

# Neural Signal Processing: From Single Neurons to fMRI

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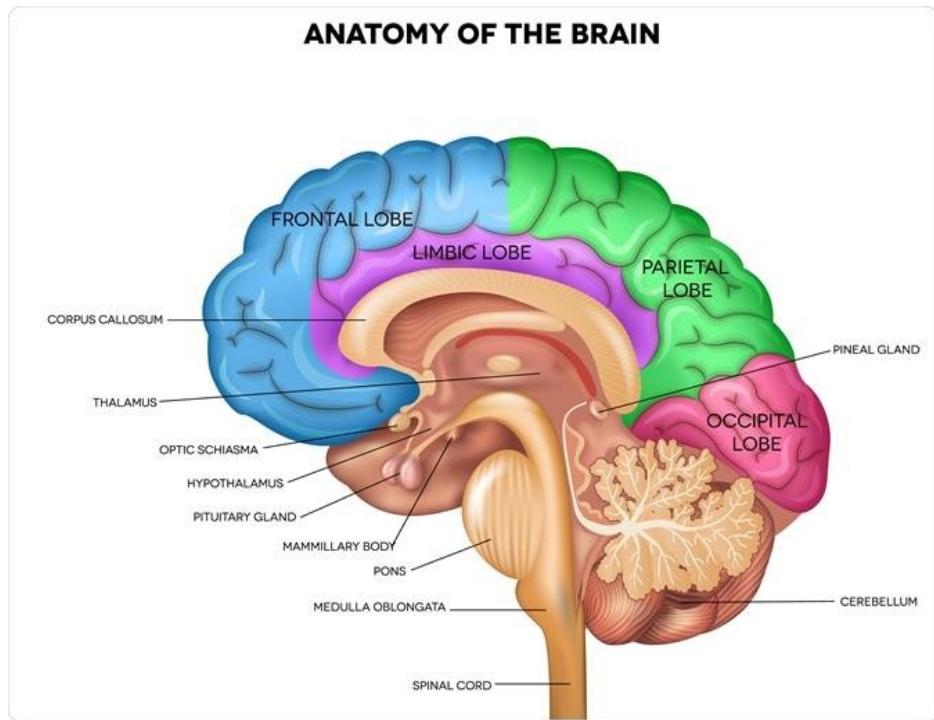


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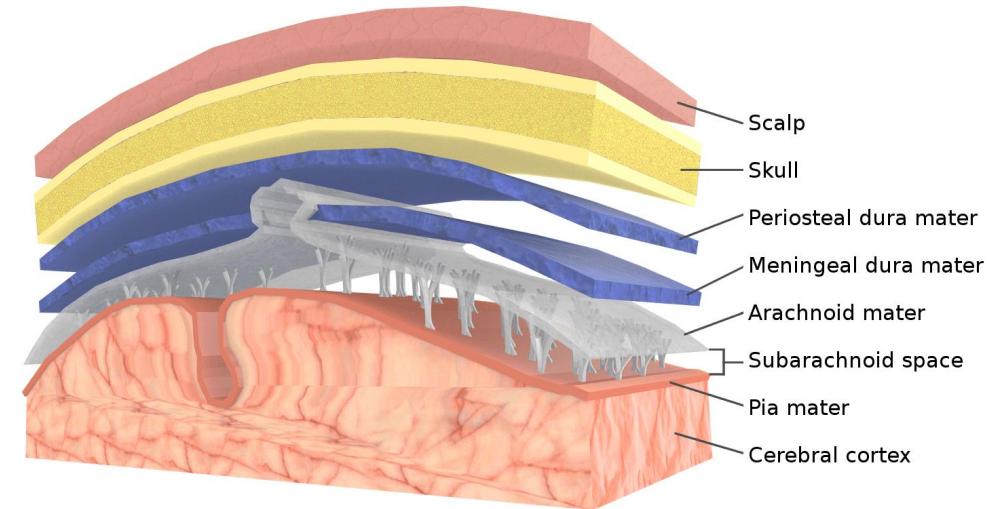


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# Measuring Brain Activity



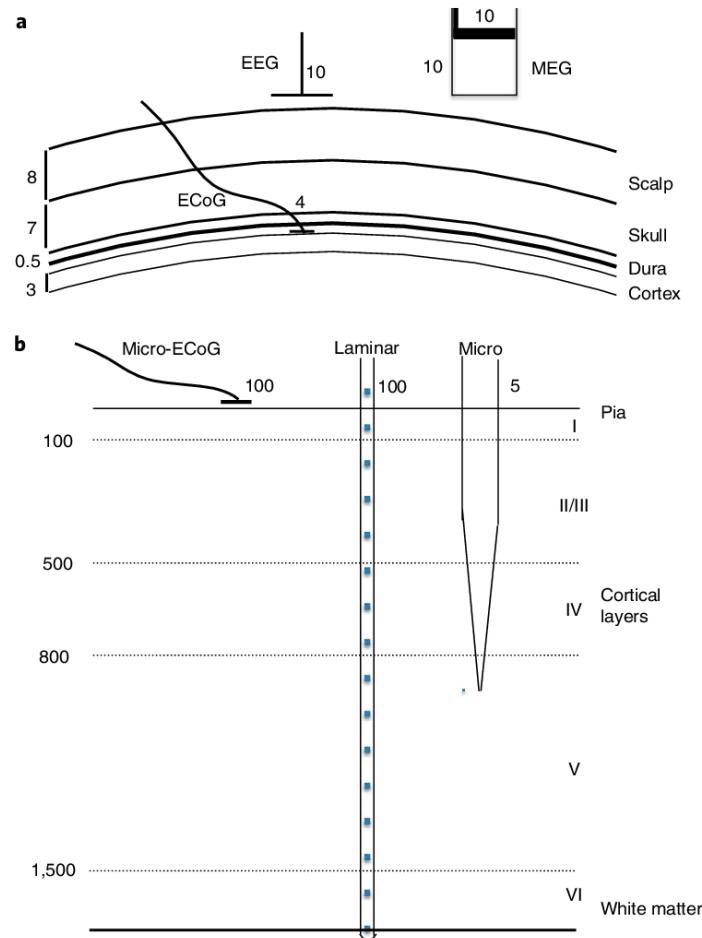
<https://www.news-medical.net/health/The-Anatomy-of-the-Human-Brain.aspx>



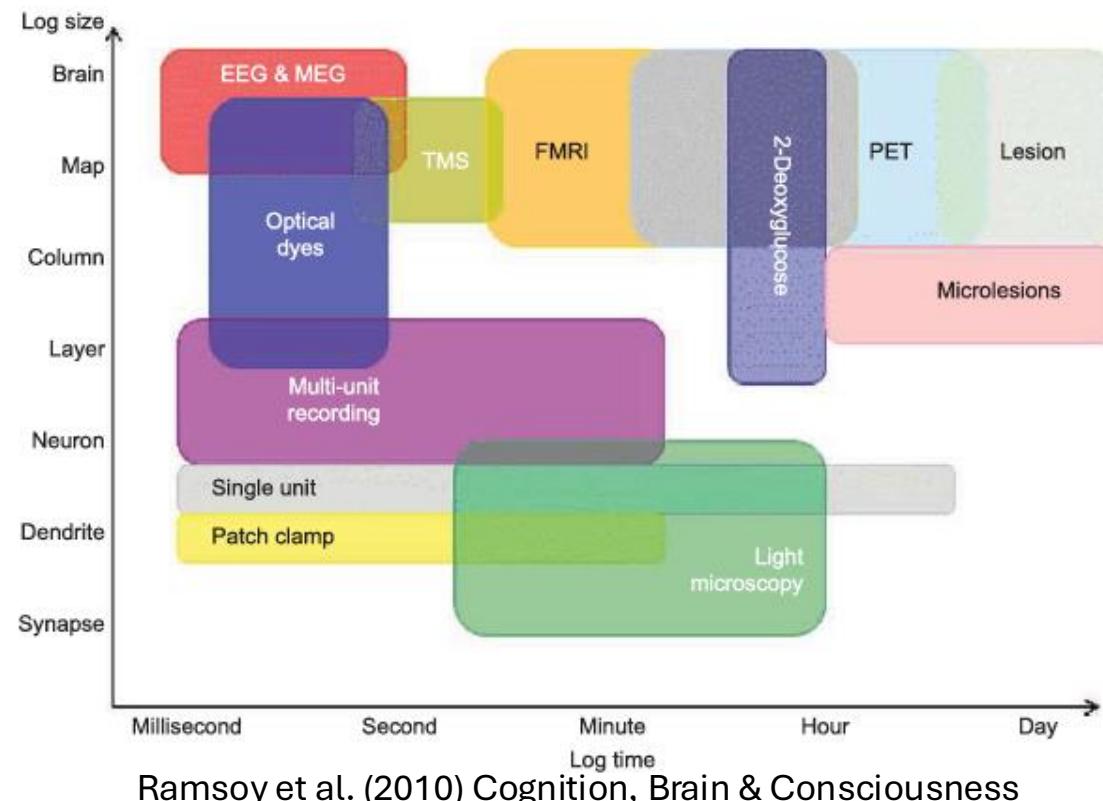
<https://www.thoughtco.com/brain-anatomy-meninges-4018883>

EIB 2016

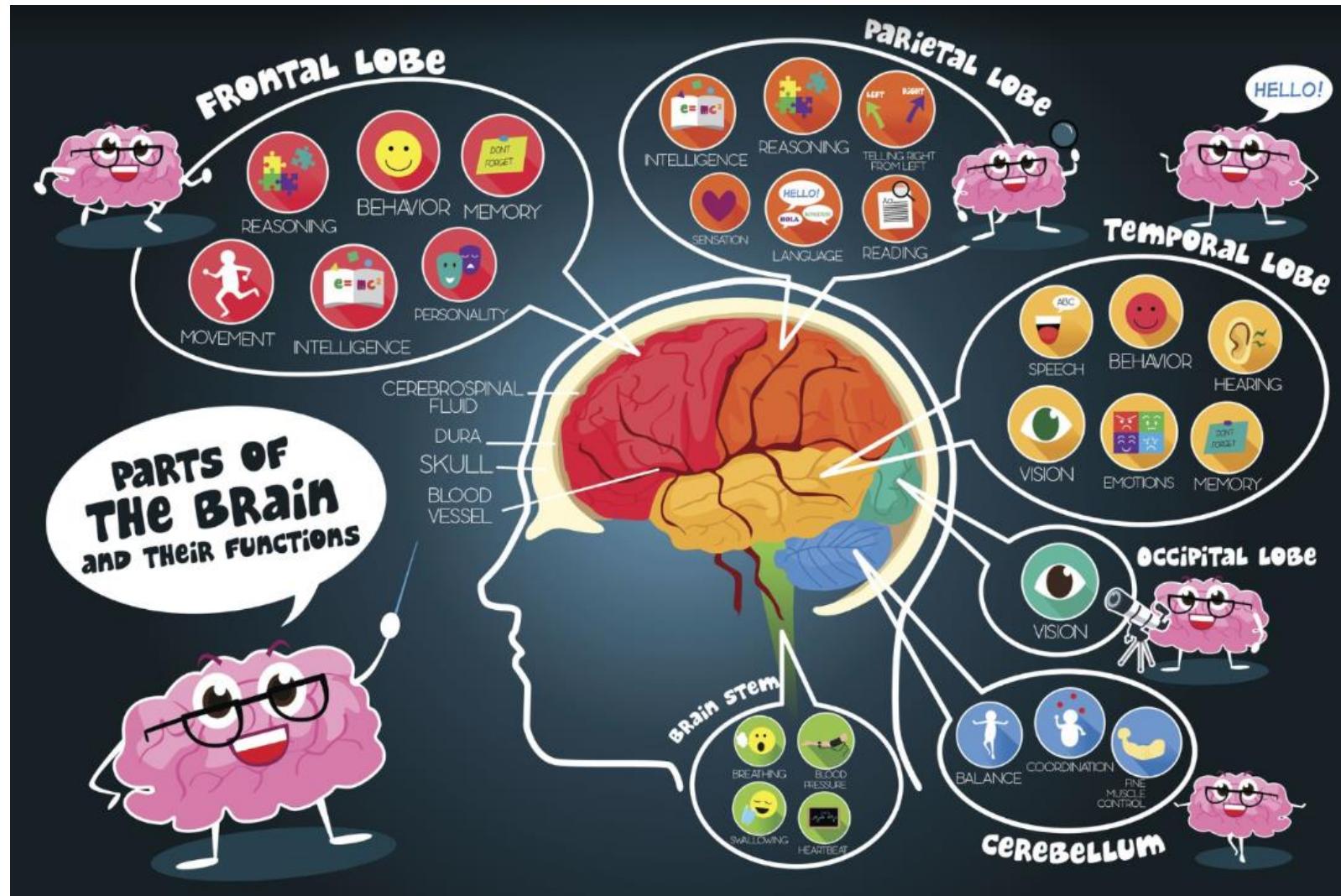
# Measuring Brain Activity



Pesaran (2018) Nature Neuroscience



# Why Measure Brain Activity?

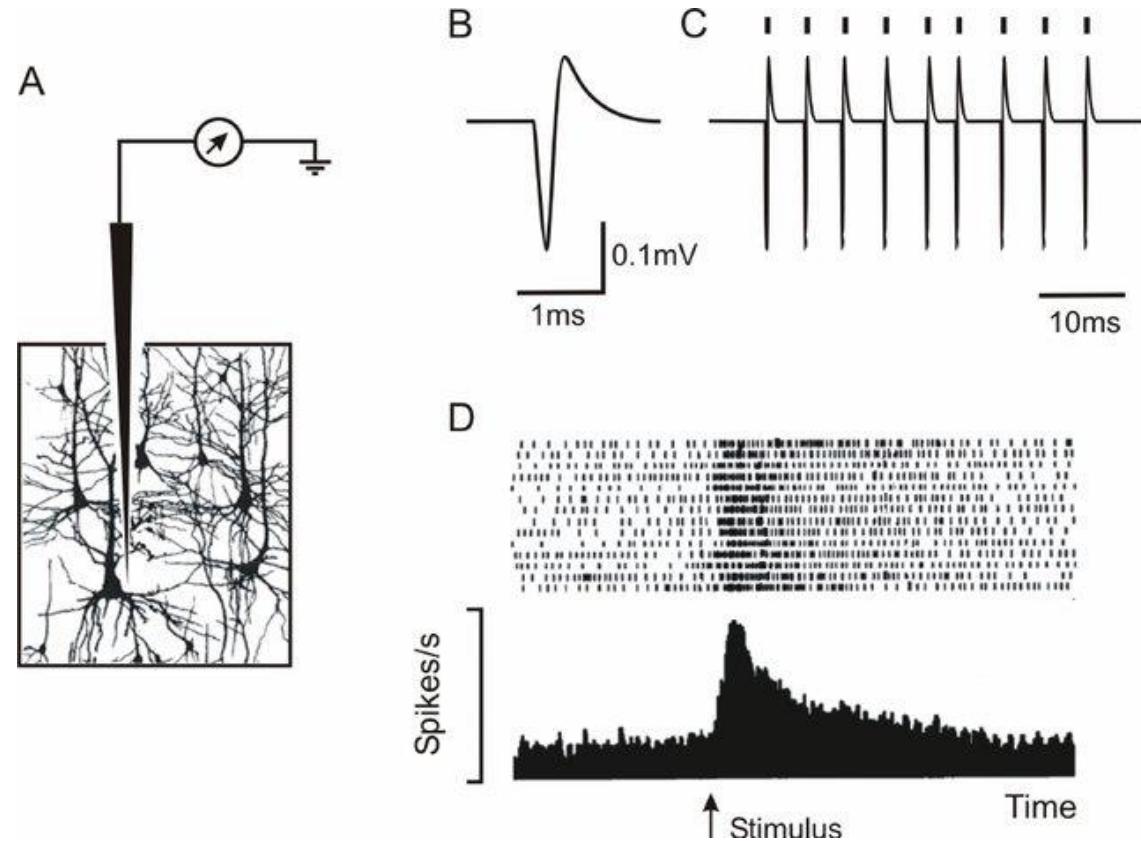


# In the first 90 minutes...

- Different Recordings – Single/Multi-Unit Recording to Functional MRI
- Common Pre-processing Approach
- Common Signal Processing and Analysis Approaches

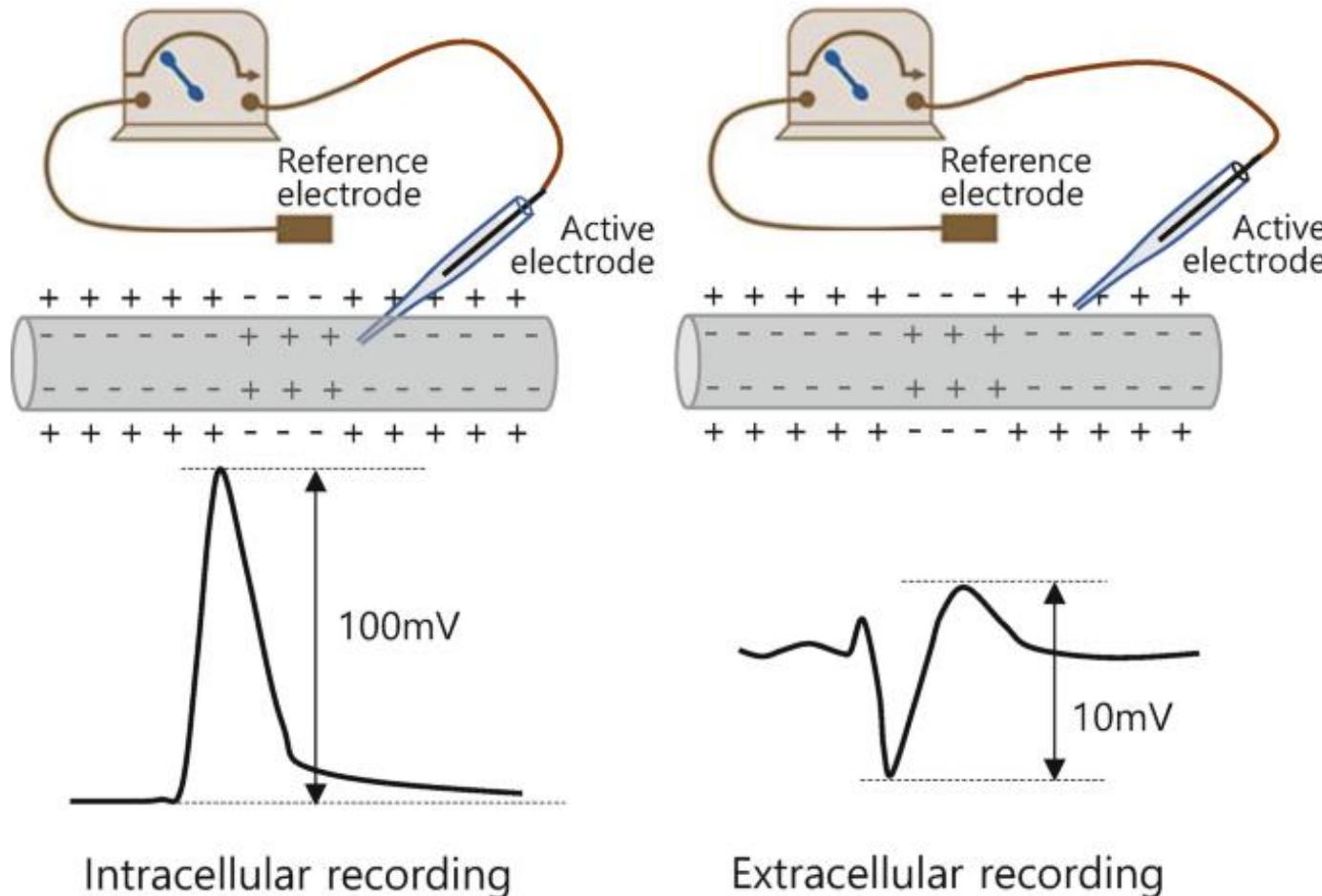
# Single-unit Recording

- It is the use of an electrode to record the electrophysiological activity (action potentials) from a single neuron.
- An electrode introduced into the brain will detect electrical activity that is generated by the neurons adjacent to the electrode tip. If the electrode is a microelectrode, with a tip size of 3 to 10 micrometres, the electrode will often isolate the activity of a single neuron.
- The activity consists of the voltages generated in the extracellular matrix by the current fields outside the cell when it generates an action potential. Recording in this way is generally called "single-unit" recording.



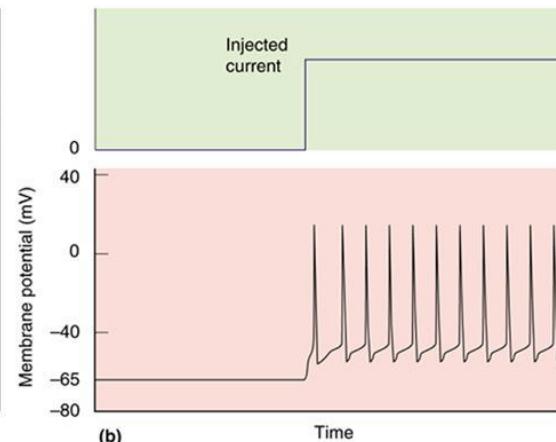
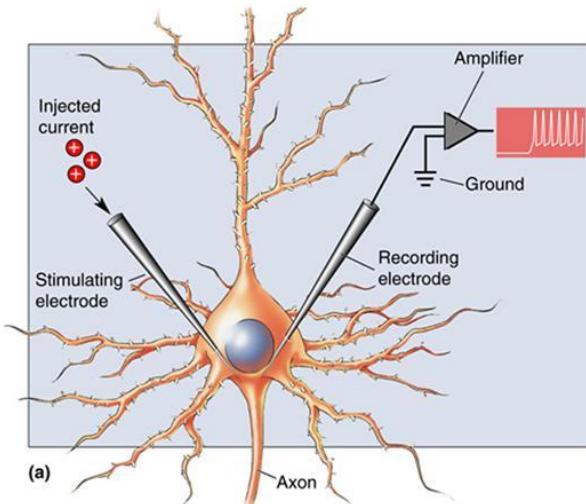
Ludvig (2011) Computational Neuroscience for Advancing Artificial Intelligence: Models, Methods and Applications

# Intracellular & Extracellular Recording



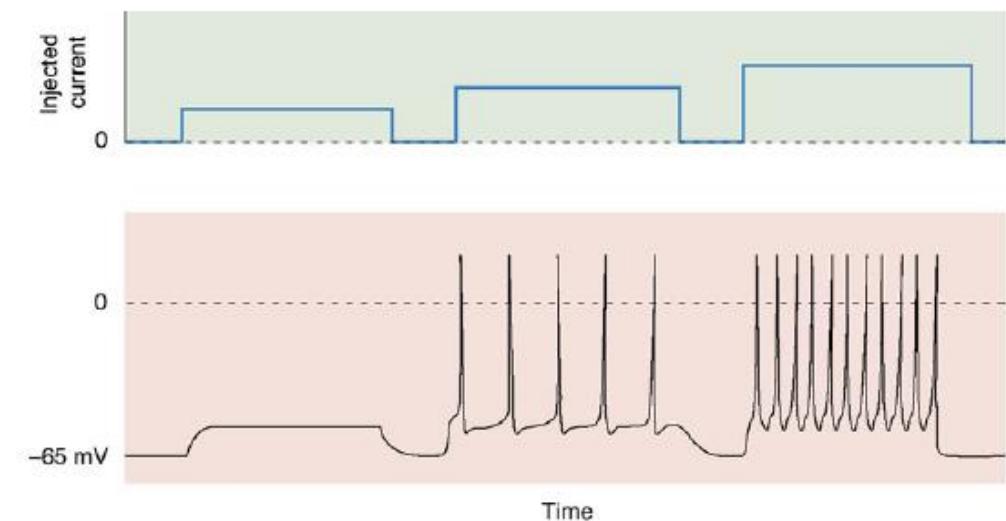
# Measuring Action Potentials

Artificially inject current into a neuron with microelectrode



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- **Firing frequency** reflects the magnitude of the depolarizing current



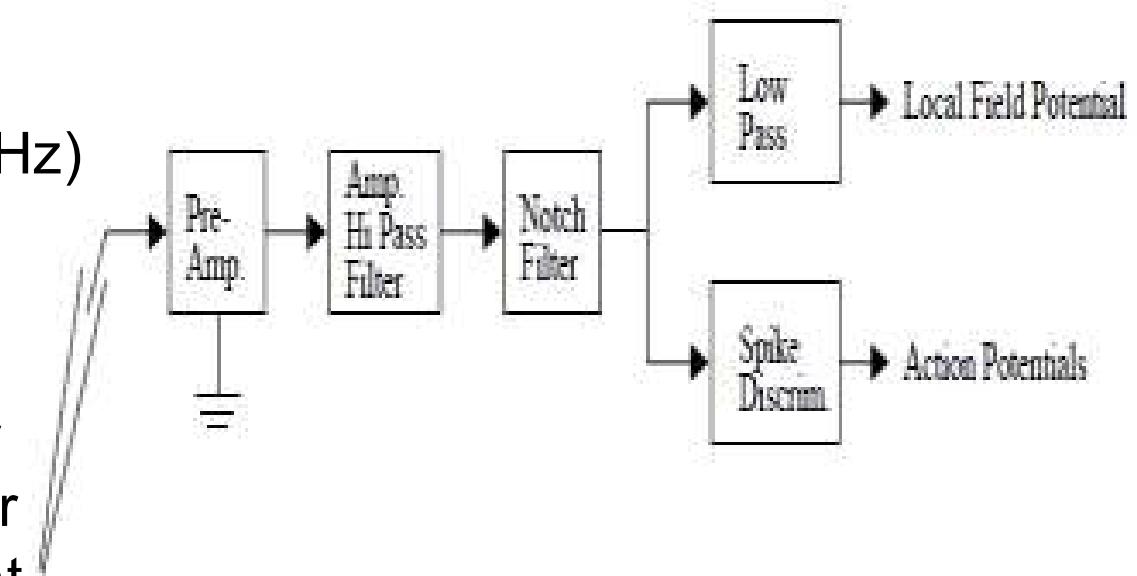
If injected current does not depolarize the membrane to threshold, no action potentials will be generated.

If injected current depolarizes the membrane beyond threshold, action potentials will be generated.

The action potential firing rate increases as the depolarizing current increases.

# Local Field Potential

- Neural recordings from intracortical extracellular microelectrodes.
- Two components super-imposed:
  - Action potential/Spikes (300Hz – 5kHz)
  - Slow Varying Field Potential (1Hz – 250Hz)
- Represents the summation of excitatory and inhibitory dendritic signals and other types of slow activity (voltage dependant membrane oscillations or spike after-potentials)



# Frequency Spectrum

- **5-50 µV**, mostly below 30 µV
- Sharp spike-waves, **light sleep** stages

Beta ( $\beta$ ) 13-30 Hz

Frontally and  
parietally



- **5-120 µV**, mostly below 50 µV
- **Awake**, eyes closed, mental inactivity,  
physical relaxation

Alpha ( $\alpha$ ) 8-13 Hz

Occipitally



- **20-200 µV**
- Strictly rhythmic or highly irregular
- Awake & drowsiness, **light sleep** stages
- LTP and phase-encoding

Theta ( $\theta$ ) 4-8 Hz

Children,  
sleeping adults



- **5-250 µV**
- Abnormality in waking adults,  
accompaniment of **deep sleep**

Delta ( $\delta$ ) 0.5-4 Hz

Infants,  
sleeping adults



+ Gamma waves?  
**31-100 Hz, 10 µV**

'binding of  
consciousness',  
unity of perception

Spikes

Epilepsy -

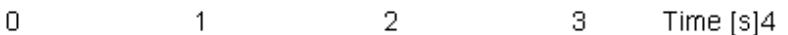
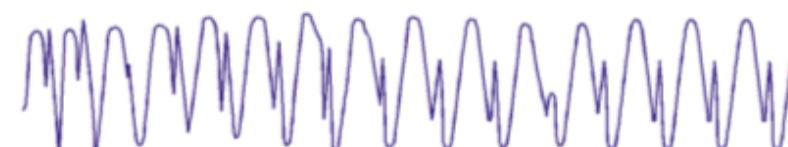
petit mal

3 Hz

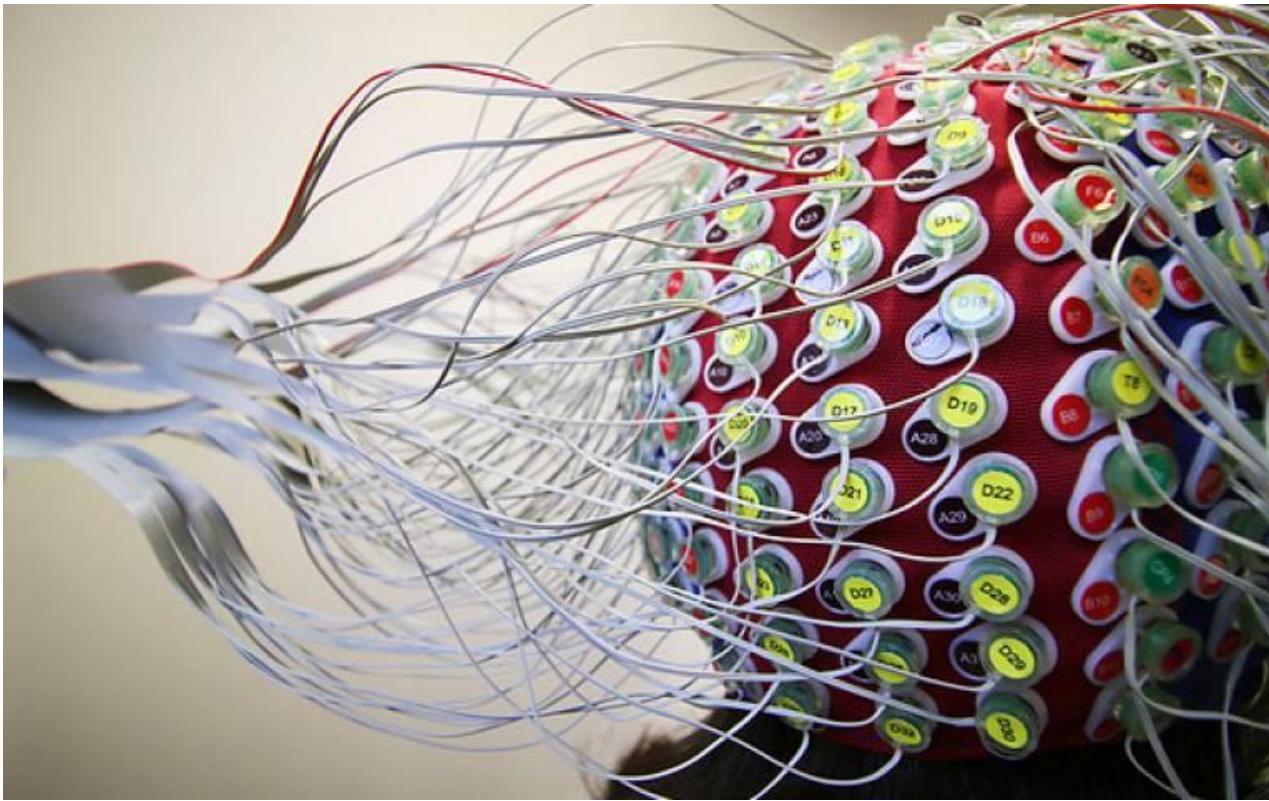
200

100

0

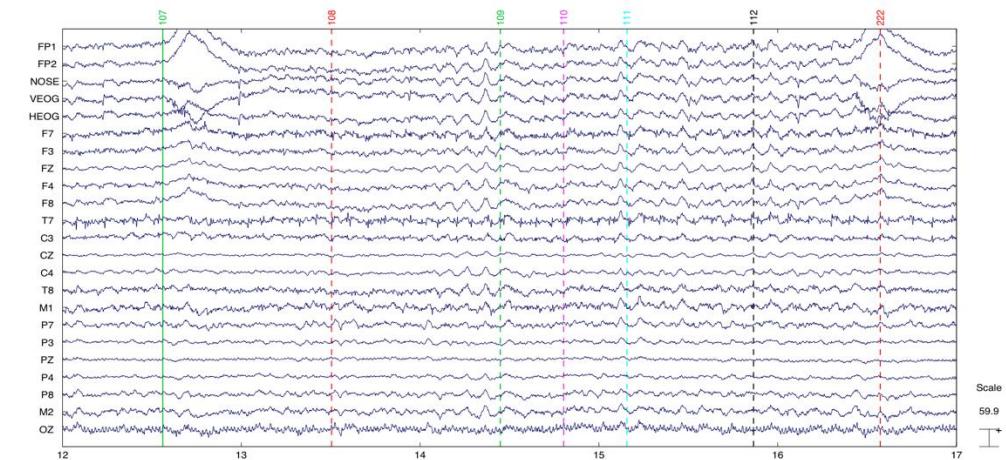


# Electroencephalography



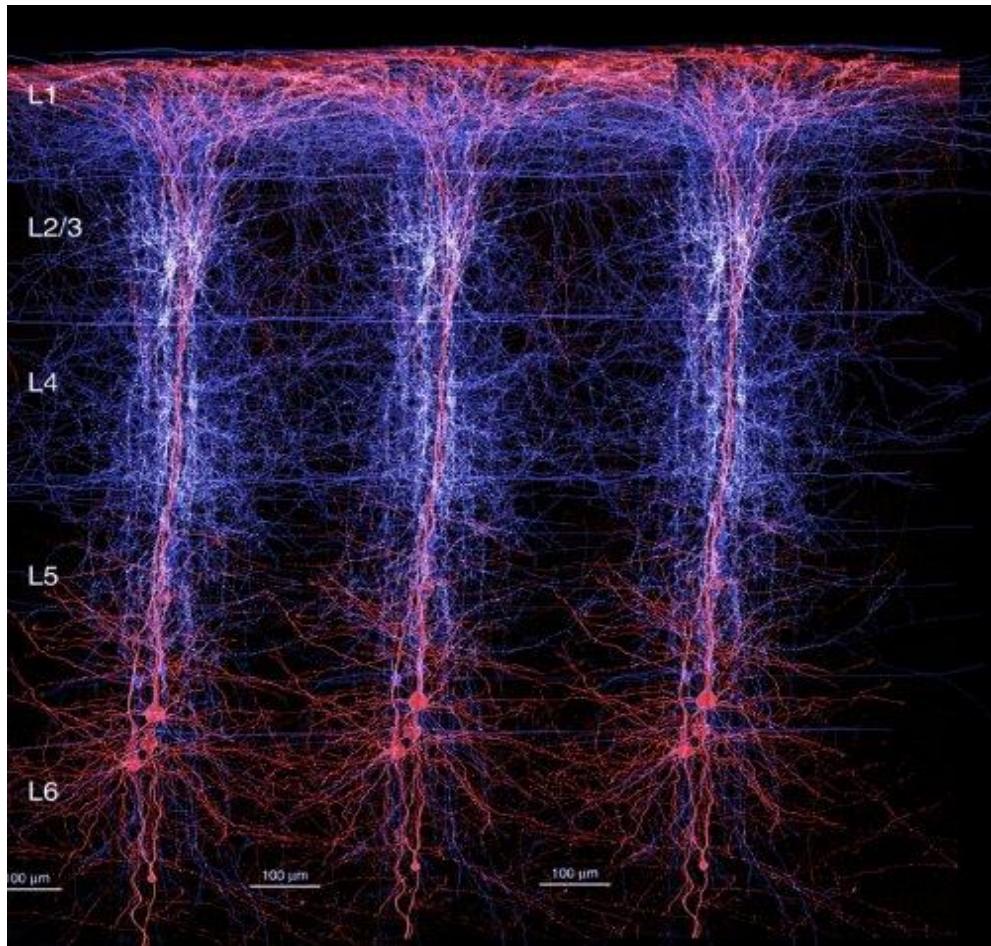
<https://www.ucl.ac.uk/brain-sciences/news/2023/jan/brain-wave-recordings-could-reveal-cause-catatonia>

- Electroencephalogram (EEG) electrodes
- Scalp recording of electrical activity of cortex => waveform signals
- Microvolts ( $\mu$ V) – small!



# Electroencephalography

## Neural Basis

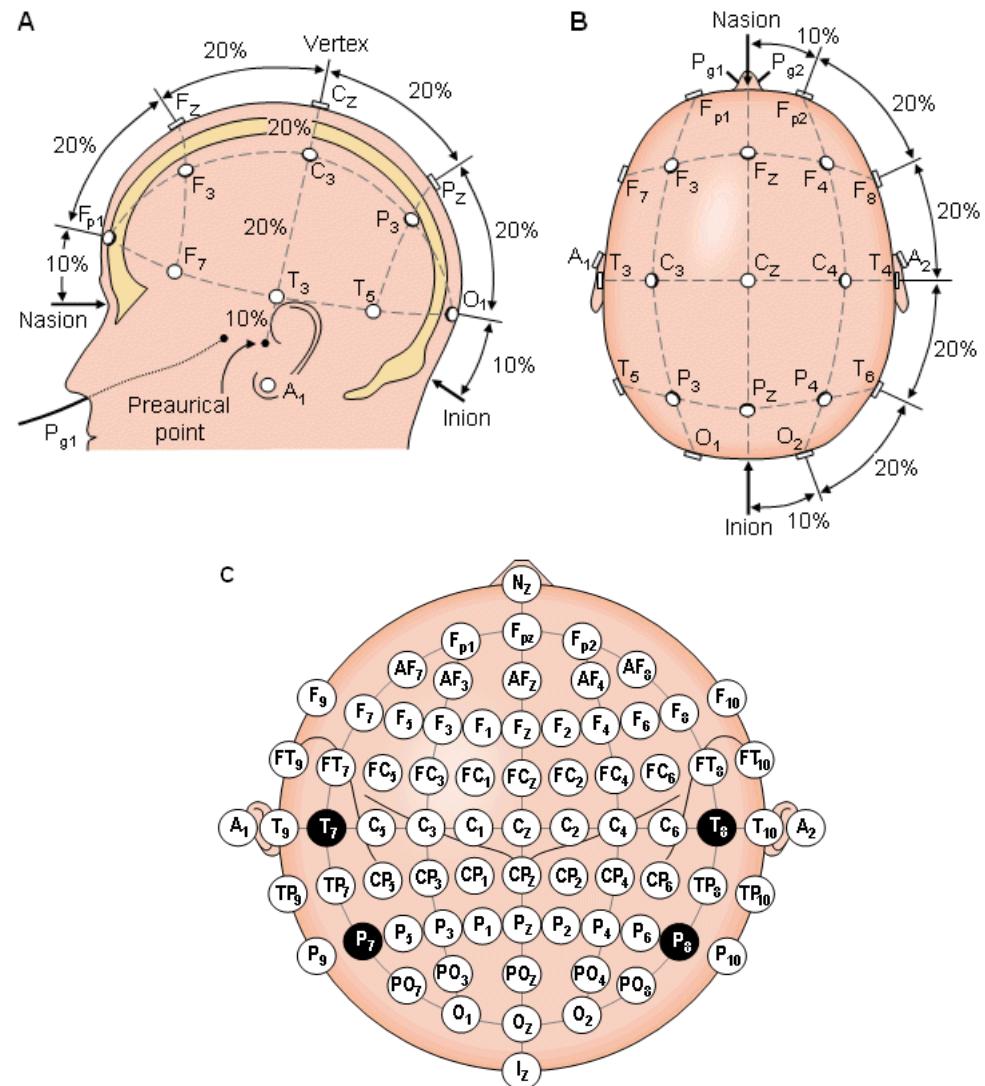


- Pyramidal neurons are spatially aligned and perpendicular to the cortical surface.
- Thus, EEG represents mainly the postsynaptic potentials of pyramidal neurons close to the recording electrode.
- The electrical activity from deeper generators gets dispersed and attenuated by volume conduction effects.

# Electroencephalography

## Surface Recordings

- **International 10/20 or 10/10 system for placing electrodes:**
  - **A:** earlobes, **C:** central,
  - **P:** parietal, **F:** frontal,
  - **O:** occipital
- Low impedance 5-10kΩ
- **Record montages:**
  - **Bipolar** (electrodes connected to each other)
  - **Referential** (electrodes connected to one reference)



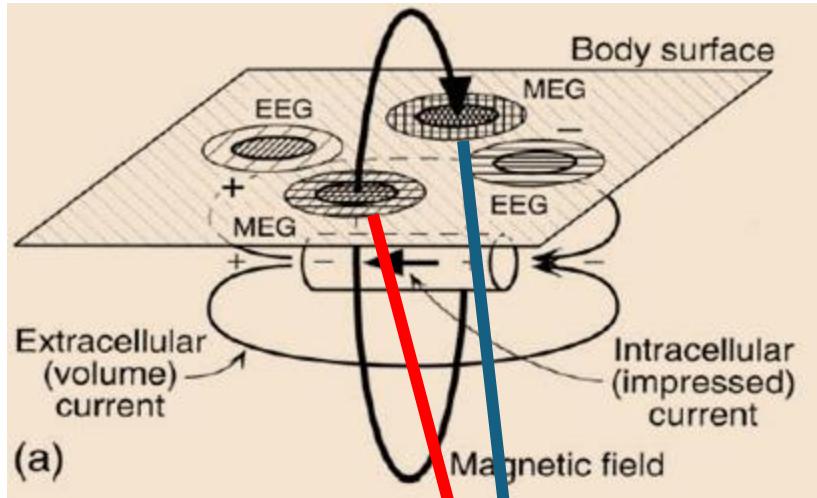
# Magnetoencephalography



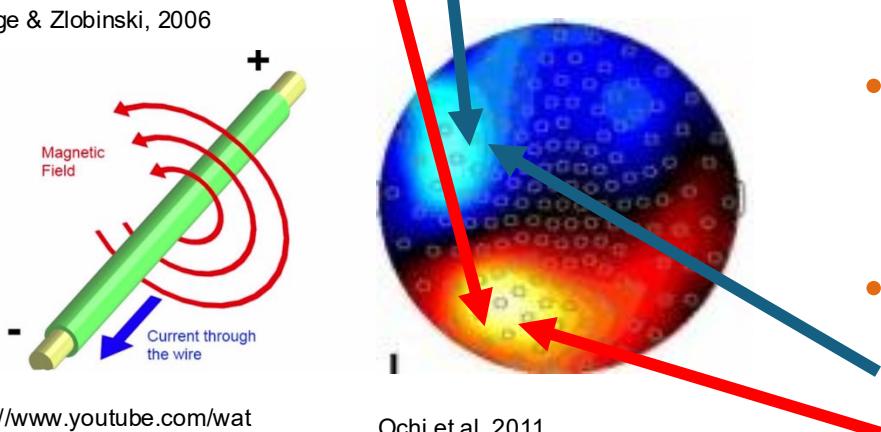
<http://www.admin.ox.ac.uk/estates/capitalprojects/previouscapitalprojects/megscanner/>

- Direct external recordings of **magnetic fields** created by electrical currents in cortex
- Measured in **fT** to **pT**
- Role of MEG in neuroimaging:
  - **Neural correlates** of cognitive/perceptual processes
  - **Localise** affected regions before surgery(?), determine regional and network functionality

# Magnetoencephalography

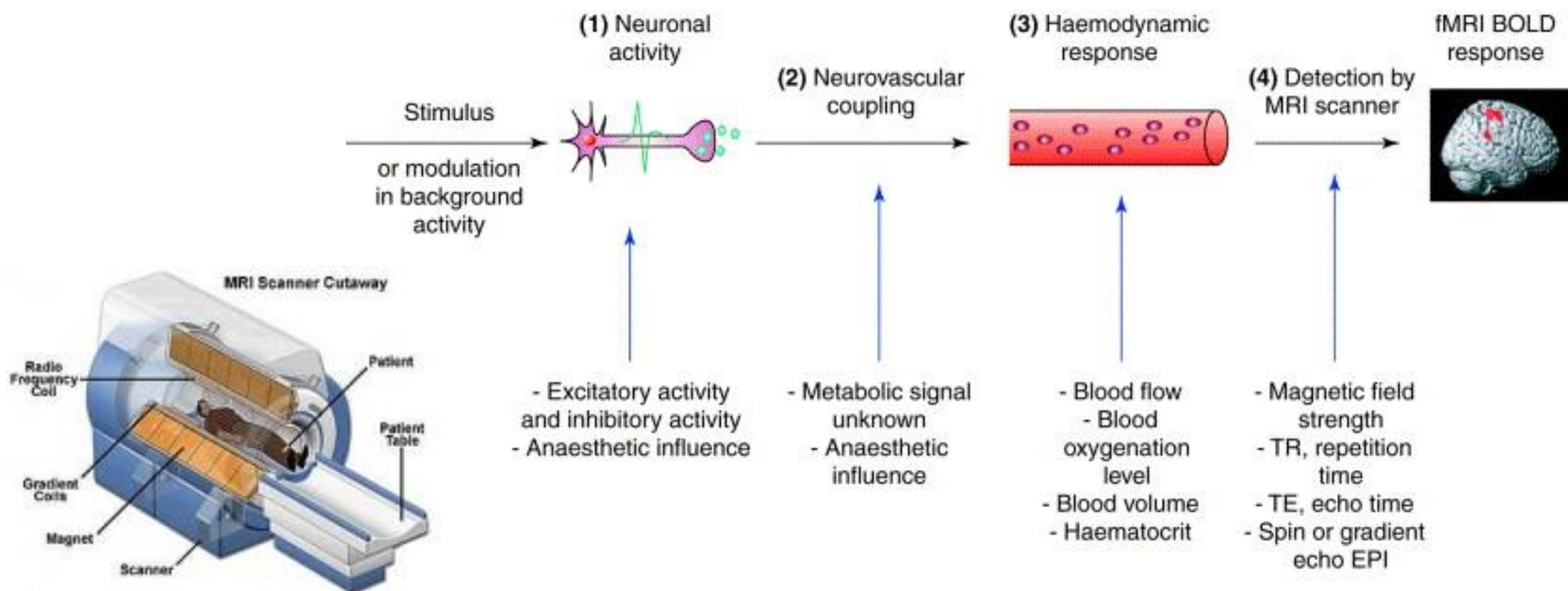


- Large pyramidal neurons in layer V of cortex, arranged in parallel, similarly-oriented, perpendicular to surface, fire synchronously
- Dipolar current flow generates a **magnetic field**.
- **10,000 to 50,000** active neurons required for detectable signal
- **Scalp topography:**
  - **Influx maxima** ‘source’
  - **Efflux maxima** ‘sink’

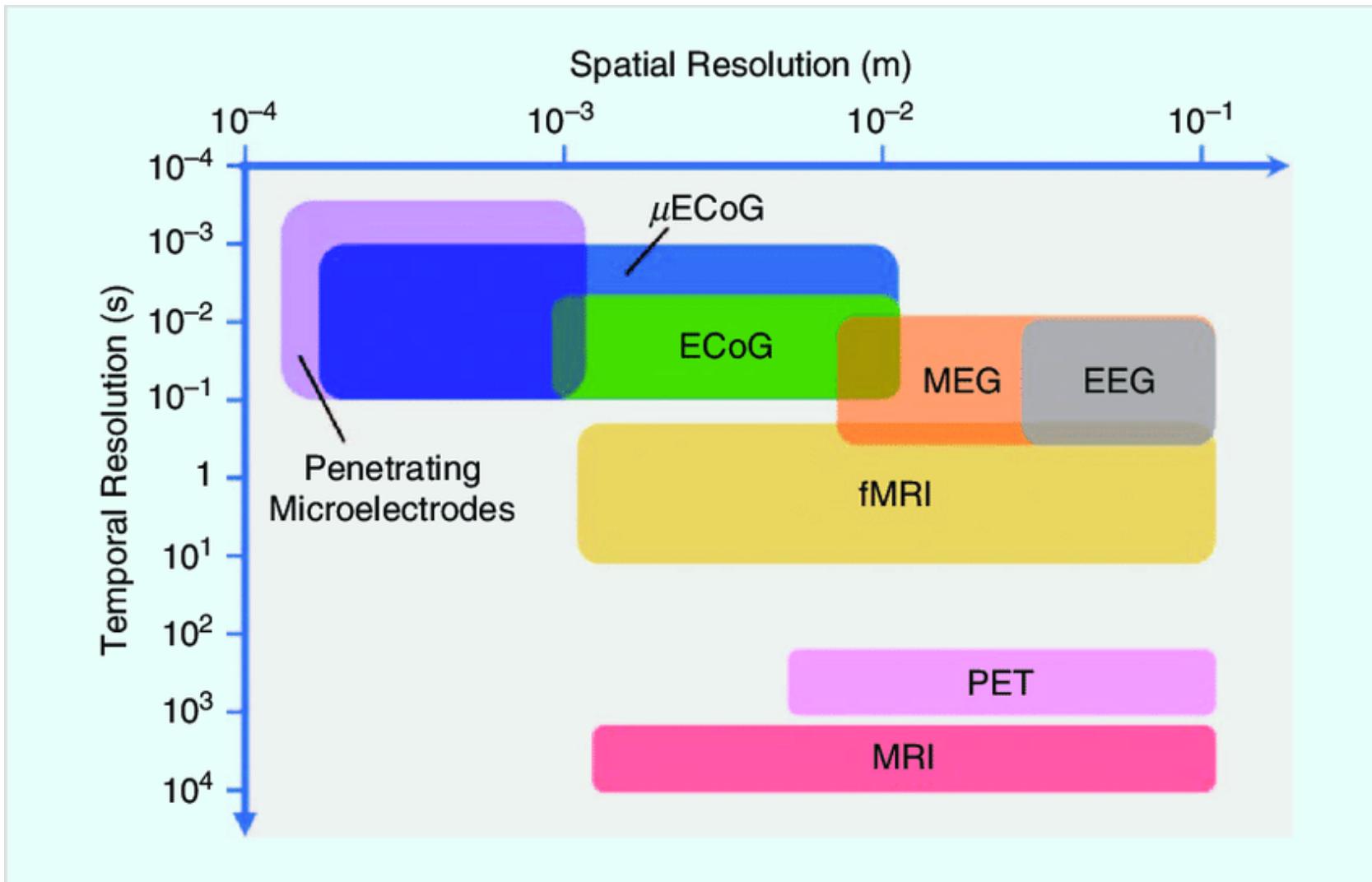


# Functional MRI

- Measuring BOLD



# Spatial & Temporal Resolution

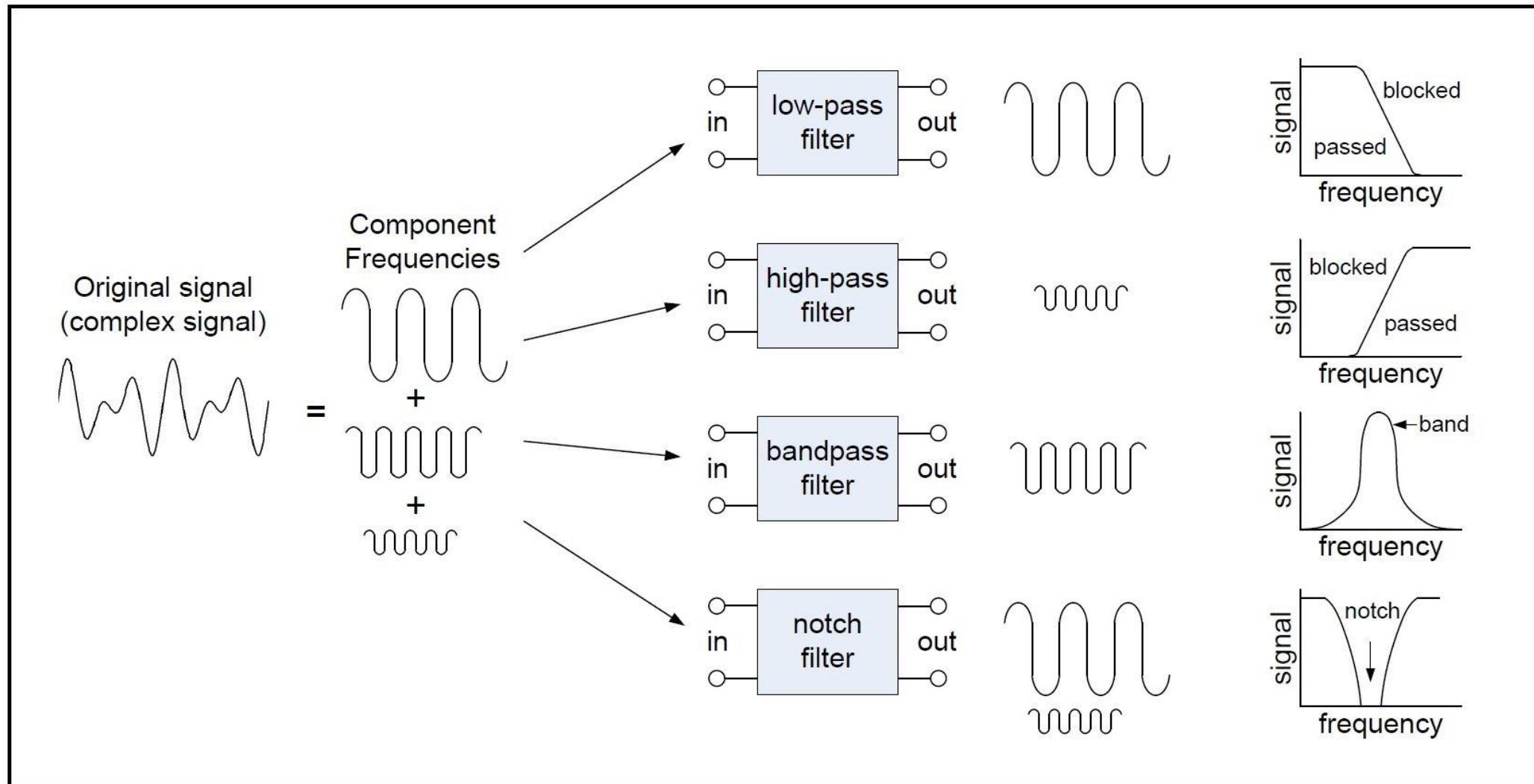


TIME FOR A  
BREAK



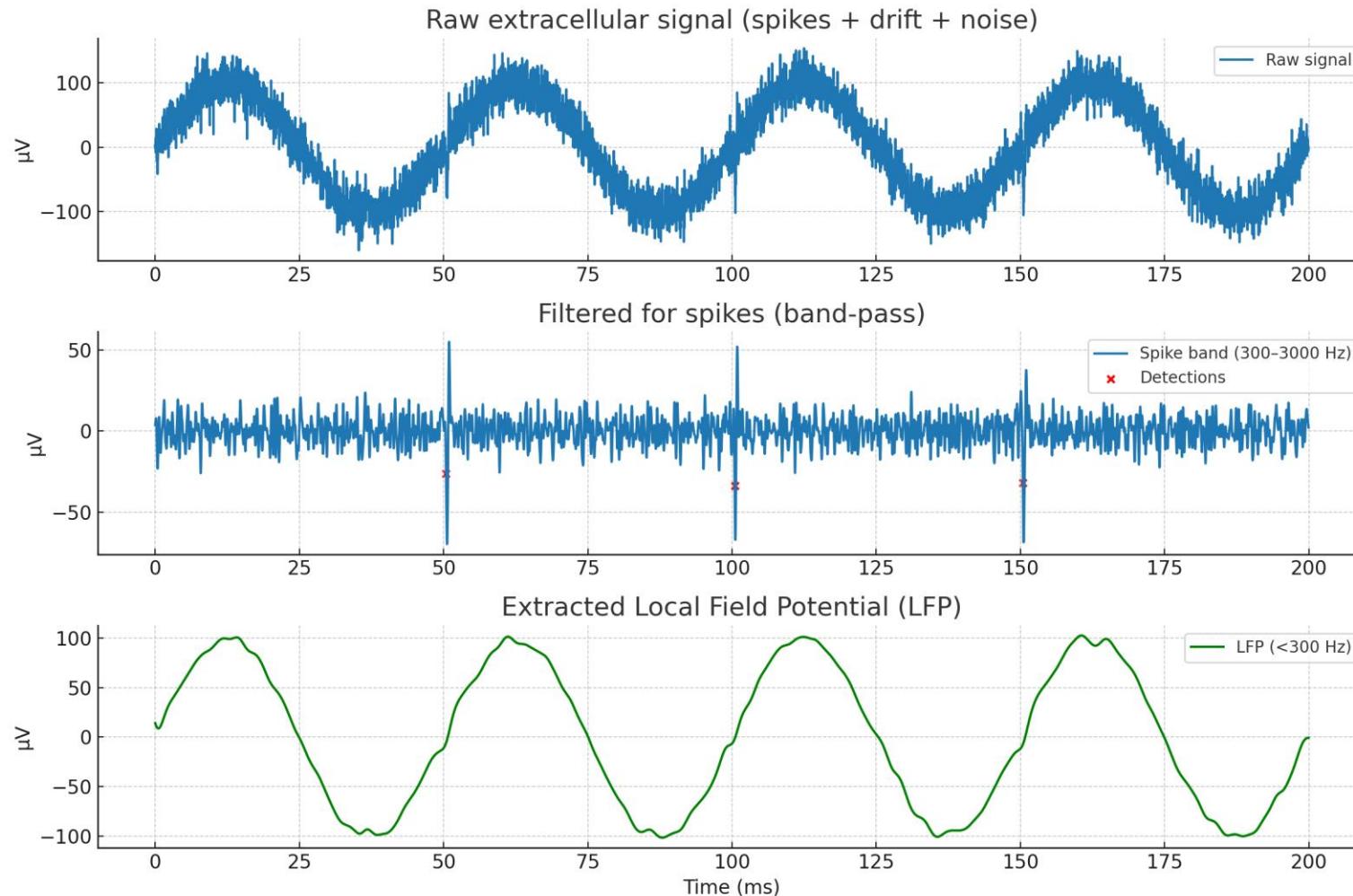
# **Common Pre-processing Approach**

# Temporal Filters



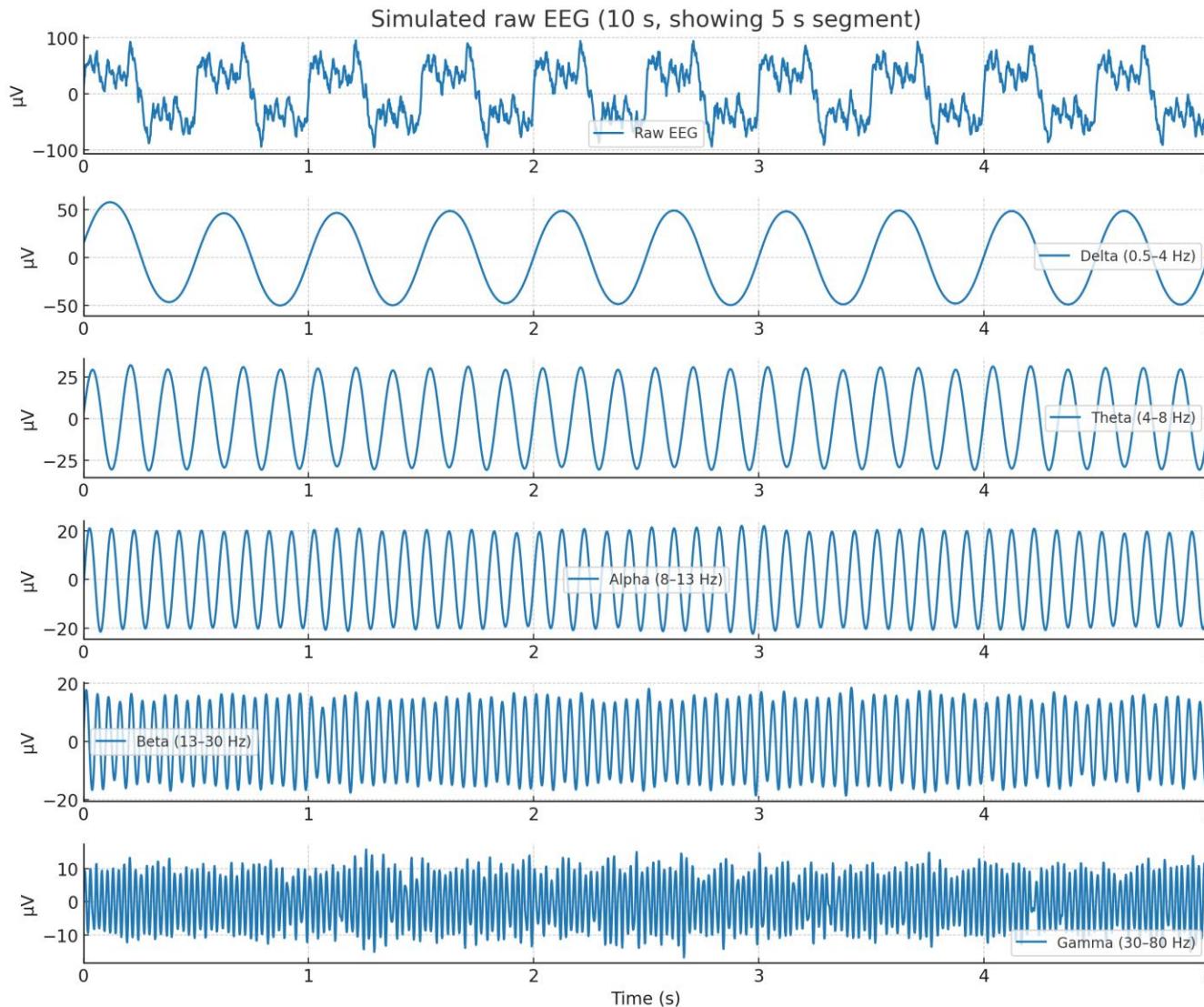
# Temporal Filters

- Spike Detection and LFPs



# Temporal Filters

- EEG



# Spatial Filters

- **Bipolar:** the voltage difference between two electrode pairs

- **Laplacian**

$$V_i^{Lap} = V_i^{ER} - \sum_j g_{ij} V_j^{ER} \quad \text{where } g_{ij} = (d_{ij} \sum_j \frac{1}{d_{ij}})^{-1}$$

- **Common Average Referencing (CAR)**

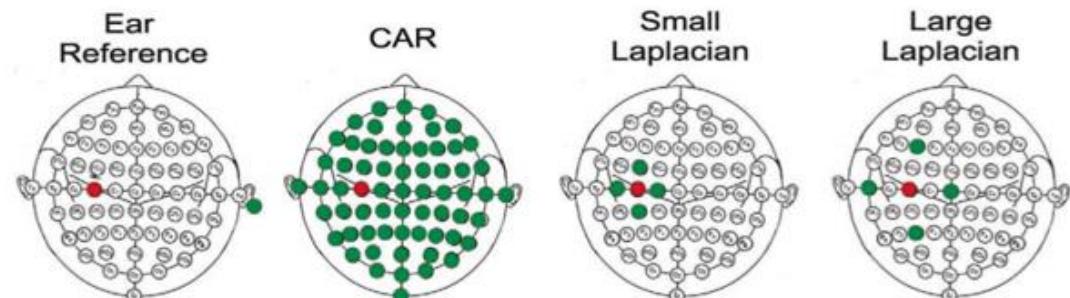
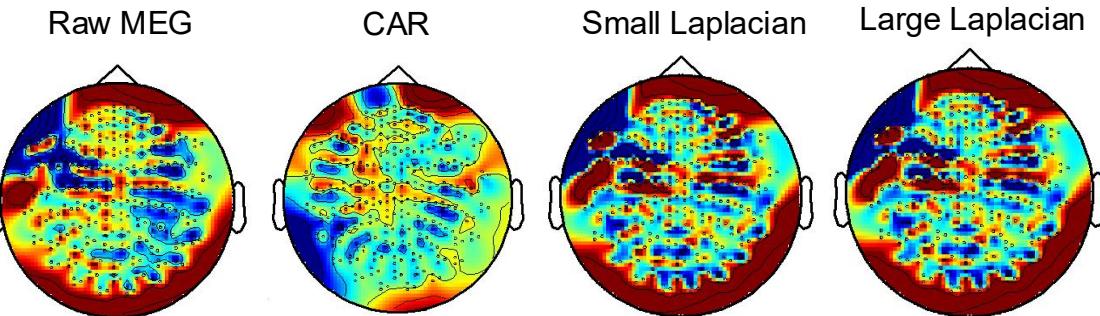


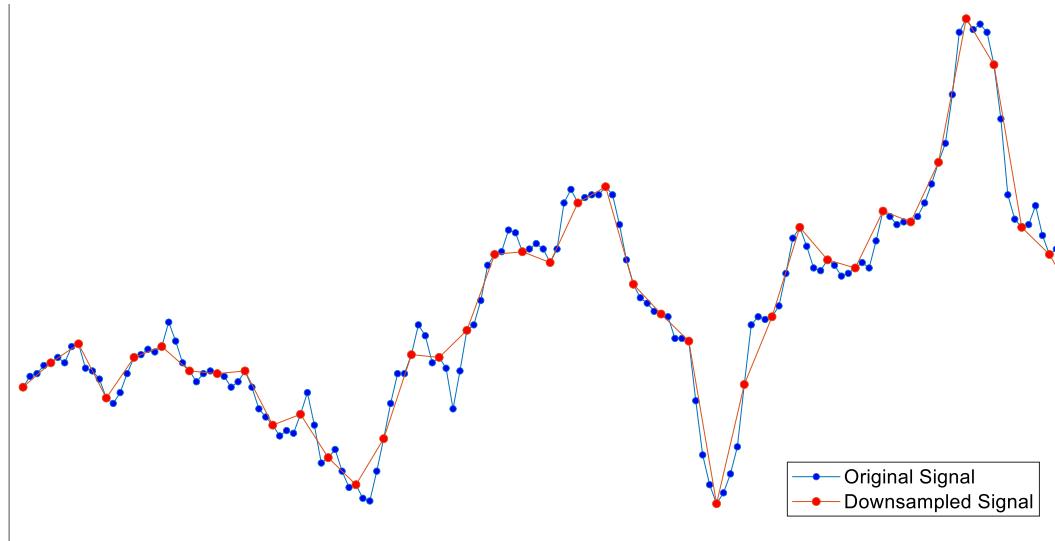
Figure 3. For a clinical EEG array, a mean or weighted mean of green electrodes would be subtracted from the red electrode for each spatial filter listed [7].

McFarland, 1997

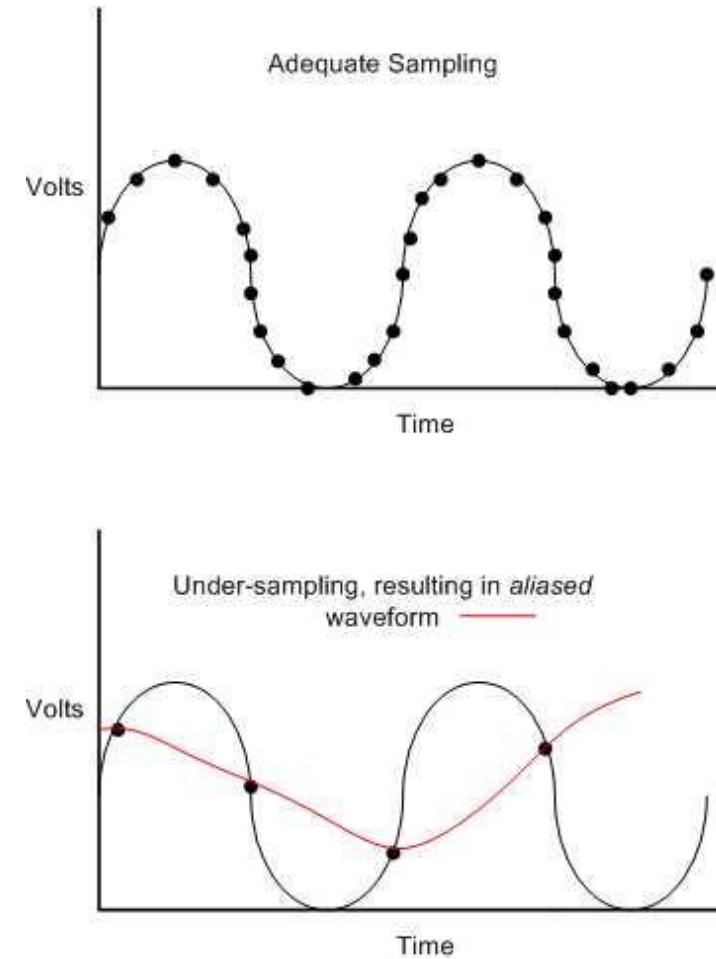


# Downsampling

Nyquist Theory – minimum digital sampling frequency must be  $>$  twice the maximum frequency in analogue signal

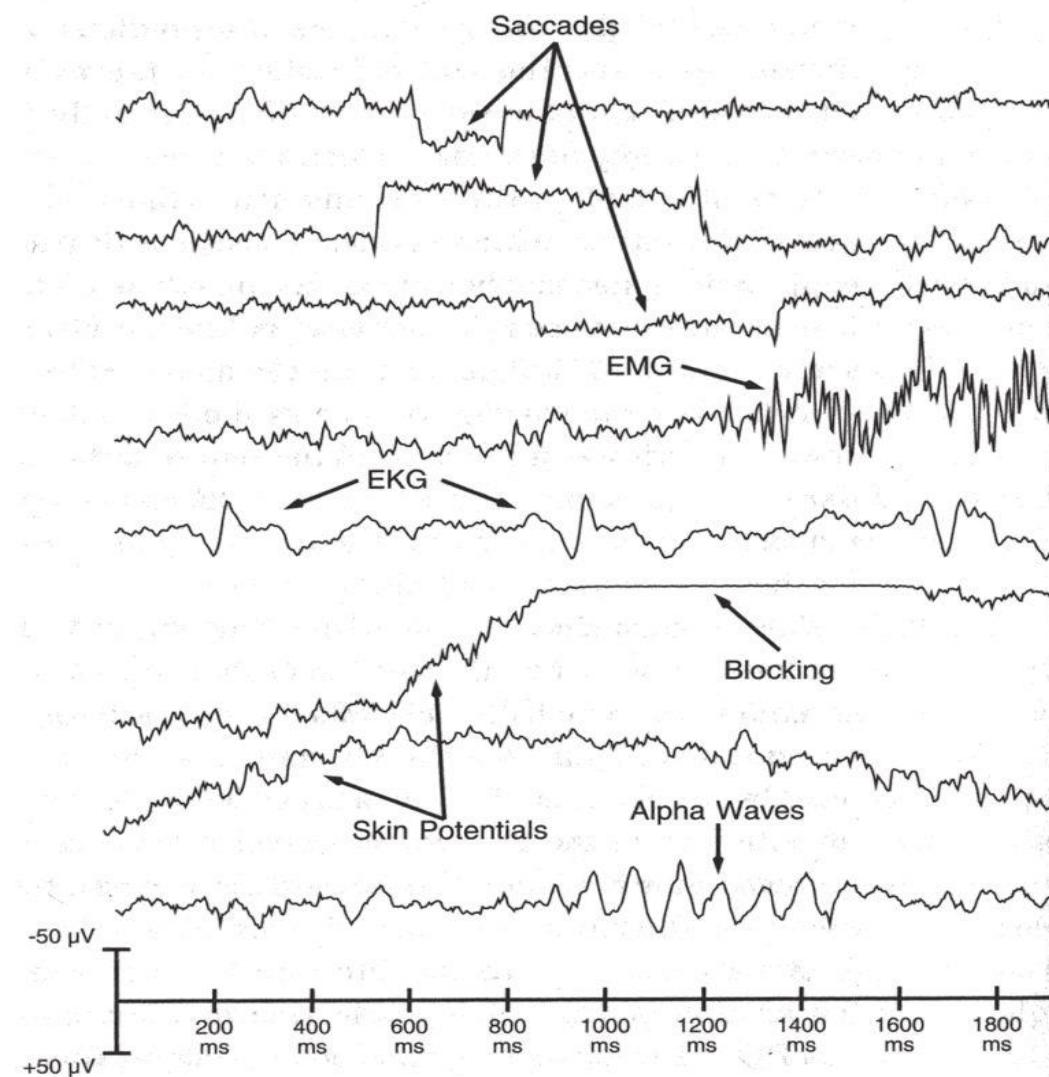


Example of downsampling



# Artefact Removal

- Blinks
- Eye-movements
- Muscle activity
- EKG
- Skin potentials
- Alpha waves



# Artefact Removal

- **Blinking**
  - Avoid contact lenses
  - Build ‘blink breaks’ into your paradigm
  - If subject is blinking too much – tell them
- **EMG**
  - Ask subjects to relax, shift position, open mouth slightly
- **Alpha waves**
  - Ask subject to get a decent night’s sleep beforehand
  - Have more runs of shorter length – talk to subject in between
  - Jitter ISI – alpha waves can become entrained to stimulus

# Artefact Removal

## EOG/Blinks

- most common contaminants of the EEG signal.

## Linear Regression

- The main assumption in this approach is that each EEG channel can be expressed as the sum of noise-free EEG signal and a fraction of the source artifact available through EOG electrodes.
- Let  $S$  be the recorded EEG signal which can be expressed as the sum of noise-free EEG signal  $E$  and EOG or eye blink signal  $B$  multiplied by a weight matrix  $W$ .

$$S = WB + E$$

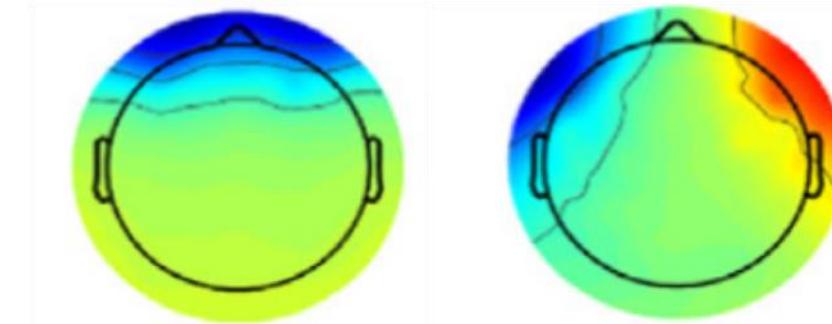
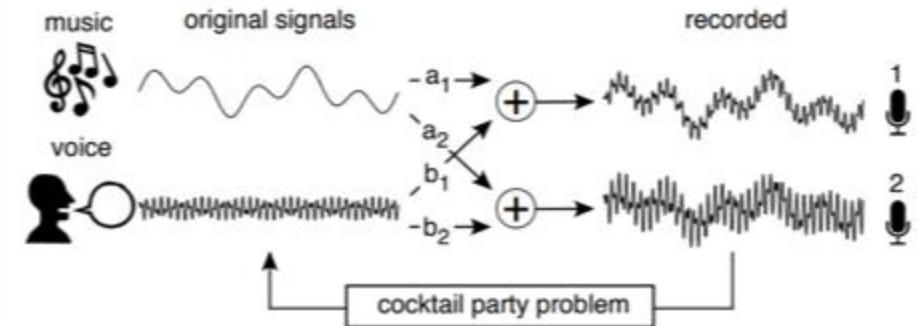
$W$  describes the contribution of the EOG artifact in each EEG channel

# Artefact Removal

## EOG/Blinks

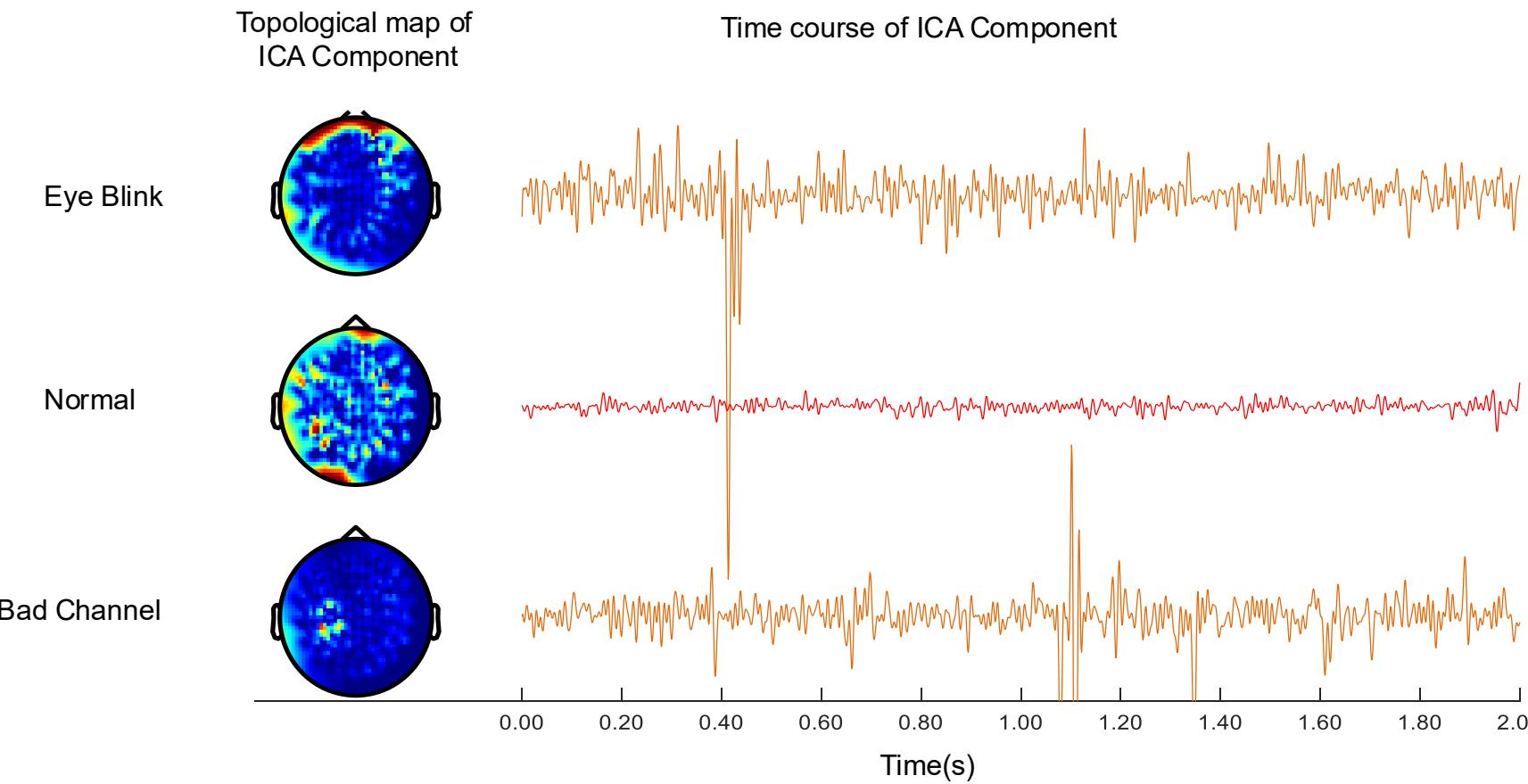
## Independent Component Analysis

- Independent component analysis (ICA) is a blind source separation (BSS) technique that is widely used in an array of signal processing applications.
- Once the components have been identified, to remove the EOG artifacts, one can visually determine which independent component corresponds to eye-blanks or movements based on the following criteria.



Presence of frontal topography (for blinks, shown on left) and bilateral with opposite sign frontal topography (for horizontal eye-movements, shown in right) in scalp map (adapted from here).

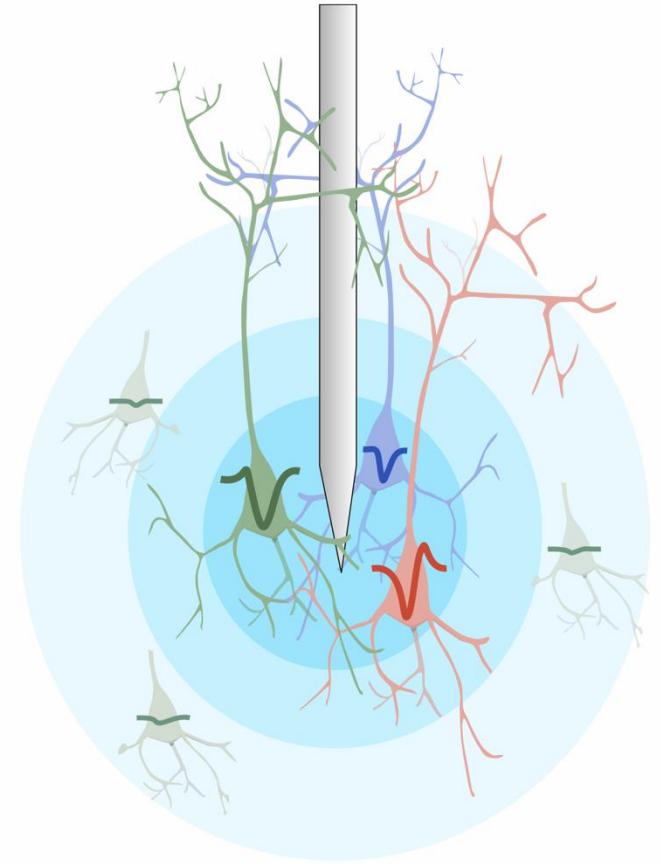
# Independent Component Analysis



# **Common Signal Processing Approach by Modality**

# Spike Sorting

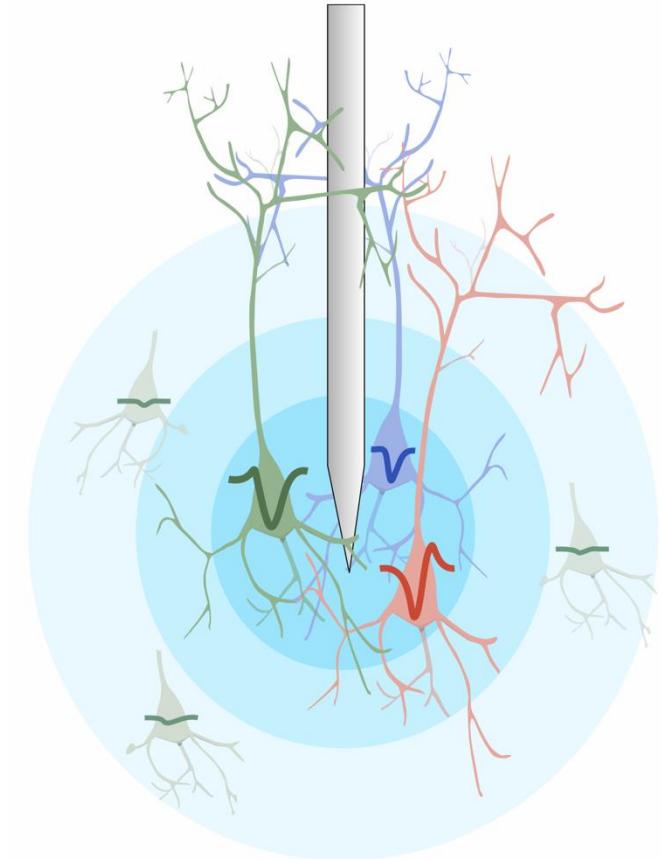
- Spike sorting is the process of **separating and identifying action potentials (“spikes”) from different neurons** recorded by the same electrode (or electrode array).
- Each spike has a slightly different **waveform shape** depending on:
  - The neuron’s distance from the electrode tip
  - Neuron size and orientation
  - Electrode properties
- Because of this, you need to sort out *which spike came from which neuron.*



[https://en.wikipedia.org/wiki/Spike\\_sorting](https://en.wikipedia.org/wiki/Spike_sorting)

# Spike Sorting

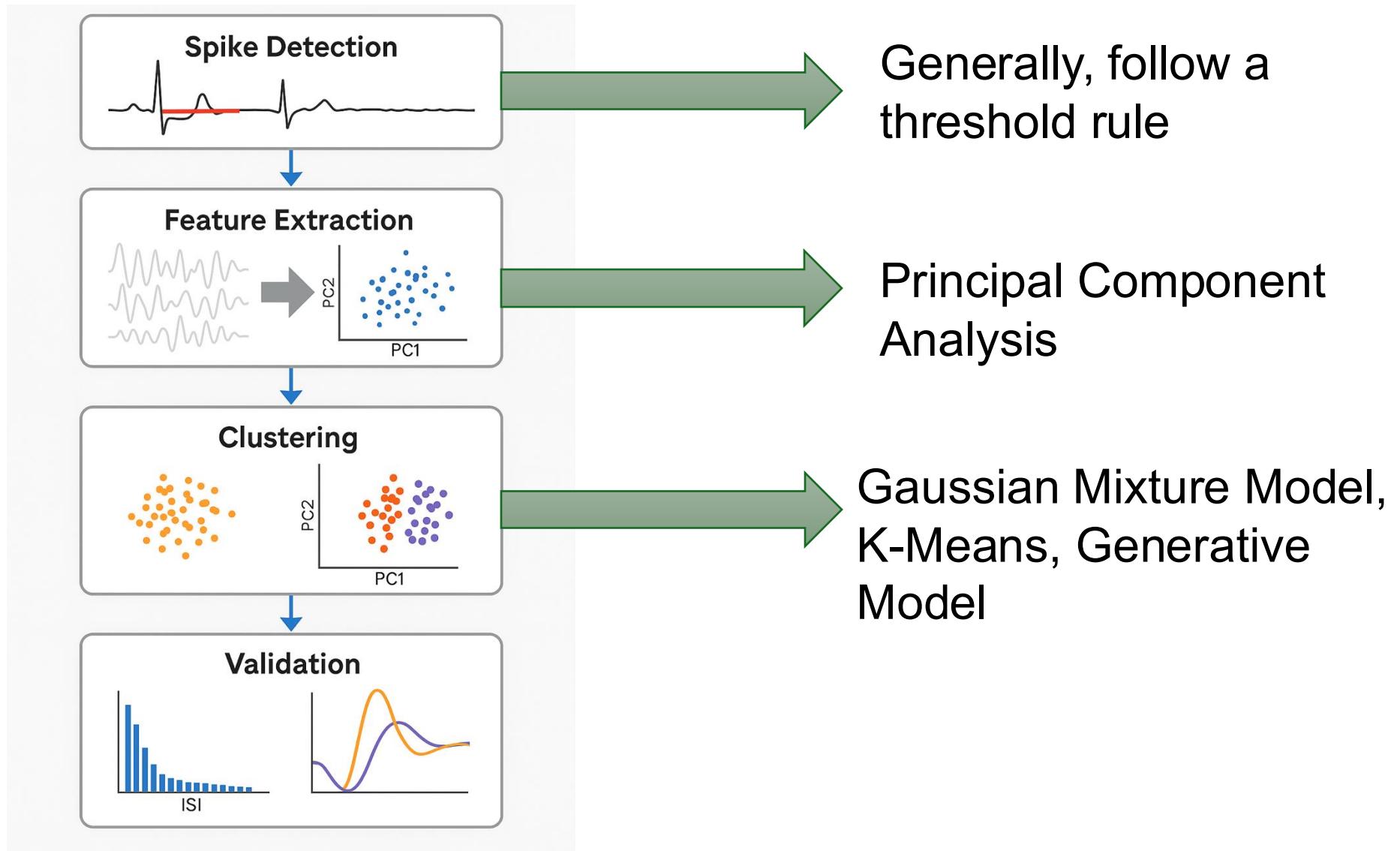
- **Why is it important?**
  - Allows you to attribute spikes to **single neurons** rather than “multi-unit” activity.
  - Essential for studying neural coding, plasticity, and brain-machine interfaces.
  - Without sorting, you’d lose information about individual neurons’ firing patterns.



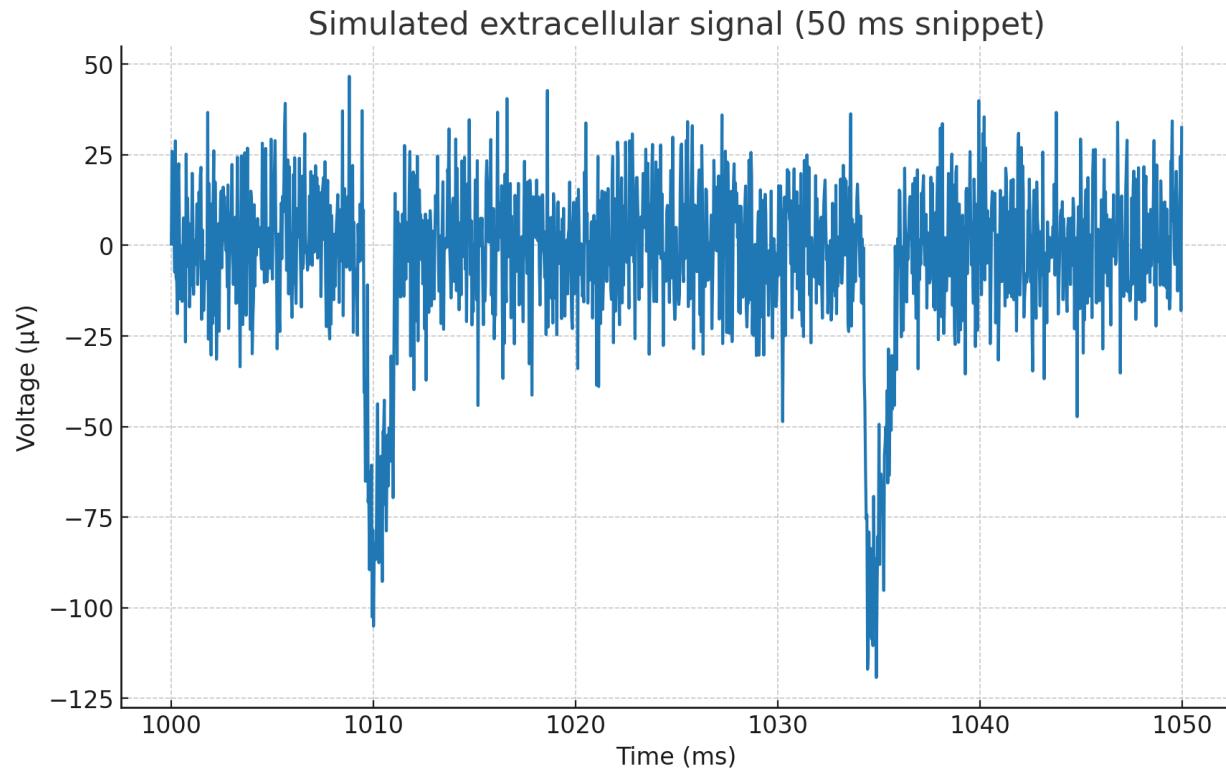
[https://en.wikipedia.org/wiki/Spike\\_sorting](https://en.wikipedia.org/wiki/Spike_sorting)

# Spike Sorting

- Steps



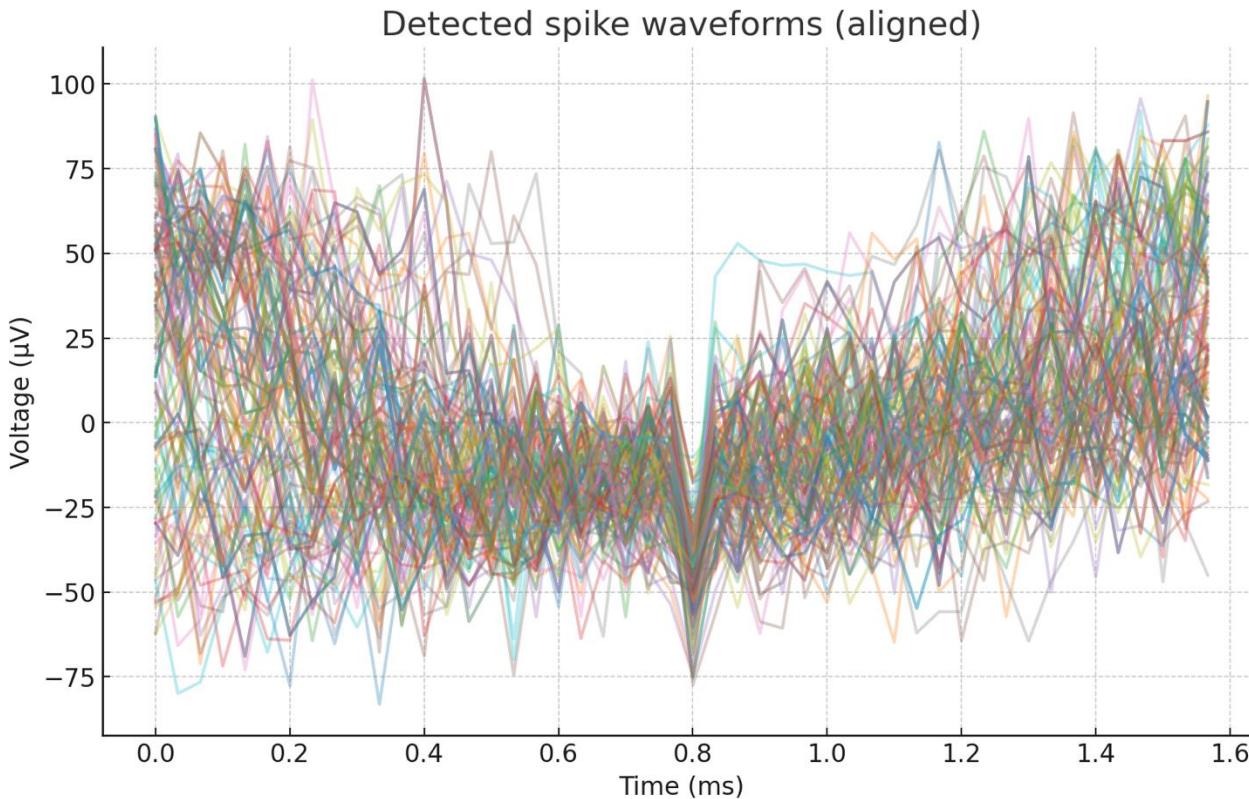
# Spike Sorting



Simulate two neurons for two different templates  $s_1$  and  $s_2$ , Poisson spike times (5 Hz and 8 Hz), small amplitude jitter, plus Gaussian noise ( $\sim 15 \mu\text{V}$  RMS).

$$x(t) = \sum_k \sum_i a_{ki} s_k(t - t_{ki}) + n(t)$$

# Spike Sorting



- Robust noise estimate  $\hat{\sigma} = \frac{\text{median}(|x|)}{0.6745}$ .
- Detects negative threshold crossings at  $-4\hat{\sigma}$ . Extract  $\sim 1.6$  ms windows and re-align to the trough.

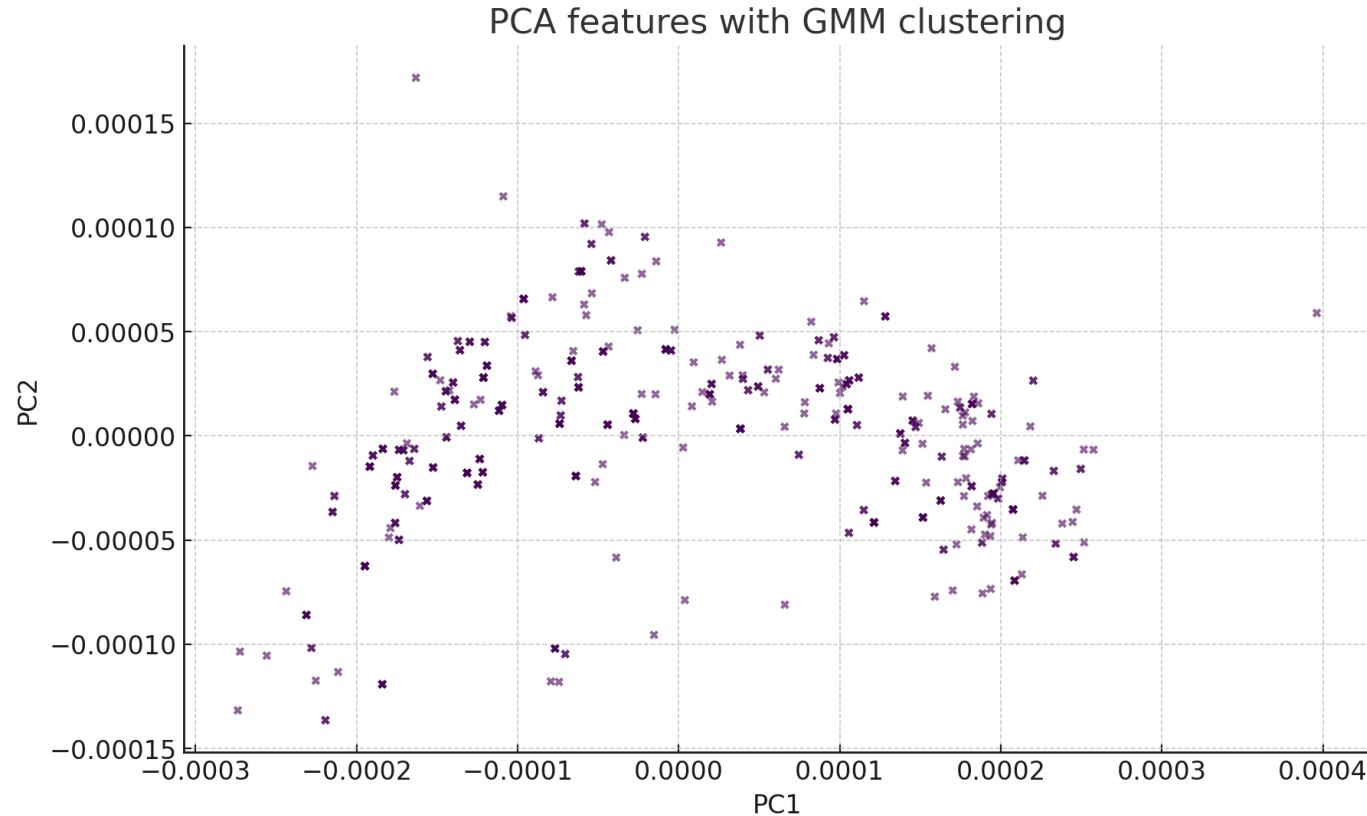
## Step 1. Spike Detection

- Often a **threshold rule**:  
Detect if  $x(t) < -k\sigma_n$

Where  $\sigma_n$  = noise standard deviation,  
and  
 $k$  = threshold multiplier (e.g. 3 to 5).

- This gives candidate spike waveform  $w_j \in \mathbb{R}^d$ , where  $d$  is the number of samples in the spike window,

# Spike Sorting



## Feature Extraction

- Each waveform (samples  $\times 1$ ) is mean-centred, projected onto the top 3 PCs:

$$y_j = U^T(w_j - \bar{w})$$

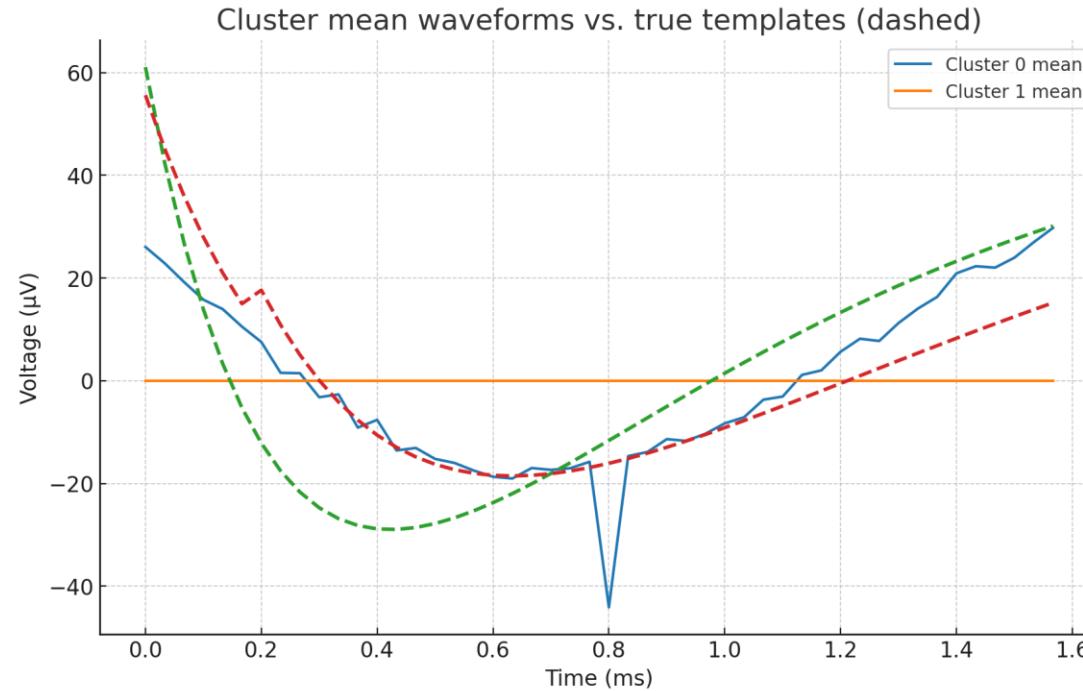
## Clustering (GMM)

- Fit a 2-component mixture via EM and assign each spike to  $\arg \max_k \gamma_{jk}$

$$p(y) = \sum_{k=1}^2 \pi_k N(y|\mu_k, \Sigma_k)$$

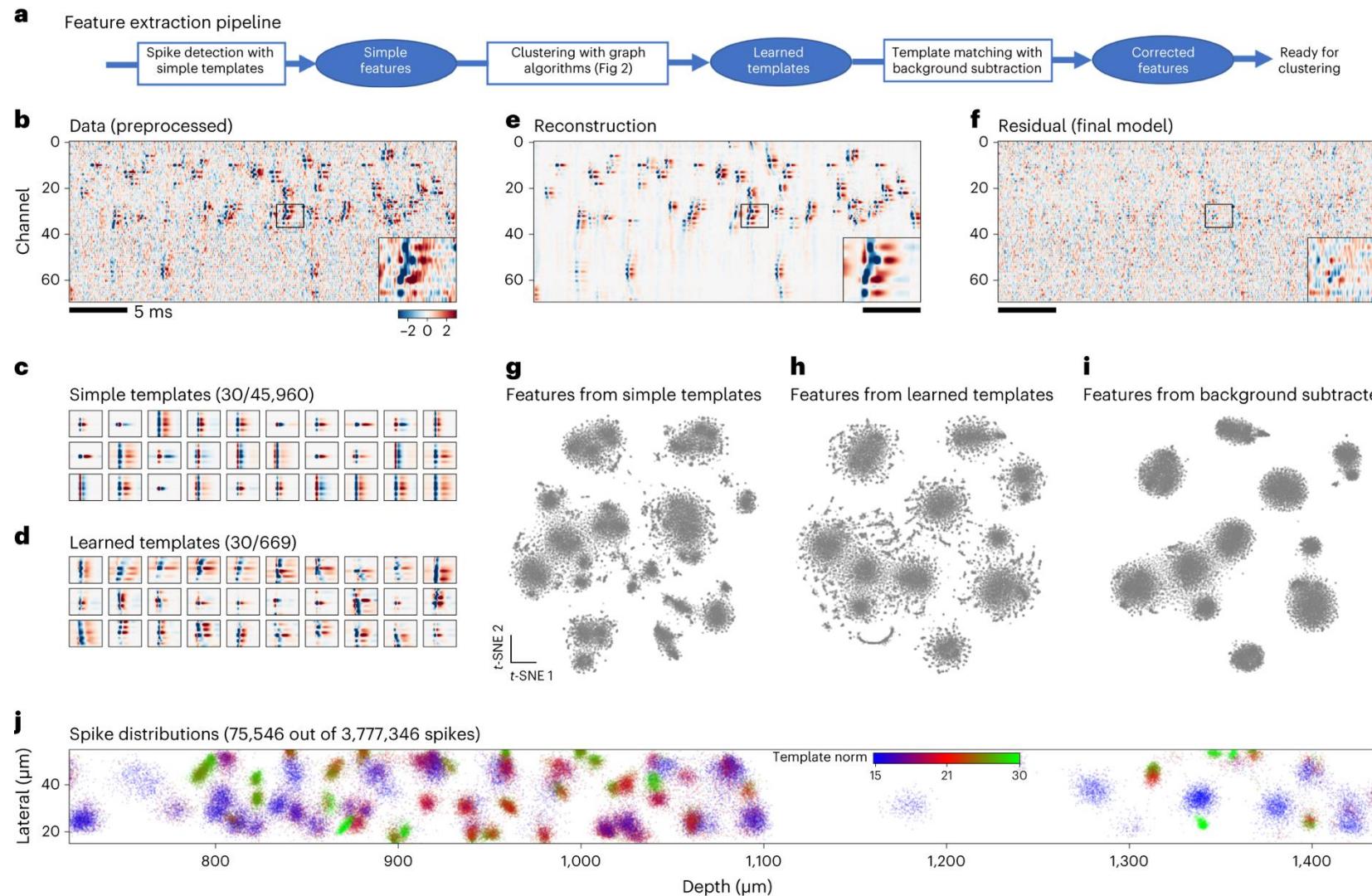
# Spike Sorting

## Step 4. Validation



Accuracy is modest (~0.60 in this run).

# Spike Sorting – KiloSort4

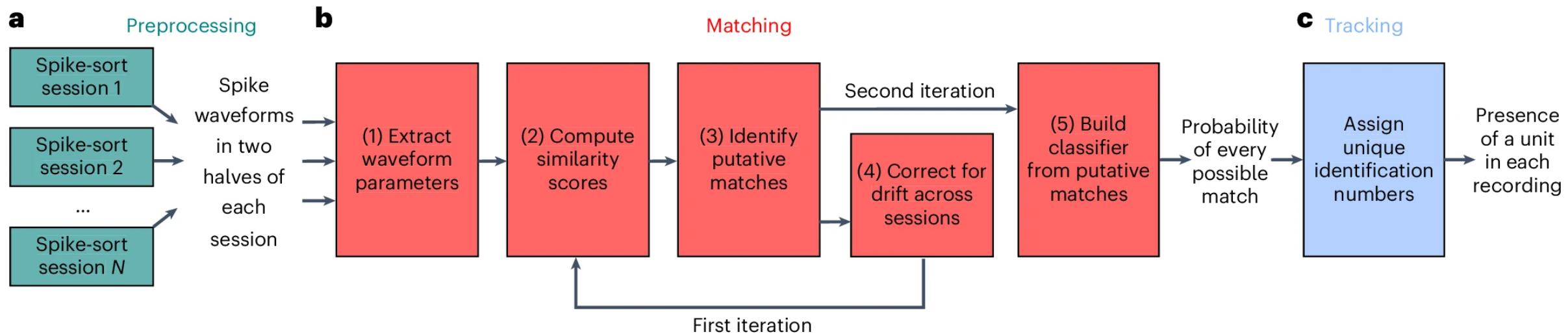


Pachitariu, M., Sridhar, S., Pennington, J. et al. Spike sorting with Kilosort4. *Nat Methods* **21**, 914–921 (2024).

<https://doi.org/10.1038/s41592-024-02232-7>

<https://kilosort.readthedocs.io/en/latest/>

# Spike Sorting – Unit match



van Beest, E.H., Bimbard, C., Fabre, J.M.J. et al. Tracking neurons across days with high-density probes. *Nat Methods* **22**, 778–787 (2025). <https://doi.org/10.1038/s41592-024-02440-1>

**Tracks individual neurons over weeks**, using only waveform signatures—crucial for longitudinal studies and stable clinical/neuroprosthetic applications

# Spike Sorting

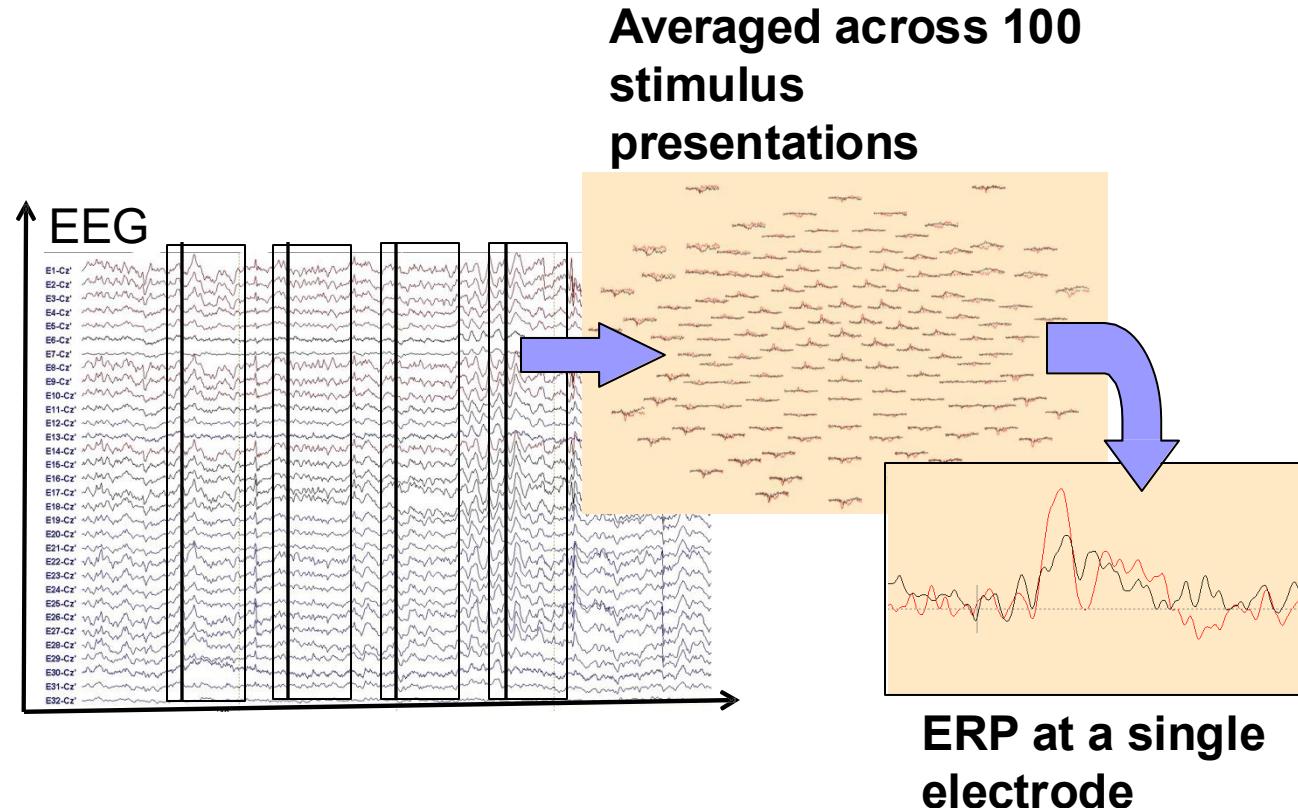
## Some interesting papers to read

- Rey, H.G., Pedreira, C. & Quiroga, R., 2015. Past, present and future of spike sorting techniques. *Brain Research Bulletin*, 119, pp.106–117. doi: <https://doi.org/10.1016/j.brainresbull.2015.04.007>.
- Buccino, A.P., Hurwitz, C.L., Garcia, S., Magland, J., Siegle, J.H., Hurwitz, R. & Hennig, M.H., 2020. SpikeInterface, a unified framework for spike sorting. *eLife*, 9, e61834. doi:10.7554/eLife.61834.
- Zhang, Y., Han, D., Wang, Y., Lv, Z., Gu, Y. & Li, D., 2025. SimSort: A data-driven framework for spike sorting by large-scale electrophysiology simulation. *arXiv* [preprint]. Available at: <https://arxiv.org/abs/2502.03198>
- Georgiadis, V. & Petrantonakis, P.C., 2025. SpikeSift: A Computationally Efficient and Drift-Resilient Spike Sorting Algorithm. *arXiv* [preprint]. Available at: <https://arxiv.org/abs/2504.01604>

# Event Related Potential

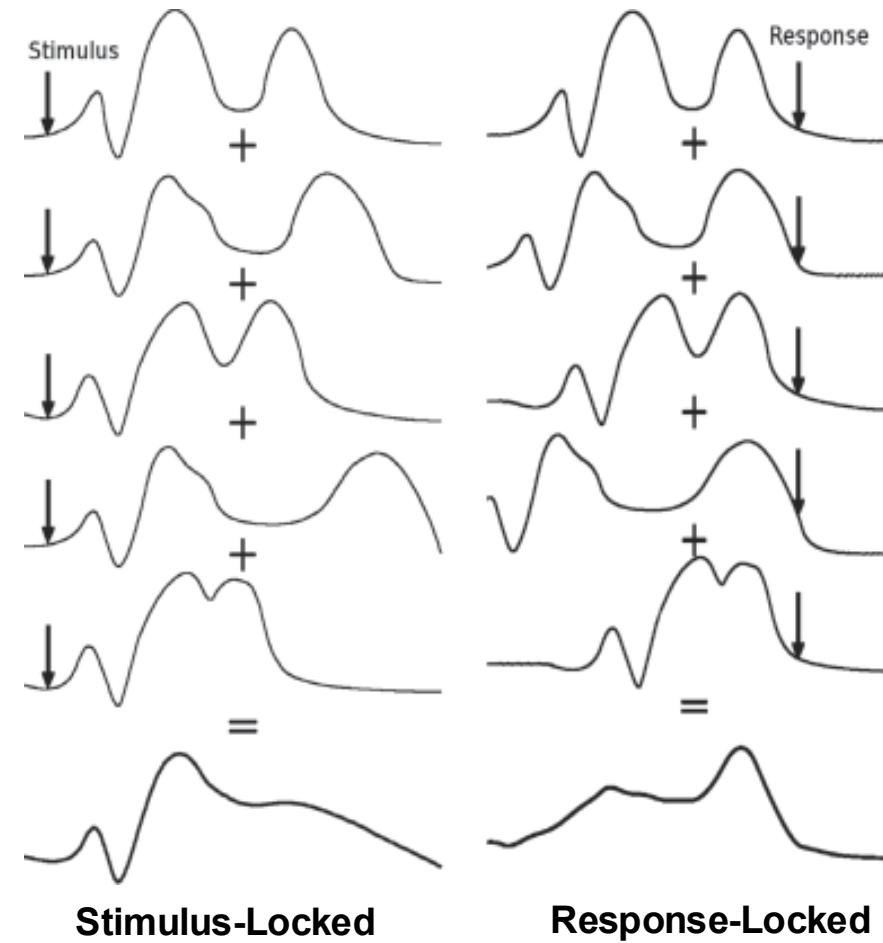
## Mostly for EEG/LFP signals

- The averaging technique is used to study the electrical activity time-locked to an event.
- Needs a considerable number of trials
- Comprises a mixture of different brain rhythms, depending on the filters applied.
- Only about 20% of the evoked activity is shown
  - Other approaches to study electrical brain activity: Time-frequency analysis

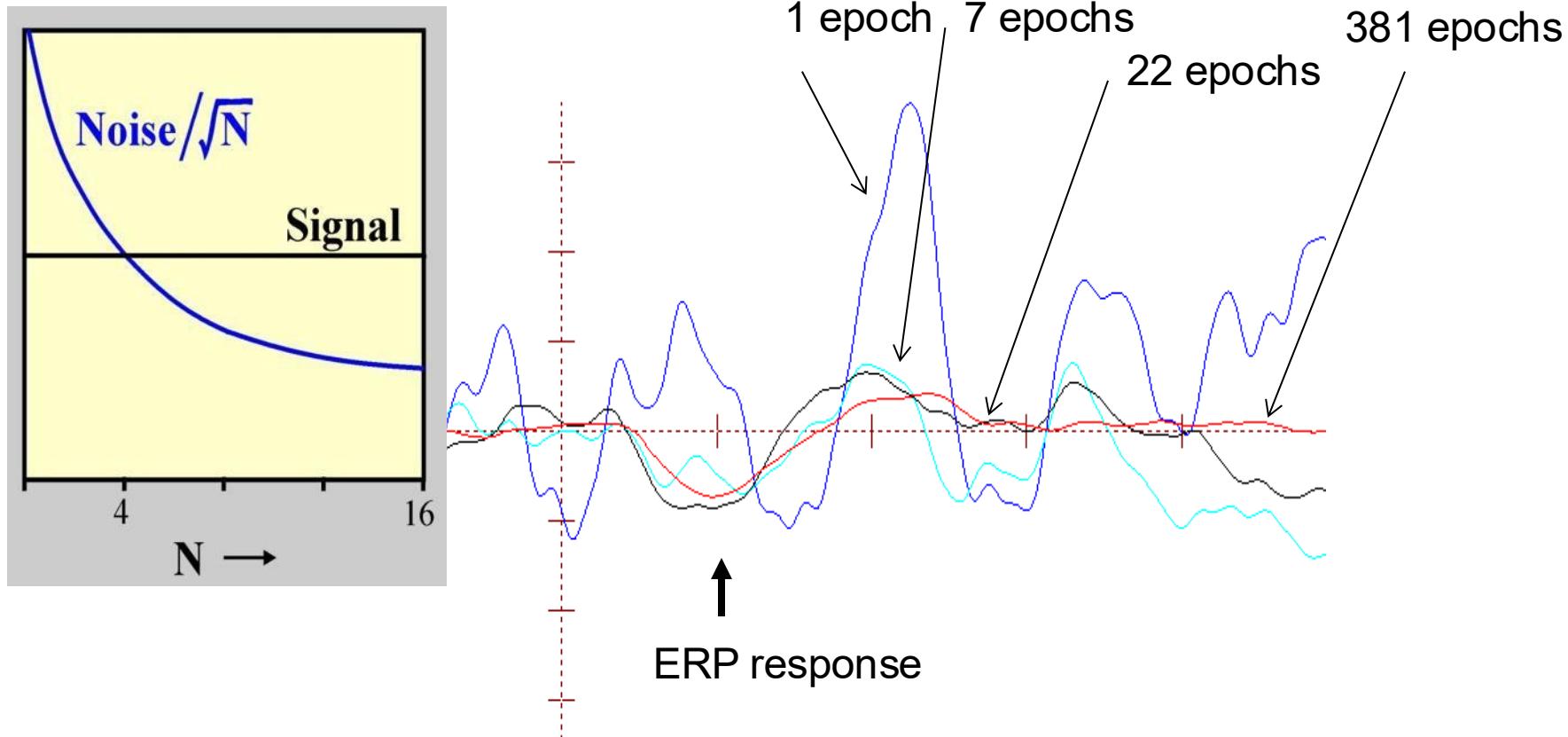


# Event Related Potential

Stimulus-Locked and Response-Locked



# Event Related Potential



# Power Spectral Density

## Frequency domain analysis

### Fourier Transform

For signal  $x(t)$ ,

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-2\pi ft} dt$$

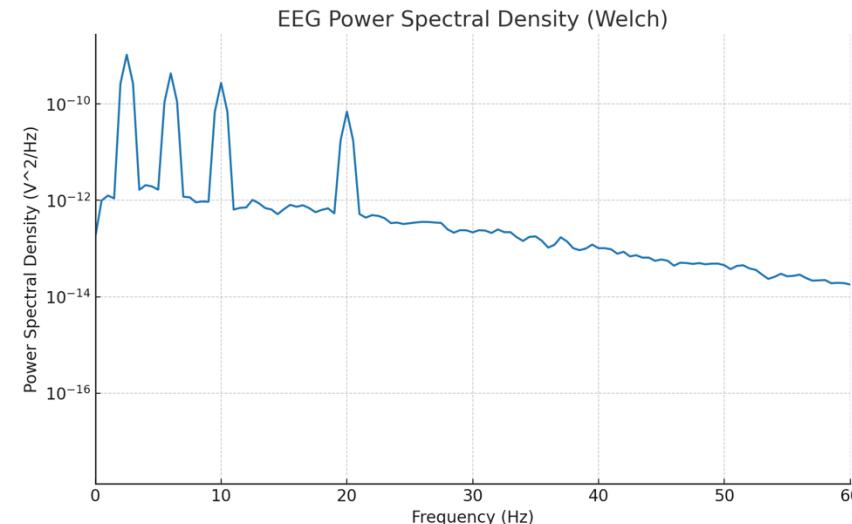
and PSD is

$$P_{xx}(f) = \lim_{T \rightarrow \infty} \frac{1}{T} |X_T(f)|^2$$

where  $X_T(f)$  is the Fourier transform over window length  $T$ .

In practice, PSD is estimated by:

1. Splitting data into overlapping windows
2. Applying a taper or window
3. Computing Fast Fourier Transform of each segment
4. Averaging squared magnitudes



# Power Spectral Density

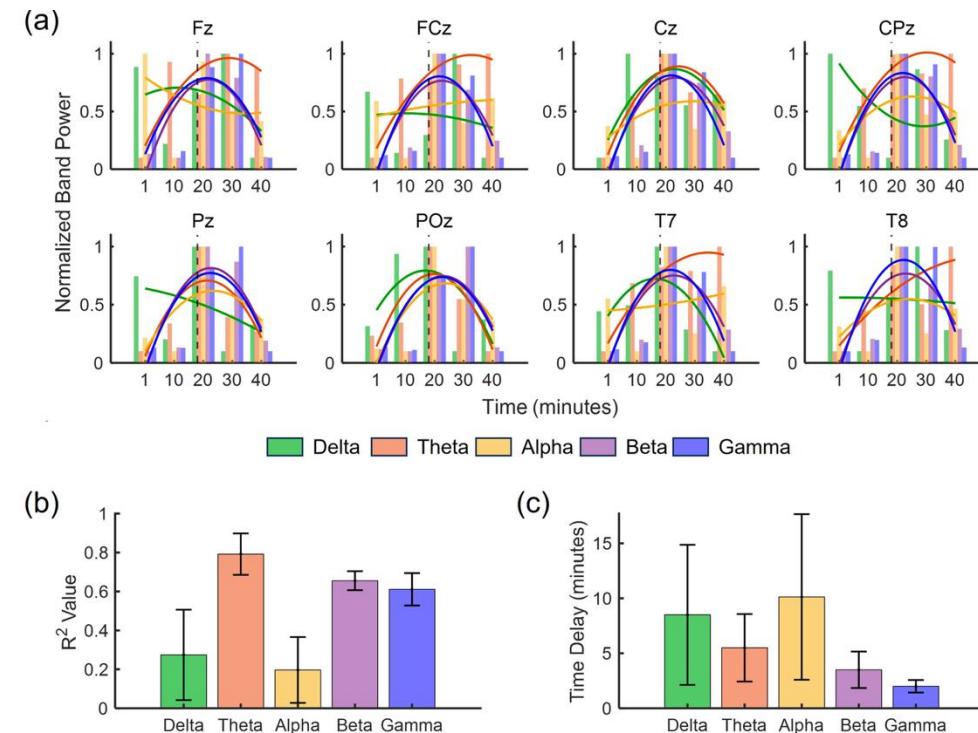
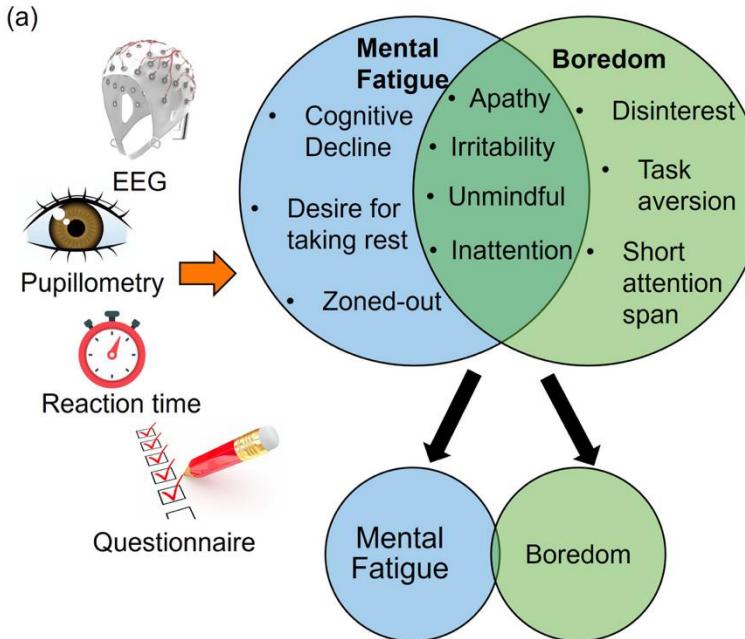
**PSD (Power Spectral Density)** shows how EEG power is distributed across frequencies.

## Why is it useful?

- Reveals **brain rhythms** (delta, theta, alpha, beta, gamma).
- Tracks **neural states** (e.g., sleep, attention, memory load).
- Allows **comparisons across conditions** (e.g., alpha power eyes-open vs eyes-closed).
- Detects **pathological patterns** (epilepsy spikes, Parkinson's beta).
- Provides **features for BCI/ML** (band power, peak frequency).

# An Example

To detect the onset of mental fatigue during task



- Increased cognitive effort often serves as an implicit compensatory mechanism by the participants to maintain task performance while counteracting the effects of mental fatigue.
- As the time on task progressed, the band power eventually decreased, suggesting late-stage mental fatigue

<https://doi.org/10.21203/rs.3.rs-7358429/v1>



# Short Time Fourier Transform

## Choose window size

- Pick a window function  $w[n]$  (e.g., Hamming, Hann) of length  $L$ .

## Segment the signal

- Slide the window across the signal with some overlap (commonly 50%).
- For each segment:

$$x_m[n] = x[n + mH] \cdot w[n], 0 \leq n < L, \text{ where } H = \text{hopsize}$$

## Fourier Transform per segment $m$ ,

- Compute the FFT of each windowed segment:

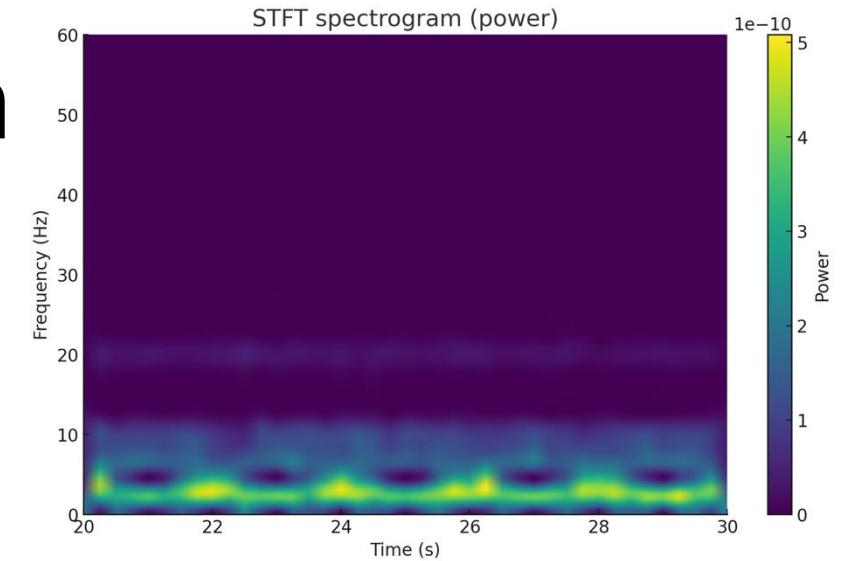
$$X_m(f) = \sum_{n=0}^{L-1} x_m[n] e^{-i2\pi f n / L}$$

# Short Time Fourier Transform

## Form time–frequency representation

- Stack all spectra across time windows to create a spectrogram:

$$S(t, f) = |X_m(f)|^2$$

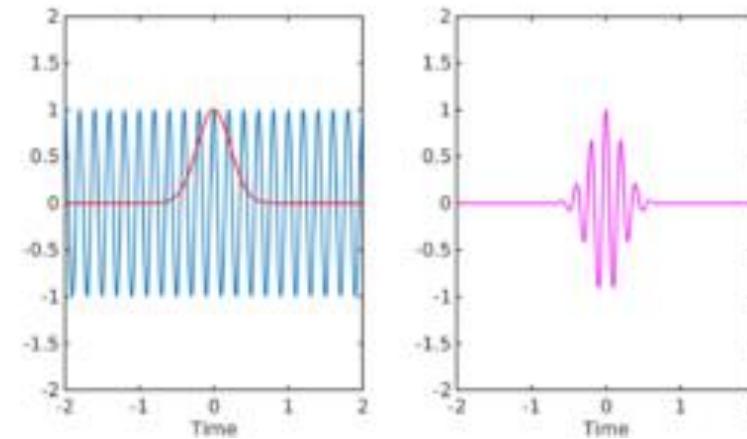


- **Why is it useful?**
- **Handles non-stationary signals:** EEG and neural signals change over time, unlike stationary signals, where one FFT is enough.
- **Tracks oscillation dynamics:** Shows how brain rhythms (alpha, beta, etc.) vary during tasks.
- **Event-related changes:** Captures transient responses (e.g., burst of theta after a stimulus).
- **Simple + fast:** Computationally efficient, widely supported.
- **Interpretability:** Easy to visualize as a spectrogram

# Wavelet Transforms

## Morlet Wavelet

- Wavelets overcome limitations of methods such as the Fourier transform by enabling a view of changes across both time and frequency.
- shape of a sinusoid, weighted by a Gaussian kernel, and they can therefore capture local oscillatory components in the time series.
- Wavelets have variable resolution in time and frequency.

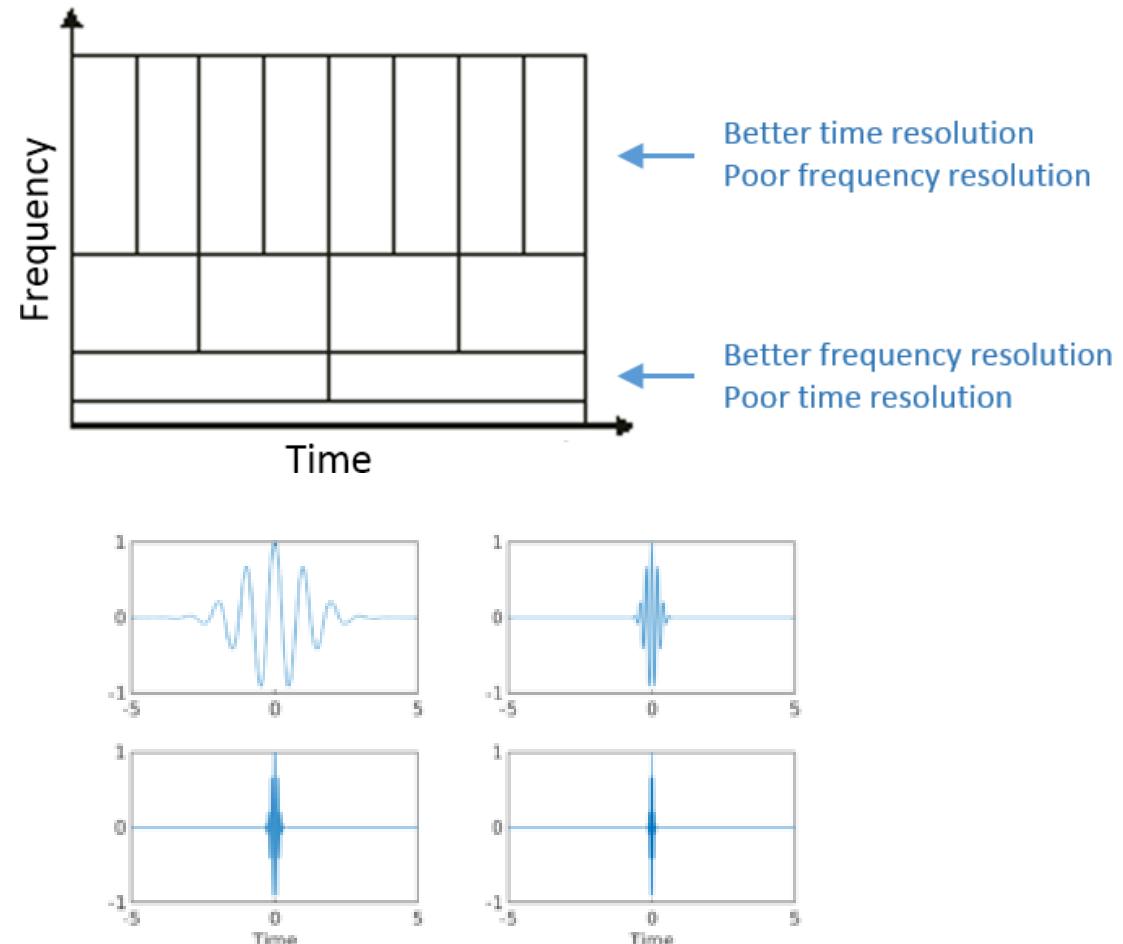


# Wavelet Transforms

## Morlet Wavelet

- Wavelet transformation then essentially involves convolving the complex wavelet with the EEG signal and moving it along the time axis (known as **translation**) and doing this with wavelets of varying frequencies (known as **scaling**).
- **higher frequency** wavelets can achieve **better localization** in time, while **low frequency** wavelets lose some information in time as they are stretched out.

wavelets of frequency 1, 5, 10 and 20 Hz 

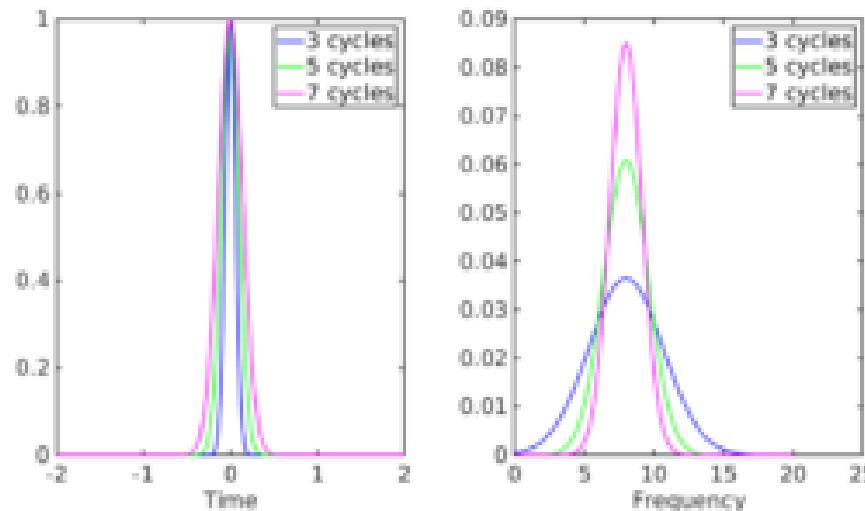


# Wavelet Transforms

## Morlet Wavelet

- Most important parameter-**number of cycles**
- As the number of cycles is increased the width of the Gaussian increases.
- When we take the FFT of these Gaussians, we see that the Gaussian with lower number of cycles is spread more in the frequency domain compared to the Gaussian with higher number of cycles.

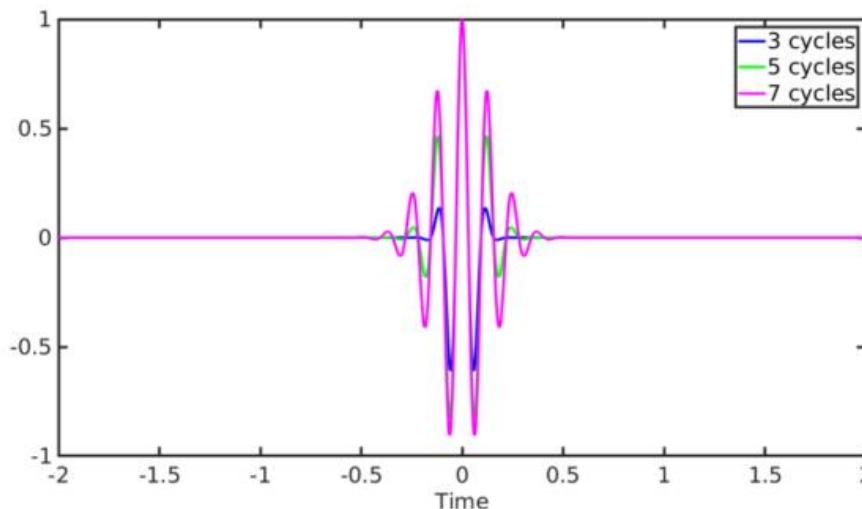
$$\sigma = \frac{n}{2\pi f}$$



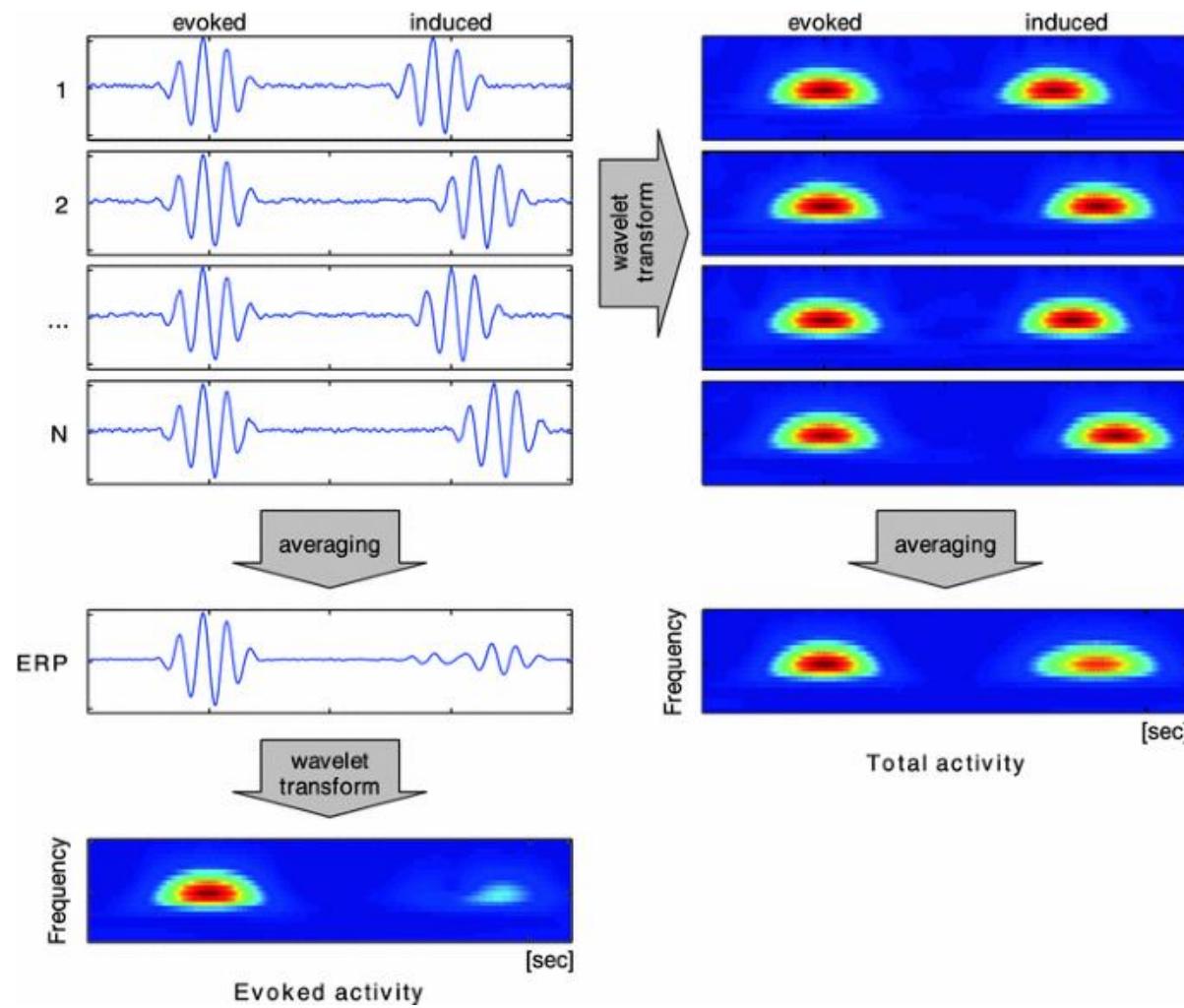
# Wavelet Transforms

## Morlet Wavelet

- **Choosing the number of cycles (n)**
- The wavelet with a higher n has a wider spread than the wavelet with a lower n, which can be interpreted as poorer temporal localisation as n increases.
- For *temporal-focused analysis*, choose a lower n
- For *frequency-focused analysis*, choose a higher n

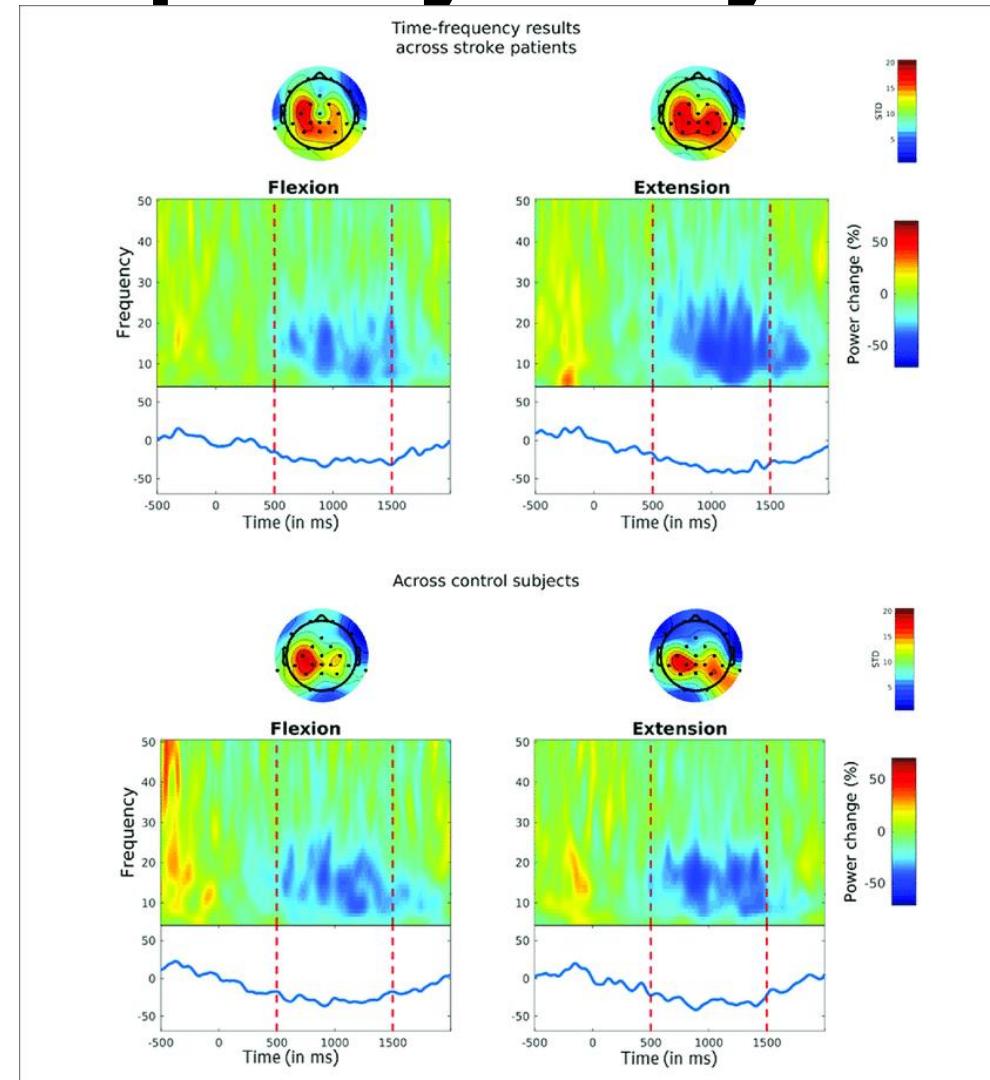


# Interpreting Time-Frequency Analysis



# Interpreting Time-Frequency Analysis

Event-related desynchronization (ERD) during MI. Time-frequency (TF) plots show the percentage change in power from baseline (i.e. from  $-0.5$  s to  $0$  s) for MI flexion trials (left panels) and MI extension trials (right panels). MI started at time point zero and was performed for  $1.5$  s. Vertical lines indicate the chosen time interval for the statistical analysis (i.e. from  $0.5$  s to  $1.5$  s). The solid blue line on the bottom reflects MI-related power changes within the  $10$ – $25$  Hz SMR frequency range.



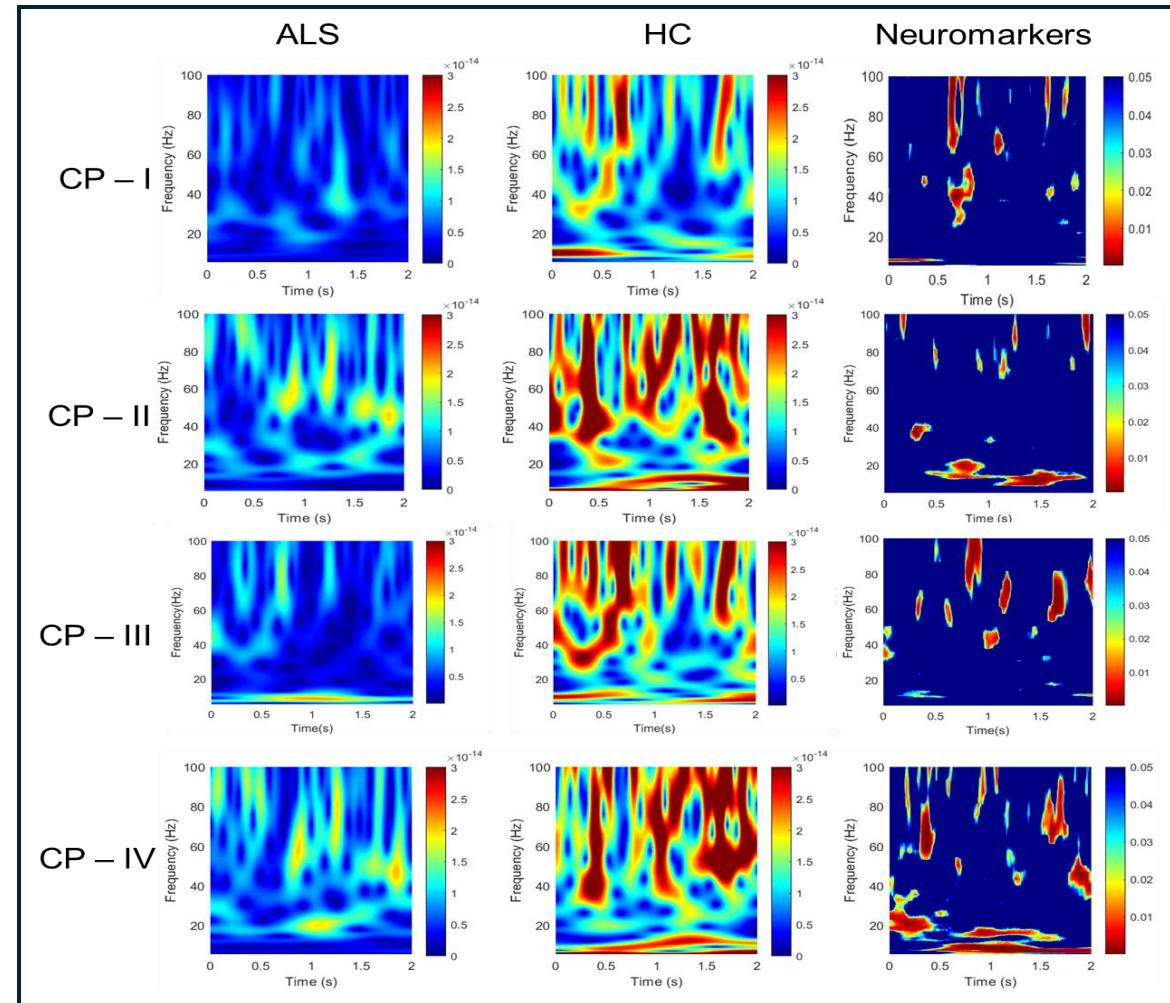
# Neuro-marker identification - ALS



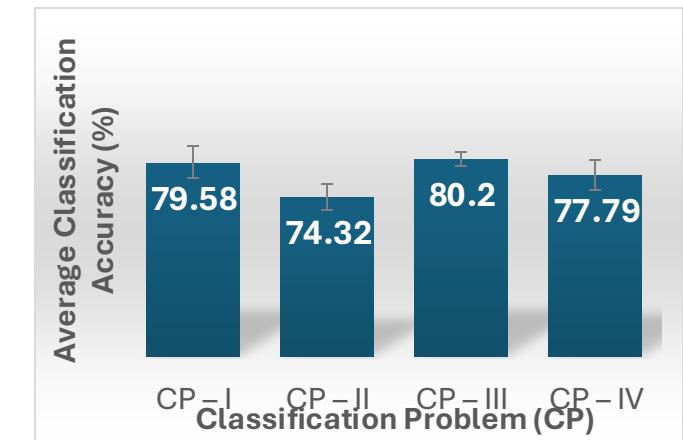
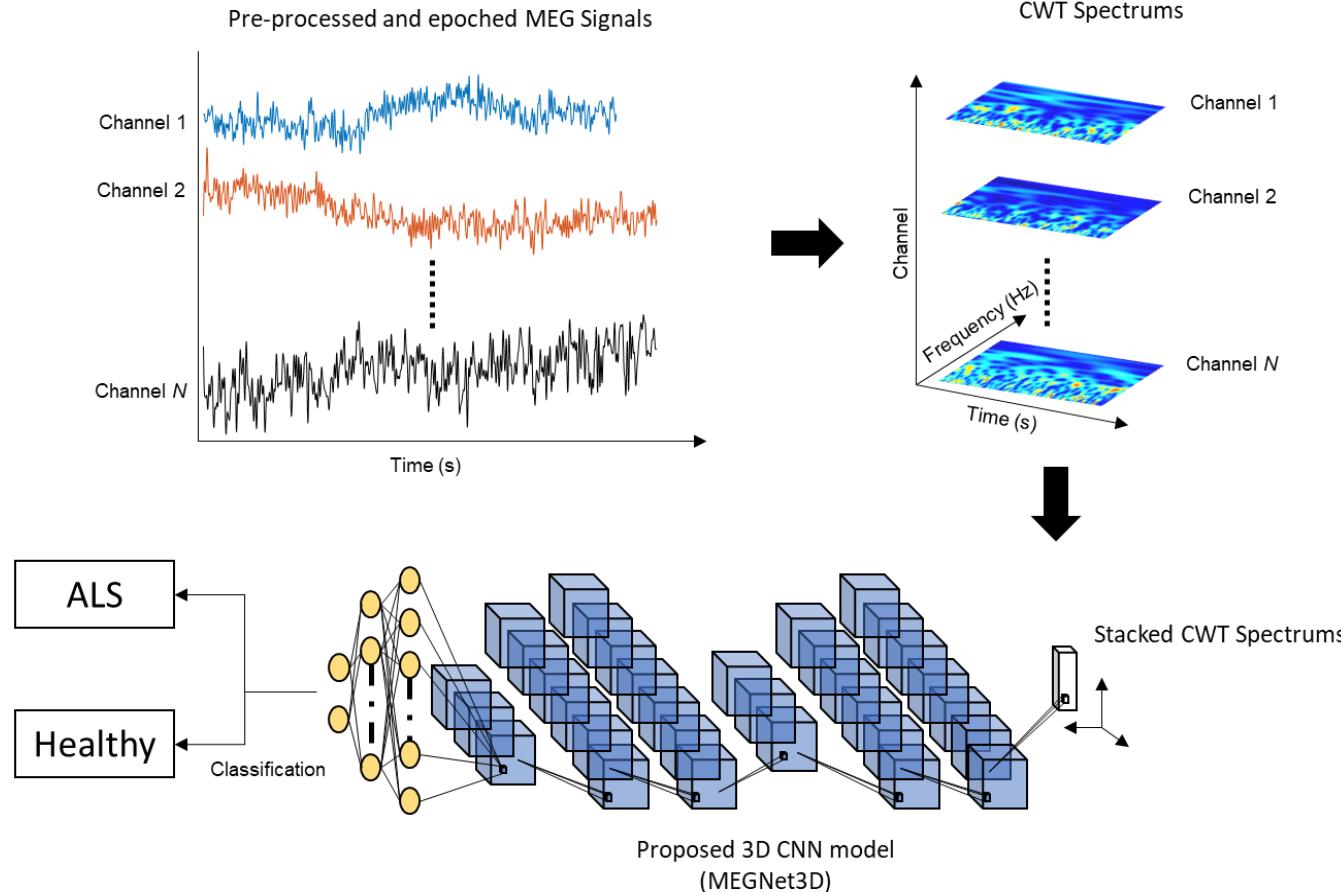
**Table: Different Classification Problems**

Classification Problem (CP)	Sensor Type	Eyelid Position
CP - I	MAG	Eye Closed
CP - II	MAG	Eye Opened
CP - III	GRAD	Eye Closed
CP - IV	GRAD	Eye Opened

**Figure: CWT spectrums from the central motor cortex region (Cz area) for HC and ALS patients**



# ALS Identification Pipeline



K. Samanta *et al.*, "An Automated Detection of Amyotrophic Lateral Sclerosis from Resting-State MEG Data Using 3D Deep Convolutional Neural Network," *2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Honolulu, Oahu, HI, USA, 2023, pp. 3337-3342, doi: 10.1109/SMC53992.2023.10393987.

# Common Brain Signal Analysis

- **Time Domain** – Event-Related Potentials, Amplitude & Latency Measurement, Single Trial Analysis, Cross-Correlation & Coherence
- **Frequency Domain** – Power Spectral Density, Fast Fourier Transform, Spectral Coherence , Cross-Spectral Density , Event related Spectral Perturbation, Band Power
- **Time-Frequency Domain** – Short-Time Fourier Transform, Inter-trial Coherence, Cross-Frequency Coupling
- **Brain and Functional Connectivity** → **Maria**

# EEG & LFP

## Some interesting papers to read

- Sun, C. & Mou, C., 2023. Survey on the research direction of EEG-based signal processing. *Frontiers in Neuroscience*, 17, Article 1203059. doi:10.3389/fnins.2023.1203059
- Zhang, H., Zhou, QQ., Chen, H. *et al.* The applied principles of EEG analysis methods in neuroscience and clinical neurology. *Military Med Res* 10, 67 (2023). <https://doi.org/10.1186/s40779-023-00502-7>
- A. Jackson and T. M. Hall, "Decoding Local Field Potentials for Neural Interfaces," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 10, pp. 1705-1714, Oct. 2017, doi: 10.1109/TNSRE.2016.2612001.
- <https://buzsakilab.com/content/PDFs/BuzsakiKoch2012.pdf>

# Useful Tools

Toolkit	Domain	Platform	Strengths
<b>SpikeInterface</b>	Spiking, LFP analysis	Python	Unified pipeline, sorting, benchmarking, reproducibility
<b>Chronux</b>	Spike, LFP, EEG/MEG	MATLAB	Spectral methods, GUI, statistical rigor
<b>MNE-Python</b>	EEG, MEG, iEEG/ECoG, fNIRS	Python	End-to-end analysis, source localization, tutorials
<b>EEGLAB</b>	EEG/MEG	MATLAB	ICA, plugins, visualization, scripting + GUI
<b>FieldTrip</b>	EEG, MEG, LFP, Spike	MATLAB	Advanced analysis, connectivity, scripting
<b>Brainstorm</b>	EEG/MEG, LFP	MATLAB / GUI	GUI-friendly, reproducible, no MATLAB required
<b>NBT</b>	EEG/MEG biomarkers	MATLAB	Biomarker focus, database, EEGLAB integration

# Reading

## Why?

- No single method captures both WHERE and WHEN brain activity happens
- Combining modalities provides a more complete picture of brain function

## Key Combinations

- **EEG + fMRI** → *ms timing + mm spatial maps*
- **MEG + fMRI** → *better source localization + spatial mapping*
- **Invasive (LFP/Unit) + fMRI/EEG** → *link neurons ↔ networks*

## Applications

Cognitive neuroscience (fast rhythms + networks),  
Clinical (epilepsy, Parkinson's), Brain–Computer  
Interfaces, Cross-validation of neural signals

**Multi-modal = “Where + When” → a complete view of brain function.**

# Comparison

Method	What it Measures	Spatial Resolution	Temporal Resolution	Invasiveness	Common Uses
<b>Extracellular Recording</b>	Action potentials from individual neurons	Microns	<1 ms	Invasive	Animal studies, BMIs
<b>LFP</b>	Local synaptic activity	~0.1–1 mm	1–10 ms	Invasive	Oscillations, circuits
<b>EEG</b>	Scalp electrical potentials	cm	ms	Non-invasive	Epilepsy, sleep, BCI
<b>MEG</b>	Magnetic fields from neural currents	mm–cm	ms	Non-invasive	Source localization, cognition
<b>fMRI</b>	BOLD (blood oxygen) response	mm	s	Non-invasive	Functional mapping, networks

TIME FOR A  
BREAK



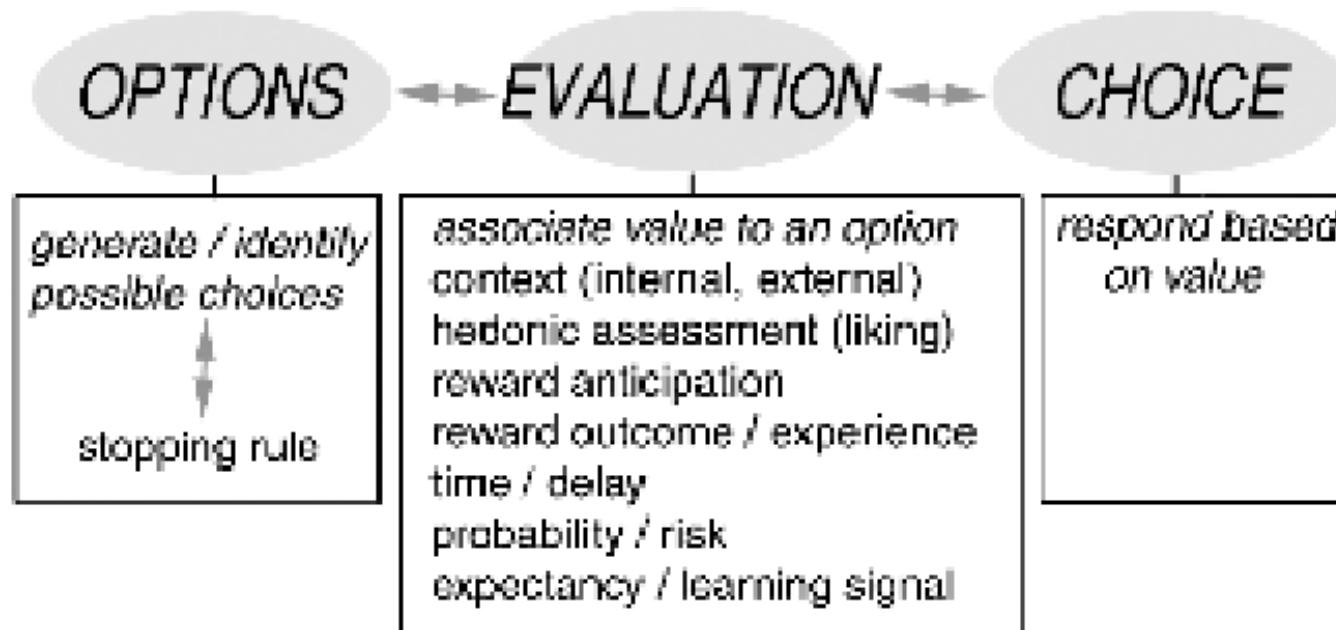
# **Group Decision Making using Collaborative Brain-Computer Interfacing**

# Making decisions

- “The average Brit makes **773,618 decisions in a lifetime** but lives to regret as many as 143,262 of them” – Huffington Post, 2011
- “[T]he average American makes approximately **70 conscious decisions every day**” – Psychology Today, 2012
- “[T]he average person makes **35,000 decisions** a day.” – The Telegraph, 2016



# The Process

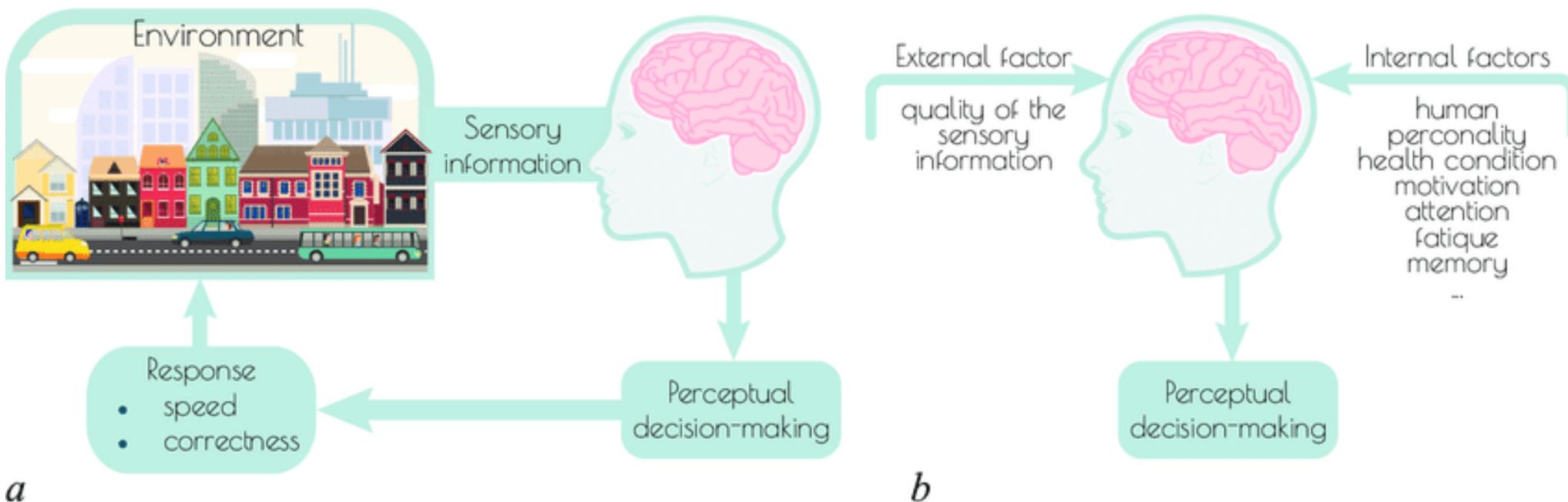


**Figure 2:** Schematic Summarizing a Simple Three-Stage Model of Decision Making and Listing Some of the Processes That May Be Involved at Each Stage.

Fellows, Behav & Cog Sci Rev 2004

# Perceptual Decision Making

- Perceptual decision making is the act of choosing one option or course of action from a set of alternatives on the basis of the available sensory evidence.
  - interpreting sensory information to make decisions.



# Individual Decision Making

- **Decision accuracy could degrade with:**
  - Limited processing time
  - Quantity and complexity of data
  - Irrelevant information, audiovisual clutters/distractors
  - High-stakes, time-pressed situations
- **Mental state of the operator also affects decision accuracy**
  - Fatigue/alertness
  - Mental workload
  - Attention level



# Group Decision Making

**Power of crowds:** groups have augmented wisdom. This is why human decisions are routinely made by committees (where members' knowledge, intelligence, experience and creativity are melded to improve outcomes).

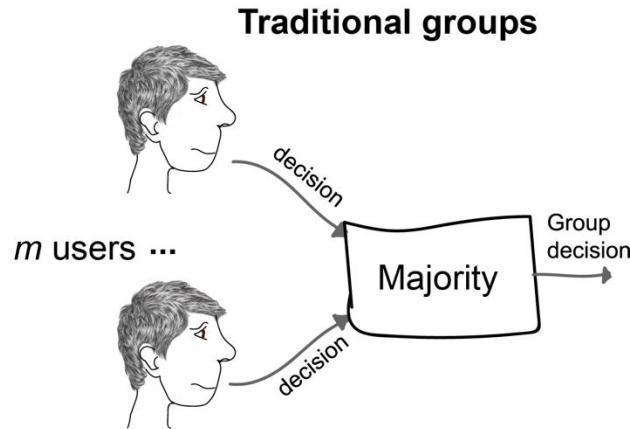
**Groups could fail:** under- and over-confidence biases, reduced member effort, time constraints, strong leadership, ...



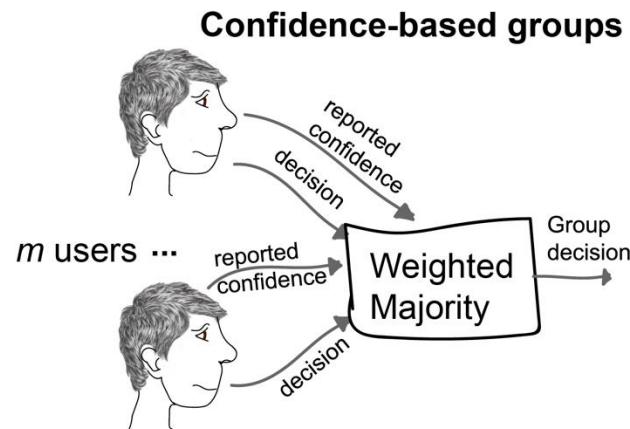
*"All those in favor say 'Aye.'"*  
*"Aye."*   *"Aye."*  
*"Aye."*   *"Aye."*

# Group Decision Making

## Traditional decision aggregation strategies



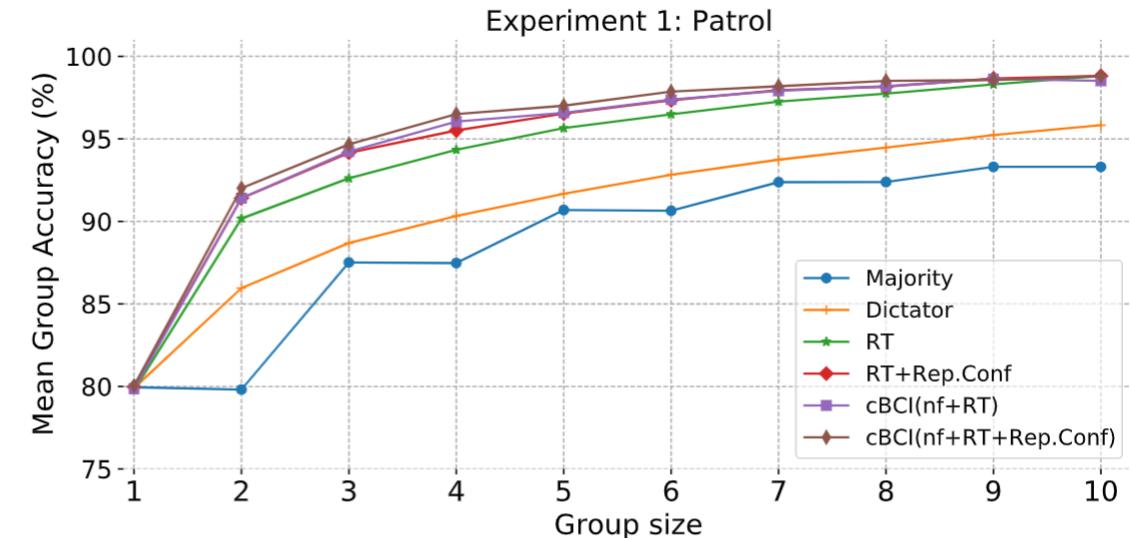
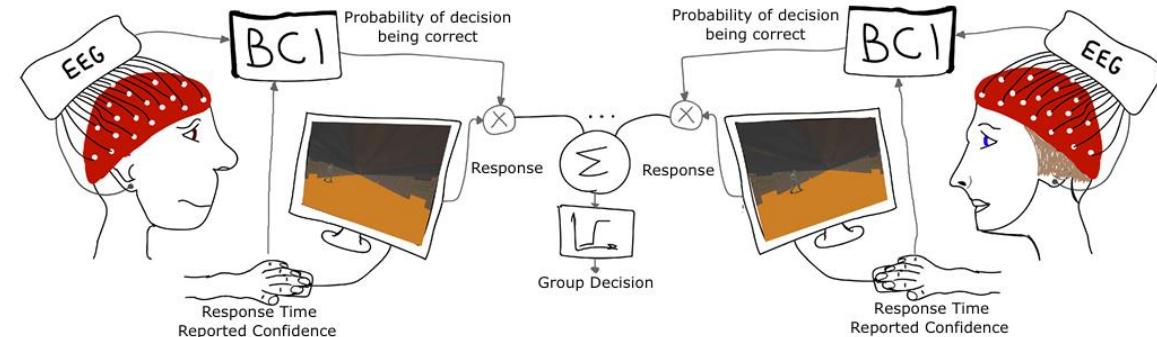
**One head = One vote**



**Confidence reported by the participants  
(SUBJECTIVE CONFIDENCE)**

# Improving group decisions

- Choice aggregation by confidence weighting (Bang and Frith 2017).
- **Collaborative brain-computer interfaces (cBCI)** reduce subjectivity.
- Confidence decoded using machine learning.



Bhattacharyya et al. 2021

# Timeline of cBCI Research

Eckstein, et al.  
2012:

- cBCI presented using noisy face/car discrimination.
- Offline EEG analysis to predict choice.



Poli, et al. 2014:

- Visual matching of sequential patterns.
- Predicting confidence.



Valeriani & Poli, 2019:

- Facial recognition with ResNet assistance.
- Offline analysis.



Valeriani, et al. 2022:

- Multimodal (fMRI & EEG) experiment pandemic resource allocation task.
- Meta-learning algorithms to speed up training, improve accuracy.



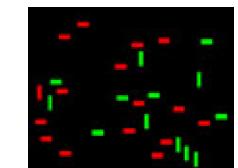
Yuan, et al. 2013:



- Face/car discrimination; offline training followed by online testing.
- Choice prediction.

Valeriani, et al. 2017:

- Traditional visual search of coloured bars. Neural confidence estimates outperformed non-BCI groups.
- Realistic visual search with simplified communication.



Bhattacharyya, et al  
2021:

- Target detection in low-light (Corridor and Outpost experiments).
- ‘Anytime’ system with estimated stim. presentation time.



Sadras, et al. 2023:

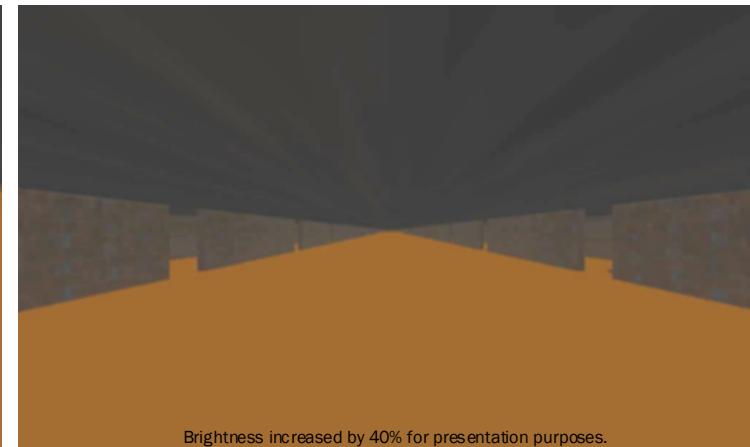
- Comparison of several classifiers from stimulus-locked ERPs.
- Offline but showed online feasibility.



# cBCI on Dynamic Environment

## □ Patrol Experiment

- We generated a **dynamic environment** where a soldier is walking along a corridor with multiple doorways present on both sides (**Corridor/Patrol Experiment**)
- **Task:** Decide whether the characters appearing wear a helmet or a cap



Brightness increased by 40% for presentation purposes.

Bhattacharyya et al., NER'19,  
Bhattacharyya et al. Scientific  
Report (2021)

# cBCI on Dynamic Environment

Dynamic Environment- Outpost Experiment

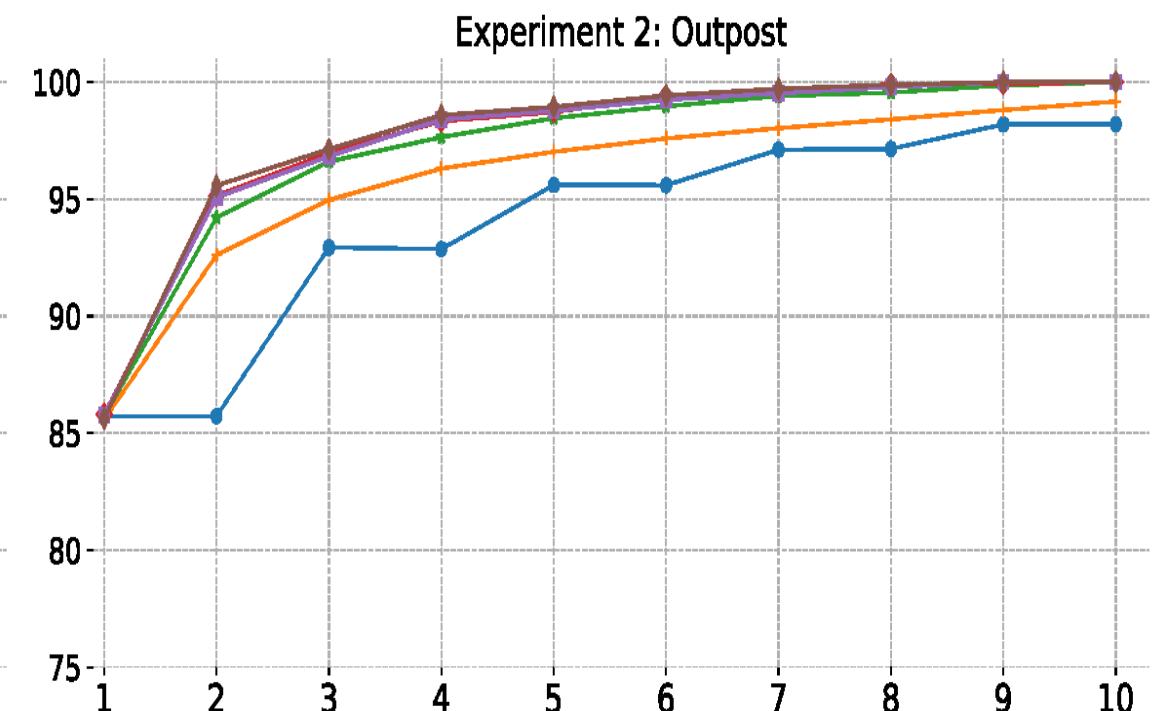
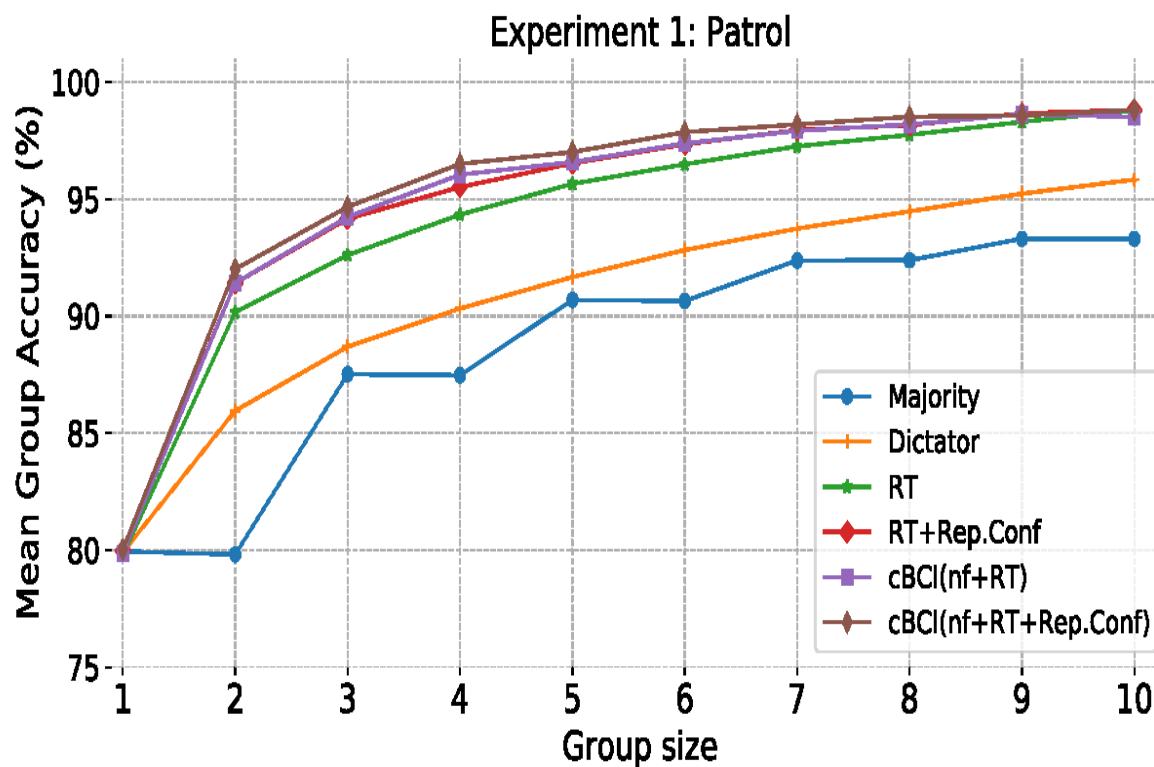
- User stationed at an outpost.
- Observes a character moving in.
- **Task:** decide whether the person is wearing a helmet or a cap, Report self-confidence
- **Reward and penalties** proportional to the correctness of the decision and the time taken by the user to respond



Bhattacharyya et al. Scientific Report (2022)

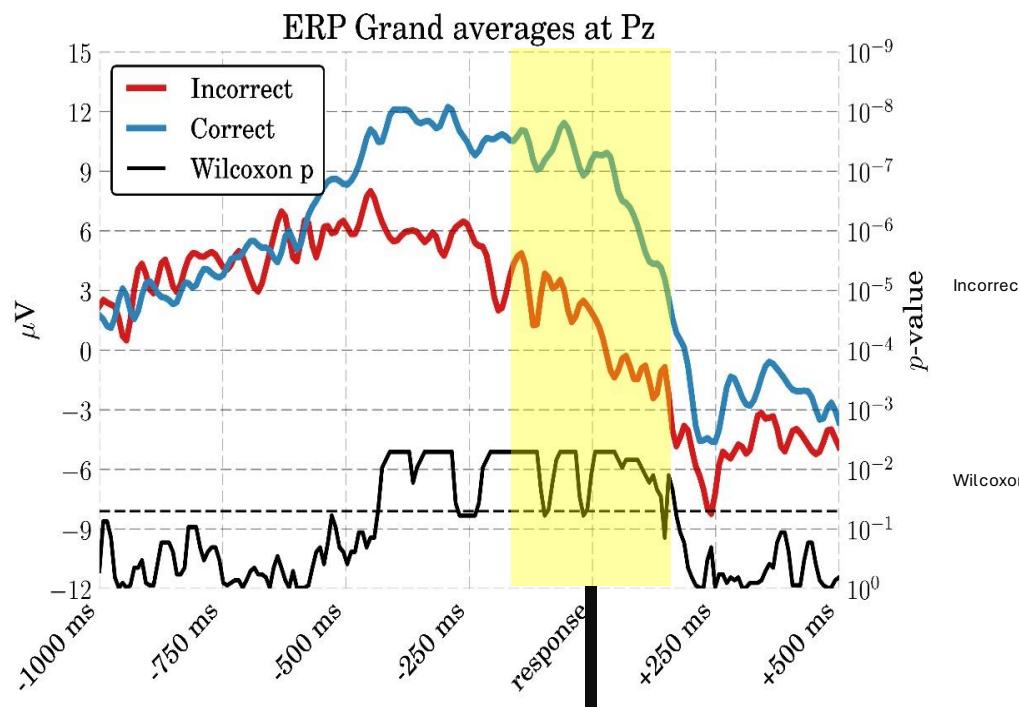
# cBCI Works

Temporal filtered + Common Spatial Patterns → Random Forest Classifier



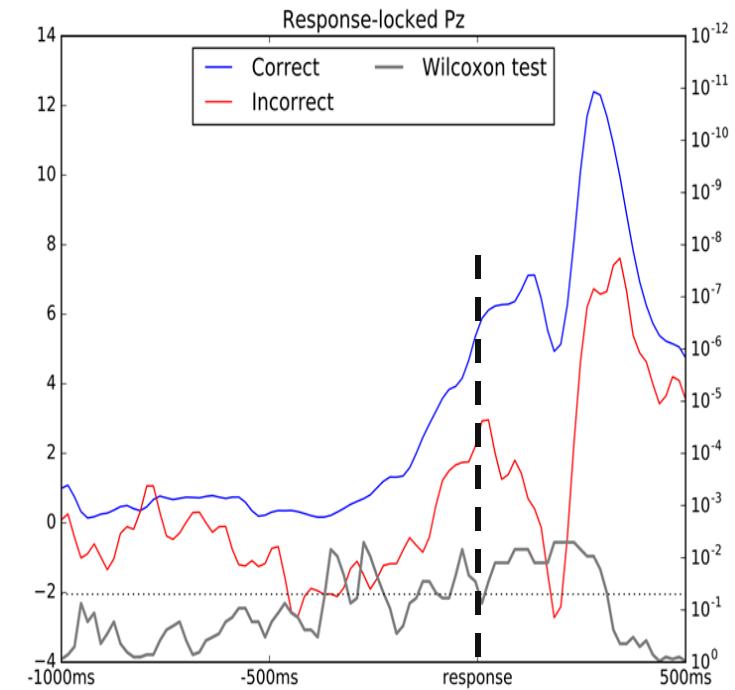
# Evidence of Neural Markers

- Patrol Experiment



→ Decision-Related  
Potential (DRP)

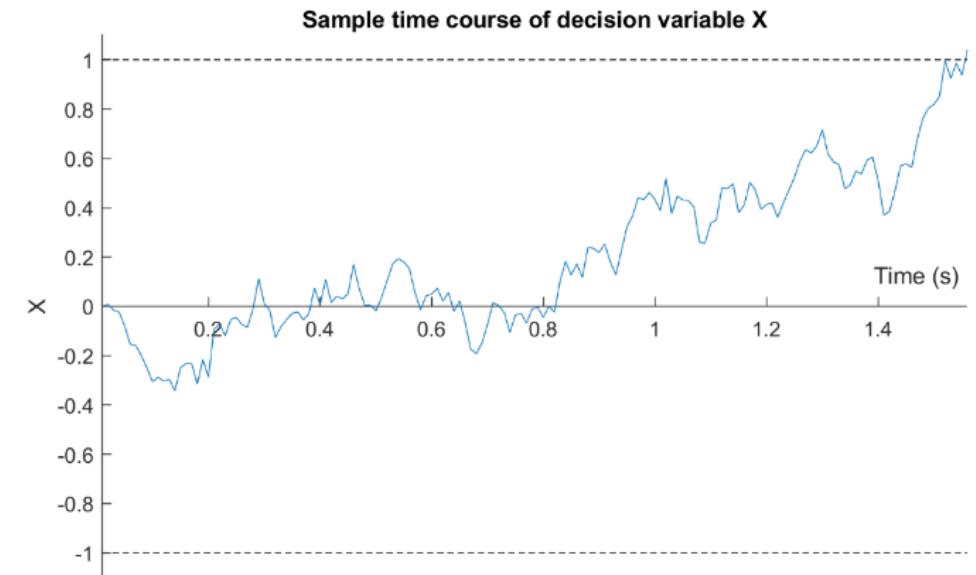
- Outpost Experiment



# Modelling Optimised Groups

## Drift diffusion models

- Models **evidence accumulation** – linked with neural signals.
- $dX = \mu dt + \sqrt{dt}\sigma\eta$
- Communication: add **social drift** variable



Drift diffusion model

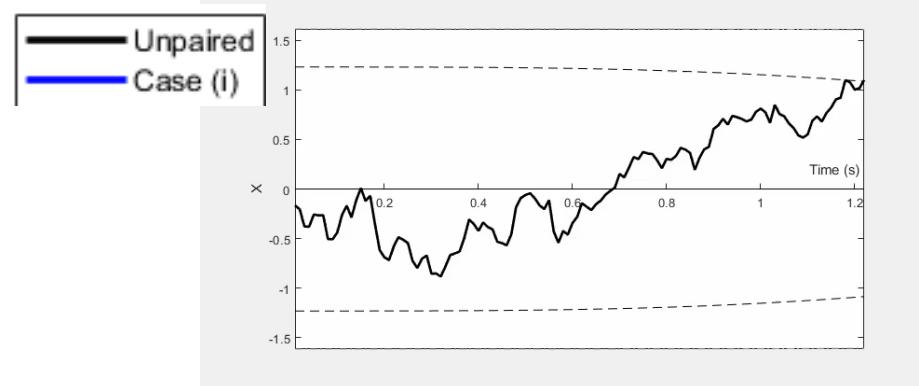
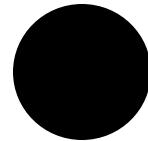
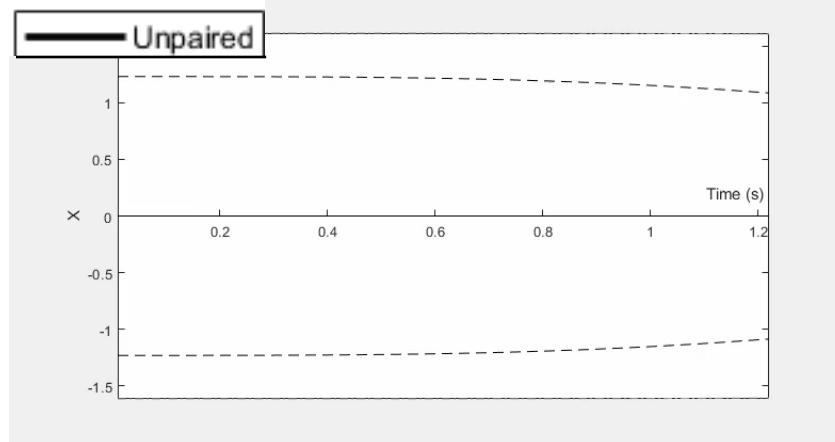
More by KongFatt





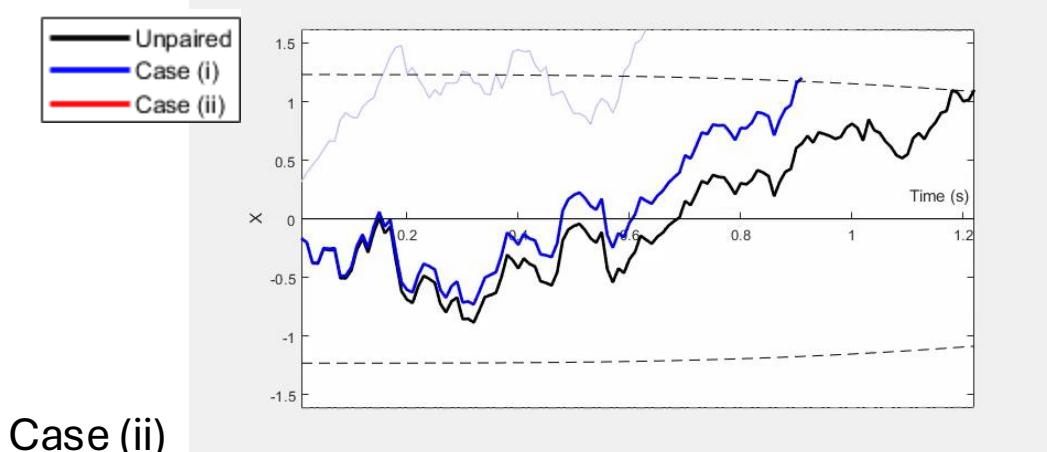
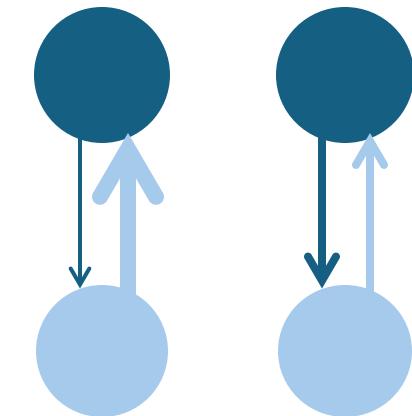
# Some Pairing

Unpaired DDM



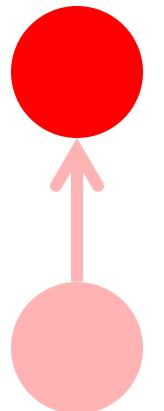
Case (i) Bidirectional, continuous communication throughout decision-making process

(a) expert exerts more influence



Case (ii)  
Unidirectional communication following choice declaration

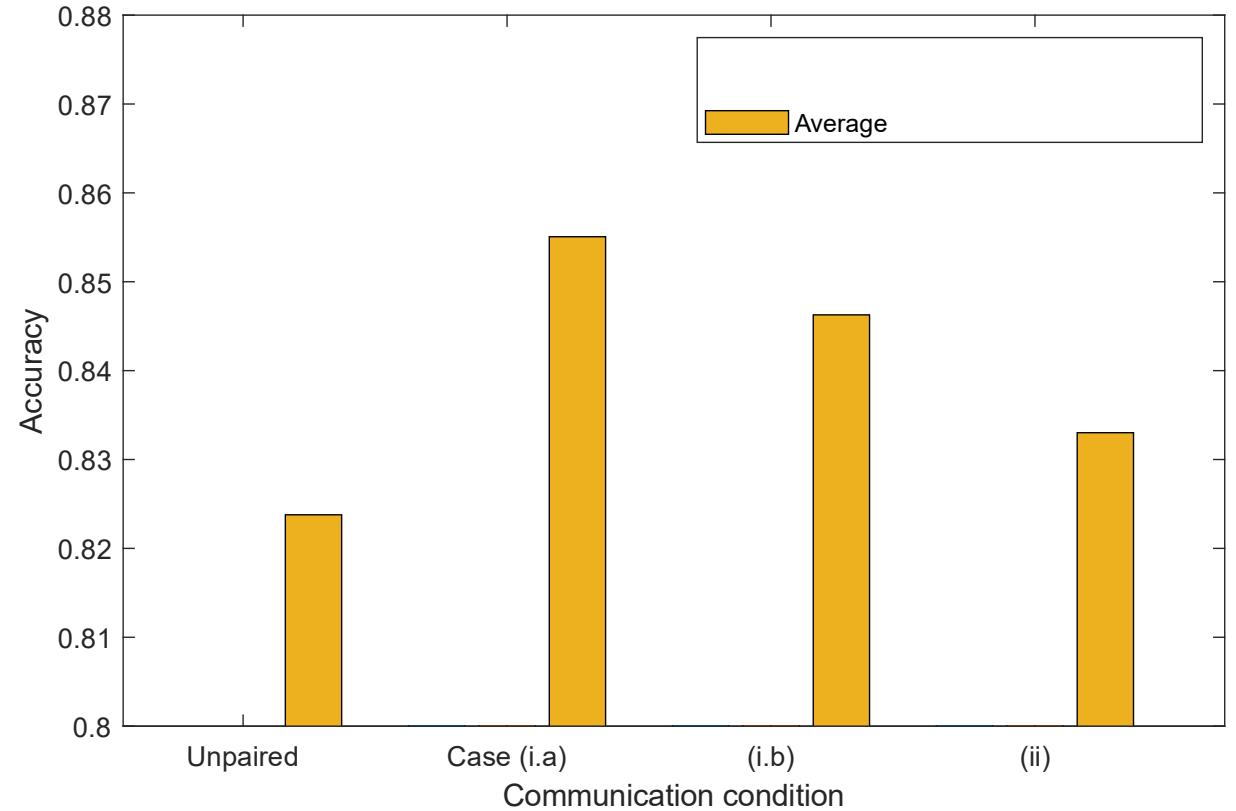
(b) equal social influence





# Results

- Communication **improved average performance in all conditions** compared to unpaired accuracy.
- Especially under continuous communication with social influence weighted by individual accuracy (Case i.a).

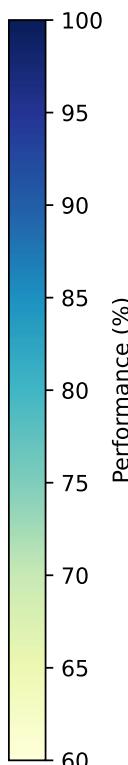
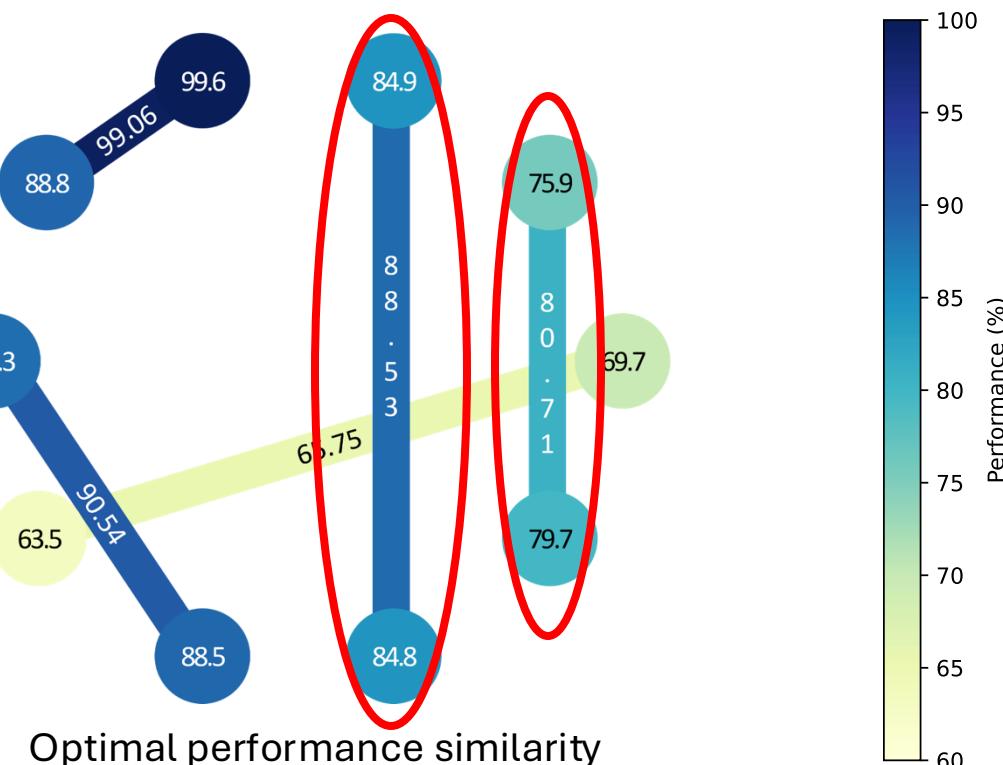
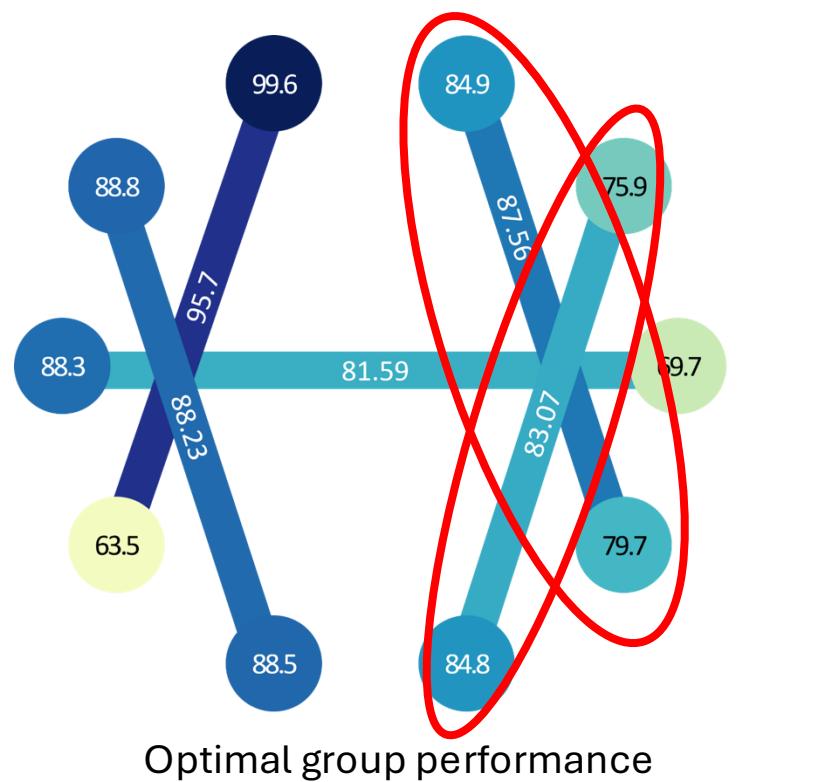




NAT 2025

# Group Optimisation Results

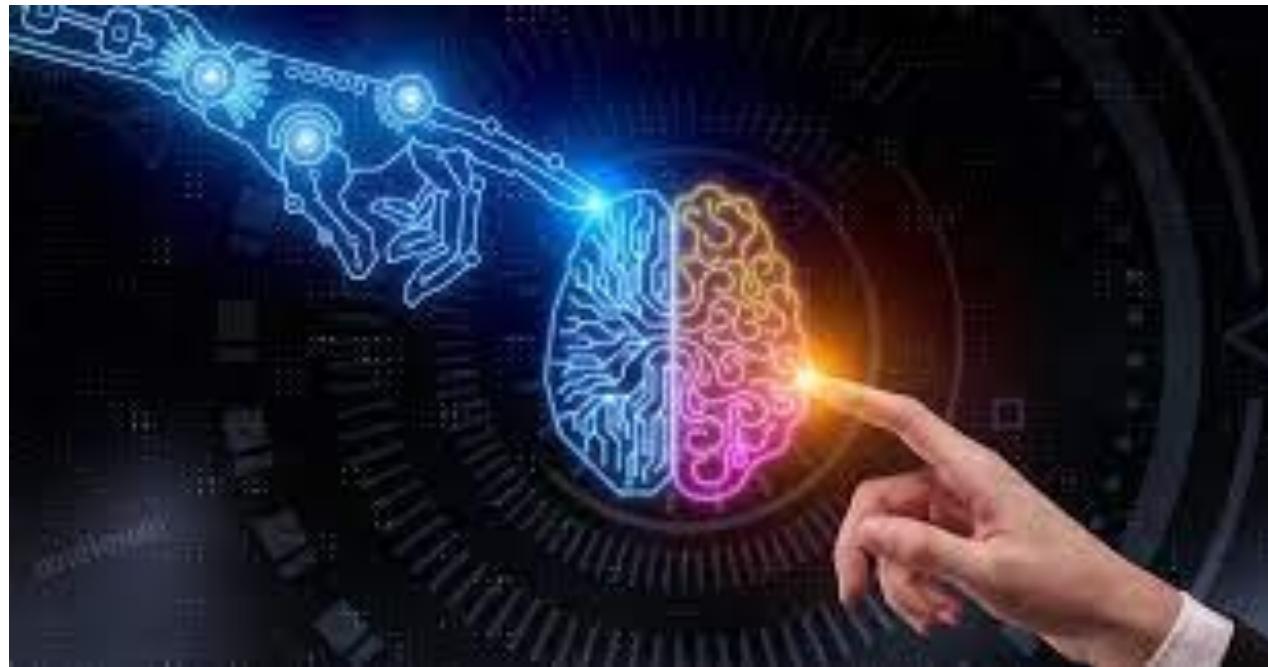
- Pairs optimised for **similarity** were *more likely* to receive a **collective benefit** from being paired (aligning with Bahrami, et al. 2010).
- However, the mean of all pairs in the **DDM-optimised group** is higher.



# THANK YOU for listening

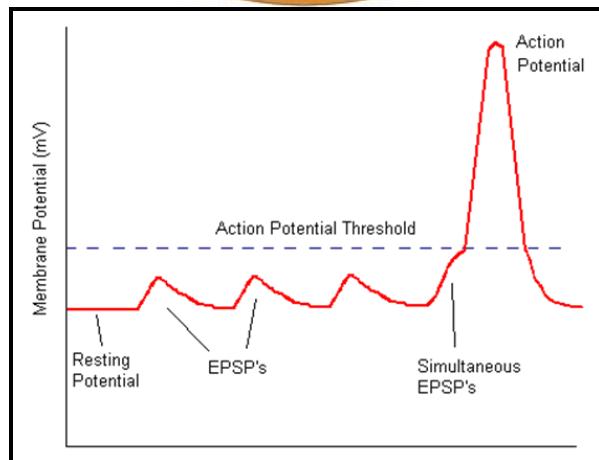
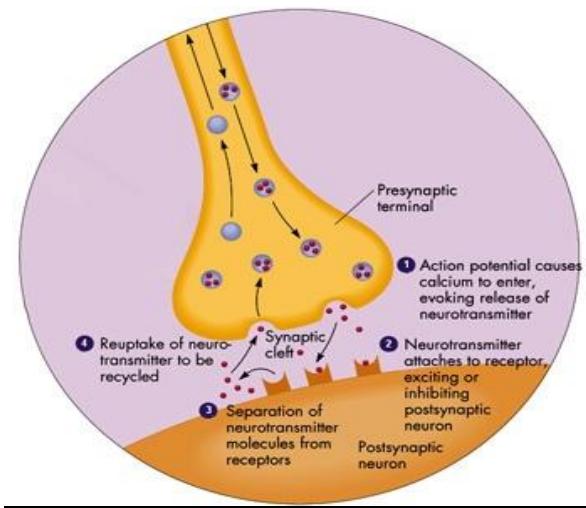
[s.bhattacharyya@ulster.ac.uk](mailto:s.bhattacharyya@ulster.ac.uk)

<https://pure.ulster.ac.uk/en/persons/saugat-bhattacharyya-2>



# Electroencephalography

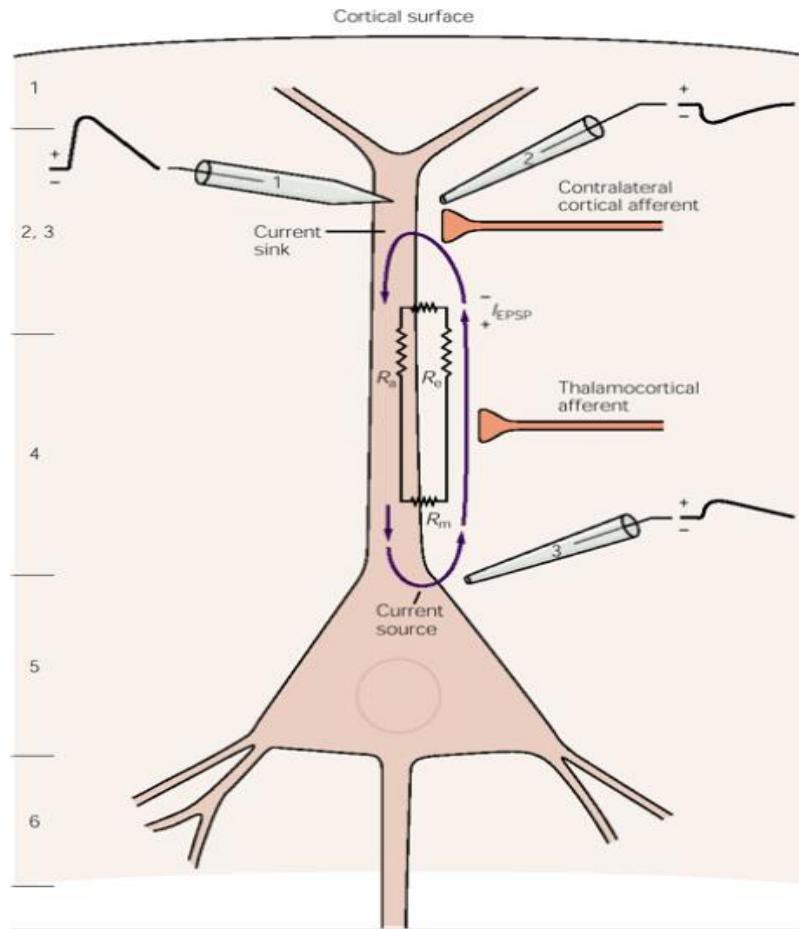
## Neural Basis



- 1) When an Action Potential reaches the axon terminal the neuron releases a neurotransmitter.
- 2) The neurotransmitter binds to the receptor.
- 3) The postsynaptic neuron gets depolarized ( $\text{Na}^+$  inward currents – excitatory - EPSP) or hyperpolarized ( $\text{Cl}^-$  inward currents – inhibitory -IPSP).
- 4) EPSP and IPSP summate temporally and spatially.
- 5) If the postsynaptic neuron reaches a given depolarization threshold, an action potential is generated.

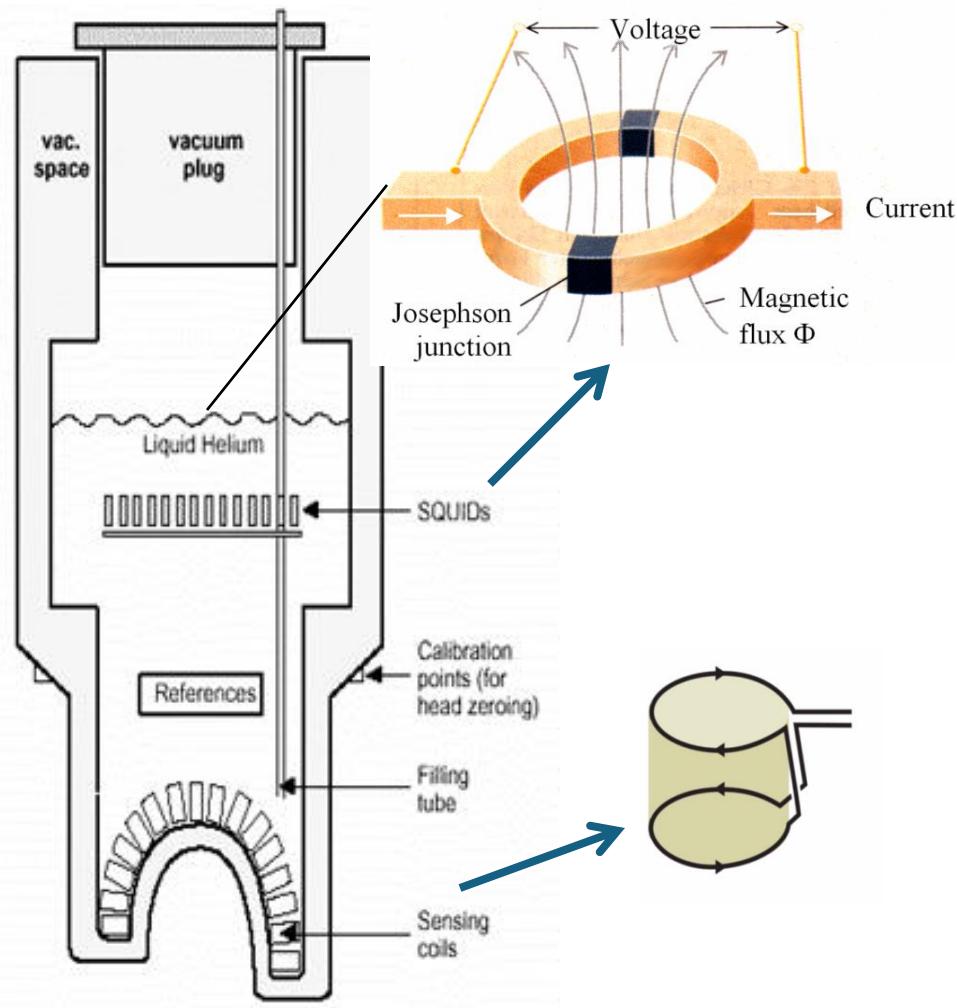
# Electroencephalography

## Neural Basis



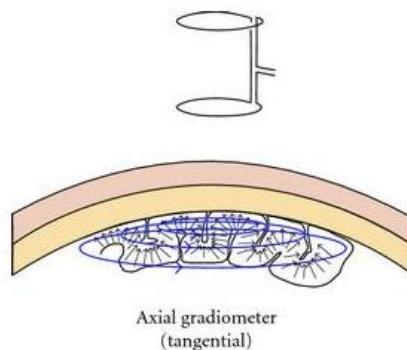
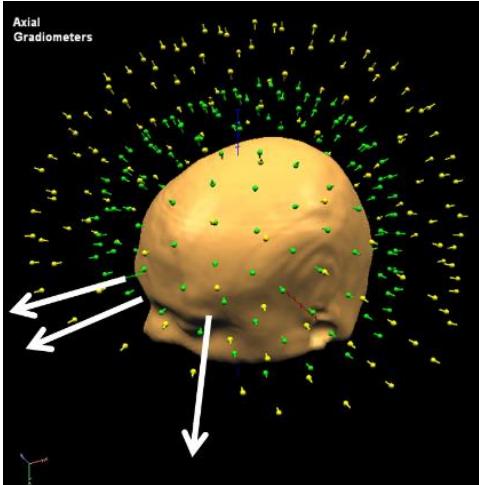
- When an EPSP is generated in the dendrites of a neuron an extracellular electrode detects a negative voltage difference, resulting from  $\text{Na}^+$  currents flowing inside the neuron's cytoplasm.
- The current completes a loop further away the excitatory input ( $\text{Na}^+$  flows outside the cell), being recorded as a positive voltage difference by an extracellular electrode.
- This process can last hundreds of milliseconds.
- **Thus, a small dipole is generated!!**

# Magnetoencephalography



- **SQUID** - Superconducting **Q**uantum Interference **D**evice, immersed in super-cool liquid helium
- Sensitive to field changes in order of femto-Tesla (10-15)
- Superconductive ring with two Josephson junctions
- Flux transformers (coils)
  - Magnetometers
  - Gradiometers (planar/axial)

# Magnetoencephalography

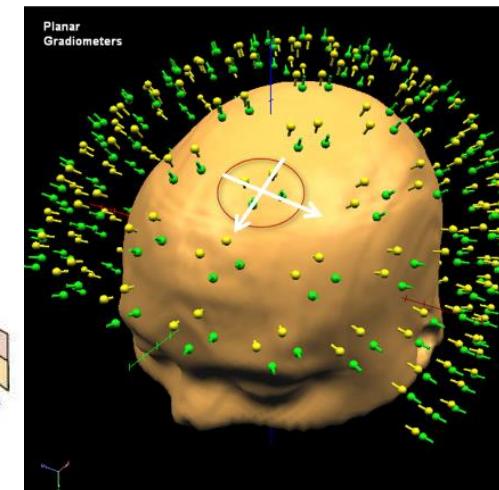
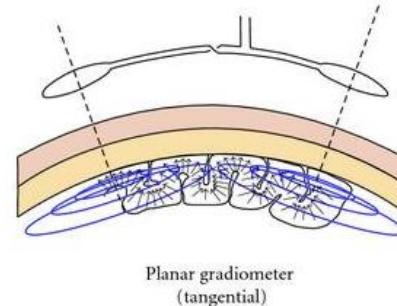


Axial Gradiometer MEG sensors...

- ...are aligned orthogonally to the scalp
- ...record gradient of magnetic field along the radial direction

Planar Gradiometer MEG sensors...

- ...two detector coils on the same plane
- ...have sensitivity distribution similar to bipolar EEG setup



# Spike Sorting

## Step 2. Feature Extraction

### PCA (Principal Component Analysis)

- We compute the covariance matrix:

$$C = \frac{1}{N} \sum_{j=1}^N (w_j - \bar{w})(w_j - \bar{w})^T$$

- Find eigenvectors  $u_k$  of  $C$ .
- Project spikes onto top  $K$  components:  
$$y_j = U^T(w_j - \bar{w}), \text{ where } U \in \mathbb{R}^{d \times K}.$$
- Now, each spike is represented by a **low-dimensional feature vector**  $y_j \in \mathbb{R}^k$

# Spike Sorting

## Step 3. Clustering

- We now want to assign spikes to neurons based on their feature vectors.

- **Gaussian Mixture Model (GMM)**

- Assume spikes come from a mixture of Gaussian distributions:

$$p(y) = \sum_{k=1}^K \pi_k N(y|\mu_k, \Sigma_k),$$

where,  $\pi_k$  is mixture weights, and  $\mu_k, \Sigma_k$  is the mean and covariance of cluster  $k$ .

- We fit parameters via **Expectation-Maximization (EM)**:

- **E-step:** Compute responsibilities (posterior probability that spike  $j$  belongs to neuron

$$k): \gamma_{jk} = \frac{\pi_k N(y_j|\mu_k, \Sigma_k)}{\sum_{m=1}^K \pi_m N(y_j|\mu_m, \Sigma_m)}$$

- **M-step:** Update parameters using weighted means & covariances:

$$\mu_k = \frac{\sum_j \gamma_{jk} y_j}{\sum_j \gamma_{jk}}, \Sigma_k = \frac{\sum_j \gamma_{jk} (y_j - \mu_k)(y_j - \mu_k)^T}{\sum_j \gamma_{jk}}$$

Iterate until convergence. Each spike is assigned to the neuron with maximum  $\gamma_{jk}$

# Spike Sorting

## Step 3. Clustering (Other approach)

### K-means (simpler model)

- Minimise within-cluster variance:

$$\min_{\{\mu_k\}} \sum_{j=1}^N \min_k \|y_j - \mu_k\|^2$$

- This assumes spherical, equally sized clusters (not always realistic).

### Template Matching (Generative Model)

- Suppose each neuron has a canonical waveform  $s_k(t)$ .
- Then the observed signal is:

$$x(t) = \sum_k \sum_i a_{ki} s_k(t - t_{ki}) + n(t)$$

- where  $a_{ki}$  is amplitude scaling and  $t_{ki}$  are spike times.
- Spike sorting becomes **deconvolution**: estimating  $t_{ki}$  and  $k$ . Solved by **sparse optimisation**.

# Spike Sorting

## Key performance measures

### 1. Spike Sorting Accuracy

- How well the spike sorting algorithm correctly assigns spikes to the right neuron.
- **Ground truth problem:** In real experiments, the true neuron identity is unknown, so accuracy is often estimated using:
  - **Simulations / ground-truth data:** Compare assigned labels to known neuron sources.
  - **Metrics without ground truth:**
    - **Isolation distance** – Mahalanobis distance between clusters.
    - **L-ratio** – overlap of spike features between clusters.
    - **Refractory period violations (RPV)** – check if sorted units show biologically implausible ISIs (<1–2 ms).
- Maximise separation between clusters, minimise misclassifications.

# Spike Sorting

## Key performance measures

### 2. Signal-to-Noise Ratio (SNR)

How large the spike waveform is relative to the background noise.

$$SNR = \frac{A_{spike}}{\sigma_{spike}}$$

where

- $A_{spike}$  = mean peak-to-peak amplitude of spike waveform,
- $\sigma_{spike}$  = standard deviation of background noise.

**High SNR makes detection/sorting easier and improves accuracy.**

# Spike Sorting

## Key performance measures

### 3. Statistical Tests for Spike Train Analysis

After sorting, the spike train (sequence of spike times) is analysed statistically.

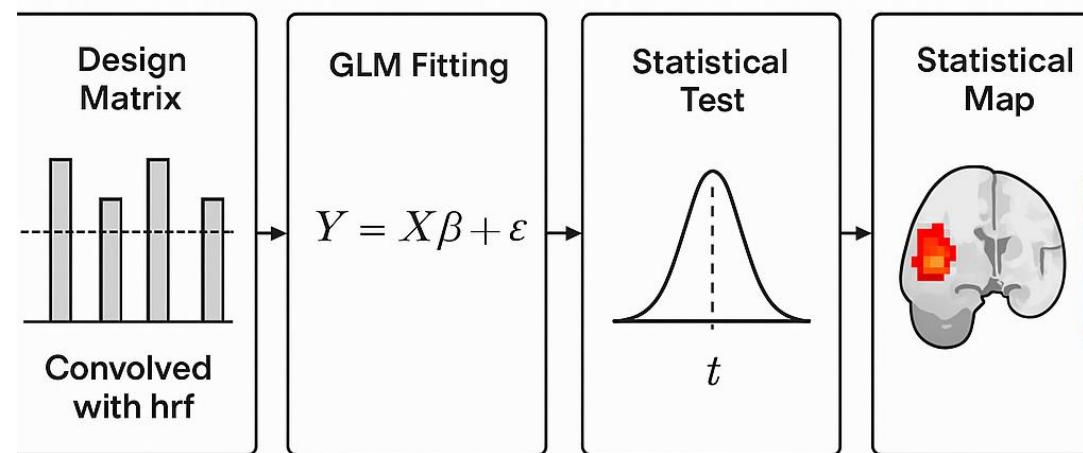
#### (a) Poisson Models

- Assume spikes occur randomly with some rate  $\lambda$ .
- **Homogeneous Poisson process:** Constant firing rate.
  - Inter-spike interval (ISI) distribution is exponential
- **Inhomogeneous Poisson process:** Rate depends on time or stimulus,  $\lambda(t)$ .
- Used to test if a neuron's spiking is consistent with random Poisson firing or has additional structure.

#### (b) Firing Rates

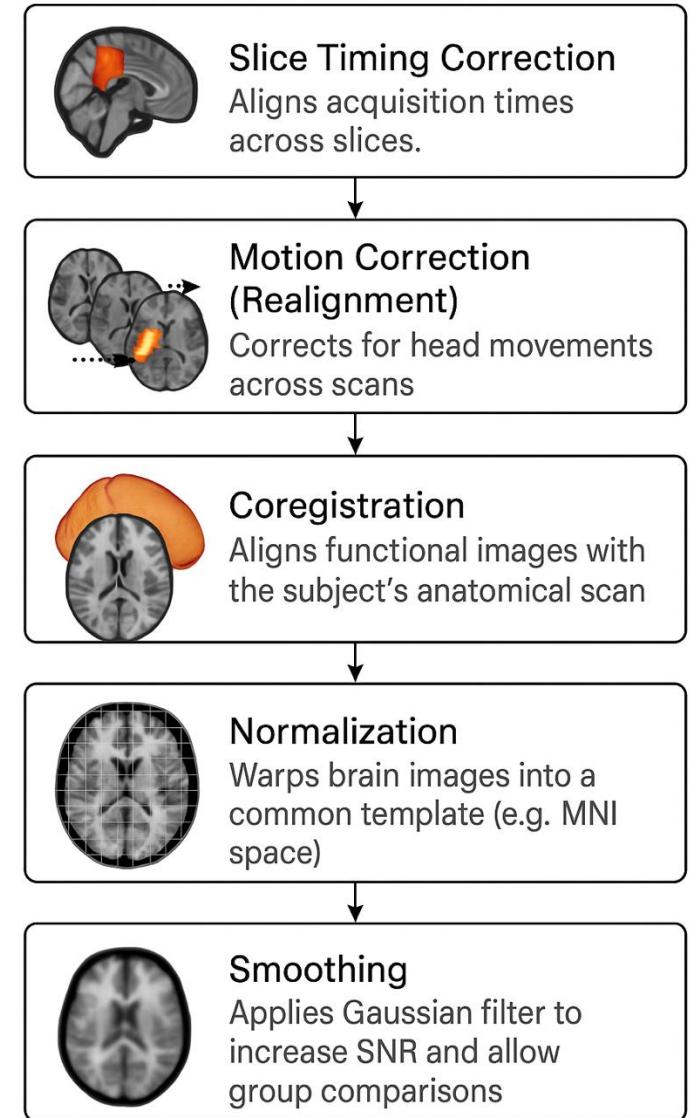
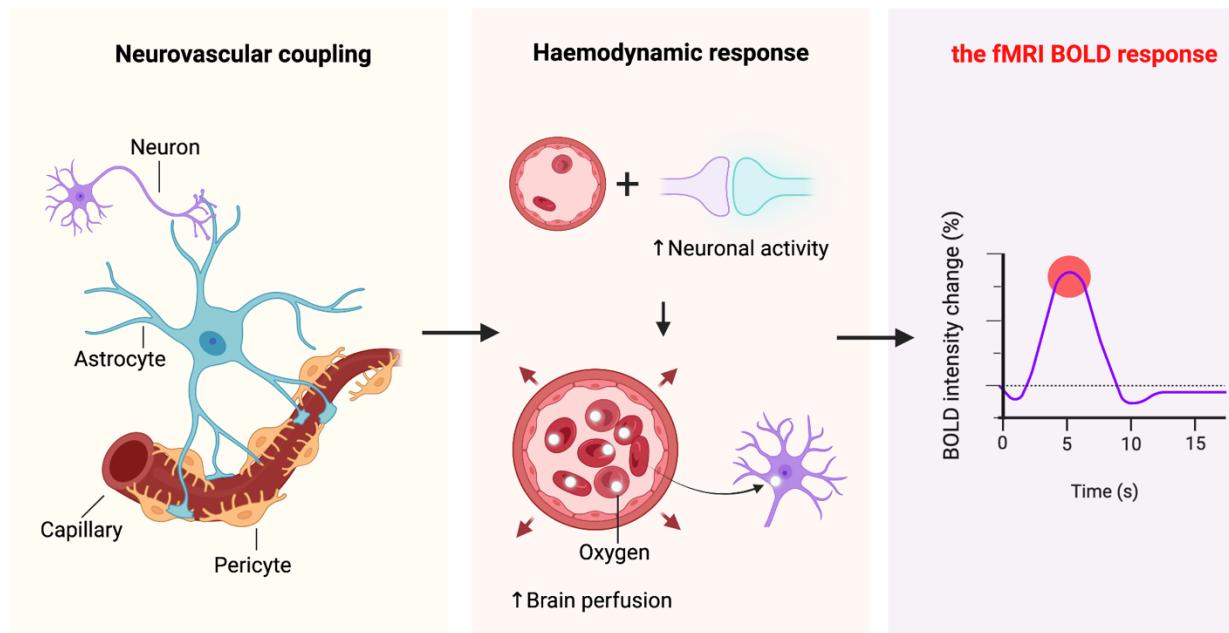
- **Definition:** Number of spikes per unit time.
  - Instantaneous firing rate can be estimated with kernel smoothing of spike trains.
  - Peri-stimulus time histogram (PSTH): firing rate relative to a repeated stimulus onset.
- **Statistical comparisons:**
  - **t-tests / ANOVA** → compare mean firing rates across conditions.
  - **Poisson regression / GLMs** → model firing rates as a function of covariates (stimulus, behaviour).

# Analysing BOLD signals



# Pre-processing BOLD signals

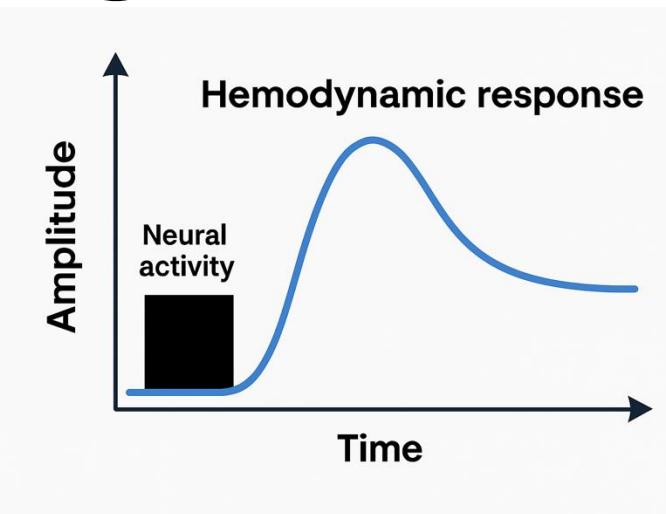
- Raw fMRI data are noisy and affected by head motion, scanner distortions, and individual brain differences.
- Preprocessing prepares the data for statistical analysis.



# Hemodynamic Response Modelling

- The BOLD signal is **not** an instantaneous reflection of neural activity.
- **Hemodynamic Response Function (HRF):**
  - A stereotypical impulse response peaking ~5 sec after a neural event, undershooting, then returning to baseline.
  - Commonly modelled as a **gamma function** or sum of gamma functions:

$$h(t) = \frac{t^{a-1} e^{-t/b}}{b^a \Gamma(a)}$$



# Hemodynamic Response Modelling

- **Convolutional Model**
  - To predict BOLD signal from neural events:
$$y(t) = (s * h)(t) + \epsilon(t)$$
Where,  $s(t)$ =stimulus time series,  
 $h(t)$  = HRF  
\* = convolution  
 $y(t)$  = predicted BOLD
  - This predicted regressor goes into the **design matrix** of the GLM.

# General Linear Model

- In fMRI, we measure the BOLD signal over time at each voxel. We aim to investigate whether the activity is linked to a specific experimental design (e.g., stimulus on/off).
- The **GLM** models each voxel's time series as a linear combination of predictors + noise.

$$Y = X\beta + \epsilon$$

where  $Y$ : vector of observed BOLD signal at one voxel (time points  $\times$  1),

$X$  : design matrix (time points  $\times$  regressors)

Columns = predictors (stimulus onset convolved with HRF, nuisance regressors like motion, baseline drifts)

$\beta$  : regression coefficients (how strongly voxel responds to each predictor)

$\epsilon$ : residual noise

# Statistical parametric mapping

- SPM is the framework (and also a software package) that applies GLM across all voxels in the brain and then performs **statistical inference**.

## Steps

1. **Preprocessing** – motion correction, spatial normalization, smoothing.

2. **GLM fitting** – for each voxel, estimate  $\beta$ .

3. **Statistical test** – compute a t-statistic or F-statistic:

$$t = \frac{\hat{\beta}_k}{SE(\hat{\beta}_k)}$$

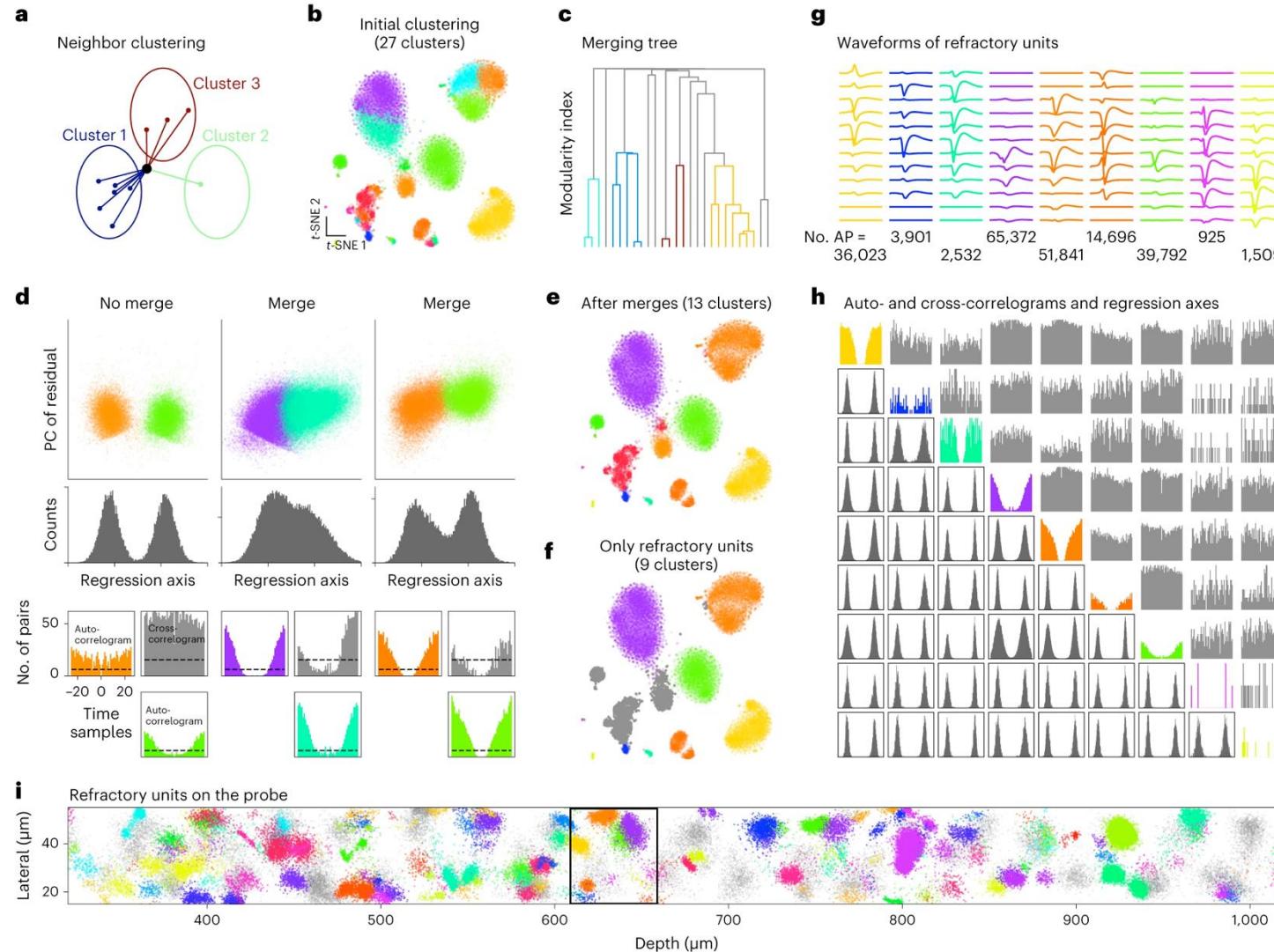
where  $\hat{\beta}_k$  is the estimated effect of interest.

4. **Statistical map** – produce a brain-wide map of test statistics (the “parametric map”).

5. **Multiple comparisons correction** – adjust for testing thousands of voxels (e.g., FWE, FDR).

6. **Thresholded SPM** – highlight only significant clusters of voxels.

# Spike Sorting – KiloSort4



Pachitariu, M., Sridhar, S., Pennington, J. et al. Spike sorting with Kilosort4. *Nat Methods* **21**, 914–921 (2024).  
<https://doi.org/10.1038/s41592-024-02232-7>

<https://kilosort.readthedocs.io/en/latest/>