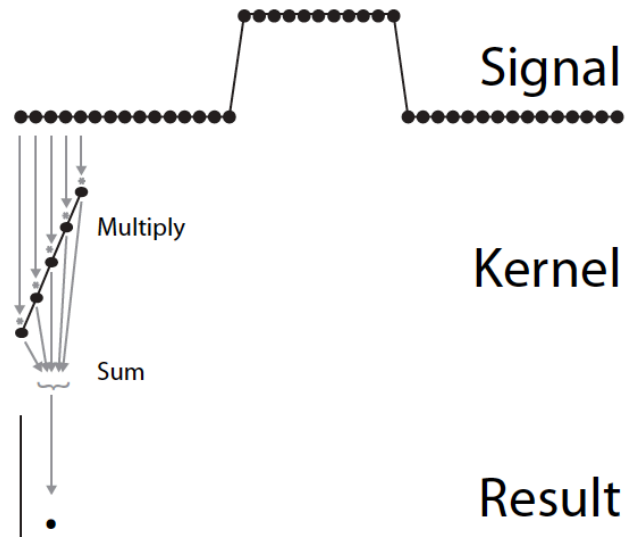


Filtering

Understanding time-domain convolution and the dot product

- **Convolution**

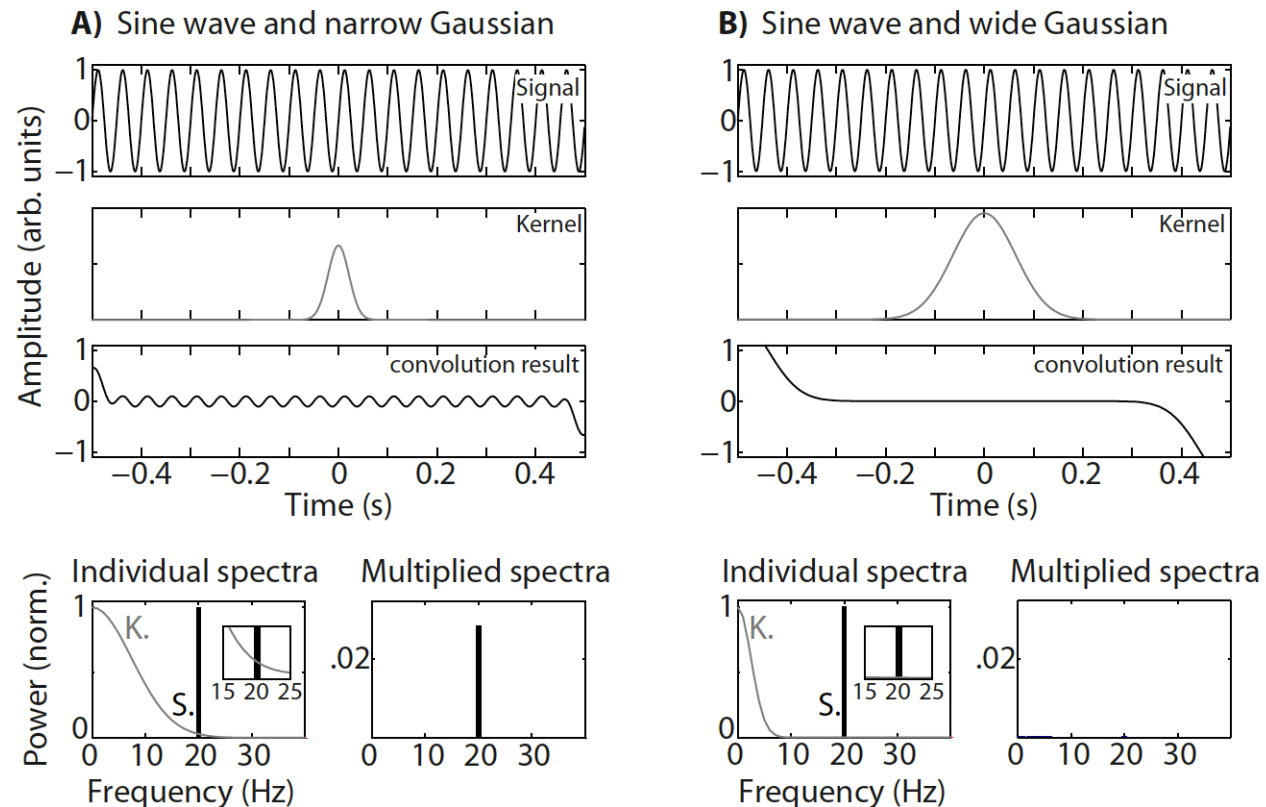
- A time series of one signal weighted by another signal that slides along the first signal
- In EEG **practice**, convolution means
 - Computing the dot product of the **signal** at one time point with a **filter kernel**
 - Computing the same dot product of the **next time point, etc.**
 - Summing up the results



Filtering

Filtering via time domain convolution

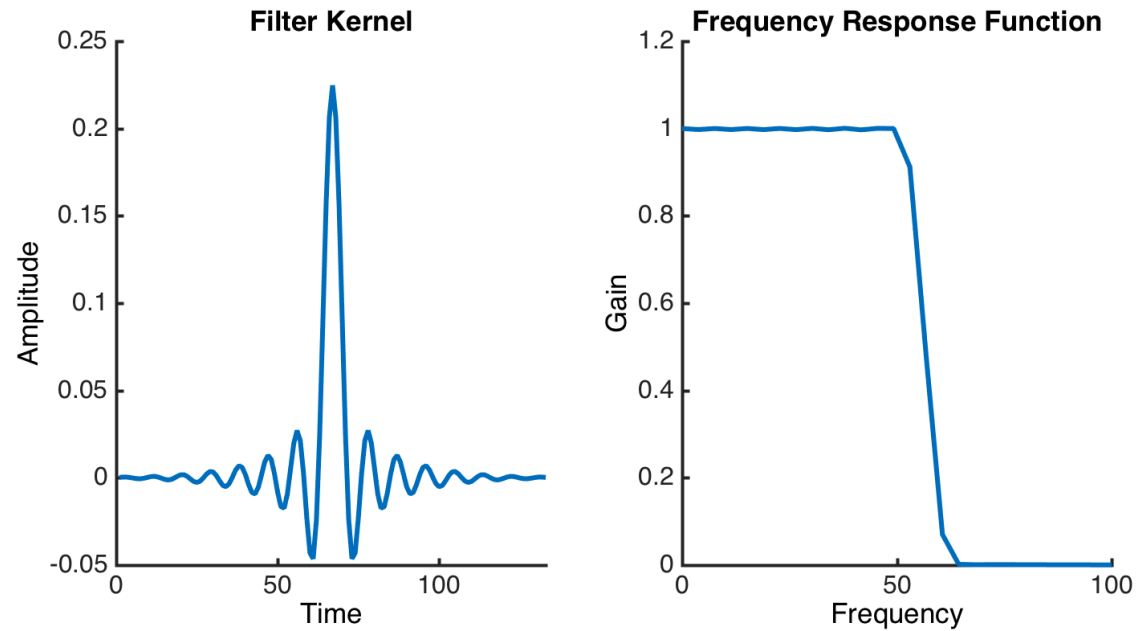
- Filtering is achieved by ***designing a kernel with a specific set of frequency properties***
 - Through the principles of convolution, the frequency profile of the signal is ***passed through the frequency profile of the kernel***



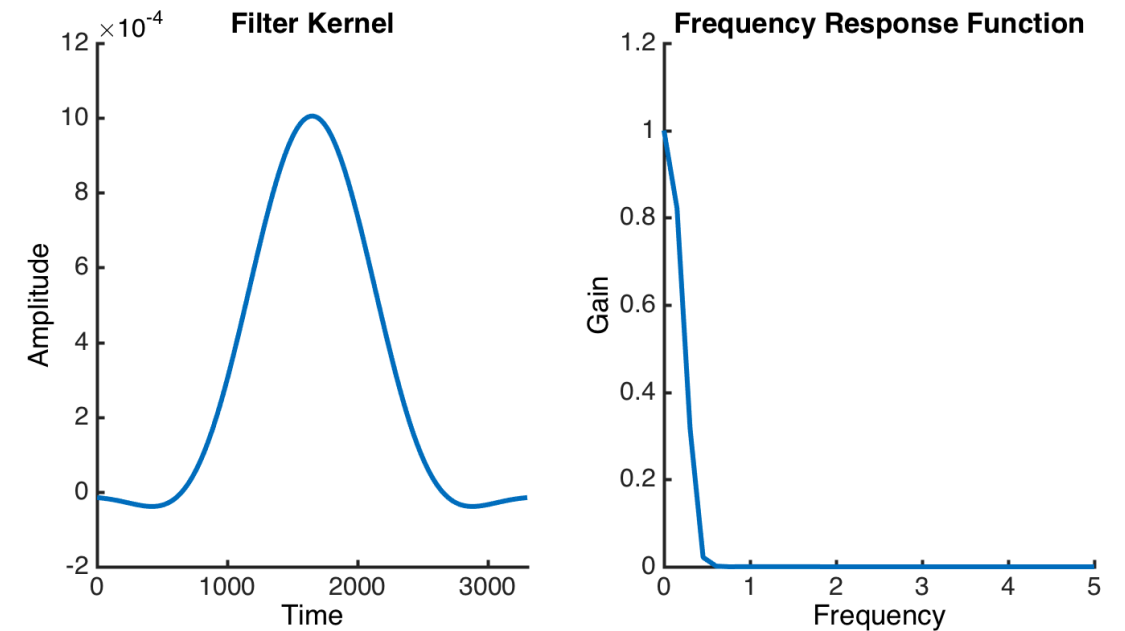
Filtering

Understanding the EEG signal as a frequency composition

LOW PASS FILTER

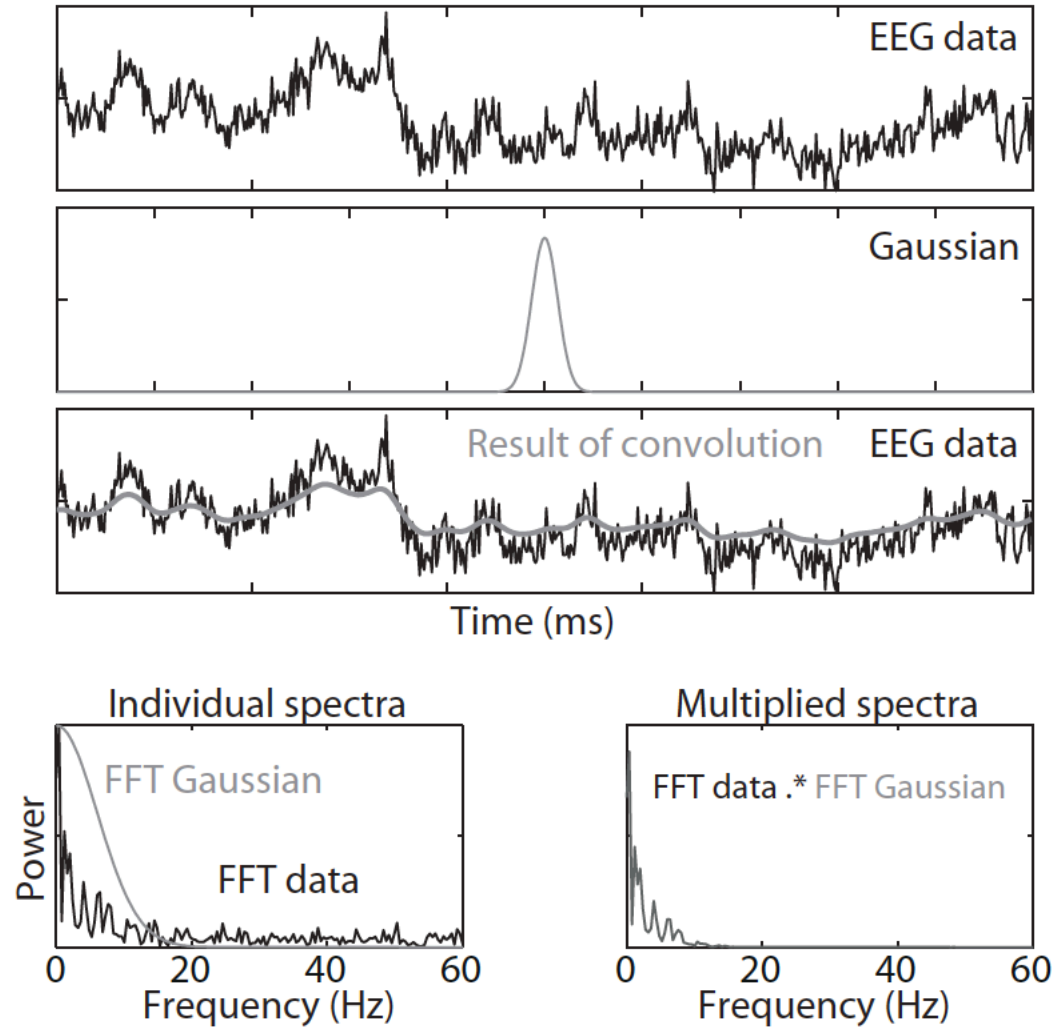


HIGH PASS FILTER



Filtering

Filtering via time domain convolution



Preprocessing step 2

Artifact rejection

Artifact rejection

Non-stereotypic artifacts

- Non-stereotypic artifacts
 - Only occur intermittently
 - Look unique every time they occur
 - Examples
 - EMG artifacts
 - Sweat artifacts
 - Some electrode artifacts
- Can be done on epochs or continuous data
- Automated algorithms
 - Use data features to identify artifacts
 - Peak
 - Range
 - Data distribution features (kurtosis, probability / dispersion / standard deviation)

Preprocessing step 3

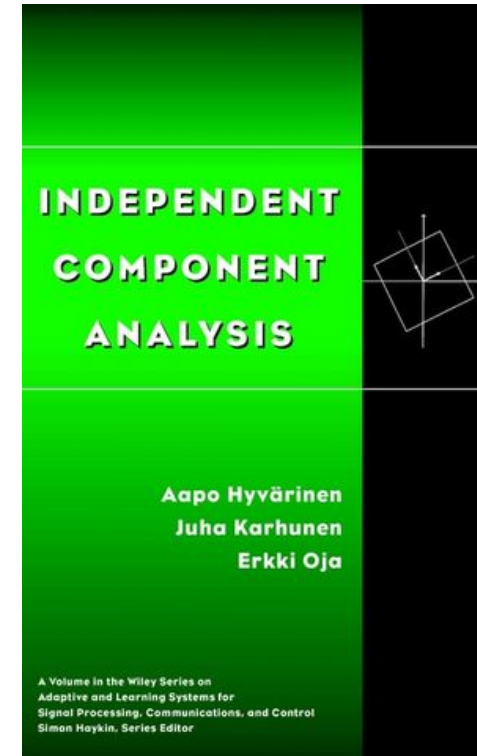
Artifact correction via ICA

Helpful resources

ICA books



James V. Stone:
Independent Component Analysis
– A Tutorial Introduction
MIT Press (2004)

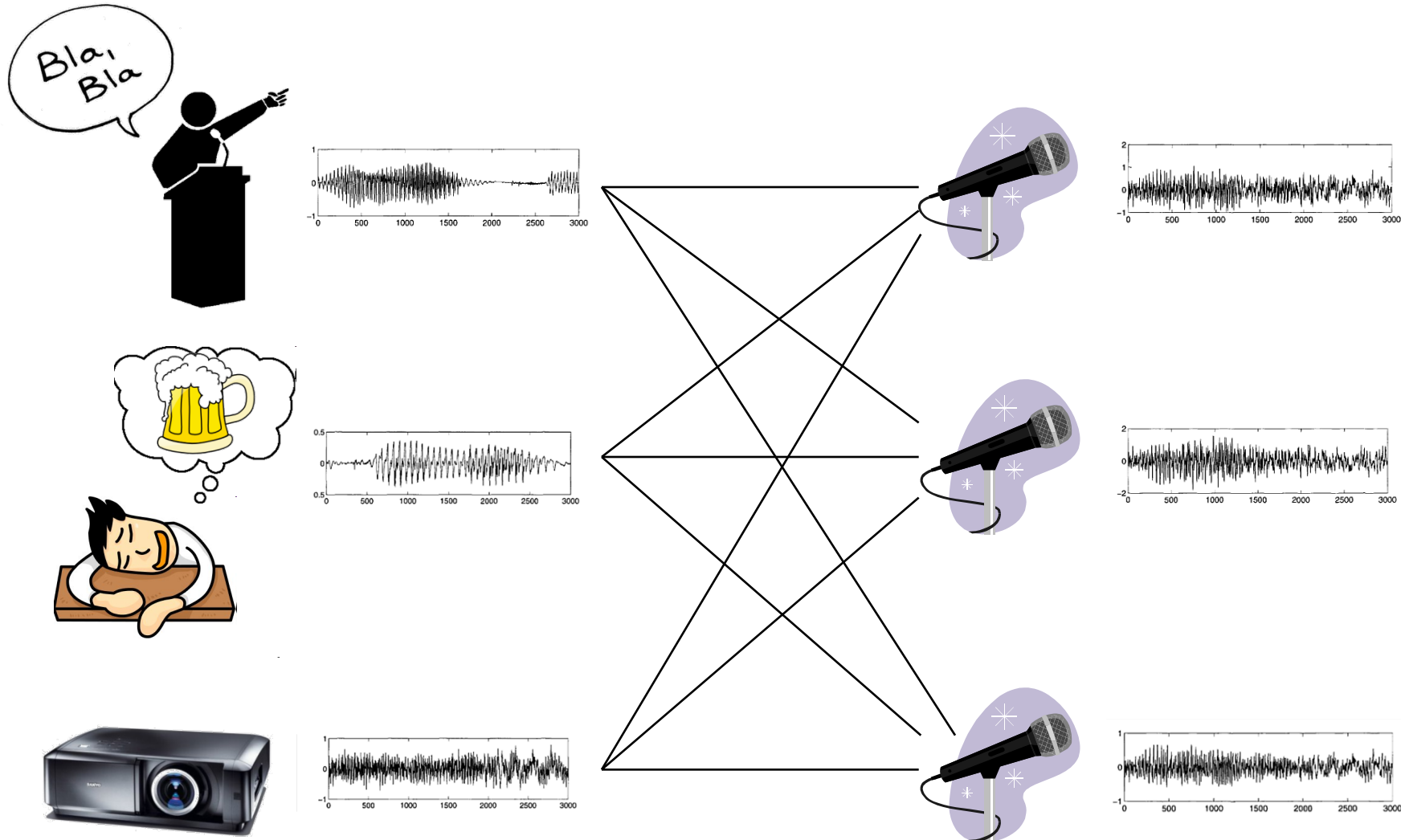


Aapo Hyvärinen, Juha Karhunen, Erkki Oja:
Independent Component Analysis

John Wiley & Sons (2001)

Blind source separation and ICA

The 'cocktail party' example



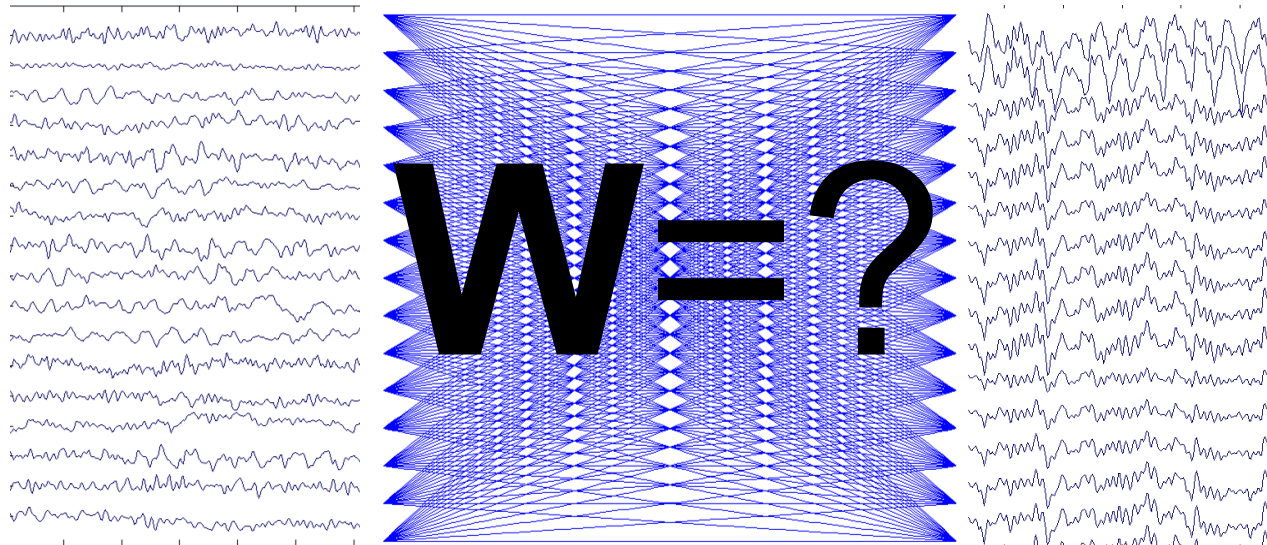
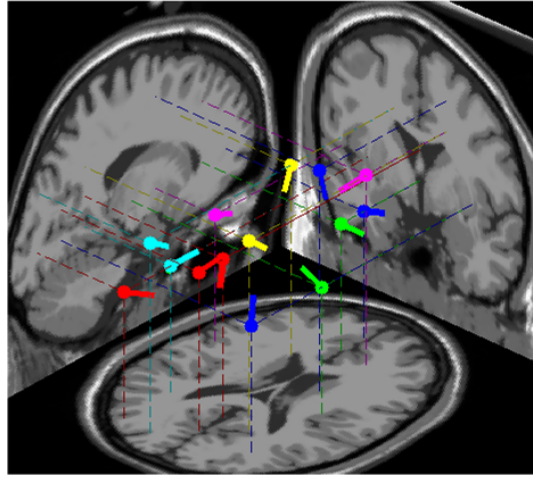
SOURCE SIGNALS

MIXING

SIGNAL MIXTURE

Why this matters for EEG

EEG is an ideal blind source separation problem



UNDERLYING DIPOLES

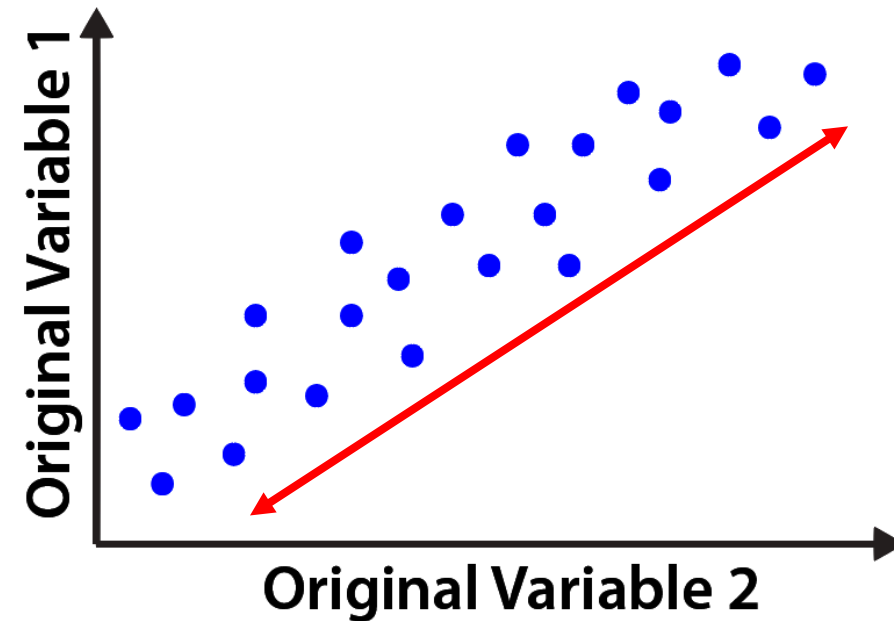
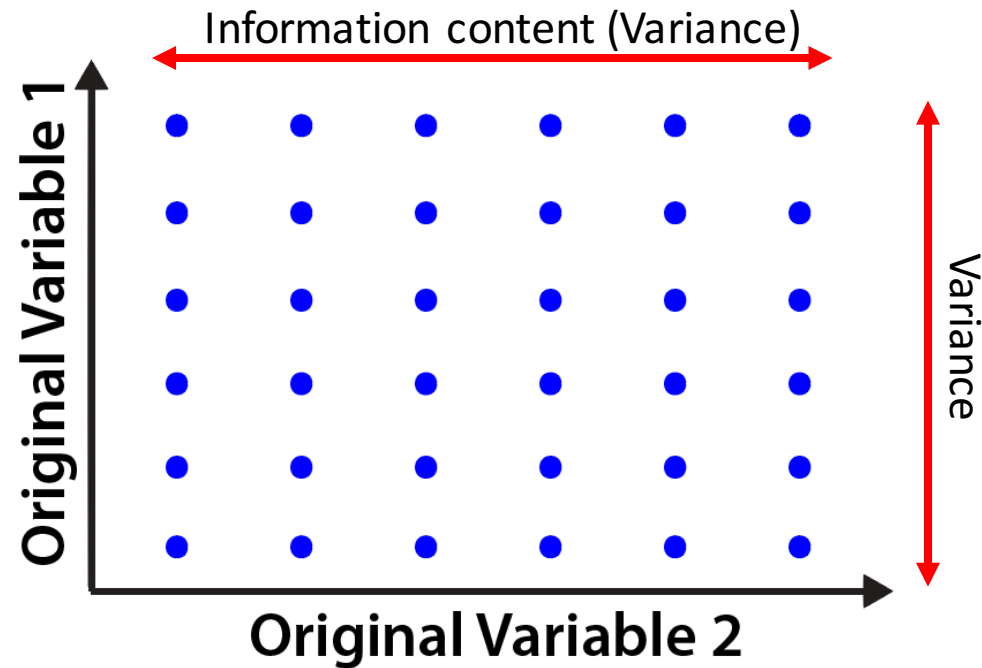
SCALP SIGNAL

Using PCA to understand ICA

PCA

Rotational data transformations

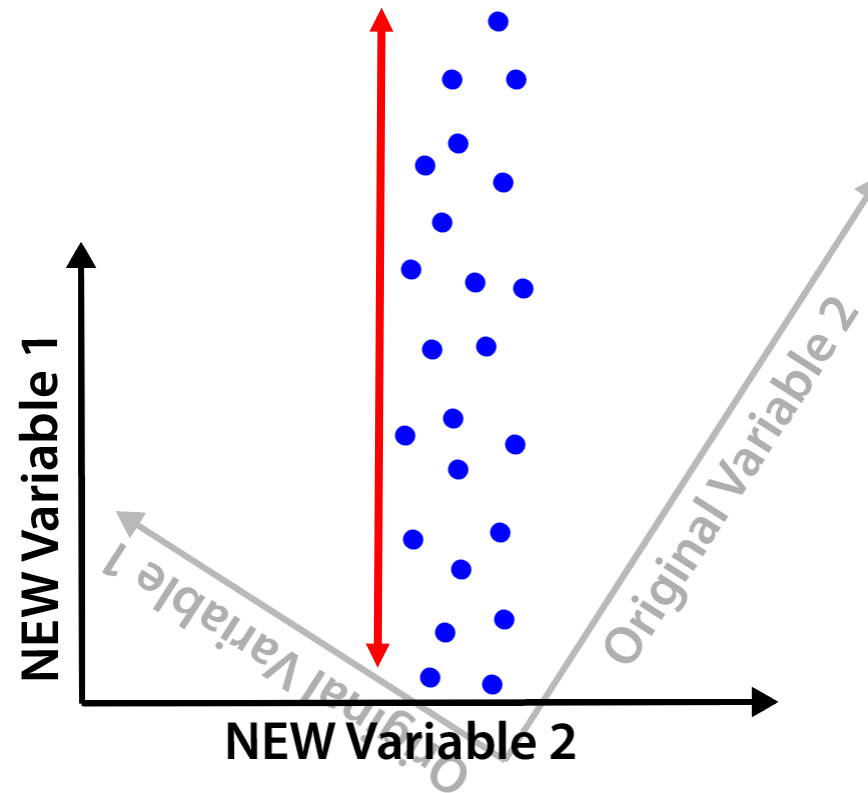
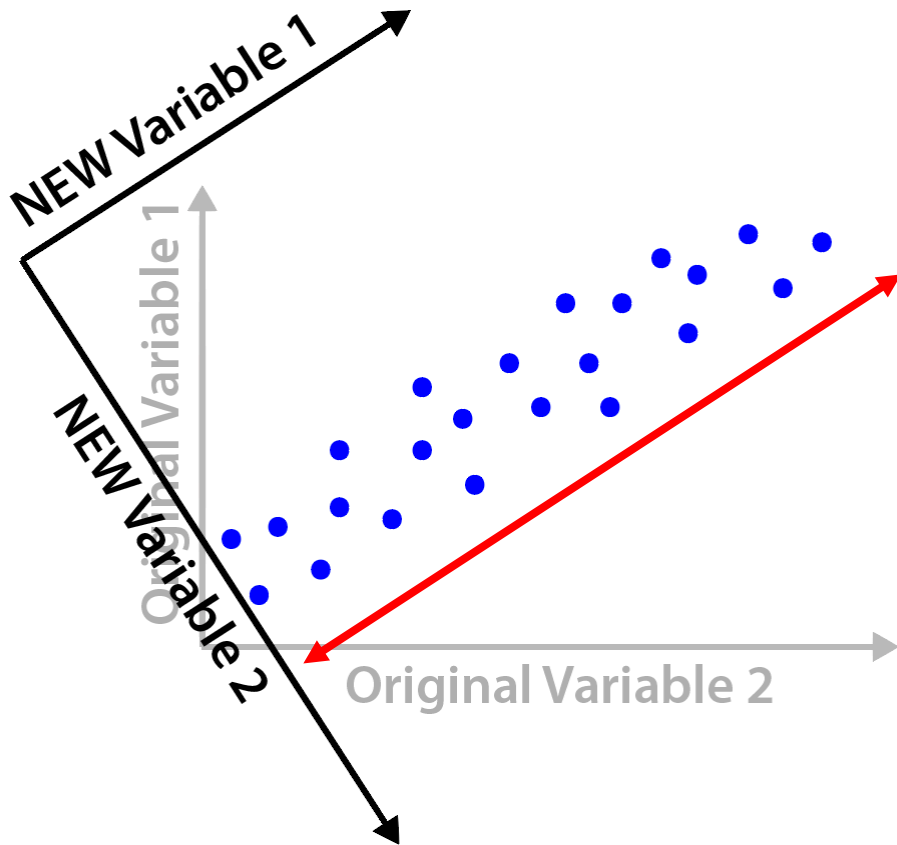
- Is the current variable layout (coordinate system) the ideal way to represent the information in my data?



PCA

Rotational data transformations

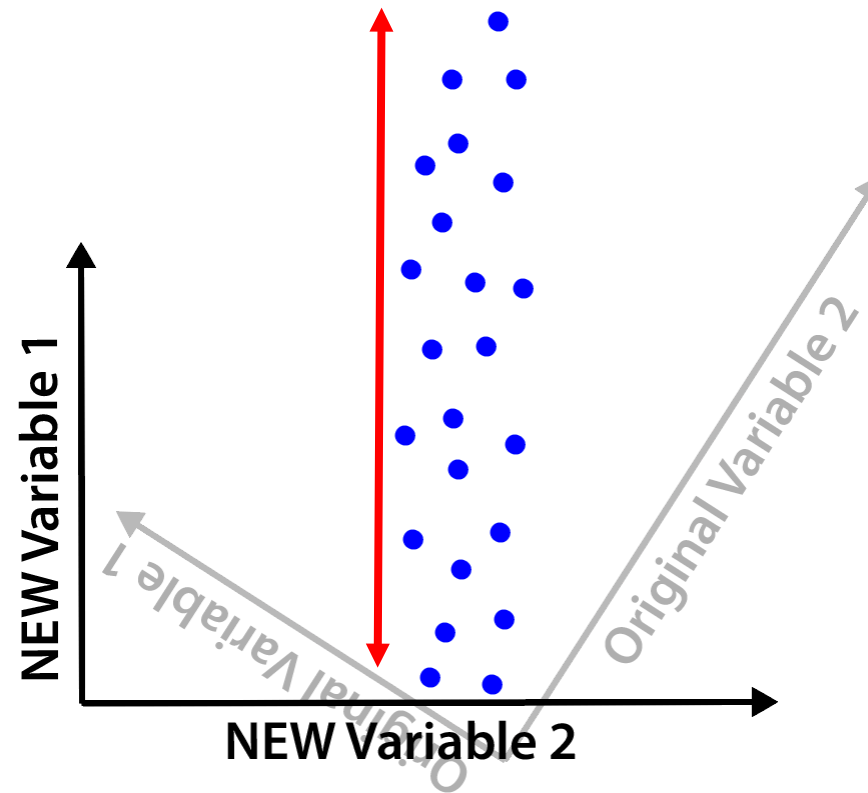
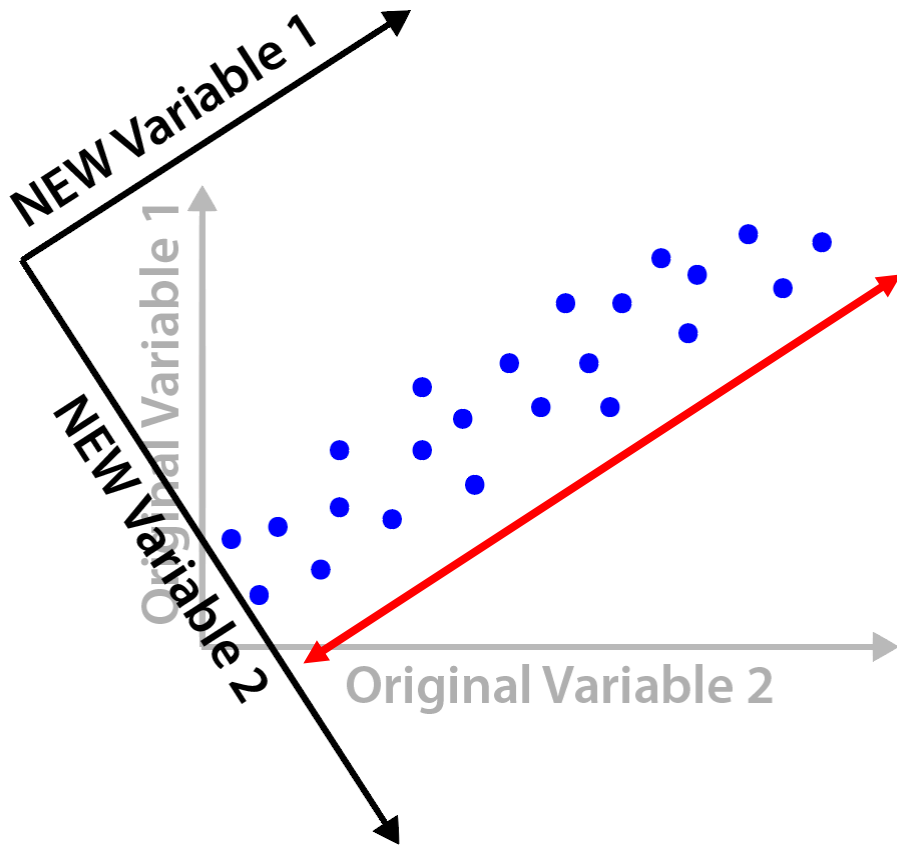
- PCA rotates the coordinate system so that the first variable catches the most possible variance in the signal. This new variable is called a 'principal component'



PCA

Rotational data transformations

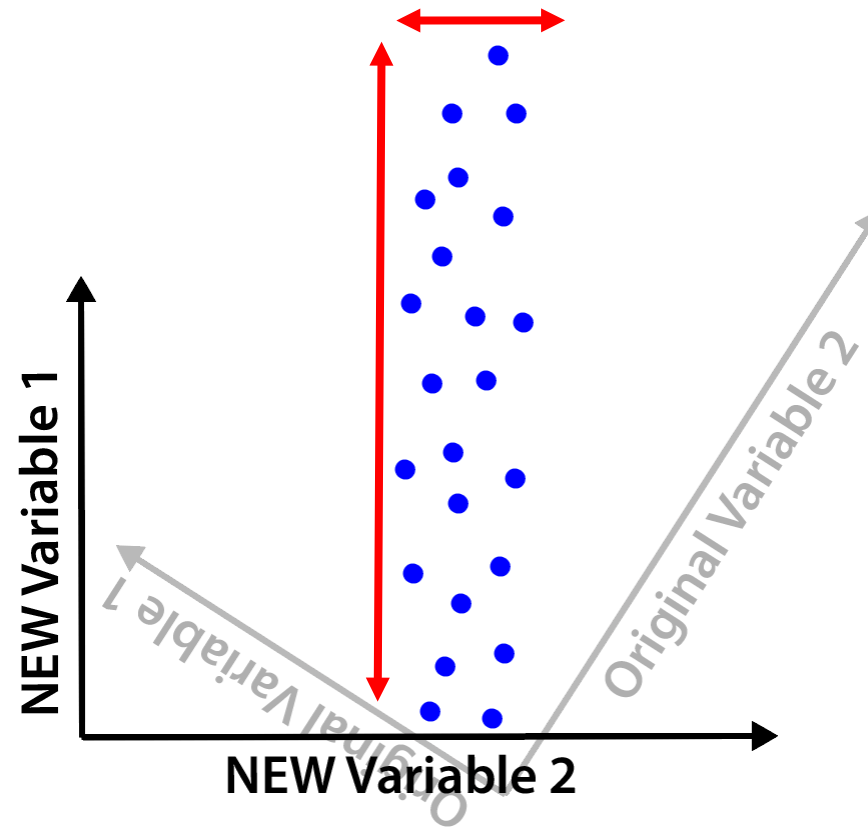
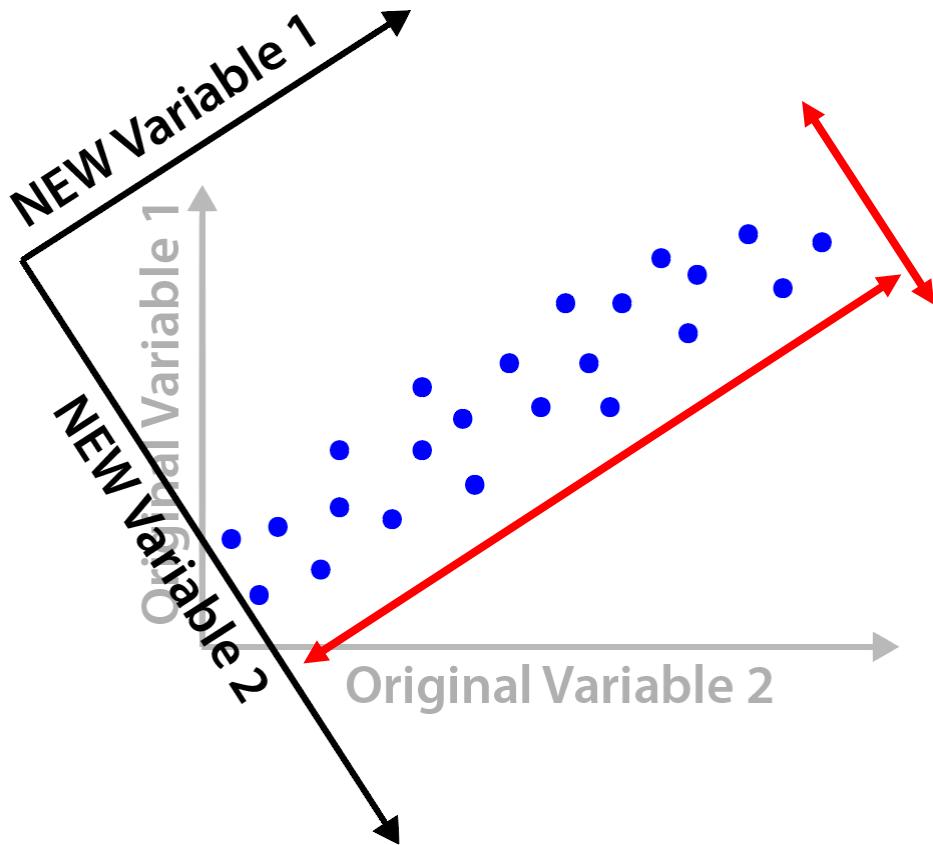
- Each subsequent variable is then extracted to capture the most possible remaining (residual) variance.



PCA

Rotational data transformations

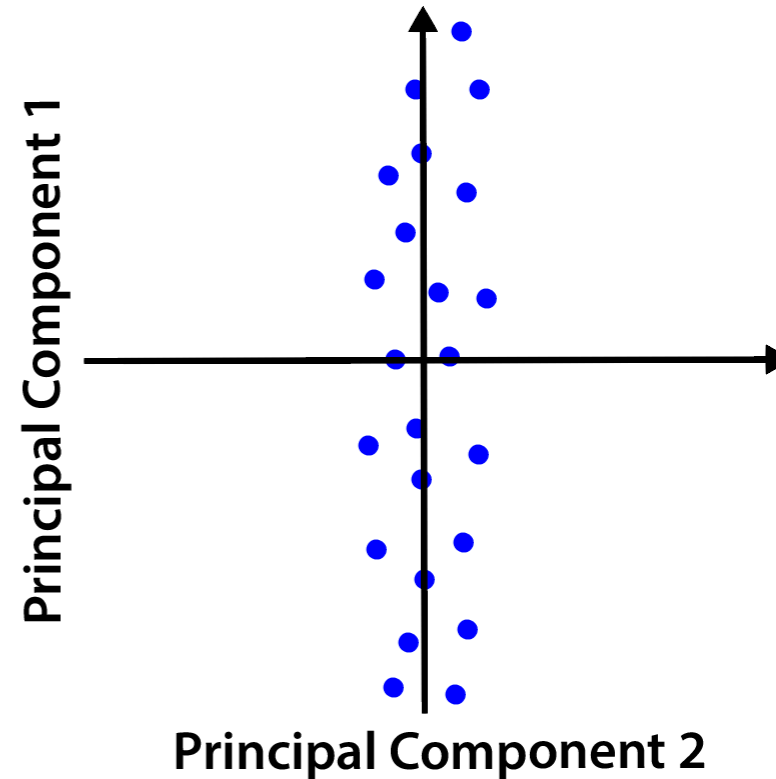
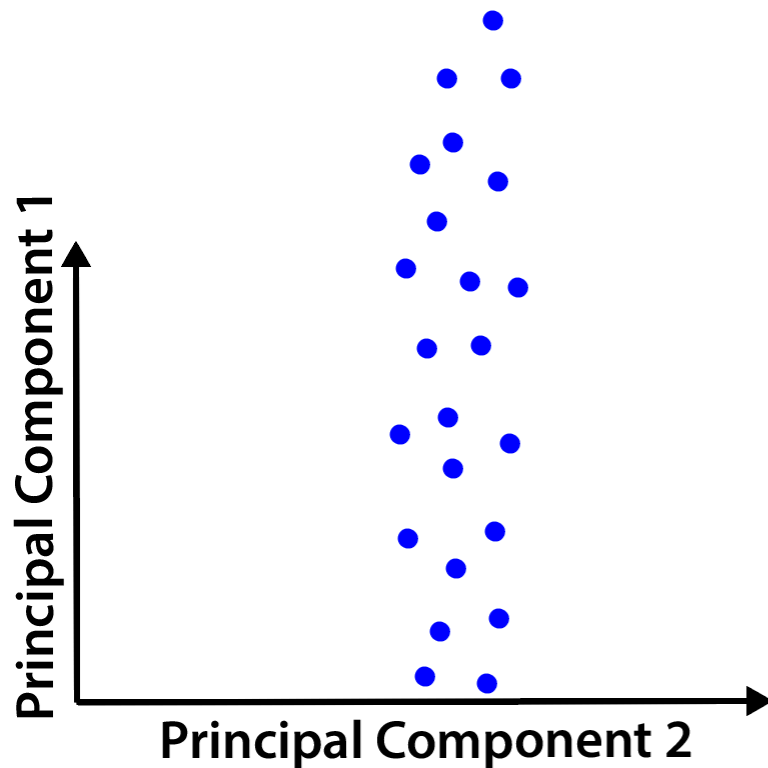
- Per definition, that variable will be orthogonal to the first variable. Otherwise, it would share variance with the first variable, and therefore explain redundant information.



PCA

Rotational data transformations

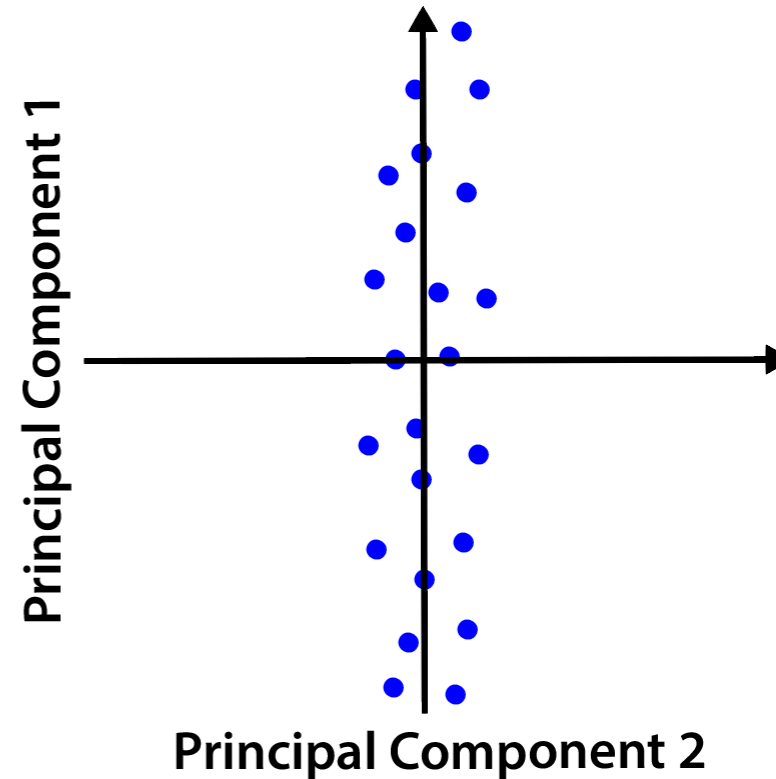
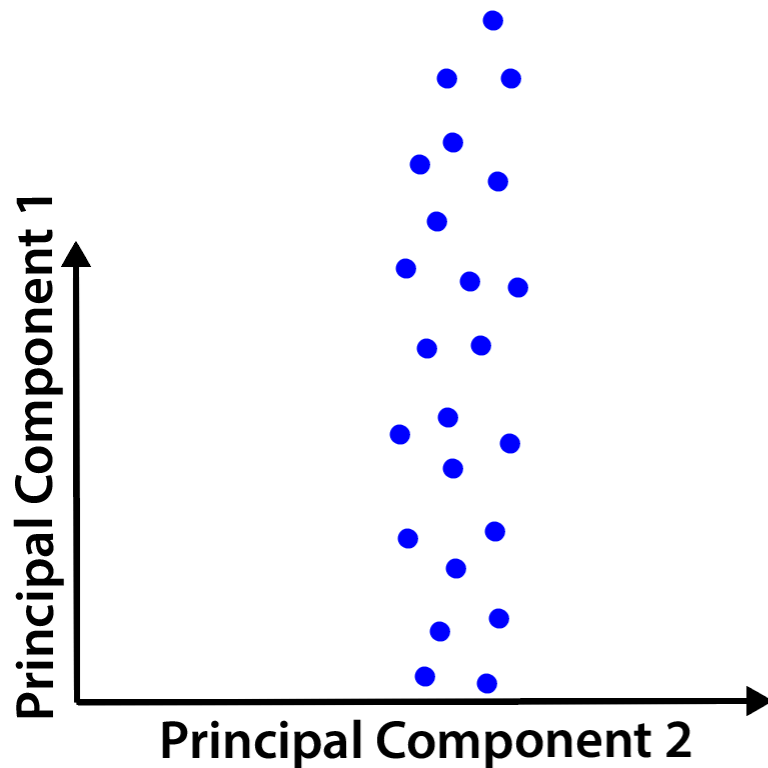
- In consequence, observations are now characterized by how strongly they load onto the new variables (components), instead of the original ones.



PCA

Rotational data transformations

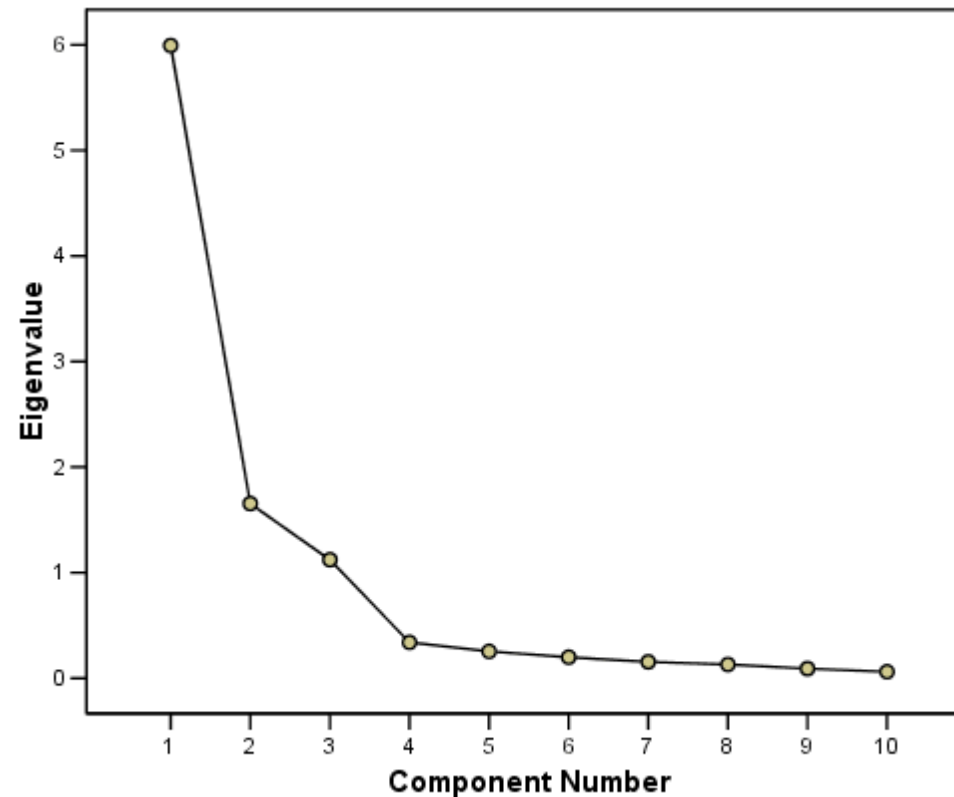
- PCA is ideal to reduce the data dimensionality – it often seeks to represent many original variables using fewer components.



PCA

Rotational data transformations

- A practical question is how many components ideally should be selected to reflect the data. This is often done via Scree plots.



PCA vs. ICA

Conceptual differences and similarities between PCA and ICA

- Purpose:
 - PCA: Reduce data to represent information using fewer variables
 - ICA: Transform data to represent underlying independent source signals
- ***Extraction property*** (“What do the new variables represent?”)
 - PCA: Variance (varimax principle)
 - ICA: Independence / non-gaussianity
- Transformational properties
 - PCA: Orthogonal transformation (most cases), dictated by varimax principle
 - ICA: Non-orthogonal transformation

Focus on ICA

Blind Source Separation

The ICA approach

- ICA infers source signals from three differences between source signals and signal mixtures
 - **Independence:** Source signals are independent, while mixtures are not
 - **Gaussianity:** A mixture of two source signals is always more gaussian (CLT)
 - *Complexity: Complexity of any mixture is greater than that of the simplest source signal*
- Basic principle for recovering (un-mixing) source signals
 - If signals that are extracted from a set of mixtures are independent, or non-gaussian, or of low complexity, then they must be source signals

ICA implementations: the non-gaussianity approach

Non-gaussianity

- (Implication of the) **central limit theorem**:

Any mixture of 2 or more random variables (signals) will be “more gaussian” than its constituent random variables (signals)

Inverse statement:

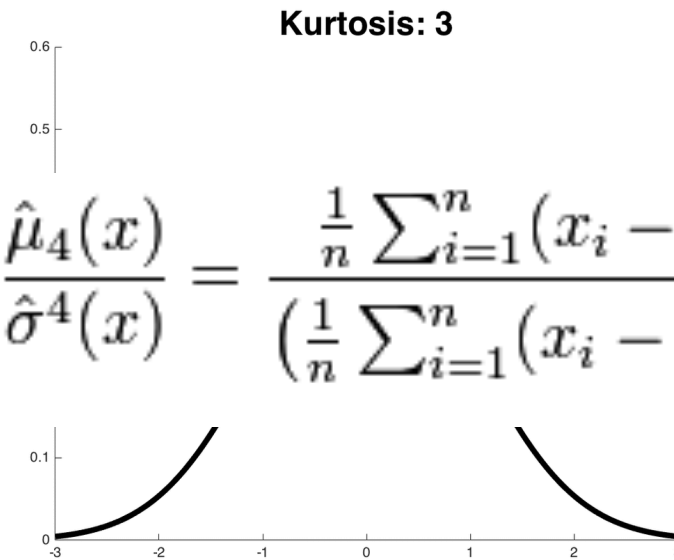
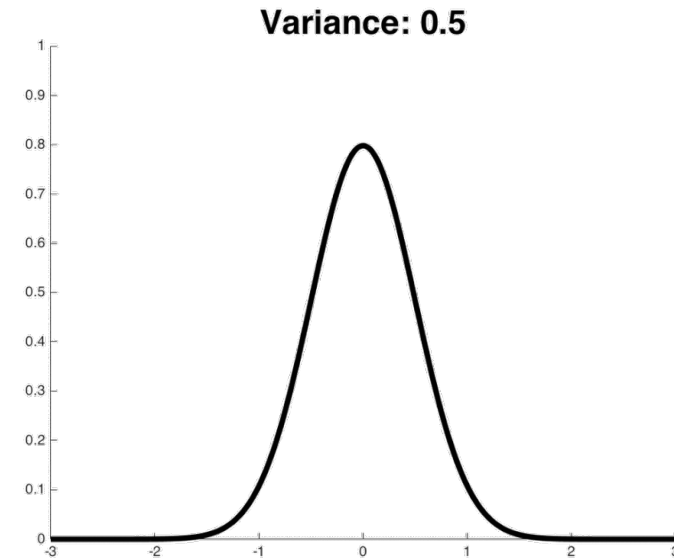
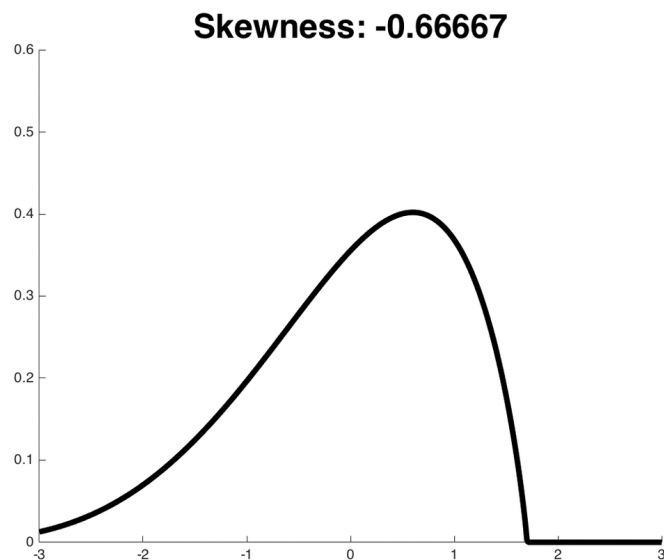
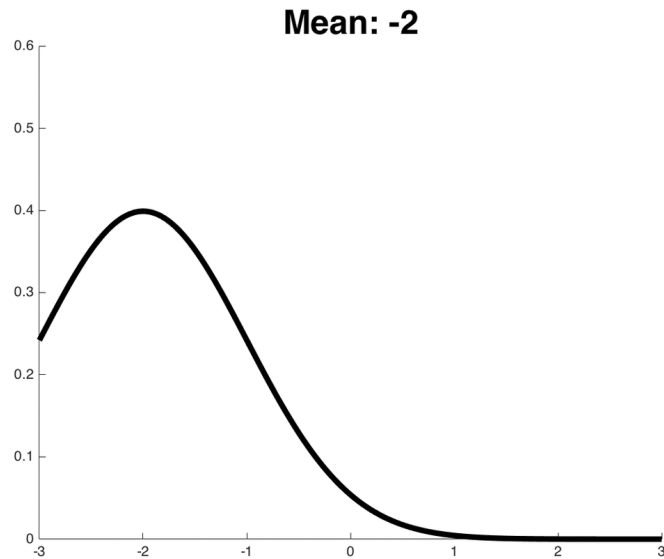
If one finds the transformation yielding the “least gaussian” signal components, these signal components are likely closest to the original source signal configuration

-> The key to (one family) of ICA is **non-gaussianity**

- Non-gaussianity of a probability density function (pdf) of a variable / signal component can be measured by
 - Kurtosis (e.g. projection pursuit)
 - Kullback-Leibler-Divergence (e.g. FastICA Algorithm)

Kurtosis

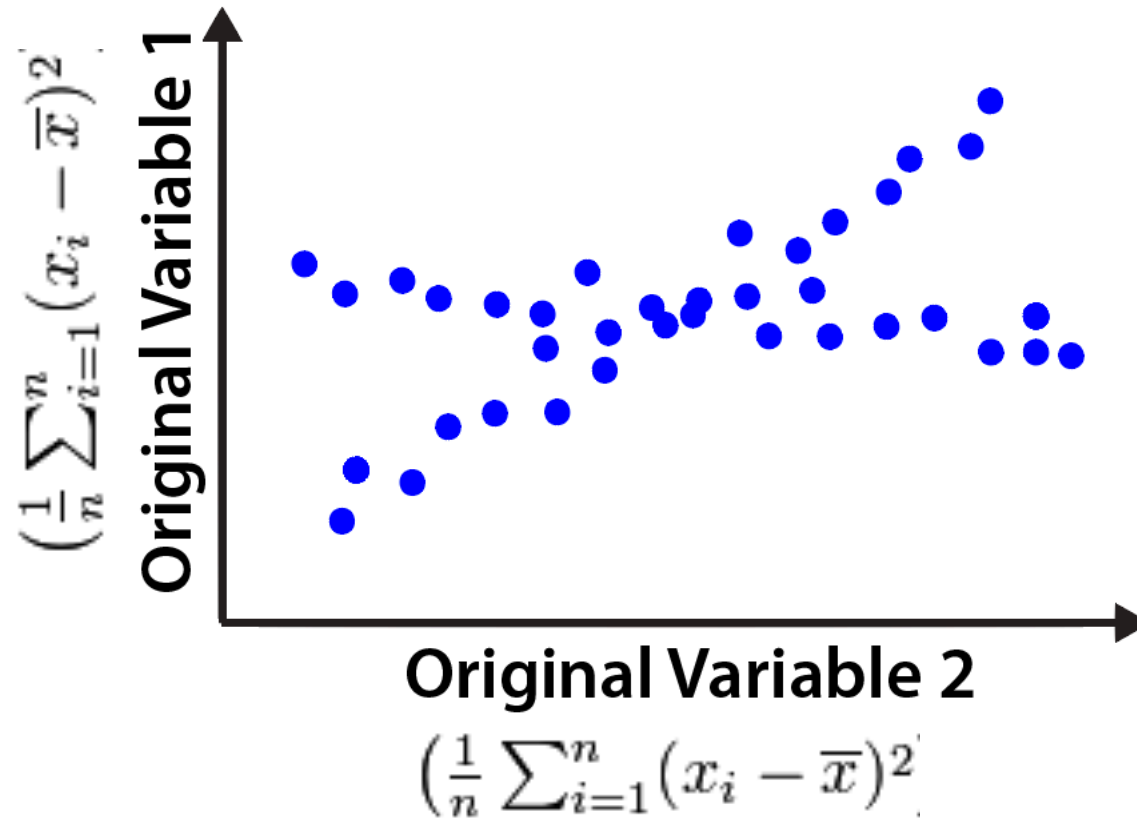
Moments of probability distributions



$$\hat{\beta}_2 = \frac{\hat{\mu}_4(x)}{\hat{\sigma}^4(x)} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^4}{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \right)^2}$$

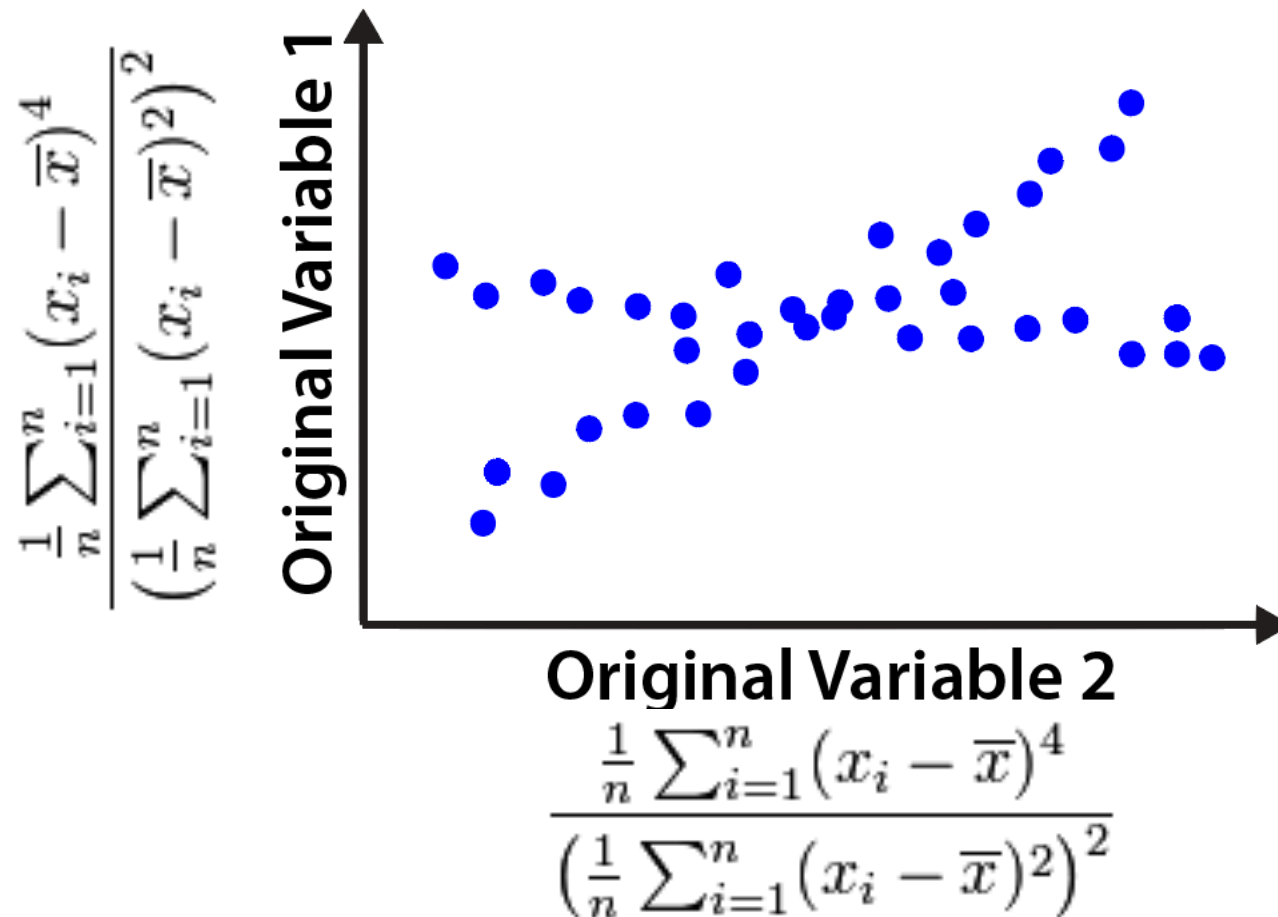
Wrapping up ICA

An example to illustrate ICA vs. PCA



Wrapping up ICA

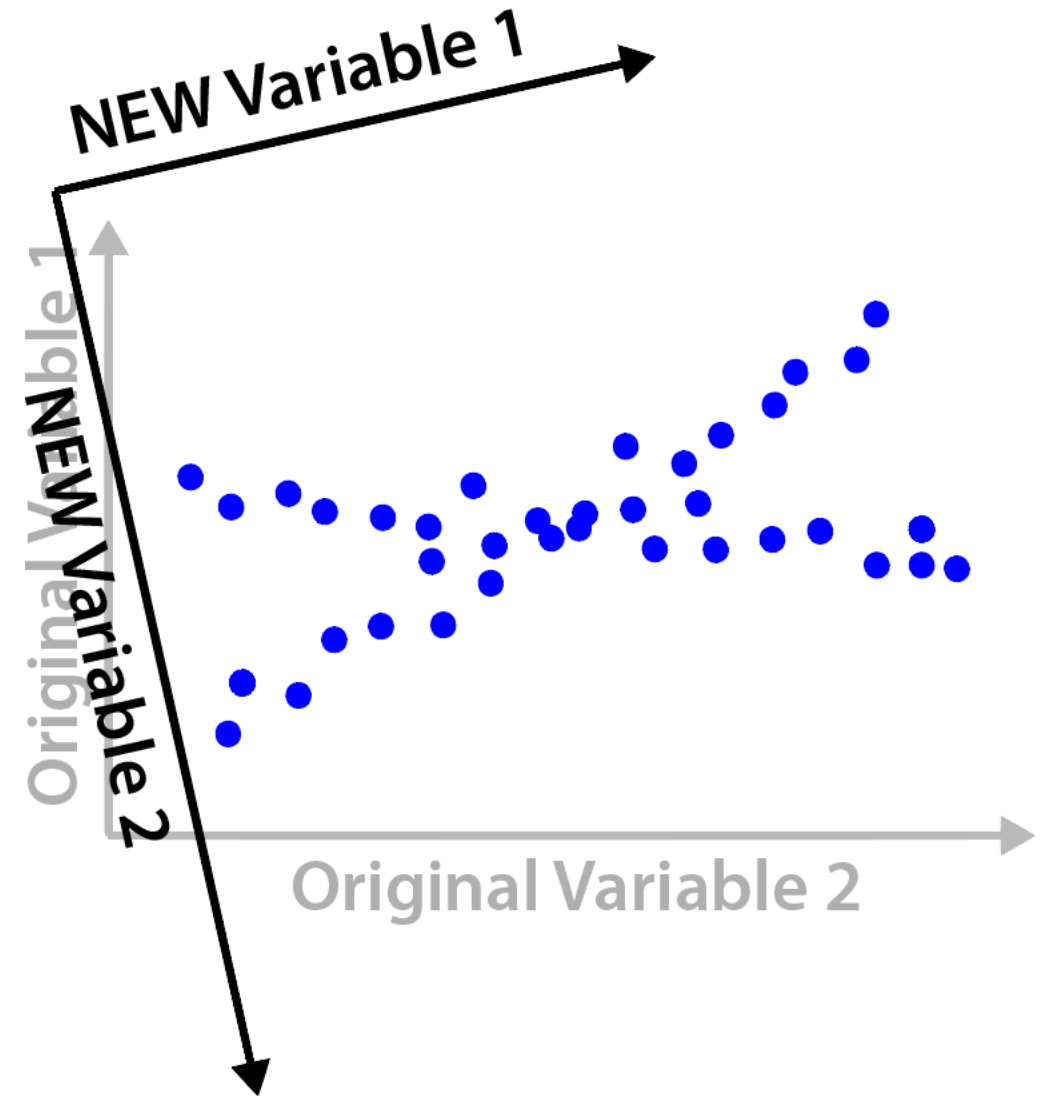
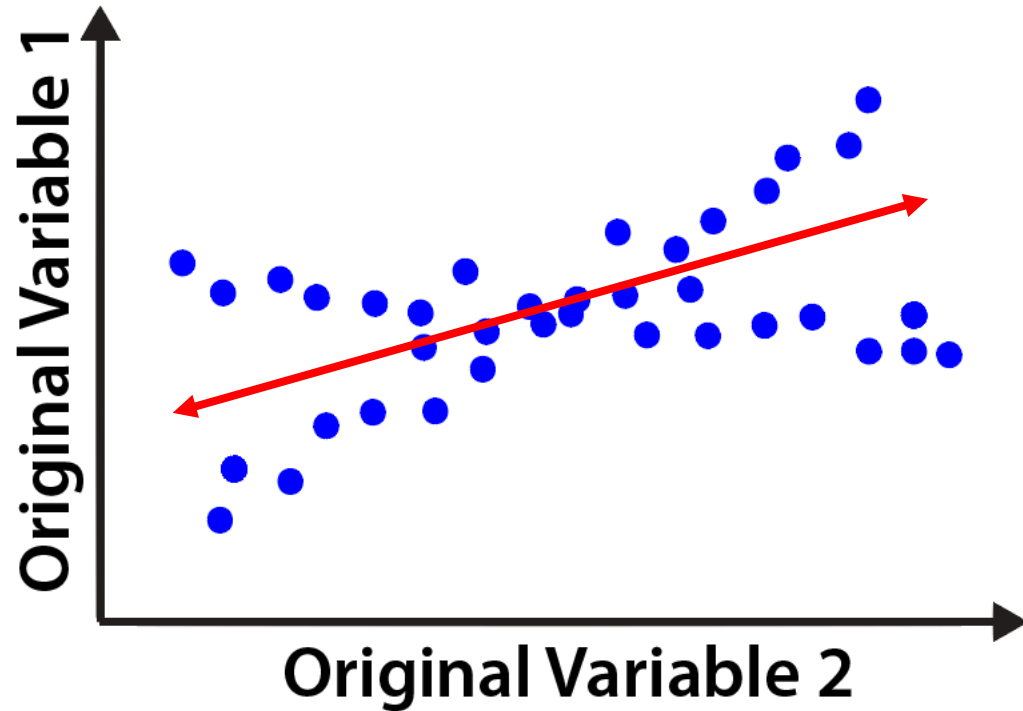
An example to illustrate ICA vs. PCA



Wrapping up ICA

An example to illustrate ICA vs. PCA

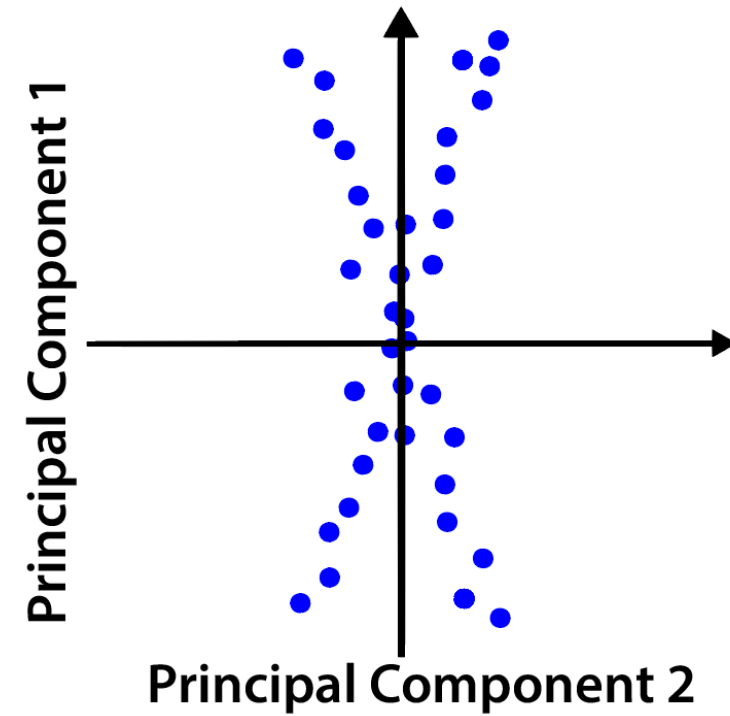
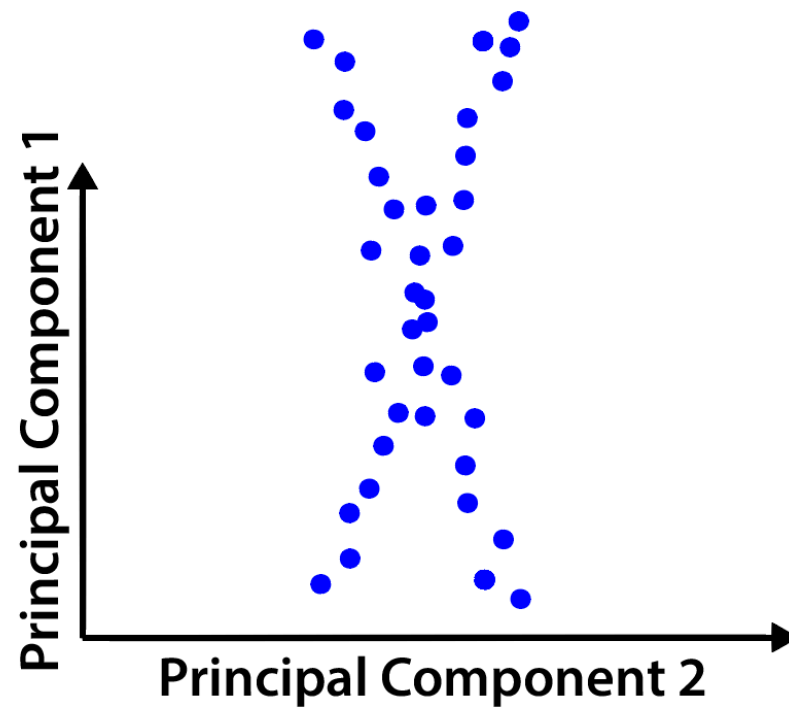
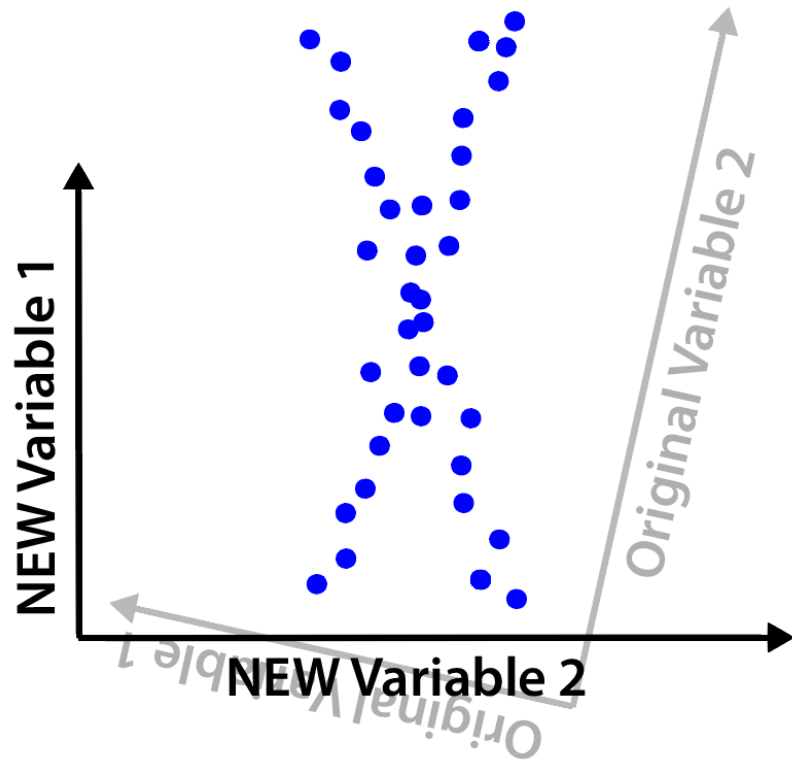
Varimax PCA solution



Wrapping up ICA

An example to illustrate ICA vs. PCA

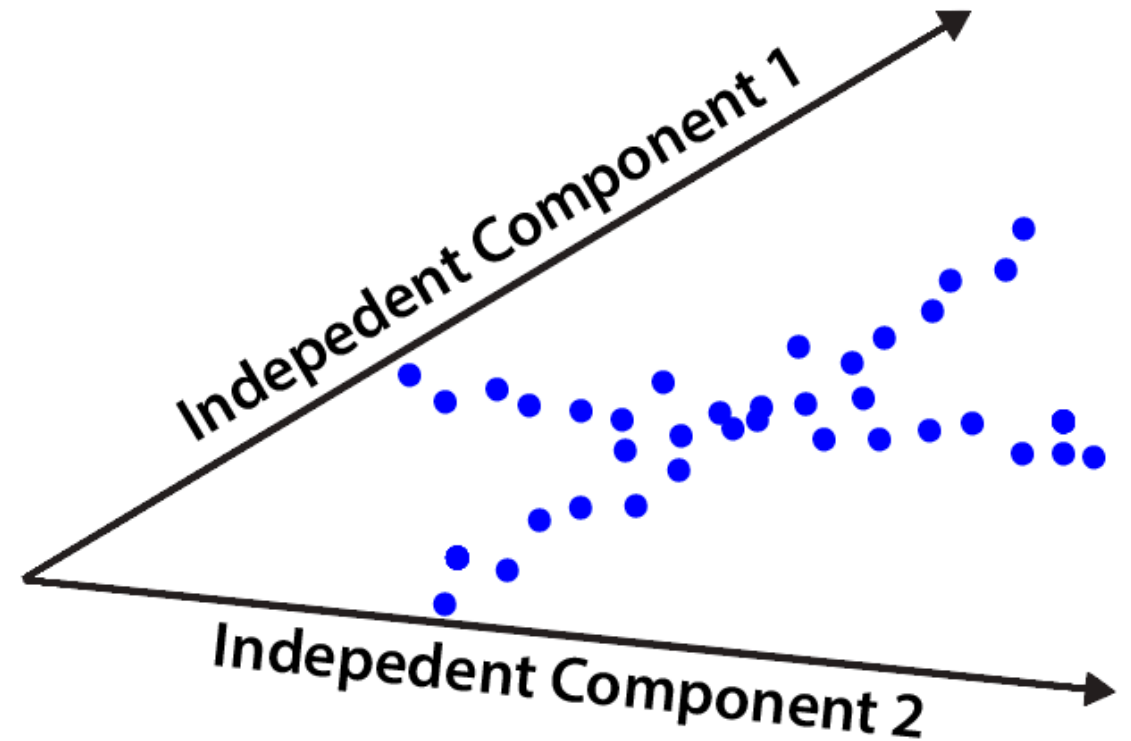
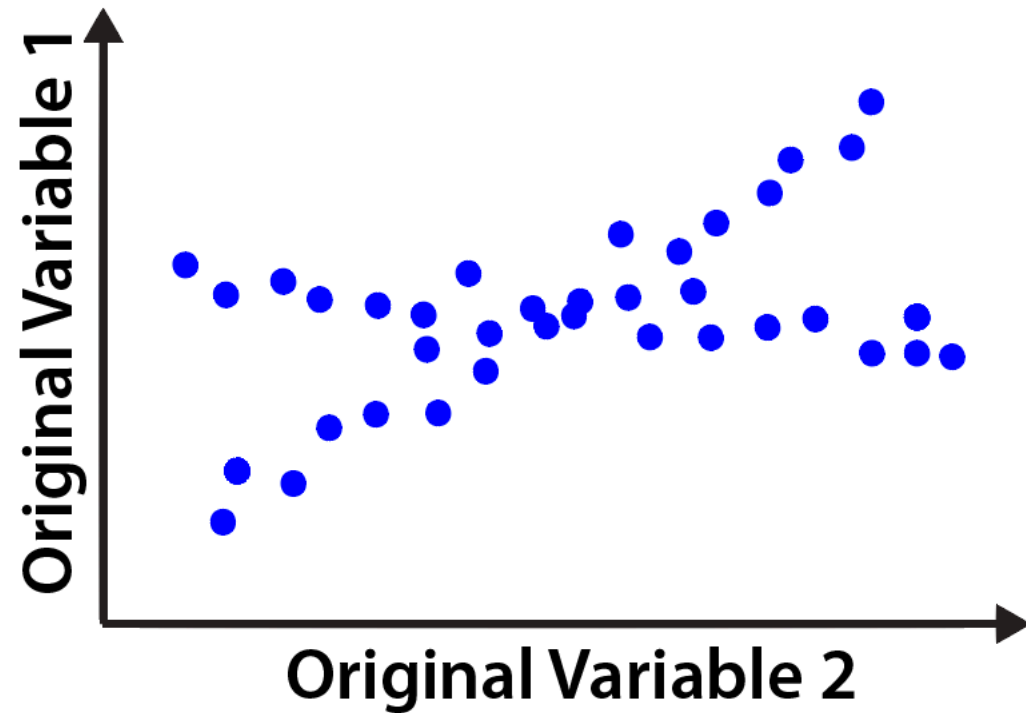
Varimax PCA solution



Wrapping up ICA

An example to illustrate ICA vs. PCA

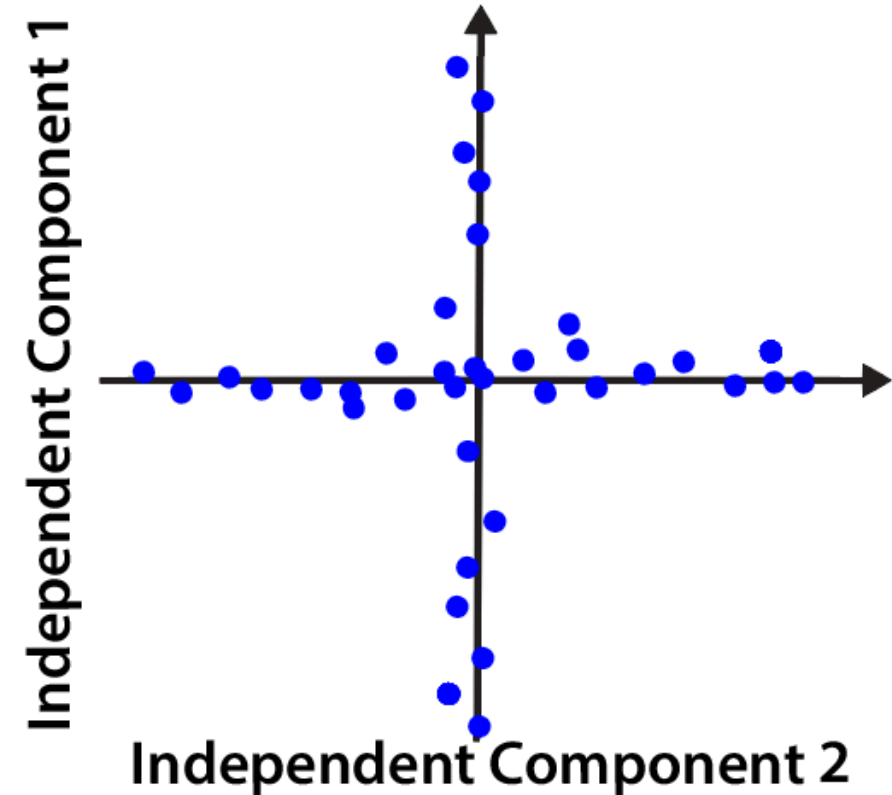
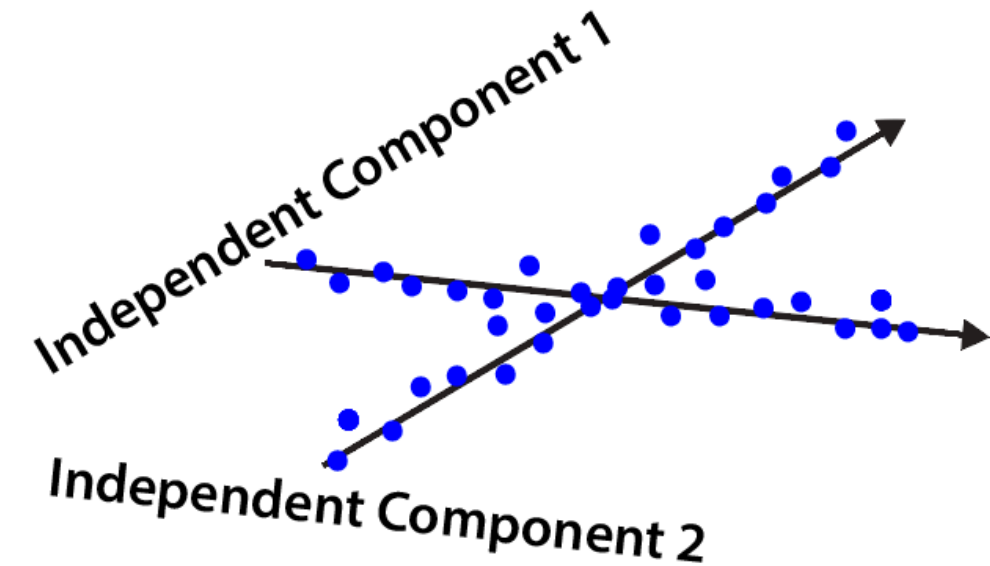
ICA solution



Wrapping up ICA

An example to illustrate ICA vs. PCA

ICA solution



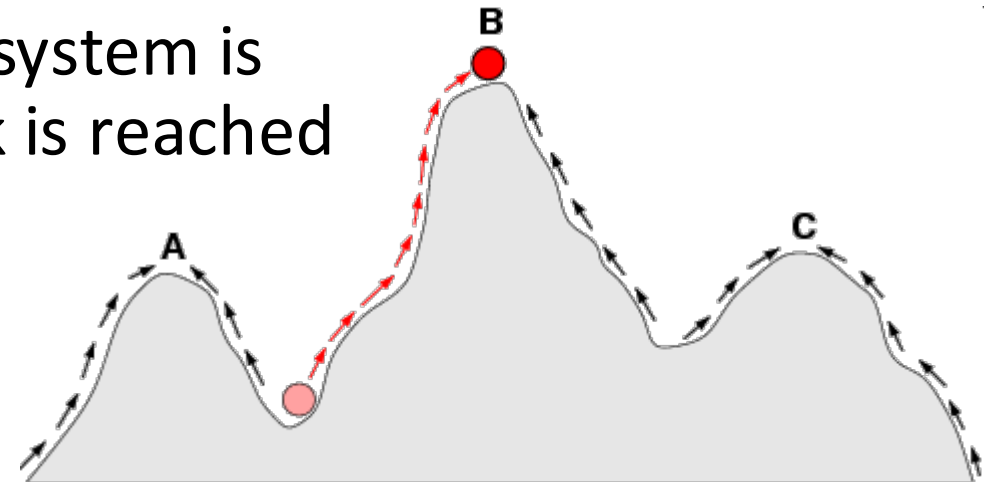
Wrapping up ICA

ICA in practice (kurtosis example)

- The original combined kurtosis is quantified for each variable

$$\hat{\beta}_2 = \frac{\hat{\mu}_4(x)}{\hat{\sigma}^4(x)} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^4}{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2\right)^2}$$

- In practice, the above equation is quantified for each EEG data channel
- Then, the ‘coordinate system’ is randomly rotated, and the kurtosis of the new variables is quantified (i.e., the above equation is applied to what is now the ‘independent component activations’)
- If the resultant kurtosis is higher, the coordinate system is rotated further in the same direction until a peak is reached
- The final ‘coordinate system’ is the one with the highest combined kurtosis



Problems and shortcomings of ICA

Overview

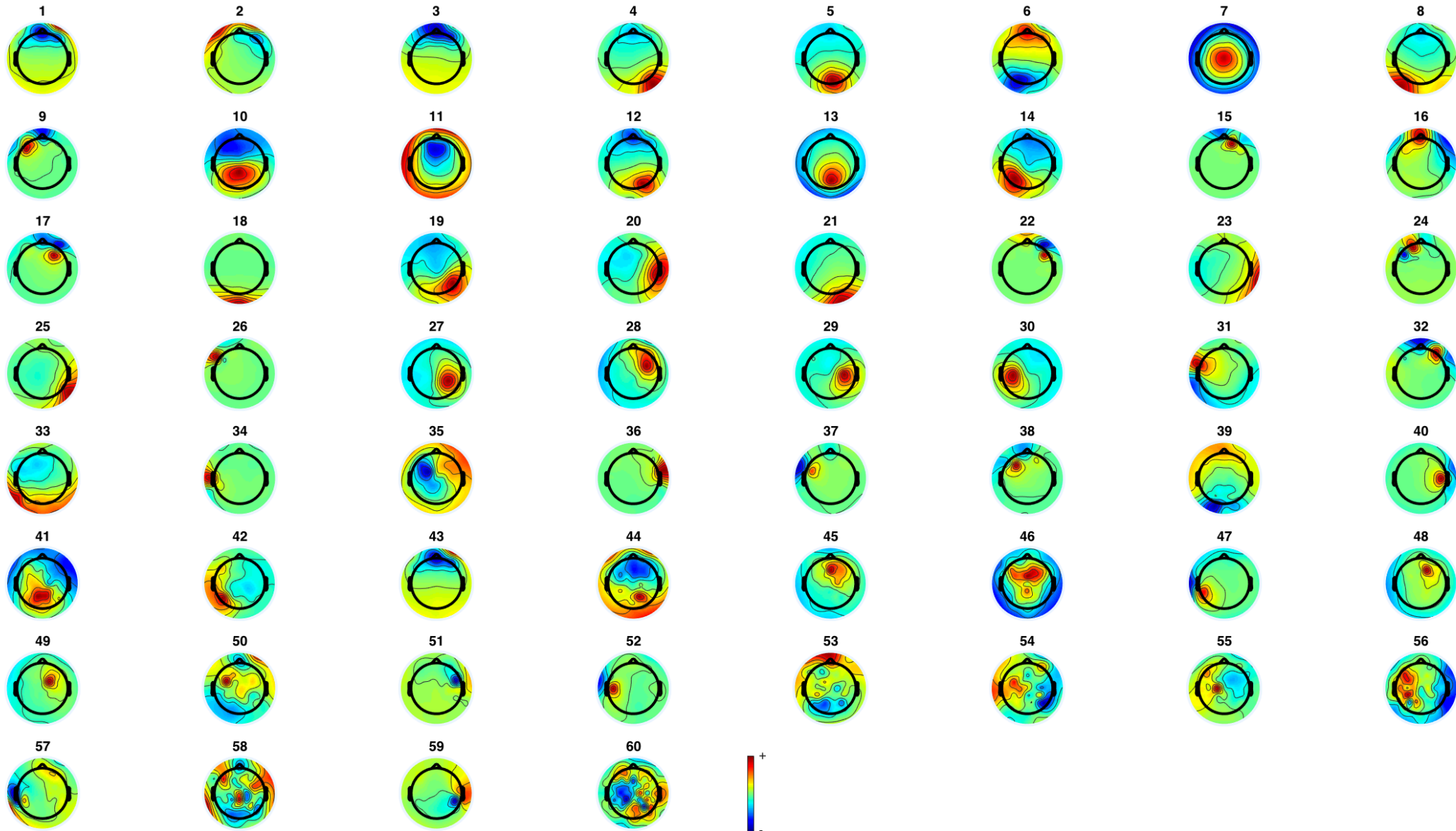
- **Overfitting:** More sensors than signals
- **Underfitting:** More signals than sensors
- **Temporal order of signals**
 - ICA disregards temporal ordering of signals
 - ICA assumes samples to be independent over time
- **Gaussian sources:** More than one gaussian source can not be modelled in standard ICA
- **Significant time delay** between sensors due to distance makes ICA unfeasible
- ICA is blind towards **source signal power**
- Gradient search methods find only **local maxima**

ICA in practice

Rejecting stereotypical EEG artifacts

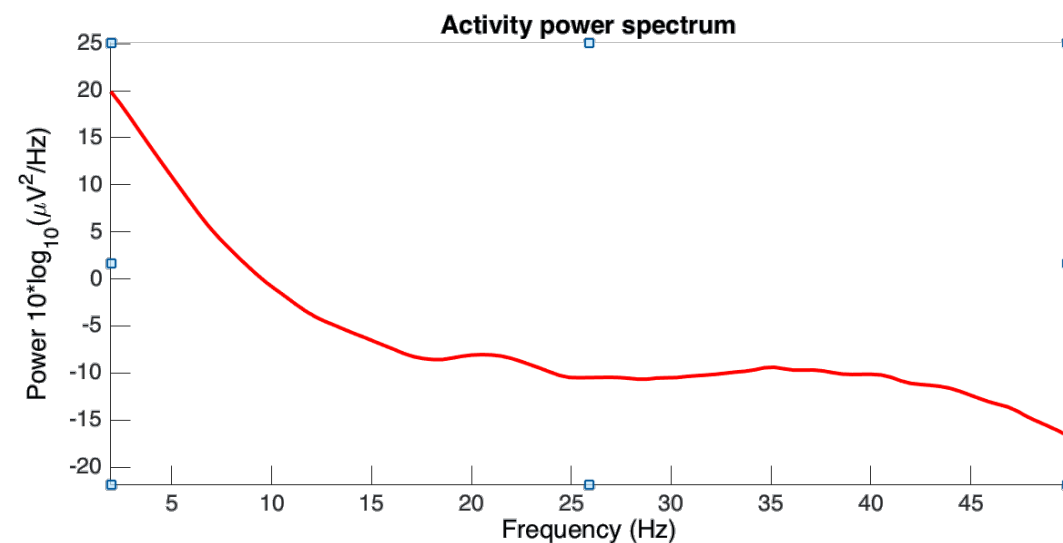
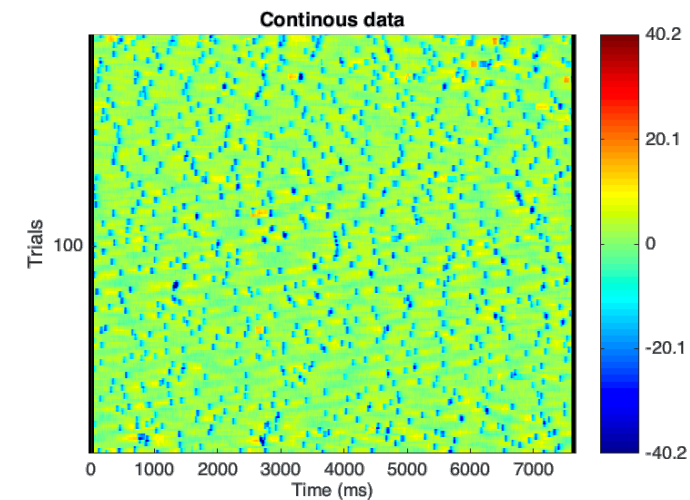
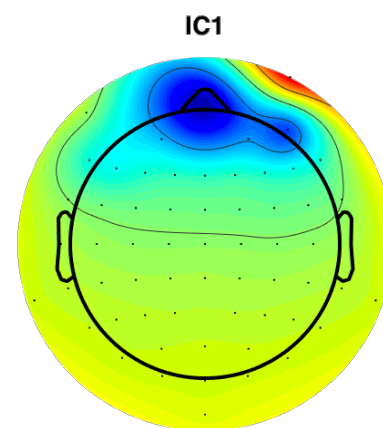
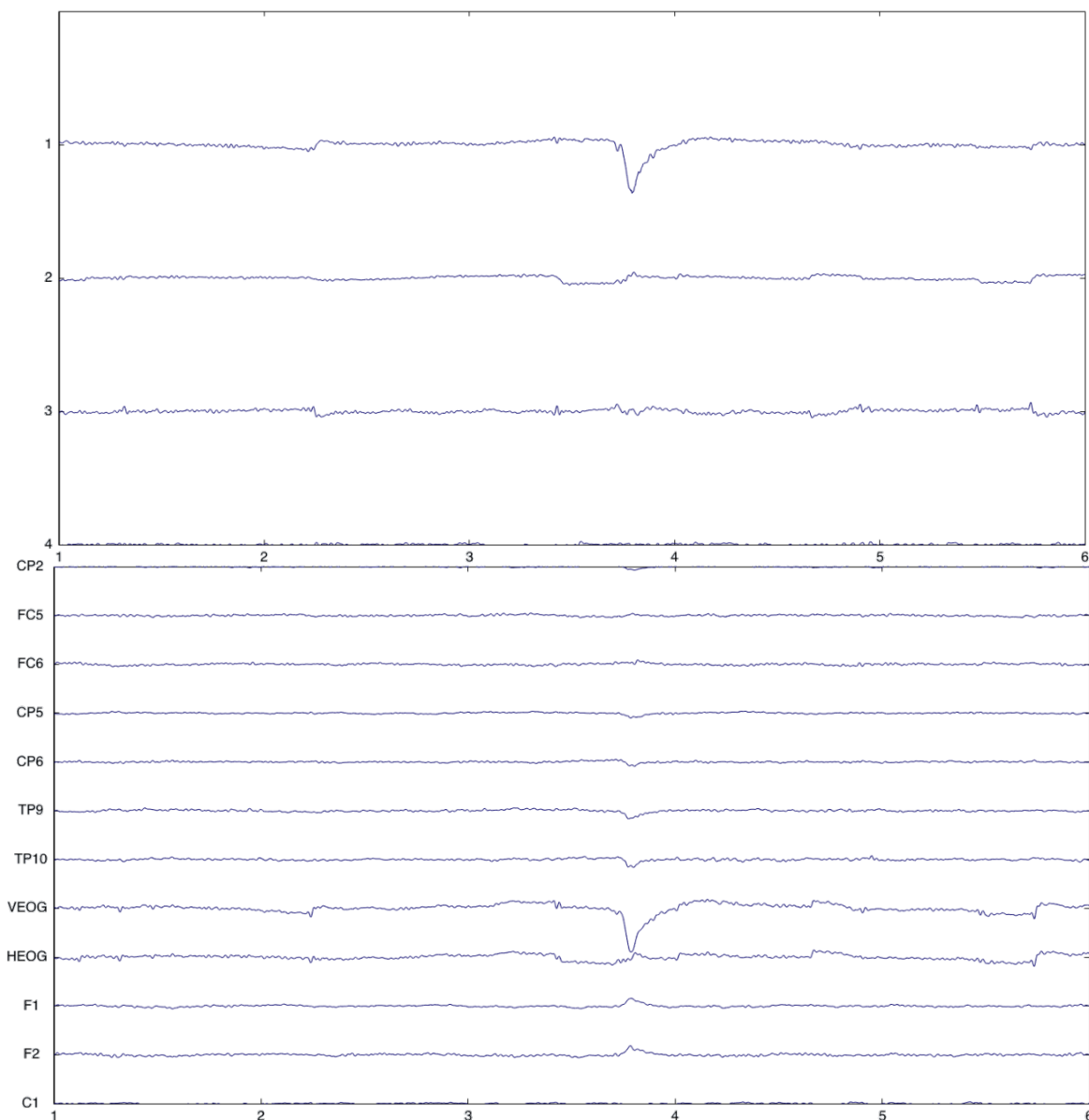
EEG in practice

Visualizing the output



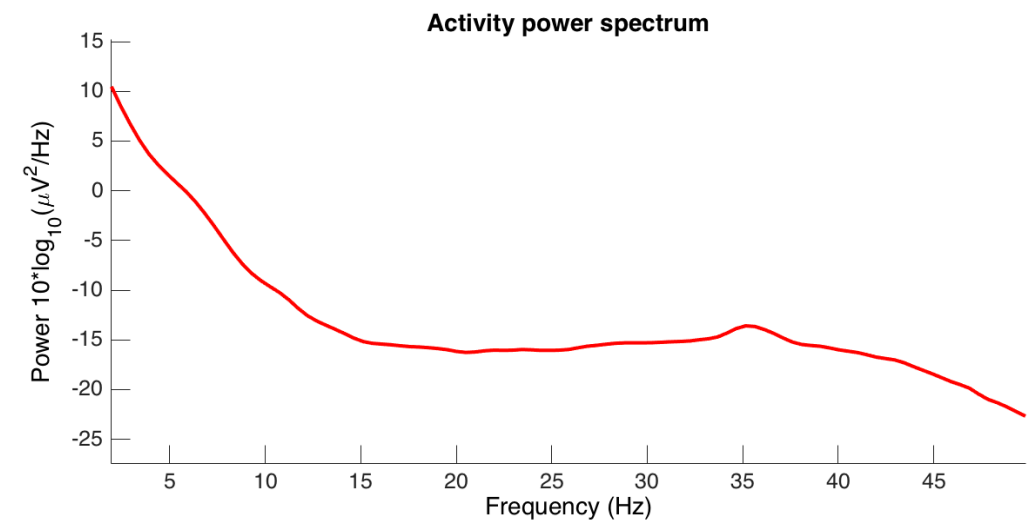
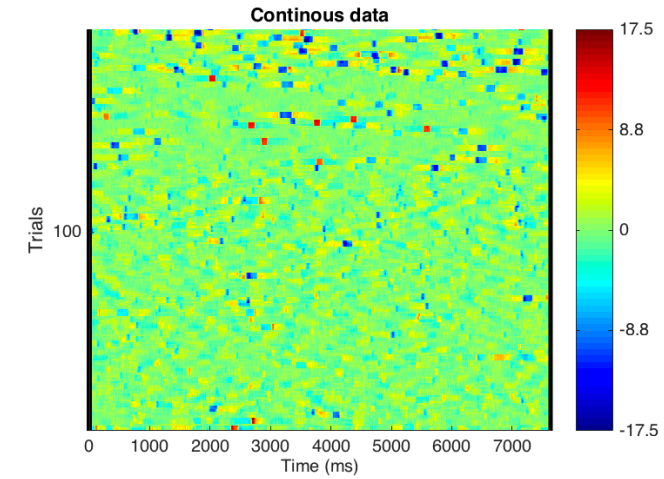
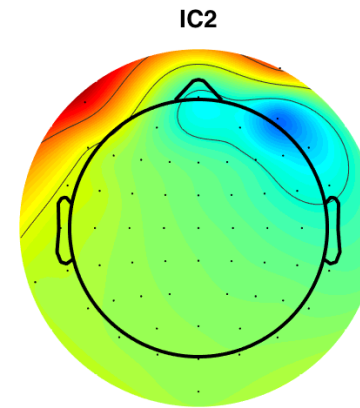
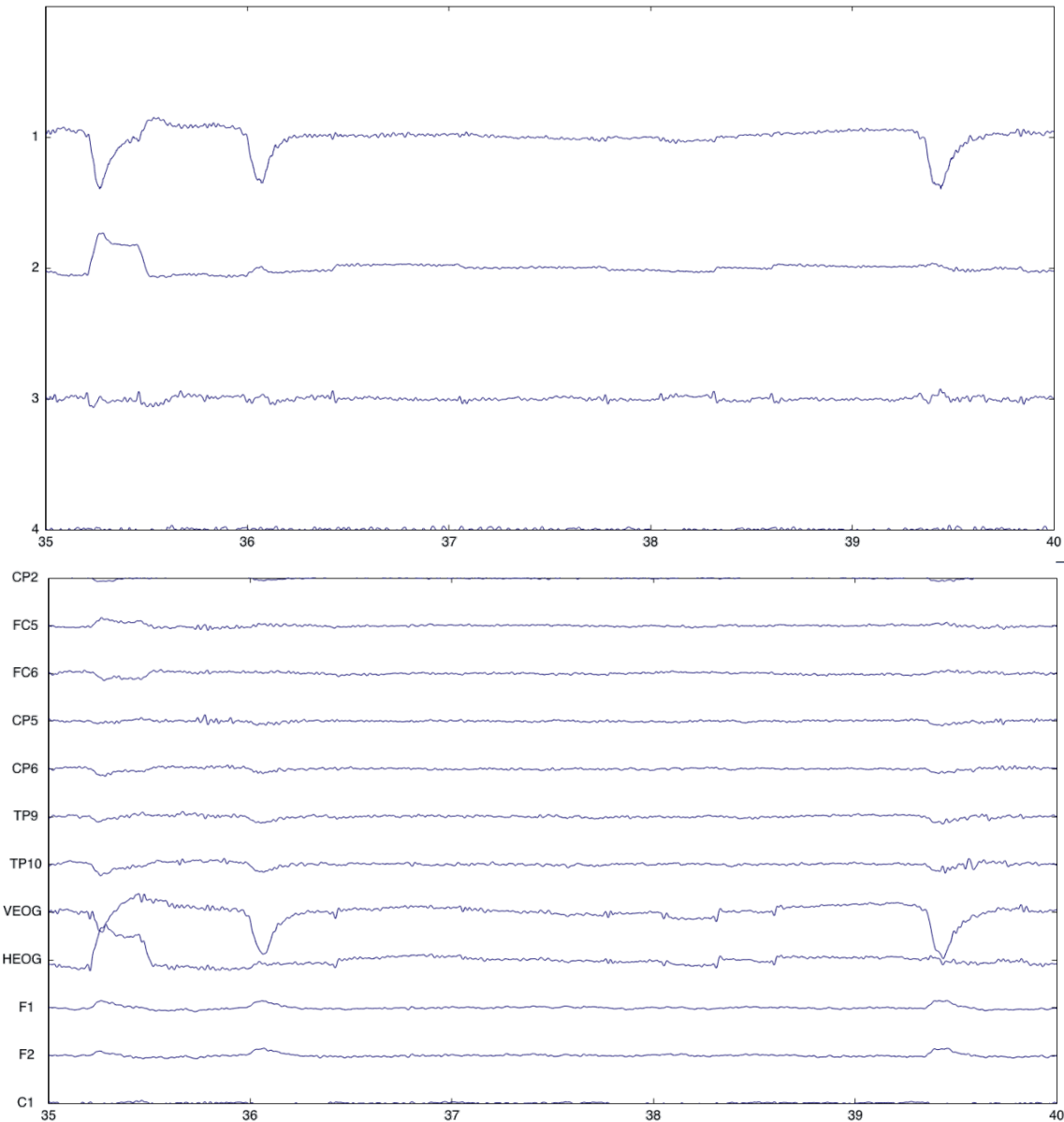
Artifact correction using ICA

Blinks



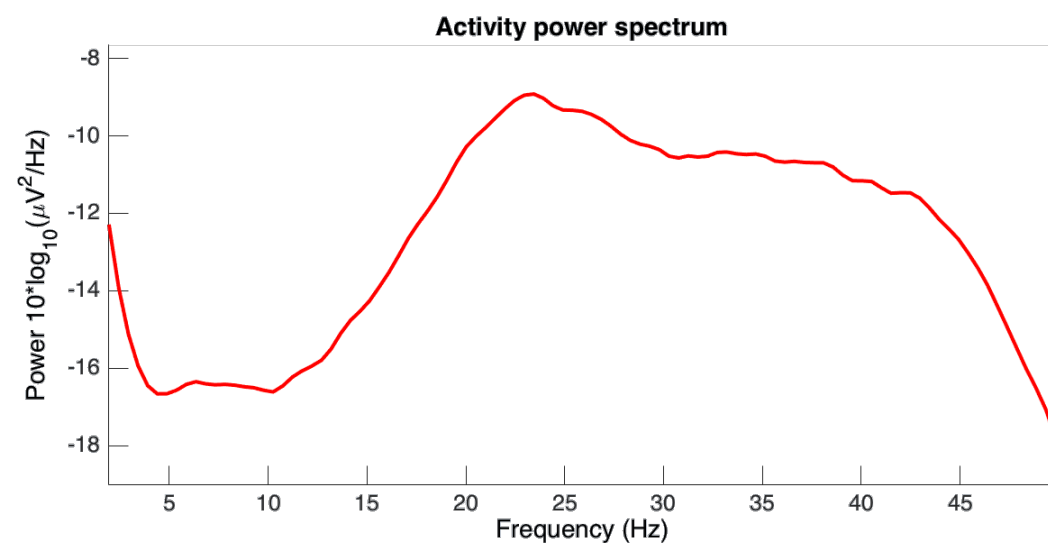
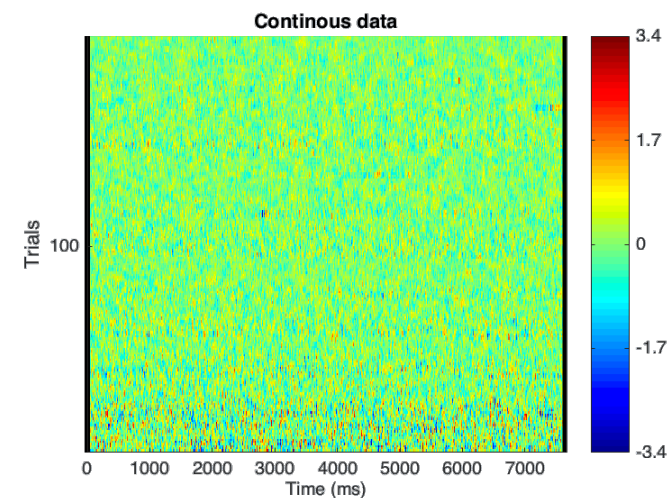
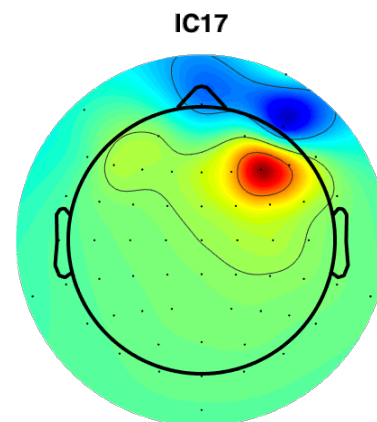
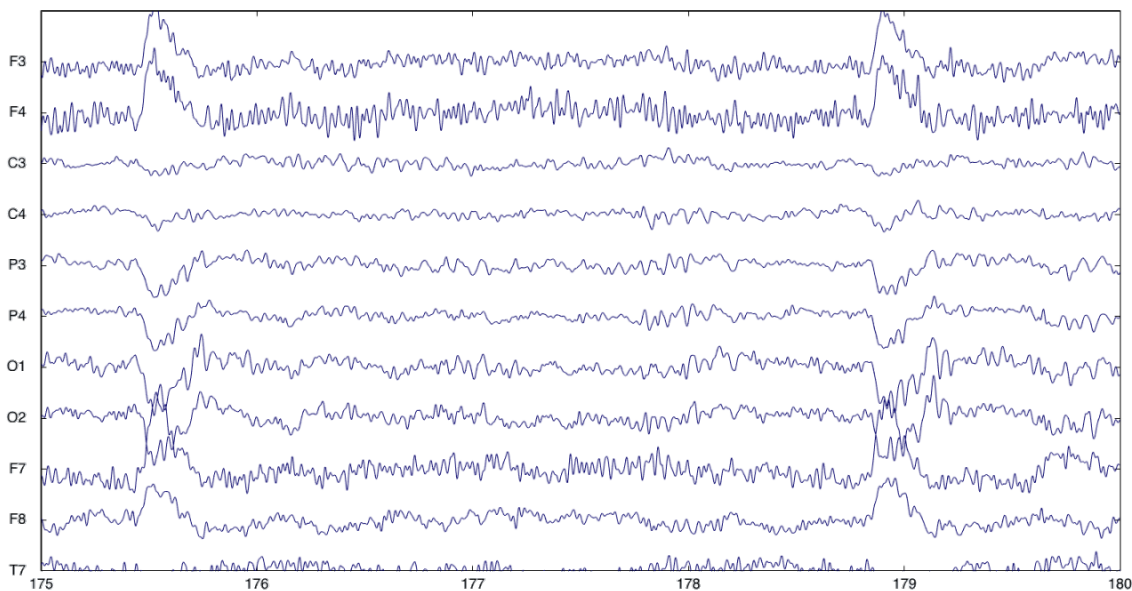
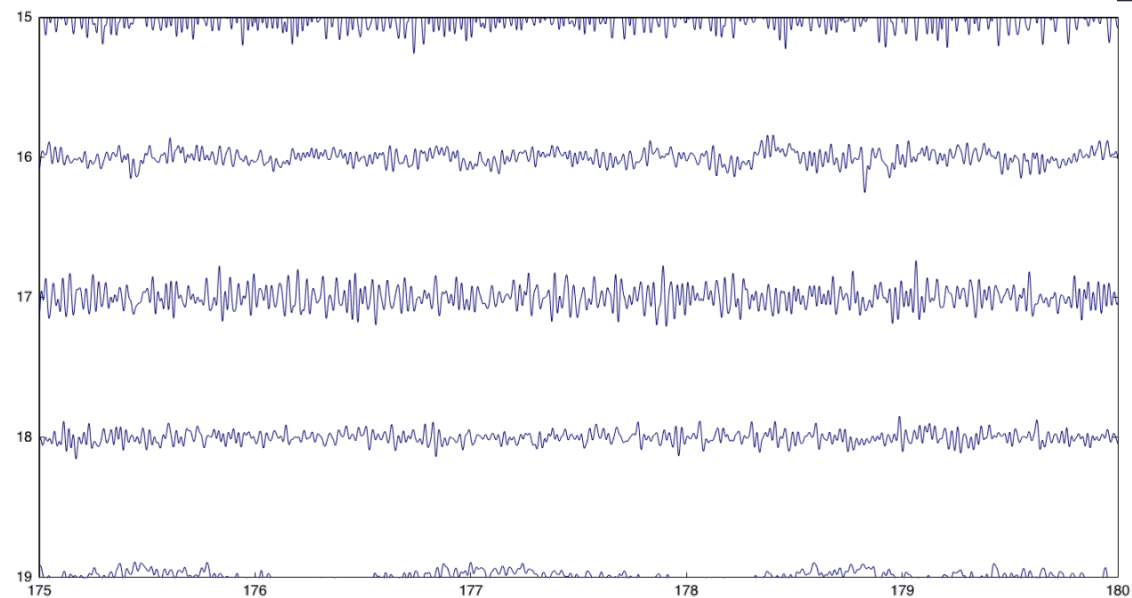
Artifact correction using ICA

Saccades



Artifact correction using ICA

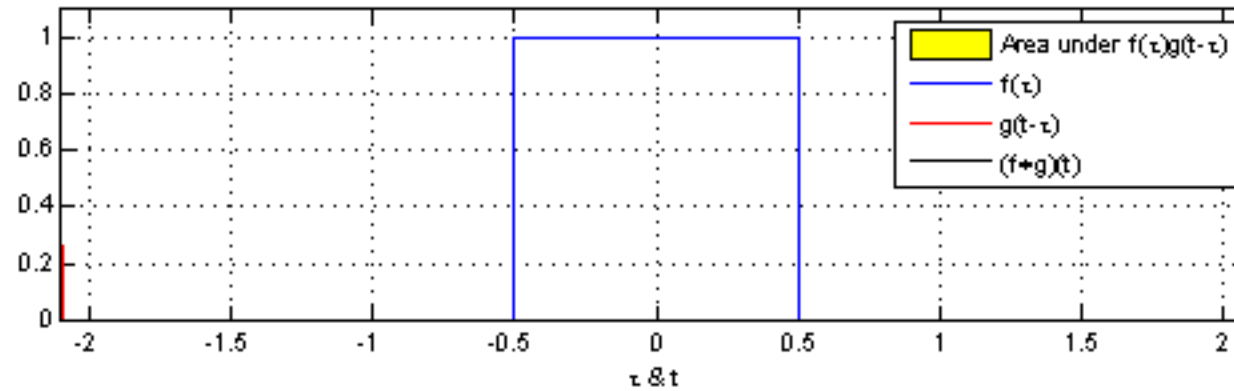
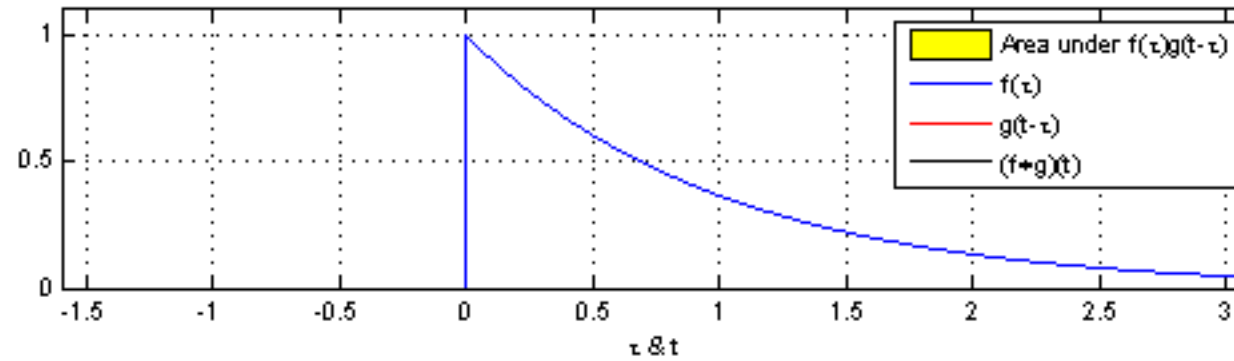
Electrode artifacts



Supplemental slides

Filtering

Convolution: visual example



Filtering

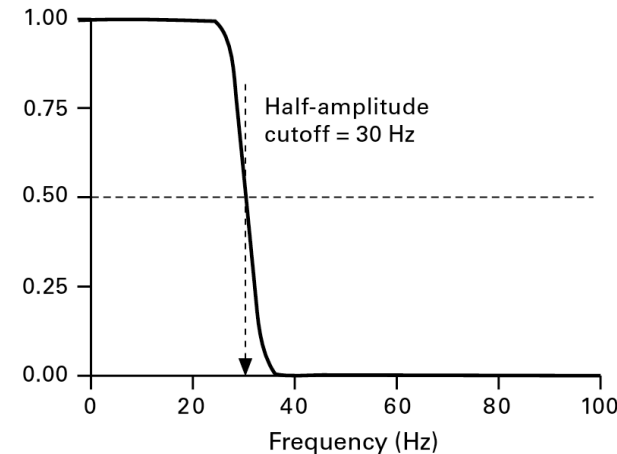
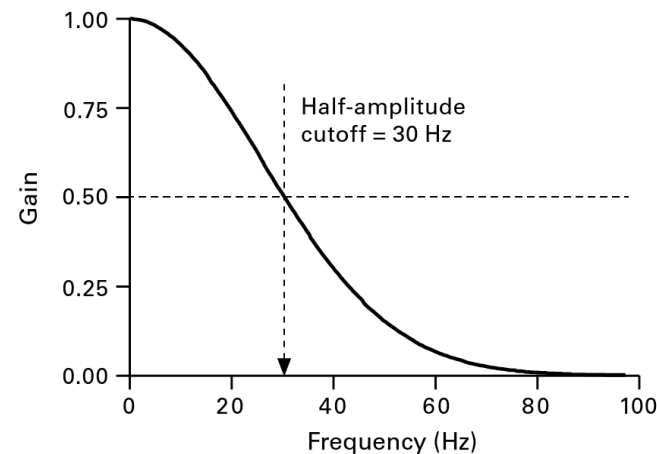
The fourier transform

- The ***fourier transform*** identifies frequency components of an EEG signal
- It works by convolving ***sine-waves*** of different frequencies with the EEG
 - Making a loop that cycles through the frequencies of interest
 - Generates a (complex) sine wave at that frequency
 - Convolutesthe sine wave with the signal
- The result of the convolution at each frequency is the '***fourier coefficient***', a measure of the power of that particular frequency
- The ***inverse fourier transform*** then denotes a reconstruction of the signal using the same principle
 - Build sine waves of specific frequencies
 - Multiply them by the timeline of fourier coefficients
 - Average all the sine waves

Filtering

Understanding a filter in the frequency domain

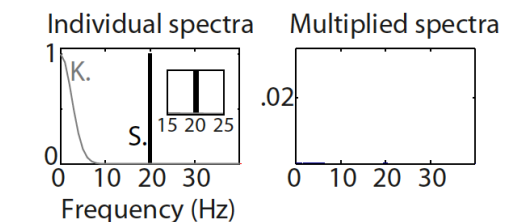
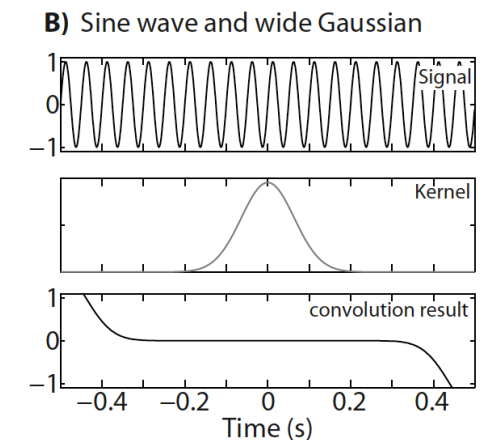
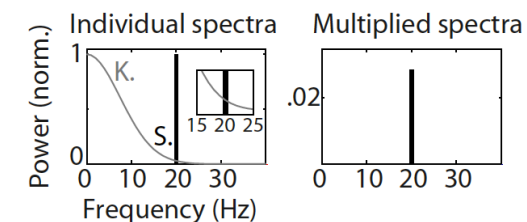
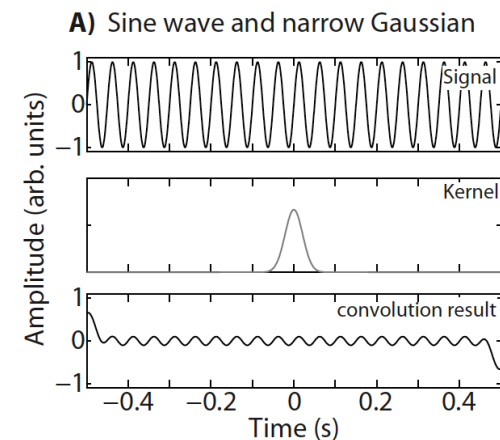
- A ***filter*** is now simply an artificially introduced (i.e., user-controlled) ***differential weighting of the sine waves*** prior to inverse fourier transforming the signal
- This weighting across frequencies is called the filter's “***frequency response function***”



Filtering

The convolution theorem

- Another way to think about filtering is through ***convolution in the time domain***
- Multiplication in the frequency domain = convolution in the time domain (***Convolution theorem***)
- In that sense, filtering is achieved by ***designing a kernel with a specific set of frequency properties***
 - Through the principles of convolution, the frequency profile of the signal is ***passed through the frequency profile of the kernel***



Single-trial EEG analysis workshop

MCC Satellite Workshop
Berlin 2019

Jan R. Wessel

Department of Neurology
Department of Psychological and Brain Sciences
Iowa Neuroscience Institute
University of Iowa

Single-trial EEG analysis workshop

Session 3

Using ICA to increase single-trial SNR

Using ICA to analyze EEG data

Three main ways

1. As a preprocessing / artifact correction method

Jung et al., *Psychophysiology* 2000; **Joyce** et al., *Psychophysiology* 2004; **Li** et al., *Physiological Measurement* 2006; **Nolan** et al., *J Neurosci Methods* 2010; **Winkler** et al., *Behavioral and Brain Functions* 2011; **Mognon** et al., *Psychophysiology* 2011; **Viola** et al., *Clinical Neurophysiology* 2009; ...

2. As a method to increase signal-to-noise ratio

Jung et al. *Human Brain Mapping* 2001; **Makeig** et al., *Science* 2002; **Cao** et al., *Neurocomputing* 2002; **Debener** et al., *J Neurosci* 2005; **Iyer** & Zouridakis, *Clinical Neurophysiology* 2007; **Eichele** et al., *Int J Psychophysiology* 2008; **Wessel** & Ullsperger, *NeuroImage* 2011; **Wessel** & Aron, *Psychophysiology* 2015; **Wessel**, *Cerebral Cortex* 2017; **Wessel**, *Psychophysiology* 2017; ...

3. To test multiple psychological processes for common neural mechanisms

Fogelson et al., *Clinical Neurophysiology* 2004; **Gentsch** et al., *NeuroImage* 2009; **Hoffmann** & Falkenstein, *Human Brain Mapping* 2010; **Roger** et al., *NeuroImage* 2010; **Wessel** et al., *J Neurosci* 2012; **Wessel** & Aron, *J Neurosci* 2013; **Torreclillos** et al., *J Neurosci* 2014; **Wessel** & Aron, *NeuroImage* 2014; **Wessel** et al., *Nature Communications* 2016; **Wessel**, *Cerebral Cortex* 2017; **Dutra** et al., *J Neurosci* 2018...

for a review, see: **Wessel**, *Brain Topography* 2018

Using ICA to analyze EEG data

Three main ways

1. As a preprocessing / artifact correction method
 - Strategy:
 - **Identify artifact components**
 - Set their weights in the mixing matrix to zero
 - Use **all non-artifact components** to reconstruct the signal
2. As a method to increase signal-to-noise ratio
 - Strategy:
 - **Identify component that reflects process of interest**
 - Set all other weights in the mixing matrix to zero
 - Use **only this component** to reconstruct the channel space signal
3. To test multiple psychological processes for common neural mechanisms
 - Strategy:
 - **Identify component that reflects process of interest**
 - Investigate whether other events in the experiment yield activity in that component

Core to all three methods

Find a way to pick the right components

- ***Component selection*** is key to all approaches
- The earliest instances of each approach used ***subjective criteria***

APPROACH 2

weights. The 30 ICs for each subject were screened for maps resembling the typical frontocentral radial ERN topography and a contribution to the ERP difference between incompatible error and incompatible correct trials, that is, a larger negative deflection at the response interval for erroneous trials. This resulted in identification of one IC for each subject,

Debener et al., *J Neurosci* 2005

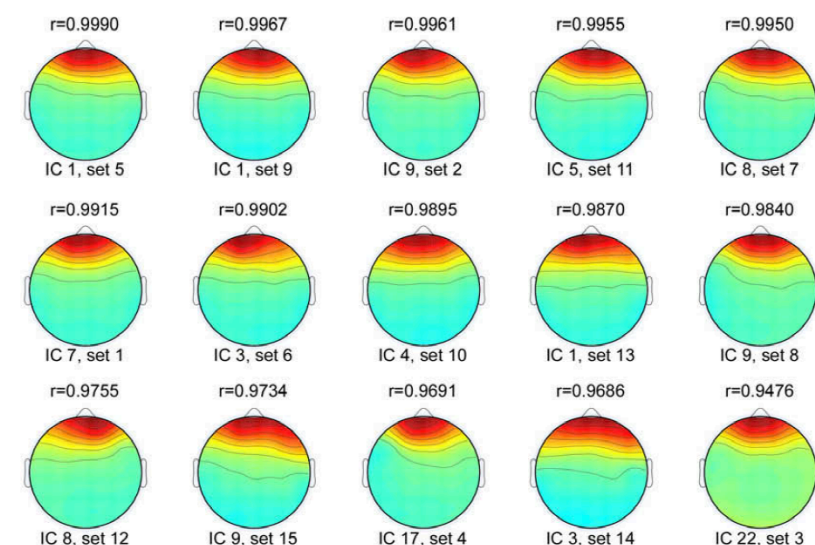
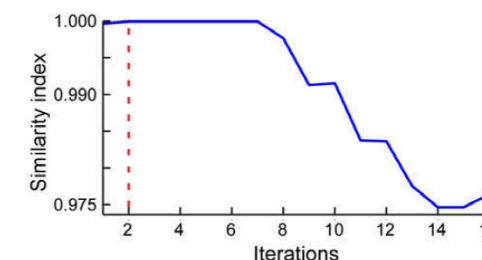
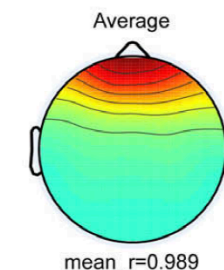
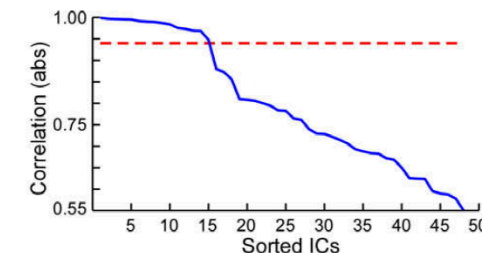
- For ***artifact correction*** purposes, this is likely fine
- However, when selecting ICs that reflect processes of interest for the purpose of ***statistical inference***, such ***researcher degrees of freedom*** are suboptimal.
- Hence, ***automatic, algorithmic*** approaches to component selection are necessary

Core to all three methods

Find a way to pick the right components

- There are many algorithmic approaches aimed at identifying **artifact components**
- Examples of toolboxes
 - CORRMAP (Viola et al., 2009)
 - FASTER (Nolan et al., 2010)
 - ADJUST (Mognon et al., 2011)
- However, these approaches are suboptimal to pick components related to cognitive processes, as they overwhelmingly focus on **spatial properties**

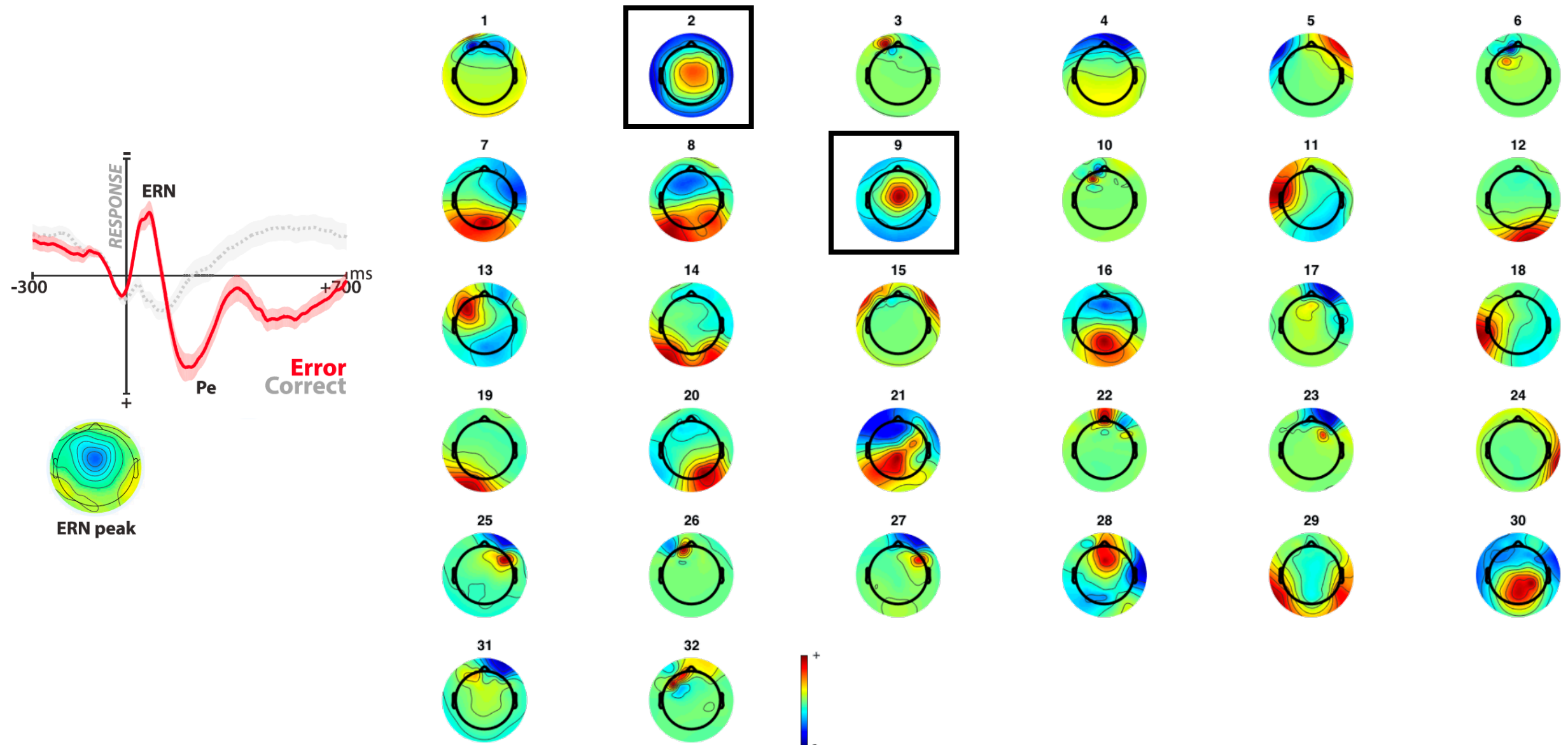
INFO:
Template: J_00_epoch; Set 1; IC 7;
Number of datasets: 16
Correlation threshold: 0.94
Max ICs from each dataset: 3
Cluster: 15 ICs from 15 sets
Sets not contributing: #16;
Similarity = 1.0000



Viola et al., *Clinical Neurophysiology* 2009

Core to all three methods

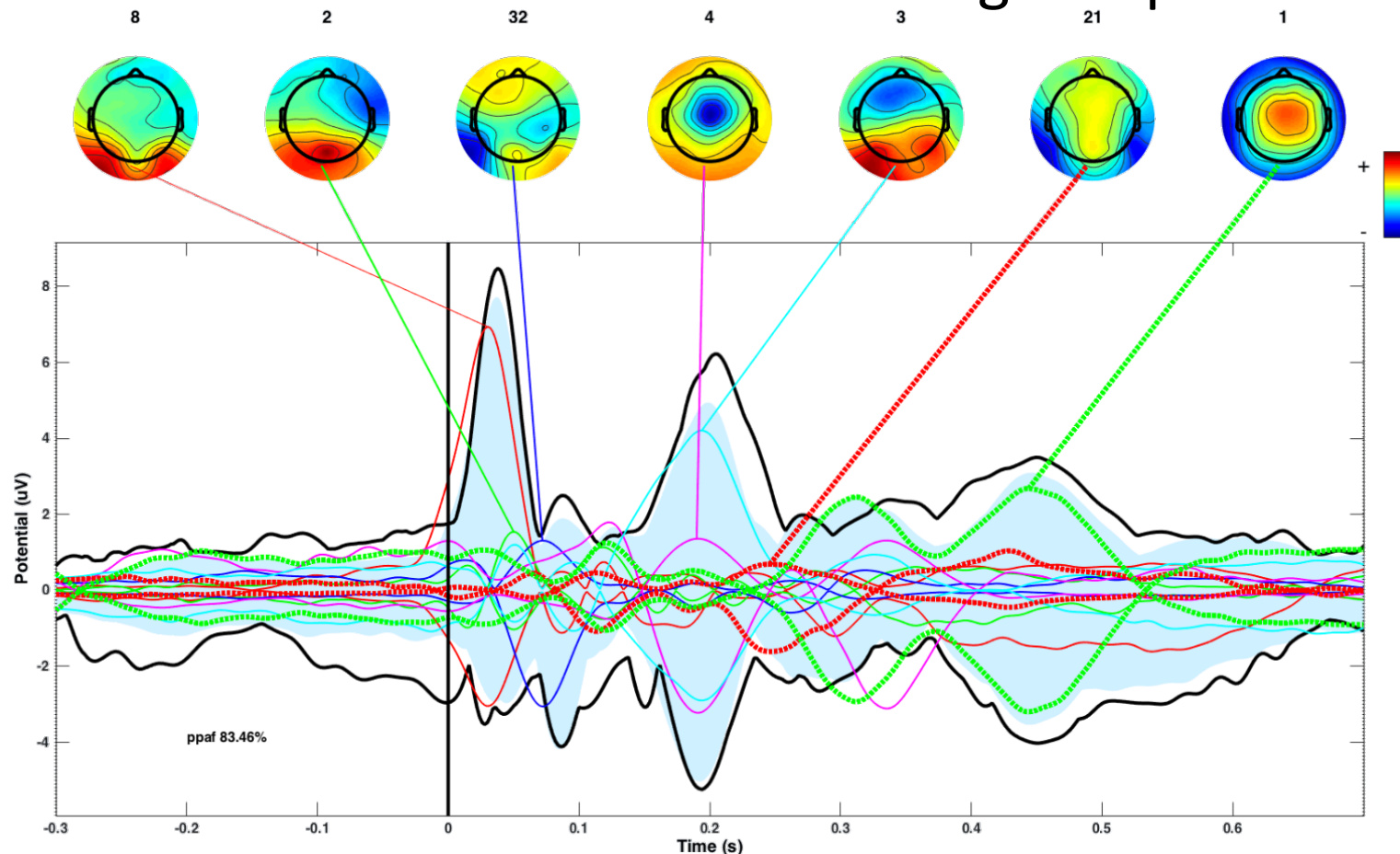
Find a way to pick the right components



Core to all three methods

Find a way to pick the right components

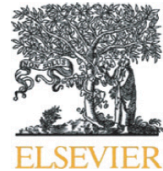
- When we are looking for independent components that explain event-related brain potentials, we want to look for event-related activity patterns
- One approach to do so is to use measures that target explained variance



An alternative approach

The COMPASS logic/tool (Wessel & Ullsperger, NeuroImage 2011)

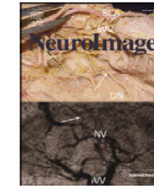
NeuroImage 54 (2011) 2105–2115



Contents lists available at [ScienceDirect](#)

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg



Technical Note

Selection of independent components representing event-related brain potentials: A data-driven approach for greater objectivity

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ABSTRACT

Following the development of increasingly precise measurement instruments and fine-grain analysis tools for electroencephalographic (EEG) data, analysis of single-trial event-related EEG has considerably widened the utility of this non-invasive method to investigate brain activity.

Recently, independent component analysis (ICA) has become one of the most prominent techniques for increasing the feasibility of single-trial EEG. This blind source separation technique extracts statistically independent components (ICs) from the EEG raw signal. By restricting the signal analysis to those ICs representing the processes of interest, single-trial analysis becomes more flexible.

Still, the selection-criteria for in- or exclusion of certain ICs are largely subjective and unstandardized, as is the actual selection process itself.

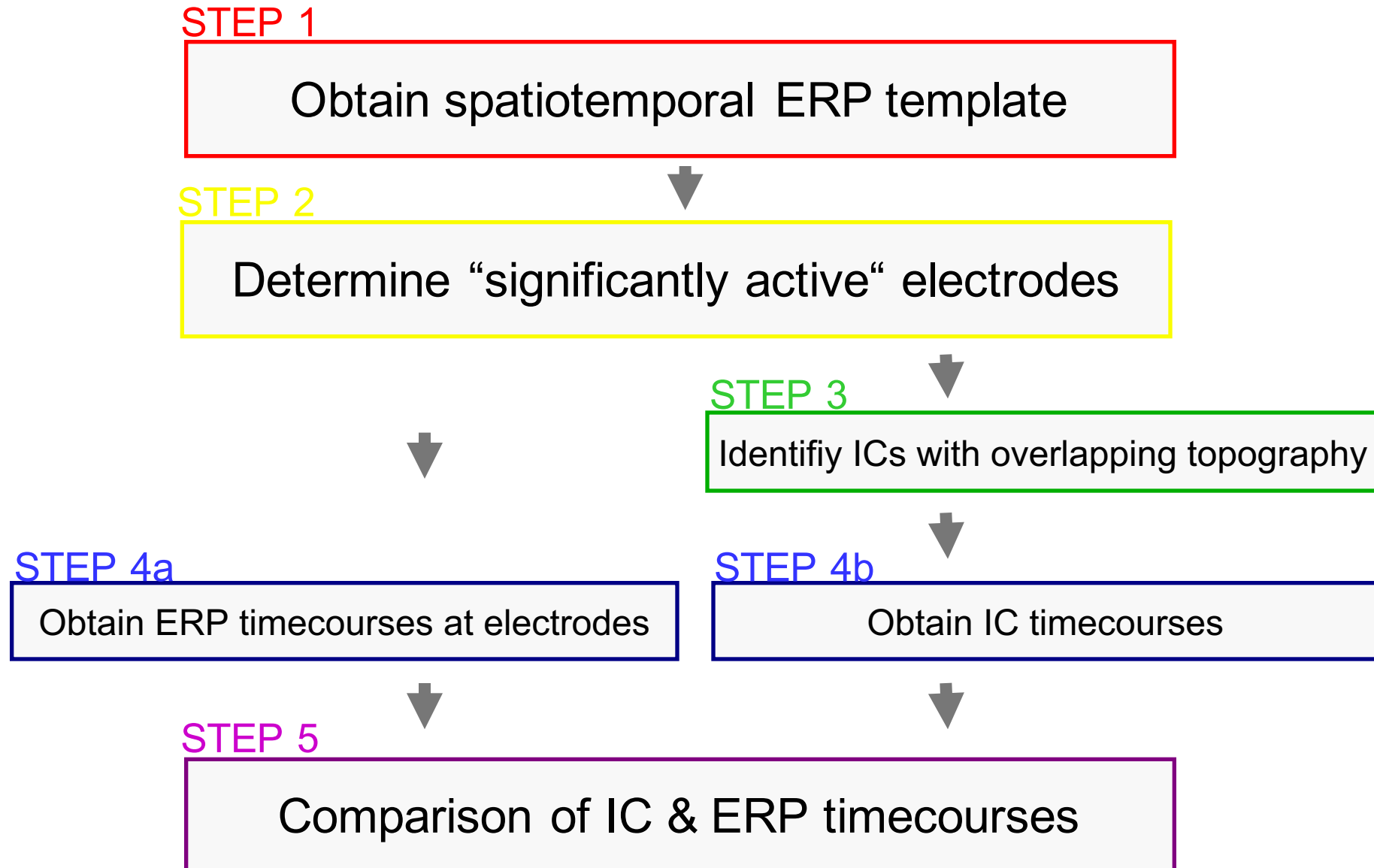
We present a rationale for a bottom-up, data-driven IC selection approach, using clear-cut inferential statistics on both temporal and spatial information to identify components that significantly contribute to a certain event-related brain potential (ERP). With time-range being the only necessary input, this approach considerably reduces the pre-assumptions for IC selection and promotes greater objectivity of the selection process itself.

To test the validity of the approach presented here, we present results from a simulation and re-analyze data from a previously published ERP experiment on error processing. We compare the ERP-based IC selections made by our approach to the selection made based on mere signal power. The comparison of ERP integrity, signal-to-noise ratio, and single-trial properties of the back-projected ICs outlines the validity of the approach presented here. In addition, functional validity of the extracted error-related EEG signal is tested by investigating whether it is predictive for subsequent behavioural adjustments.

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An alternative approach

The COMPASS logic/tool (Wessel & Ullsperger, NeuroImage 2011)



Contrast: the manual approach

Assumptions and decisions

- „classic“ manual approach; utilizes information about:

- **TOPOGRAPHY**

- e.g.: frontocentral voltage distribution

- **TIMERANGE**

- e.g.: Peaks at approx. 100ms post-response

- **POLARITY**

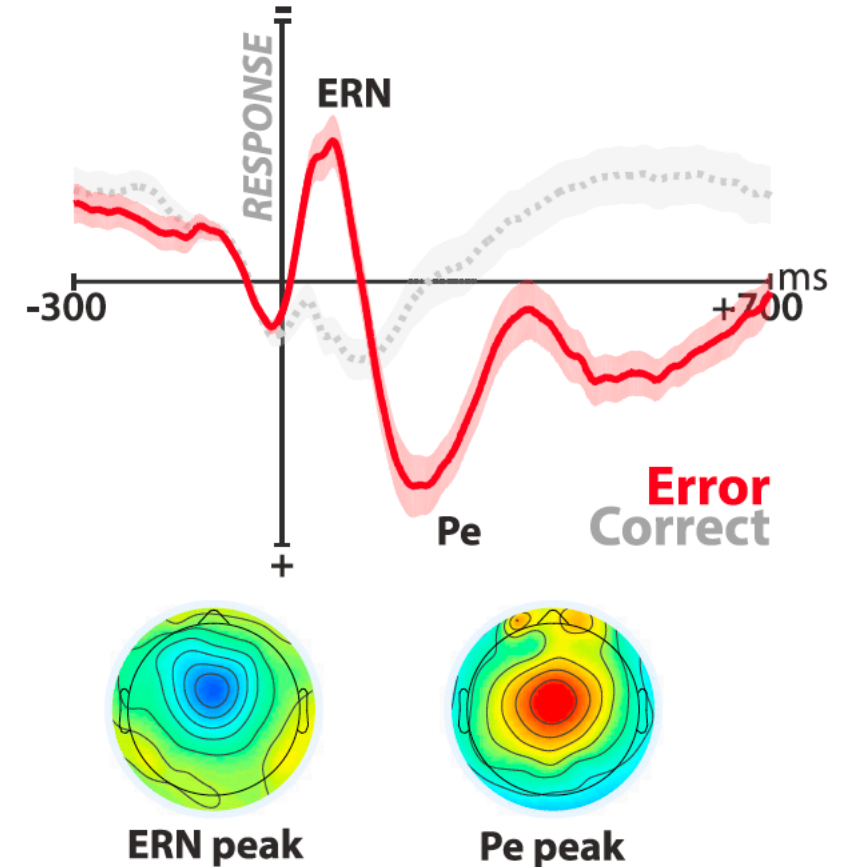
- e.g.: Is a Negativity

- **FREQUENCY COMPOSITION**

- e.g.: Prominent theta-band activity

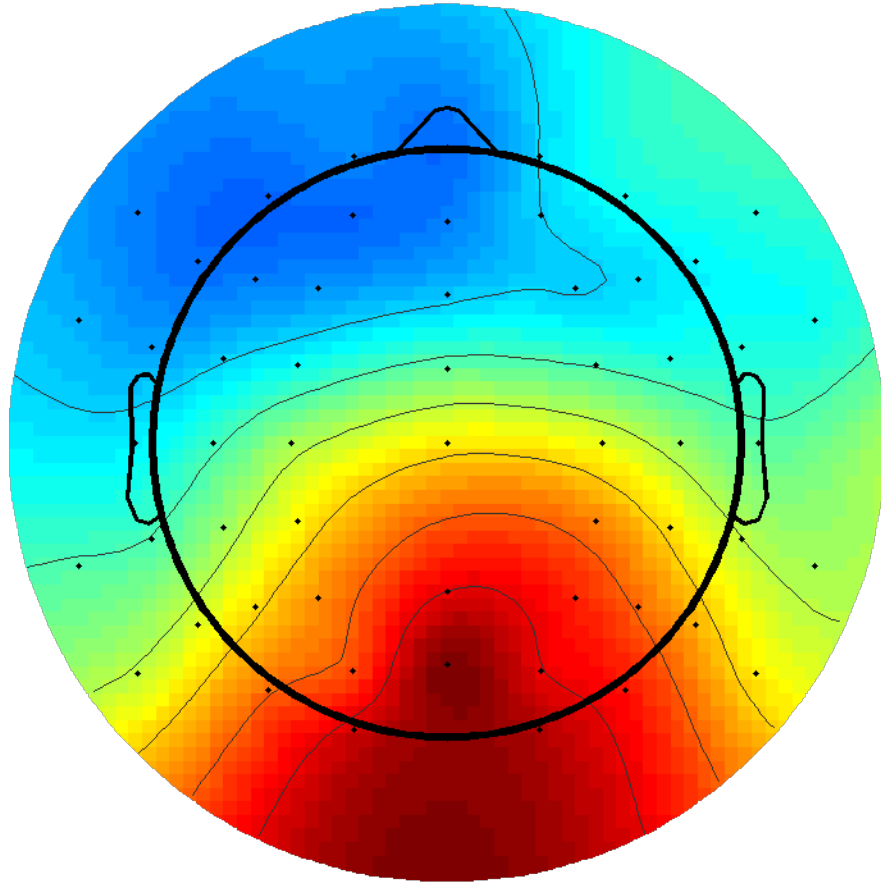
- **FUNCTIONAL PROPERTIES**

- e.g.: Is enlarged for a specific subset of trials



The COMPASS approach

Only assumption: time range



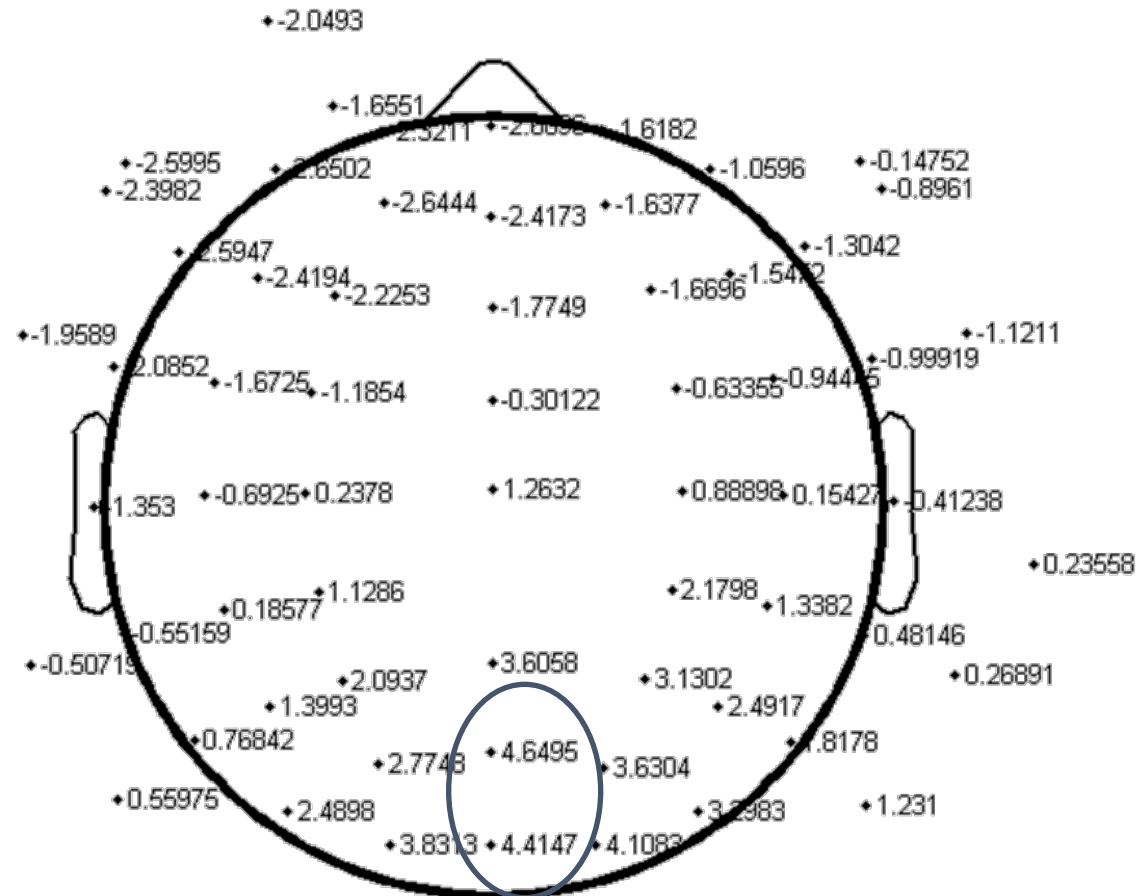
The COMPASS approach

Step 1: What is a 'significantly active electrode'?

Grubbs Test for Outliers

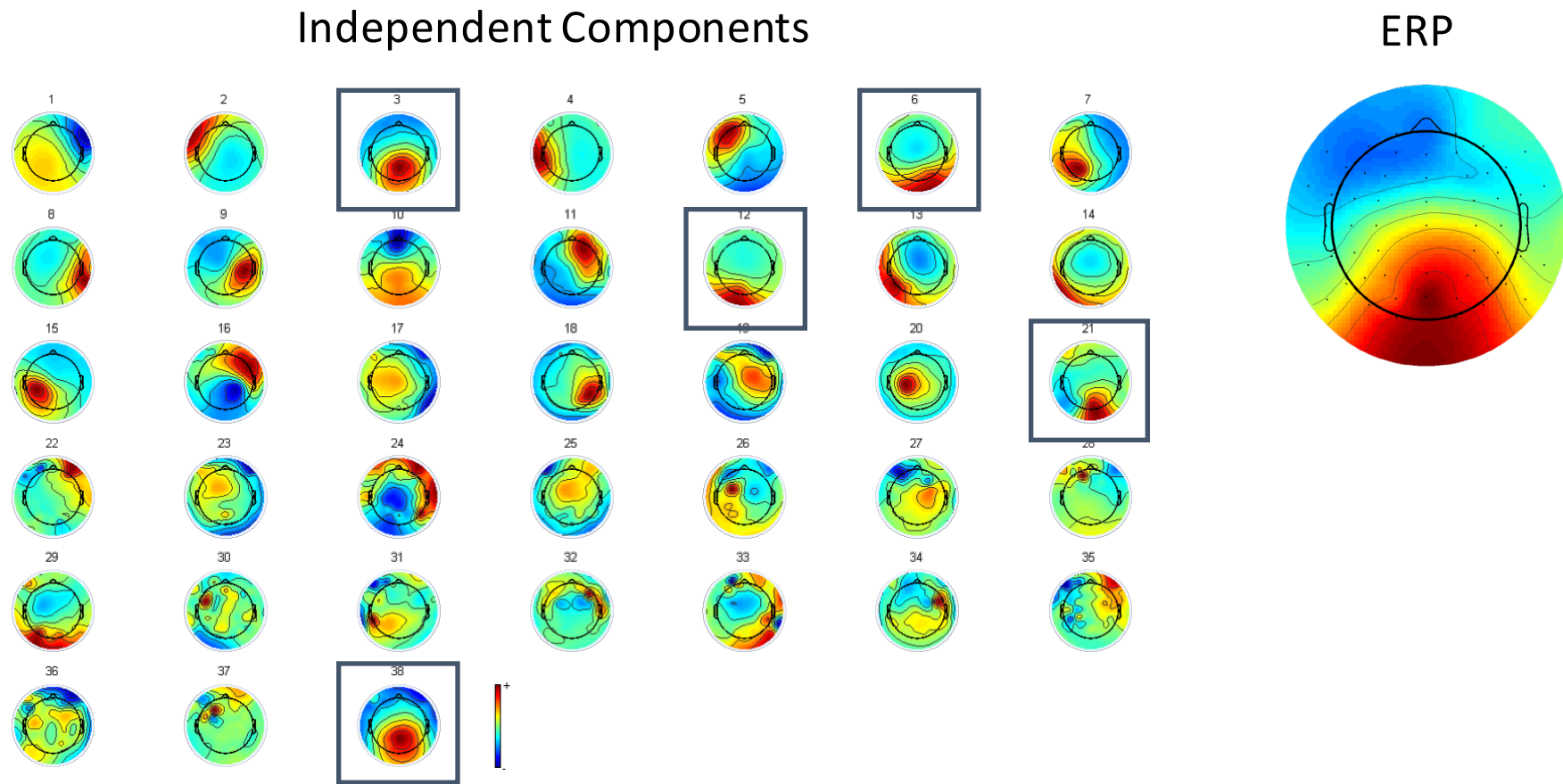
$$G = \frac{\max |X_i - \bar{X}|}{S_n}$$

$$G > \frac{N-1}{\sqrt{N}} \sqrt{\frac{t_{\alpha/(2N), N-2}^2}{N-2 + t_{\alpha/(2N), N-2}^2}}$$



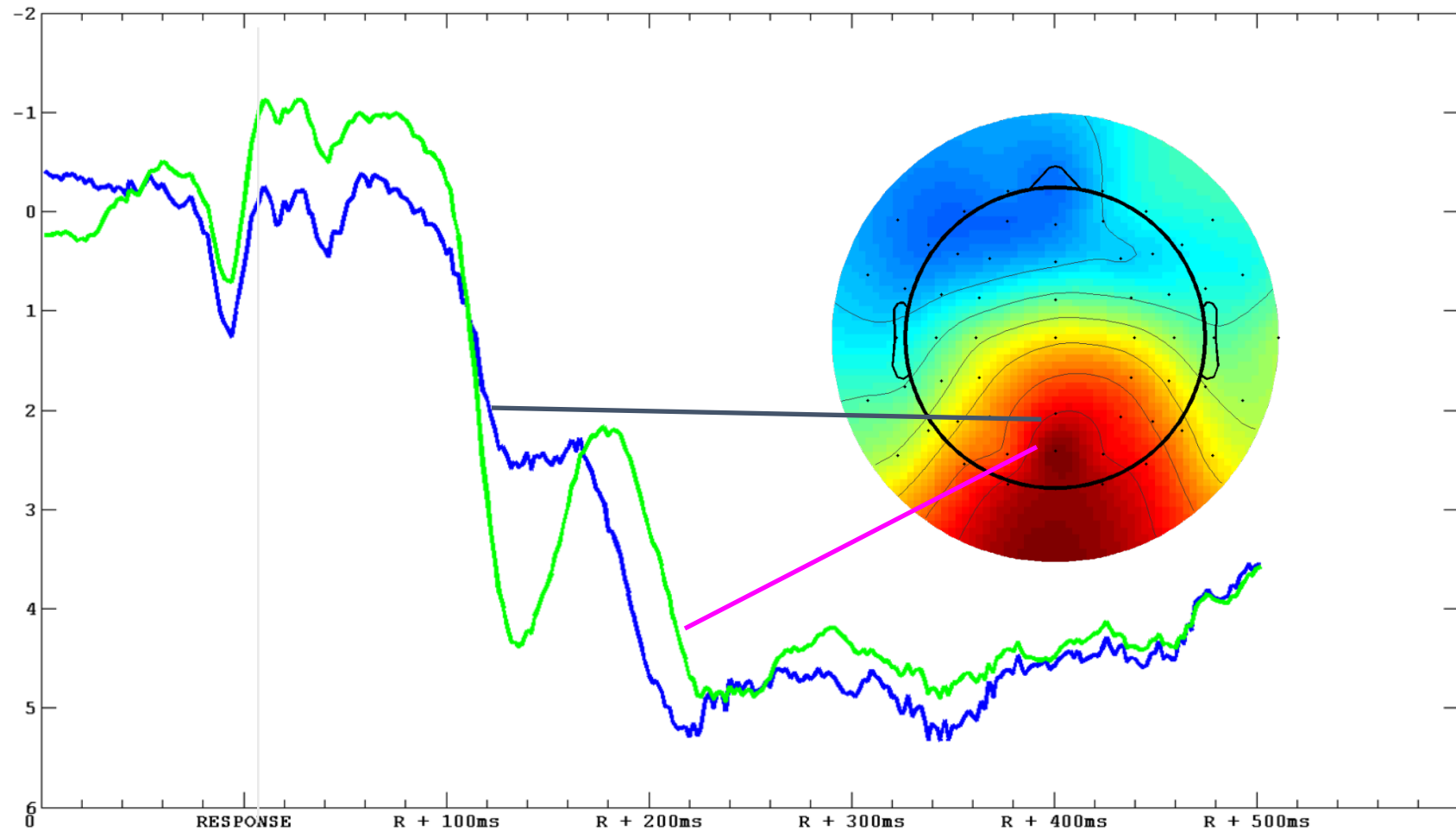
The COMPASS approach

Step 2: Find components whose weight matrix shows maxima at those electrodes



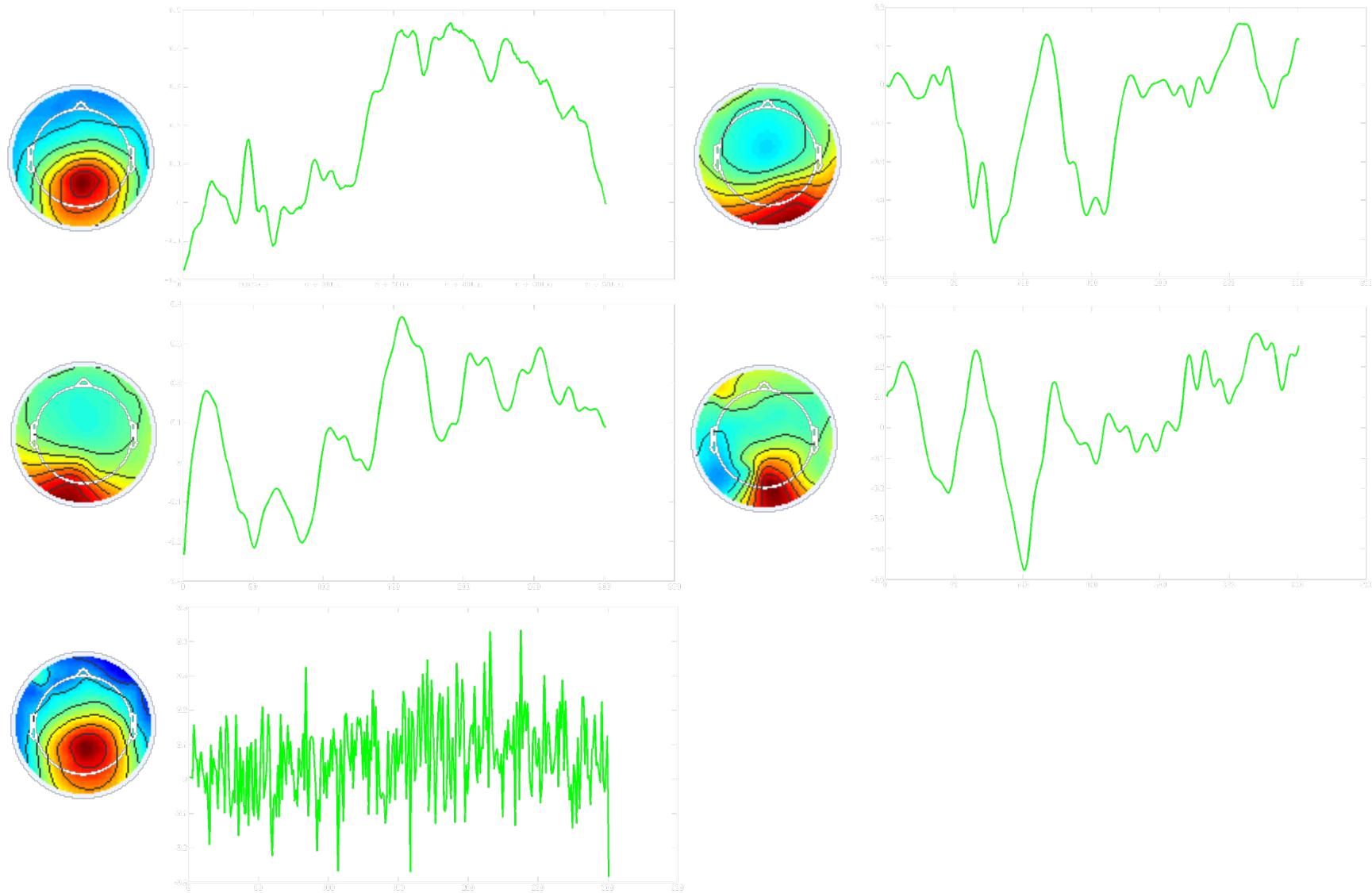
The COMPASS approach

Step 3: Pull out template ERP at each 'significant' electrode



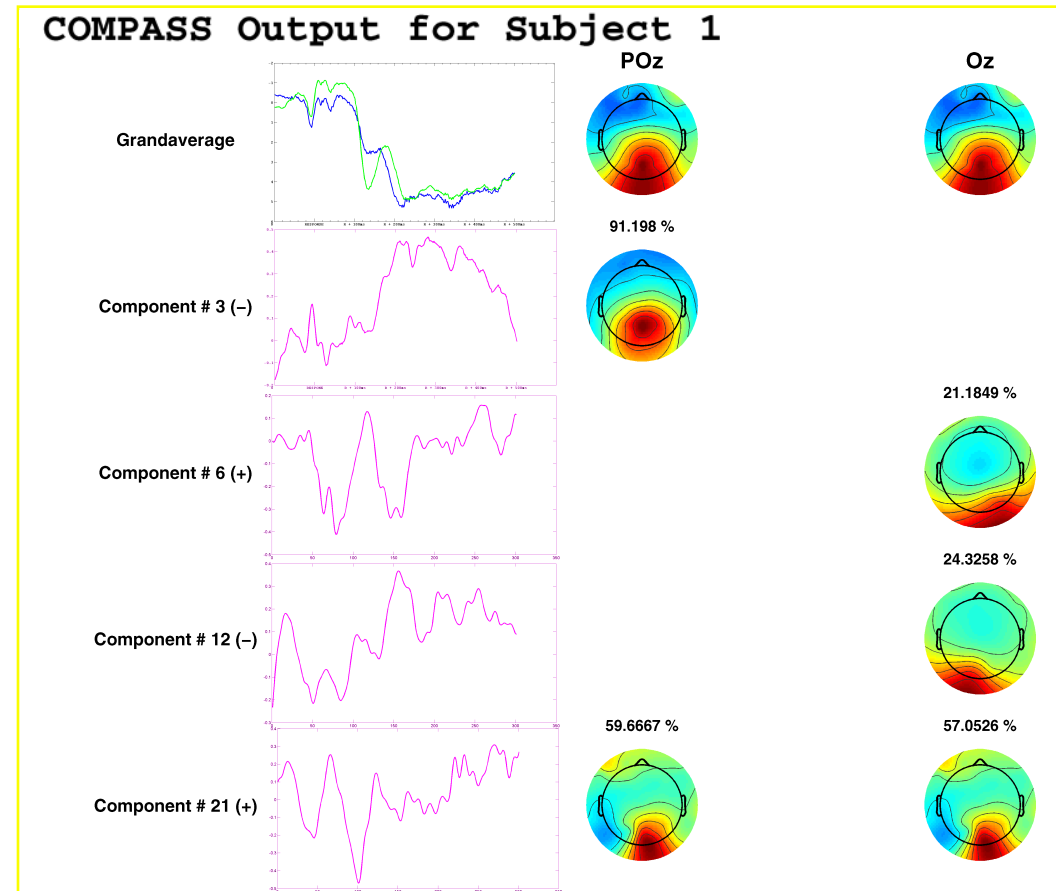
The COMPASS approach

Step 4: Pull out component activations

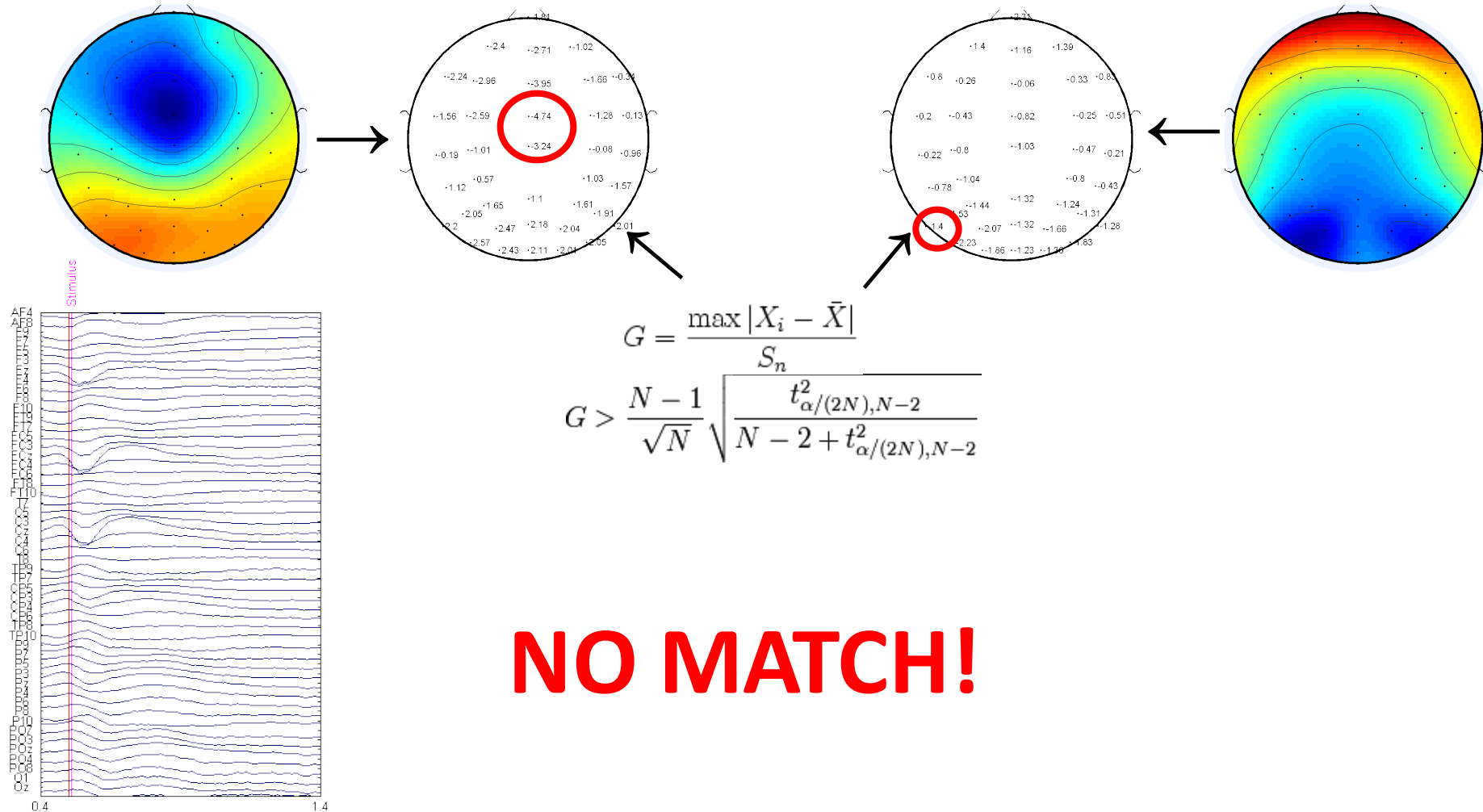


The COMPASS approach

Step 5: Test time courses for significant correlations with template ERP

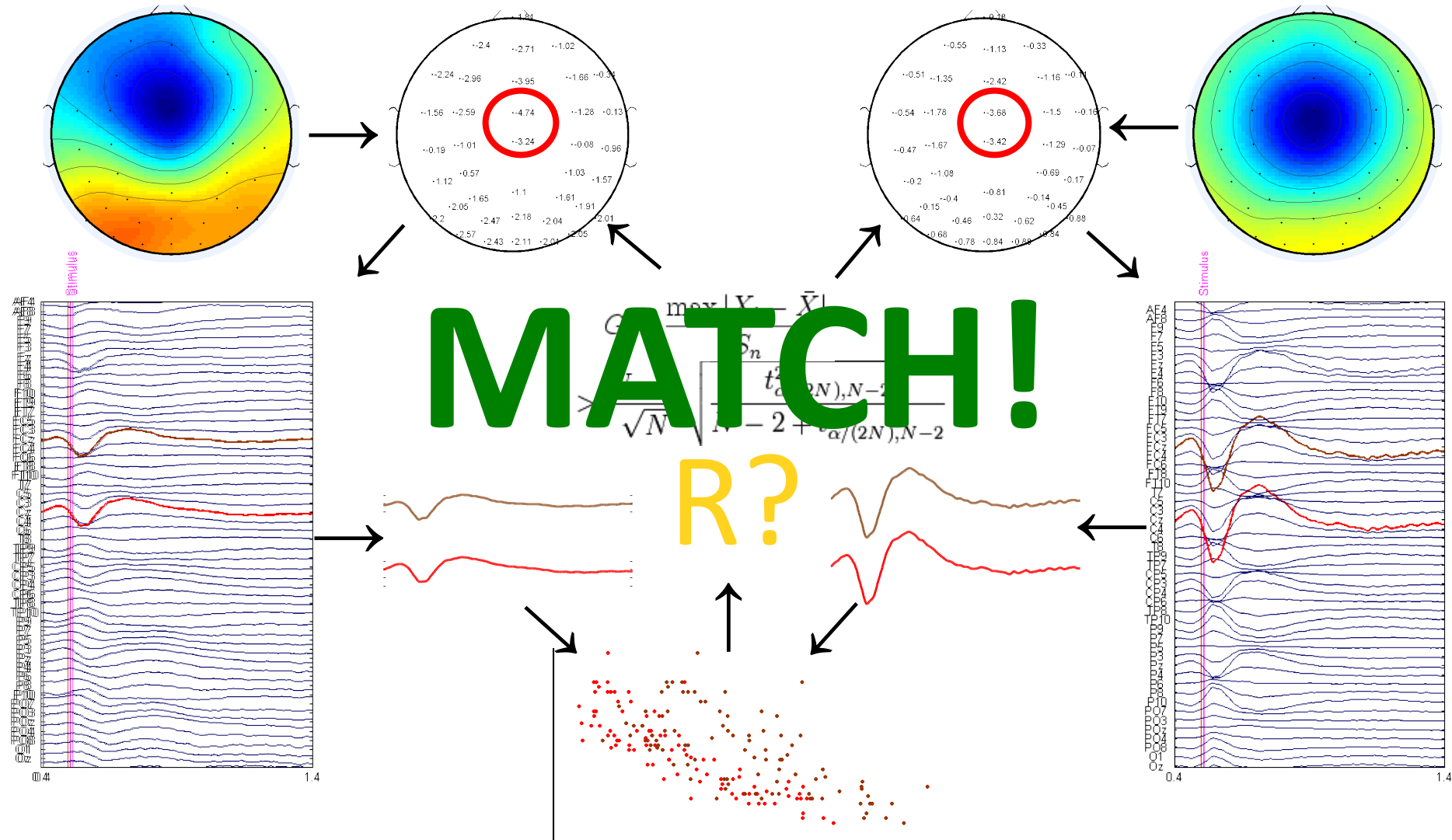


Wessel & Ullsperger, Neurolmage, 2011



COMPASS Algorithm

Wessel & Ullsperger, NeuroImage, 2011



COMPASS

GUI layout

The screenshot shows the Compass v1.3 GUI with a yellow background and a grey title bar. The title bar contains the text "Compass v1.3" and three window control buttons (red, yellow, grey). The main window is divided into three sections: "Basic Algorithm", "Parameters", and "Optional inputs".

Compass v1.3 by Jan R. Wessel
wessellab.org

Basic Algorithm

Output folder pathname
Output folder path ...

Input ICA file(s)
Location of input file ...

Input ICA file(s) for Diffwave (optional)
Location of input file ...

Search window (ms)
Beginning End

Parameters

Outlier method
auto

Timecourse alpha
0.01

Outlier alpha
0.05

Alpha correction
Global

Optional inputs

Load external template

☐ Peak latency

☐ CSD transformation

☐ Periphery matching

Polarity Both

Metric Euclidian Value 0.7

Run Analysis

Cognitive Neurology Lab

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COGNITIVE NEUROLOGY LABORATORY

CARVER COLLEGE OF MEDICINE & COLLEGE OF LIBERAL ARTS & SCIENCES, UNIVERSITY OF IOWA

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Thanks for visiting the Cognitive Neurology Lab at the University of Iowa. The lab is directed by Dr. Jan R. Wessel. We are affiliated with the [Department of Psychological and Brain Sciences](#), as well as the [Department of Neurology](#). We also participate in the [Interdisciplinary Graduate Program in Neuroscience](#), the [Aging Mind and Brain Initiative](#), the [Behavioral and Biomedical Interface Program](#), and the [Iowa Informatics Initiative](#).

If you are looking for the compass EEG toolbox, [click here](#).

News [More »](#)

Welcome Cheol & Nathan

August 30, 2017 - 3:45pm

We are welcoming two new members into our lab: Cheol Soh hails from Seoul, South Korea...

New paper in JEP:HPP

May 30, 2017 - 5:45pm

Our new paper, now available online, shows that unexpected perceptual events (in this...

Lab receives two grants from INI/Carver Trust

April 27, 2017 - 2:00pm

The lab has received two grants through the newly conceived...

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 **COMPASS** beta

Brought to you by: [janwessel](#)

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Looking for the latest version? [Download COMPASSv1.3.zip \(554.4 kB\)](#)

[Add File](#) [Add Folder](#)

Home 

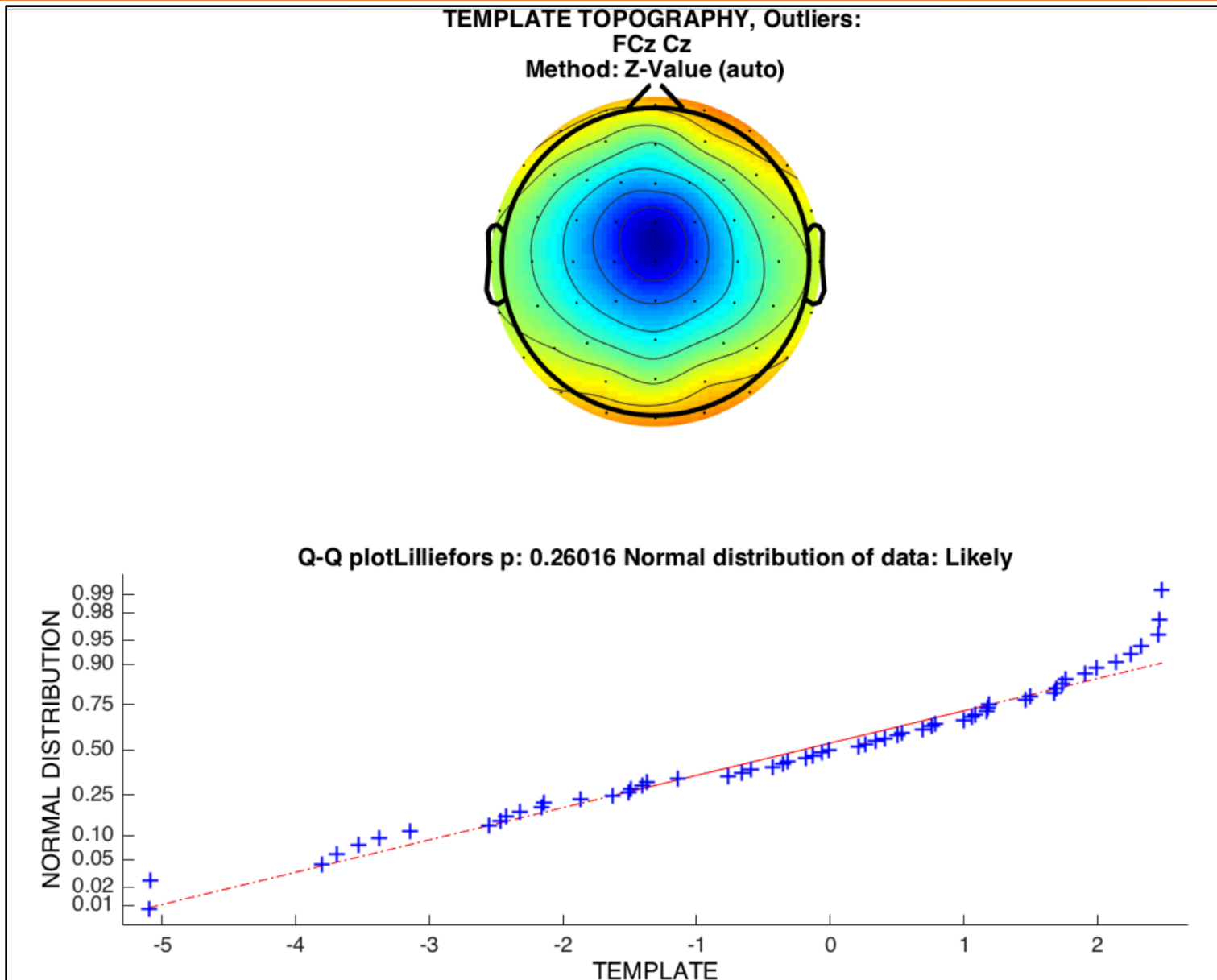
Name ▾	Modified ▾	Size ▾	Downloads / Week ▾
old_versions	2010-10-21		0
COMPASSv1.3.zip	2017-10-06	554.4 kB	1
COMPASSv1.2.zip	2012-11-09	528.3 kB	1
COMPASSv1.1.zip	2011-08-05	539.0 kB	0
COMPASSv1.1.tar.gz	2011-08-05	530.9 kB	0
COMPASSv1.0.tar.gz	2010-11-15	530.7 kB	0
COMPASSv1.0.zip	2010-11-15	535.2 kB	0
Totals: 7 Items		3.2 MB	2

COMPASS

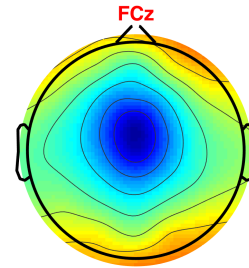
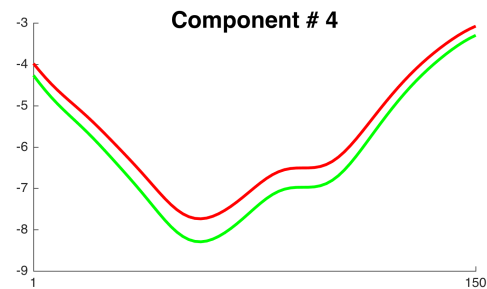
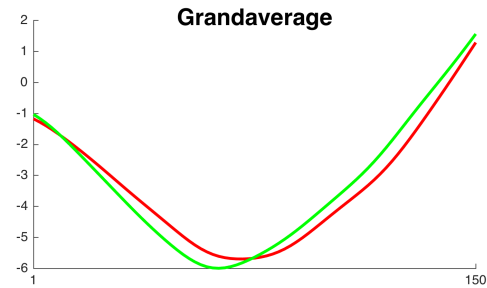
Data input

- Channel * timepoint * epoch datafile
 - Time-locked to event of interest
 - Essentially, what would go into your ERP analysis
- Optional: A second matrix of another condition, identical layout
- Remove non 10-20 EEG channels (EOG, Mastoids, etc.)

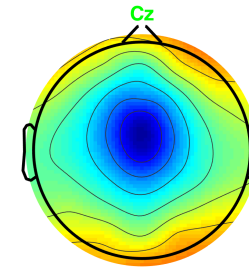
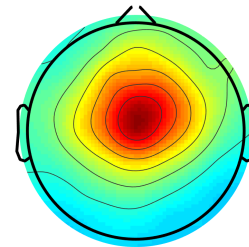
```
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filename: 'VP0045.set'
filepath: '/Users/janwessel/Desktop/COMPASS/compass_input/error/'
subject: ''
group: ''
condition: ''
session: []
comments: [10x59 char]
nbchan: 59
trials: 160
pnts: 500
srate: 500
xmin: -0.3
xmax: 0.698
times: [1x500 double]
data: [59x500x160 single]
icawinv: [59x61 double]
icasphere: [59x59 double]
icaweights: [61x59 double]
icachansind: [1x59 double]
chanlocs: [1x59 struct]
urchanlocs: []
chaninfo: [1x1 struct]
ref: 'averef'
event: [1x532 struct]
urevent: [1x3329 struct]
```



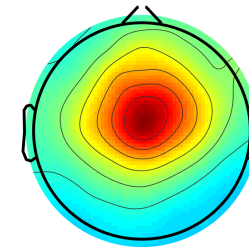
COMPASS Output for Subject 1



91.6828 %



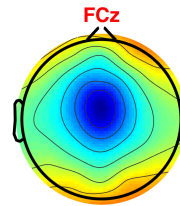
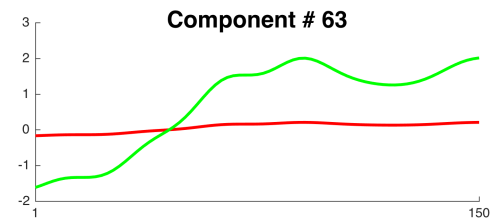
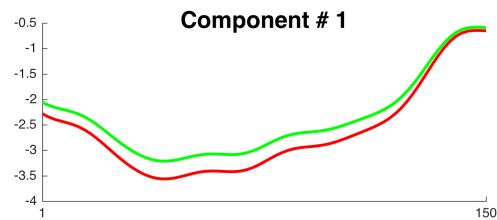
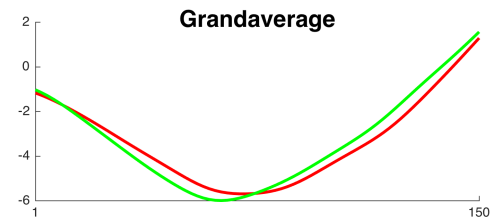
97.6416 %



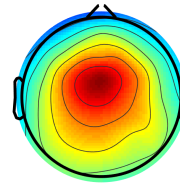
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Output: /Users/janwessel/Desktop/COMPASS/compass_output
Search Window: 1 : 150
Method: z-Value @ 0.05
Polarity: Both
Correlation alpha: 0.05
CSD: Off

SUMMARY
Initial ICs: 59; Additional TopoMatch:

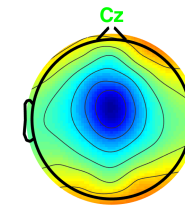
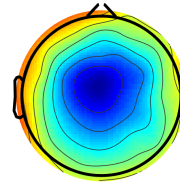
COMPASS Output for Subject 12



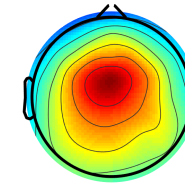
75.6978 %



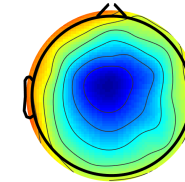
54.5542 %



85.5205 %



66.9669 %



PARAMETERS
 Template: Generated from user input
 Input: /Users/janwessel/Desktop/COMPASS/compass_nput/error/VP0037.set
 Output: /Users/janwessel/Desktop/COMPASS/compass_utput
 Search Window: 1 : 150
 Method: z-Value @ 0.05
 Polarity: Both
 Correlation alpha: 0.05
 CSD: Off

SUMMARY
 Initial ICs: 59; Additional TopoMatch: 8 20 25

Single-trial EEG analysis workshop

MCC Satellite Workshop
Berlin 2019

Jan R. Wessel

Department of Neurology
Department of Psychological and Brain Sciences
Iowa Neuroscience Institute
University of Iowa

Single-trial EEG analysis workshop

Session 4

Time-frequency analyses

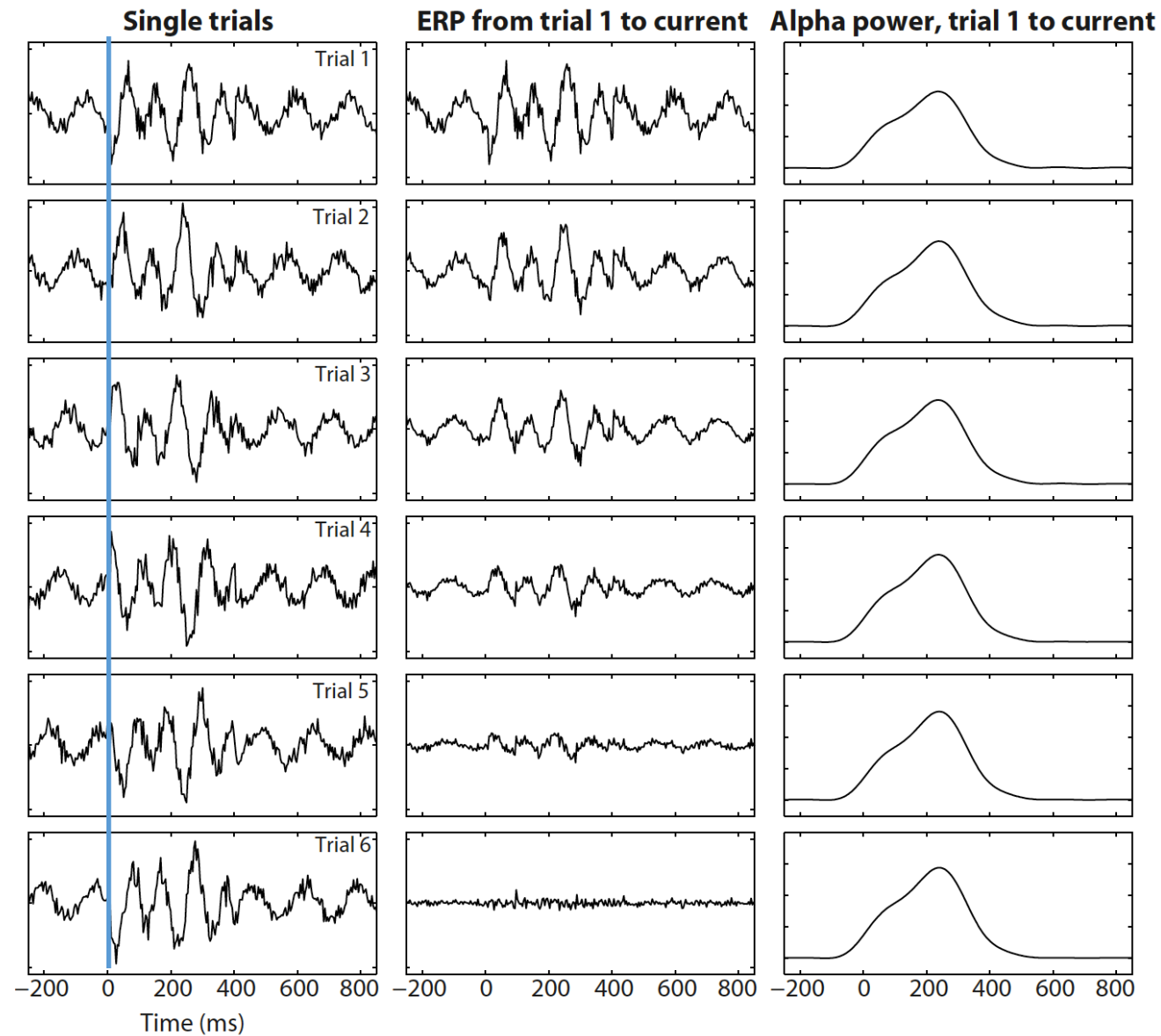
Introduction to time-frequency analysis

Why do it?

- Downsides of the ERP method
 - Physiological Basis
 - Phase-locked vs. non-phase-locked information
 - Informational representation of a physiological signal

Event-related potentials

The phase-locking problem



Event-related potentials

Information content of the EEG

- Bits of information in typical event-related EEG dataset

e number of electrodes

p number of time-points after event

t number of individual trials

f number of informative frequencies

phase & power

$$\text{INFORMATION}(\text{bits}) = e * p * t * f * 2$$

- Example of a typical experiment:
64 electrodes, 500 Hz sampling rate.
400 instances (trials) of interest for event-type in question.
- Assuming that there are ~5 meaningful frequency bands in EEG and we're interested in brain activity ~500ms after the event, the informational content of the recording is
 $64 * 250 * 400 * 5 * 2 = \underline{64 \text{ million bits of information}}$

Event-related potentials

Information content of the EEG

- The ERP method
 - **Disregards phase information** / only includes phase-locked activity
-> $64 \text{ million} / 2 = 32 \text{ million bits}$
 - Averages information **across all frequencies** / does not resolve the signal by frequency
-> $32 \text{ million} / 5 = 6.4 \text{ million bits}$
 - Averages across **all trials**
-> $6.4 \text{ million} / 400 = 16,000 \text{ bits}$
 - Selects only **one electrode**
-> $16,000 / 64 = 250 \text{ bits}$
 - Cares only about **one latency** (or averages across a range)
-> $250 / 250 = 1 \text{ bit}$
- Hence, in this example, for each subject and condition, the ERP method reduces a signal with 64 million bits of information to 1 bit of information
- Single trial time-frequency analysis adds information by a factor of $t * f * 2$

What's in a time series?

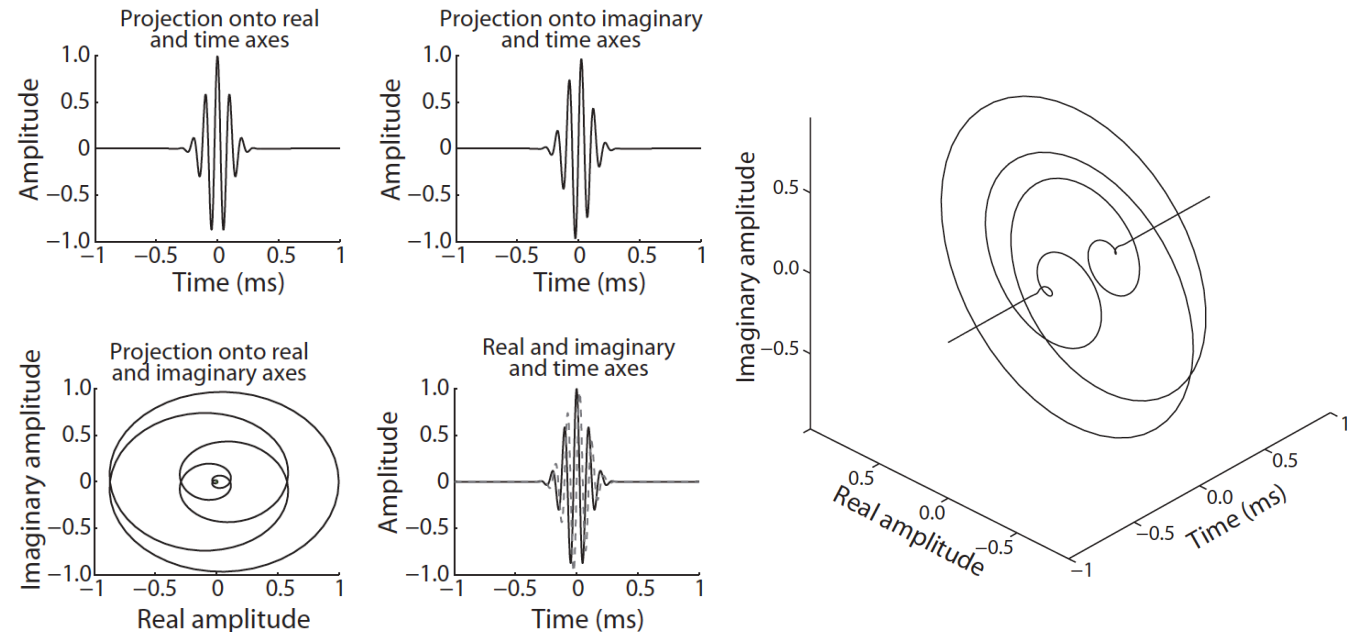
Frequency, phase, power



Time-frequency analysis

Most common approaches

- Sliding-window **Fast-fourier transform** using (multi)tapers
 - Convolution is used in the fourier transform (a series of complex sine waves are convolved with the data to extract power and phase at the frequencies of the sine waves)
- Bandpass-filter + **Hilbert** transform
 - Convolution is used during filtering and during the Hilbert transform itself (where a Hilbert / Cauchy kernel is used to extract an analytic signal)
- **Wavelet** Convolution
 - Complex wavelets are convolved with the signal to extract power and phase information according to the wavelet properties



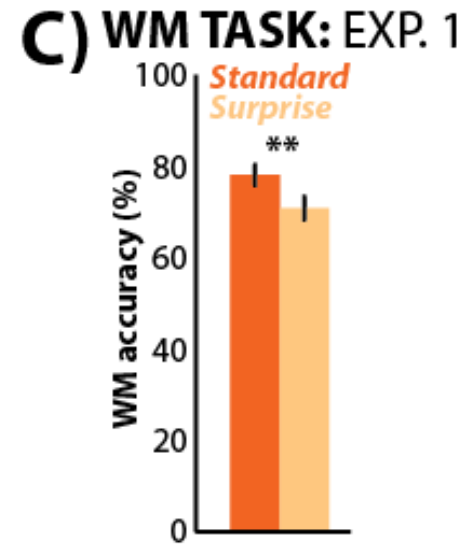
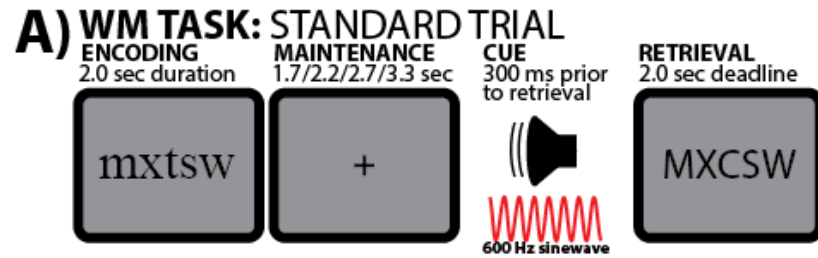
Time-frequency analysis

Data structures

- These analyses do two things:
 - They **resolve** your time domain signal into its constituent frequencies
 - They allow an independent quantification of **power** and **phase**
- Hence, unlike in an ERP, you are not looking at a vector of values
 $\text{size(ERP)} = 1500 \times 1$
but instead, you are looking at **two time * frequency matrices**
 $\text{size(TF_ERP)} = 1500 \times 30$
(one for phase, one for power)
- However, the principles of single-trial regression remain **exactly the same**
 - Instead of modelling every time point after an event, you now model **every point in the time X frequency matrix**.
 - Be sure to account for the additional test using **corrections for multiple comparisons**

Example

Surprise interrupts working memory



Does this relate to WM interruption?

Example

Every single Novel trial

CUE
300 ms prior
to retrieval



RETRIEVAL
2.0 sec deadline



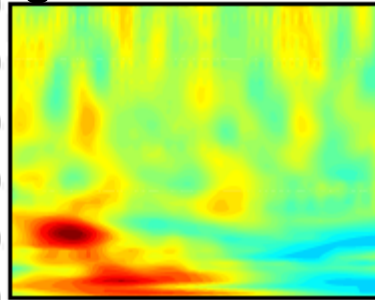
Amount of surprise $S_i = \log_2 \left(\frac{p_{\text{novel}}(1 \dots i)}{p_{\text{novel}}(1 \dots i - 1)} \right)$

WM failure? (0/1)

SURPRISE * WM Interaction

IV

Single-trial EEG response (after cue onset)



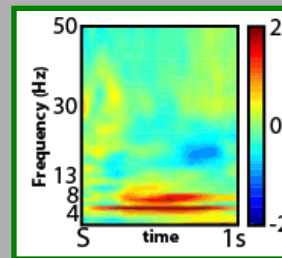
Freq * samples
Analytic matrix

DV

EACH INDIVIDUAL SUBJECT:

$\forall f = \{1 \dots n_{\text{freq}}\}; \forall s = \{1 \dots n_{\text{samp}}\} :$

$$\hat{Y}_{f,s} = \beta_0 + \beta_{\text{Surprise}} + \beta_{\text{WM}} + \beta_{\text{Surprise*WM}} + \varepsilon$$



Output

Does this relate to WM interruption?

Example

