Spectral Analysis

How to process neural oscillatory signals

Peter Donhauser, PhD student, Baillet lab
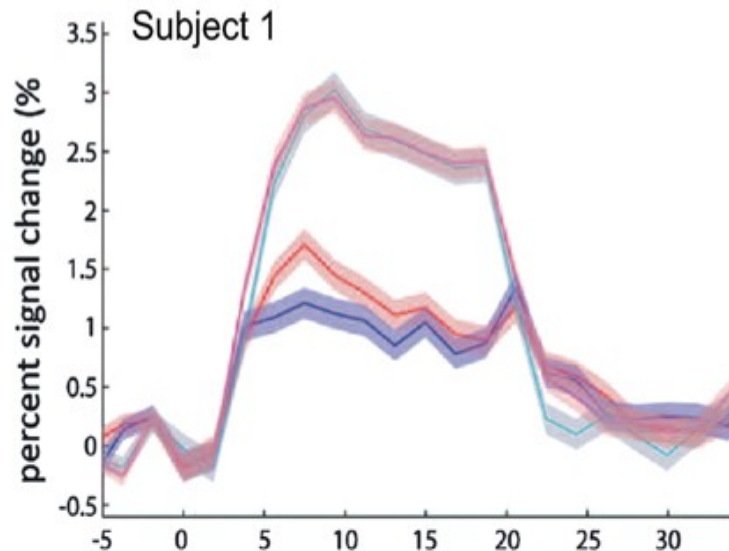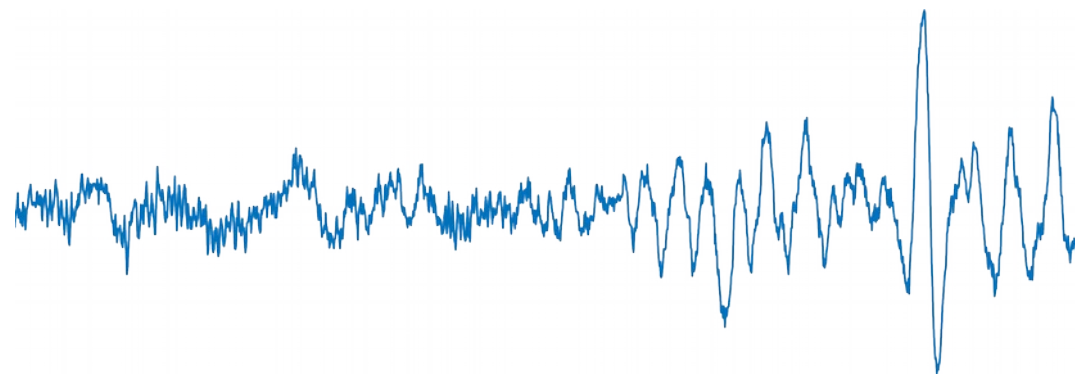
MEG @McGill

neuro
montréal

Why spectral analysis?

- MEG signals contain a wide range of components

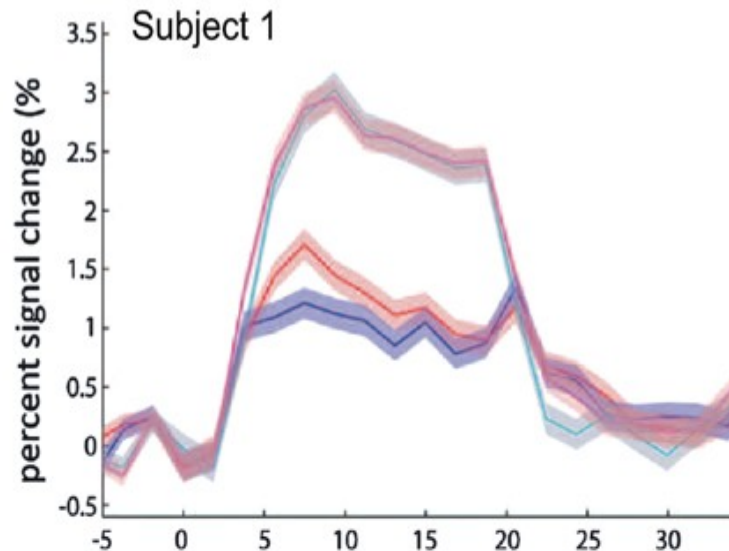- Electrophysiology vs. BOLD: what is 'activity'?

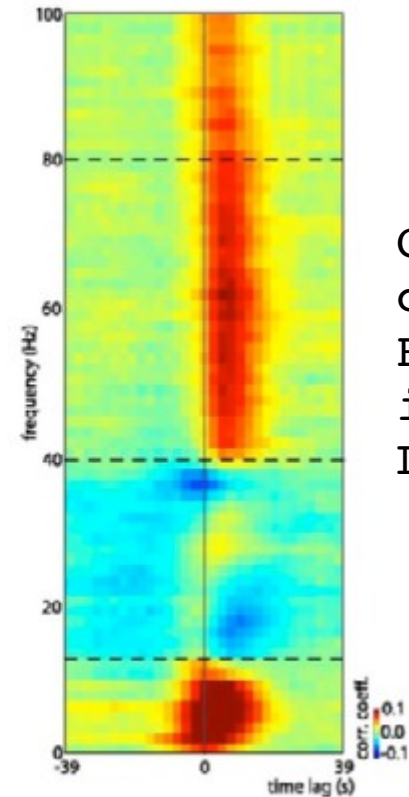BOLD fMRI example

MEG example

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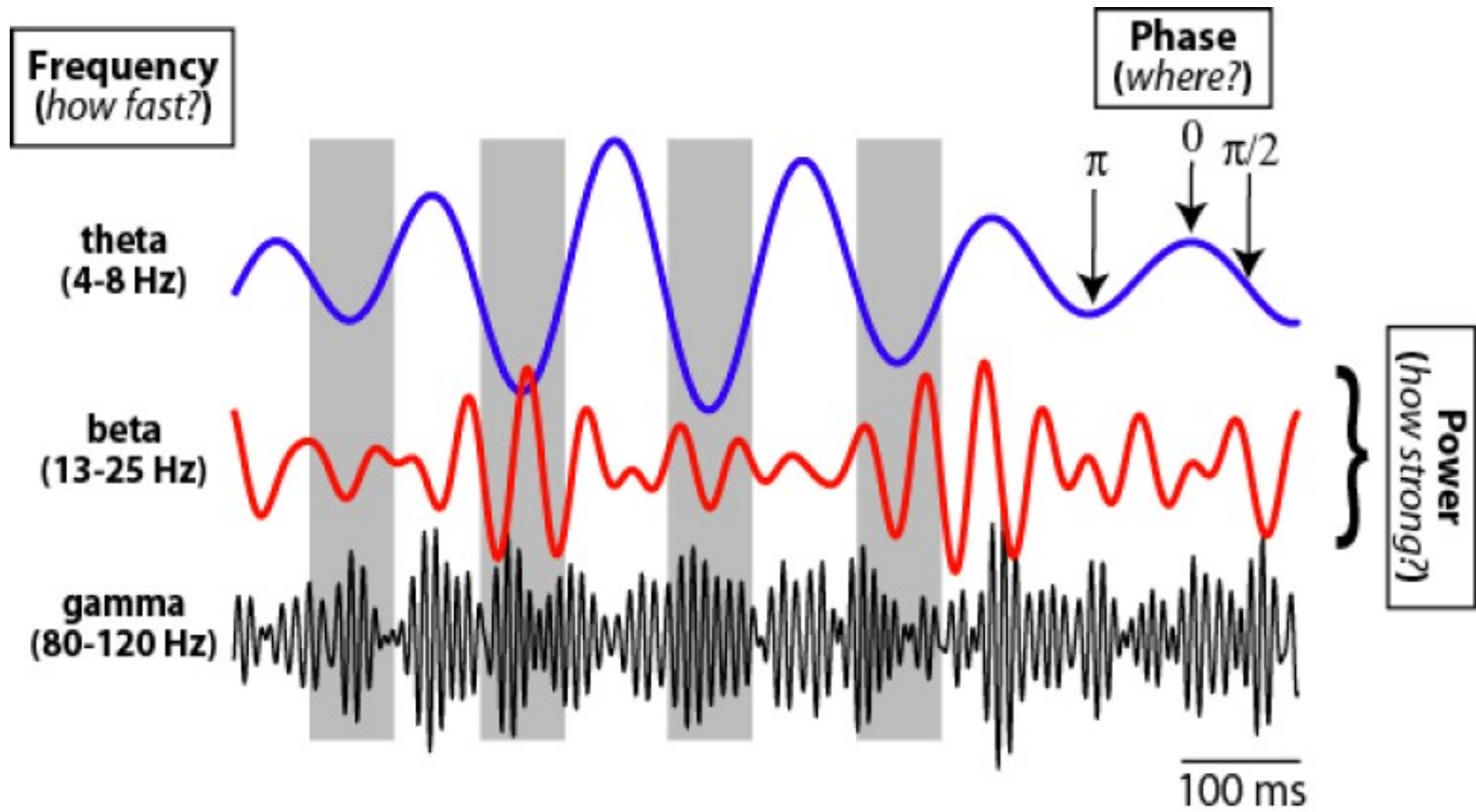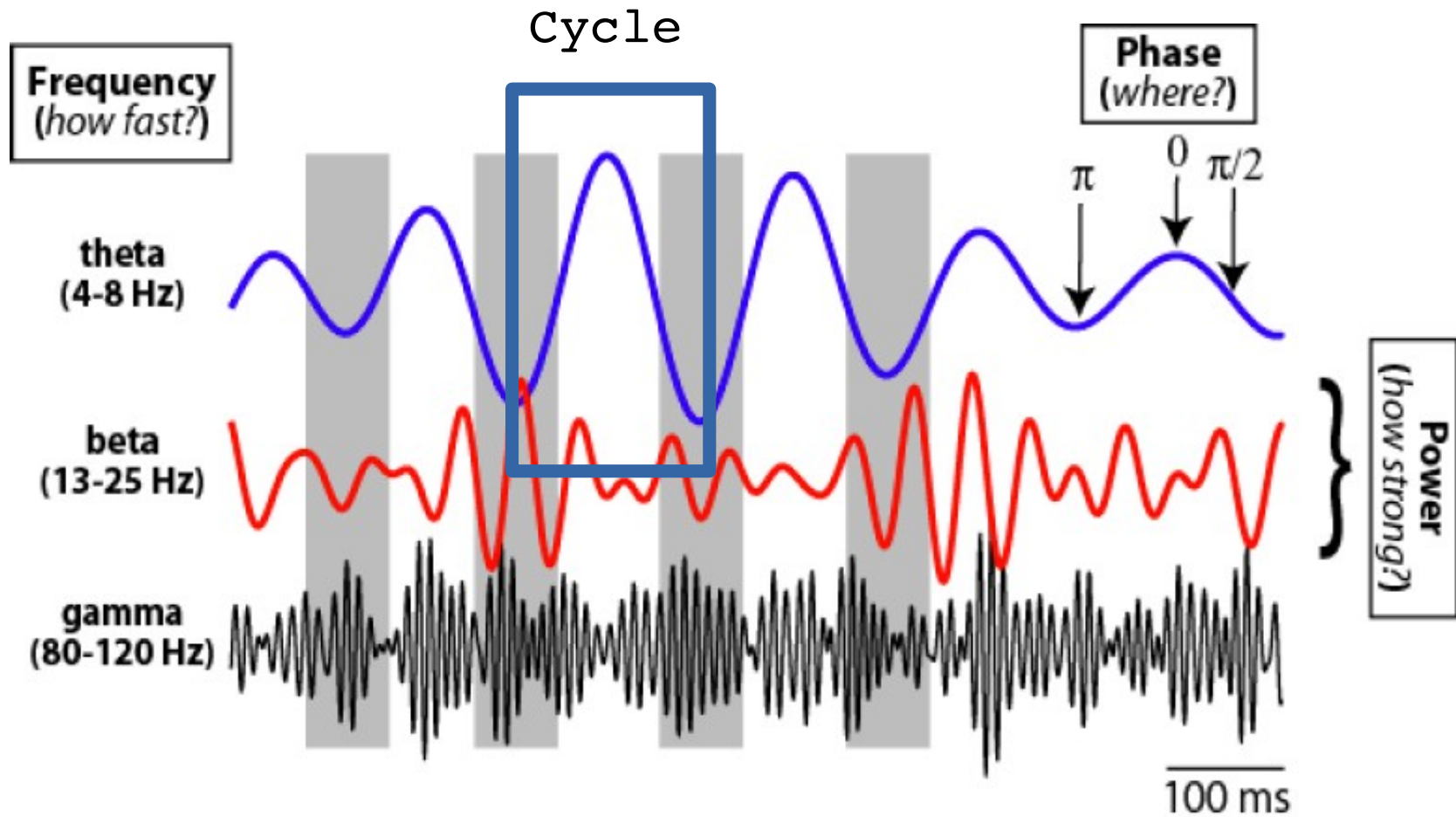

BOLD fMRI example

Cross-correlation of BOLD with intra-cranial LFP recordings
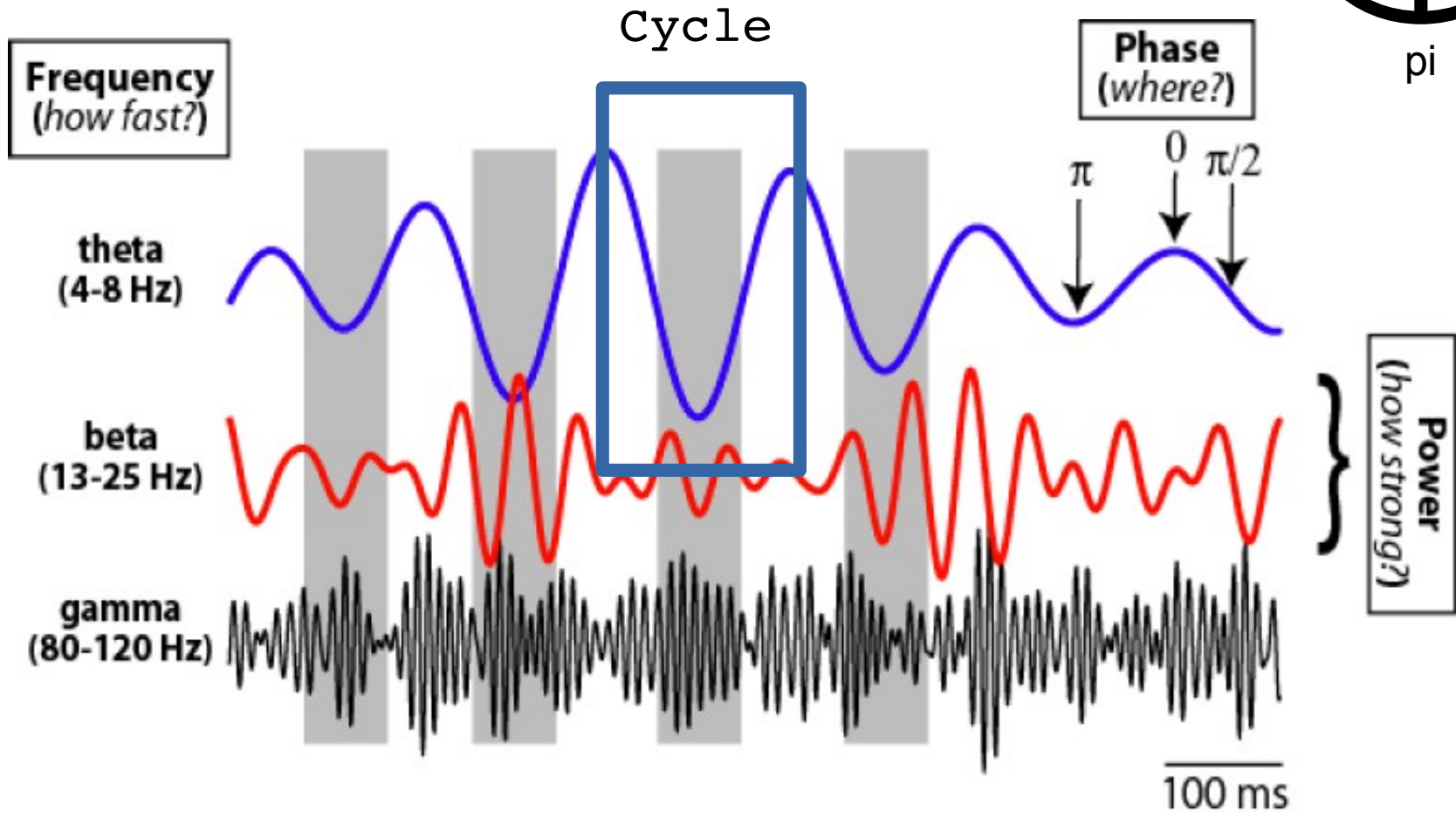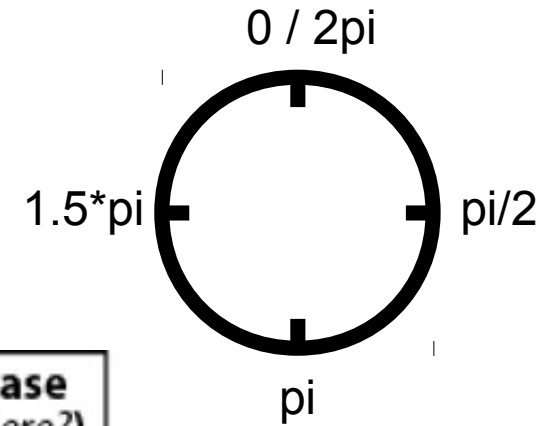
Schölvinck et al., PNAS (2010)
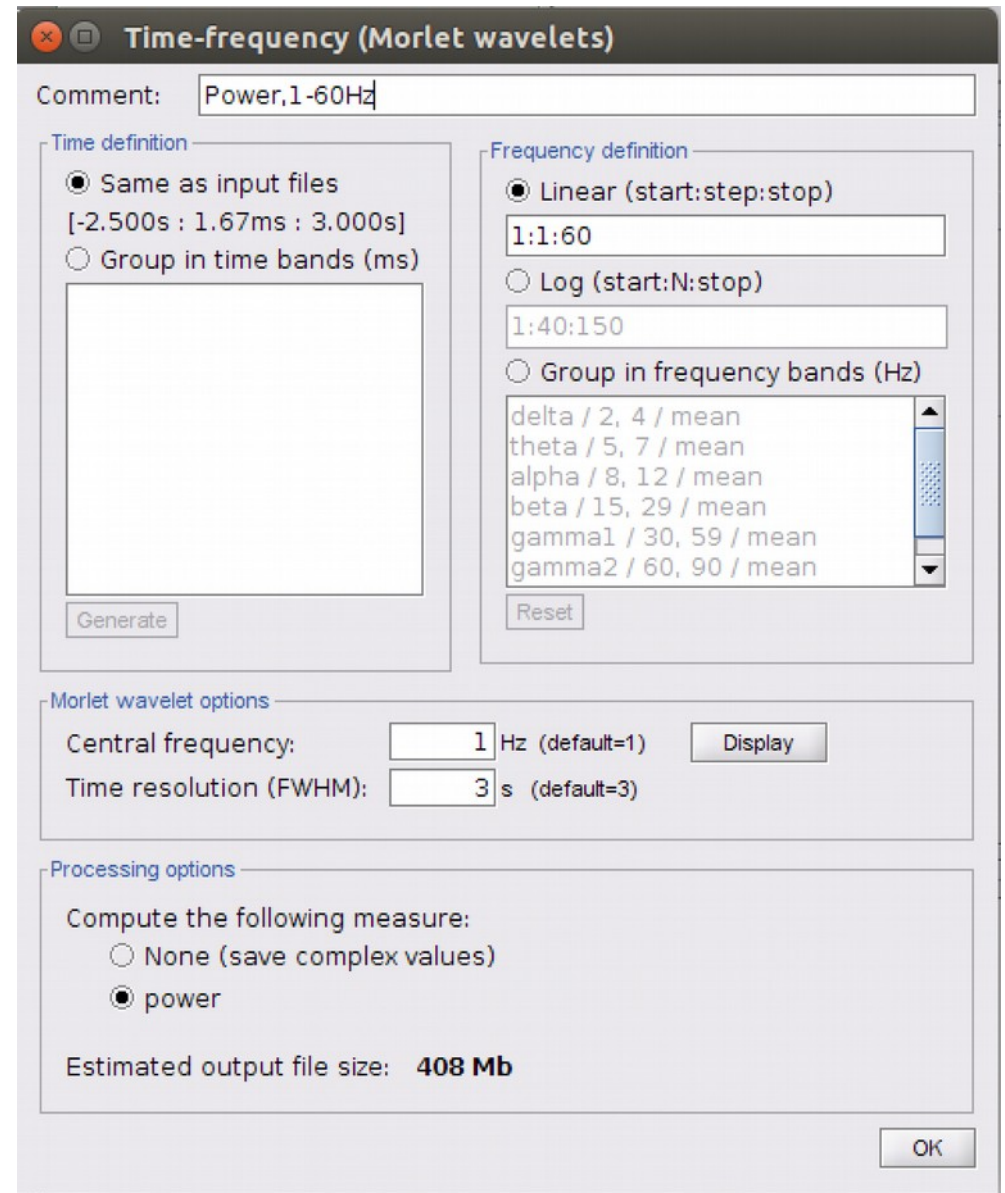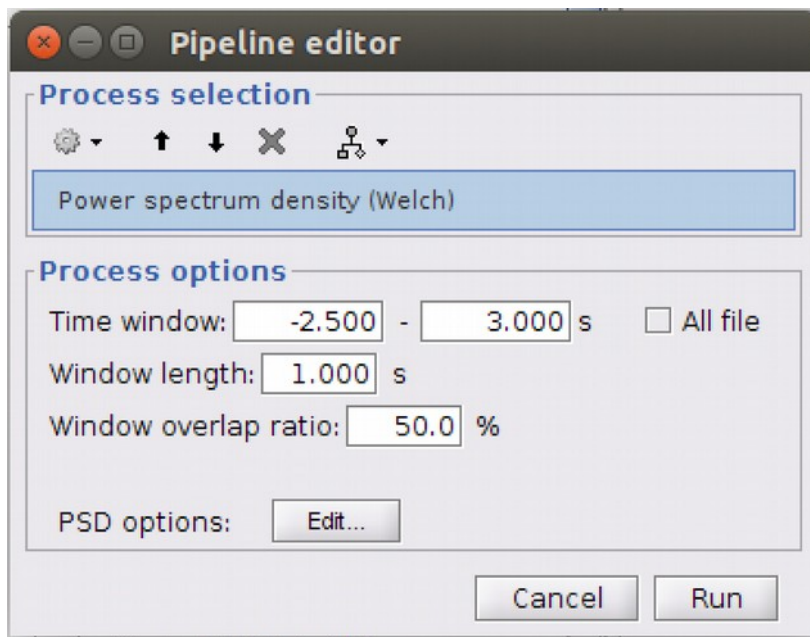
Basic concepts

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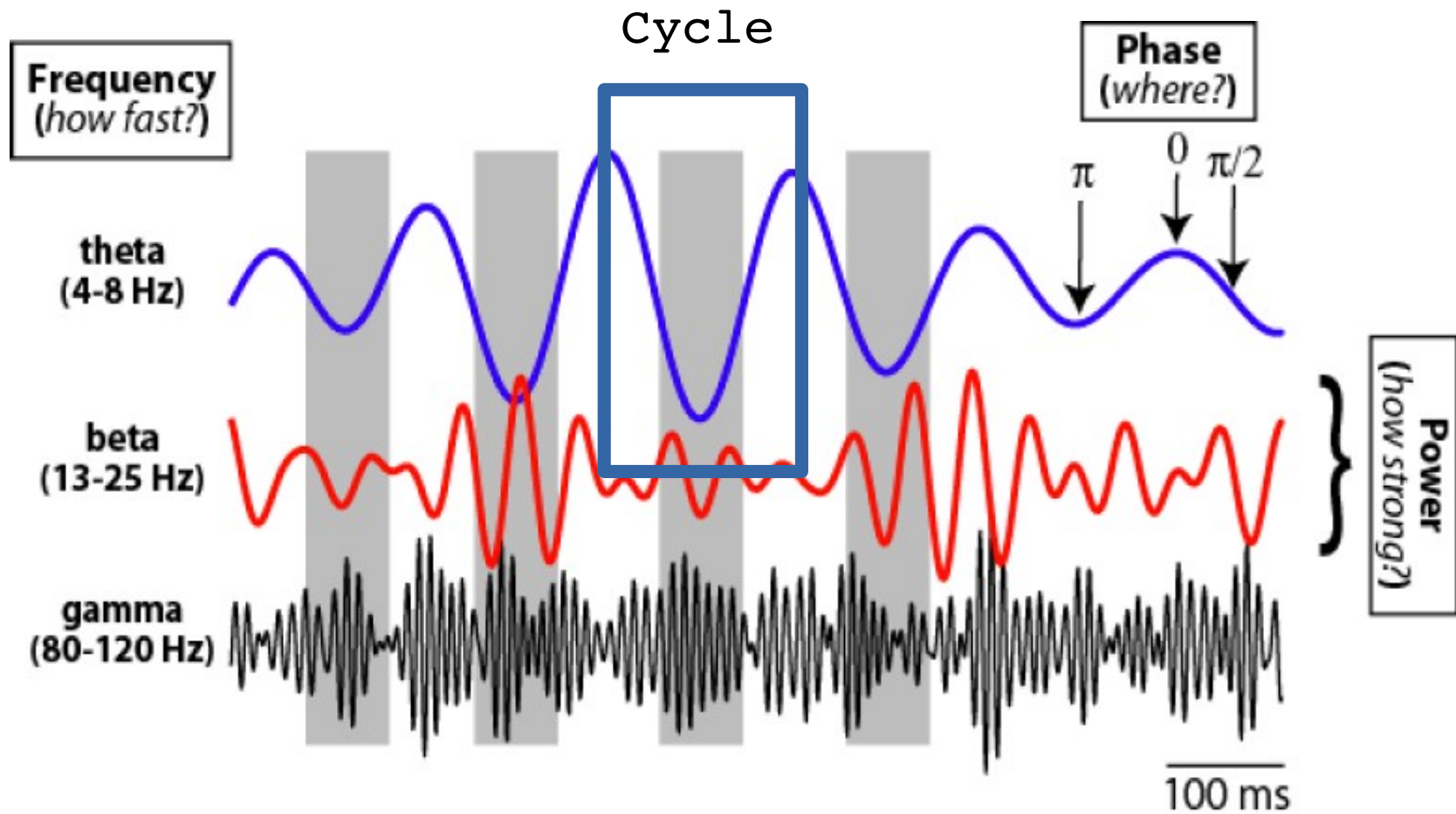
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How to do it? Brainstorm!

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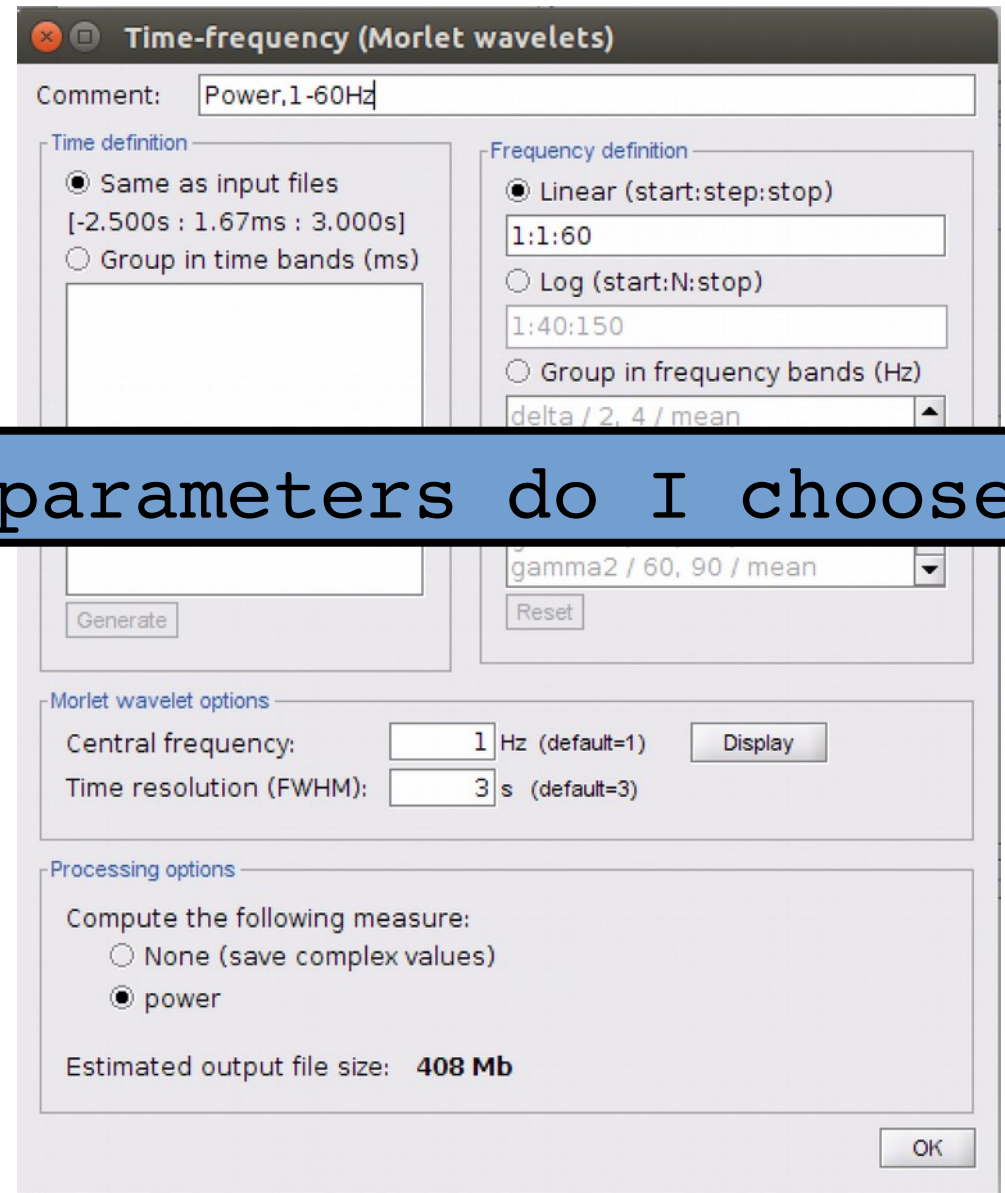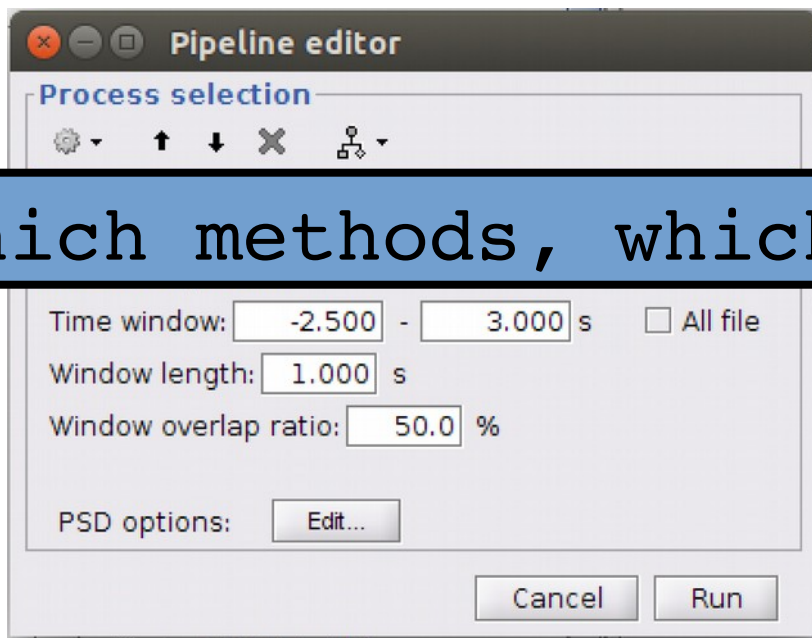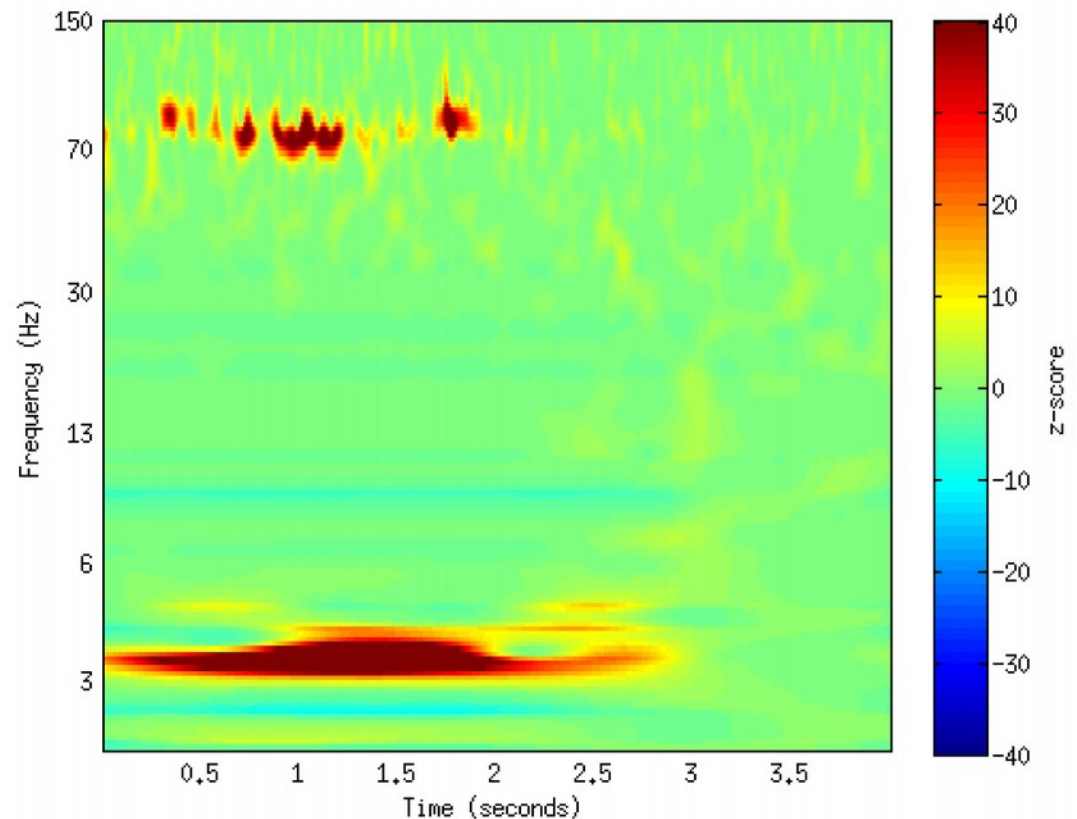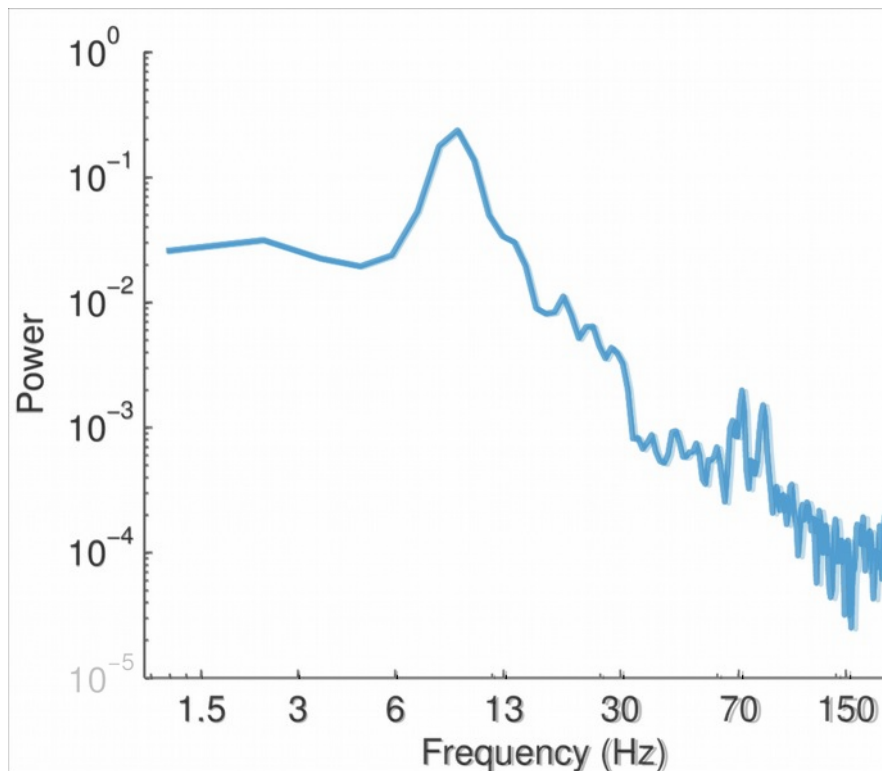
Methods covered today

Two main groups:

- Estimation of spectral power (stationary) vs.

- Localization of Power in time & frequency

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Usage:

- Quality check (noise level)
- Resting-state dynamics
- Extended task periods

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Two main groups:

- Estimation of spectral power (stationary) vs.

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Usage:

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- Extended task periods

Usage:

- Task-induced responses
- Transient oscillatory phenomena (HFOs)

Methods covered today

Two main groups:

- Estimation of spectral power (stationary) vs.

- Localization of Power in time & frequency

Stationary:

- Fourier transform

- Power spectral density (Welch's method)

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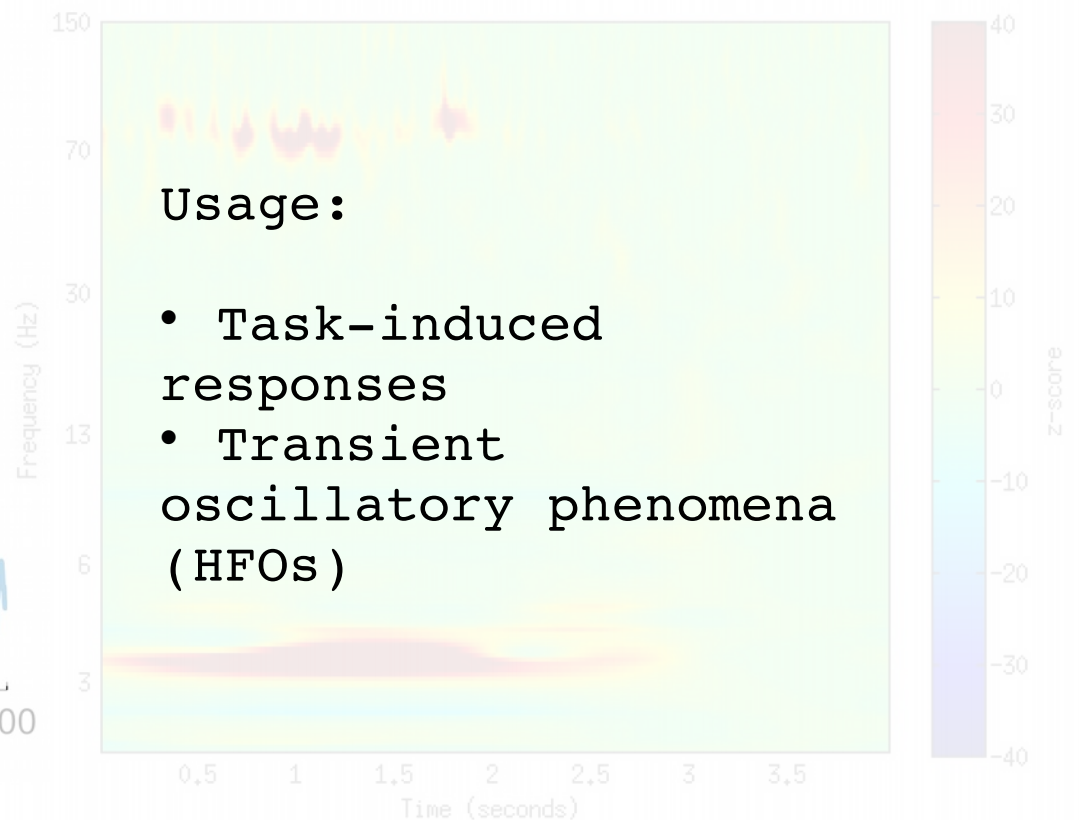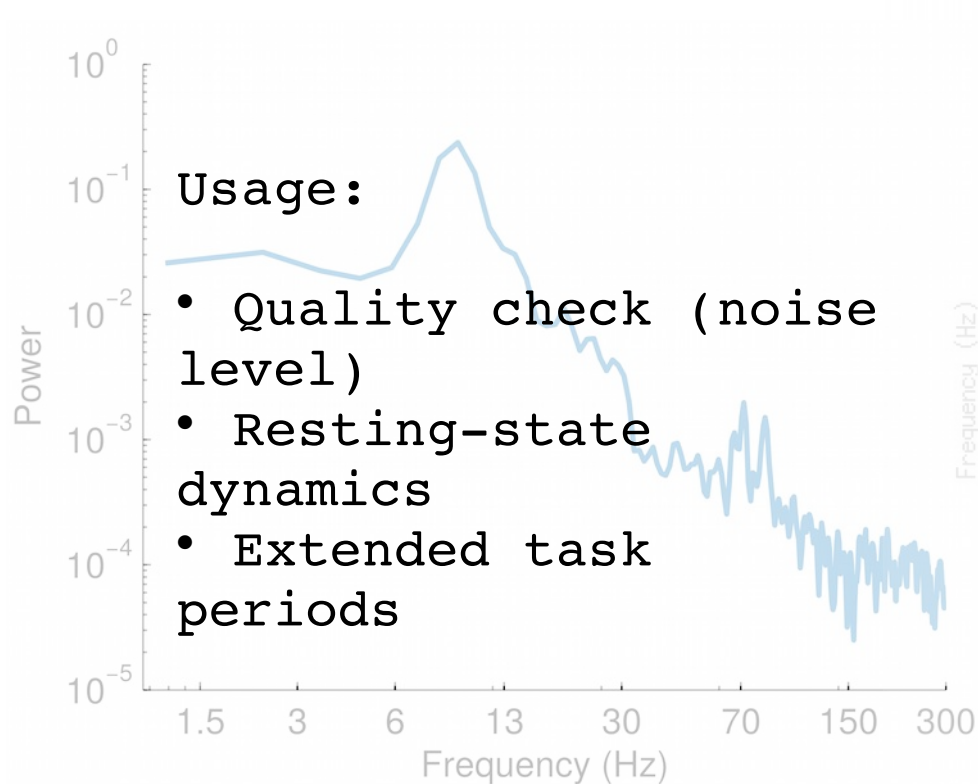Time-resolved:

- Wavelet transform

- Filtering & Hilbert transform

Methods covered today

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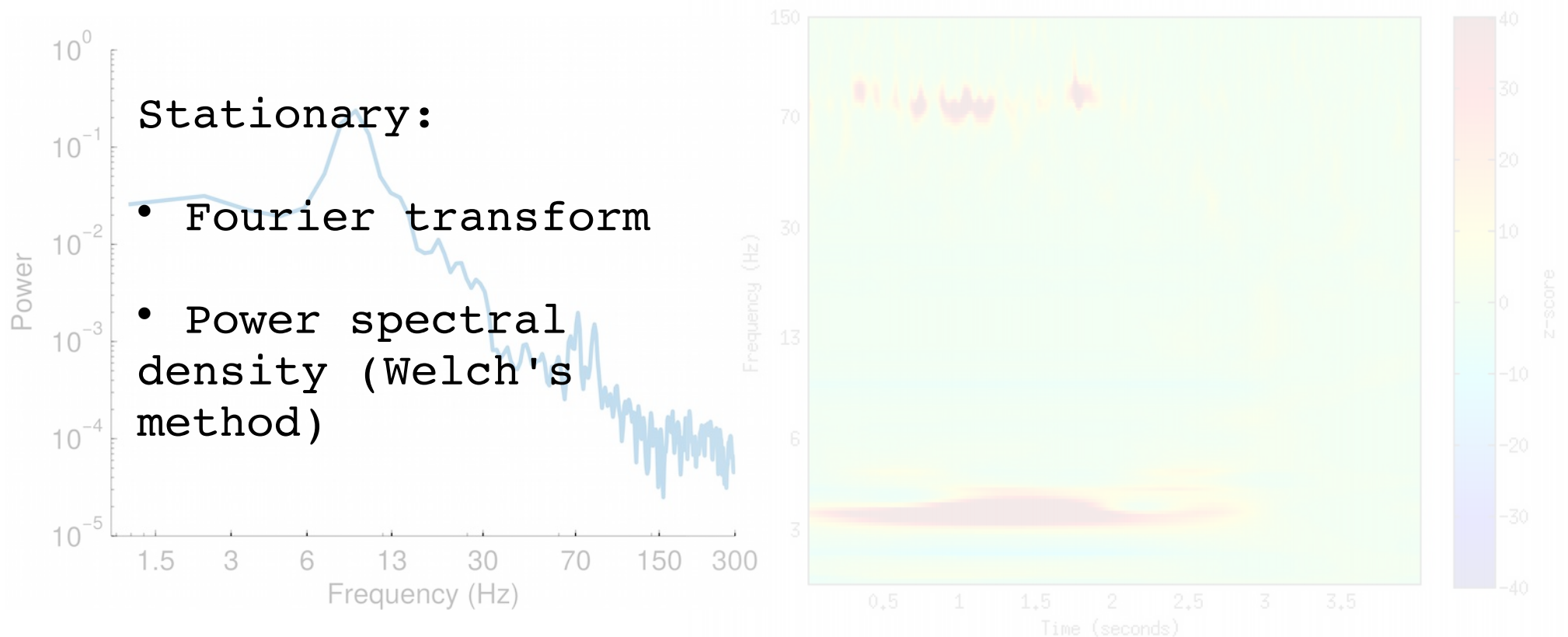
- Localization of Power in time & frequency

Short introduction to cross-frequency coupling
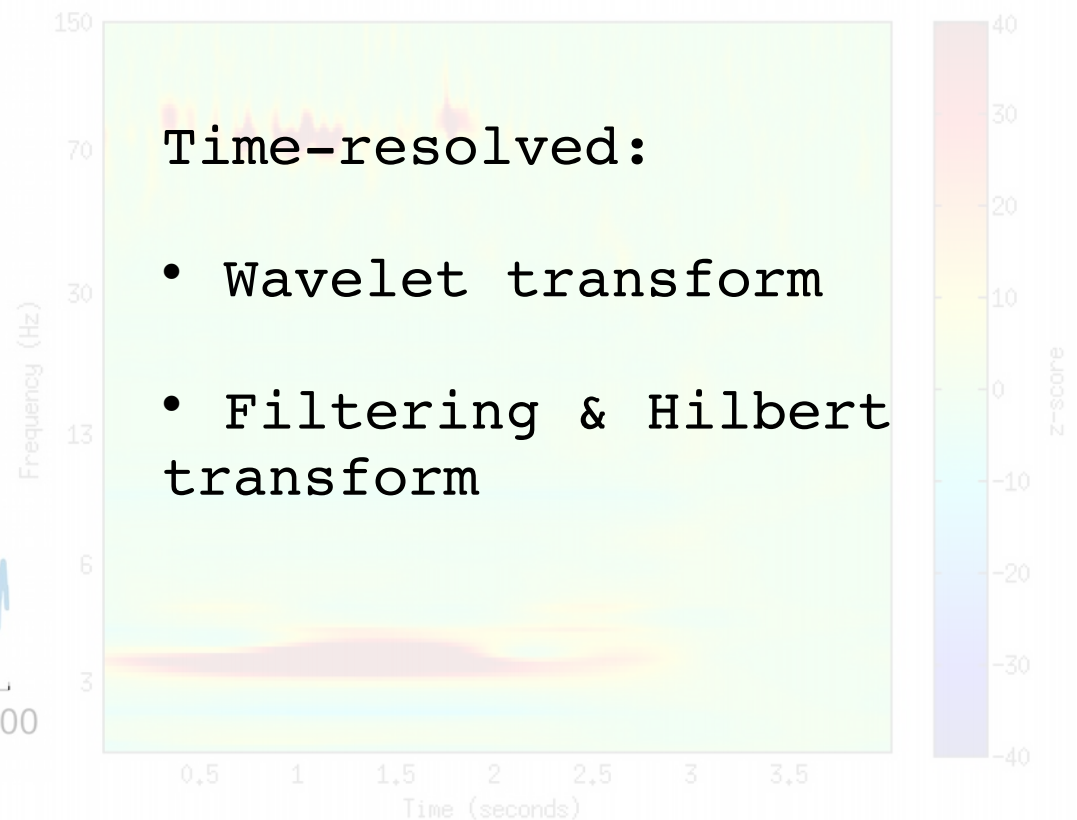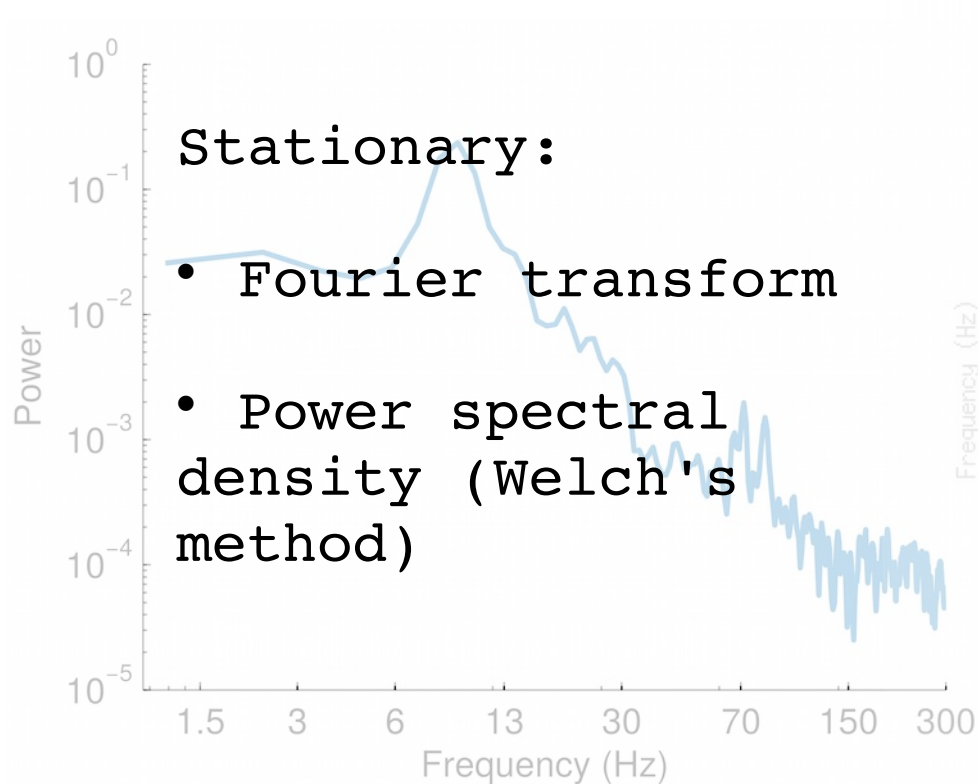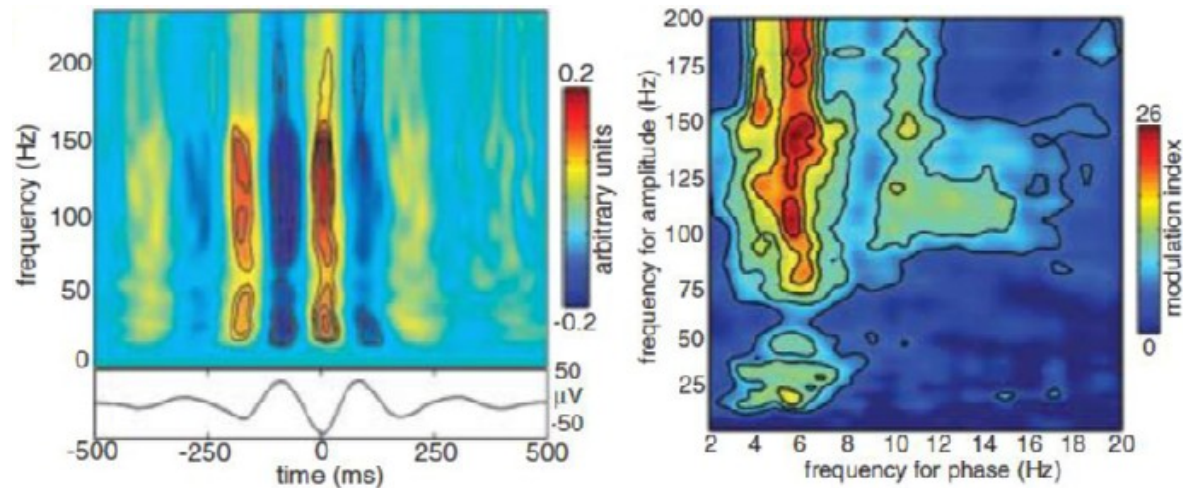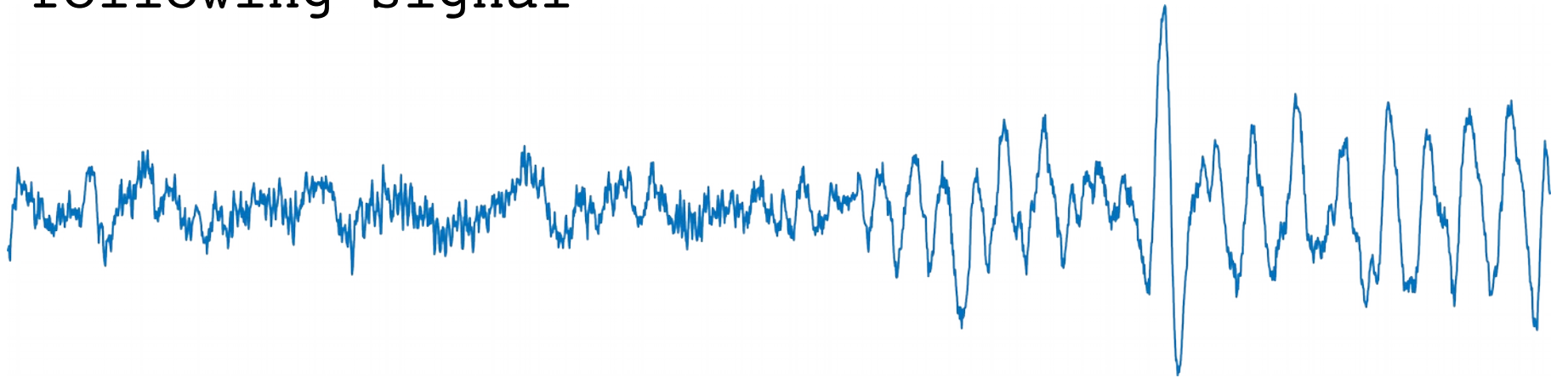measures
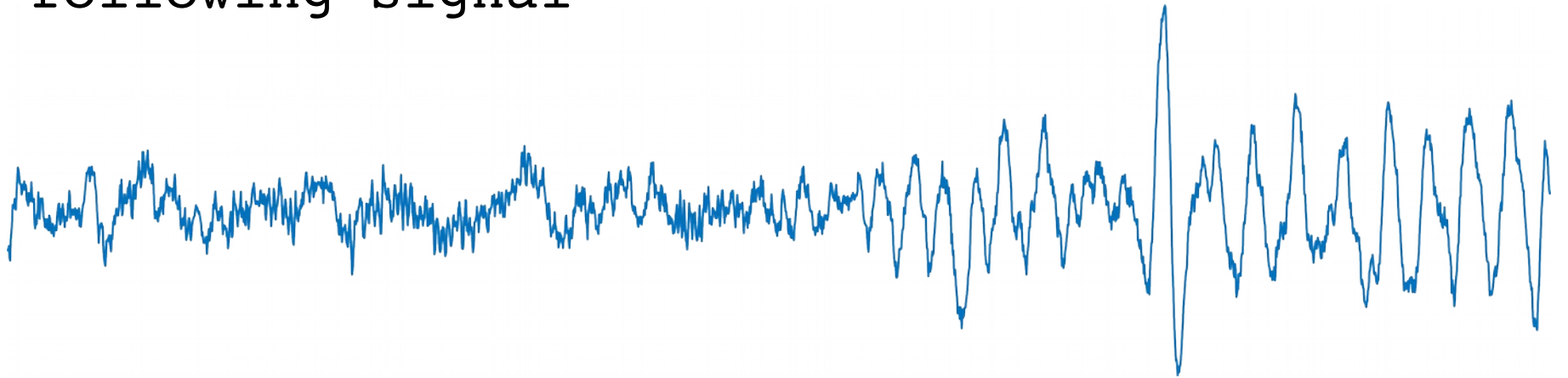

R. Canolty, et al., Science, 2006.

Example signal

- Concepts will be illustrated using the following signal
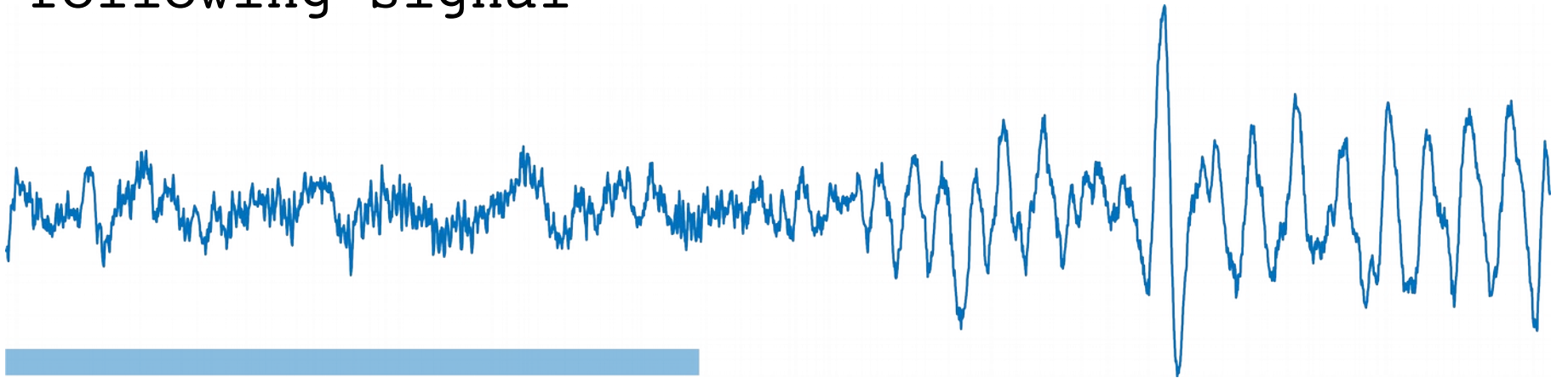
Example signal

- Concepts will be illustrated using the following signal

- MEG source signal from visual cortex

- 4 seconds

- Sampling frequency: 600 Hz

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- MEG source signal from visual cortex

- 4 seconds

- Sampling frequency: 600 Hz

- Visual stimulus

Contents

Stationary:

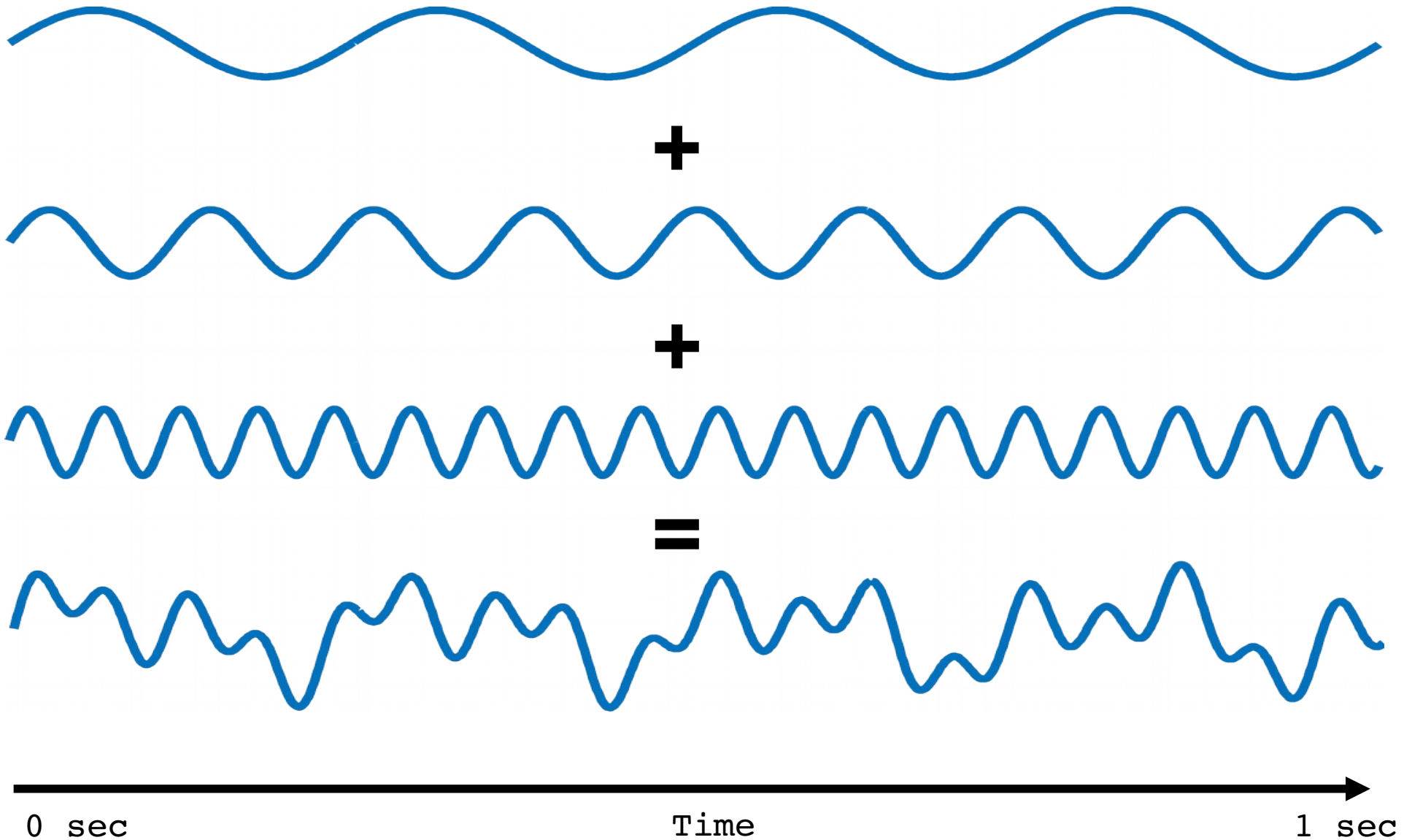- Fourier transform

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Time-resolved:

- Wavelet transform
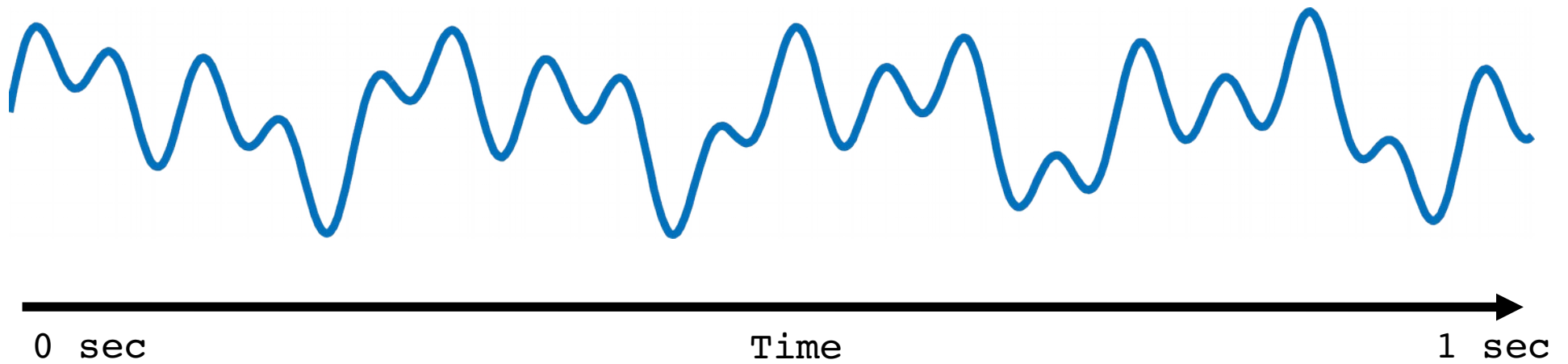
- Filtering & Hilbert transform

(Fast) Fourier Transform, FFT

- Transforms a signal from time to frequency domain.

- Hugely important in many fields of science and engineering.

- Not so powerful in its raw form for estimating spectral components in neural signals
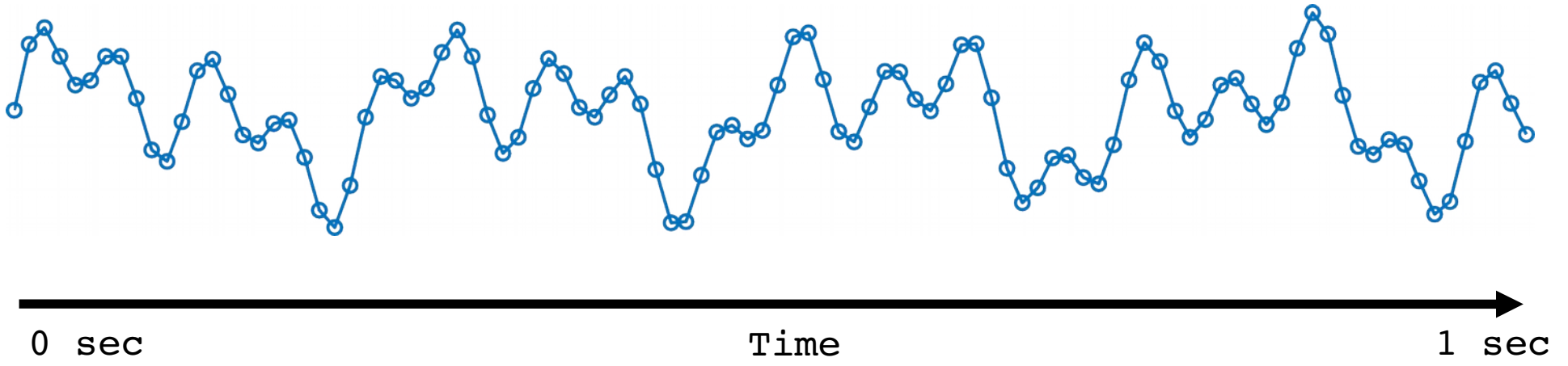
- BUT: forms the basis for many of the following methods
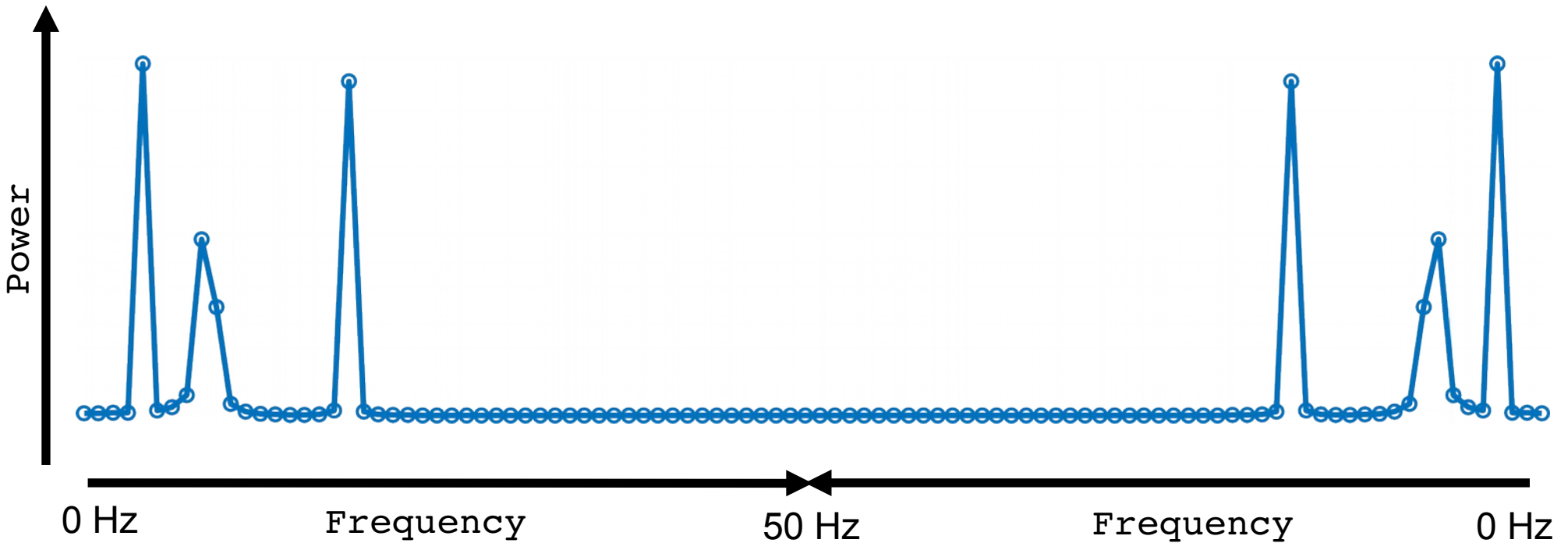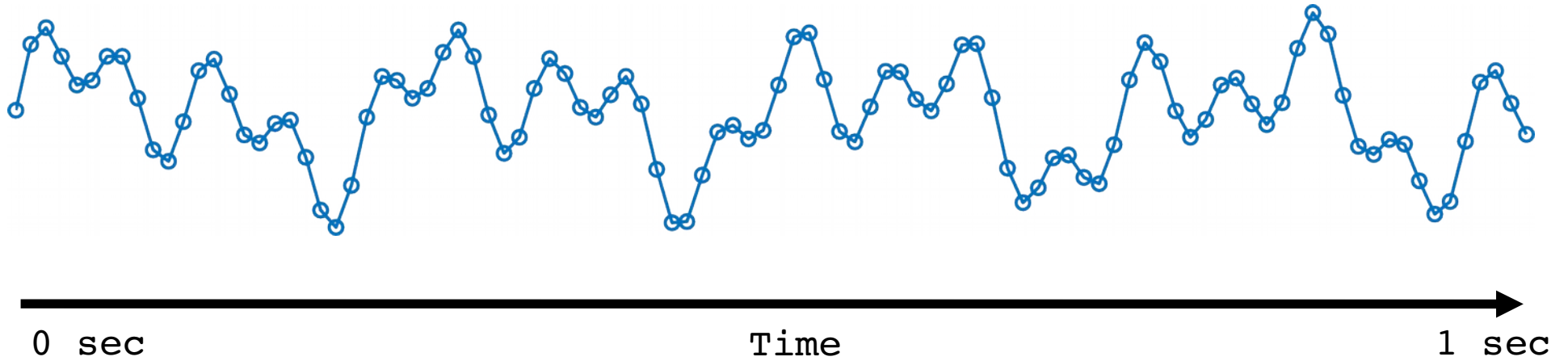
(De-)__Composing__ a signal

0 sec   Time   1 sec

(De-) Composing a signal

0 sec   Time   1 sec

(De-)Composing a signal

0 sec   Time   1 sec

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Power

0 Hz   Frequency   50 Hz   Frequency   0 Hz

(De-)Composing a signal

- FFT output is symmetric, second half usually removed

- Peaks in frequency domain correspond to an oscillatory component in time domain
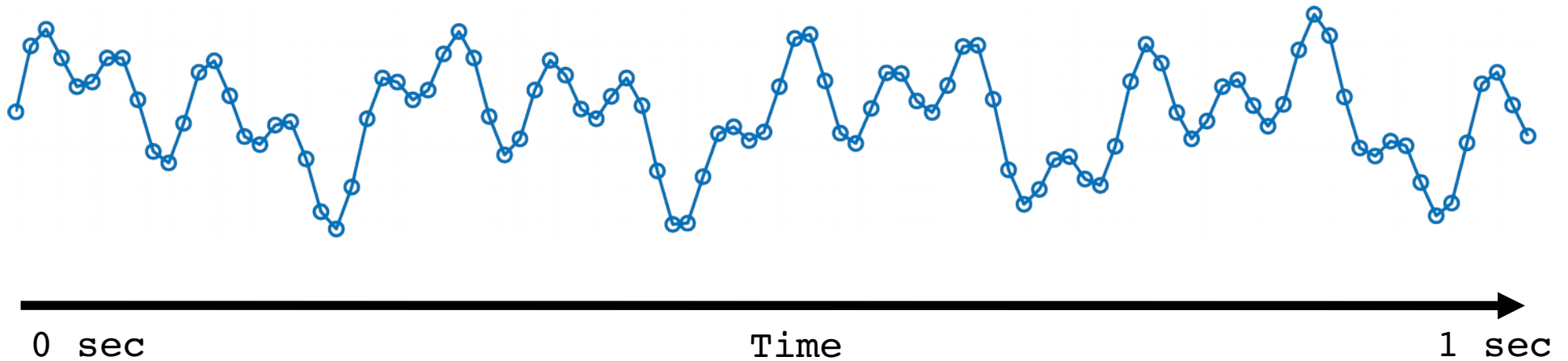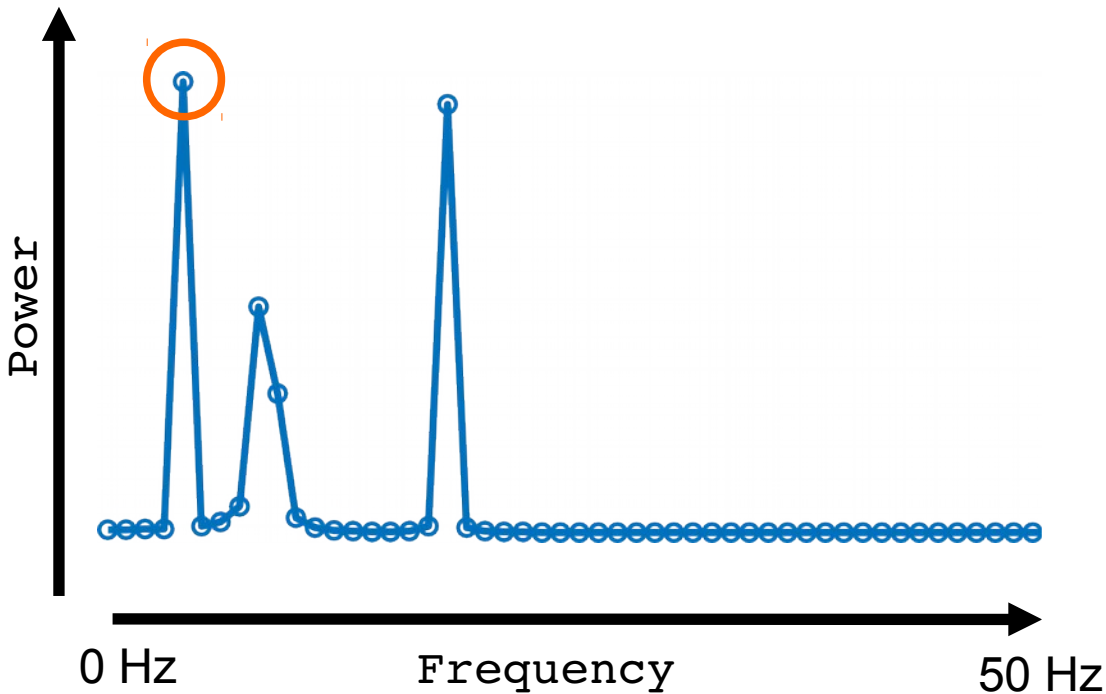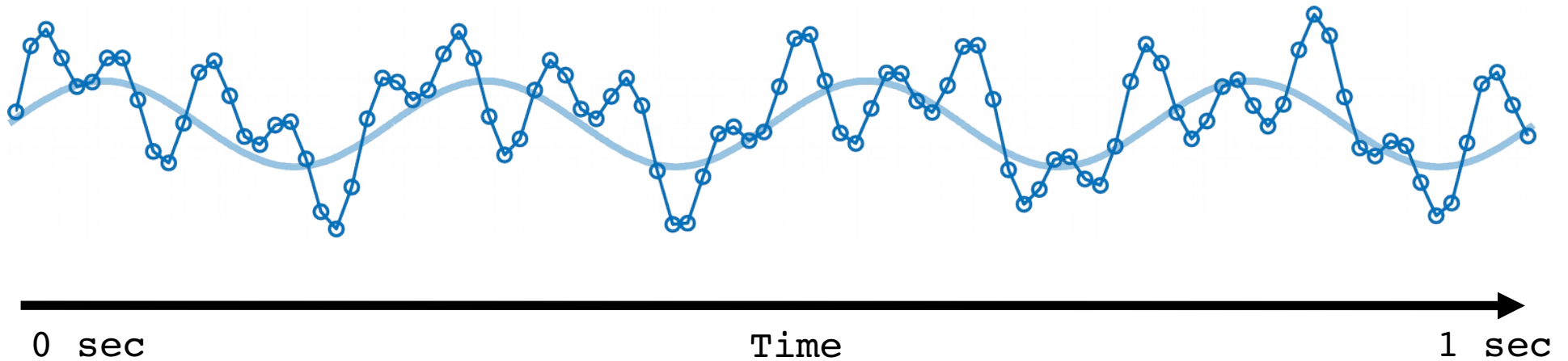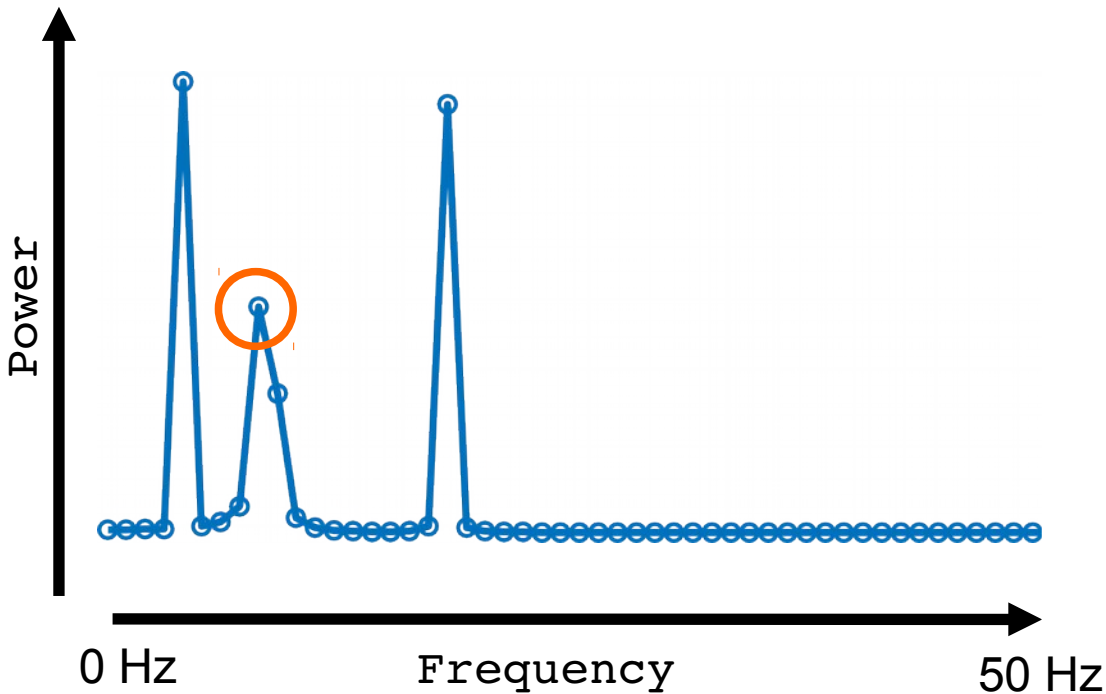
(De-)Composing a signal

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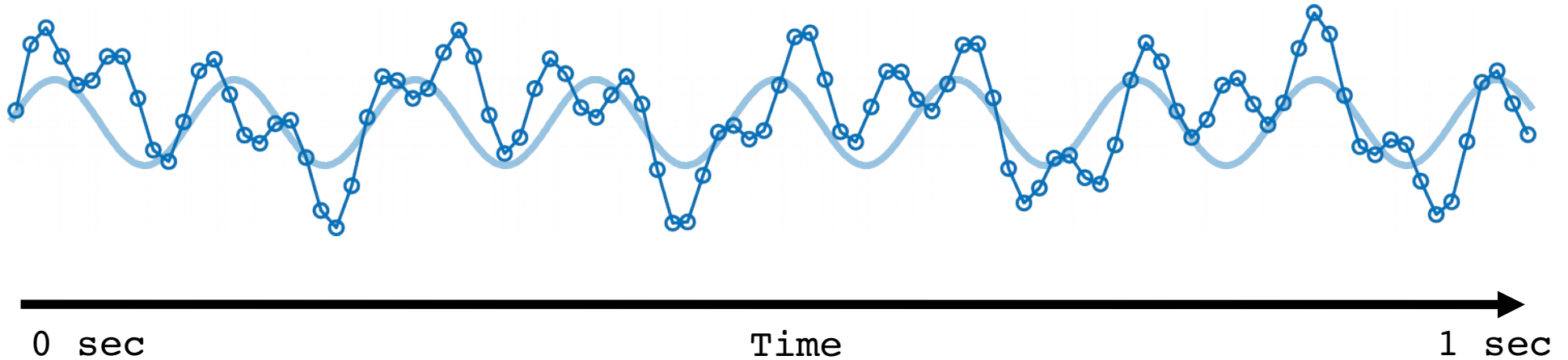
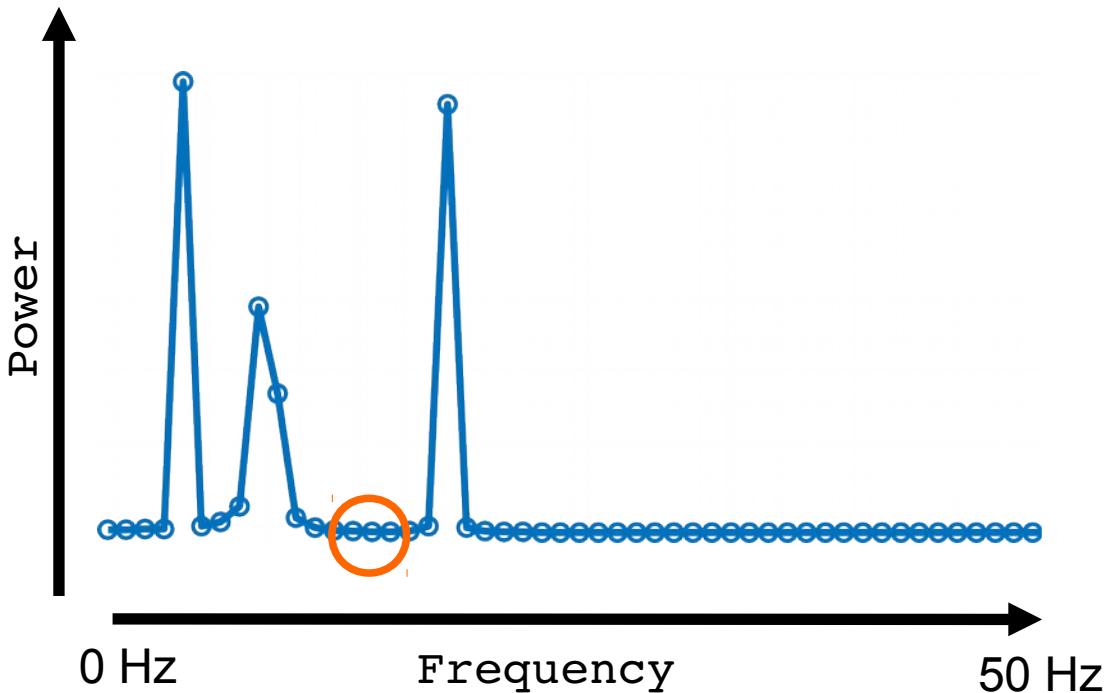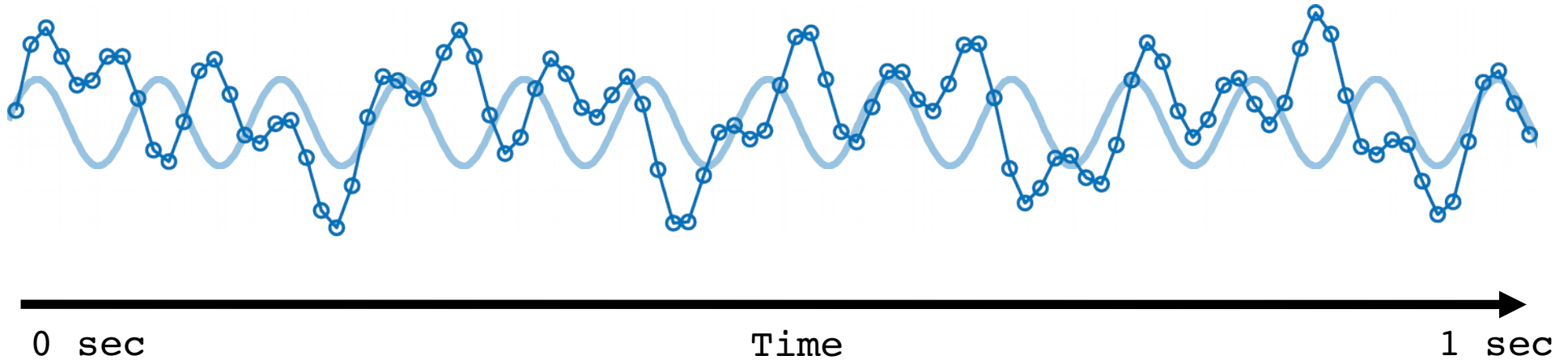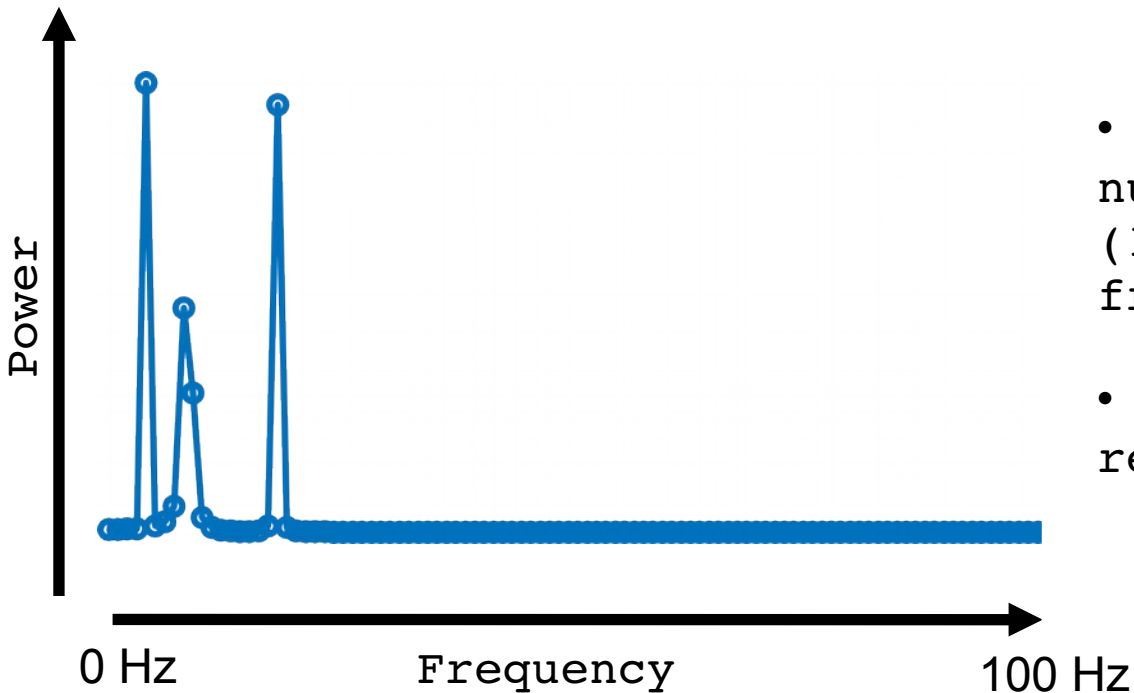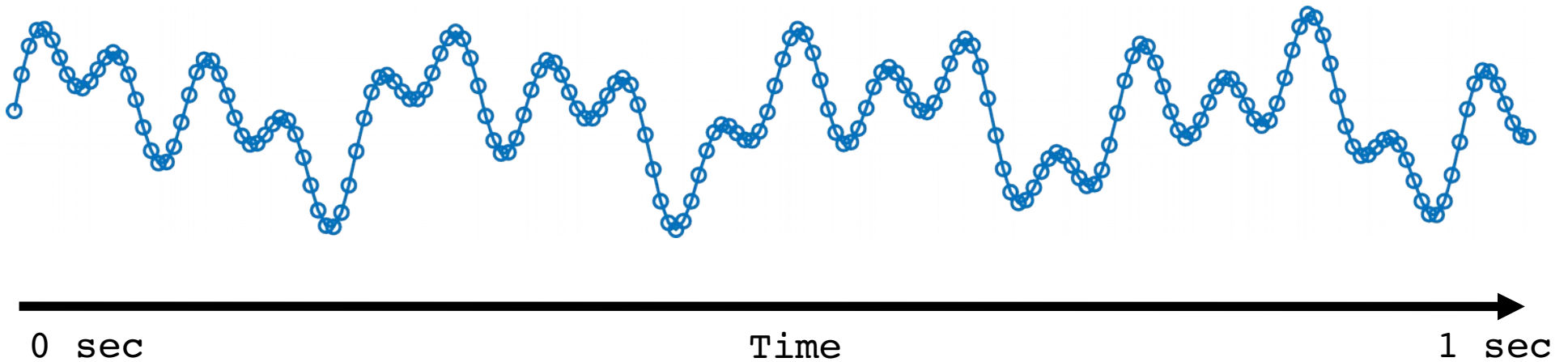# (De-)Composing a signal

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(De-)Composing a signal

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Power

0 Hz   Frequency   50 Hz

(De-)Composing a signal

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Power
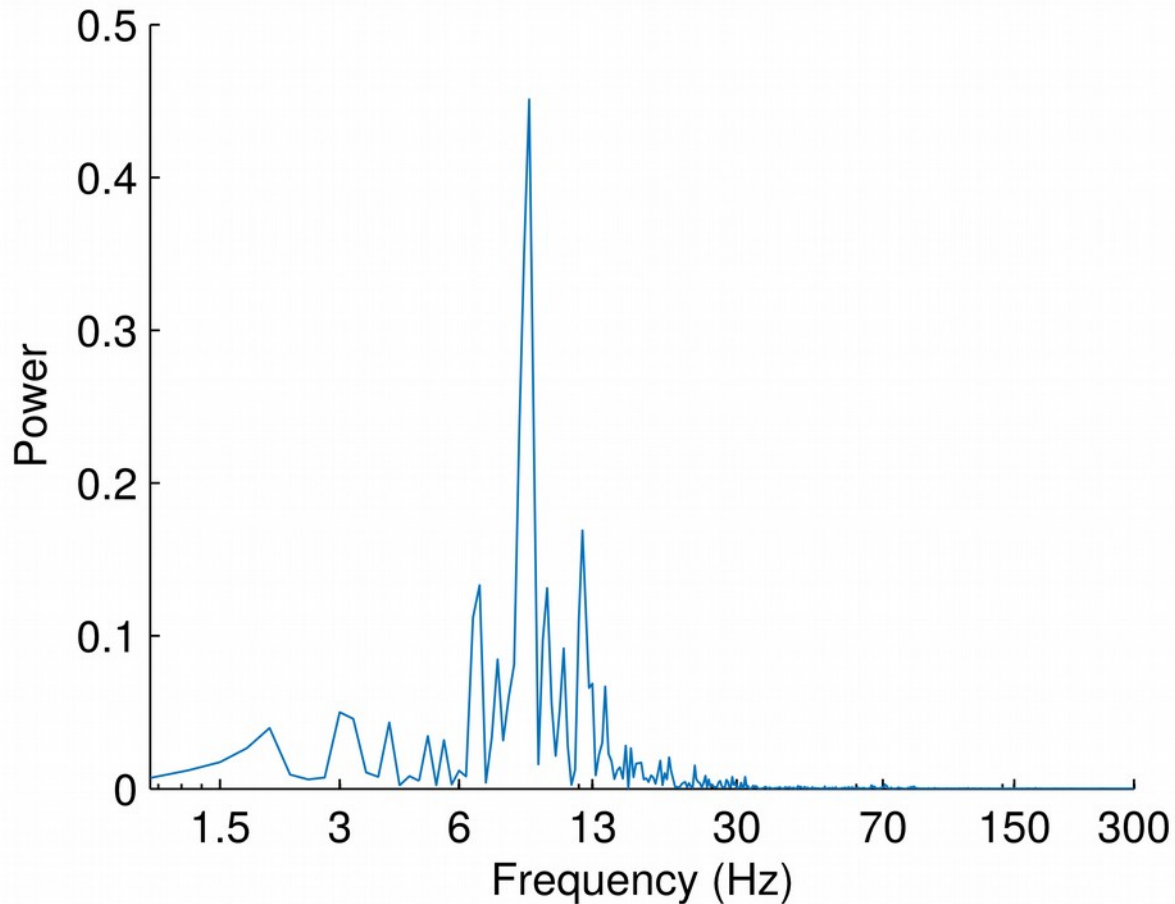
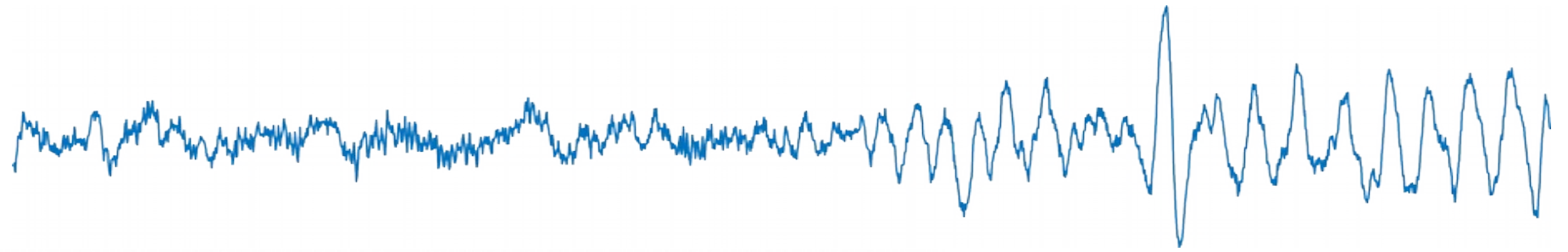0 Hz   Frequency   100 Hz

- Number of samples in time = number of samples in frequency (1/2 without 'negative frequencies')

- Higher sampling rate can resolve higher frequencies

Fourier Transform

~ 9 Hz
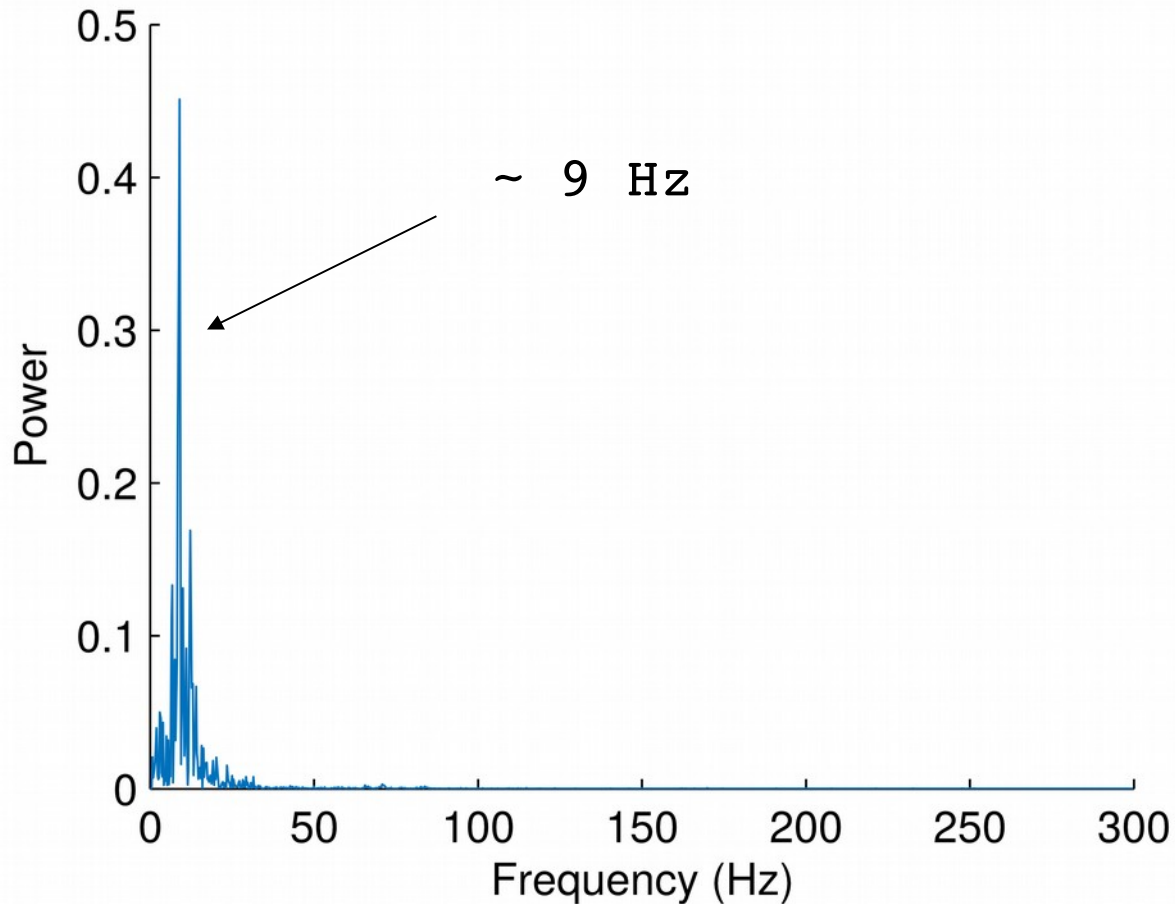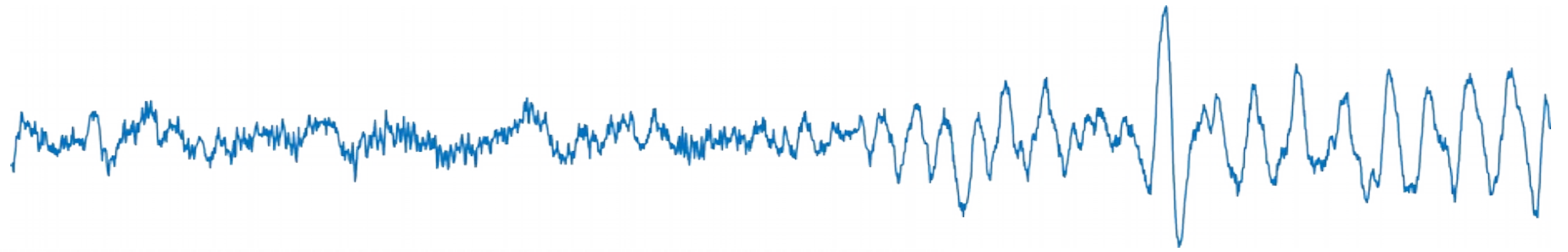
- We can see a peak in the alpha band (8-12 Hz)

Fourier Transform

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- Sometimes helpful to display frequency axis in log-scale (see next)
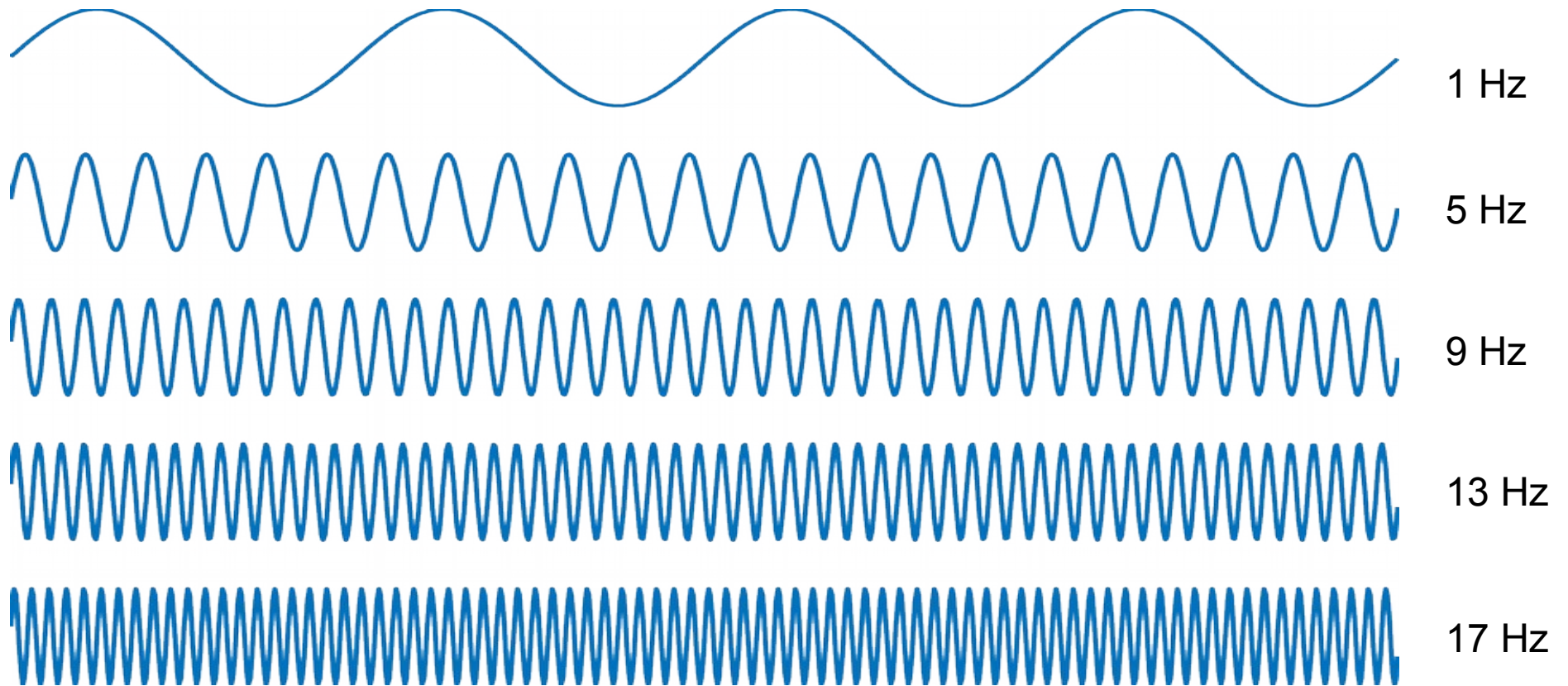
Linear- vs. Log-scaled spectrum

Compare:

1 or 2 cycles per second

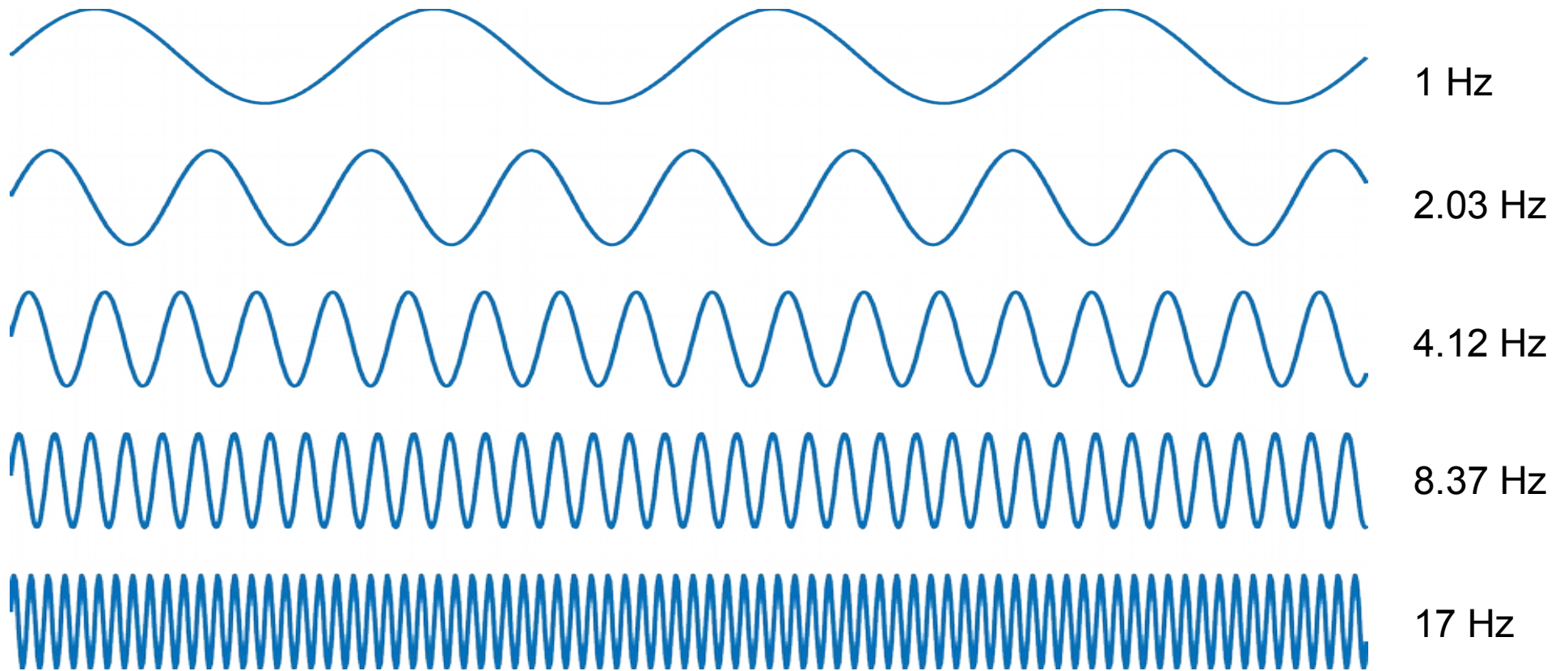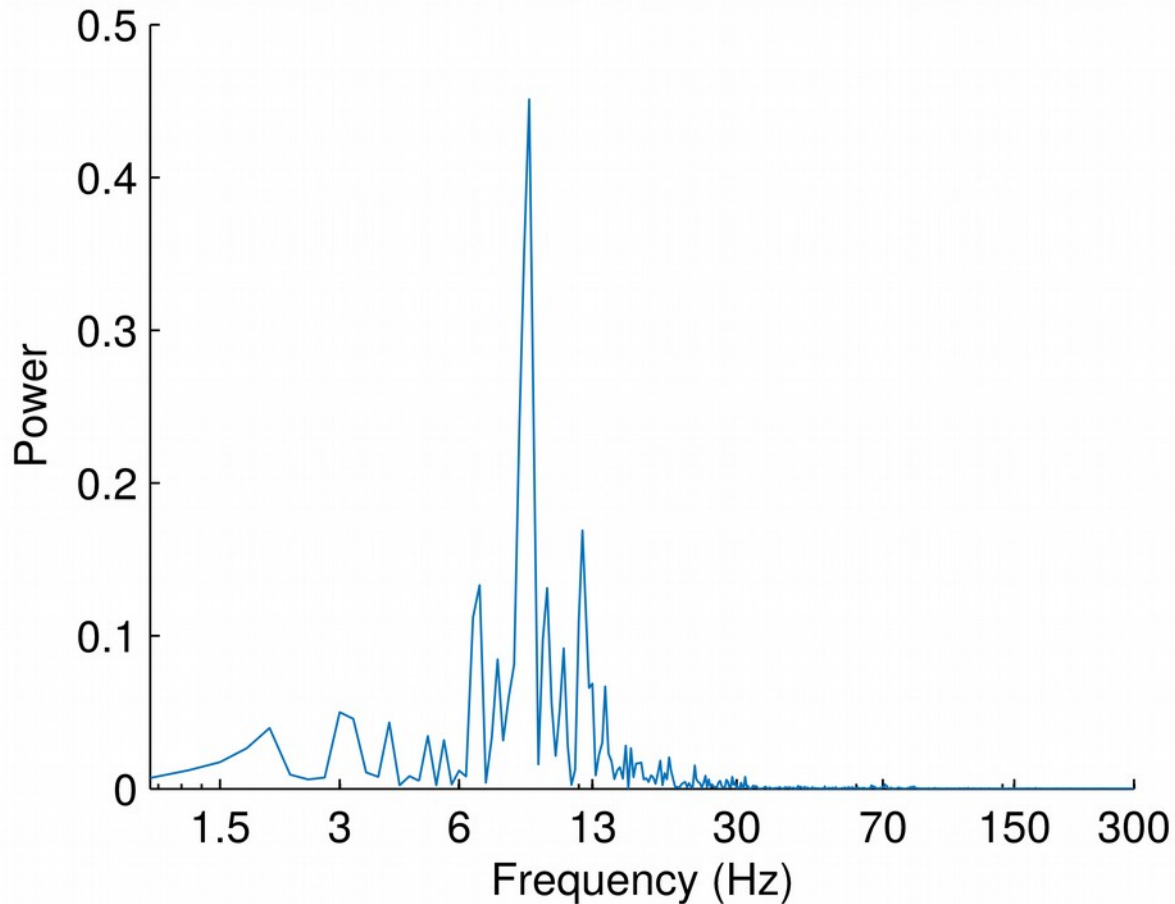50 or 51 cycles per second

Linear- vs. Log-scaled spectrum

1 Hz

5 Hz

9 Hz

13 Hz

17 Hz

Sinusoids linearly spaced from 1 Hz to 17 Hz

Linear- vs. Log-scaled spectrum

1 Hz
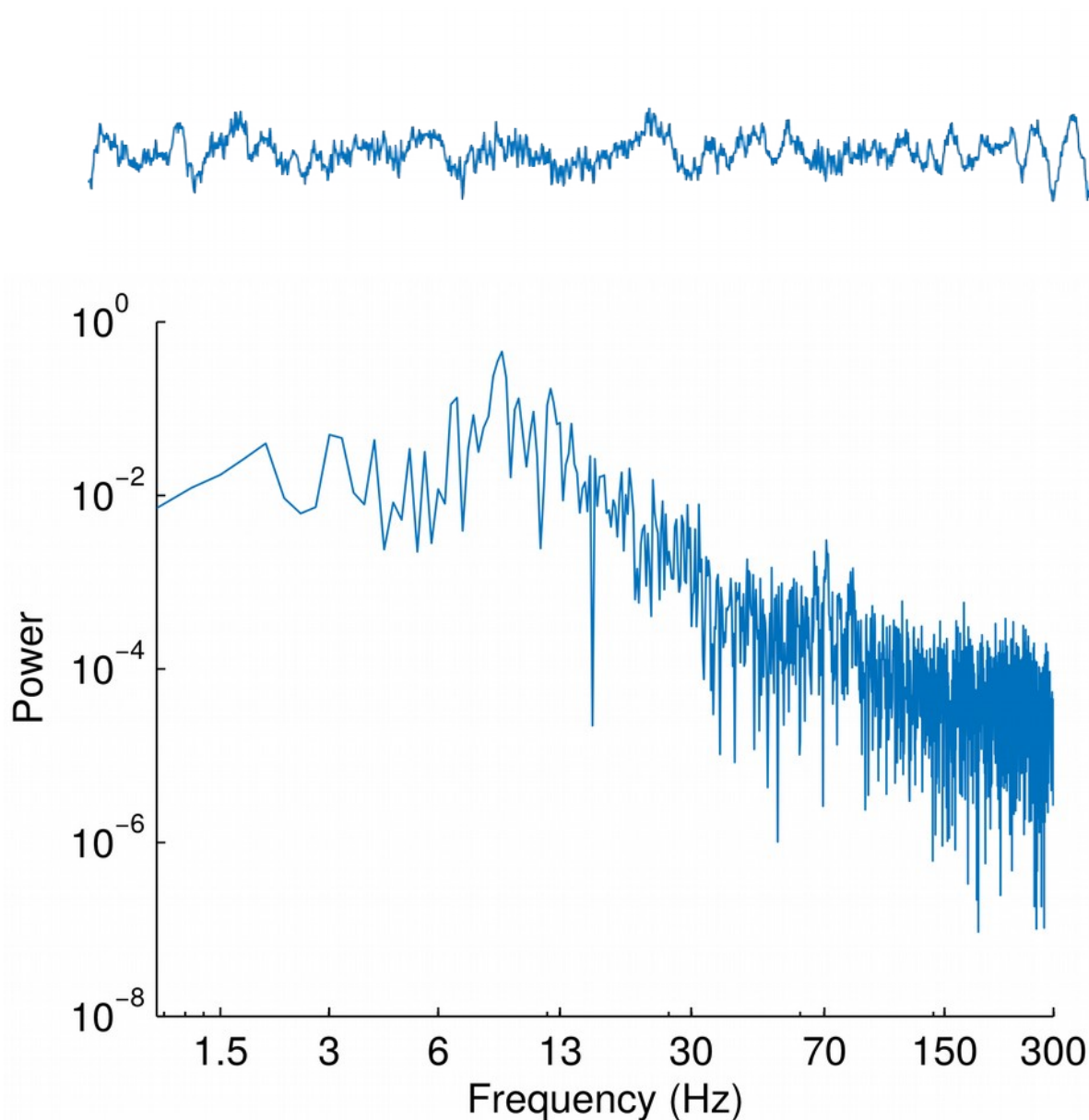
2.03 Hz

4.12 Hz

8.37 Hz

17 Hz

Sinusoids log spaced from 1 Hz to 17 Hz
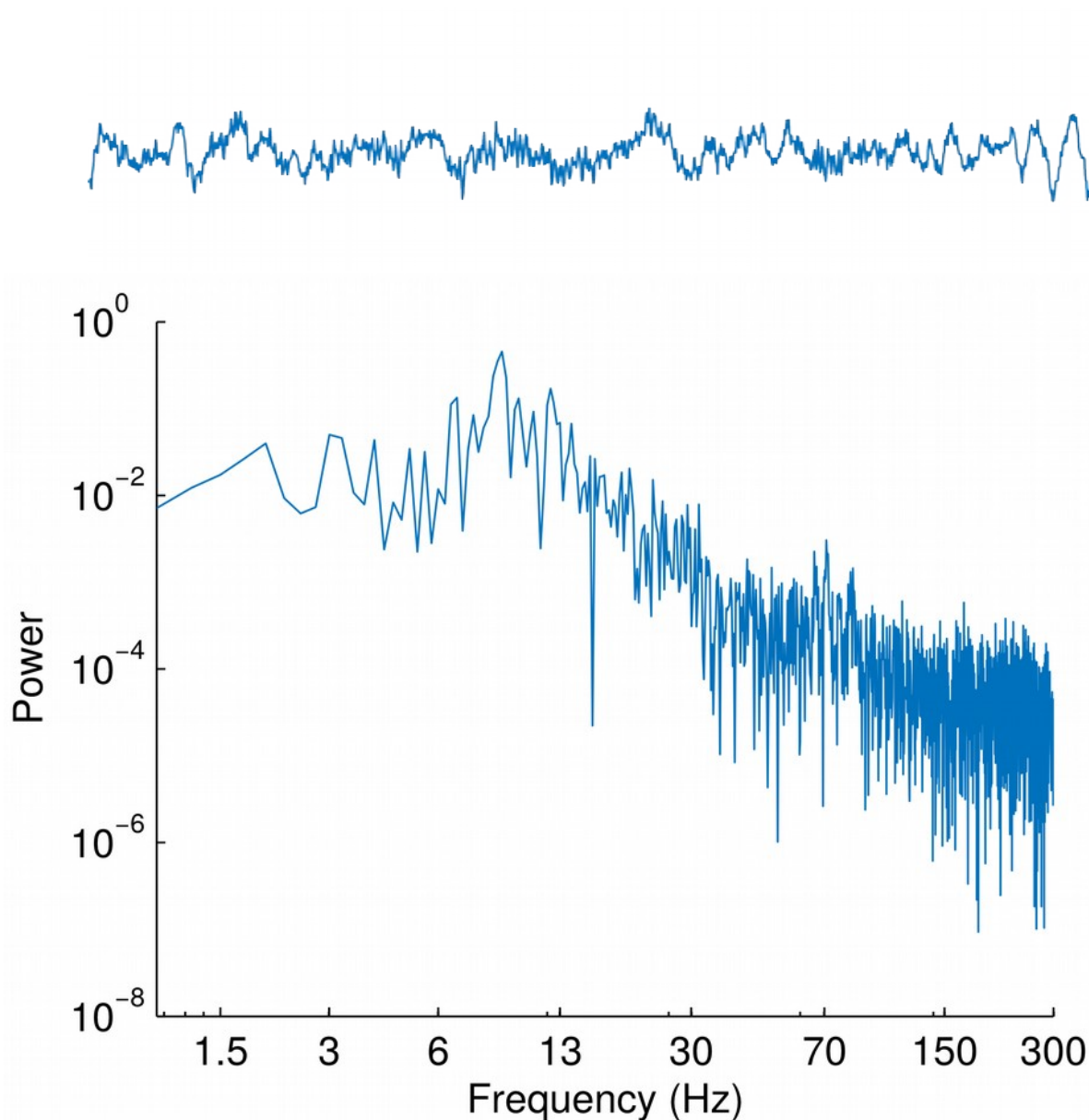
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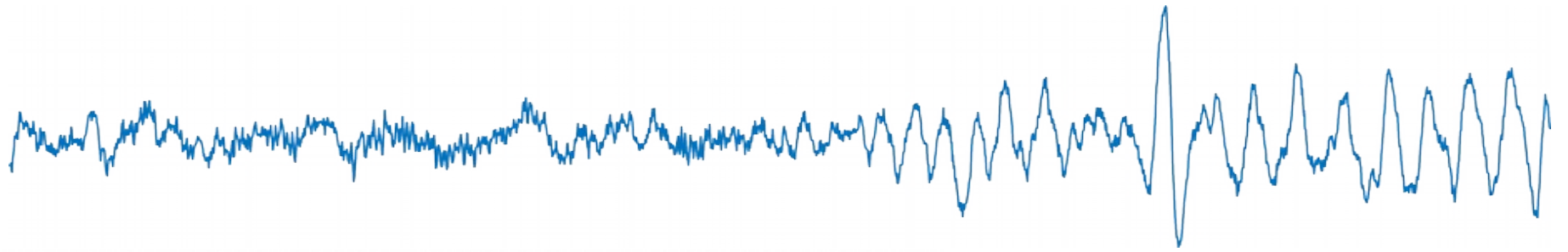
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    - 1/f phenomenon
    - Log-scaling the power axis

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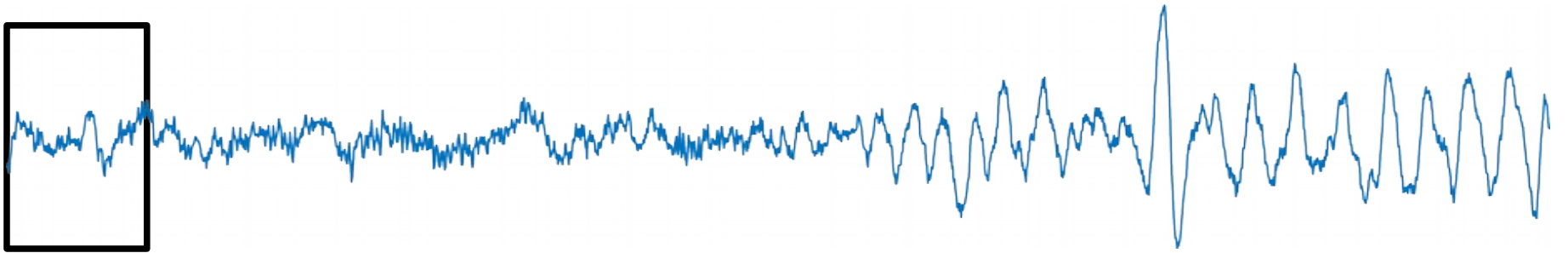
- Raw FFT can be very noisy
    - see next

Contents

Stationary:

- Fourier transform

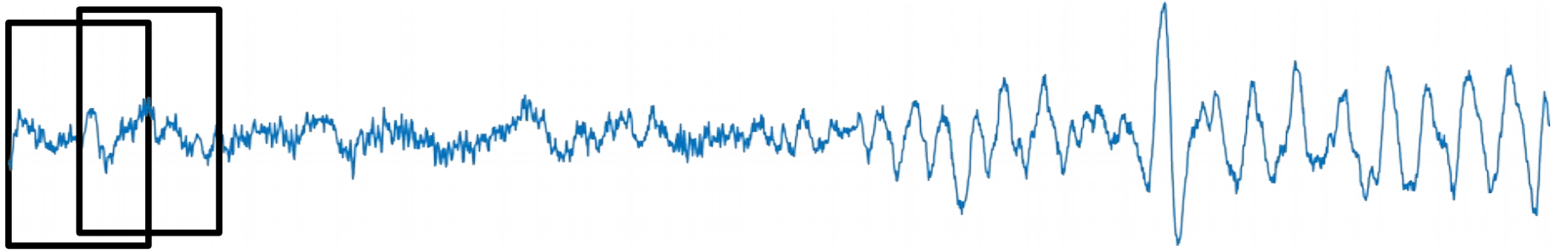- Power spectral density (Welch's method)

Time-resolved:

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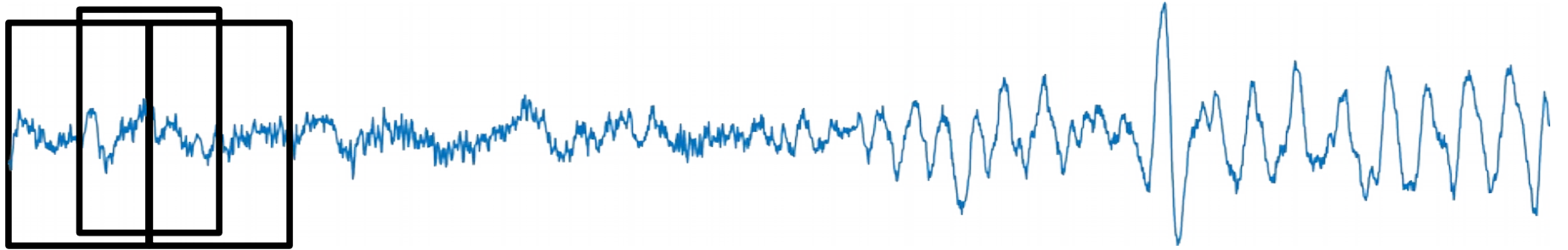
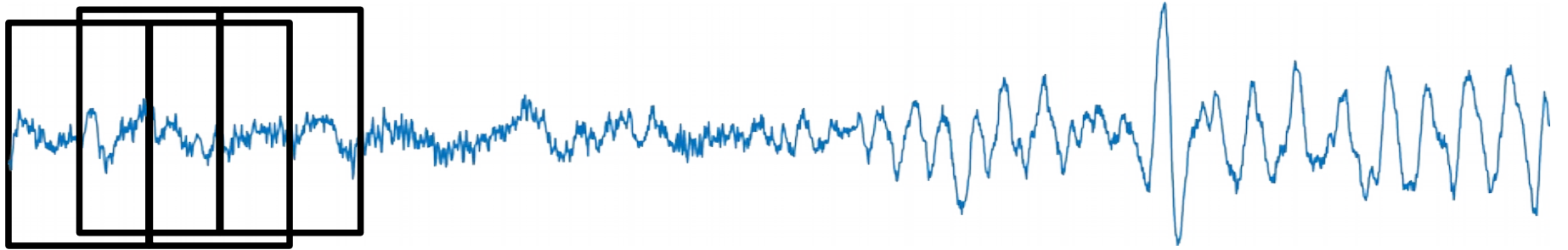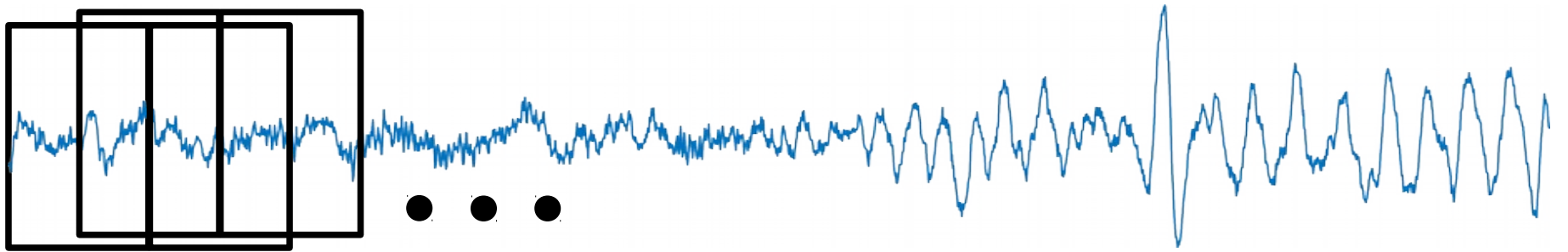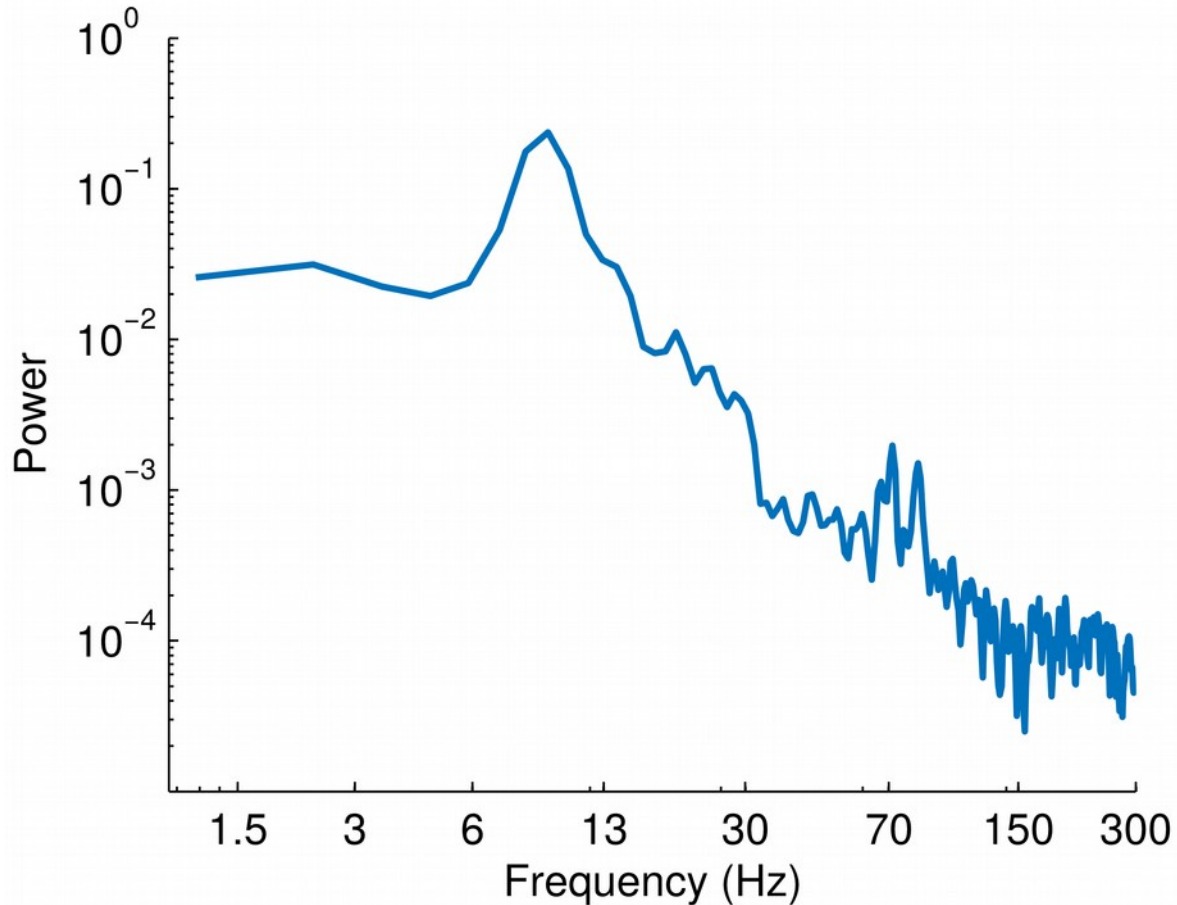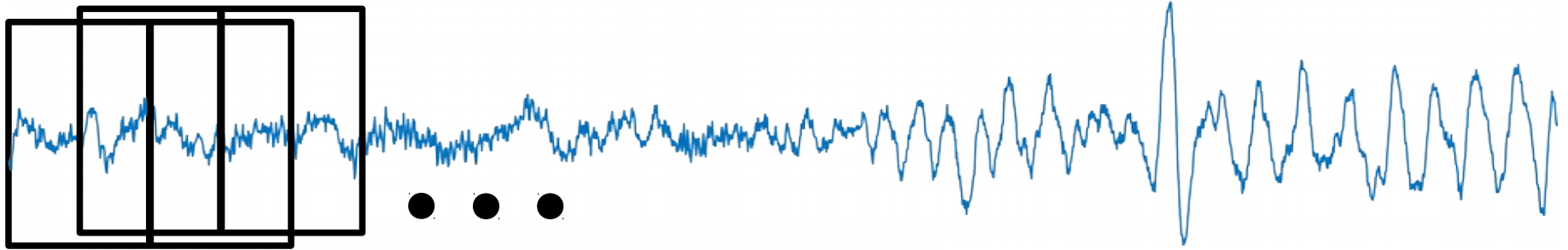- Filtering & Hilbert transform

Power spectral density

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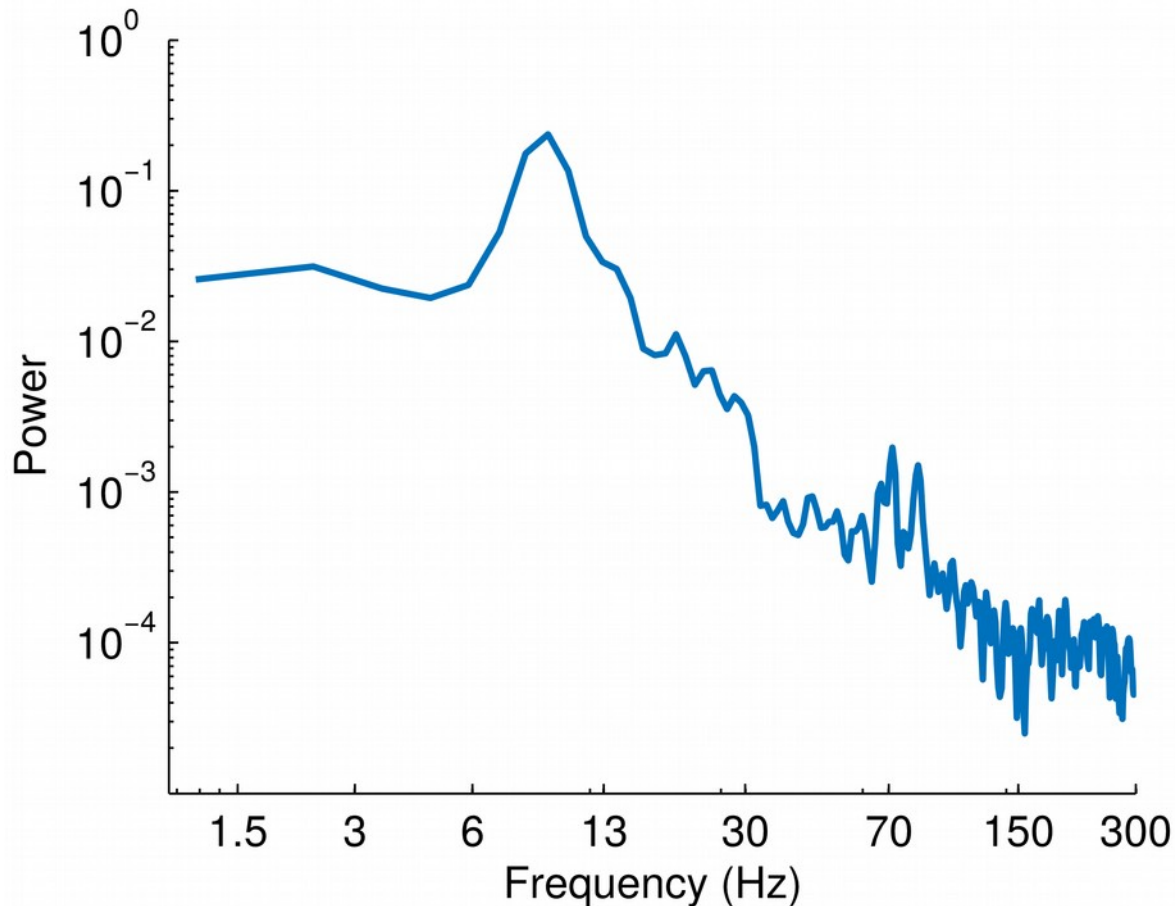
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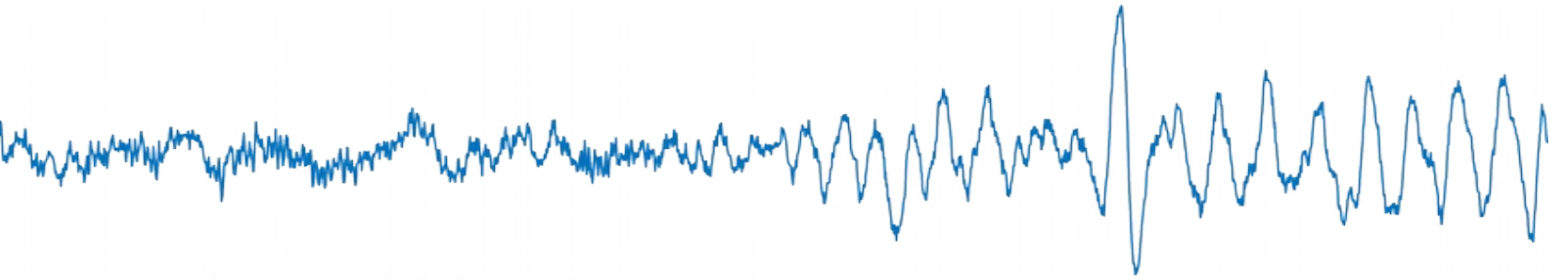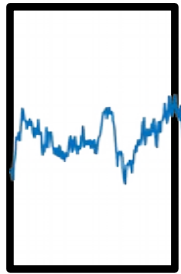- Repeated averaging over sliding windows decreases noise in the estimation

- Resulting spectrum is less noisy

PSD: effect of window size

- Window length determines frequency resolution

- Smaller window: lower resolution, more averaging/ less noise

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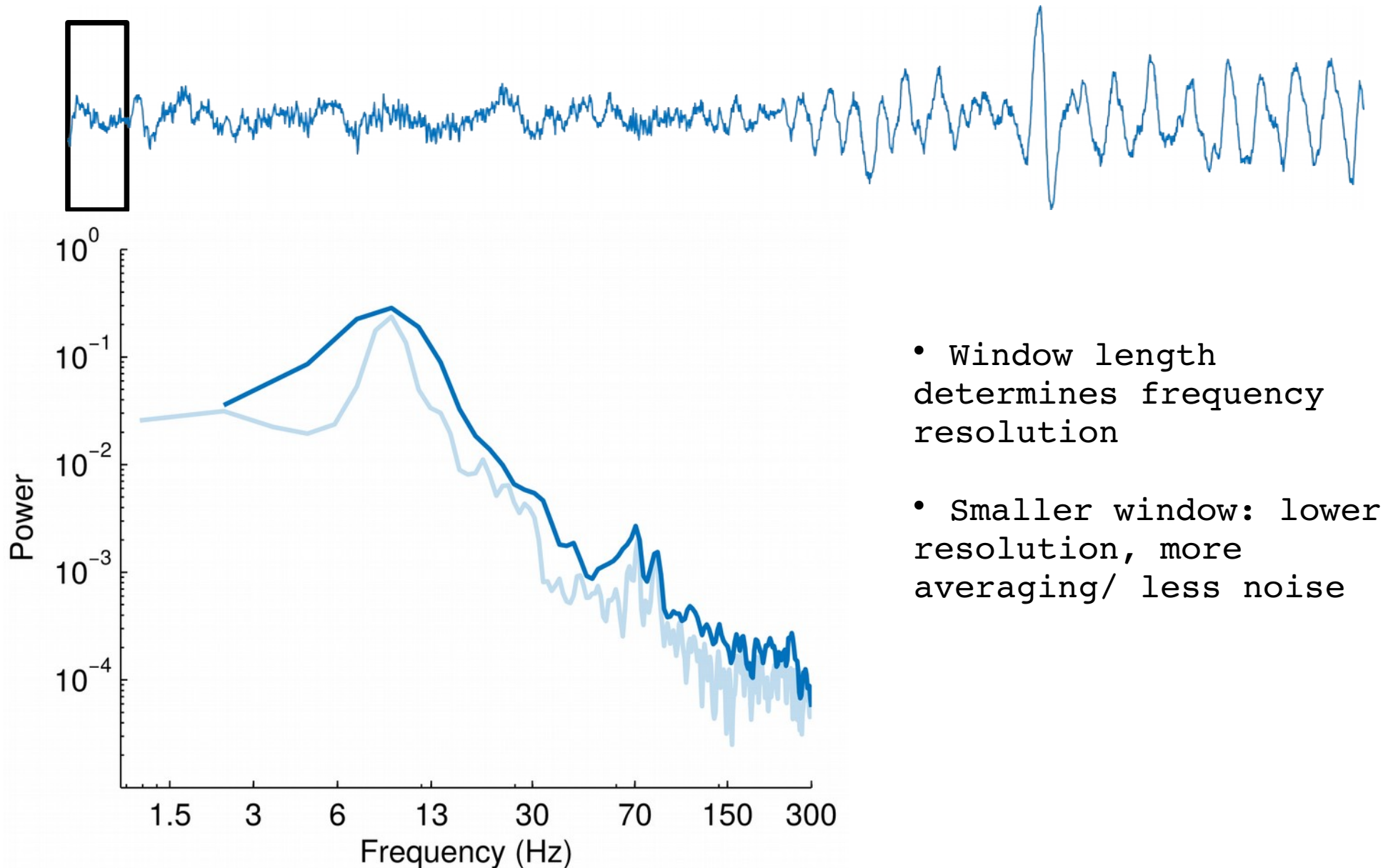
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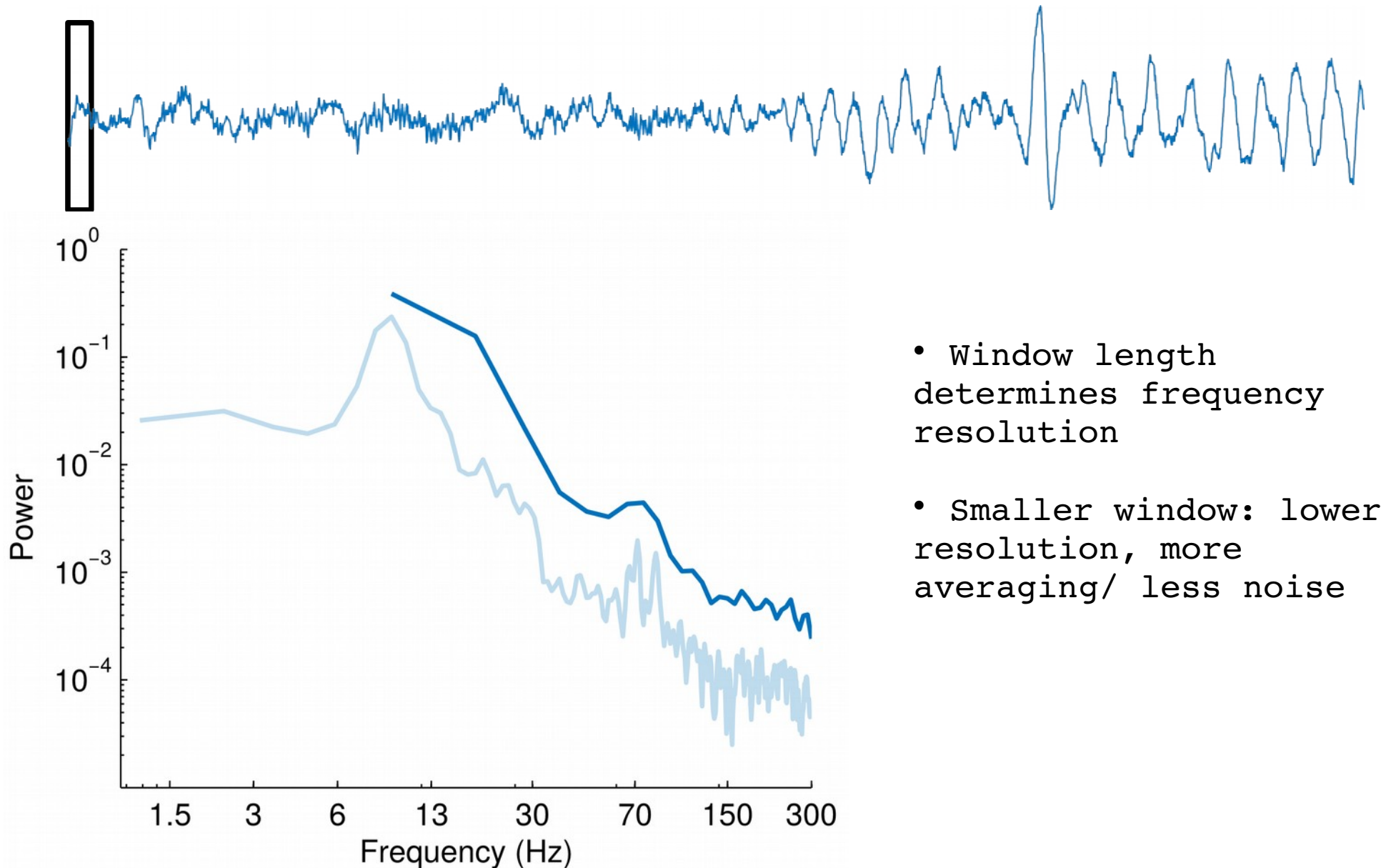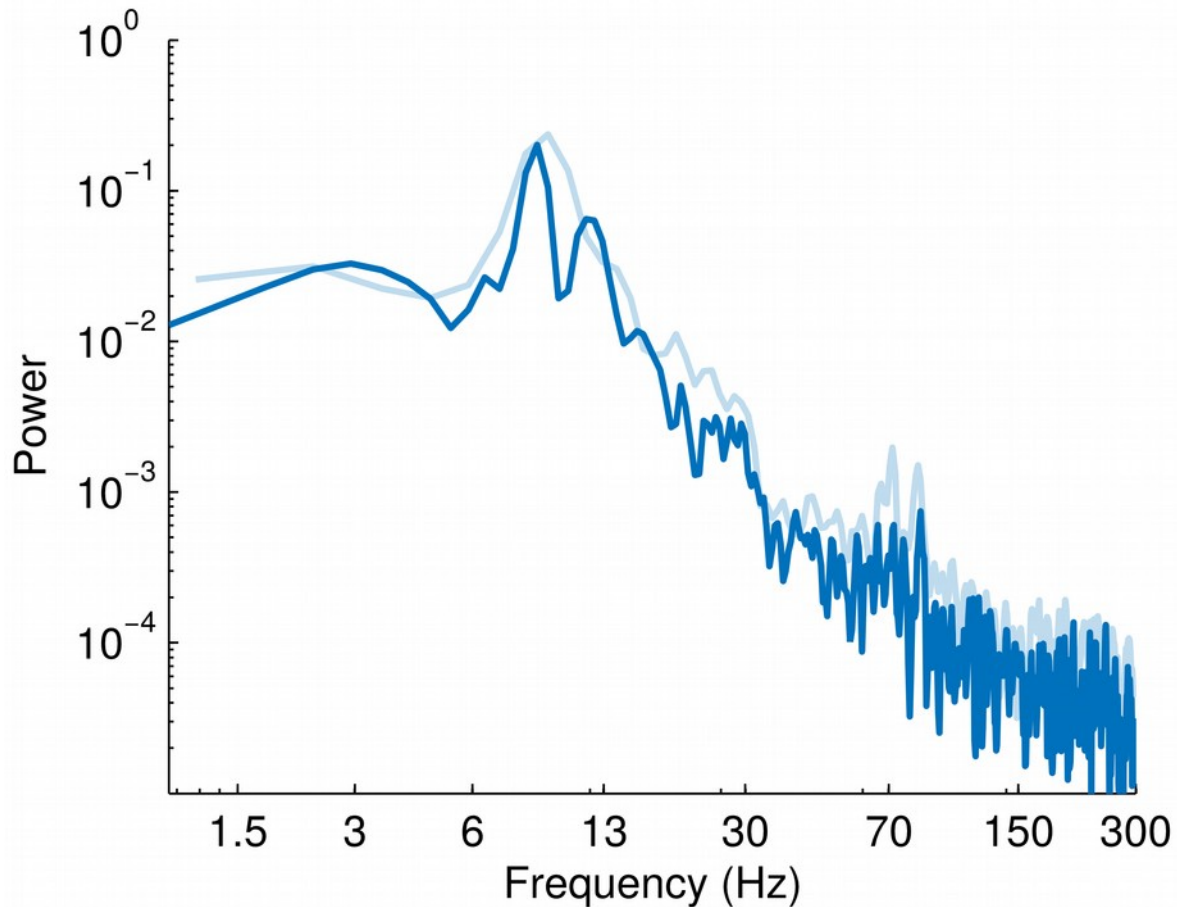

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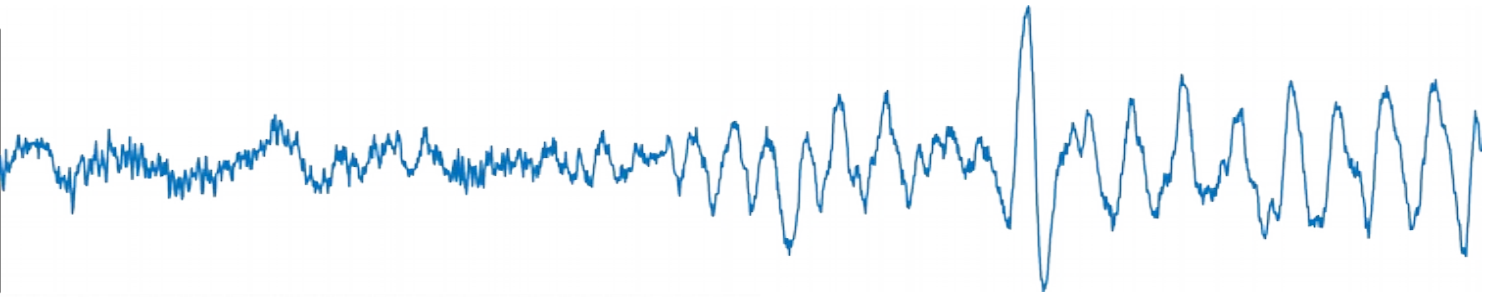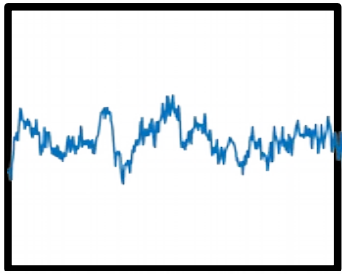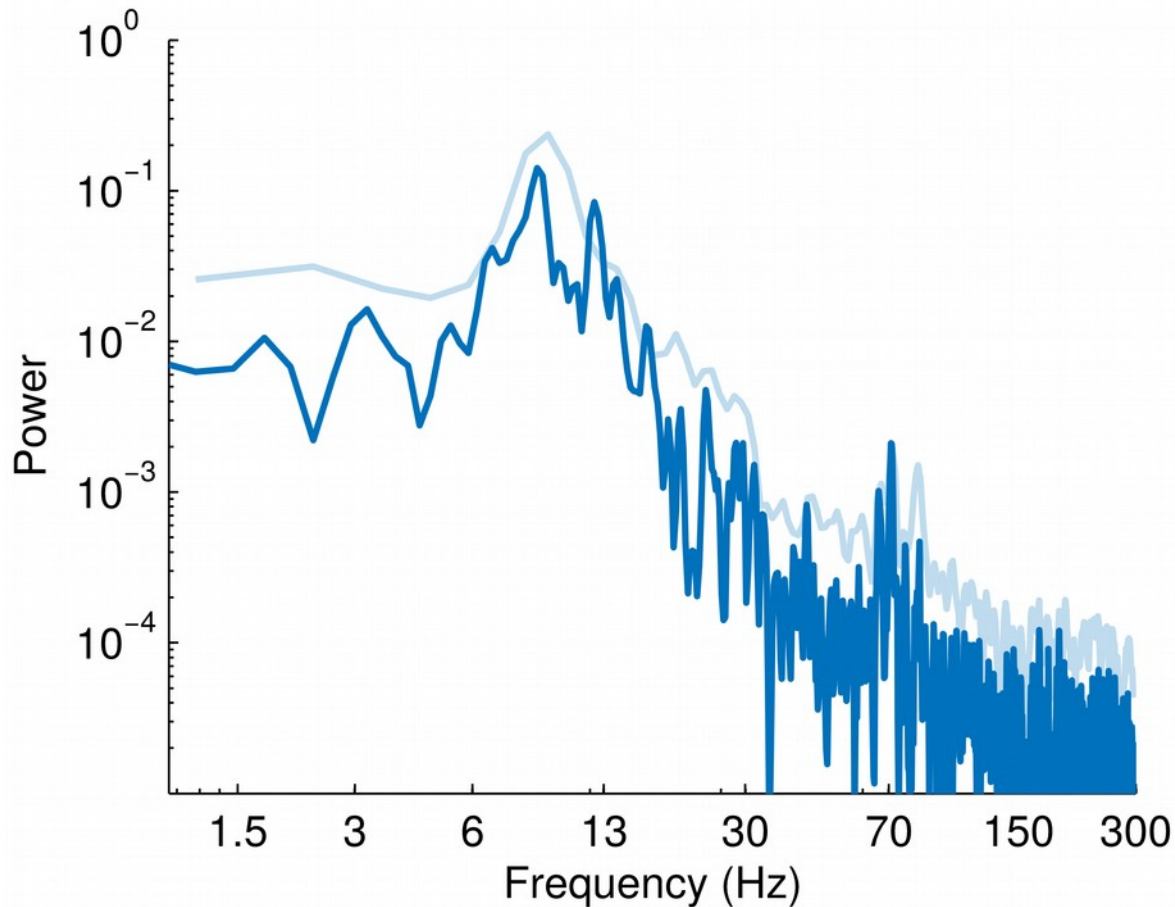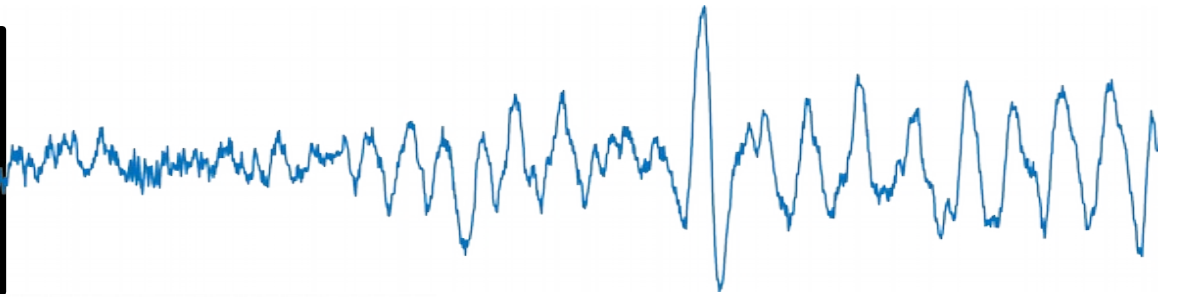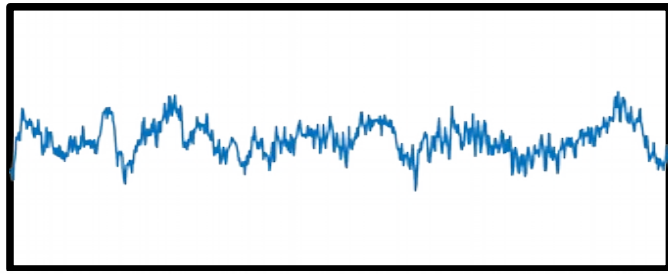- Smaller window: lower resolution, more averaging/ less noise

PSD: effect of window size

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Contents

Stationary:

- Fourier transform

- Power spectral density (Welch's method)

Time-resolved:

- Wavelet transform

- Filtering & Hilbert transform

Time-frequency analysis

- Analysis of transient oscillatory activity

- Examples: auditory cortex / motor cortex

- Event-related synchronization vs. desynchronization
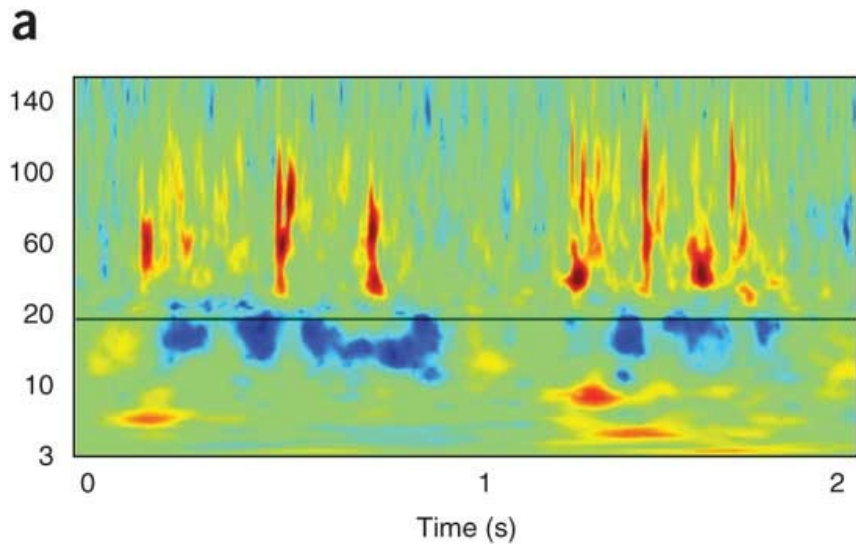
Spoken sentence, auditory cortex responses (Fontolan, Morillon et al, 2014)
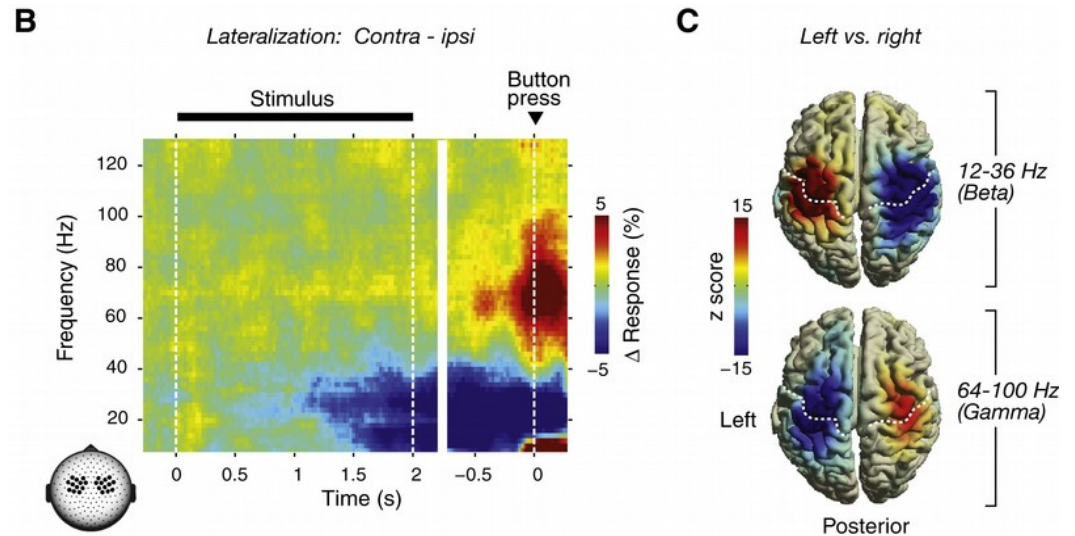
Build-up of choice predictive activity in motor cortex (Donner et al., 2009)

Wavelet transform
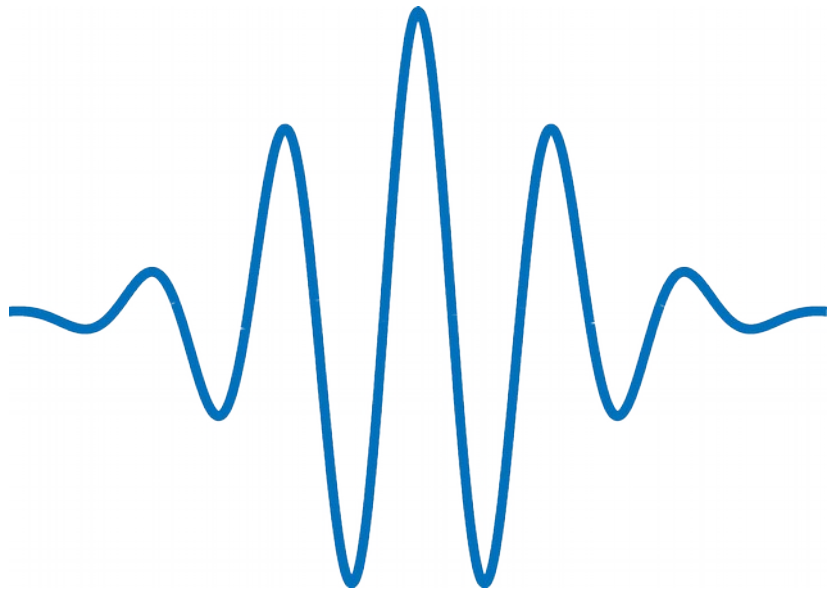
Morlet wavelet (used in Brainstorm):

• Sine wave, power is modulated in time with a gaussian centered at time zero

• Serves as a 'template'

Wavelet transform
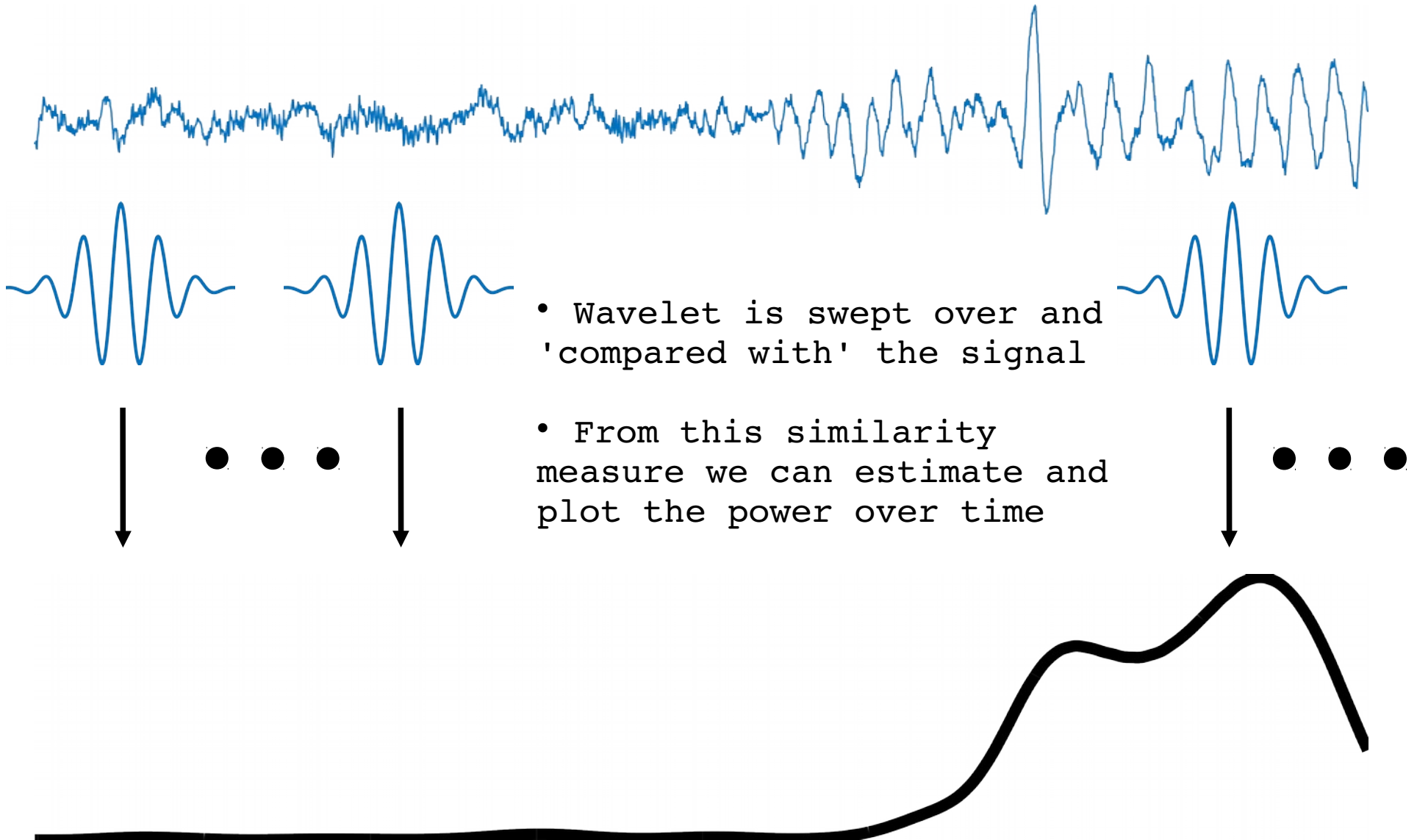
- Wavelet is swept over and 'compared with' the signal

- From this similarity measure we can estimate and plot the power over time

Wavelet transform

• Wavelet is contracted and expanded to estimate power over different center frequencies

Wavelet transform

- Wavelet is contracted and expanded to estimate power over different center frequencies

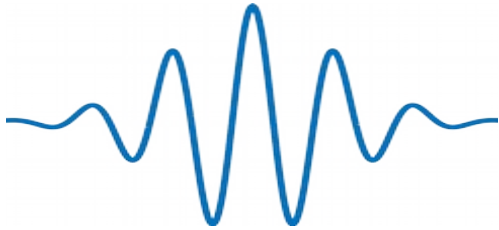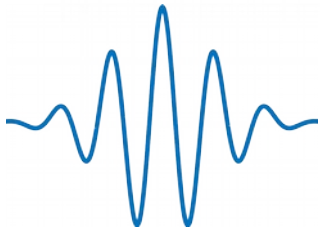- Important: time and frequency resolution changes for different frequencies

  ➔ Compare with PSD window length

Wavelet transform

Wavelet transform

• Repeating this over a range of center frequencies produces a time-frequency map

Wavelet transform

- Repeating this over a range of center frequencies produces a time-frequency map

- Remember the 1/f phenomenon: high frequencies tend to have less power

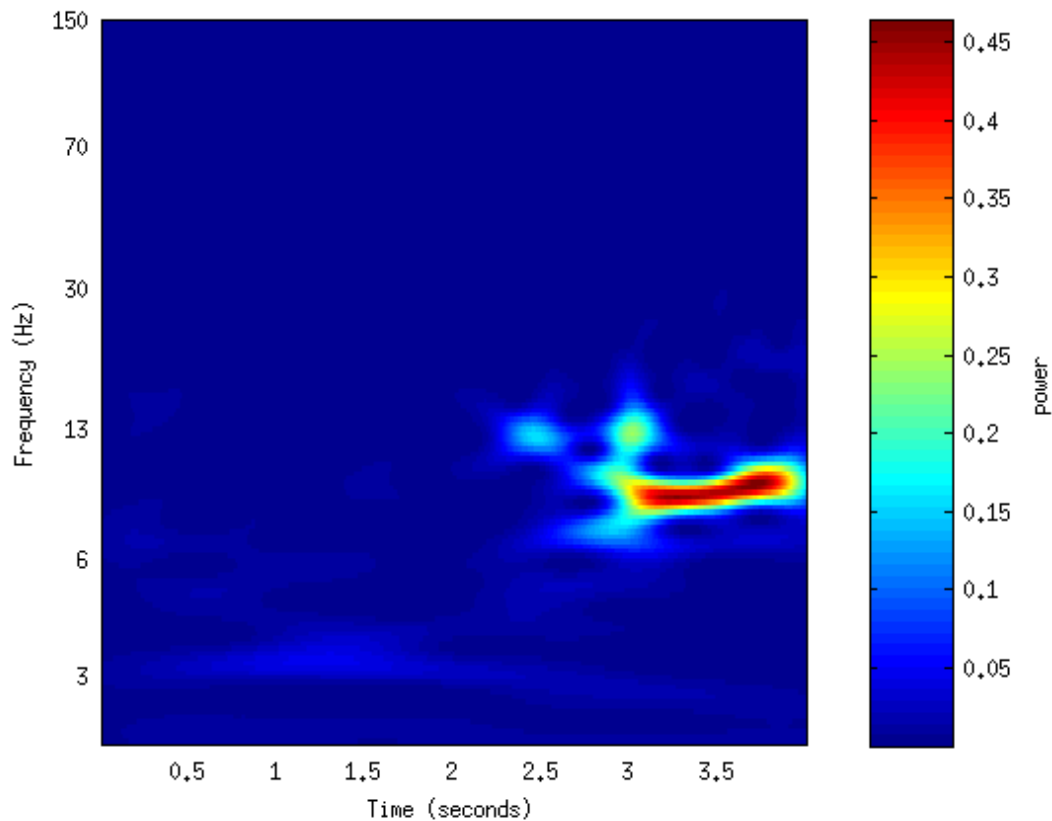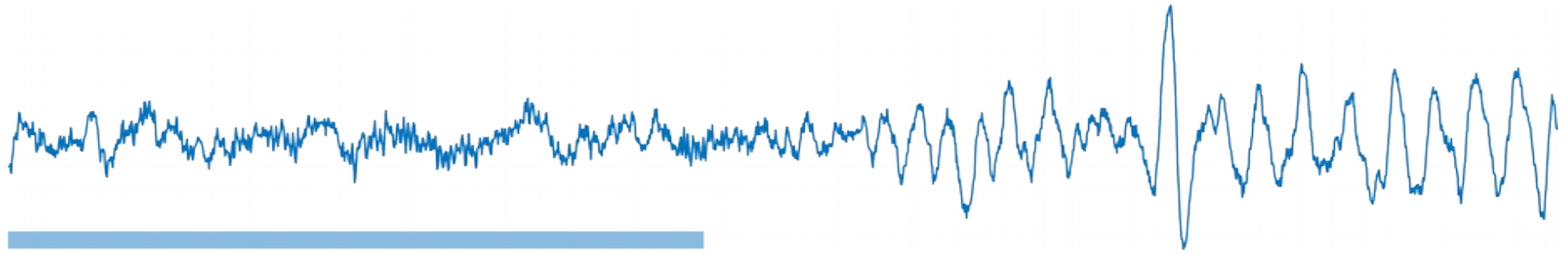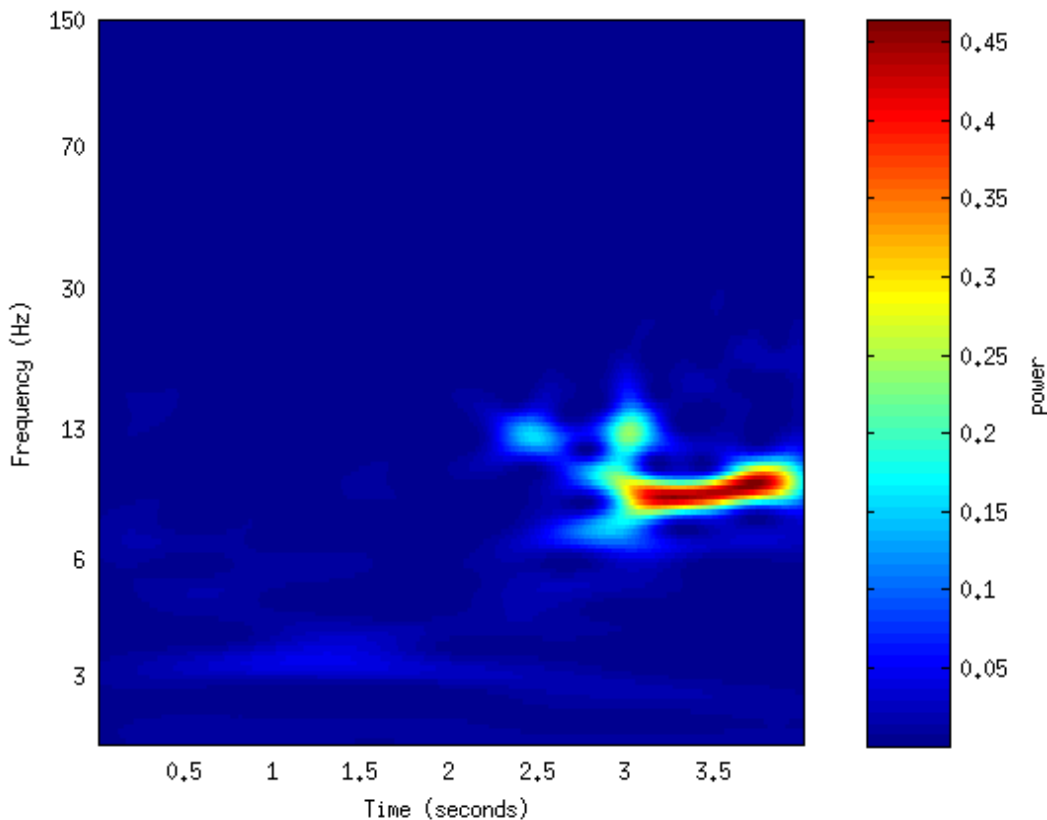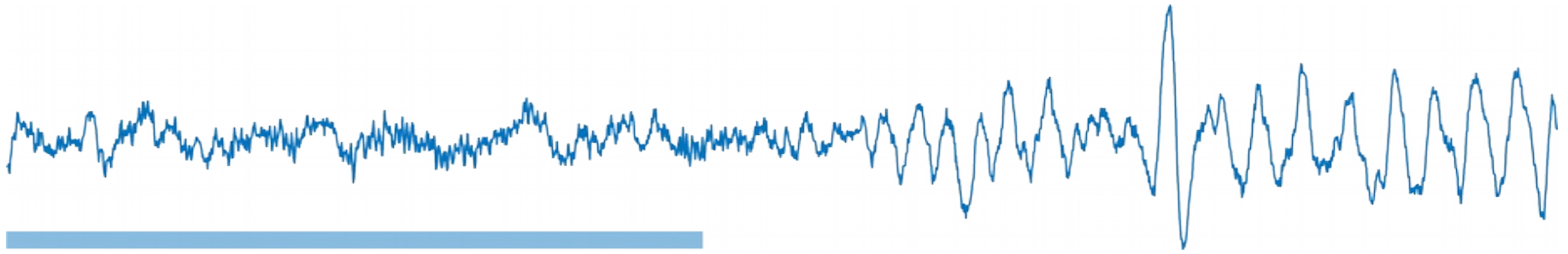# Wavelet transform

- Repeating this over a range of center frequencies produces a time-frequency map

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- Map can be normalized using a z-score based on the mean and std of a 'baseline period'
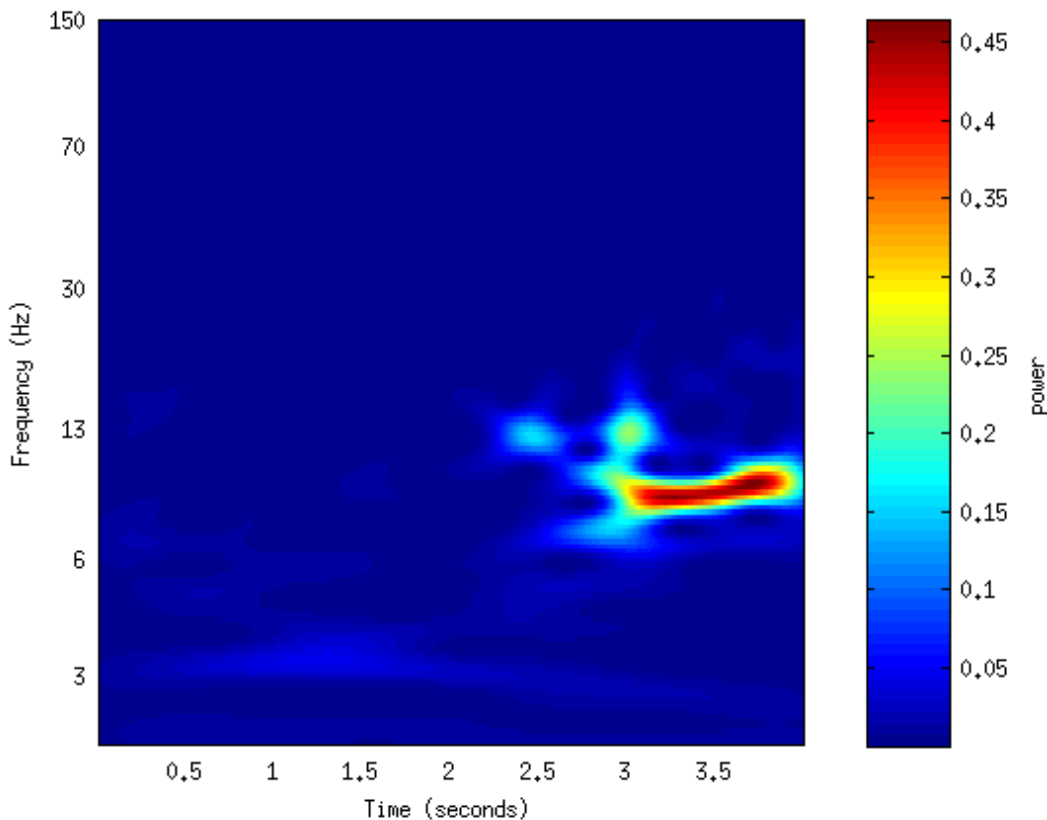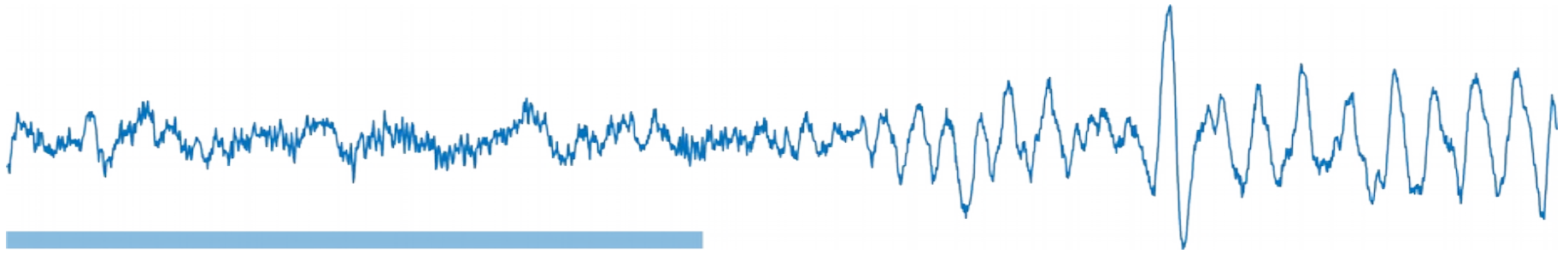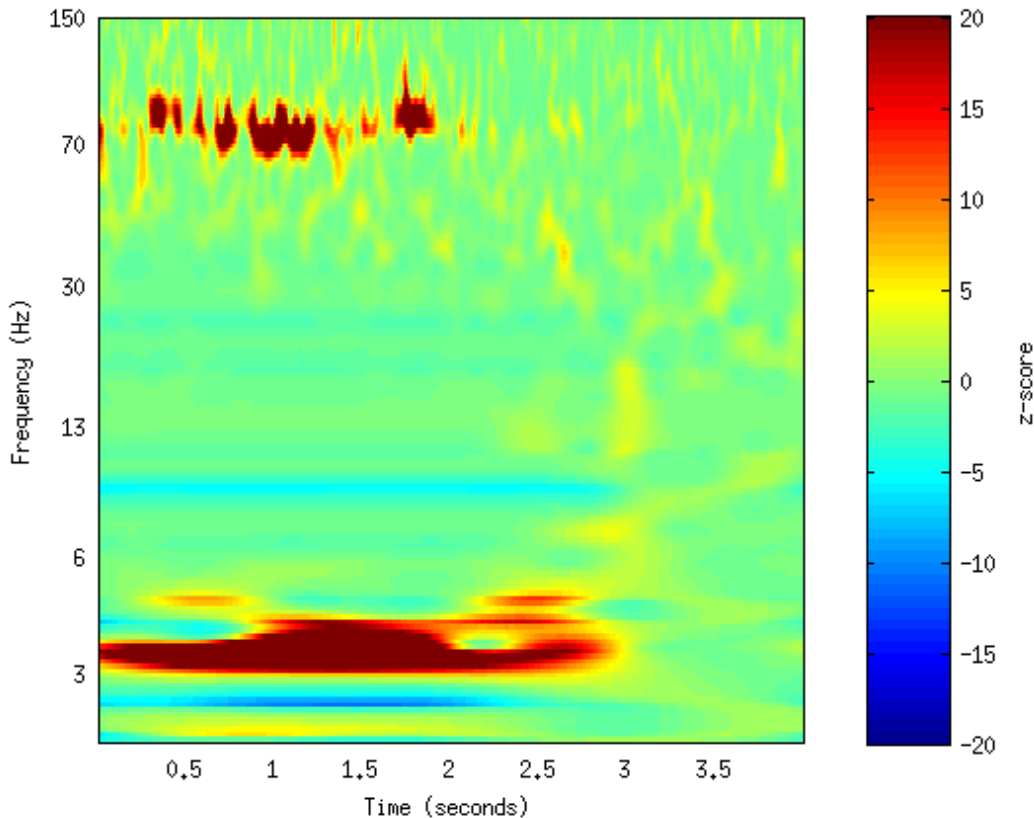
Wavelet transform

'baseline'

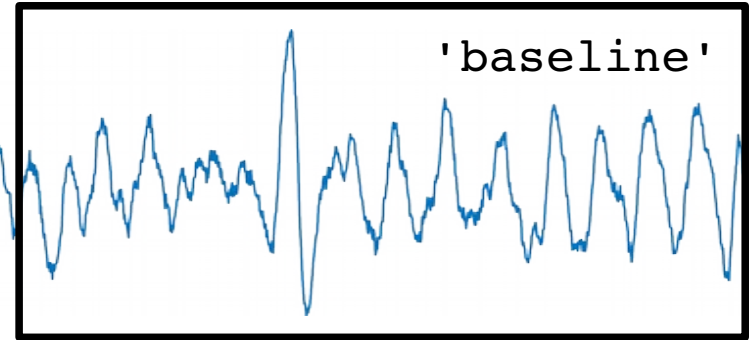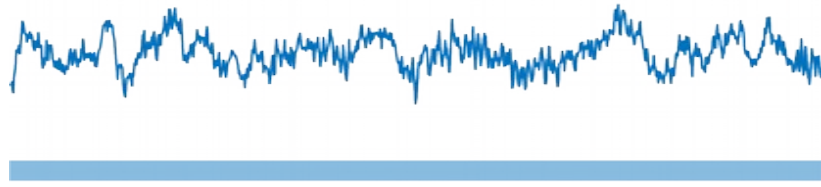- Repeating this over a range of center frequencies produces a time-frequency map

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Wavelet transform

'baseline'

- Map can be normalized using a z-score based on the mean and std of a 'baseline period'

- What is the right baseline?!?

Wavelet transform

'baseline'

- Map can be normalized using a z-score based on the mean and std of a 'baseline period'

- What is the right baseline?!?

Wavelet transform

- Changing the parameters of the 'mother wavelet' affects time vs. Frequency resolution of the results

Wavelet transform
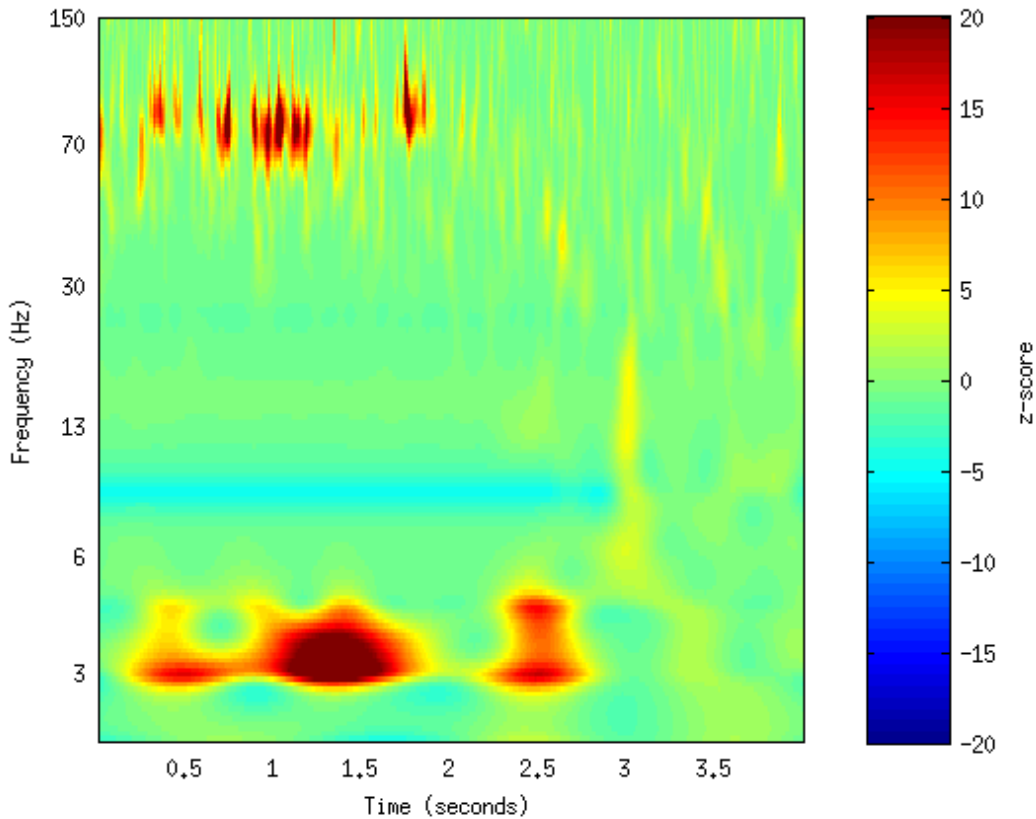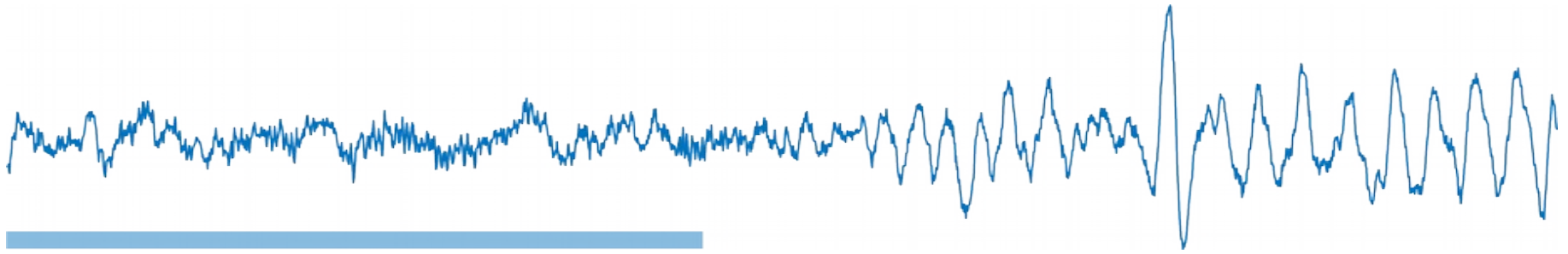
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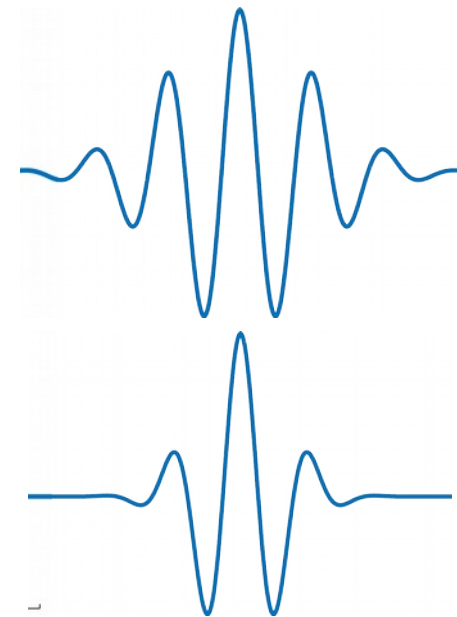
Evoked vs induced responses

Event related oscillator activity
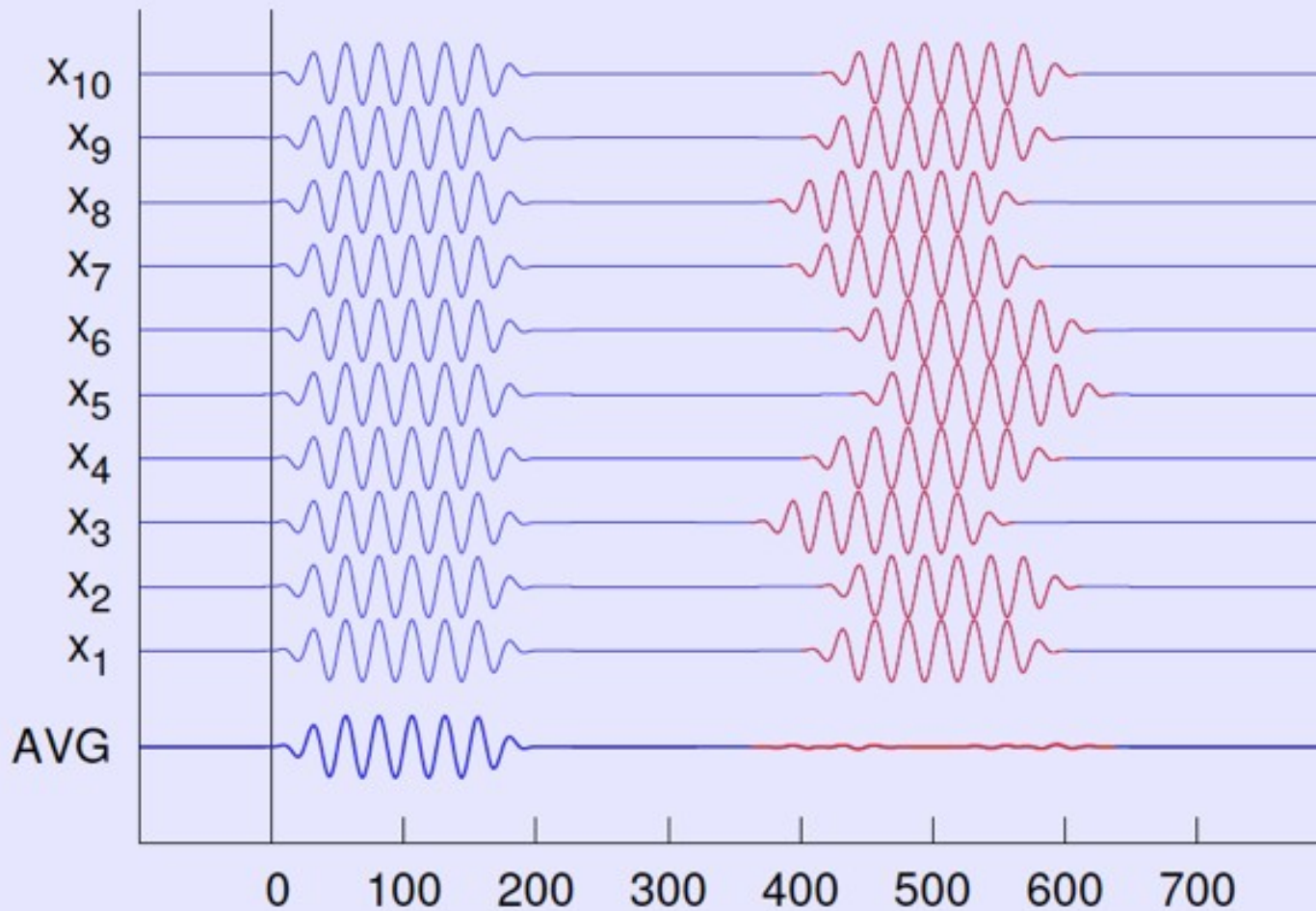
Evoked vs induced responses
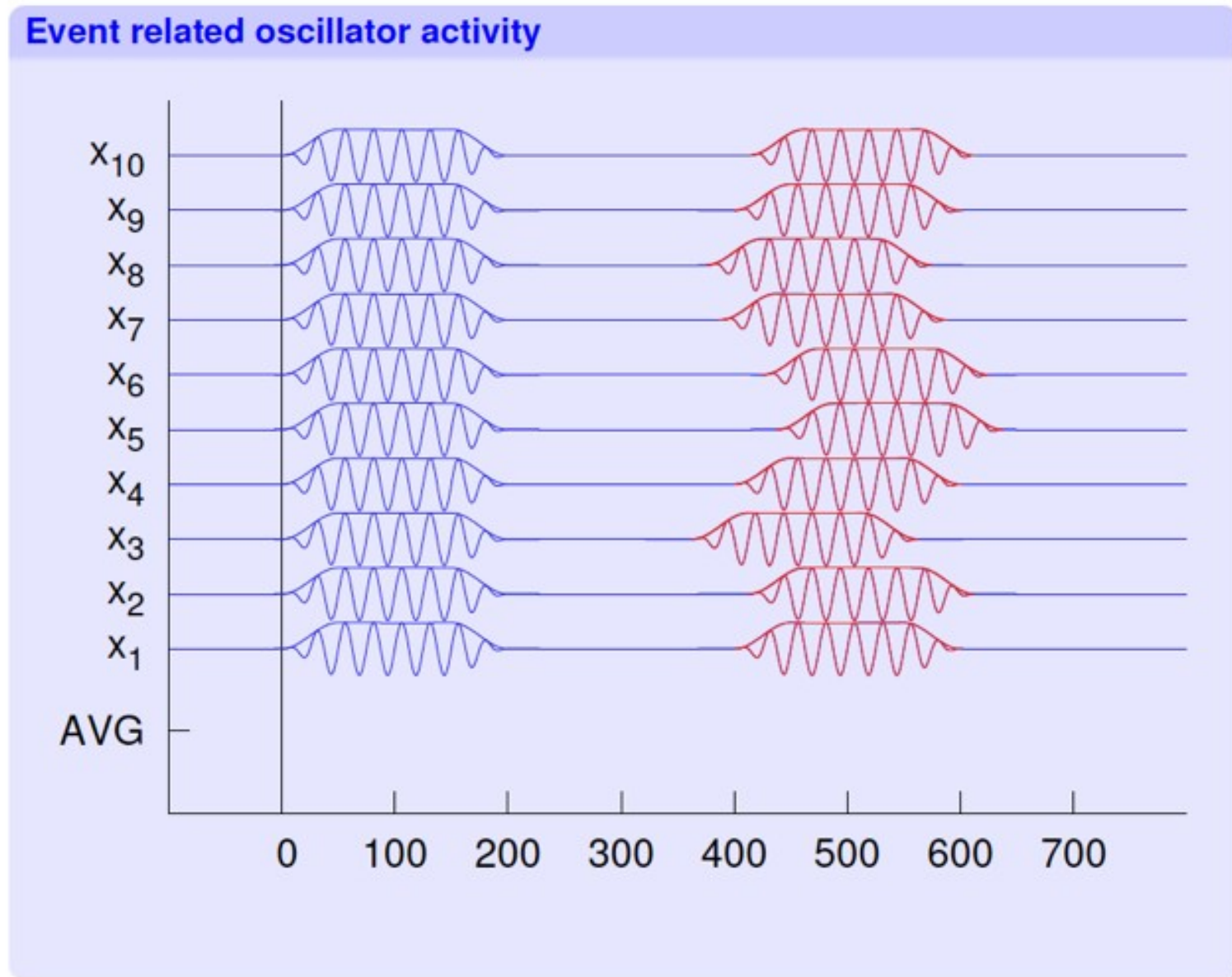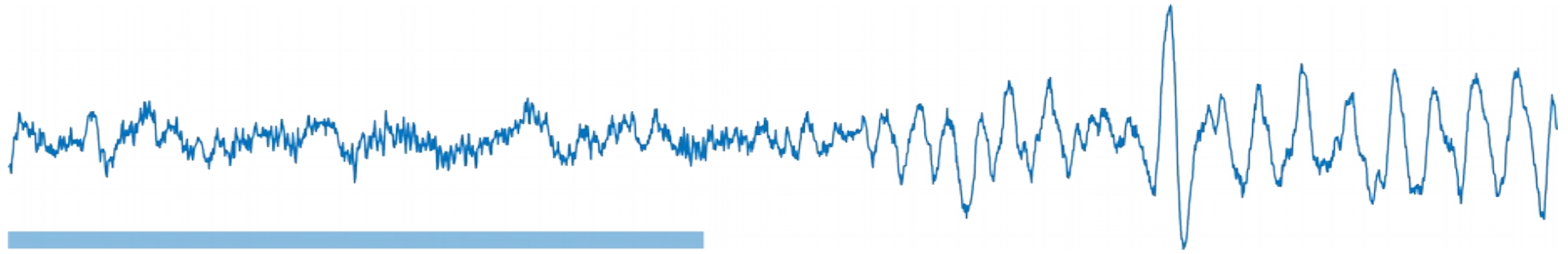
Evoked vs induced responses
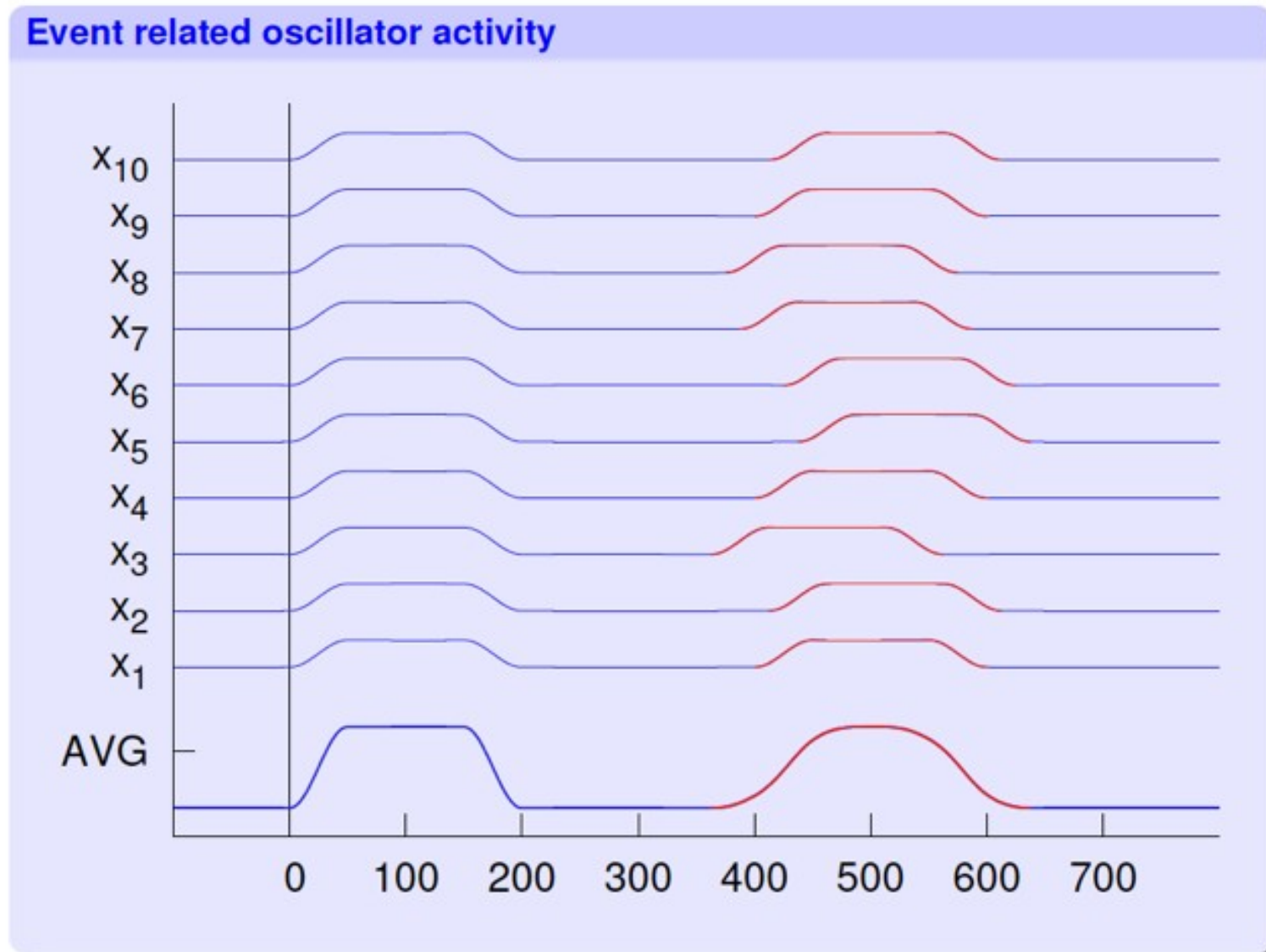
Evoked vs induced responses
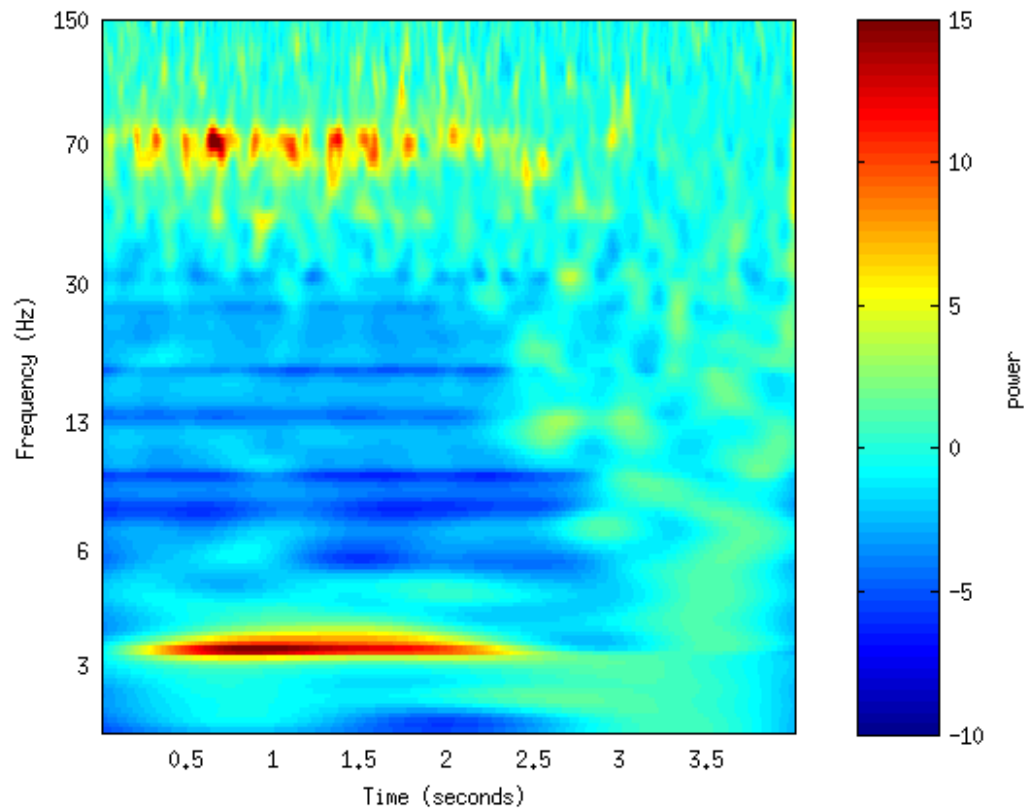
- Averaging
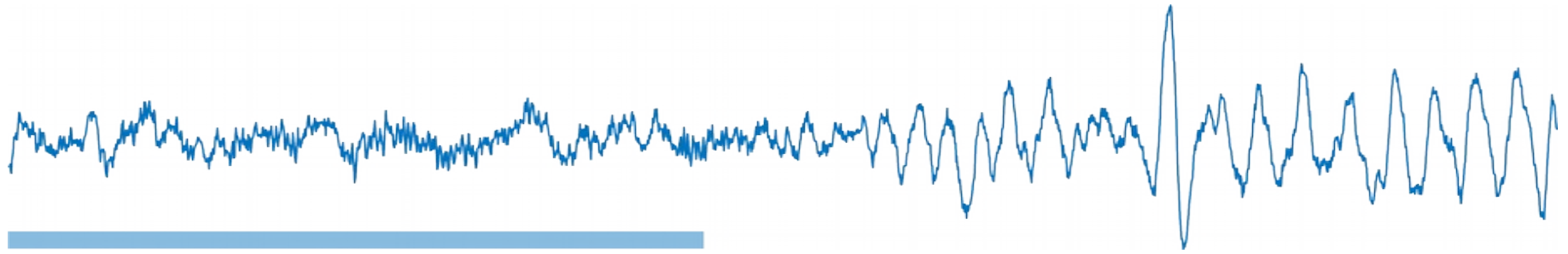
    - 10 trials

Evoked vs induced responses
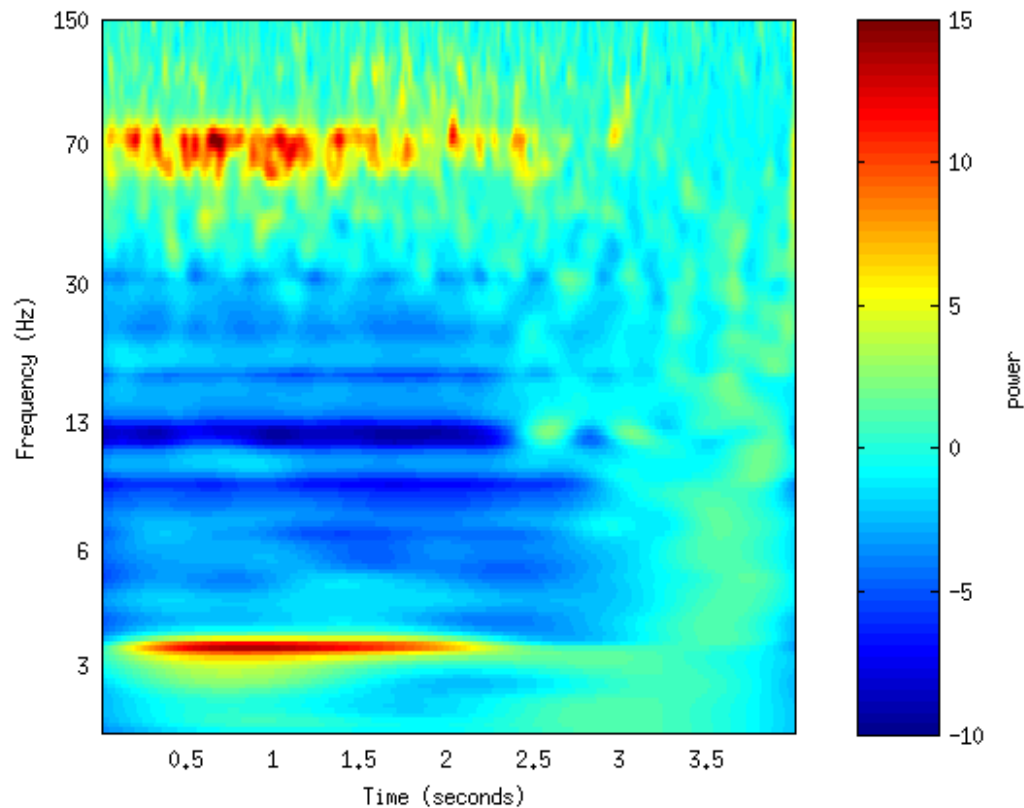
- Averaging

  - 10 trials
  - 20 trials

Evoked vs induced responses
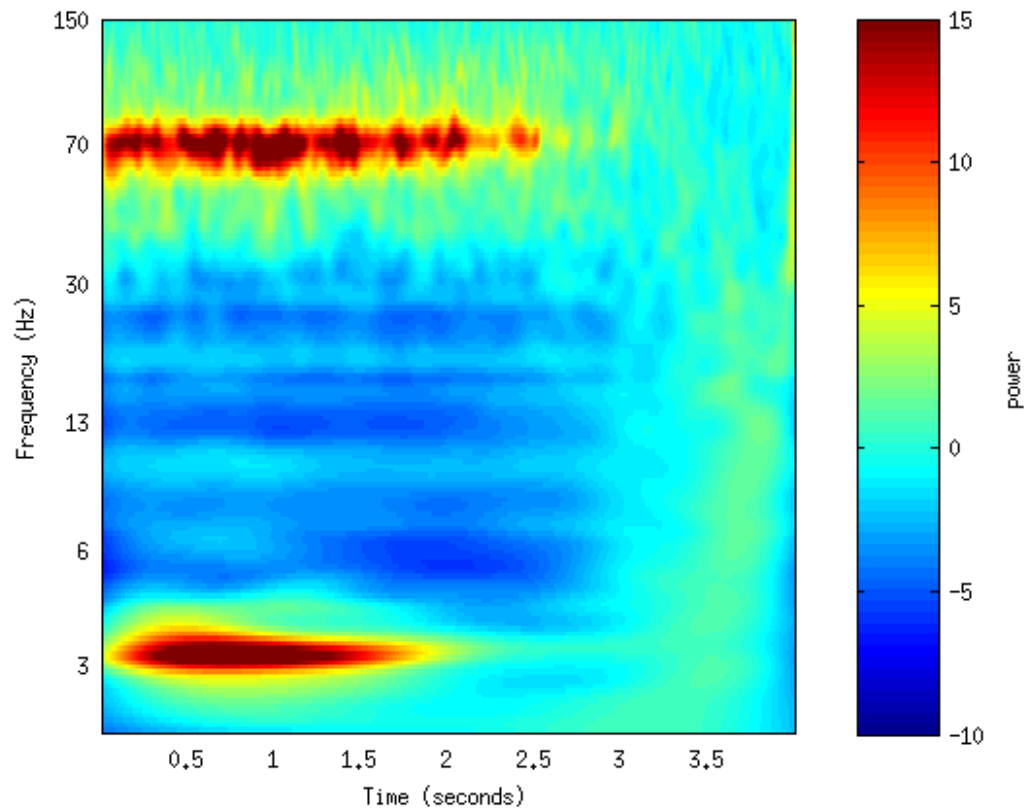
- Averaging

  - 10 trials
  - 20 trials
  - 100 trials

Contents

Stationary:

- Fourier transform

- Power spectral density (Welch's method)

Time-resolved:

- Wavelet transform

- Filtering & Hilbert transform
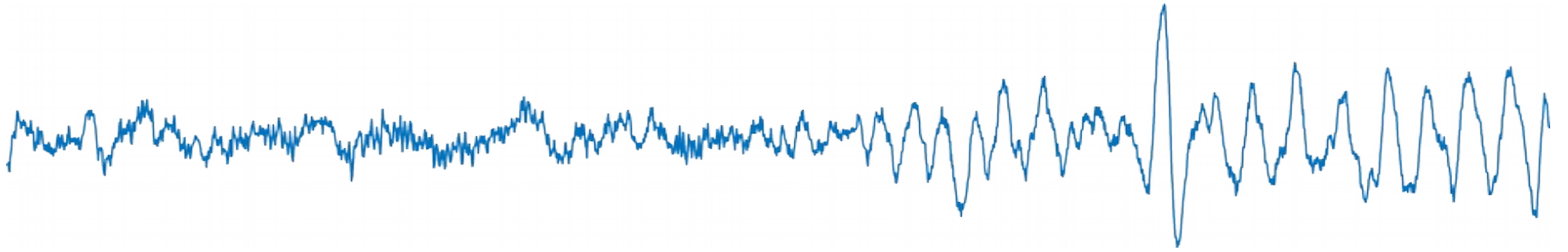
Hilbert transform

- Useful for estimating time-resolved power (or phase) in a pre-defined frequency band (e.g. Delta: 2-4 Hz)

Hilbert transform
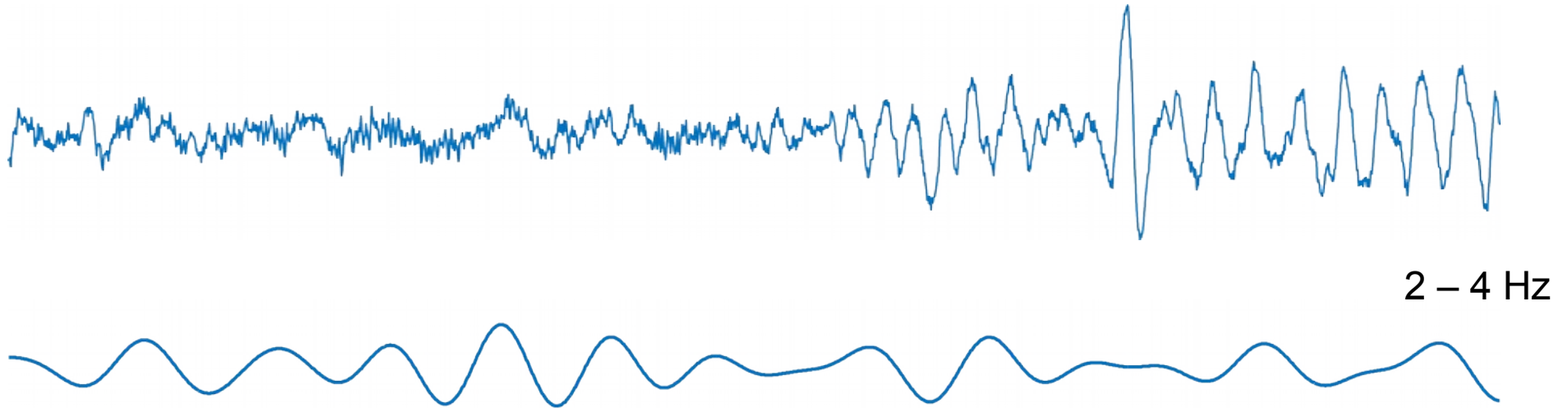
$2-4\,\mathrm{Hz}$

- Useful for estimating time-resolved power (or phase) in a pre-defined frequency band (e.g. Delta: 2-4 Hz)

- Signal is first filtered in the specified band

Hilbert transform
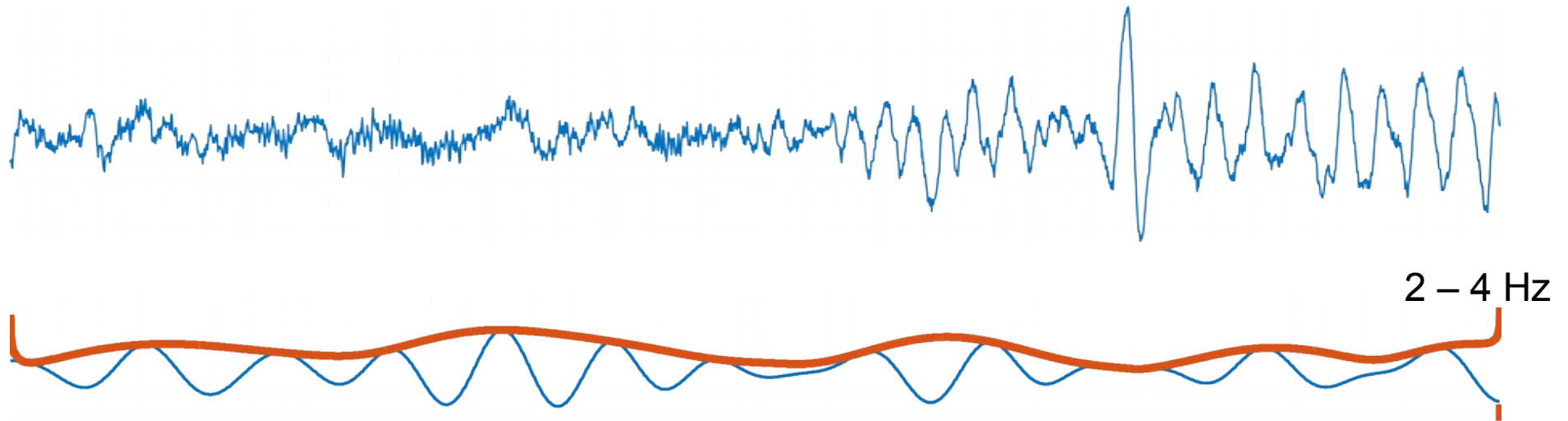
2 − 4 Hz

- Useful for estimating time-resolved power (or phase) in a pre-defined frequency band (e.g. Delta: 2-4 Hz)

- Signal is first filtered in the specified band

- Envelope (power) is computed using the Hilbert transform
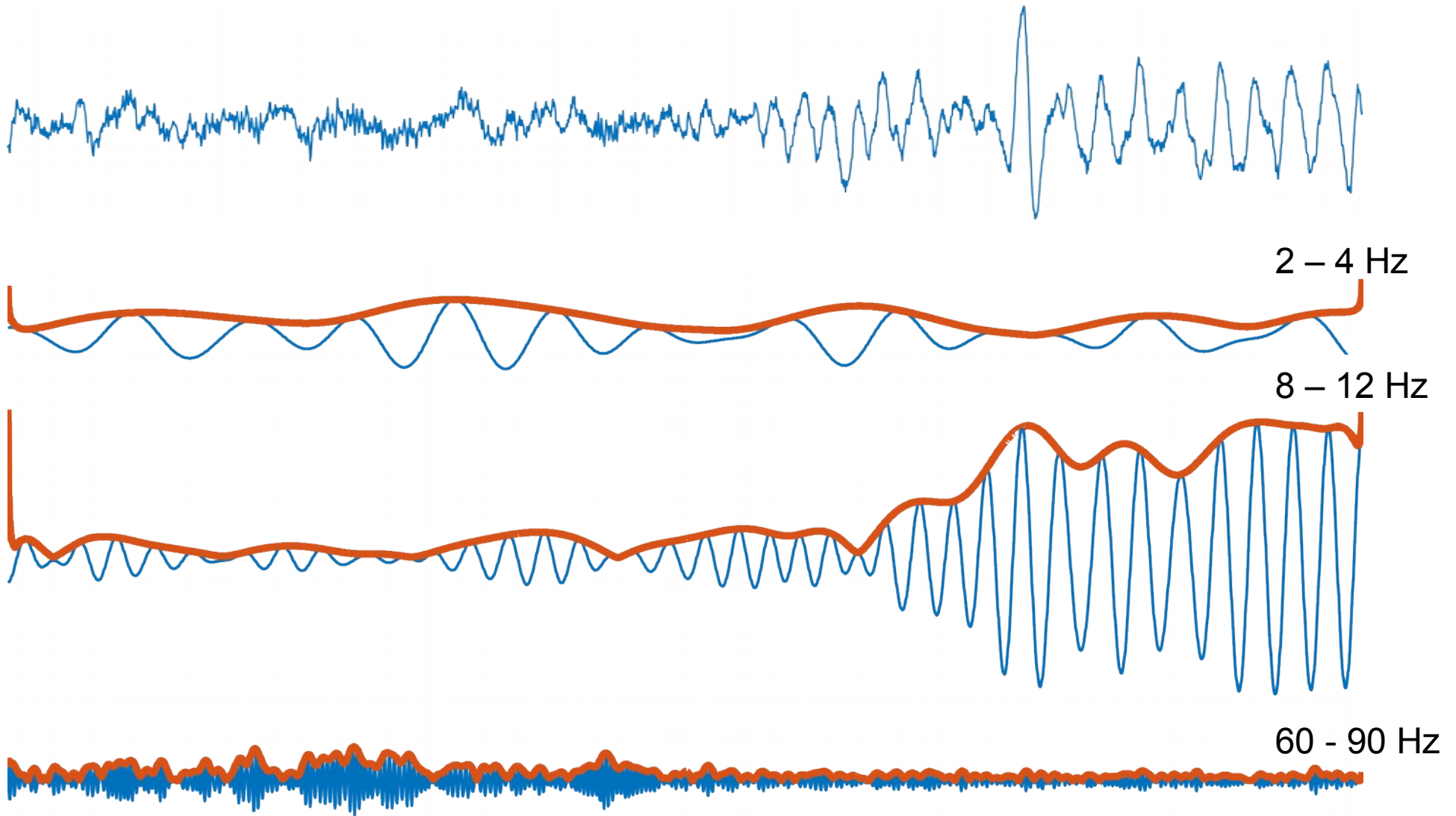
Hilbert transform

2 − 4 Hz

8 − 12 Hz

60 - 90 Hz

Hilbert transform

2 − 4 Hz
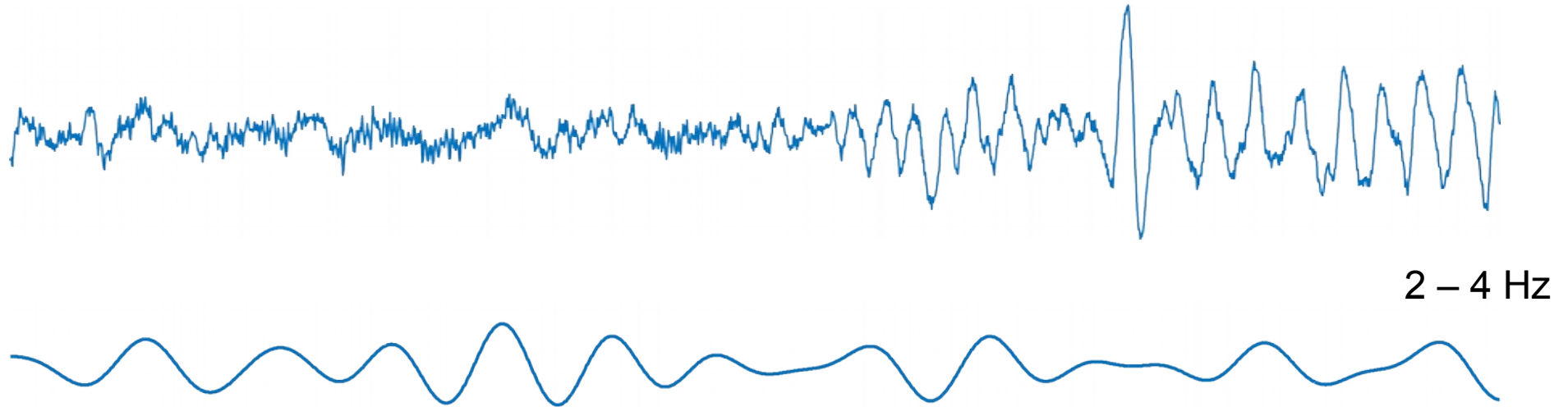
- The hilbert transform can also extract the phase of the bandpassed signal in time

Hilbert transform

$2 - 4 \, Hz$

2pi

0

- The hilbert transform can also extract the phase of the bandpassed signal in time

0 / 2pi

1.5*pi

pi/2

pi

Hilbert transform

$2 - 4\,Hz$

$2pi$

0
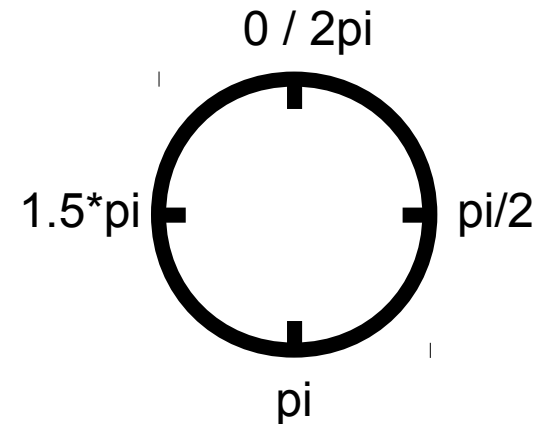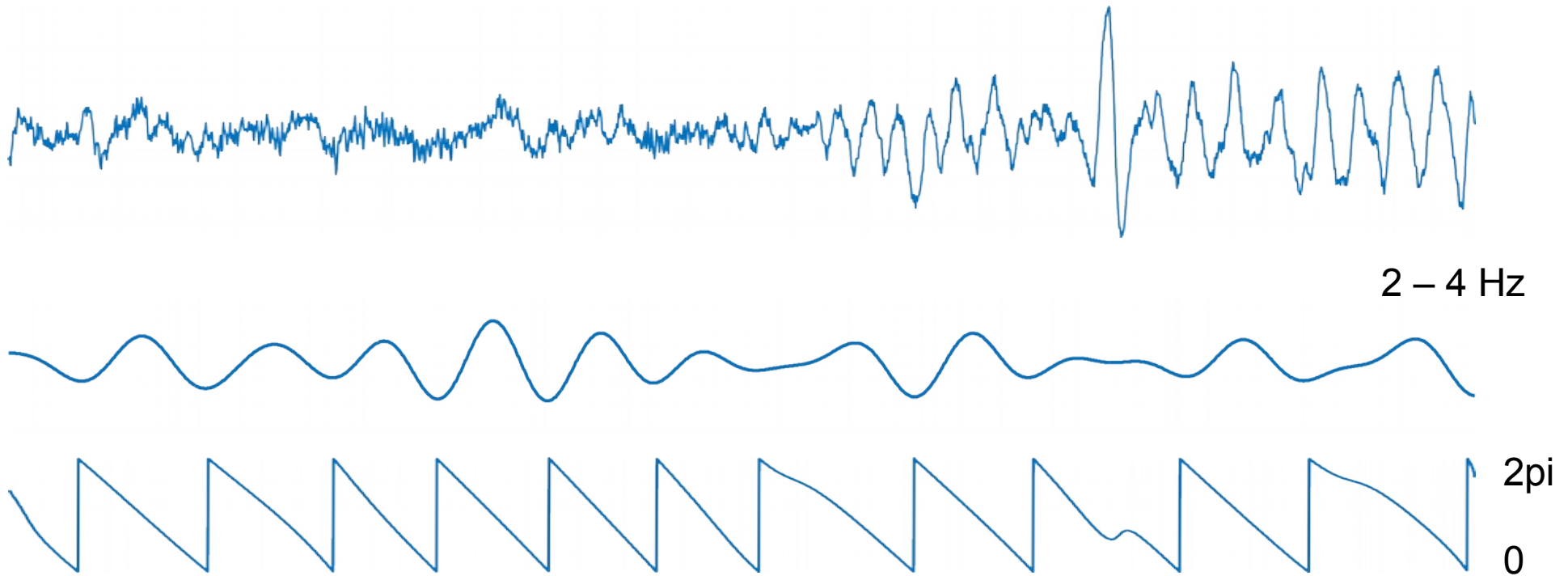
- The hilbert transform can also extract the phase of the bandpassed signal in time

- Usage: phase-locking value, stimulus-brain coupling, phase-amplitude coupling

  ➔ All of that later in the day
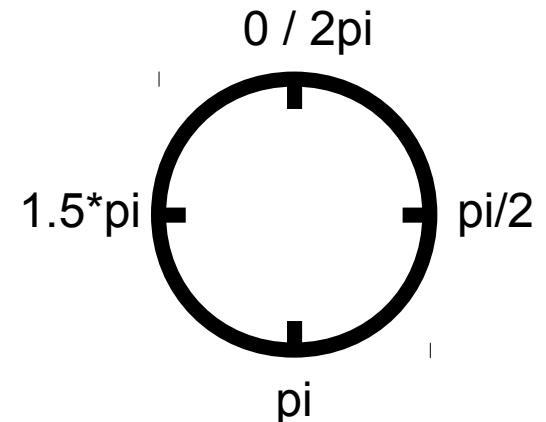
0 / 2pi

1.5*pi

pi/2

pi

Hilbert vs. Wavelet

- Hilbert method in BST uses FIR filters
- Important: frequency response of the bandpass filter

Stop signals in this band

Pass signals in this band

Stop signals in this band
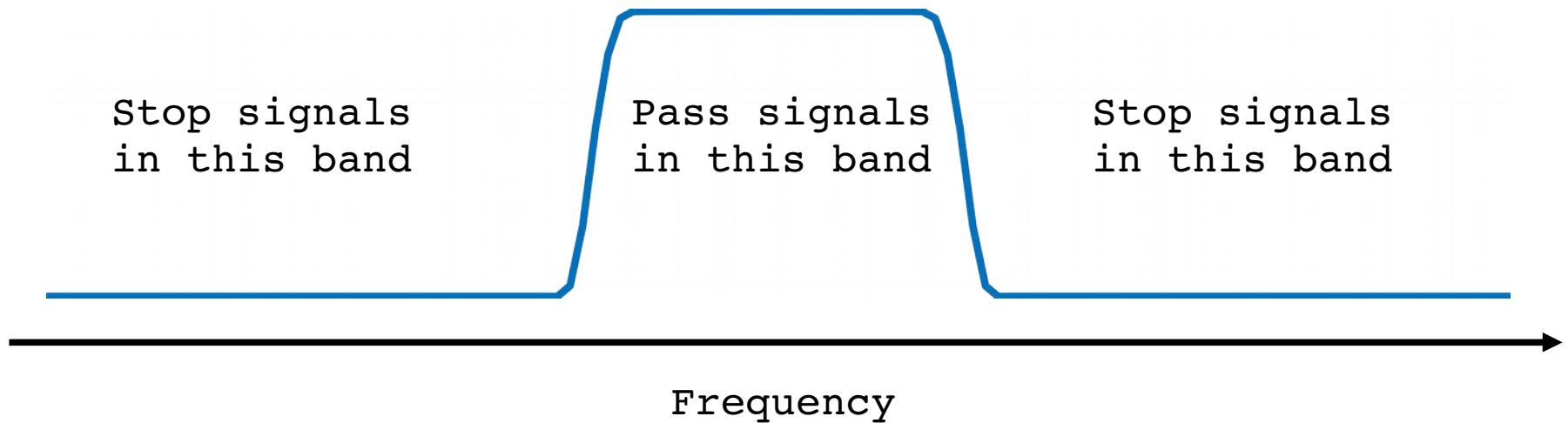
Frequency

Hilbert vs. Wavelet

- Hilbert method in BST uses FIR filters
- Important: frequency response of the bandpass filter
- Wavelets more localized around center frequency
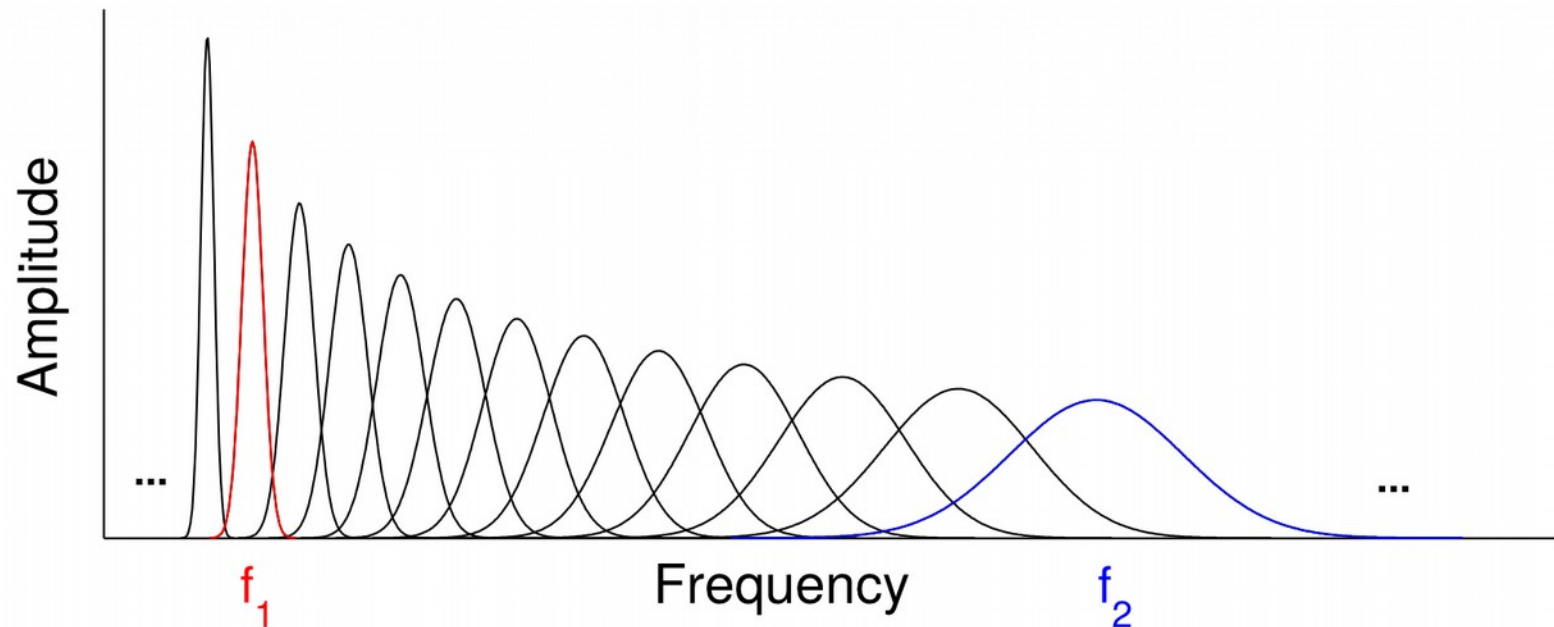
Defining frequency bands

- 'Based on the literature': many definitions
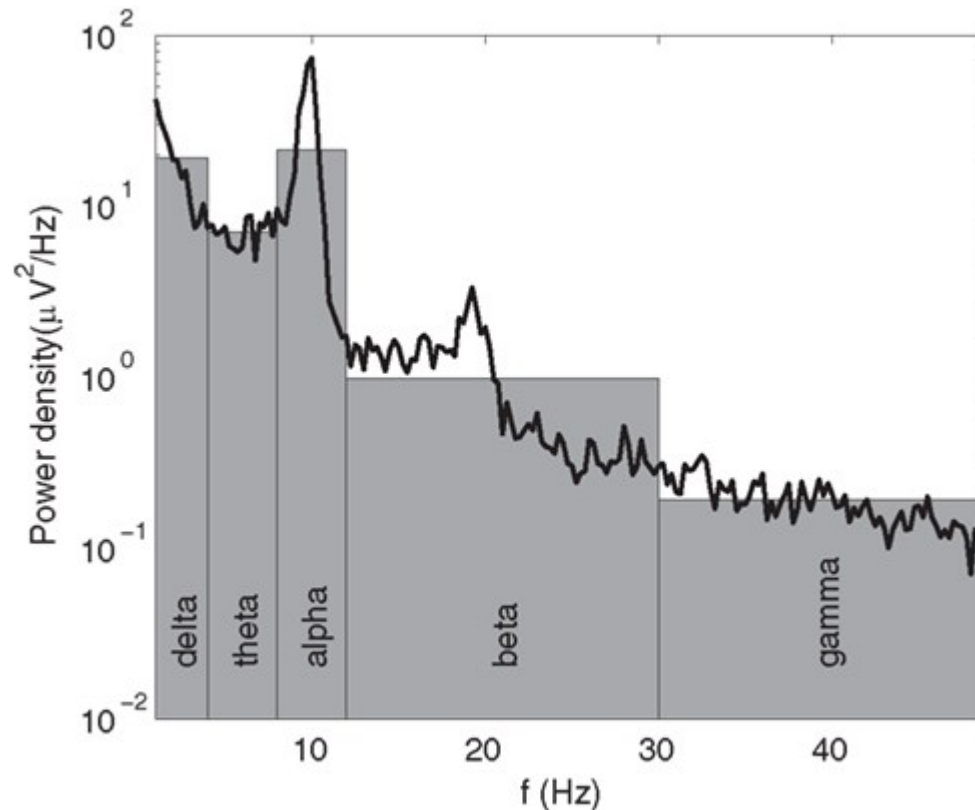
Defining frequency bands

- Should I collapse over frequency bands or keep the full spectrum?

  - Information might be lost (peaks)
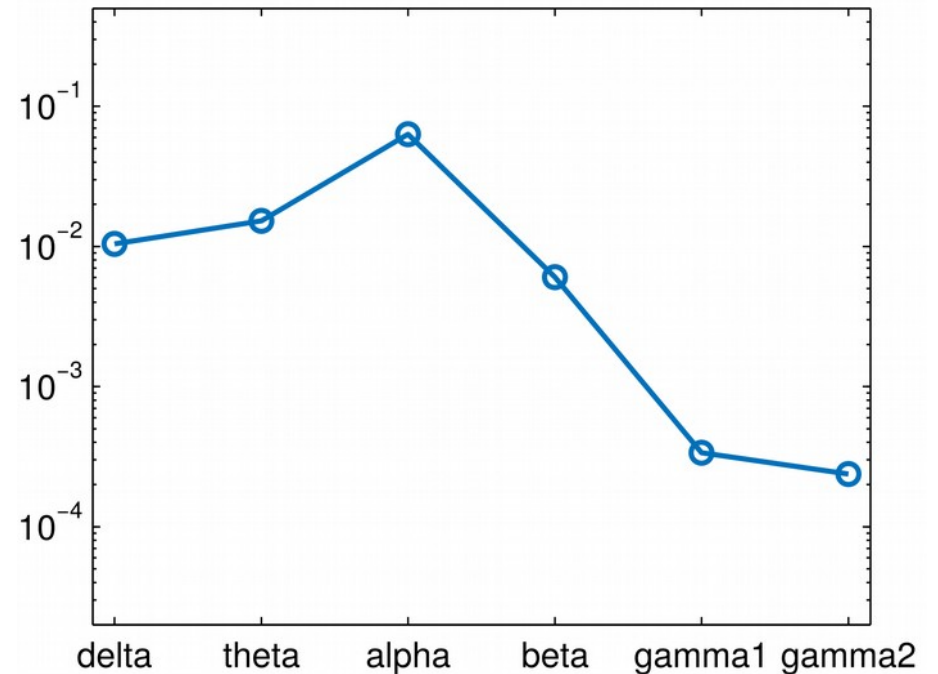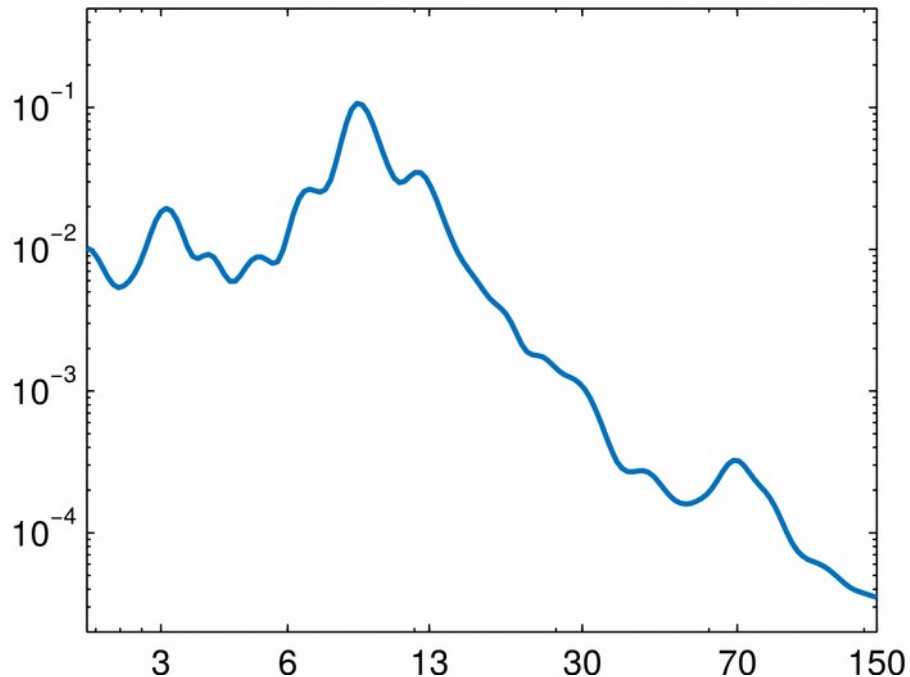
Defining frequency bands

- Should I collapse over frequency bands or keep the full spectrum?

  - Sometimes necessary for reducing dimensionality (e.g. in source space)

  - Can increase sensitivity (due to averaging)
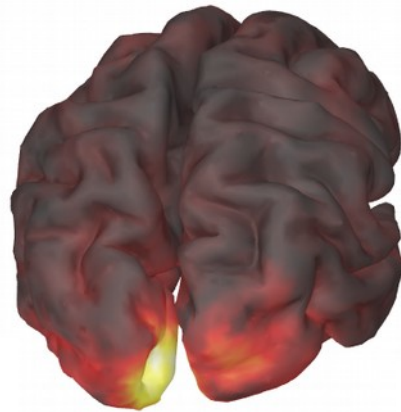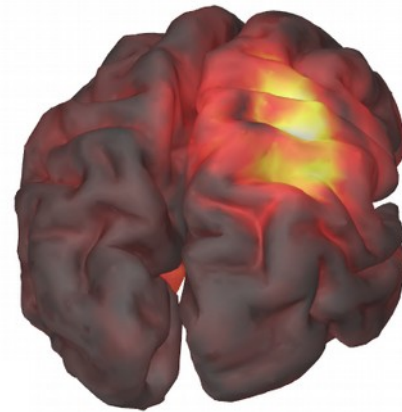
Gamma 60-90 Hz   Beta 15-30 Hz

Cross-frequency Coupling

- **Cross frequency coupling (CFC):**
  - Interaction between oscillations at different frequency bands

- **Several synchronized neuronal assemblies in the brain:**
  - Each supports a frequency band of the network rhythm

- **Relationship between these frequencies:**
  - Interaction between local neural circuits
  - Changing of intrinsic properties in each circuit

- G. Buzsaki. Cerebral Cortex, 1996
- A. Bragin, et al., The Journal of Neuroscience, 1995.
- A. Roopun, et al., Frontiers in Neuroscience, 2008.

Types of CFC

- Types:
  - Phase-phase coupling
  - Amplitude-amplitude coupling
  - Phase-amplitude coupling

Jirsa et al., Front. Neurosci. , 2013

Jirsa et al., Front. Neurosci. , 2013
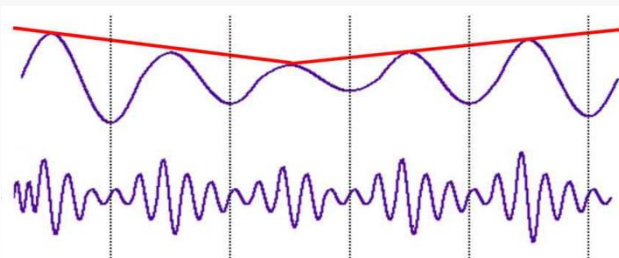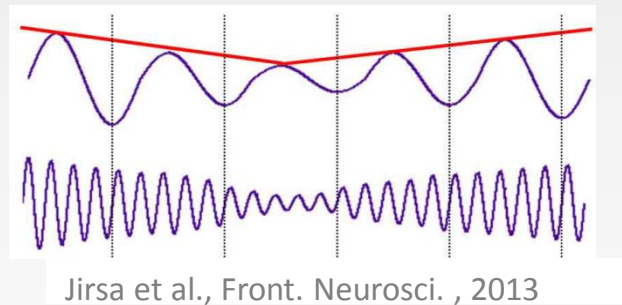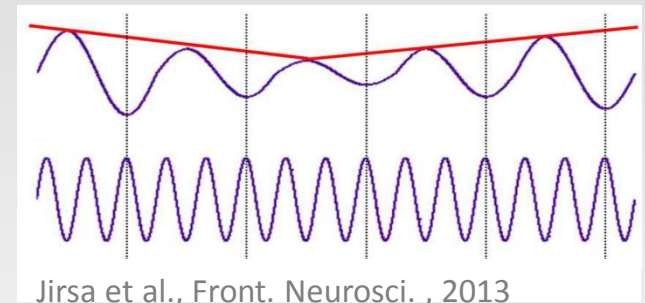
Jirsa et al., Front. Neurosci. , 2013

Cross-frequency Phase-amplitude Coupling

- Phase-amplitude coupling

f_P

$+$

f_A

- Canolty and Night, Trends Cogn Sci, 2010
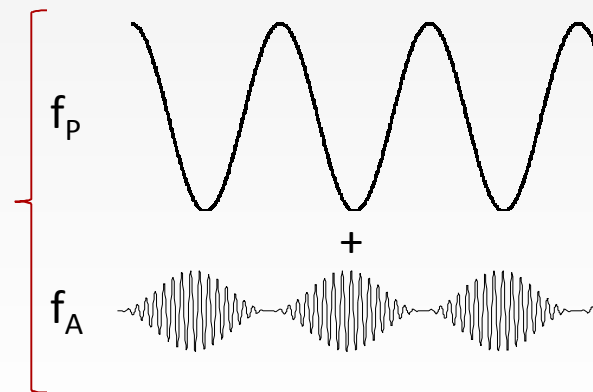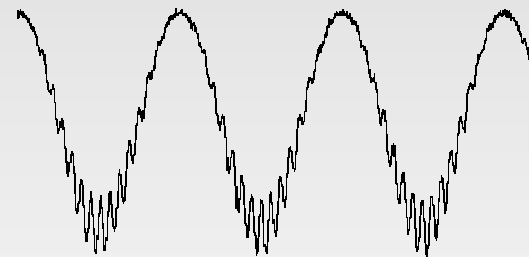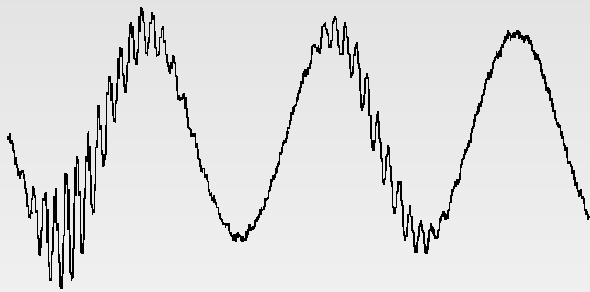
Cross-frequency Phase-amplitude Coupling

- ## Phase-amplitude coupling

  - ✓ Plausible physiological mechanisms

    - Low frequency phase reflects local neuronal excitability

    - High frequency power increases reflect:

      – A general increase in population synaptic activity (broad-band power increase)

      – Selective activation of a connected neuronal subnetwork (narrow-band power increase)

  - ✓ Functional correlations

• Canolty and Night, Trends Cogn Sci, 2010
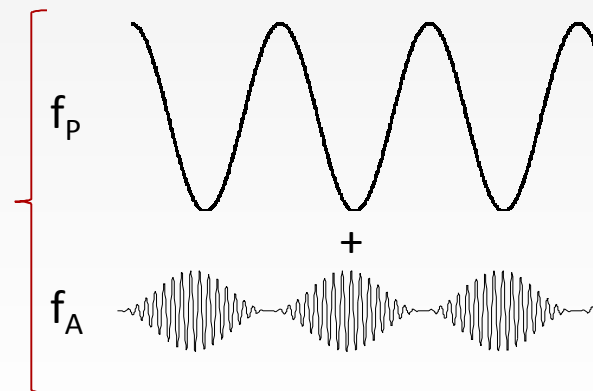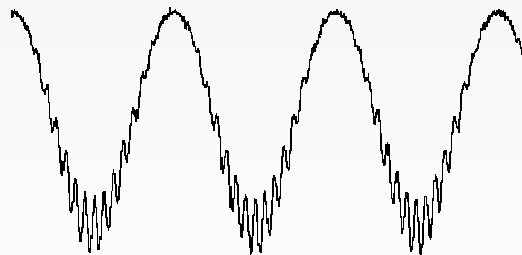
Functional Correlations

- Several studies have been conducted in this field

  - Phase of the low-frequency theta (4 to 8 hertz) rhythm modulates power in the high gamma (80 to 150 hertz) band
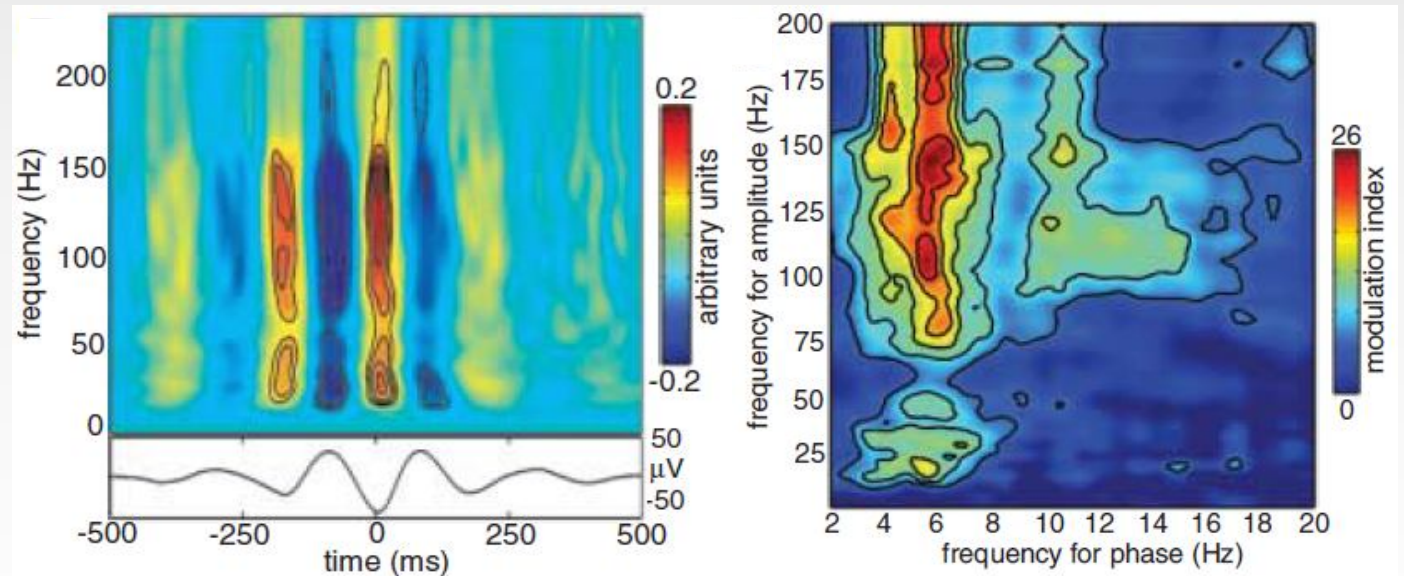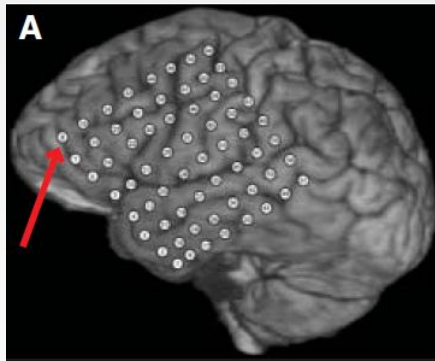
Measuring Cross–frequency Coupling

- Several algorithms available

  – Each proper for a particular case

  – No single method has been elected as a preferred standard so far

Detecting coupled frequencies

Measuring coupling intensity

Measuring Cross-frequency Coupling

- Available measures:

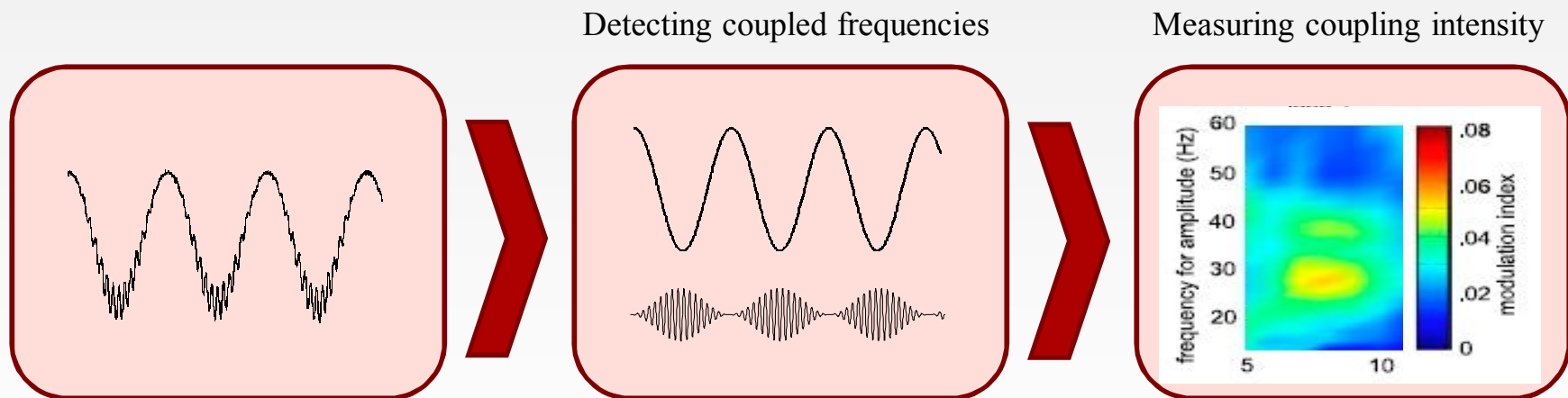|		Method		Limitation
1	ESC	The envelope to signal correlation	[Bruns and Eckhorn, 2004]	⭐ ⭐
2	PLV	Phase-locking value	[Vanhatalo et al., 2004]	⭐
3	MVL	Mean vector length	[Canolty et al., 2006]	⭐
4	GLM	The general linear model measure	[Penny et al., 2008]	⭐
5	APSD	Amplitude power spectral density	[Cohen, 2008]	⭐
6	CV	Coherence Value	[Colgin et al., 2009]	⭐
7	KL-MI	Kullback-Leibler based modulation index	[Tort et al., 2010]	⭐
8	ERPAC	Event related phase amplitude coupling	[Voytek et al., 2012]	⭐ ⭐

⭐ Sensitive to coupling phase (Negative feature)

⭐ Need long data length

⭐ Only works on event-related datasets

⭐ Potentially not capable of calculating coupling intensity

Summary

Stationary:

- Fourier transform

- Power spectral density (Welch's method)

Time-resolved:

- Wavelet transform

- Filtering & Hilbert transform

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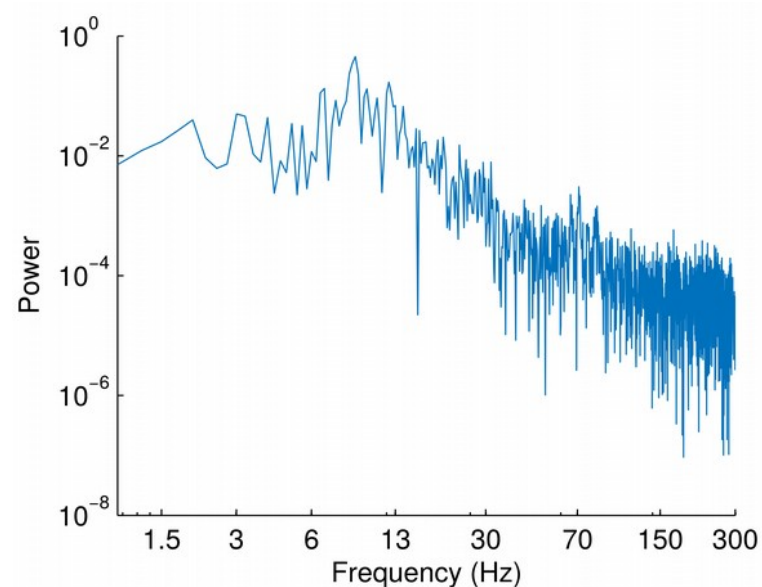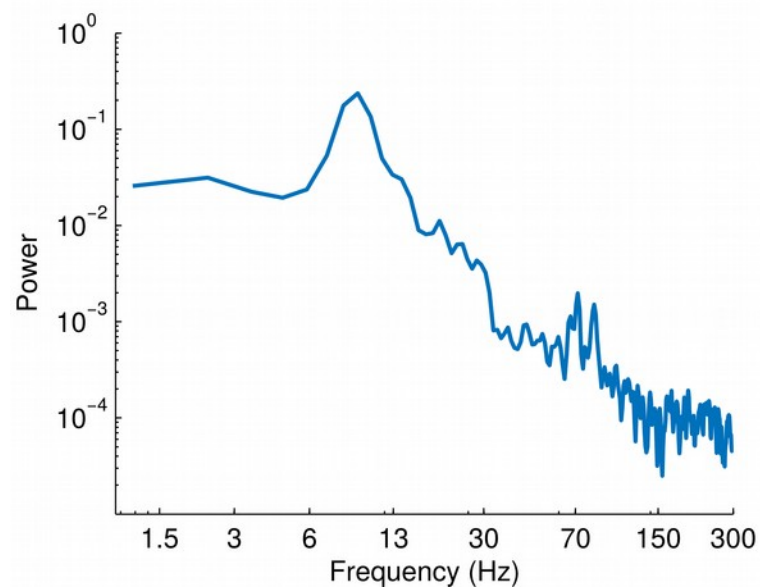- Wavelet transform

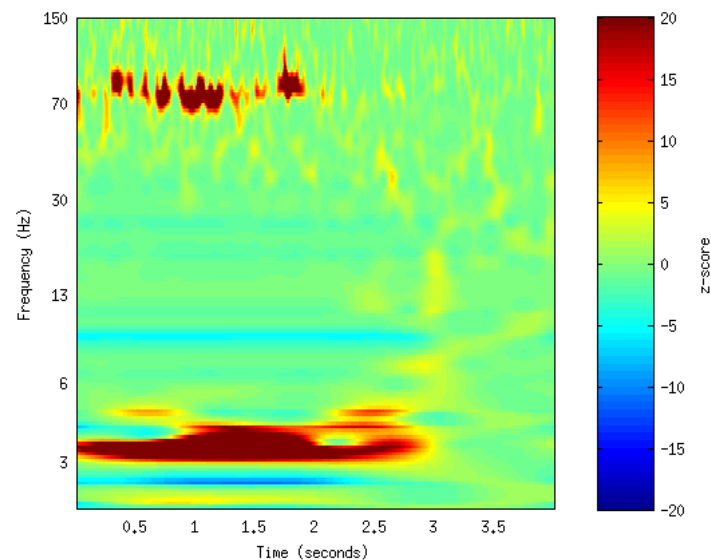- Filtering & Hilbert transform

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