



Radboud University



Get to know your data preprocessing, segmentation and artifacts



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Get to know your data

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$



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Get to know your data – learning goals

What are the characteristics of the data that we use in the analysis?

How to organize your raw data?

Quality assessment and control

What are the artifacts and why are they relevant?

Preprocessing and segmenting (or vice versa)

Selective averaging to get ERPs/ERFs

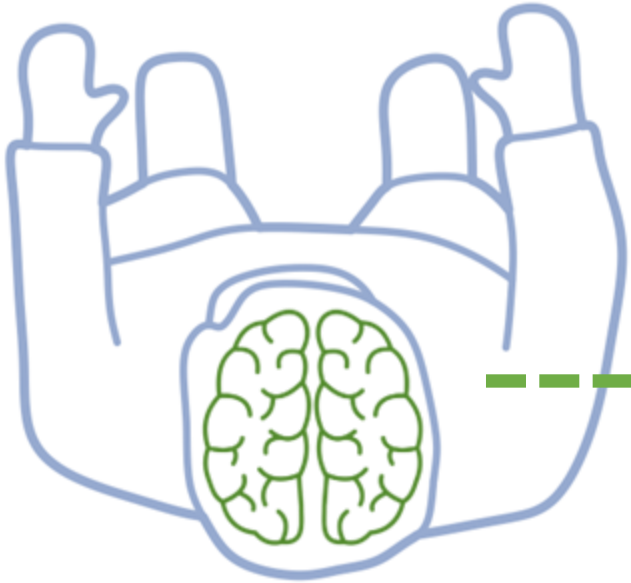


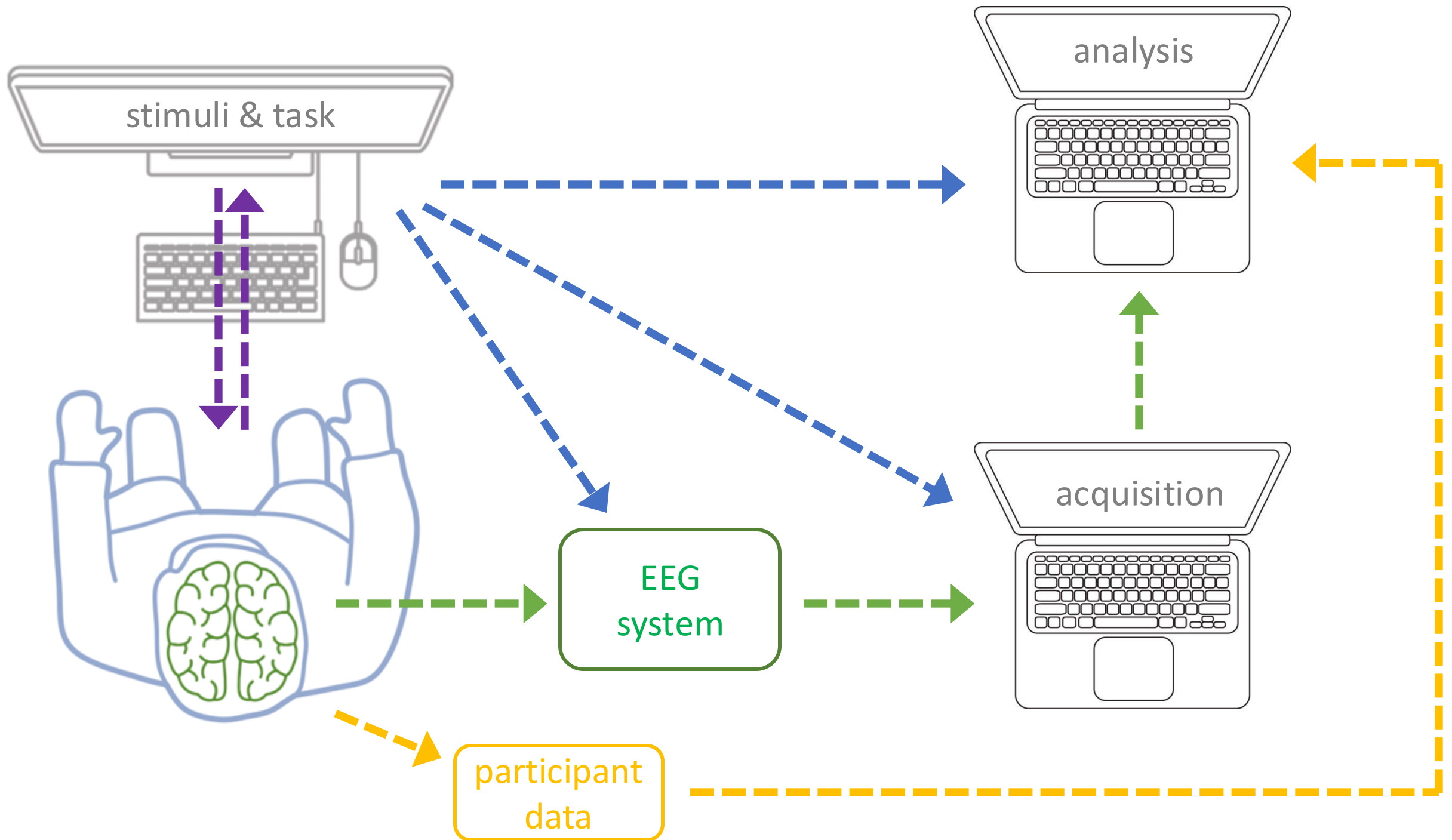
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Collecting your data – in the lab or not

1. You have designed your own study, recruited your own participants, and collected your own data in the lab.
2. You have received data from a (former) colleague in the lab, or downloaded it from an online repository.

*Either way: **organize it!***





Preprocessing, processing, analysis

Prior to preprocessing

Data curation: collecting all files, naming them consistently, etc.

*EEG/MEG data is **large, consists of many files, and is complex***

EEG data characteristics

64 channels, 500 Hz, 1 hour is approx. 500 MB

Typical study ~30 subjects, 15 GB of raw data

Many EEG companies, hence many file formats.

Analysis often done on laptops.



MEG data characteristics

SQUID-based systems

275 or 306 channels, 1000 Hz, 1 hour is approx. 4 GB

Typical study ~30 subjects, 120 GB of raw data

Few MEG companies, hence small number of formats

Neuromag/Elekta/MEGIN: one recording is one *.fif file

CTF: one recording is one *.ds directory with ~10 files

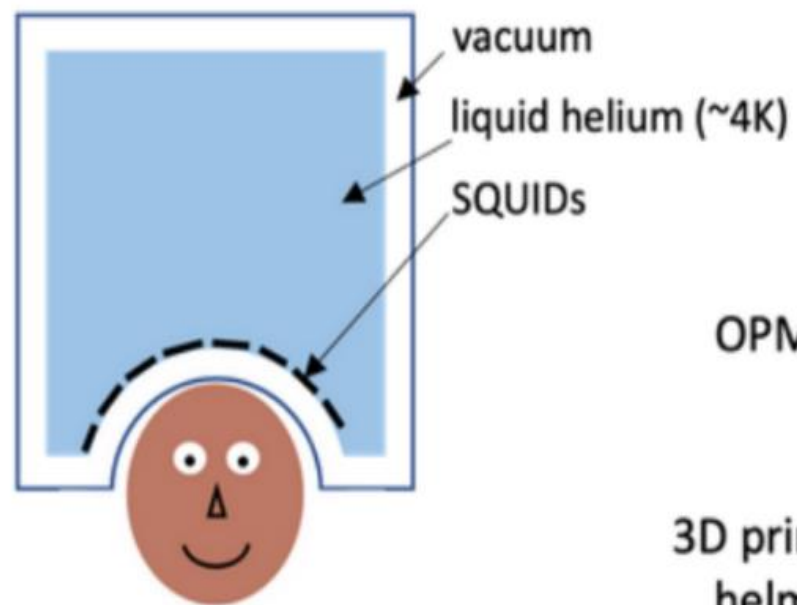
Analysis often done on “large” computers.



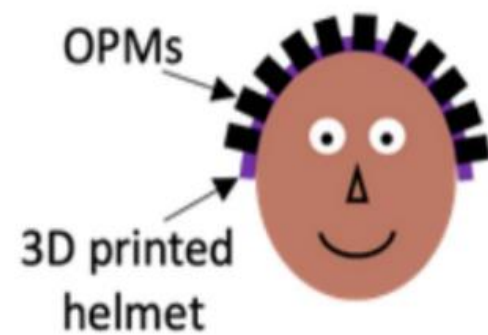
MEG data characteristics

OPM-based systems

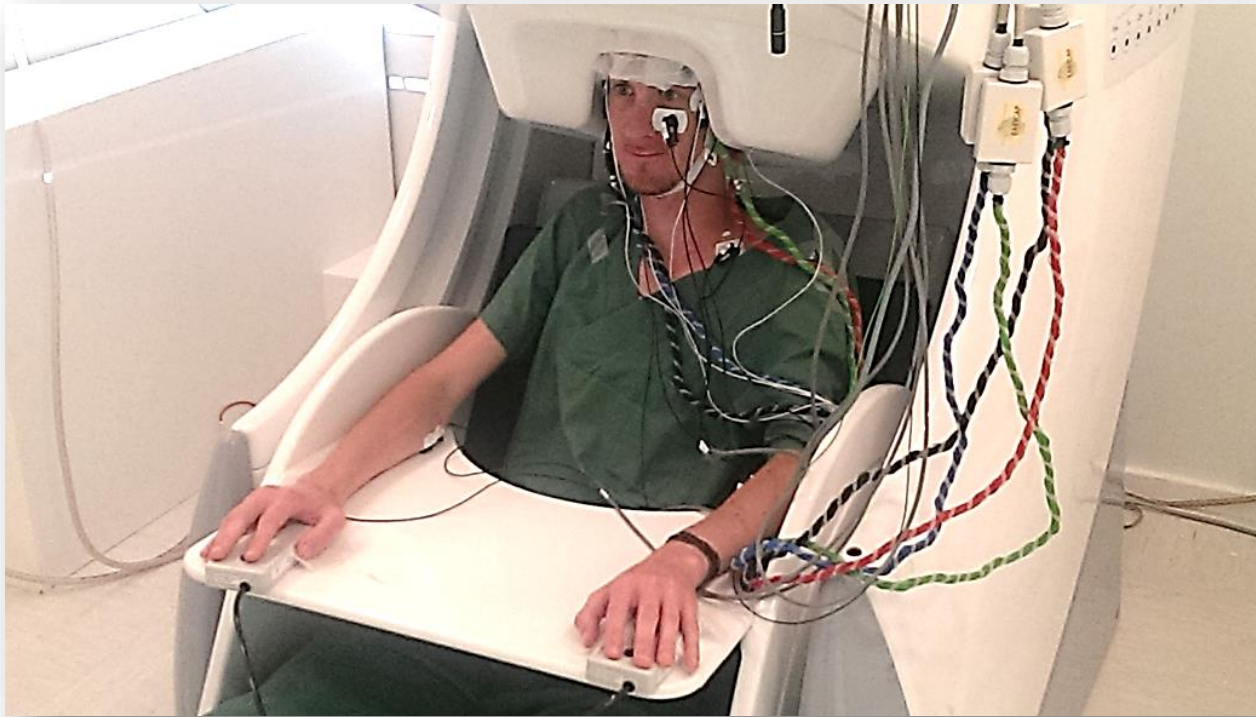
SQUIDs



OPMs

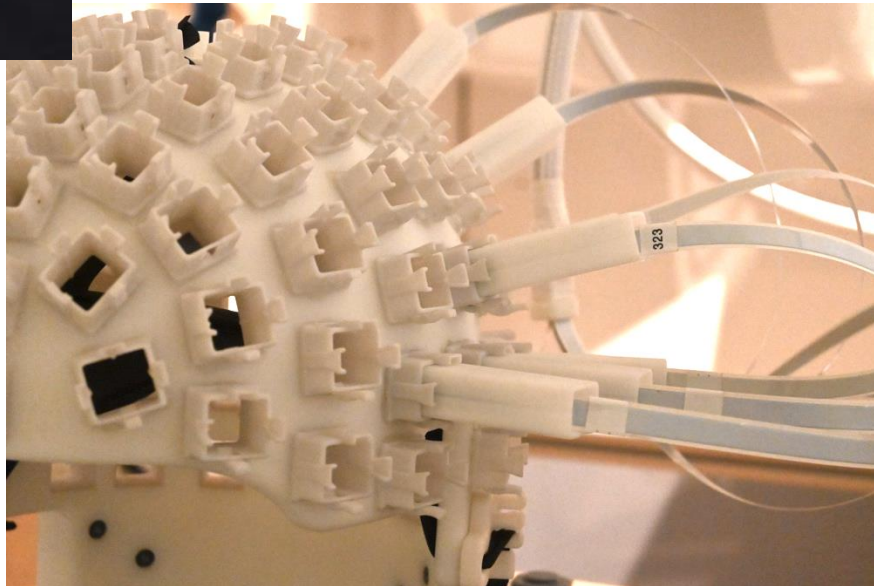
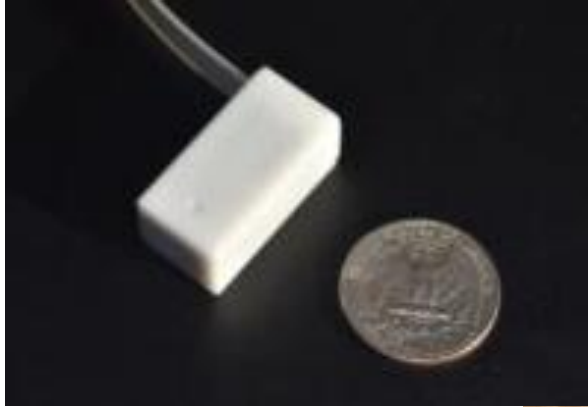


SQUIDs versus OPMs

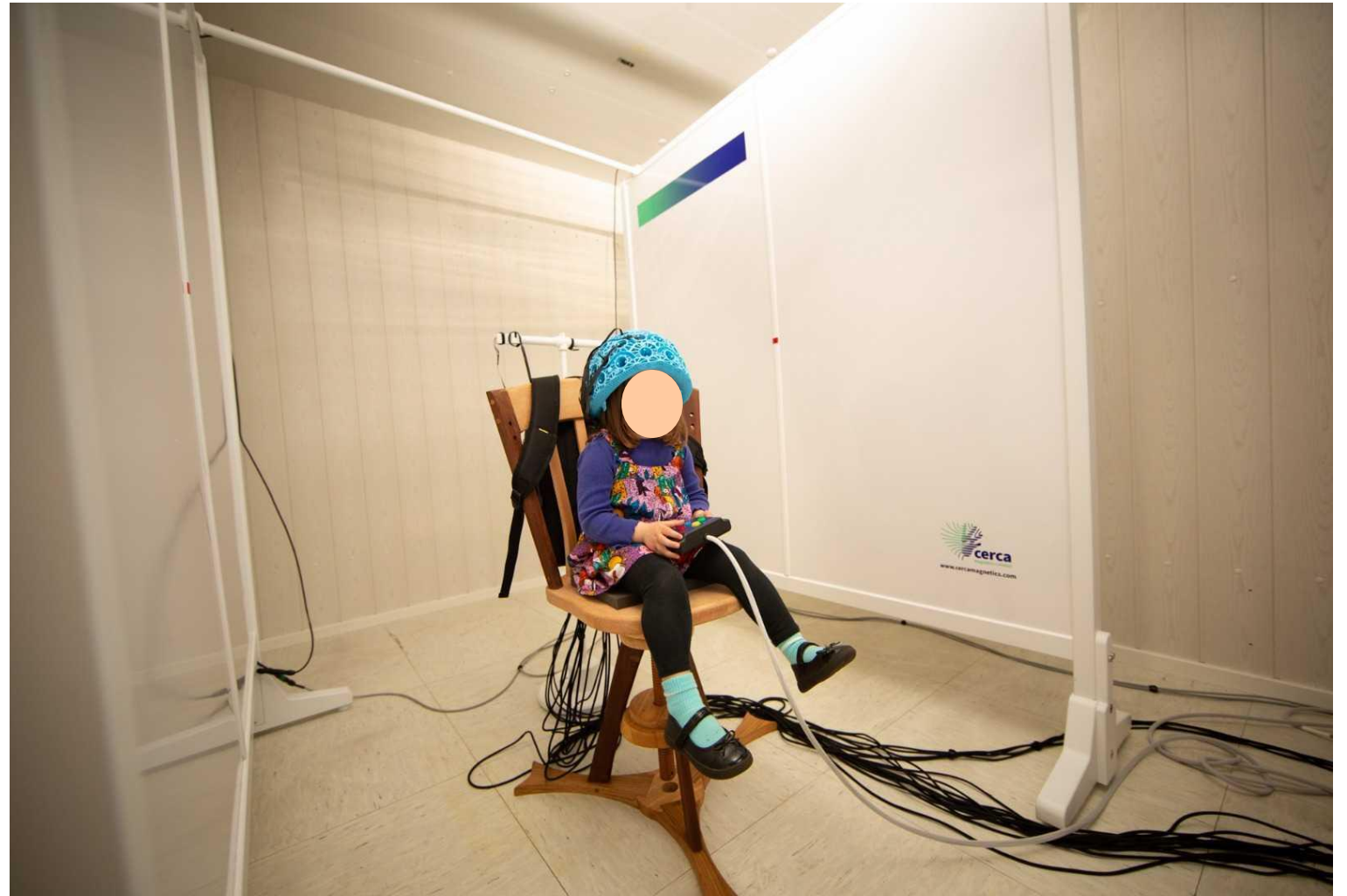
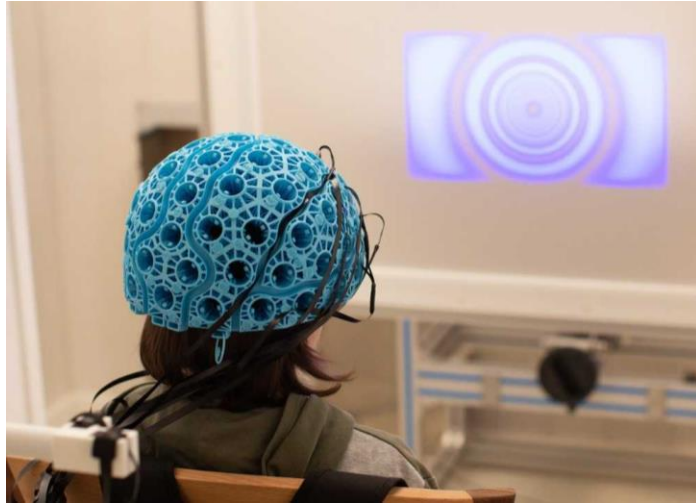


FieldLine OPM system at Karolinska/Stockholm

now upgraded to 128 sensors (256 channels) and a smart helmet



CercaMagnetics OPM system installed in Cardiff



MEG data characteristics

OPM-based systems



A single OPM sensor can have 1-3 channels (x, y, z)

Total system has anywhere between 1 to 384 channels

Typical study ~30 subjects, 120 GB of raw data

OPM sensors can be placed in a flexible cap, like EEG, or in a 3D printed helmet

Position of the sensors relative the cap/helmet and to the head.

3D scans of the head and sensors, Polhemus digitizer, etc.

Auxiliary data

Anatomical MRI data

Directly from the scanner as ~200 DICOM files (*.ima, *.dcm)

~ 50 MB

Commonly converted to NIfTI format, one file (*.nii or *.nii.gz)

Behavioural data (time-resolved)

Mostly encoded as “triggers” together with the MEG or EEG data stream

kB to GB

Stimulus presentation log file

Video and/or audio recordings (e.g., for verbal responses)

Eye tracker for gaze and pupil diameter

...

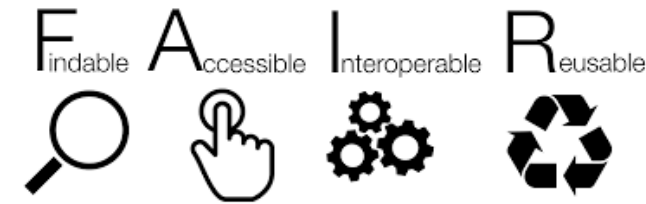
Other data (usually tabular, not time-resolved)

Handedness, gender, age, ...

~ 1 kB

Questionnaire outcomes

Organize your data FAIR



Findable

Make your data available in a catalog or repository
with a persistent identifier (DOI, handle) and metadata

Accessible

Be explicit about data usage terms (agreement with downloader)

Interoperable

Make your data human and machine readable, e.g. BIDS

Reusable

Make sure you document enough details, e.g. “data descriptor” paper
that can be cited, along with citing our data -> measurable impact!

Organize your data FAIR

BIDS is a community initiative to make your data more FAIR

BIDS is a way to organize your existing raw data

To improve consistent and complete documentation

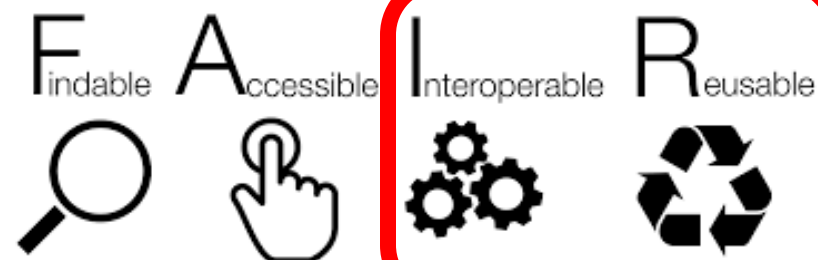
To facilitate re-use by your future self and others

BIDS is *not*

A new file format

A search engine

A data sharing platform



BIDS for EEG and MEG

also for iEEG, MRI, NIRS, PET, motion capture, ...

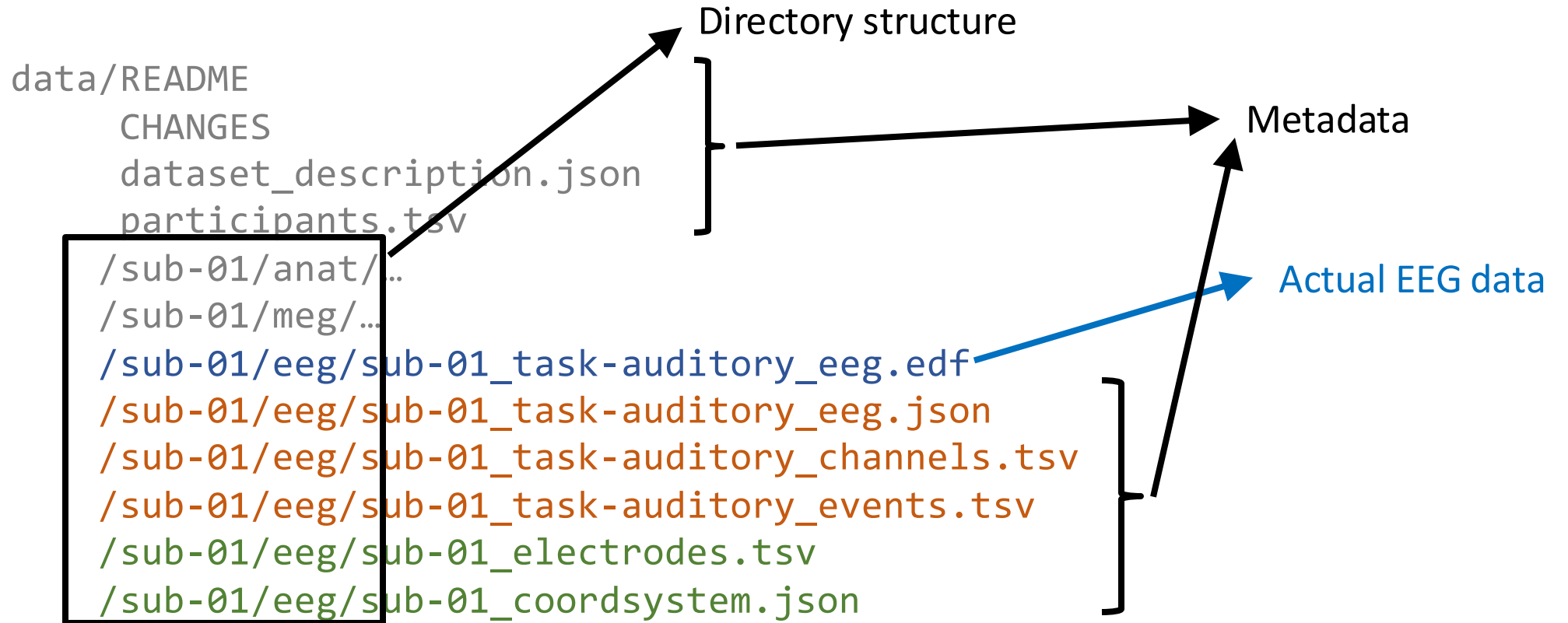


Just a bunch of directories and files on disk.

No special software required (although tools are available).

BIDS for EEG and MEG

also for iEEG, MRI, NIRS, PET, motion capture, ...



BIDS “sidecar” files for metadata

see also <https://github.com/bids-standard/bids-examples>



- 1) represent otherwise missing data
- 2) make it easier to query/search

As example for EEG and MEG:

_participants.tsv and json

_sessions.tsv and json

_scans.tsv and json

_meg.json

_events.tsv and json

_channels.tsv and json

_electrodes.tsv and json

_coordsystem.json

_photos.jpg

```
"TaskName": "facerecognition",  
"SamplingFrequency": 1100,  
"Manufacturer": "ElektaNeuromag",  
"ManufacturersModelName": "ElektaVectorview",  
"MEGChannelCount": 306,
```

onset	duration	onset_sample	stim_type	trigger	stim_file
23.93	0	26323	Unfamiliar	13	meg/u101.bmp
27.1709	0	29888	Unfamiliar	14	meg/u101.bmp
30.3782	0	33416	Famous	5	meg/f043.bmp
33.4355	0	36779	Famous	5	meg/f046.bmp
36.6091	0	40270	Unfamiliar	13	meg/u061.bmp
39.85	0	43835	Unfamiliar	14	meg/u061.bmp
43.0073	0	47308	Famous	5	meg/f050.bmp
46.1318	0	50745	Famous	6	meg/f050.bmp
49.3055	0	54236	Scrambled	17	meg/s082.bmp
52.3455	0	57580	Famous	5	meg/f147.bmp
55.67	0	61237	Famous	6	meg/f147.bmp
58.7273	0	64600	Famous	7	meg/f043.bmp
62.0682	0	68275	Famous	5	meg/f130.bmp
65.2591	0	71785	Famous	6	meg/f130.bmp
68.3836	0	75222	Famous	7	meg/f046.bmp
71.5909	0	78750	Unfamiliar	13	meg/u106.bmp
74.8309	0	82314	Unfamiliar	13	meg/u140.bmp
78.0545	0	85860	Unfamiliar	14	meg/u140.bmp
81.2118	0	89333	Scrambled	17	meg/s020.bmp
84.4527	0	92898	Scrambled	18	meg/s020.bmp
87.6936	0	96463	Scrambled	19	meg/s082.bmp
90.8682	0	99955	Famous	5	meg/f066.bmp
94.0582	0	103464	Unfamiliar	13	meg/u091.bmp

10% system",
stimuli on a screen

Get to know your data – learning goals

What are the characteristics of the data that we use in the analysis?

How to organize your raw data?

Quality assessment and control

What are the artifacts and why are they relevant?

Preprocessing and segmenting (or vice versa)

Selective averaging to get ERPs/ERFs

Preprocessing, processing, analysis

Prior to preprocessing

Data curation: collecting all files, naming them consistently, etc.

First processing steps do not depend so much on the research question

Quality assessment

Artifact removal

Filtering, baseline correction

Aligning stimulus presentation and behavioral data with EEG/MEG

Segmenting/epoching

Aligning MRI with EEG/MEG sensors and anatomical processing

Later steps are more tightly linked to the research question

Averaging ERPs in specific conditions

Computing power spectra, time-frequency analysis, connectivity

Source reconstruction

Modelling (e.g., using GLM)

Statistical inference

Preprocessing, processing, analysis

Prior to preprocessing

Data curation: collecting all files, naming them consistently, etc.

First processing steps do not depend so much on the research question

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Averaging ERPs in specific conditions

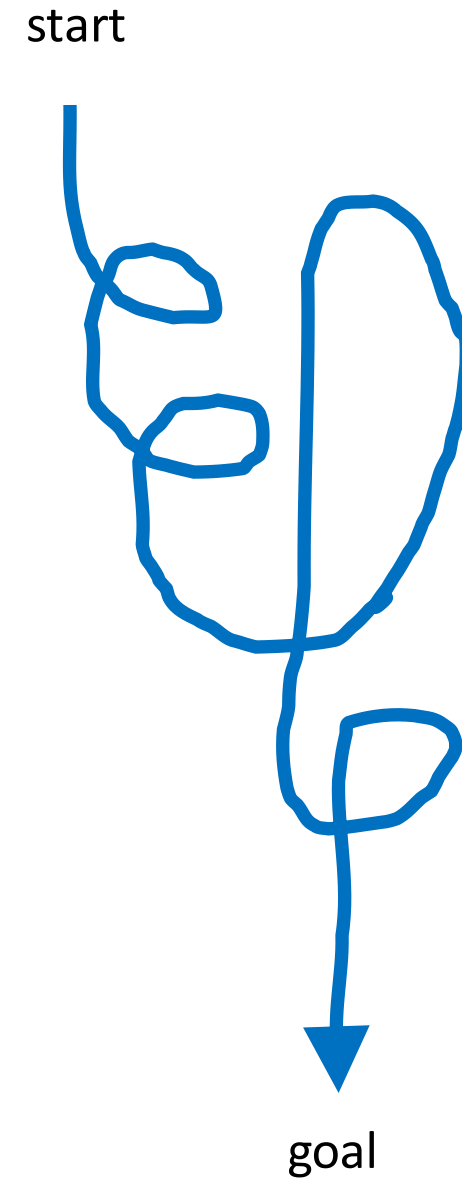
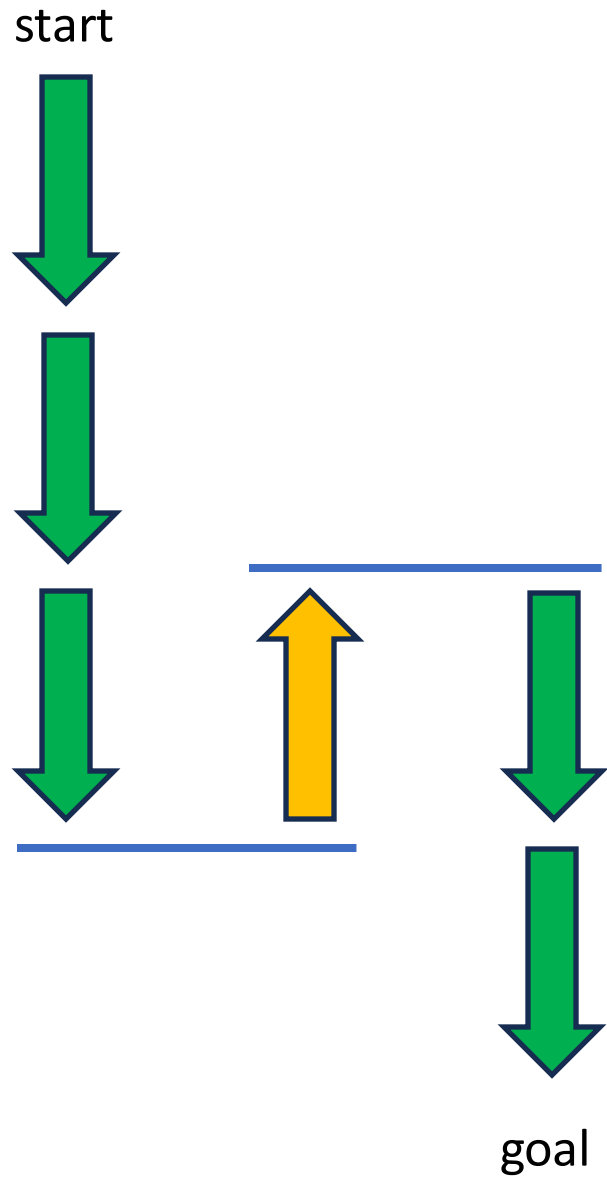
Computing power spectra, time-frequency analysis, connectivity

Source reconstruction

Modelling (e.g., using GLM)

Statistical inference

You should plan for multiple iterations of the preprocessing



Quality control and artifacts

EEG electrodes attached to subject's head

Bad attachment -> bad signals

MEG is not directly attached to subject

Few bad channels (dependent on hardware tuning)

EEG artifacts

Anything that causes potential differences

MEG artifacts

Anything that causes magnetic fields

EEG artifacts



~1.000.000 Volt



1,5 Volt



1-10 micro Volt

EEG artifacts

Poor contact with the scalp

Electrochemical noise (sweating)

Electrostatic noise (e.g., rubbing feet over the carpet)

Mostly common-mode, i.e., similar on all channels

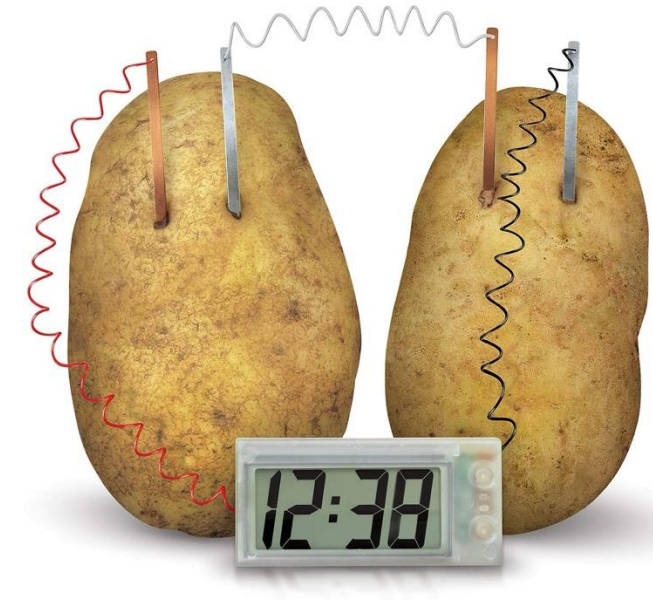
Power line noise, 50Hz electrical equipment

Other types of (physiological) bioelectricity

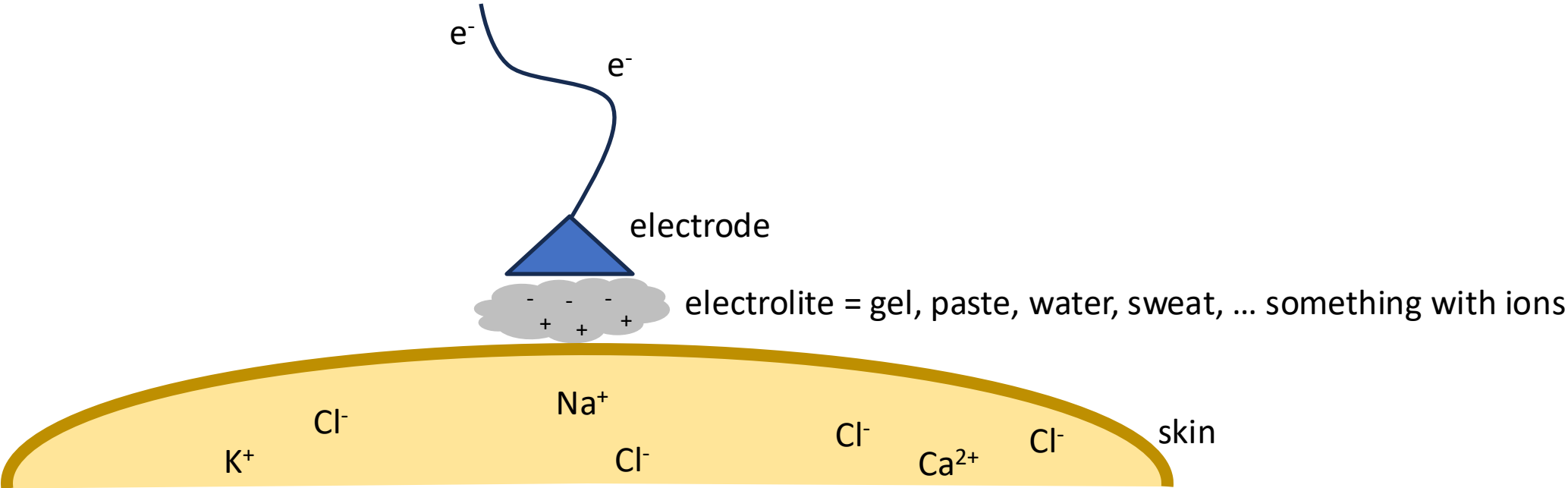
Muscle (EMG)

Heart (ECG)

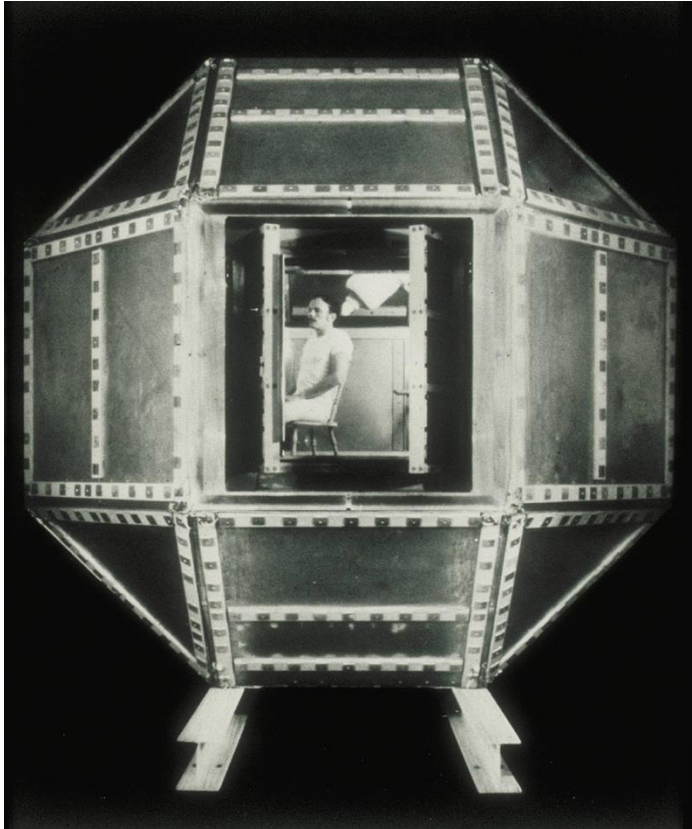
Eye movements (EOG)



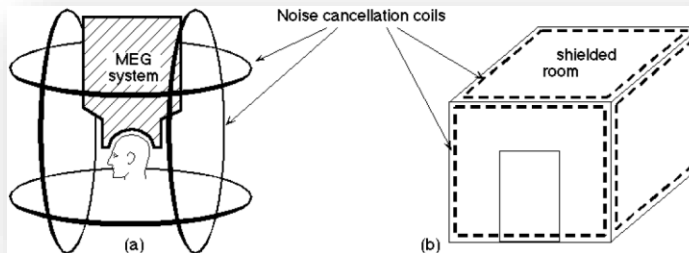
EEG electrode movement



MEG artifacts (and shielding)



magnetically shielded room (MSR)
built by David Cohen at MIT in 1969



MRI magnet

3 T

Earth field

10^{-5} T

Human brain

10^{-12} T

Common MEG artifacts

Power line noise, 50Hz equipment

Large metal objects moving outside the MSR

Car, trolley, elevator, the fan of airconditioning

Residual field of the earth

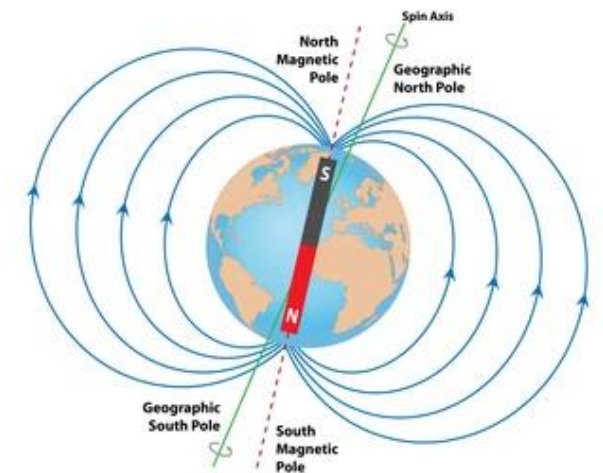
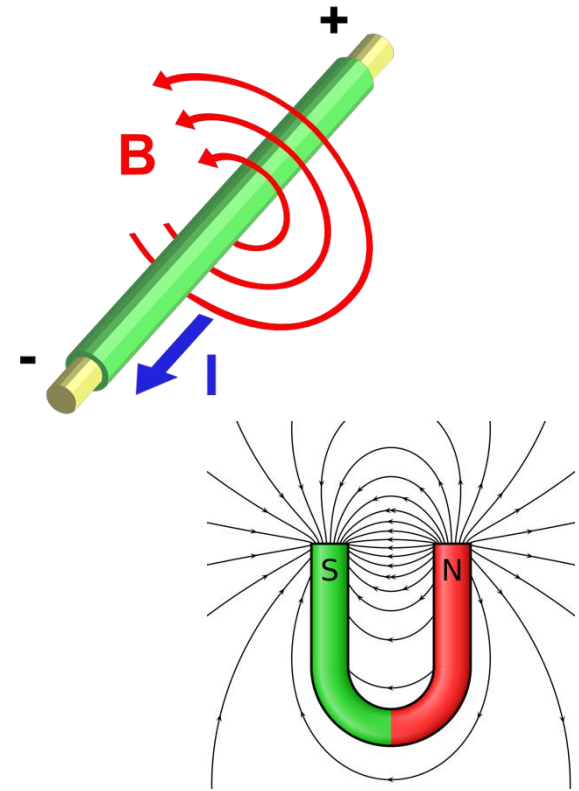
Building vibrations cause movements of the MSR walls and dewar

Other types of (physiological) bioelectricity

Muscle (EMG)

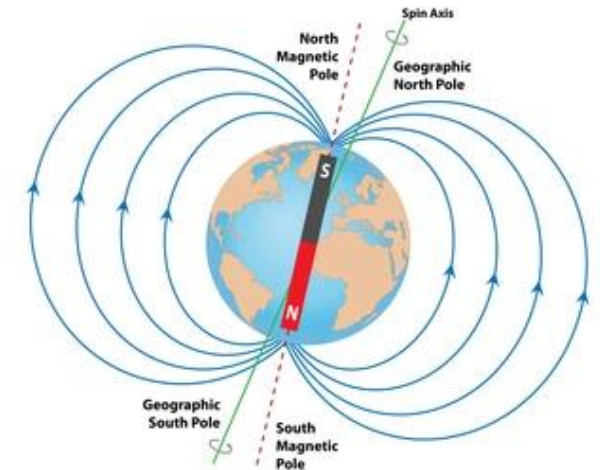
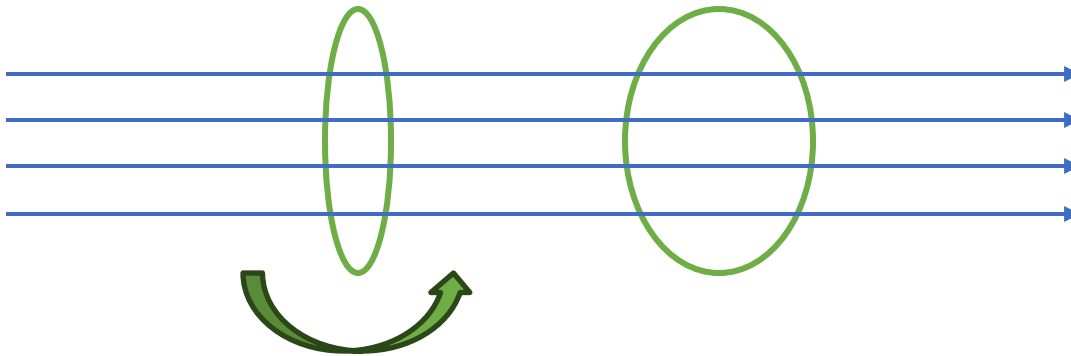
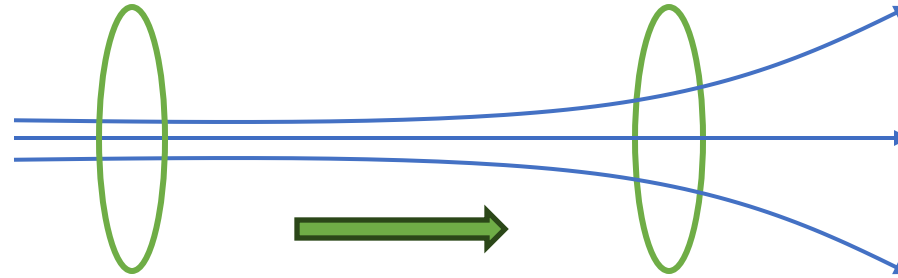
Heart (ECG)

Eye movements (EOG)



Movements in mobile MEG with OPMs

moving the sensor in the residual gradient or rotating the sensor in the residual field



EEG/MEG artifact removal

Identify and remove bad channels (or interpolate)

Identify and remove bad segments

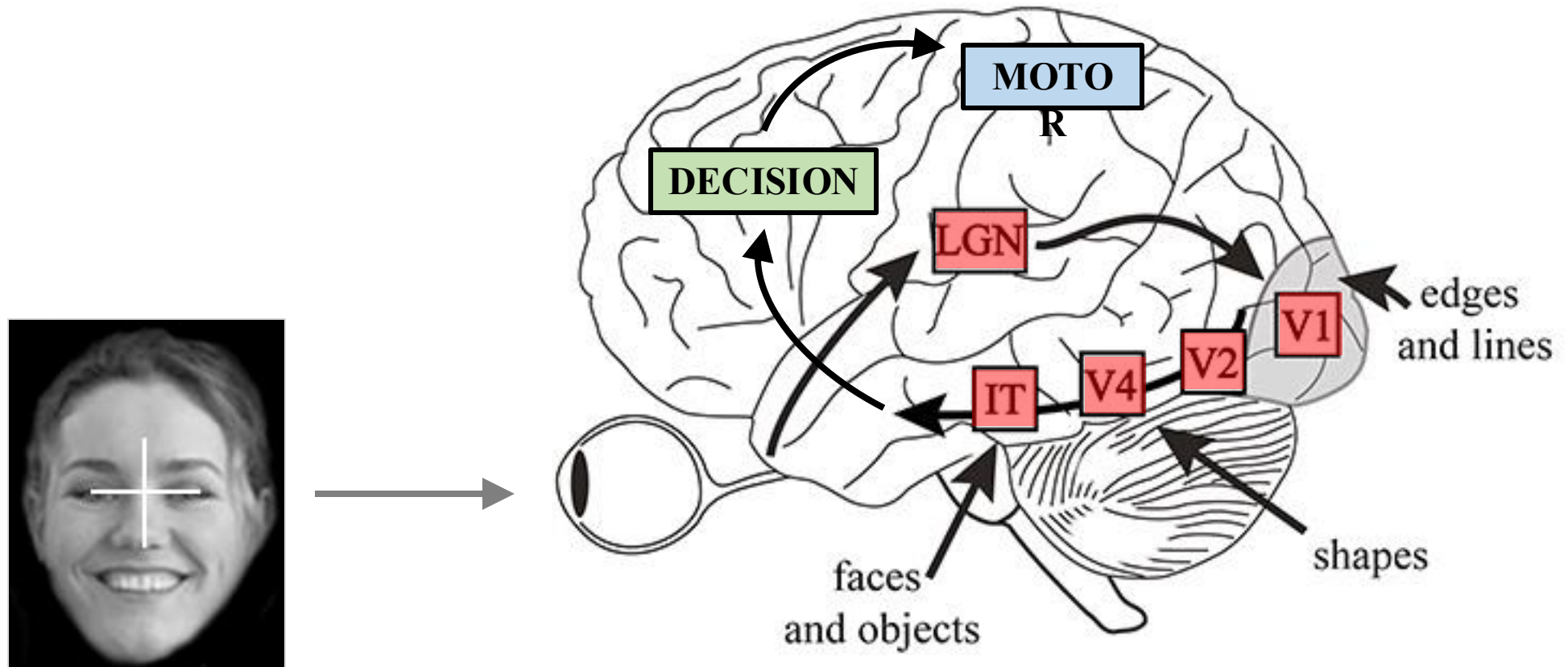
Continuous data

Segmented data, only the pieces of interest

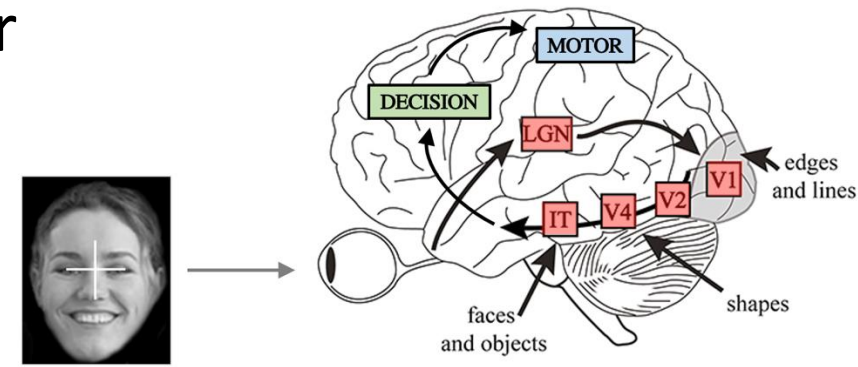
*Identify trials in which the **behavior was incorrect**
or in which the data **cannot be recovered**.*

The brain is a hierarchical functional network

both sequential and parallel processing, ff and fb



EEG/MEG to study perception, cognition and behavior



Our experimental task and behavioral readouts ensure that we are tapping in to the desired cognitive processes.

Infant EEG, baby looking away -> they did not see the stimulus

Participant blinks at the stimulus -> they did not see the stimulus

No response in stimulus-response task -> the stimulus was probably processed differently

Participant responds too slow -> a different cognitive process was interfering

The experimental task often involves attention monitoring, includes catch trials, or an extra condition with responses, these **behavioral responses (or artifacts)** need to be analyzed.

EEG/MEG data cleaning

*Only **after** rejecting data corresponding to bad behavior and broken data, we proceed to clean the remainder.*

The data is a spatio-temporal mixing of different sources.
Spatio-temporal models can separate brain and noise sources.

For EEG: ICA, PCA, IClabel, ASR, MARA, GEDAI

For MEG: 3rd order gradients, SSS/tSSS (Maxfilter), SSP, HFC, AMM, ICA

These are based on **data-driven** or **biophysical** models of the spatial distribution of the brain activity or the noise.

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Analyzing the brain activity in an event-related task

Signal-to-Noise-Ratio (SNR) is not sufficient to directly observe the brain responses

Stimulus or task is repeated many times (i.e. trials)

For example: one trial every 4 seconds, ~900 trials in one hour

Experimental manipulation is usually a subtle difference between trials

EEG/MEG response of interest is only about 1 second around the stimulus

So 1 hour recording results in only ~900 seconds of useable data

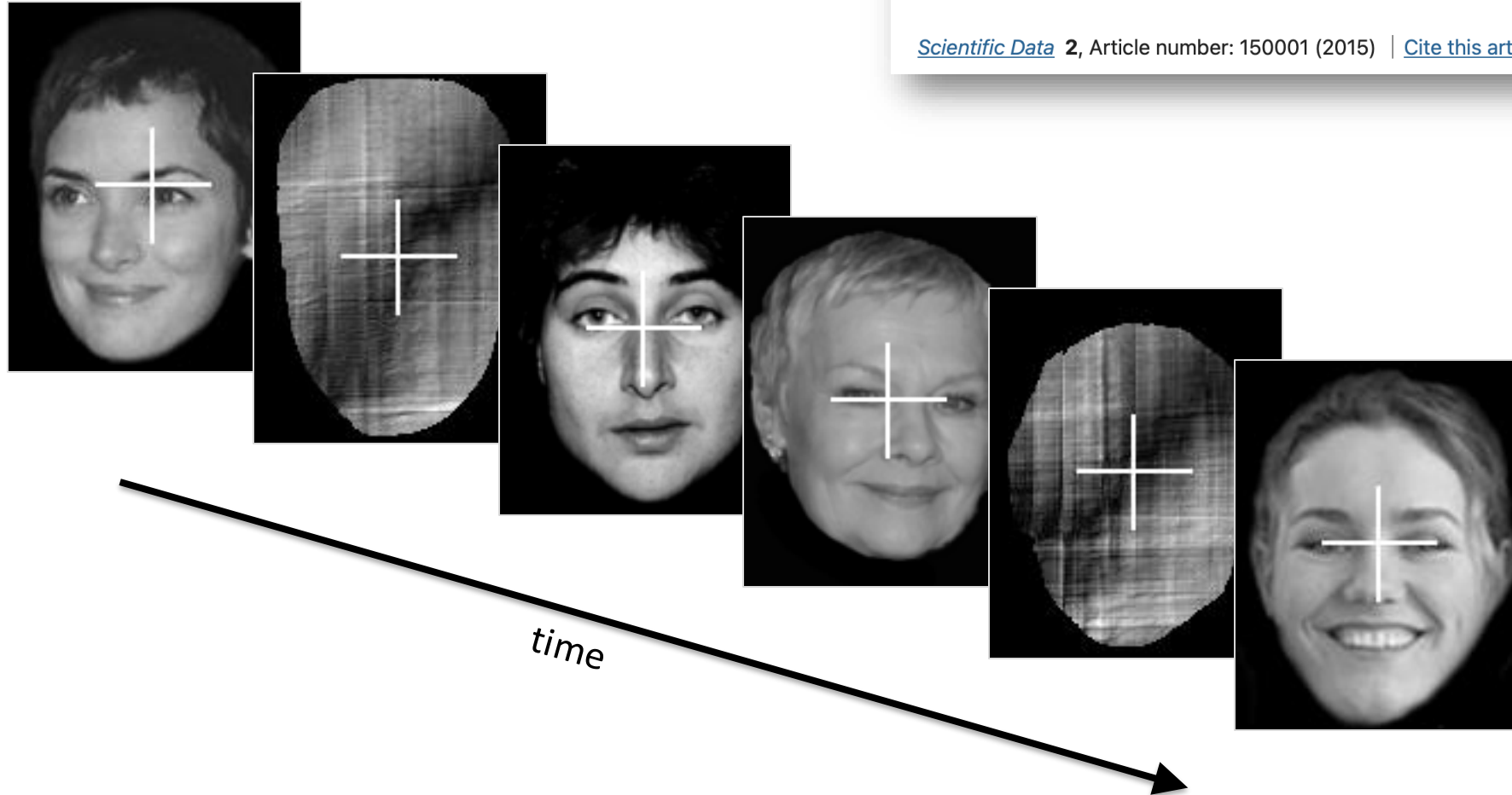
Analyzing the brain activity in an event-related task

Data Descriptor | [Open access](#) | Published: 20 January 2015

A multi-subject, multi-modal human neuroimaging dataset

[Daniel G Wakeman](#) ✉ & [Richard N Henson](#) ✉

[Scientific Data](#) 2, Article number: 150001 (2015) | [Cite this article](#)



<http://doi.org/10.1038/sdata.2015.1>

Analyzing the brain activity in an event-related task

900 trials

900 times a picture of “something”

900 trials

600 faces

300 unfamiliar

300 familiar (i.e., celebrities)

300 scrambled faces

900 trials

150 unfamiliar faces 1st time, 150 unfamiliar faces 2nd time

150 familiar faces 1st time, 150 familiar faces 2nd time

150 scrambled faces 1st, 150 scrambled 2nd time

	<i>1st presentation</i>	<i>2nd presentation</i>
<i>unfamiliar</i>	150	150
<i>familiar</i>	150	150
<i>scrambled</i>	150	150

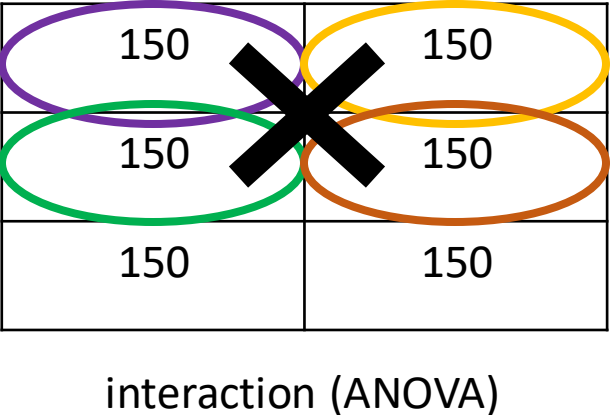
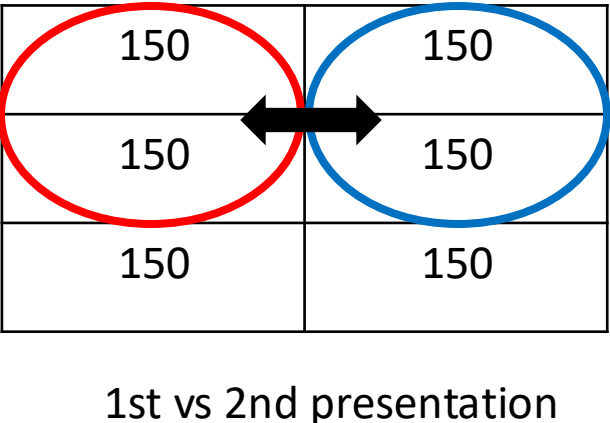
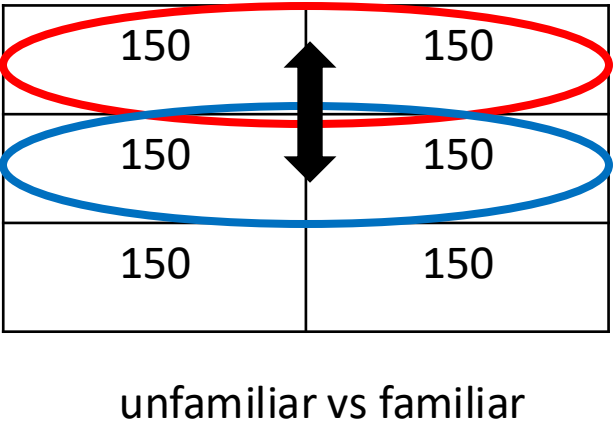
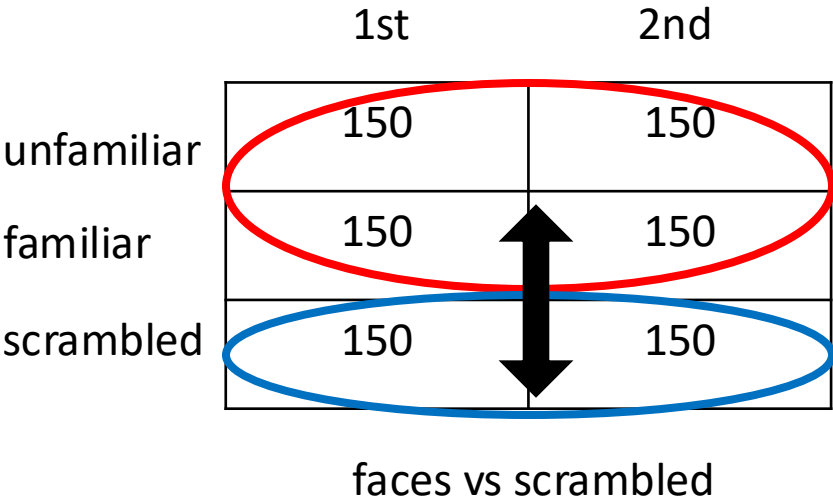
Also other dimensions: gender, emotional expression, gaze direction, ...

Analyzing the brain activity in an event-related task

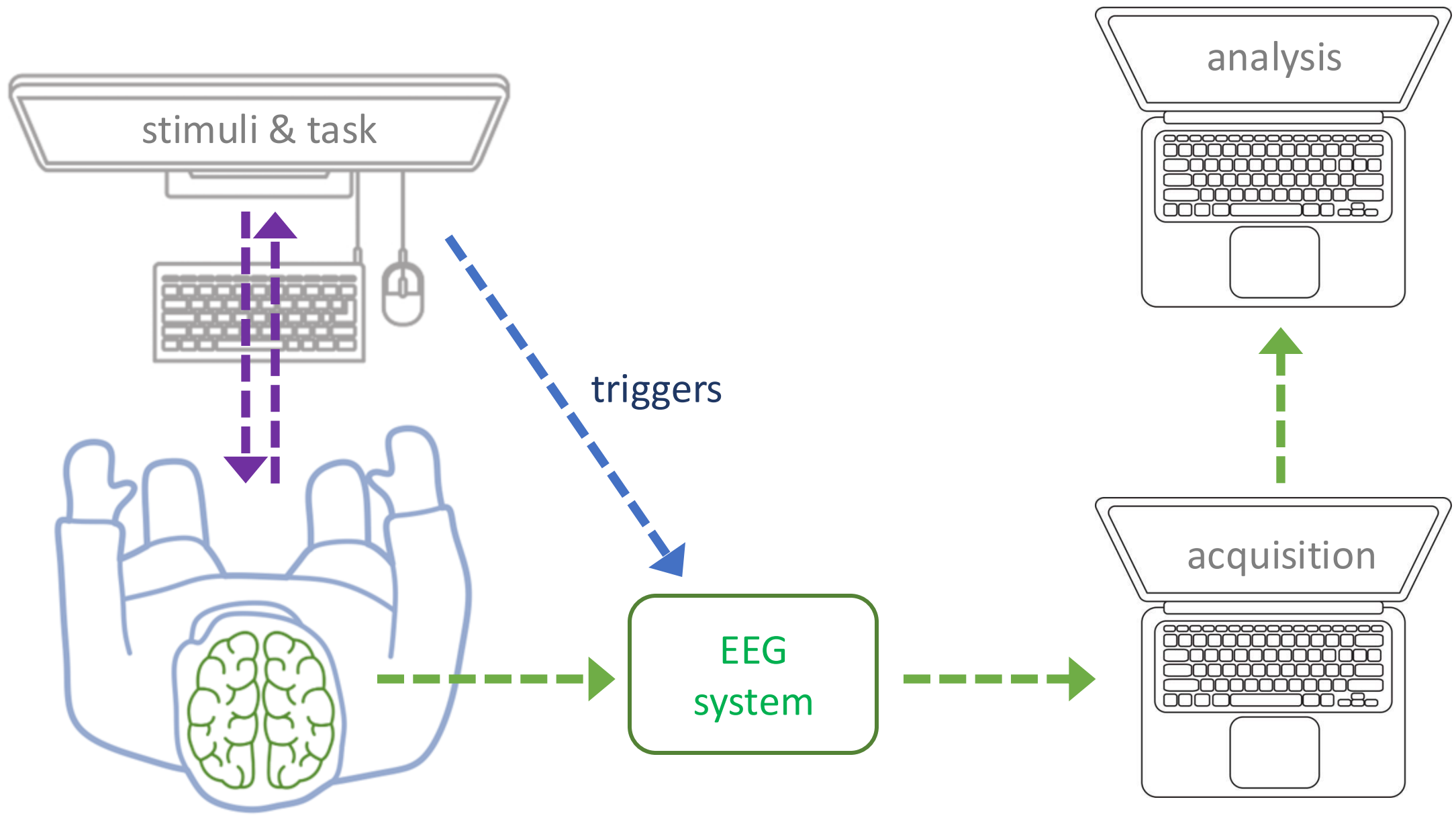
Multi-factorial design:

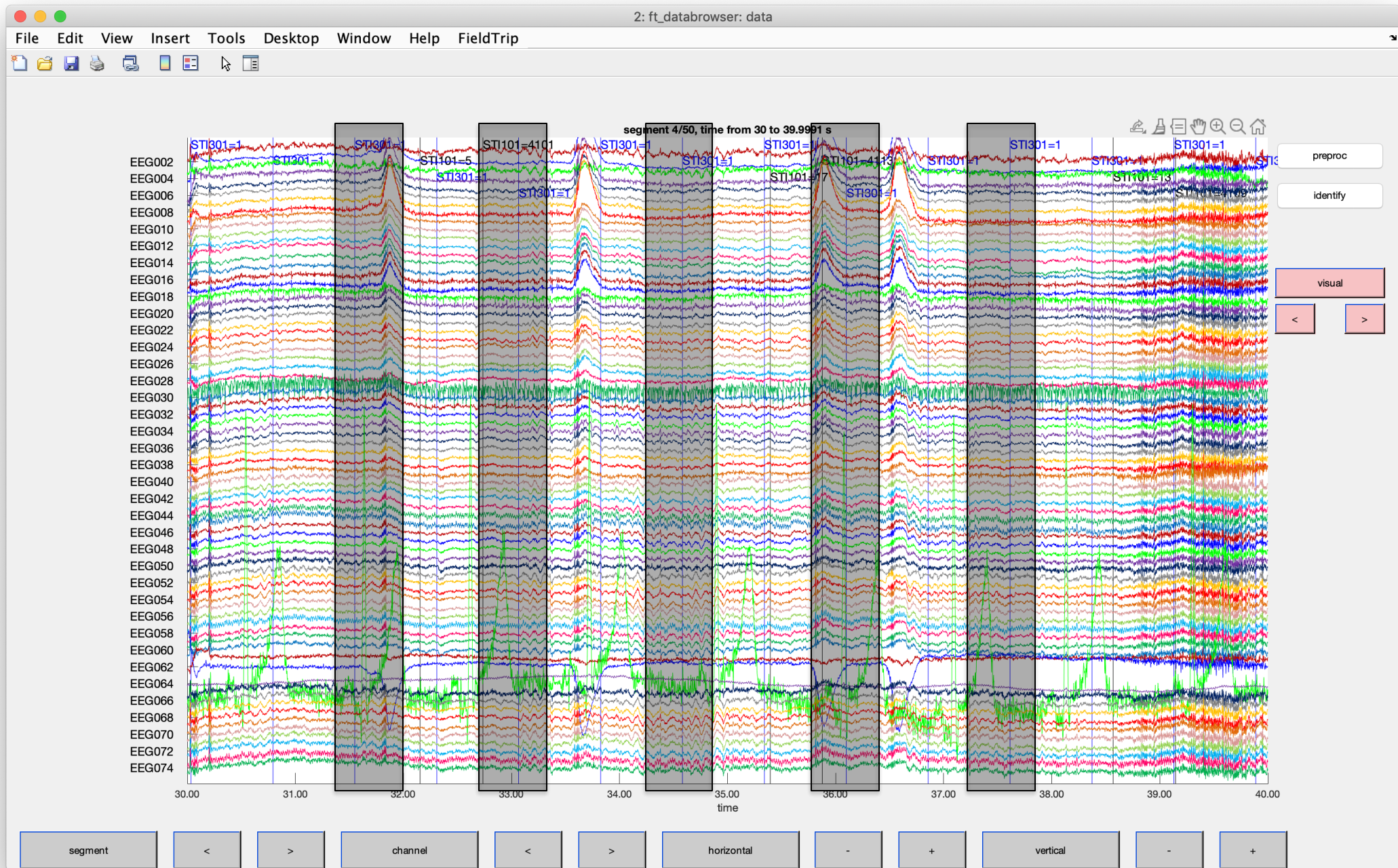
stimulus × presentation × gender × emotional expression × gaze direction × ...

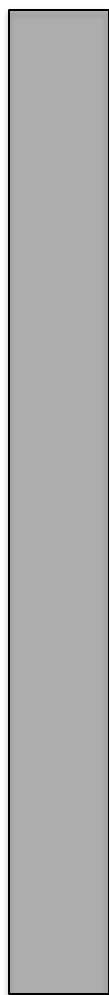
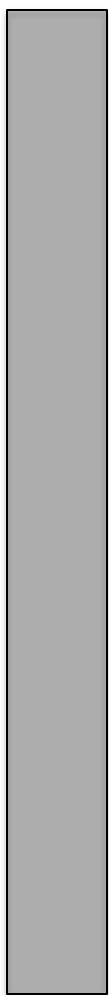
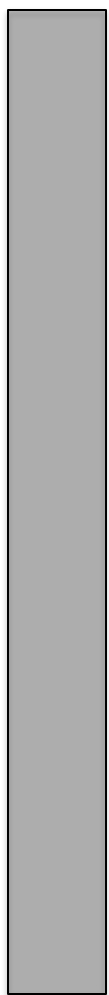
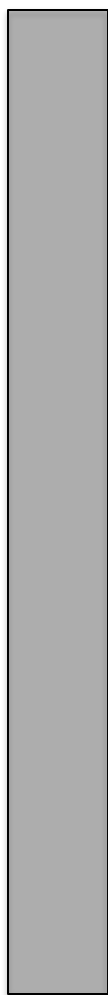
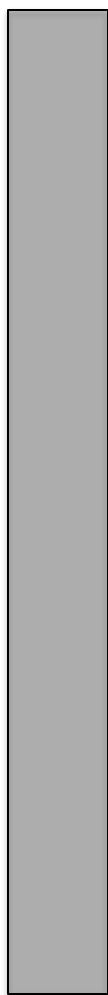
Analyzing the brain activity in an event-related task

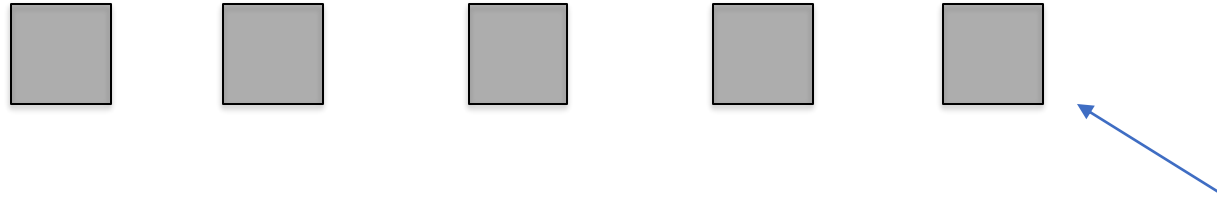












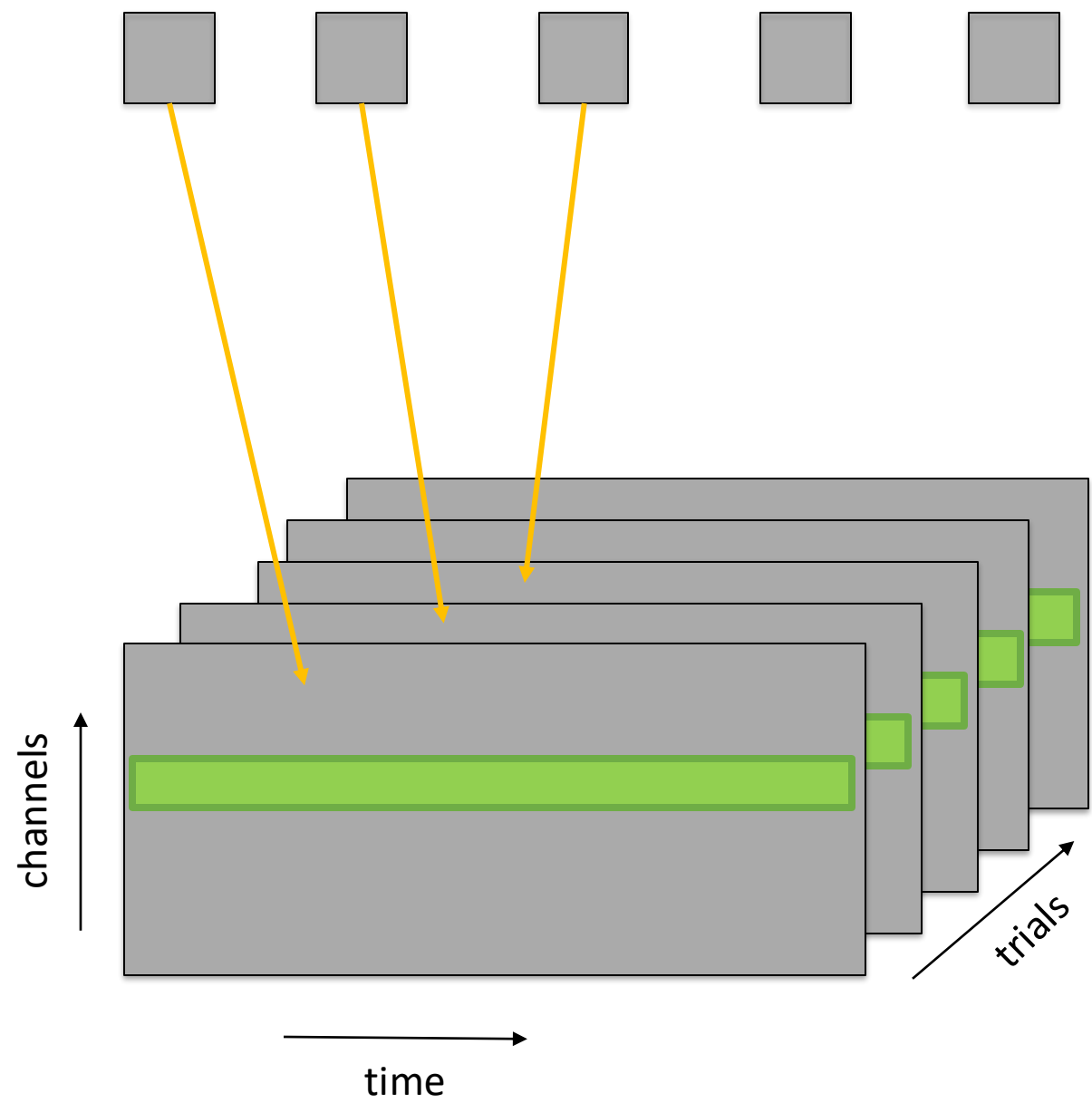
~900 trials

~64 channels

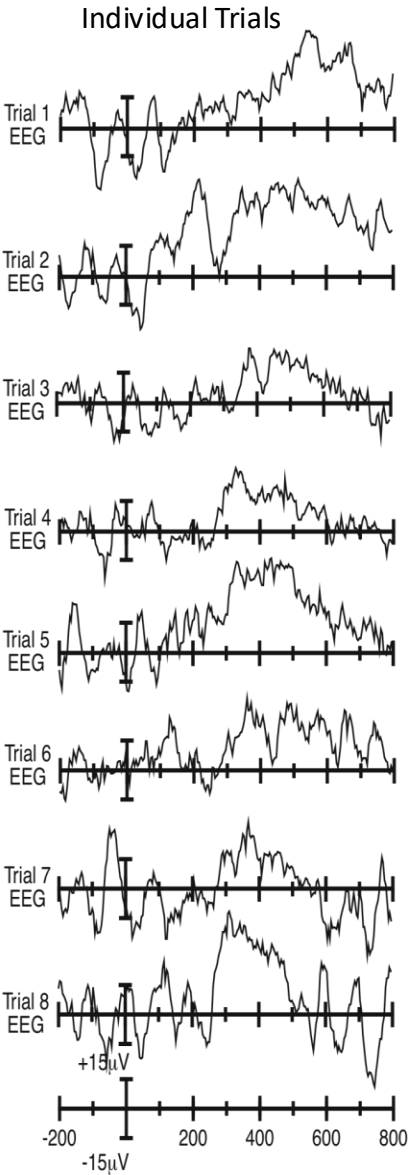
~ 1 second = 1100 samples

So $900 \times 64 \times 1100 = 63.000.000$ numbers

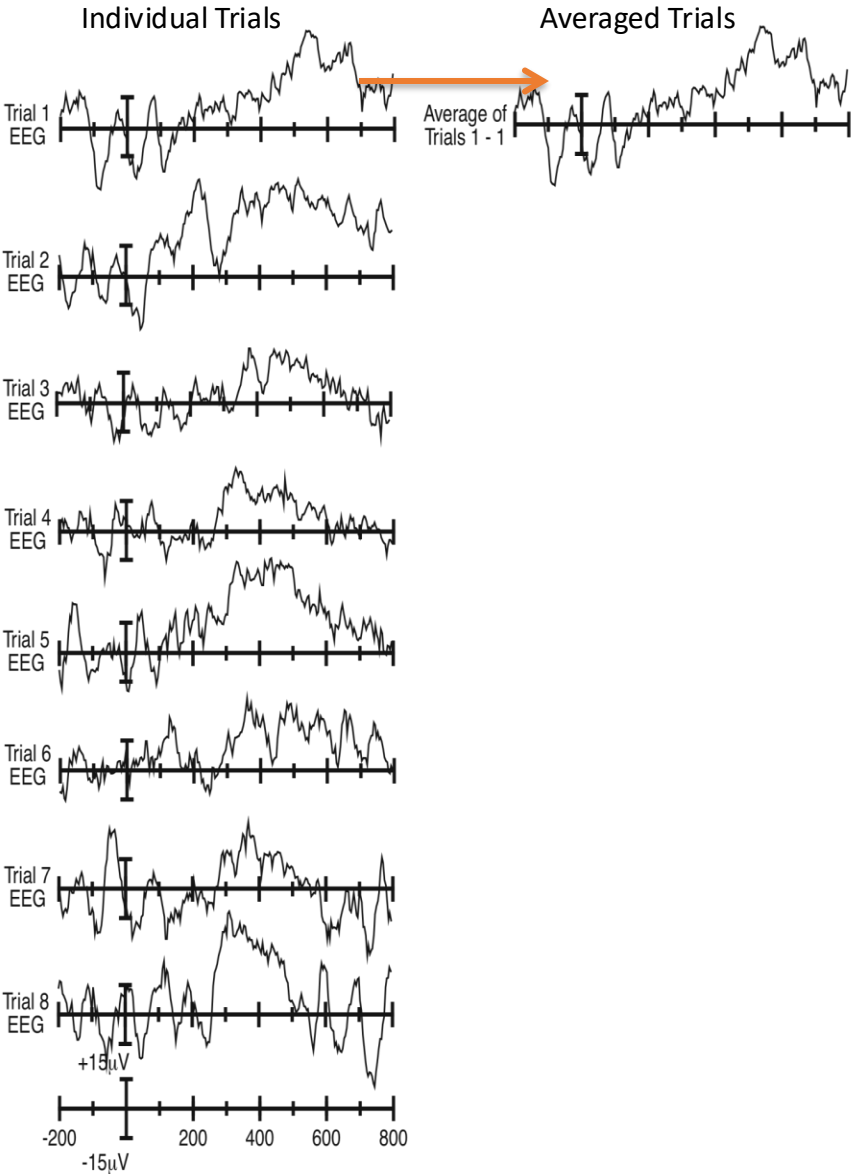
... times 16 subjects



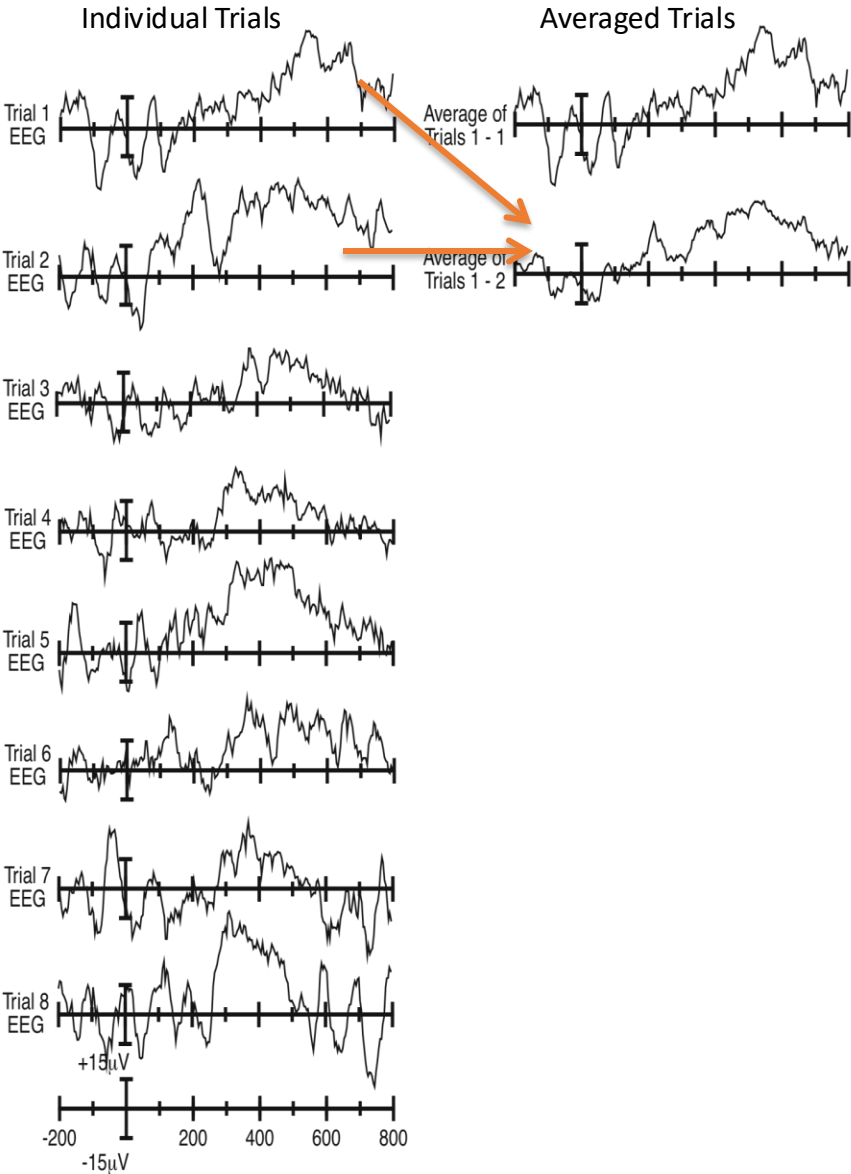
Event-Related Potential ERP



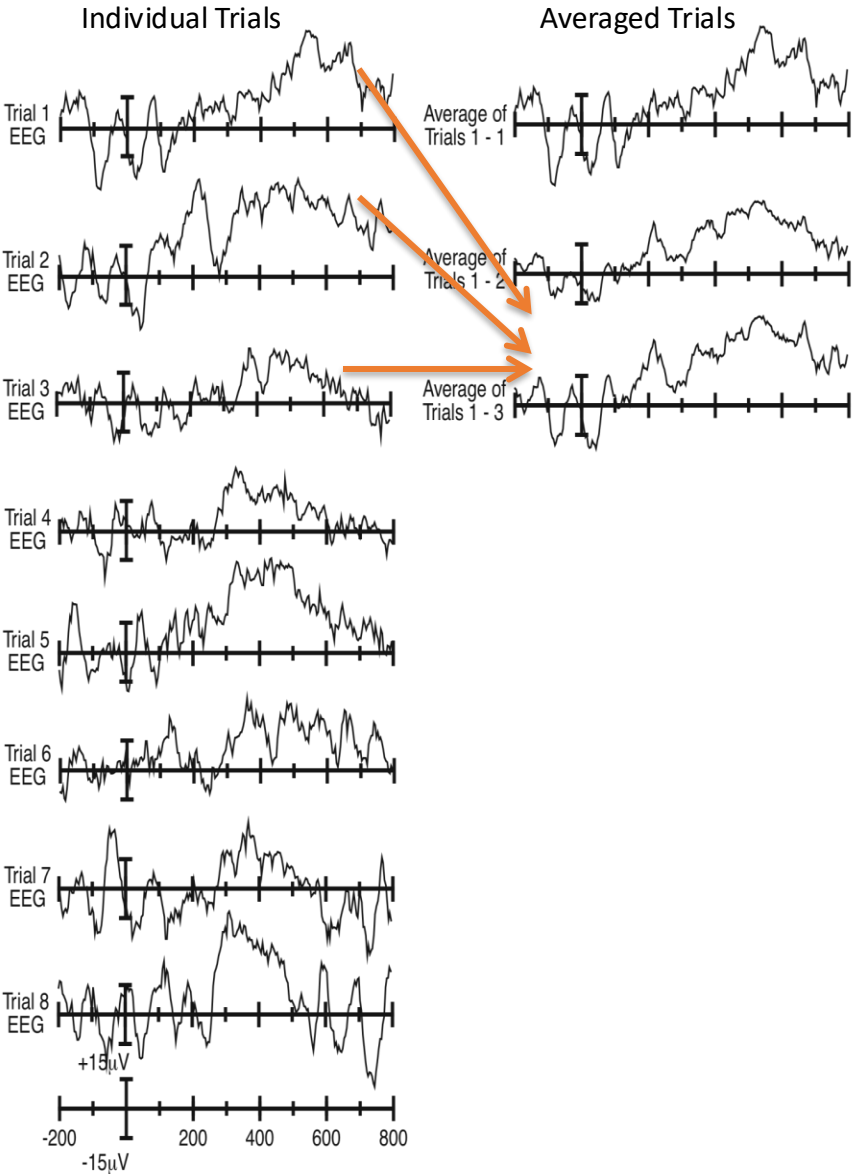
Event-Related Potential ERP



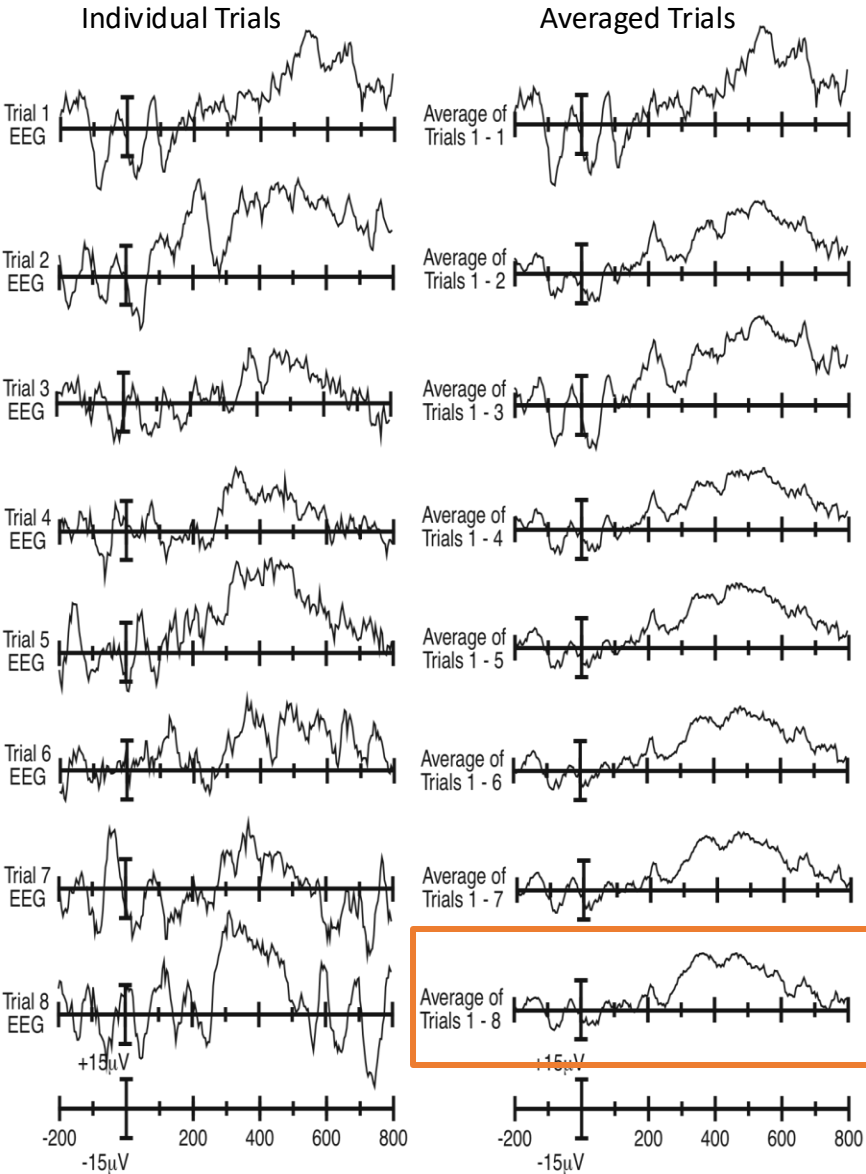
Event-Related Potential ERP



Event-Related Potential ERP



Event-Related Potential ERP



Event-Related Potential ERP

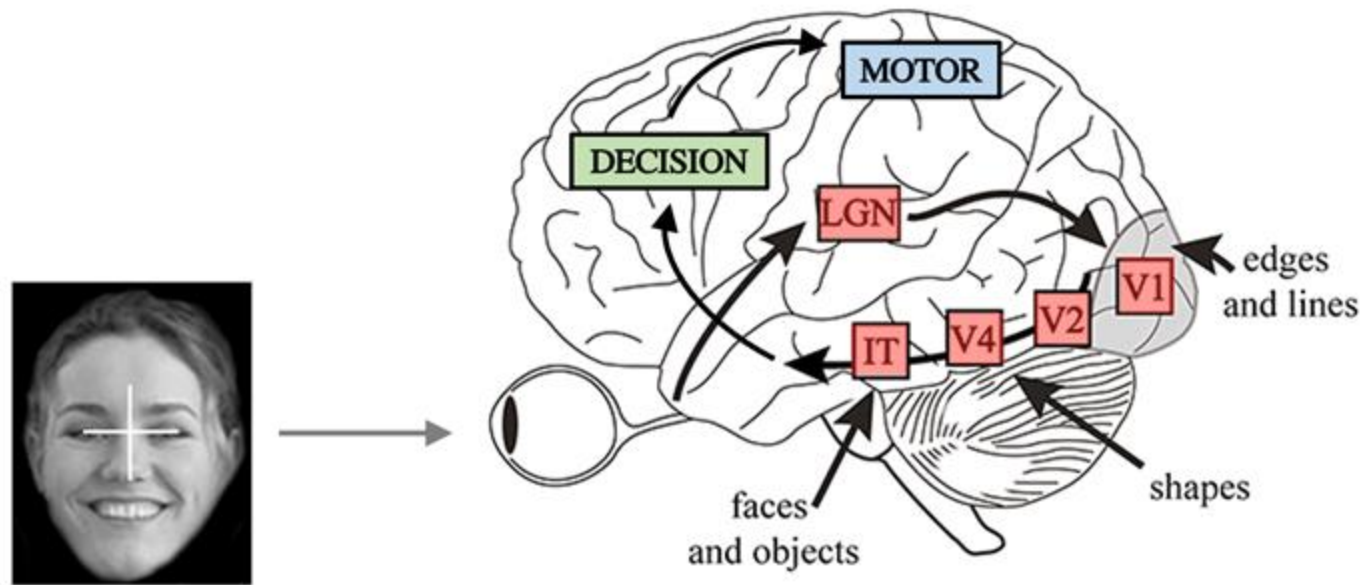
The brain ***signal*** of interest is assumed to be constant over all trials.
The ***noise*** is independent over trials.

After averaging the noise is proportional to $1/\sqrt{N_{\text{trials}}}$.

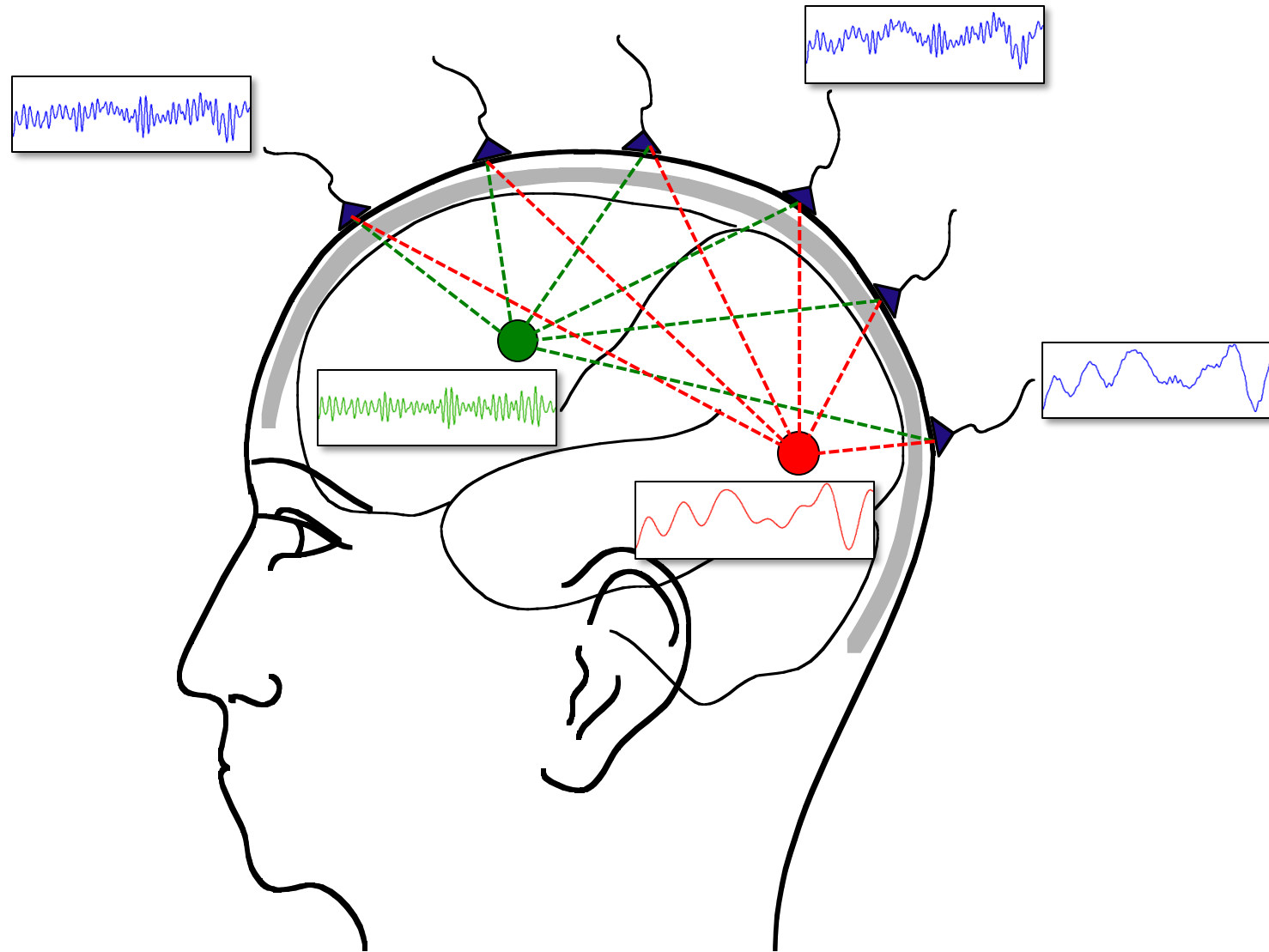
Averaging over trials improves the signal-to-noise ratio (SNR).

10 trials	-> SNR is $\sqrt{10}$	$\cong 3x$ better
100 trials	-> SNR is $\sqrt{100}$	$\cong 10x$ better

Linear model for ERP superposition



Linear model for ERP superposition



Linear model for ERP superposition

$$\text{Data} = \text{signal} + \text{noise}$$

Related to the task, constant over trials

$$\text{Data in condition 1} = \text{signal}_1 + \text{noise}$$

Not related to the task

$$\text{Data in condition 2} = \text{signal}_2 + \text{noise}$$

$$\text{ERP}_1 = \text{average}(\text{Data in condition 1}) = \text{signal}_1 + \text{noise}$$

$$\text{ERP}_2 = \text{average}(\text{Data in condition 2}) = \text{signal}_2 + \text{noise}$$

$$\text{ERP}_1 - \text{ERP}_2 = \text{signal}_1 - \text{signal}_2 + \text{noise}$$

Linear model for ERP superposition

Data = signal + noise

Data in condition 1 = visual + recognition₁ + noise

Data in condition 2 = visual + recognition₂ + noise

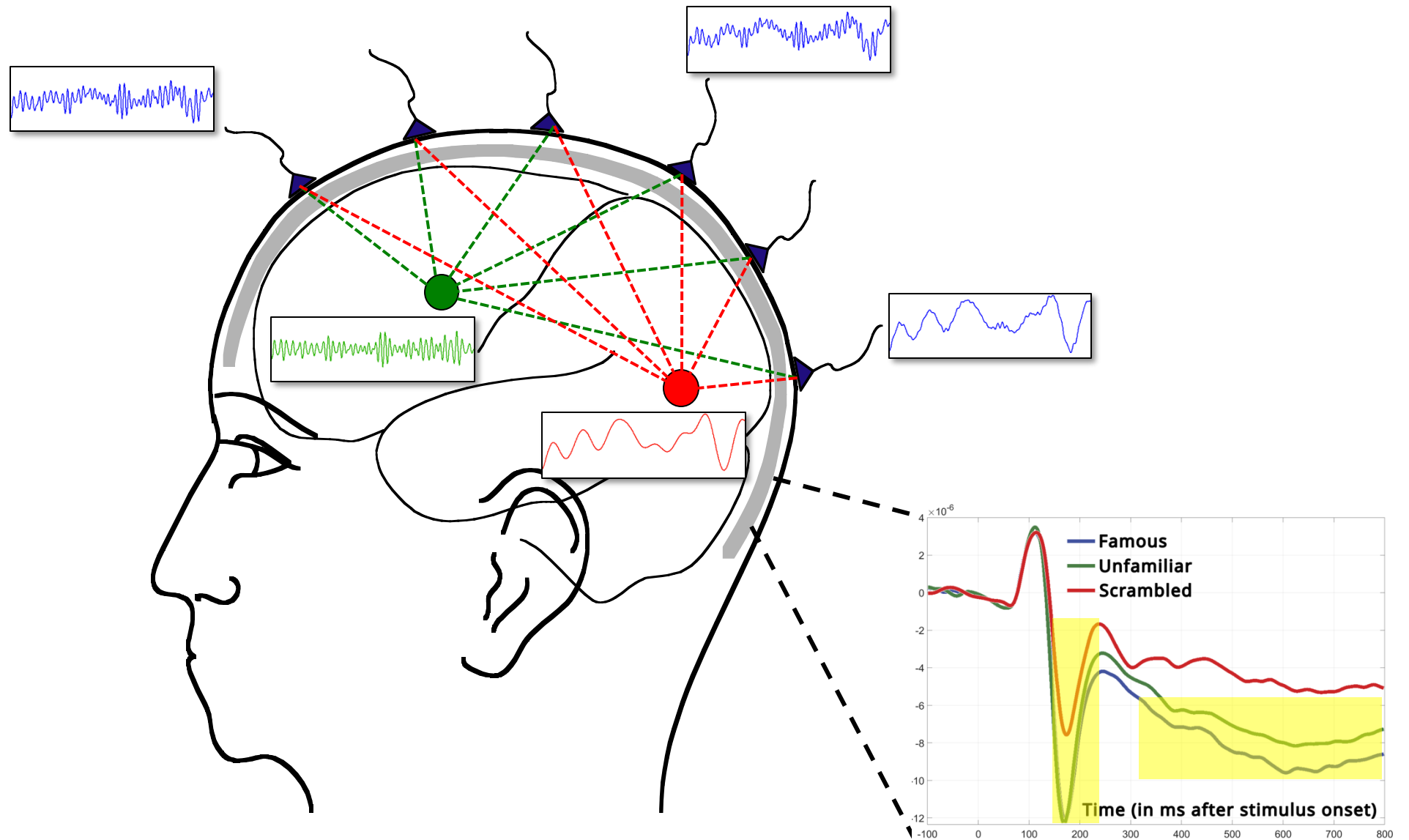
ERP₁ = average(Data in condition 1) = visual + recognition₁ + noise

ERP₂ = average(Data in condition 2) = visual + recognition₂ + noise

ERP₁ - ERP₂ = recognition₁ - recognition₂ + noise

ERP difference to tap into specific cognitive process

followed by statistics, etc.



Get to know your data – learning goals

What are the characteristics of the data that we use in the analysis?

How to organize your raw data?

Quality assessment and control

What are the artifacts and why are they relevant?

Preprocessing and segmenting (or vice versa)

Selective averaging to get ERPs/ERFs



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Get to know your data artifacts, segmentation, preprocessing



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shared slides

