# Analyzing the time-frequency content of EEG data

Alexander Enge

Neuro Lab @ Humboldt-Universität zu Berlin

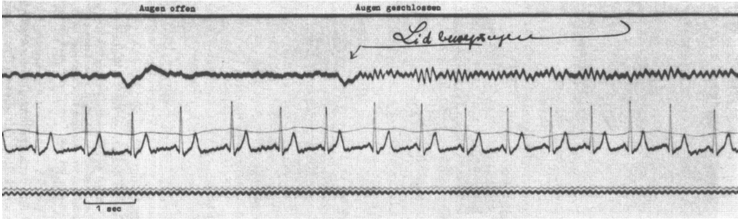
25/05/2022

# Today

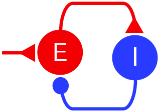
1. Why study neural oscillations?
   - Evoked vs. induced activity
2. Frequency analysis
   - Sine waves, Fourier transform
3. Time-frequency analysis
   - Morlet wavelets
4. Example workflow
   - MNE-Python style, hu-neuro-pipeline style

# Why study neural oscillations?

## Empirical data



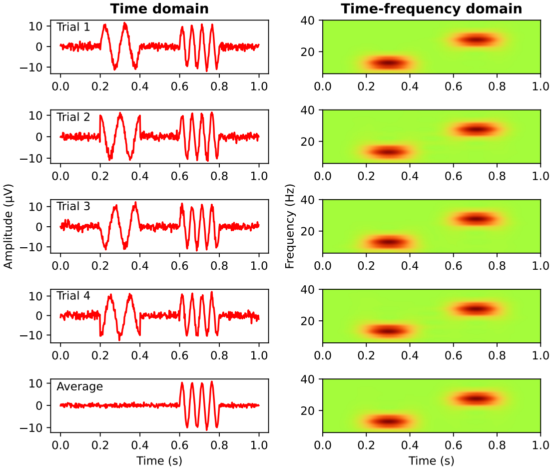

## Algorithm




## Computation

- Working memory
- Language
- Consciousness

# Evoked vs. induced activity

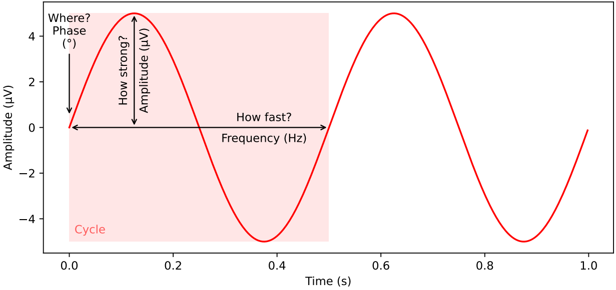


# Frequency analysis

**Goal:** Examine which frequencies (oscillations) contribute to a stretch of continuous EEG

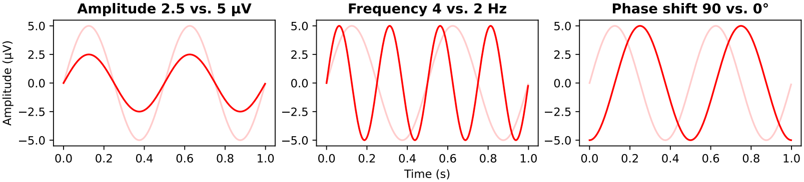
**Approach:** Decompose the continuous EEG into a set of sine waves $\rightarrow$ Fourier transform

# Sine waves



Where?
Phase
(°)
How strong?
Amplitude (µV)
How fast?
Frequency (Hz)
Cycle
Amplitude (µV)
Time (s)
4
2
0
−2
−4
0.0
0.2
0.4
0.6
0.8
1.0

# Sine waves


Amplitude 2.5 vs. 5 µV
Frequency 4 vs. 2 Hz
Phase shift 90 vs. 0°
Amplitude (µV)
Time (s)
5.0
2.5
0.0
−2.5
−5.0
0.0
0.2
0.4
0.6
0.8
1.0

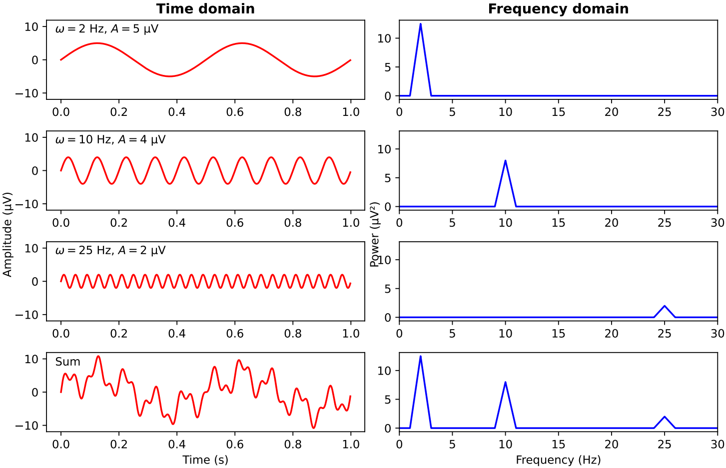
# Fourier transform

**Joseph Fourier** (1768–1830):

*Any signal can be expressed as sum of weighted sine waves, each with its own frequency, amplitude, and phase*

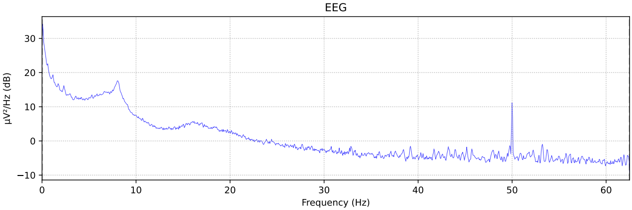
$$f(t) = A_0 + A_1 \cos(\omega t + \varphi_1) + A_2 \cos(\omega t + \varphi_2) + \ldots + A_N \cos(\omega t + \varphi_N)$$
$$= \sum_{n=0}^{N} A_n \cos(\omega t + \varphi_n) \quad \text{where } A = \text{amplitude}, \omega = \text{frequency}, \varphi = \text{phase}$$

# Fourier transform



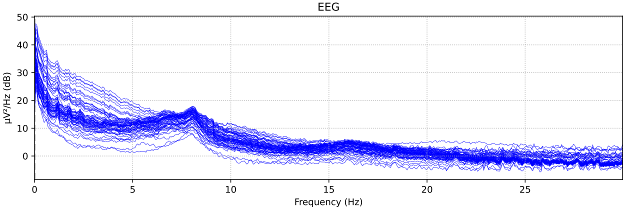
# Frequency analysis in MNE

```
# Read raw data and downsample
from mne.io import read_raw_brainvision
raw = read_raw_brainvision('data/raw/05.vhdr')
raw = raw.resample(125.)

# Spectrum for a single channel
_ = raw.plot_psd(picks='Cz', color='b', spatial_colors=False)
```

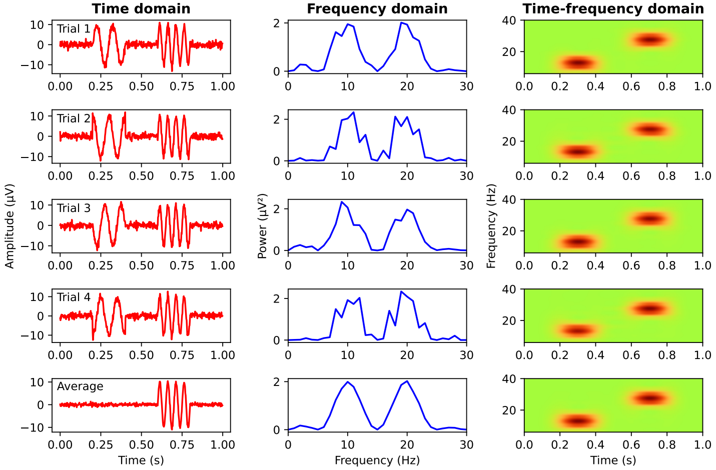


# Frequency analysis in MNE

```
# Spectrum for all channels, restricted to 0--30 Hz
_ = raw.plot_psd(fmax=30, color='b', spatial_colors=False)
```



# Frequency analysis

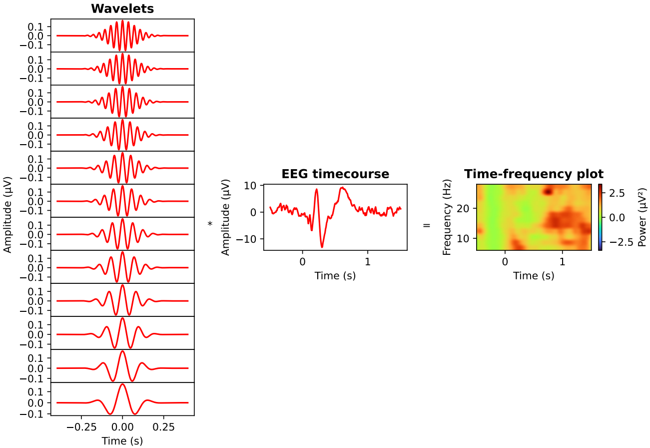


# Time-frequency analysis

**Goal:** Estimate how power (or phase) at each frequency changes over time, e.g., in response to a stimulus

**Approach:** Apply the Fourier transform to a short time window and move this window over time points in the epoch $\rightarrow$ Short-term Fourier transform (STFT), Morlet wavelet convolution

# Morlet wavelets



# Basline correction

- Must account for the $\frac{1}{F}$ scaling $\rightarrow$ Divisive baseline
  - Subtract $+$ divide: Percent signal change
  - Divide $+$ take logarithm: Decibel
- Should end *before* stimulus onset to prevent smearing

# Time-frequency analysis in MNE-Python

```python
import numpy as np
from mne import events_from_annotations, Epochs
from mne.time_frequency import tfr_morlet

# Segmentation to epochs
events, _ = events_from_annotations(raw, regexp='Stimulus')
triggers = [201, 205]
epochs = Epochs(raw, events, triggers, tmin=-0.5, tmax=1.5, baseline=(-0.2, 0.))
print(epochs.get_data().shape)
```

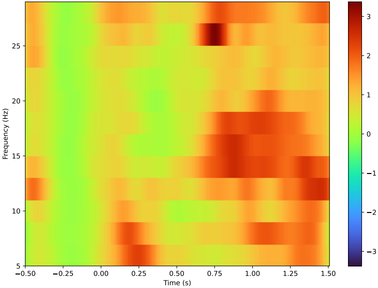
```
## (240, 64, 251)
```

```python
# Morlet wavelet decomposition
freqs = np.arange(6., 30., step=2.)
n_cycles = np.arange(3., 15., step=1.)
tfr = tfr_morlet(epochs, freqs, n_cycles, return_itc=False, average=False)
print(tfr.data.shape)
```

```
## (240, 64, 12, 251)
```

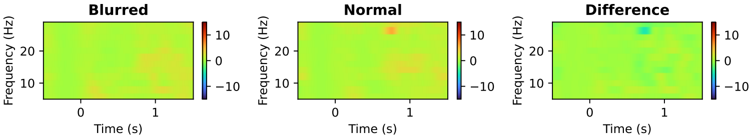
# Time-frequency analysis in MNE-Python

```
# Divisive baseline correction to get percent signal change
tfr = tfr.apply_baseline((-0.3, -0.1), mode='percent')

# Plot power averaged across all epochs and channels
tfr_ave = tfr.average()
tfr_ave.plot(picks='Cz', cmap='turbo')
```



# Time-frequency analysis in MNE-Python

```
# Compute power per condition and the difference between conditions
tfr_aves = {'Blurred': tfr['201'].average(),
            'Normal': tfr['205'].average(),
            'Difference': tfr['201'].average() - tfr['205'].average()}

# Create multi-panel plot
import matplotlib.pyplot as plt
fig, axs = plt.subplots(nrows=1, ncols=len(tfr_aves), figsize=(9, 2))
for ix, (label, tfr_ave) in enumerate(tfr_aves.items()):
    axs[ix].set_title(label, weight='bold')
    tfr_ave.plot(picks='Cz', cmap='turbo', vmin=-15, vmax=15,
                 axes=axs[ix], show=False)
```



# Time-frequency analysis with the pipeline

```r
# Import the Python package from R
pipeline <- reticulate::import("pipeline")

# Run the pipeline
res <- pipeline$group_pipeline(
  vhdr_files = "data/raw",
  log_files = "data/log",
  output_dir = "output",
  ocular_correction = "data/cali",
  triggers = c(201:208, 211:218),
  average_by = c("n_b", "DeviantPosRL", "n_b/DeviantPosRL"),
  perform_tfr = TRUE,
  tfr_freqs = seq(6, 30, 2),
  tfr_cycles = seq(3, 15, 1),
  tfr_baseline_tmin = -0.3,
  tfr_baseline_tmax = -0.1,
  tfr_components = list(
    "name":list("alpha"),
    "tmin":list(0.0),
    "tmax":list(0.2),
    "fmin":list(8.),
    "fmax":list(14.),
    "roi":list(
      c("PO9", "PO7", "PO3", "POz", "PO4", "PO8", "PO10", "O1", "Oz", "O2"),
    )
  )
)
```

## Time-frequency analysis with the pipeline

- New column in the single trial data frame → Linear mixed model
- Permutation tests extended to the third (frequency) dimension

## General considerations

- New parameters to be taken care of:
  - Design: Longer inter-trial interval
  - Wavelet frequencies + number of cycles (!)
  - Baseline correction window and method
  - Interpretation (narrow-band vs. broad-band, oscillation vs. rate of change)
- Everything matters