

# Brain-Computer Interfaces

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# Overview

## ① Introduction

## ② EEG Analyses

Time-domain analyses

Frequency-domain analyses

Time-frequency domain analyses

Spatial Analyses

Topological Analyses

Source Localization

Artifact Removal  
Other Niche Analyses

## ③ In Action

## ④ Deep Learning Architectures

Basic CNN

EEGNet

Cross-Modal Learning

## ⑤ Good Resources

## ⑥ Future Research

# Sources

- [https://sccn.ucsd.edu/wiki/Introduction\\_To\\_Modern\\_Brain-Computer\\_Interface\\_Design](https://sccn.ucsd.edu/wiki/Introduction_To_Modern_Brain-Computer_Interface_Design)
- Delorme, A., Sejnowski, T., and Makeig, S. (2007). Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis. *Neuroimage*, 34(4), 1443-1449.
- Malmivuo, J., and Plonsey, R. (1995). Bioelectromagnetism: principles and applications of bioelectric and biomagnetic fields. Oxford University Press.
- Rashid, M., Sulaiman, N., Majeed, A. P. A., Musa, R. M., Nasir, A. F. A., Bari, B. S., and Khatun, S. (2020). Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface: A Comprehensive Review. *Frontiers in neurorobotics*, 14.

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# What is a BCI?

- the idea of using brain signals for communication and control.
- three main components: (1) **Signal acquisition** (e.g., EEG, fNIRS), (2) **Signal Processing** (i.e., feature extraction, classification), (3) **Signal Translation** (e.g., mapping the signal to particular usage).
- an interdisciplinary field concerning signal processing, machine learning, human-computer interaction, cognitive/neuroscience.

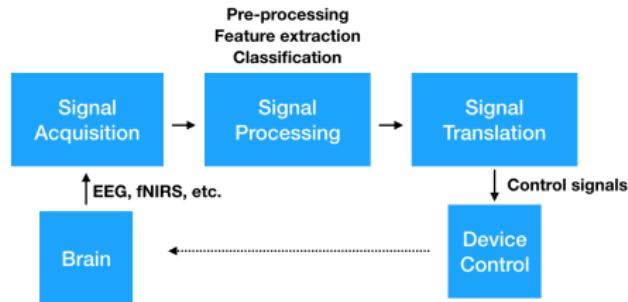


Figure: Basic procedure of a BCI

# Underlying Neural Processes

- All BCIs have to operate on observable effects of brain activity
- Except for fMRI and fNIRS, they operate on effects of neural firing processes
- EEG, MEG, and ECoG can only detect *large-scale* neural dynamics
- For example, 50,000 neurons firing in near-synchrony

# Underlying Neural Processes

- Largest contributors to the EEG are the pyramidal cells
- Radially oriented in the cortex (orthogonal to the surface)
- Electromagnetic fields of co-aligned and co-activated neurons add up
- <https://www.youtube.com/watch?v=AIvlNNFQLEk>

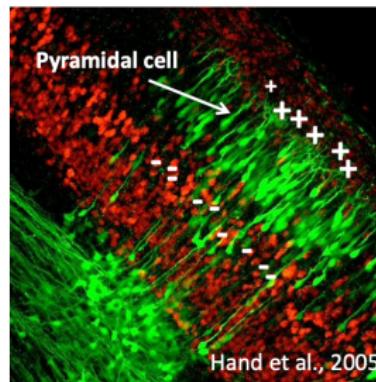


Figure: Hand et al., 2005

# Large-Scale Neural Processes

- When would 50,000 neurons fire near-synchronously?
  - An external even triggers a cascade of related neural processes (e.g., in perception)
  - An internal event triggers a cascade of related neural processes (e.g., a sudden aha!)
  - Neural populations enter a synchronized steady-state firing pattern (e.g., idle oscillations)

# Why BCI is so hard?

- The field of BCI has been established since the 1960s - 1970s with a lot of promise. However, contrary to the belief that "most obvious areas" are done (e.g., Neuralink), **BCI is still at its infancy.**
- Most of the time, BCI suffers from two key scientific challenges:
  - ① **Variability** - individuals variability in brain signals. These variability is task-specific and user-specific. Thus all BCI systems must be calibrated before they can be used. Current research focuses on developing a transferable model of BCI that work across users.
  - ② **Signal-to-noise ratio** - concerns the removal of artifacts while preserving the "weak" EEG signal. Effective signal processing and machine learning is key here. All approaches here are fundamentally statistical and computational.

# Three main types of BCI (Zander et al. 2009)

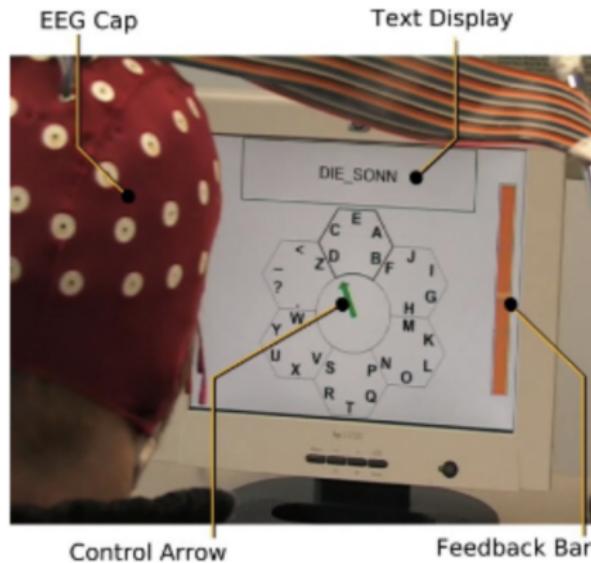
- ① **Active** BCI: A BCI of which users consciously control/manipulate their thoughts to control an application, e.g., *motor imagery*
- ② **Reactive** BCI: A BCI of which output from brain activity arise from external stimulation, independent of users' conscious thoughts, e.g., *P300, SSVEP*
- ③ **Passive** BCI: A BCI focused on utilizing our daily brain signals (without users' conscious thoughts) to enrich our daily life/interaction, e.g. *spectral analysis*

# BCI paradigms

BCI paradigms define how signals are being induced from the brain:

- **Motor Imagery**: a dynamic state during which an individual mentally simulates a physical action
- **SSVEP**: steady state visually evoked potentials are signals that are natural responses to visual stimulation at specific frequencies
- **P300**: a positive deflection in the EEG signal that appears approximately 300 ms after the presentation of an attended stimulus
- **Spectral analysis**: analysis in terms of a spectrum of frequencies (e.g., alpha beta, gamma)

# Motor imagery



**Hex-o-Spell (Blankertz et al.)**

**Figure:** Motor Imagery based speller

# Motor imagery



**Brain2Robot  
(Fraunhofer FIRST)**

Figure: Motor Imagery based prosthetic arm

# P300



P300 Speller

Figure: P300 speller

<https://www.youtube.com/watch?v=y3lGJVnSSsg>

# SSVEP

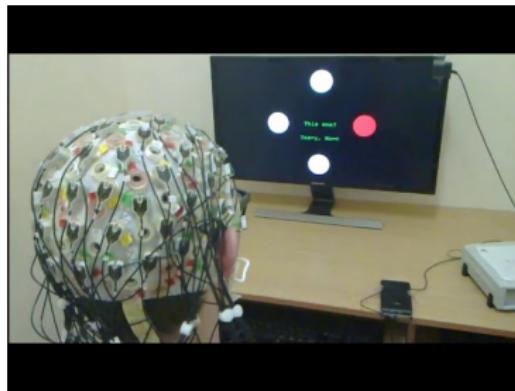


Figure: SSVEP

<https://www.youtube.com/watch?v=t96rl1SFHlI>

# Spectral analysis



Farwell et al. 2000

Figure: Lie detection

# Spectral analysis



Welke et al., 2011

Figure: Cognitive load detection

# Future Applications

- **Communication** - focuses on developing speller for locked-in patients so they can communicate with their caregivers. FB is making a speller for normal people to type even faster!
- **Control** - focuses on using BCI to controlling prostheses device, for home automation, for gaming and etc.
- **Therapy/Rehabilitation** - focuses on using neurofeedback for rehabilitating users' attention or emotion.
- **Monitoring** - an area concerning affect/intent/cognitive state detection using the brain signals. Workload, fatigue, breaking intent, lie detection are some example states.
- **Cross-Modal learning** - converting EEG to image/speech.

# Available tools

- **BioSig** - oldest open-source BCI toolboxes for offline processing (no GUI)
- **BCI2000** - written in C++ and mainly for online processing (acquisition, running experiments) but lack offline processing (e.g., algorithms)
- **OpenViBE** - written in C++; gives a block programming (for non-programmers). Requires Lua knowledge to extend/customize.
- **BCILAB** - matlab-based; lots of algorithms. Requires Matlab knowledge to extend/customize. Little support for acquisition systems but can tie to Lab Streaming Layer (LSL), a low-level technology that allow exchange of time series data between devices.
- **EEGLAB** - matlab-based; lots of algorithms. Requires Matlab to extend/customize
- **MNE-python + other python libraries** - python-based; for programmers. Lots of examples online. Work well with other python libraries. Requires python knowledge to extend/customize.

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# Event-Related Potentials (ERPs)

- Averaging EEG activity relative to an event results in primarily event-induced activity (trial-to-trial variability averaged out)

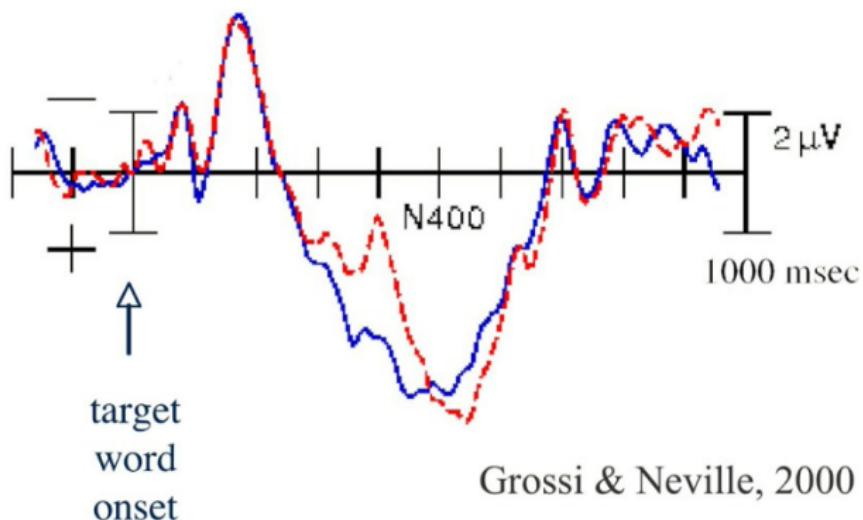


Figure: ERP of N400

# Event-Related Potentials (ERPs)

- Single-trial ERPs are much harder to identify

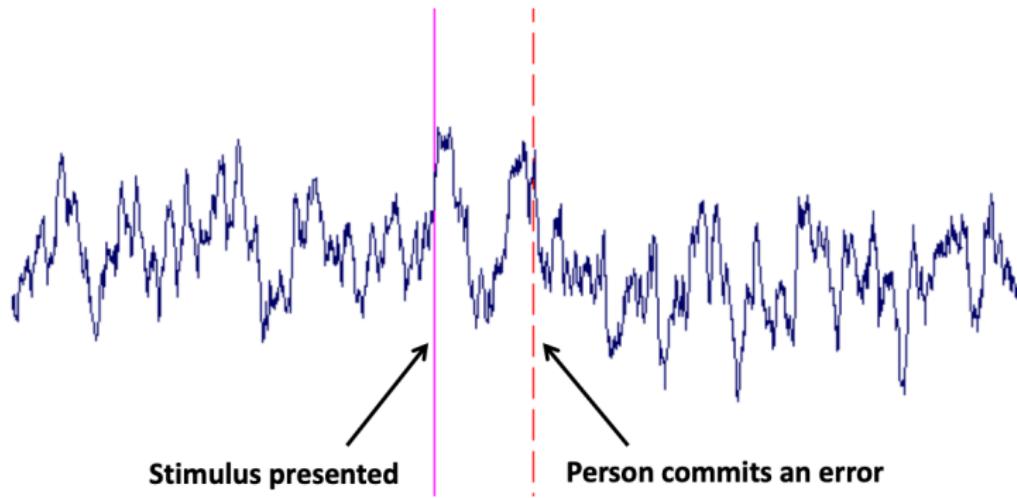


Figure: Single-trial ERPs

# Pros and Cons

## Pros:

- Computationally simple
- Decades-old literature
- Used in P300 and N400

## Cons:

- Jittered and non-phase locked activities are lost
- Limited analysis possibilities (e.g., connectivity)
- Unclear biological mechanism

# Frequency-domain analyses

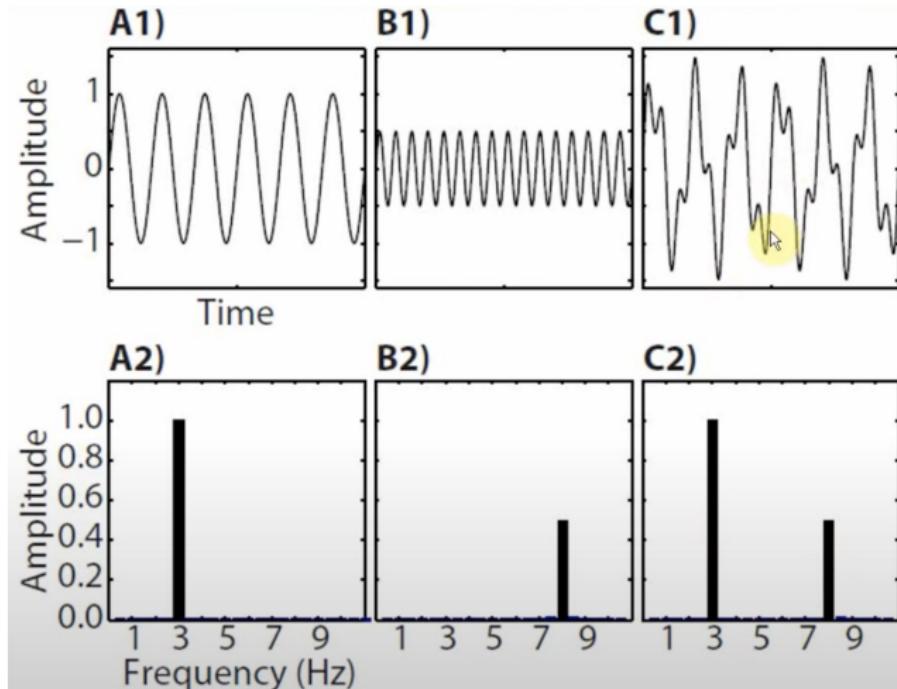
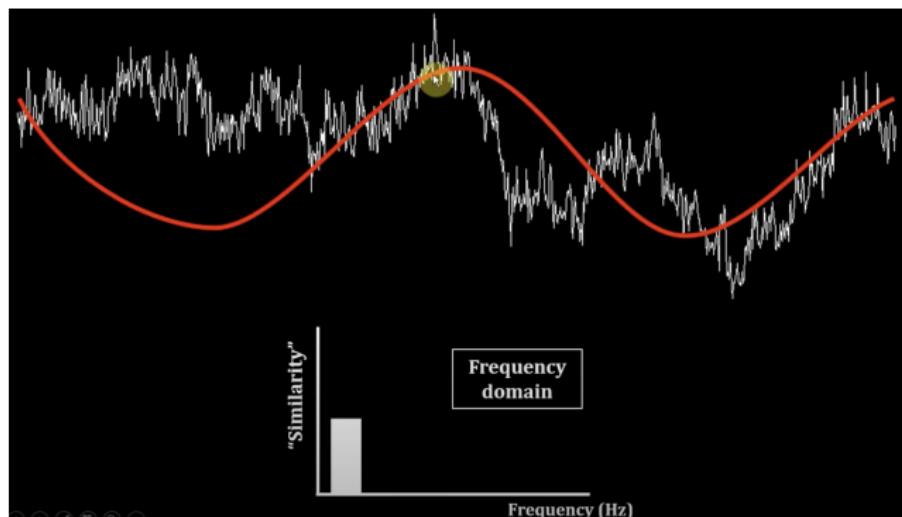


Figure: Changing time to frequency domain

# Fourier Transform



**Figure:** Dot product of particular sine wave with the EEG signal will give the corresponding similarity index. For example, a sine wave of 2Hz dot product with the EEG will give the frequency component of 2Hz.

# Pros and Cons

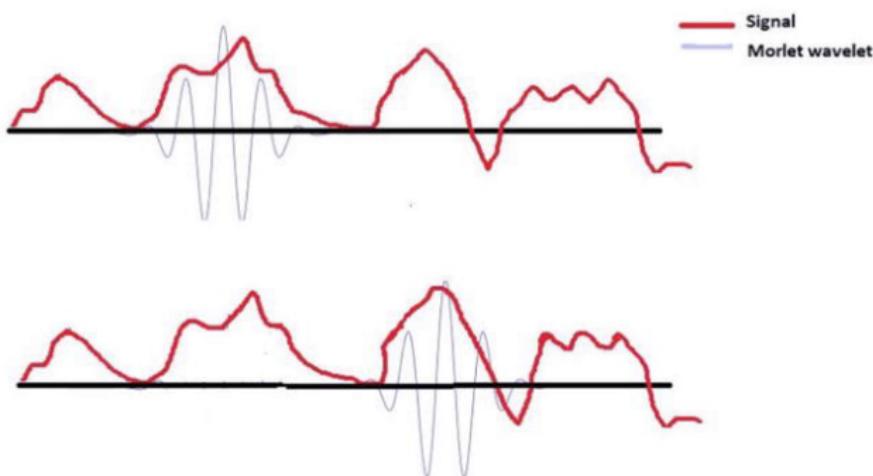
Pros:

- Computationally fast
- Ubiquitous in science and engineering
- Useful for oscillatory processes, e.g., delta (0-4Hz), theta (4-7Hz), alpha (8-13Hz), beta(12-30Hz), and gamma(25-100Hz)
- Used in SSVEP, emotion recognition, cognition recognition

Cons:

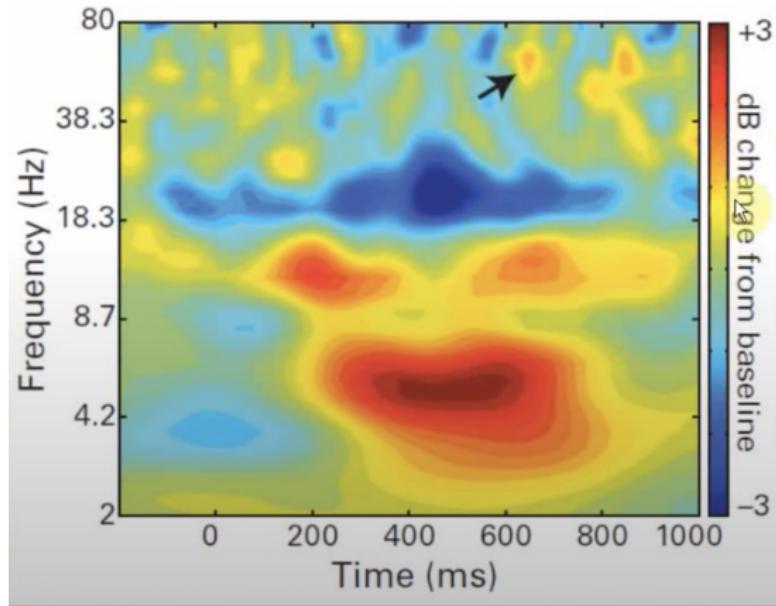
- Lost time information
- Only good for stationary data. Is EEG stationary?

# Time-frequency domain analyses



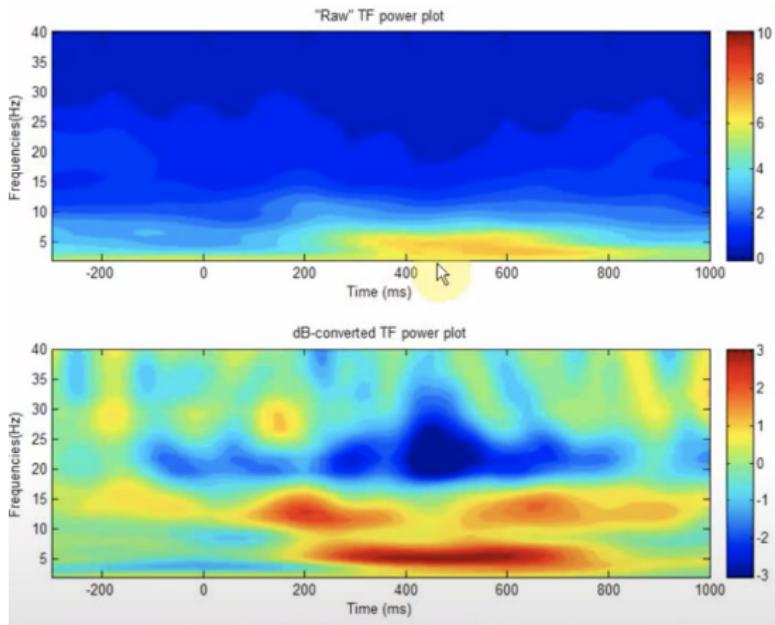
**Figure:** Instead of using a never ending sine wave, we can create a specific wavelet that captures only a specific time window.

# Time-frequency domain analyses



**Figure:** This will result in a spectrogram with both time and frequency information.

# Time-frequency domain analyses



**Figure:** Often wise to perform baseline normalization. It transforms all data to same scale, disentangle task-related from background activity, and more likely to be normally distributed thus good for classification.

# Pros and Cons

Pros:

- Almost the best.. Thus common neural network often transform EEG to spectrograms first, and then use CNN

Cons:

- Reduced temporal precision but it is a parameter we can fine tune....

# Spatial Filters

- Transform a multi-channel signal  $X(n)$  such that  $Y(n)$  depends only on  $X(n)$ ; most spatial filters are linear, i.e.,  $Y(n) = MX(n)$  for some matrix  $M$
- Linear spatial filters can approximately invert volume conduction and remap channel signals to approximate source signals - this is the main use in BCIs
- Examples: Re-referencing, Surface Laplacian, Independent Component Analysis (ICA), Common Spatial Patterns (CSP)

# Common Spatial Patterns

- Spatial filters designed to recover motor-cortex source activity, calculated via the Common Spatial Patterns algorithm

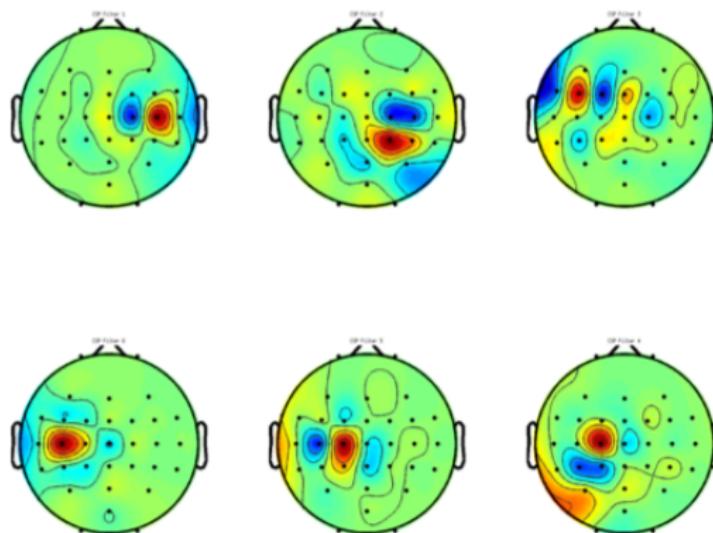


Figure: Common Spatial Patterns

# Spatial Filters vs. Forward Projections

- Spatial filters are not the same as forward project maps of some source signal - they are the inverse operation

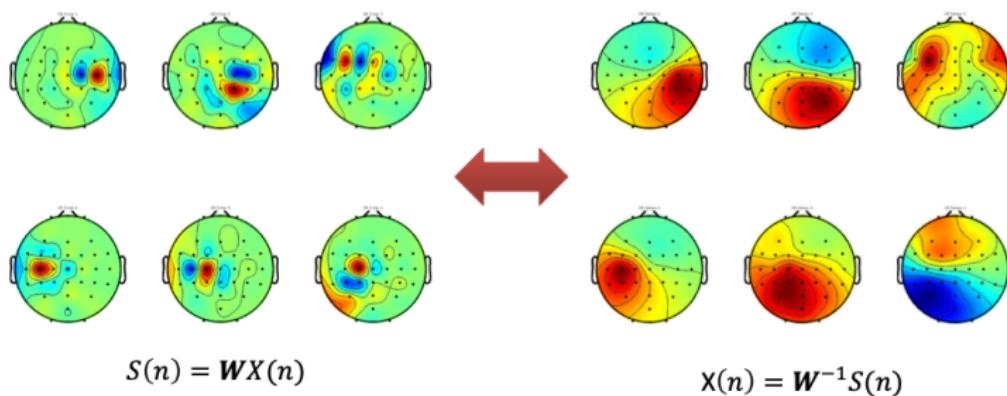


Figure: Inverse operation of one another

# Common Spatial Filters

```
# Assemble a classifier
lda = LinearDiscriminantAnalysis()
csp = CSP(n_components=4, reg=None, log=True, norm_trace=False)

# Use scikit-learn Pipeline with cross_val_score function
clf = Pipeline([('CSP', csp), ('LDA', lda)])
scores = cross_val_score(clf, epochs_data_train, labels, cv=cv, n_jobs=1)

# Printing the results
class_balance = np.mean(labels == labels[0])
class_balance = max(class_balance, 1. - class_balance)
print("Classification accuracy: %f / Chance level: %f" % (np.mean(scores),
                                                             class_balance))

# plot CSP patterns estimated on full data for visualization
csp.fit_transform(epochs_data, labels)

csp.plot_patterns(epochs.info, ch_type='eeg', units='Patterns (AU)', size=1.5)
```

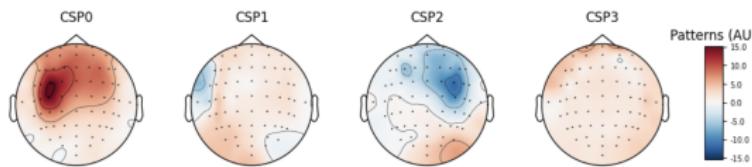
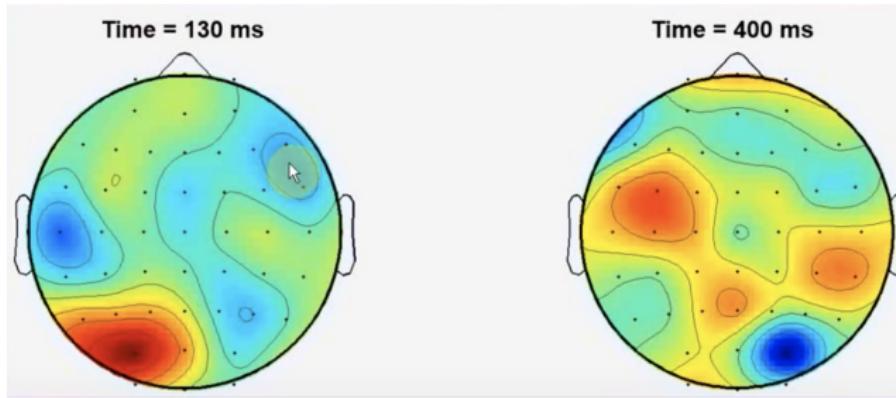


Figure: Common Spatial Filters

# Topological Analyses

- Topological analyses create scalp maps that allow for rough source localization
- Topological analyses are NOT source localization



**Figure:** Left: Likely the participants are looking using the right eye; Right: Likely the participants are using the right hand to click.

# More Scalp Maps

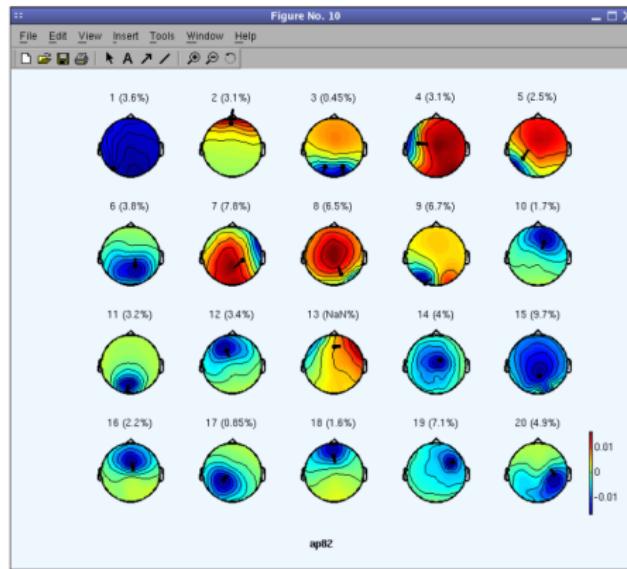


Figure: Scalp maps

# Python MNE with scalp maps

```
all_times = np.arange(-0.2, 0.5, 0.03)
evoked.plot_topomap(all_times, ch_type='mag', time_unit='s',
                    ncols=8, nrows='auto')
```

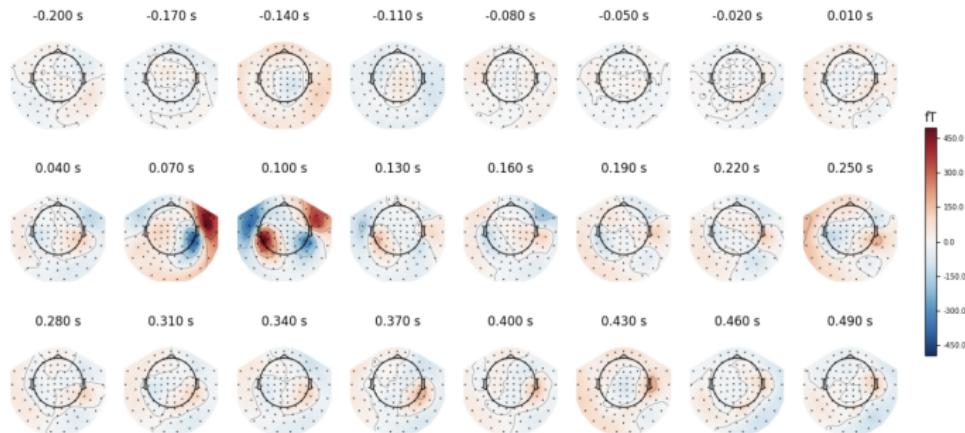


Figure: Plot evoked topographies using MNE

# Volume Conduction

- Neural activity is conducted through the brain volume to the scalp which is instantaneous, and characterized by a electromagnetic field
- Volume conduction is linear, thus each sensor measures a (weighted) sum of each neuron's activity

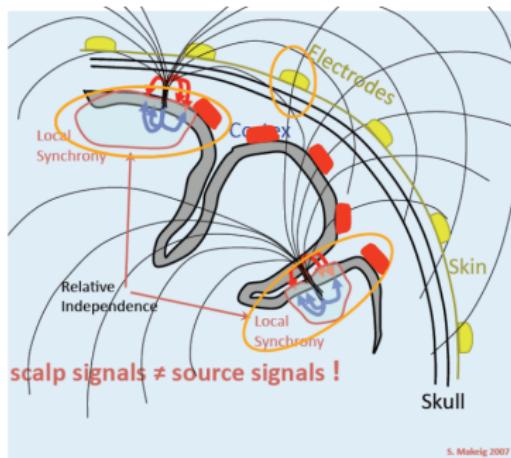


Figure: Neural activity

# Volume Conduction

- Note: the point-spread function from a source patch to the scalp is extremely broad

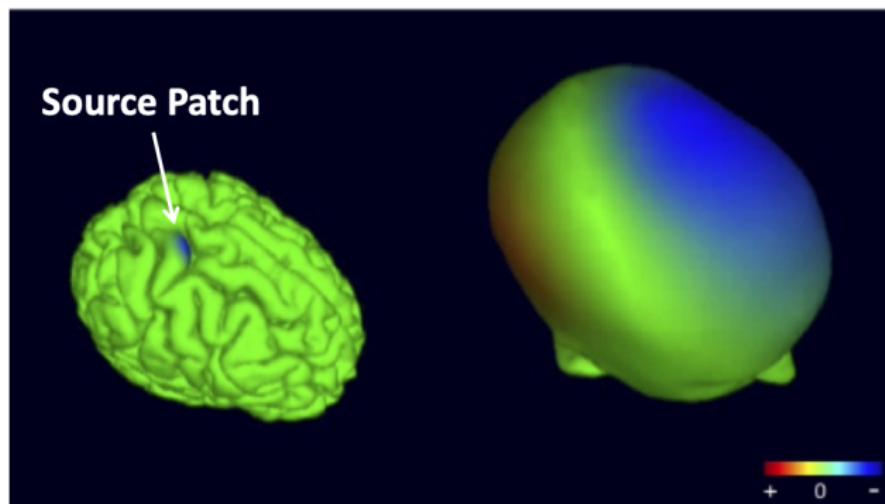


Figure: Akalin Acar et al., 2011

# Dipole Fitting

- Electromagnetic field sustained by a compact collection of neurons can be modeled as a single equivalent dipole
- This facilitates localization of the field source

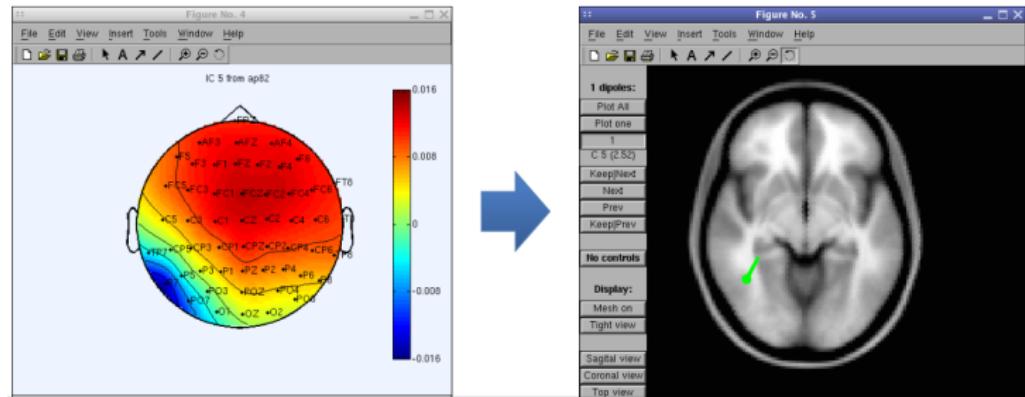


Figure: Source localization

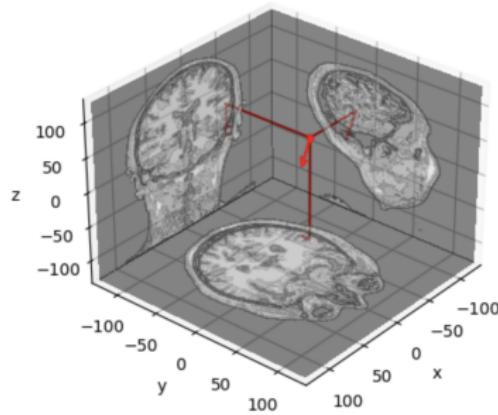
# Dipole Fitting

```
evoked = mne.read_evokeds(fname_ave, condition='Right Auditory',
                           baseline=(None, 0))
evoked.pick_types(meg=True, eeg=False)
evoked_full = evoked.copy()
evoked.crop(0.07, 0.08)

# Fit a dipole
dip = mne.fit_dipole(evoked, fname_cov, fname_bem, fname_trans)[0]

# Plot the result in 3D brain with the MRI image.
dip.plot_locations(fname_trans, 'sample', subjects_dir, mode='orthoview')
```

Dipole #7 / 7 @ 0.080s, GOF: 56.9%, 39.6nAm  
MRI: (-56.9, -19.7, 26.1) mm



# Dipole Modeling Problems

- High-quality fits are hard to achieve
  - Requires knowledge about sensor locations
  - Require assumptions about conductivities of scalp, skull, cerebrospinal fluid (CSF), brain tissue
  - Requires knowledge of the folding of the cortex (candidate dipoles) unless simplistic spherical model is used
  - Some brain tissues has anisotropic conductance (white matter)
  - Scalp maps are usually not perfect (arise from data processing) - fit accuracy suffers
  - Scalp maps can be a sum of multiple dipole sources - requires a distributed source model

# Distributed Source Modeling

- Allow to recover and image distributed cortical support of given scalp maps

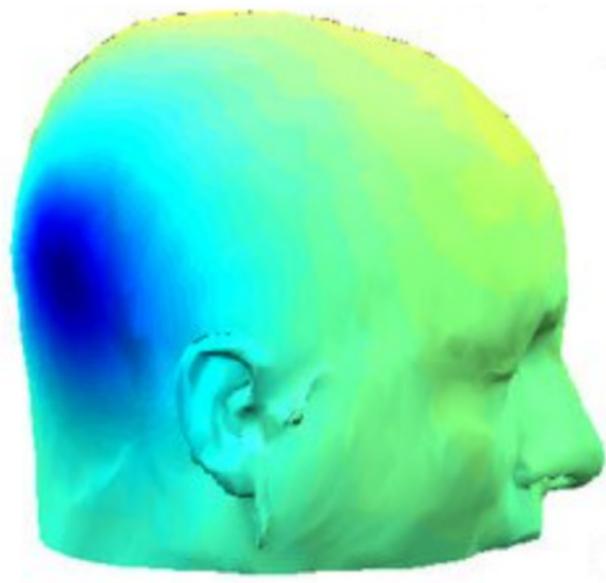


Figure: Ray Ramirez (Scholarpedia)

# Distributed Source Modeling

- Wide range of methodologies and underlying assumptions (sLORETA, Beamforming, Sparse Bayesian Learning, ...)
- Prone to finding only locally optimal solutions

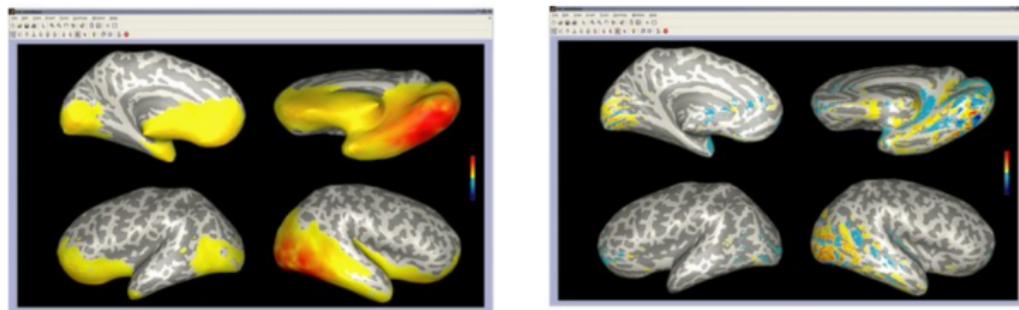


Figure: LCMV Beamforming (Left), Anatomically Constrained Beamforming (Right)

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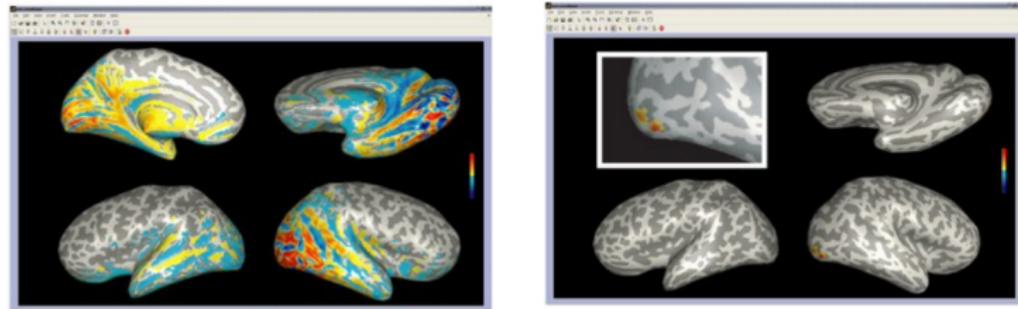


Figure: sLORETA (Left), Sparse Bayesian Learning (Right)

# Non-Brain Artifacts

- Often far outscale the brain processes in the EEG (when present)
- **Internally generated:** neck, face, and eye muscles, eye dipoles, heart activity
- **Externally generated: 50/60Hz line noise, EM spikes from equipment**
- **Sensor-related:** DC offset drifts, cable sway, thermal noise, quantization noise

# Muscle Artifacts

- High-frequency / broadband, large amplitude

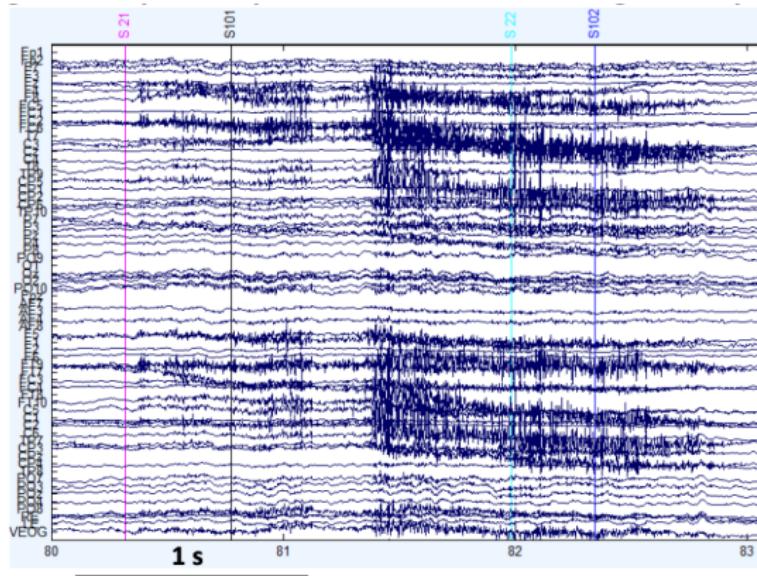


Figure: Muscle Artifacts

# Muscle Artifacts

- Scalp projections are spatially stereotyped

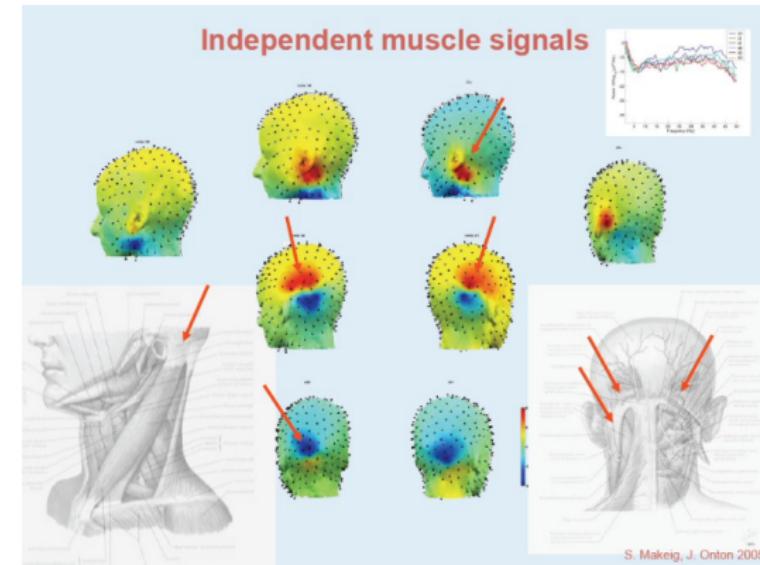


Figure: Muscle Artifacts

# Eye Blinks

- Large low-frequency peak and rebound, mainly frontal
- Can also incur non-linear effects in occipital cortex

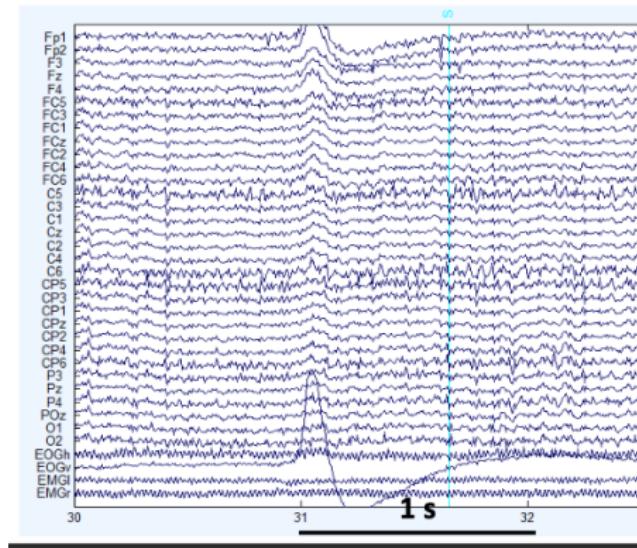


Figure: Eye Blinks Artifacts

# Bandpass Filters

- Easiest way to remove artifacts is simply to select only the frequency of interest

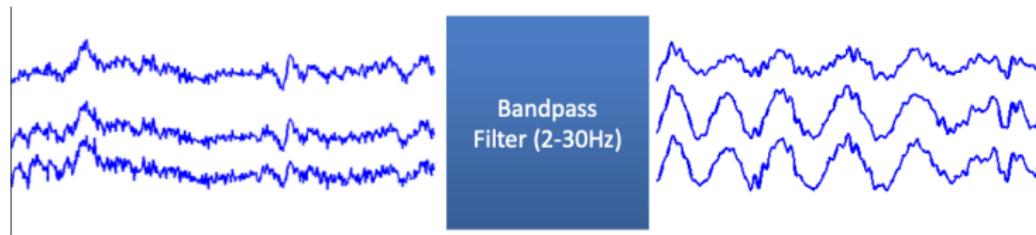


Figure: Bandpass filter

# Independent Component Analysis

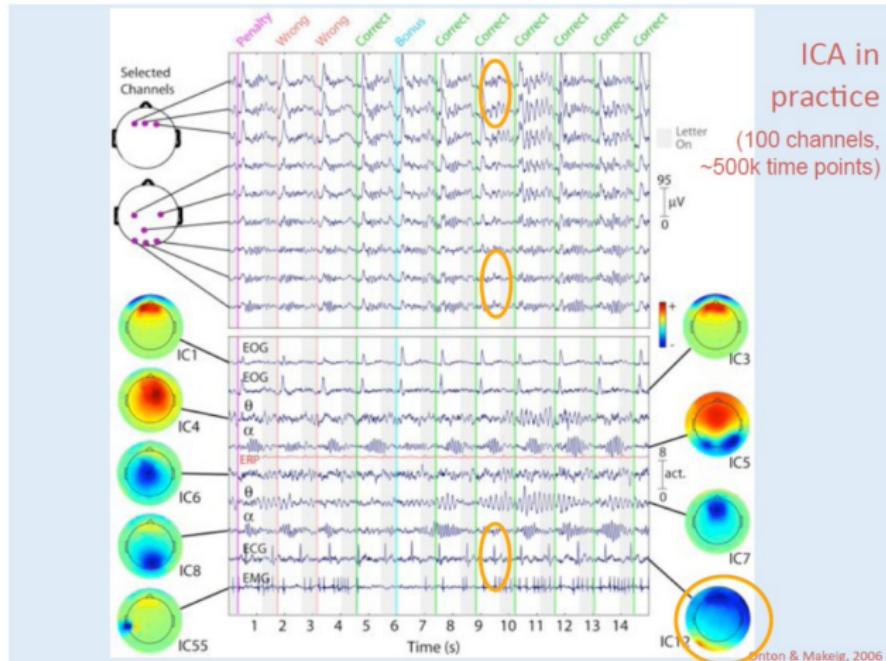


Figure: Onton and Makeig 2006

# Deep Neural Network

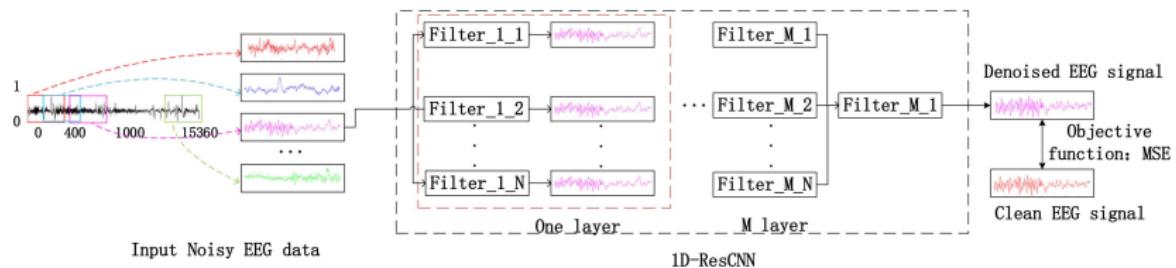


Figure: <https://www.sciencedirect.com/science/article/abs/pii/S0925231220305944>

# Event-Related Coherence

- Event-Related Coherence between two signal components

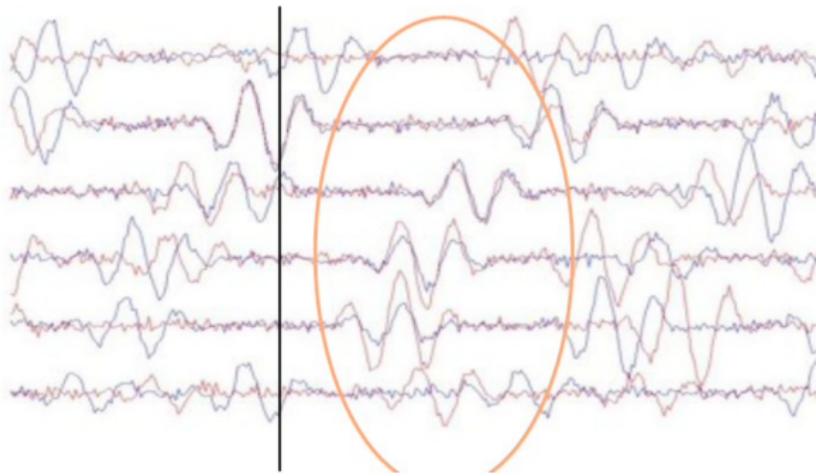


Figure: Makeig 2007

# Connectivity

- Sophisticated measure of interaction between multiple signals
- By getting the source estimates along the time, we can construct the connectivity plot

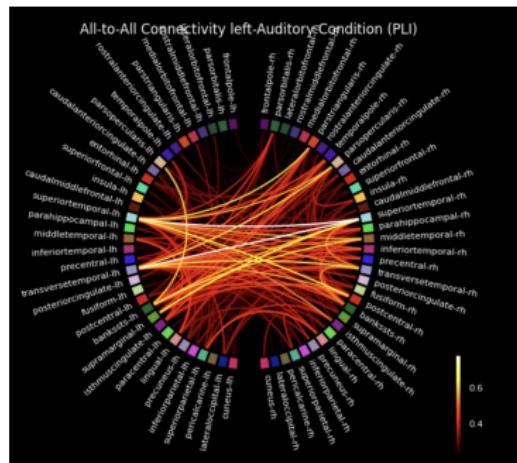


Figure: Python MNE

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# Measurement Sites

- Standardized location system (10-20 system)
- Saves a lot of hassle vs. custom labels
- Often defined in 8, 16, 32, and 64 channels

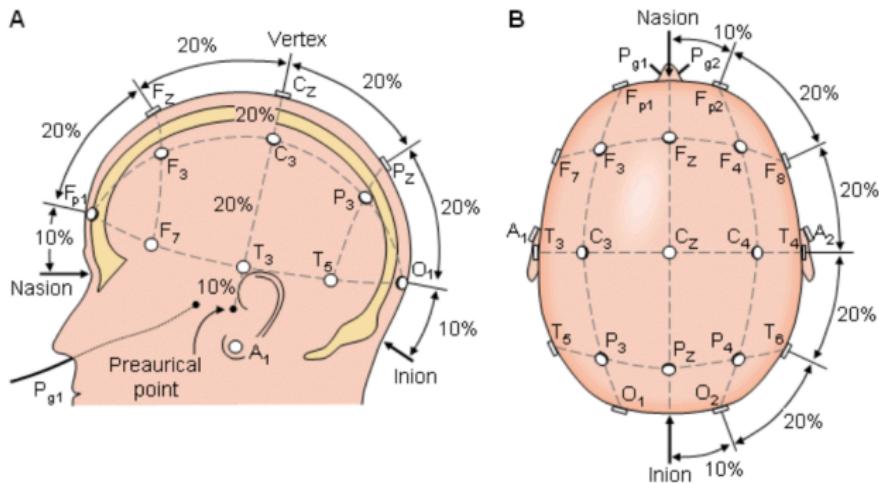
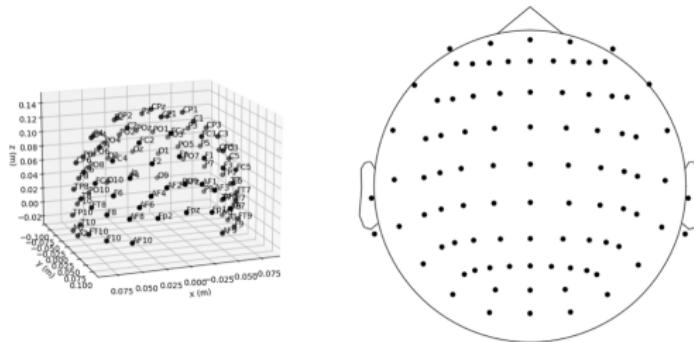


Figure: International 10-20 system (Malmivuo and Plonsey, 1995)

# Measurement Sites

```
ten_twenty_montage = mne.channels.make_standard_montage('standard_1020')
print(ten_twenty_montage)
```

```
fig = ten_twenty_montage.plot(kind='3d')
fig.gca().view_init(azim=70, elev=15)
ten_twenty_montage.plot(kind='topomap', show_names=False)
```



**Figure:** Montage objects have a `plot()` method for visualization of the sensor locations in 3D; 2D projections are also possible by passing `kind='topomap'`

# Where to put electrodes?

- Some notable large-scale brain features are the hemispheres, lobes, gyri and suli
- No nerves coming to frontal lobe thus it's less obvious what they do

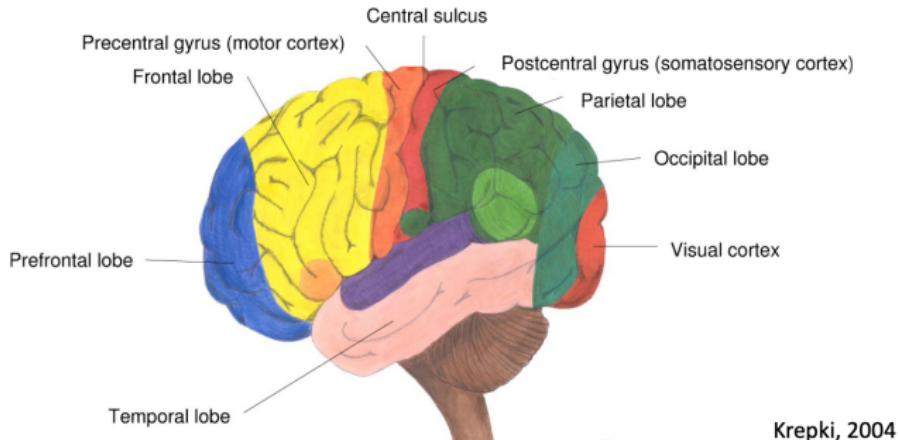
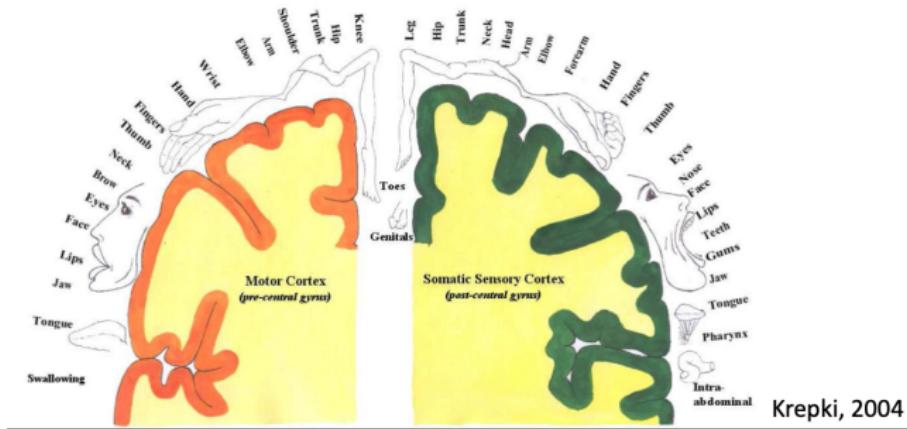


Figure: Major anatomical regions

## Functional Mapping

- For most regions more or less well known functional associations exist - the motor cortex is one of the best examples



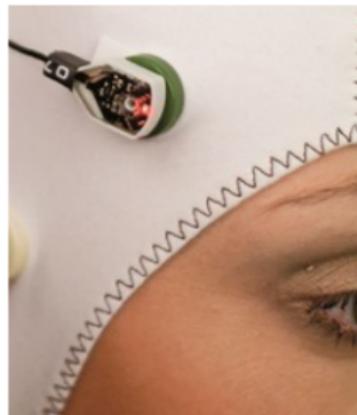
**Figure: Homunculus: Functional mappings of the motor cortex**

# EEG Sensor Designs

- Most EEG systems are gel-based
- Nowadays mostly using active electrodes (i.e., with amplifiers)



Passive, gel-based  
(EasyCap)



Active, gel-based  
(Brain Products)

Figure: EEG gel-based sensor

# EEG Sensor Designs

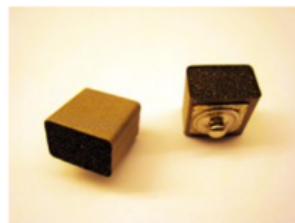
- Dry systems are emerging quickly



Pins  
(g.SAHARA)



Spring-loaded Pins  
(NCTU)

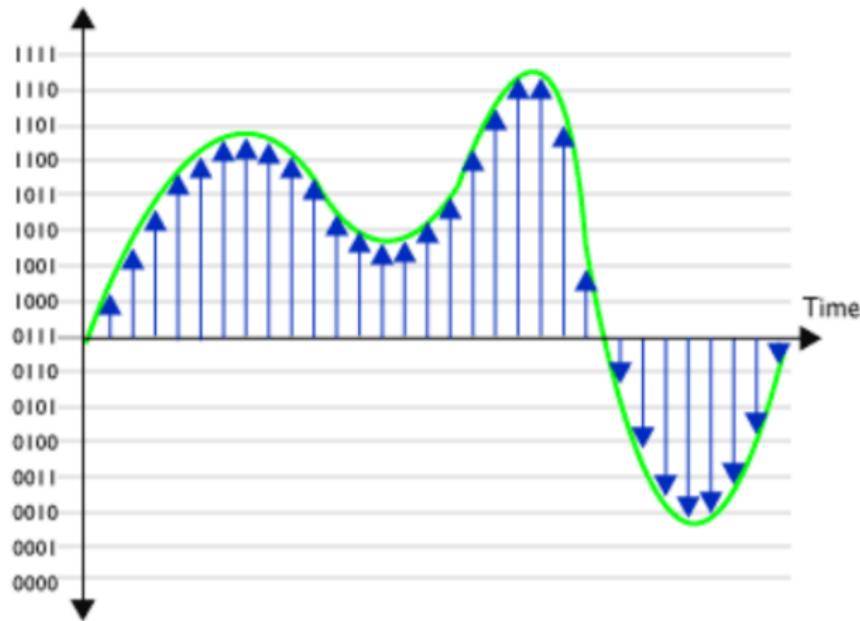


Foam-based sensors  
(NCTU)

Figure: EEG dry-based sensor

# Digitization

- After amplification (e.g. 50000x), signal is low-pass filtered using an analog filter, then digitally sampled at fixed rate



# Sampling Theorem

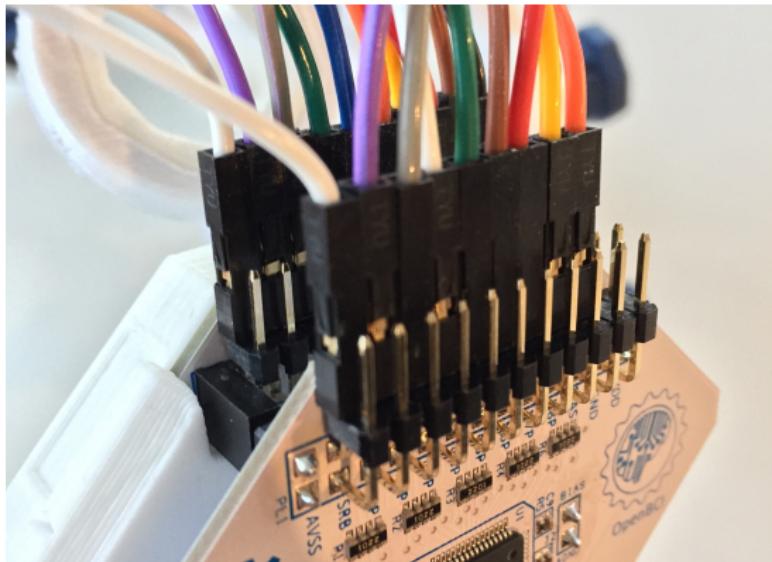
- If the signal is band-limited below the Nyquist frequency  $B$  (i.e., contains no higher frequency than  $B$ ), it can be exactly reconstructed using the interpolation function:

$$g(t) = \frac{\sin 2\pi Bt}{2\pi Bt} \quad (1)$$

$$s(t) = \sum_{n=-\infty}^{\infty} s\left(\frac{n}{F_s}\right) g\left(\frac{t-n}{F_s}\right) \quad (2)$$

- The Nyquist Frequency is  $\frac{1}{2}$  sampling rate

# OpenBCI connection



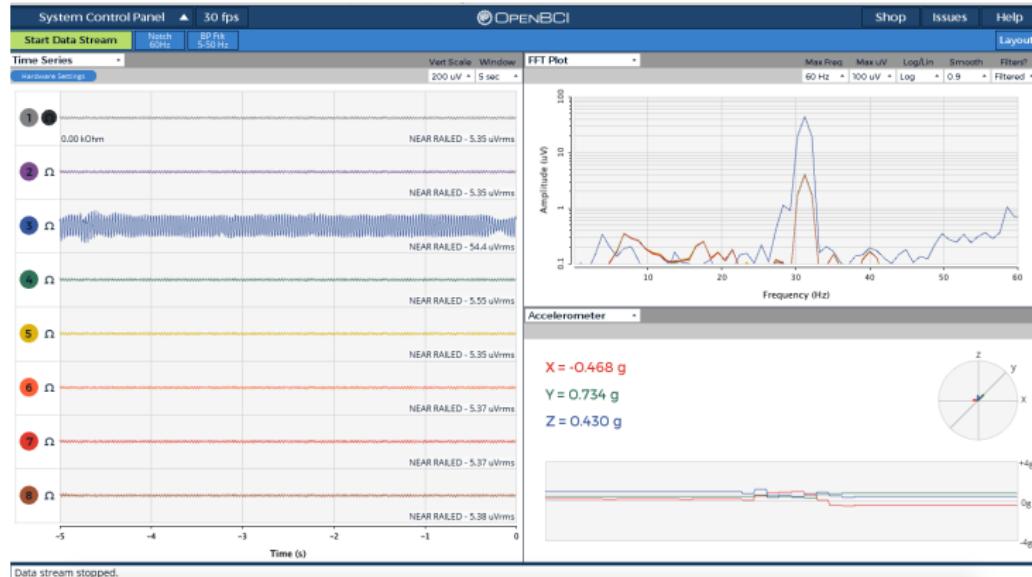
**Figure:** Cyton with Daisy configuration. The Y splitter (white) on SRB, connecting to earlobe. Another reference wire on BIAS (black), connecting to another earlobe. Earlobe is used as reference because it has no muscles or neurons and therefore very low electrical signals.

# OpenBCI connection



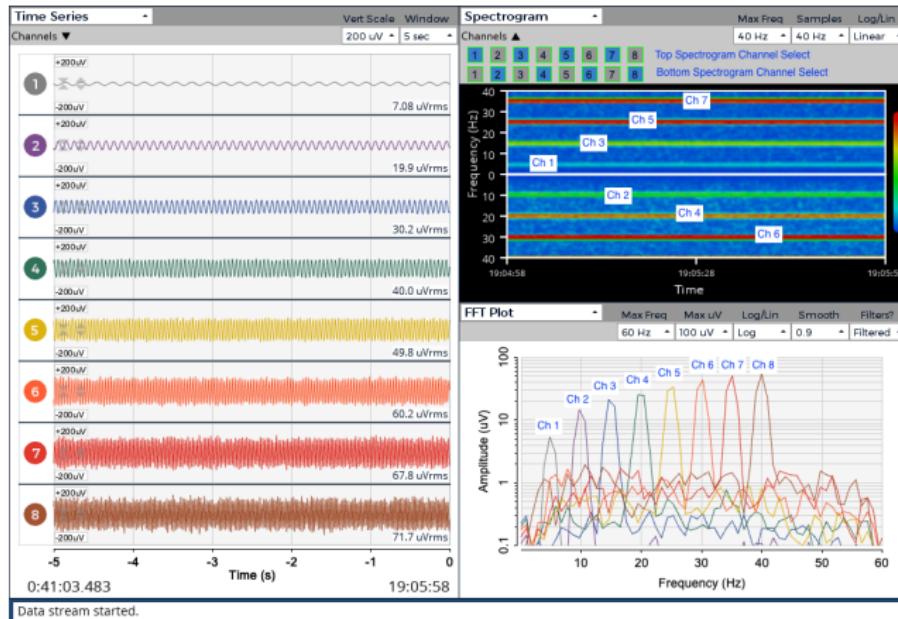
**Figure:** Gold cup electrodes can be used to connect to other part of the body to the Cyton and Daisy board. First scope the electrode paste into the electrode. Then paste accordingly.

# OpenBCI connection



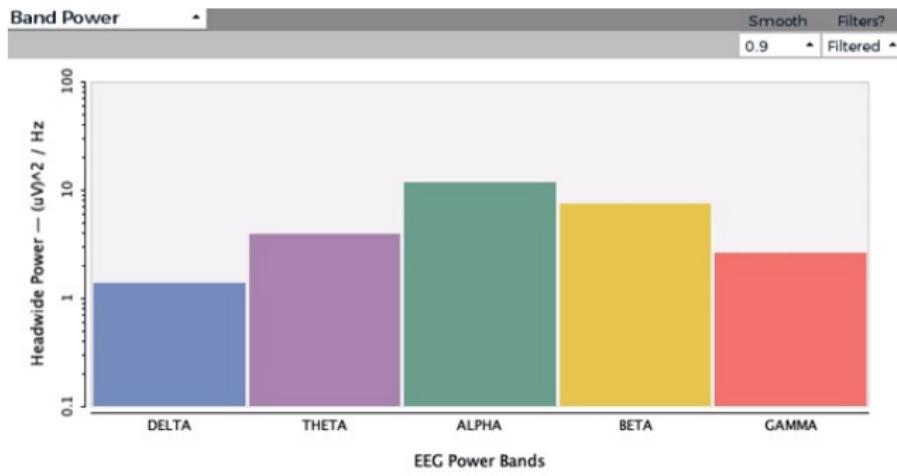
**Figure:** When the Ohm icon is toggled on, the board sends a small current through the selected channel to obtain the impedance value. For this reason, you won't be able to stream data on a channel and obtain the impedance value simultaneously.

# OpenBCI connection



**Figure:** A dual spectrogram display which allows users to see changes in FFT data over time

# OpenBCI connection



**Figure:** One easy way to test the system is to ask users to close their eyes, the alpha should be low

# OpenBCI connection

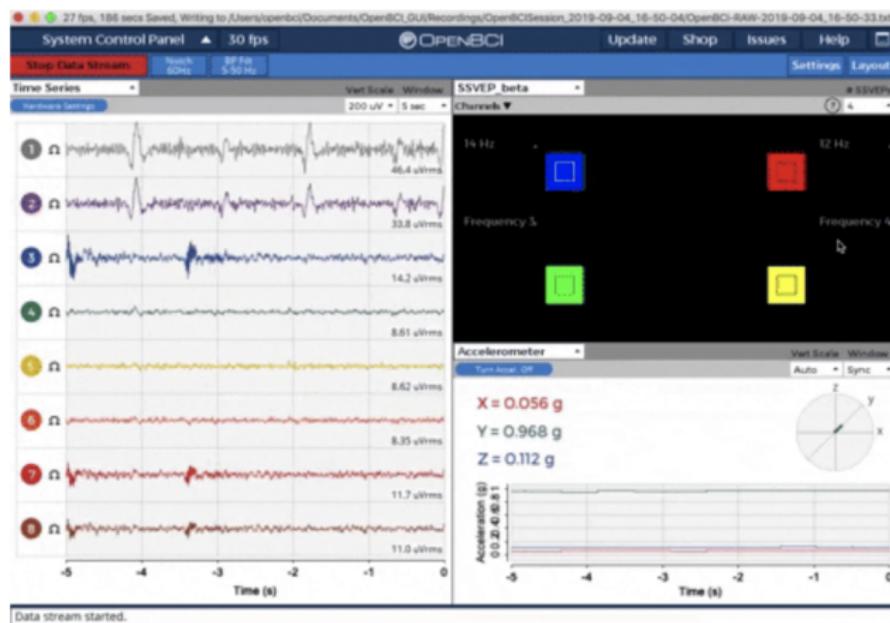
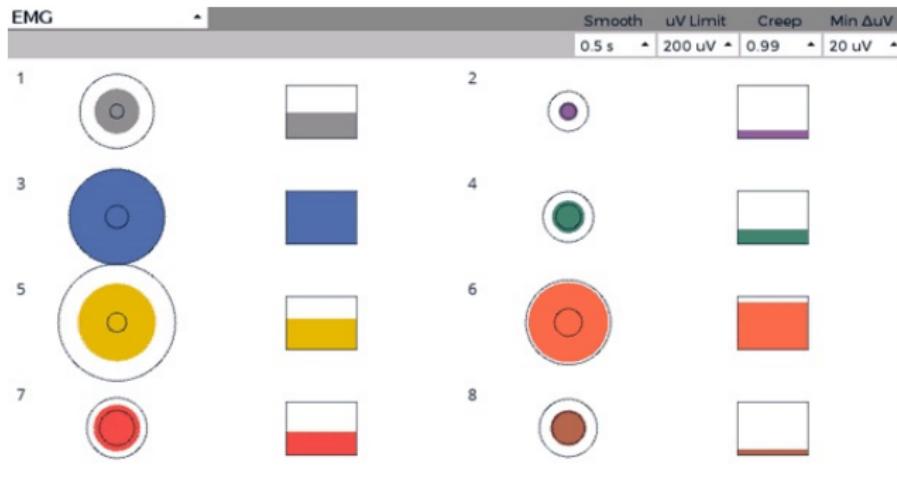


Figure: SSVEP widget

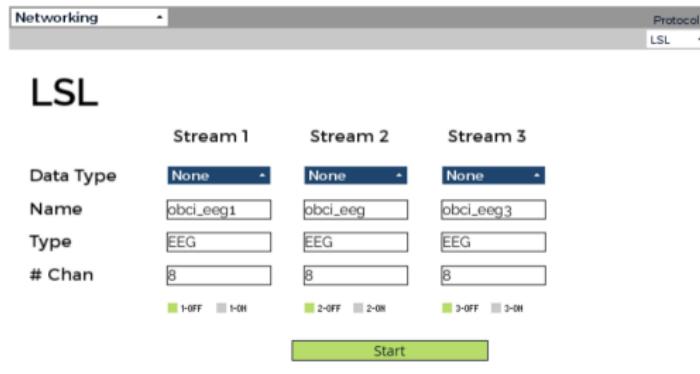
# OpenBCI connection



**Figure:** EMG widget: if you relax, the value will be 0, and if you flex, the value will go to 1

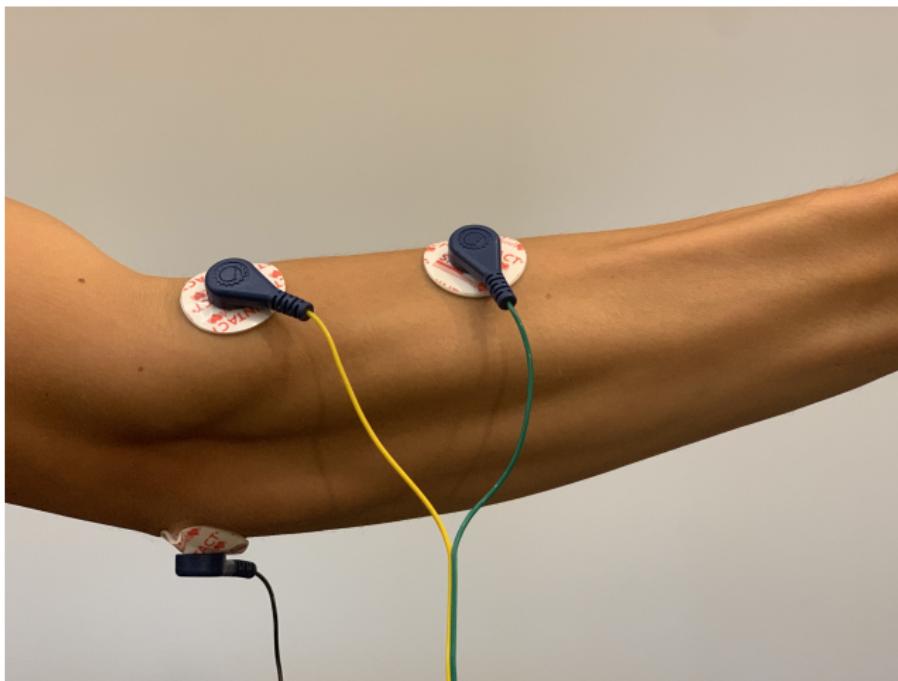
# OpenBCI connection

LSL



**Figure:** Lab Streaming Layer is a system for synchronizing streaming data for live analysis or recording. LSL is a good way to send your OpenBCI stream to applications like Python.

# Example: Using EMG to stop/start music



**Figure:** Connect to top N1pin and bottom N1pin for measuring potential difference. The elbow is connected to the bottom AGND pin for reference.

# Example: Using EMG to stop/start music

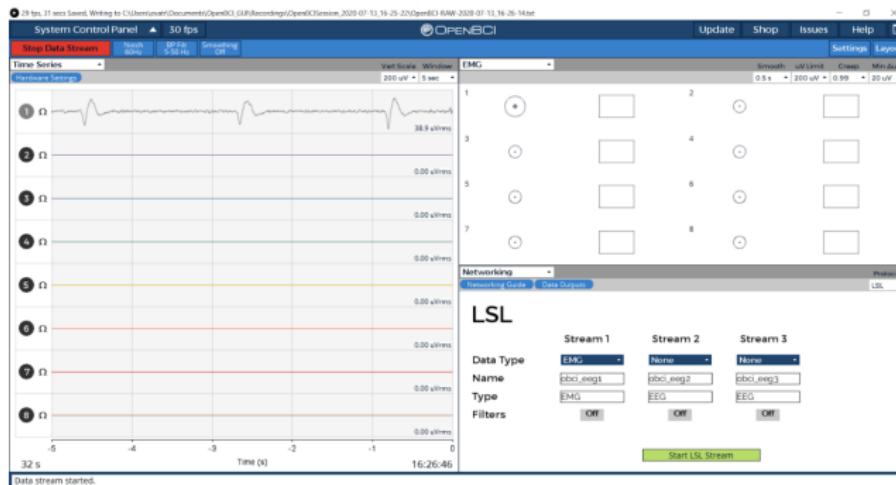


Figure: Turn on the EMG and LSL widgets.

# Example: Using EMG to stop/start music

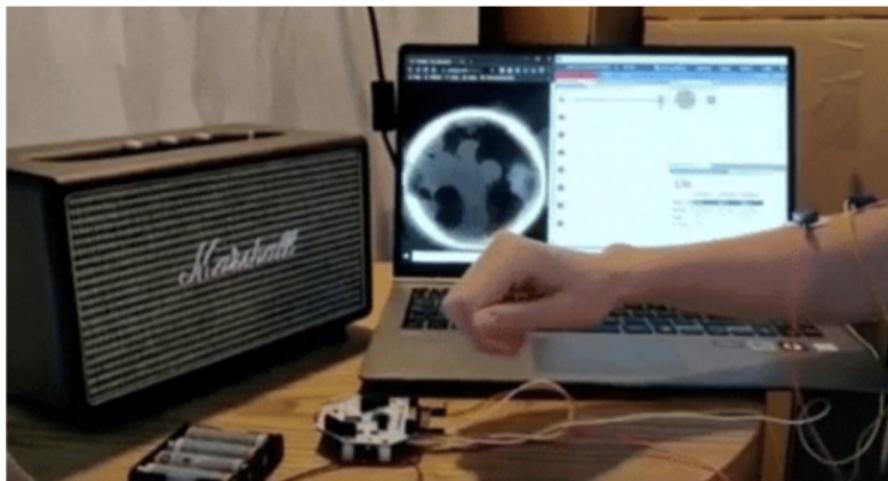


Figure: EMG to start/stop music

## ① Introduction ② EEG Analyses

Time-domain analyses  
Frequency-domain analyses  
Time-frequency domain analyses  
Spatial Analyses  
Topological Analyses  
Source Localization

Artifact Removal  
Other Niche Analyses

- ## ③ In Action ④ Deep Learning Architectures
- Basic CNN  
EEGNet  
Cross-Modal Learning
- ## ⑤ Good Resources ⑥ Future Research

# Basic CNN

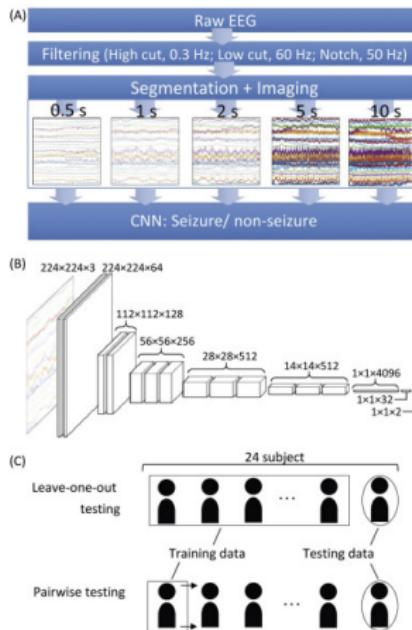


Figure: <https://www.sciencedirect.com/science/article/pii/S2213158219300348>

# EEGNet (2018)

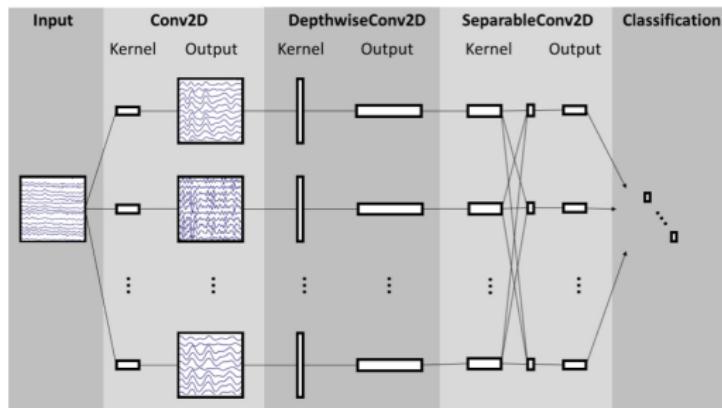


Figure 1: Overall visualization of the EEGNet architecture. Lines denote the convolutional kernel connectivity between inputs and outputs (called *feature maps*). The network starts with a temporal convolution (second column) to learn frequency filters, then uses a depthwise convolution (middle column), connected to each feature map individually, to learn frequency-specific spatial filters. The separable convolution (fourth column) is a combination of a depthwise convolution, which learns a temporal summary for each feature map individually, followed by a pointwise convolution, which learns how to optimally mix the feature maps together. Full details about the network architecture can be found in Table 2.

**Figure:** <https://arxiv.org/abs/1611.08024>

# Cross-Modal Learning (2020)

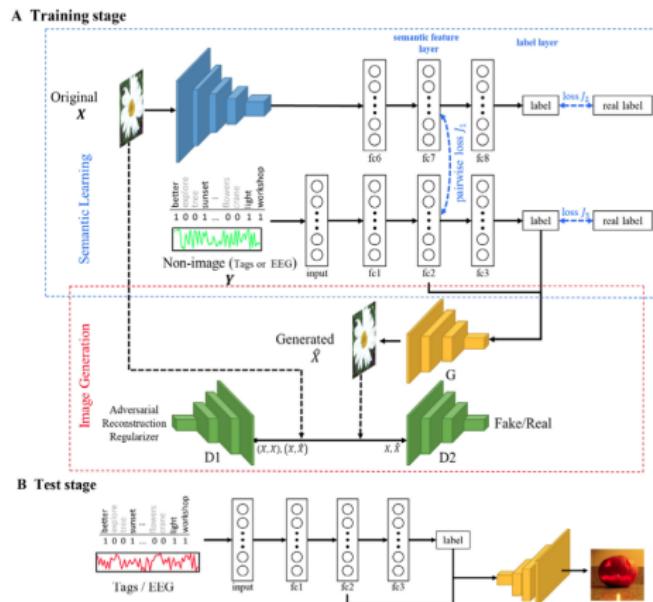


Fig. 2. The framework of our proposed cross-modal generation method. It contains two parts: the semantic learning part and the image generation part. We use the image modality and the non-image modality in the training stage. In the test stage, we only use non-image modality to generate image modality.

Figure: <https://www.sciencedirect.com/science/article/pii/S0031320319303863>

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# Good Resources

- Use **Python MNE** - is made by neuroscientists. Documentation is also VERY well written. They have (1) source estimation, (2) machine learning, (3) connectivity, (4) awesome data visualization modules. You will learn A LOT of neuroscience here.
- Although we did not use **MATLAB**, it has many good tutorials that will allow us to better understand how EEG works - <https://sccn.ucsd.edu/eeglab/index.php>
- Use **LSL** protocol with **pyOpenBCI (python way)** or **OpenBCI GUI (GUI way)** to acquire data from the OpenBCI board.
- Use **pygame**, **tkinter** or **javascript** if you want to make BCI application. You have to use **threads** a lot so learn it.
- EEG datasets: <https://github.com/meagmohit/EEG-Datasets>
- Best **youtube** channel for learning EEG - Mike X Cohen - [https://www.youtube.com/channel/UCUR\\_LsXk7IYyueSnXcNextQ](https://www.youtube.com/channel/UCUR_LsXk7IYyueSnXcNextQ). Our lab also has his book - **Analyzing Neural Time Series Data**.
- Another easy-to-read yet very good book is **Practical Approach to Electroencephalography** by Libenson. Once you learn it, you can read **Rowan's Primer of EEG** (our lab also has it) which teaches you how to read EEG.
- Read **EEGNet** and **EEG-ChannelNet** if you are interested in deep learning + EEG



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# Future Research

The key questions in BCI remains unchanged and is still in the **infancy** stage. The problem remains **unroboust accuracy, impracticality** due to many restrictions (e.g., many artifacts, many variations in users), does not really know what is **EEG** (e.g., where does it come from, what different features mean). Here are some topics I often come across in recent years.

- **Mobile real-time EEG**
- **Feature Extraction** (e.g., functional connectivity)
- **Fusion model** (e.g., LSTM + GCNN)
- **Artifact Removal / Source Localization**
- **Multimodal EEG + other sources of input** (e.g., fNIRS, facial, EMG, EKG)
- **One shot learning** from few training data (e.g., only 1 minute of EEG recordings! or only 1 electrode!)
- **Participant independent** model
- **Cross-modal learning** - EEG ↔ audio/image/text
- **Data Augmentation**
- Understanding the underlying **neural processes** via EEG

# Questions