Spectral Analysis

How to process neural oscillatory signals

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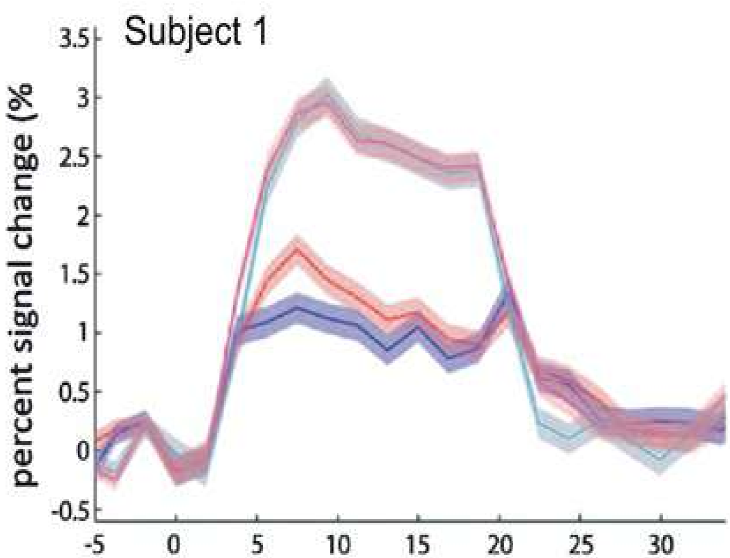
Baillet lab

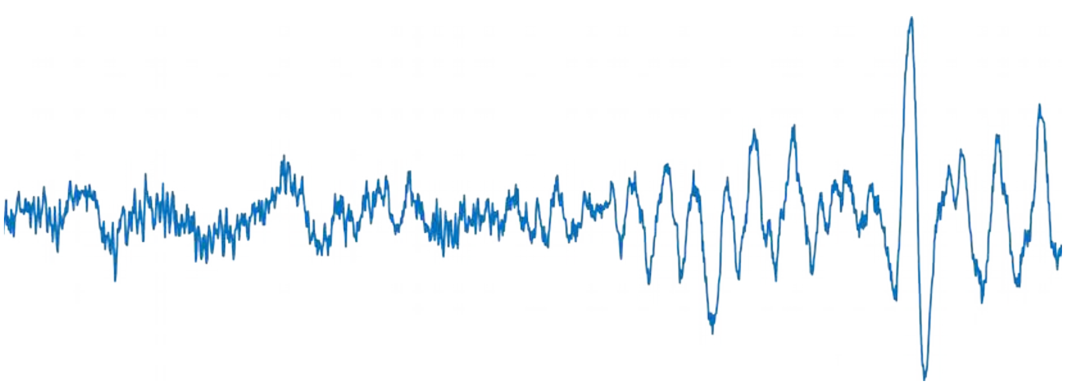
Meg@Mcgill
Comprehensive Training
November 2015

Why spectral analysis?

- MEG signals contain a wide range of components
- Electrophysiology vs. BOLD: what is 'activity'?



BOLD fMRI example



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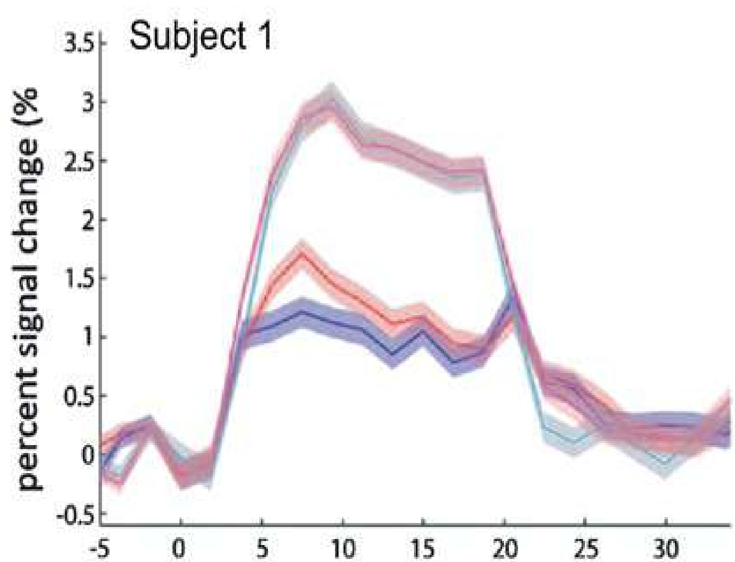

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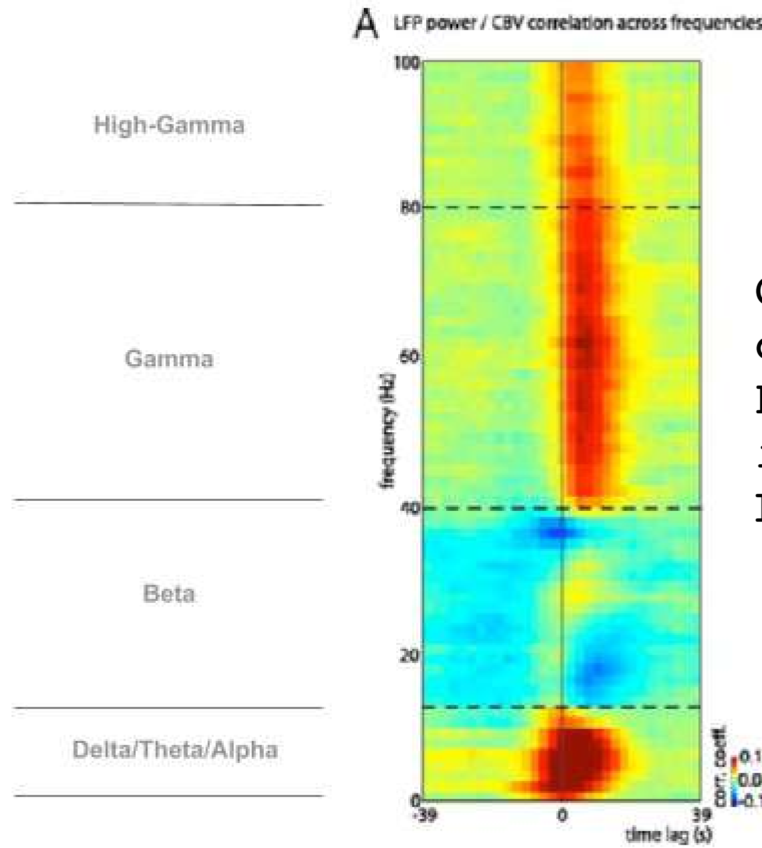
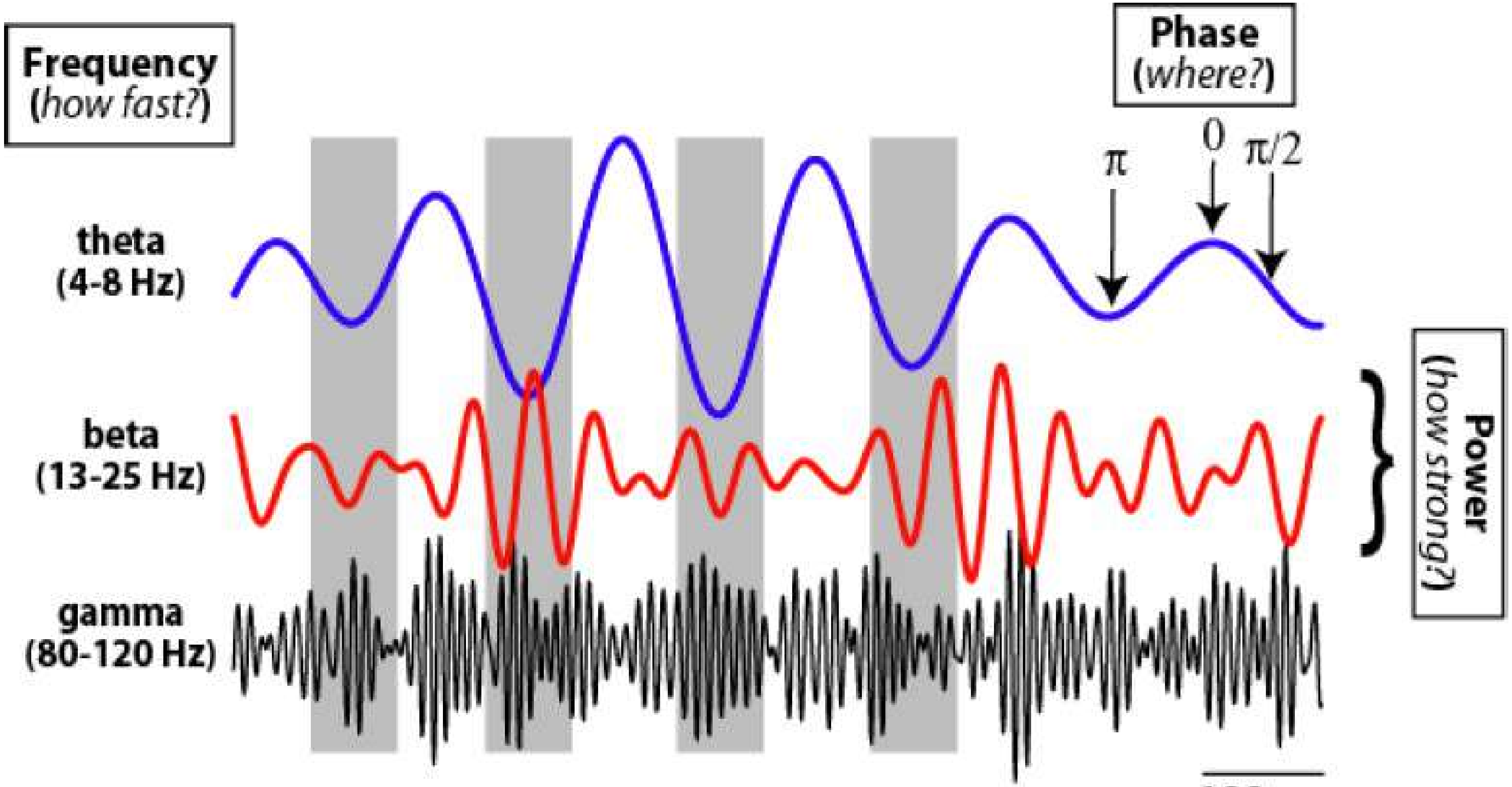


Schölvinck et al., *PNAS* (2010)

Cross-correlation of BOLD with intra-cranial LFP recordings

Basic concepts



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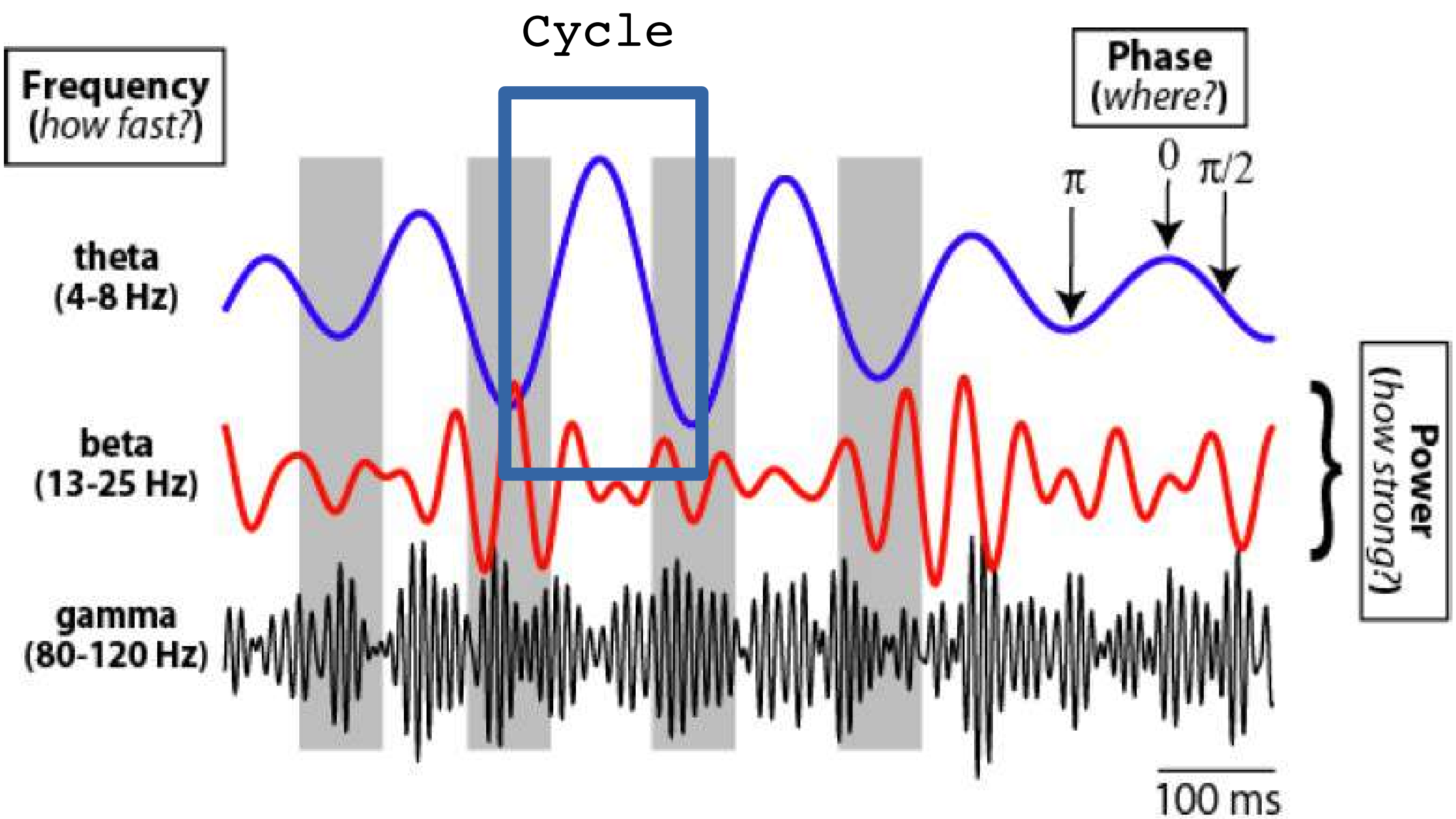

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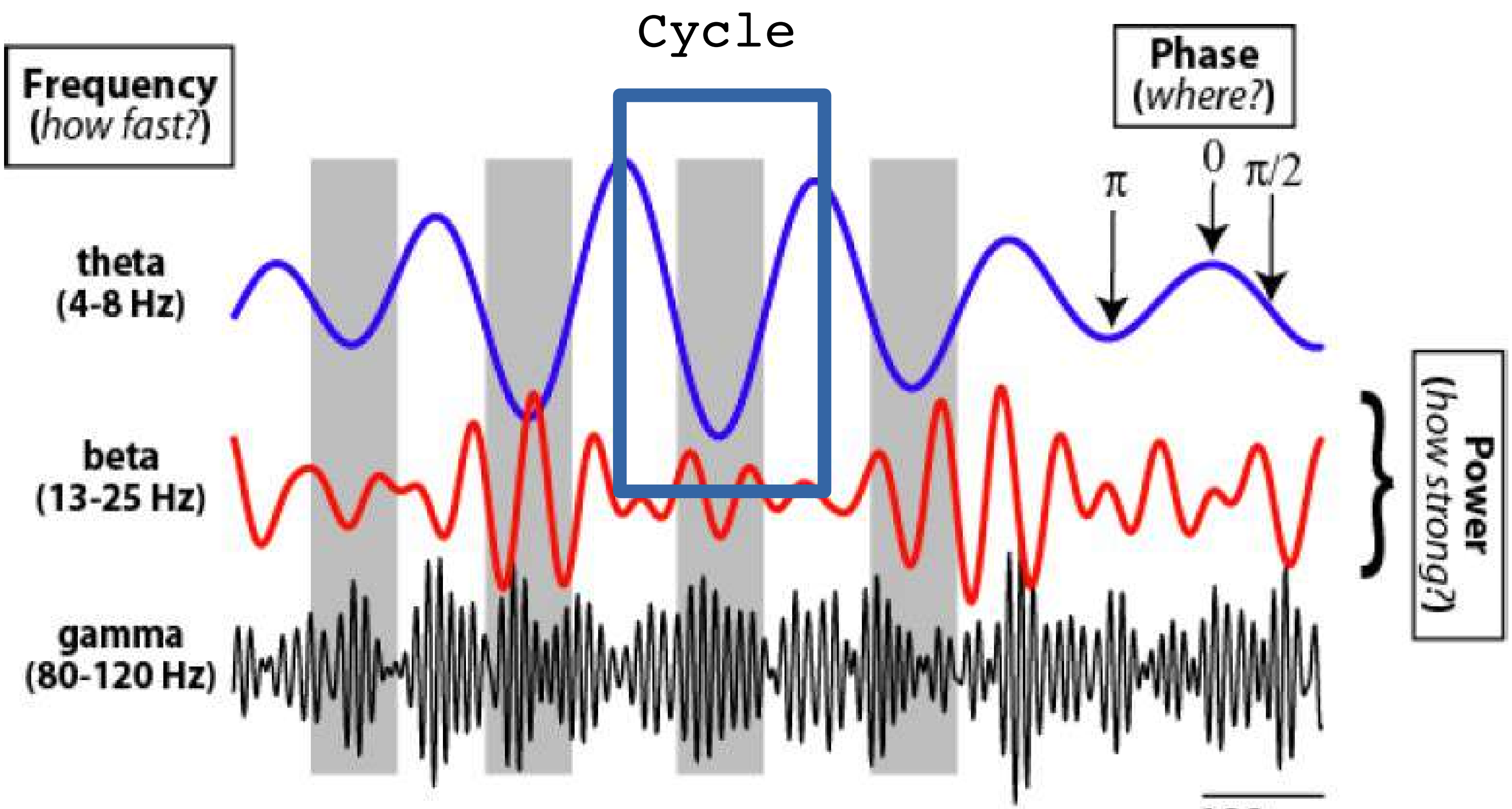

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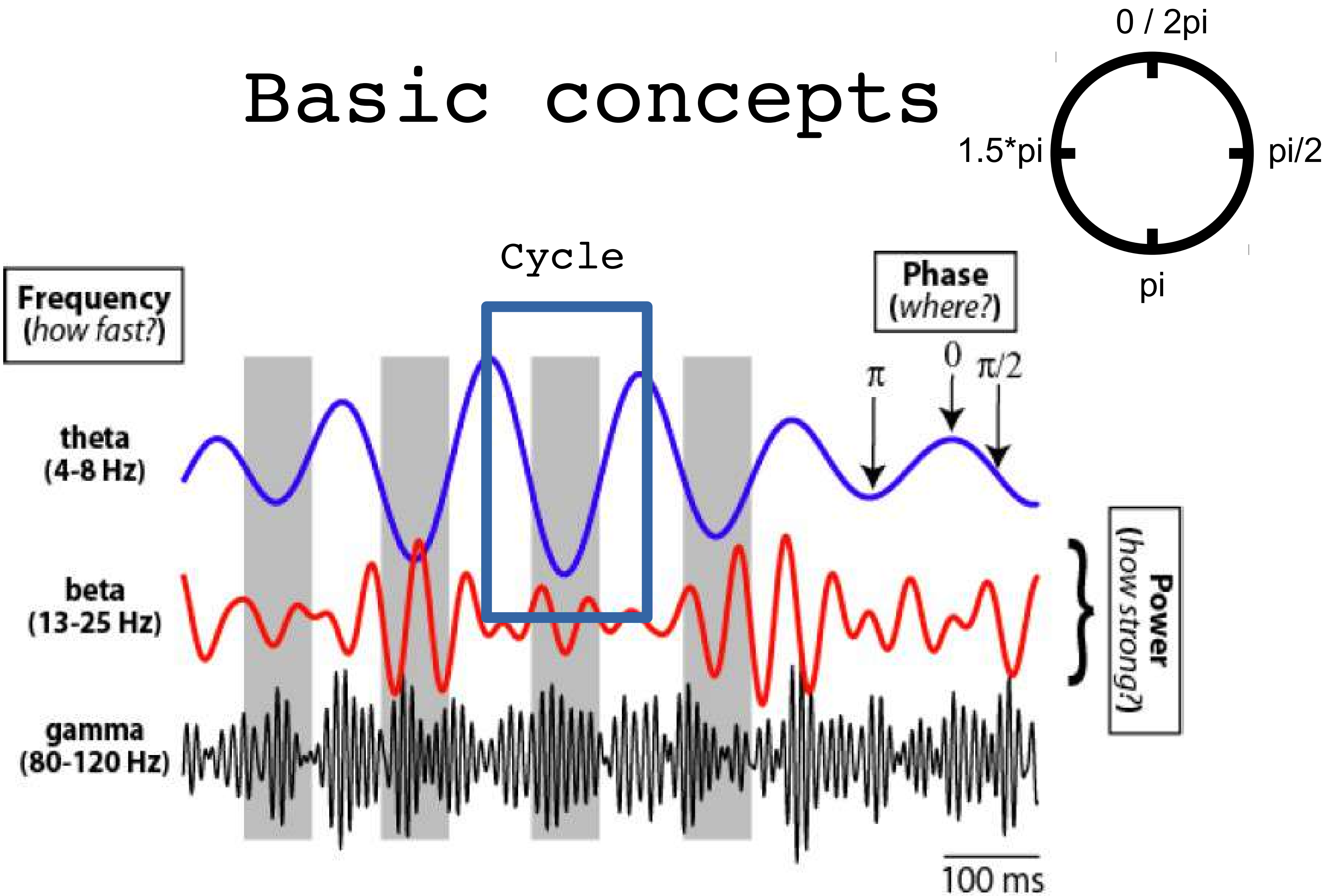

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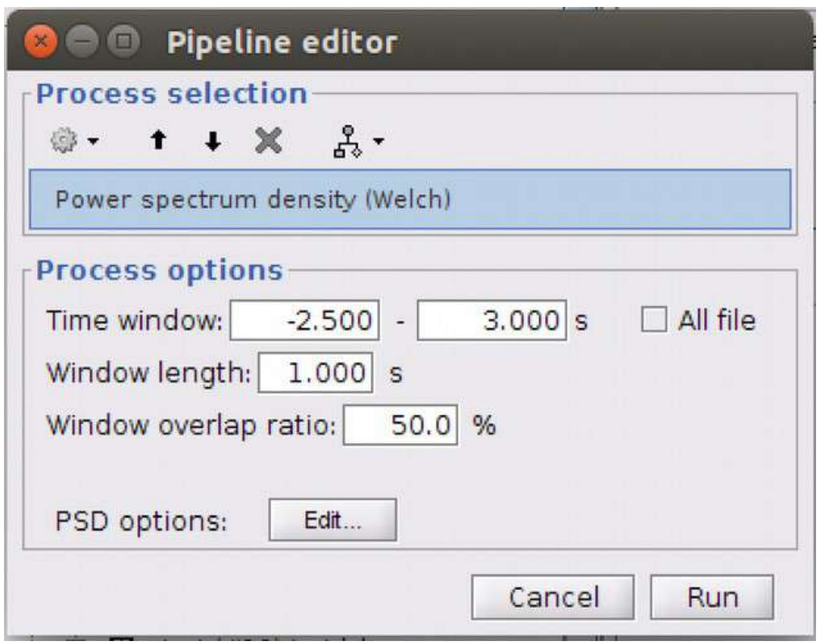

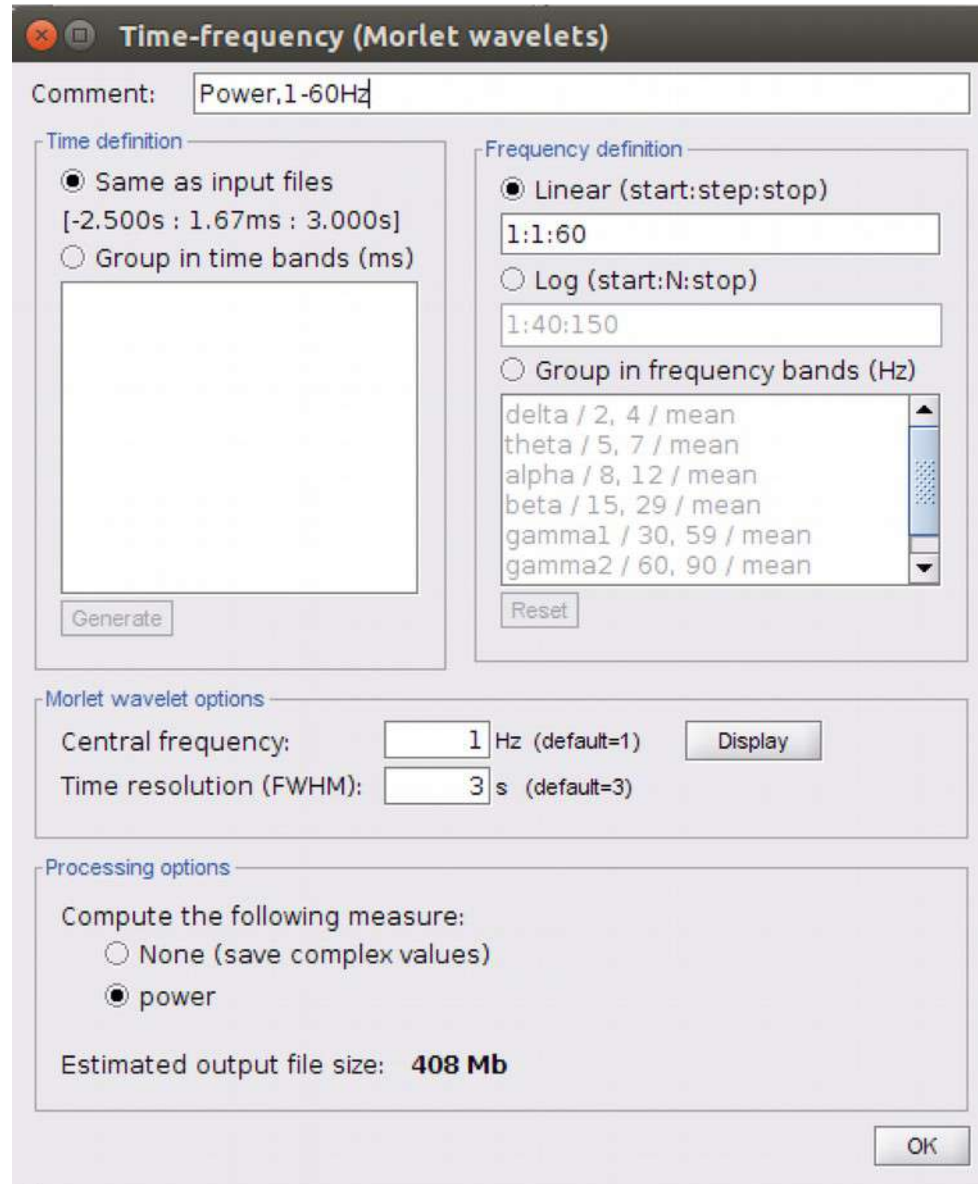

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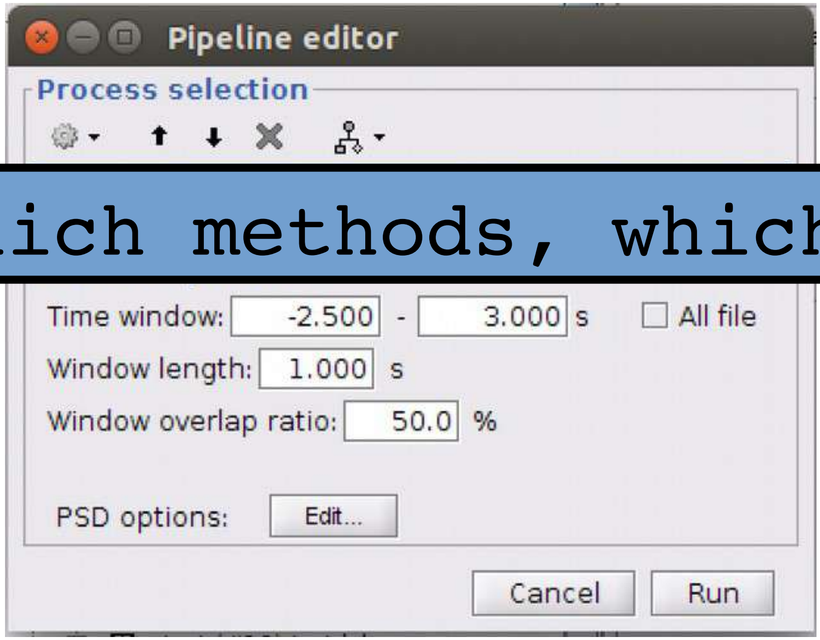
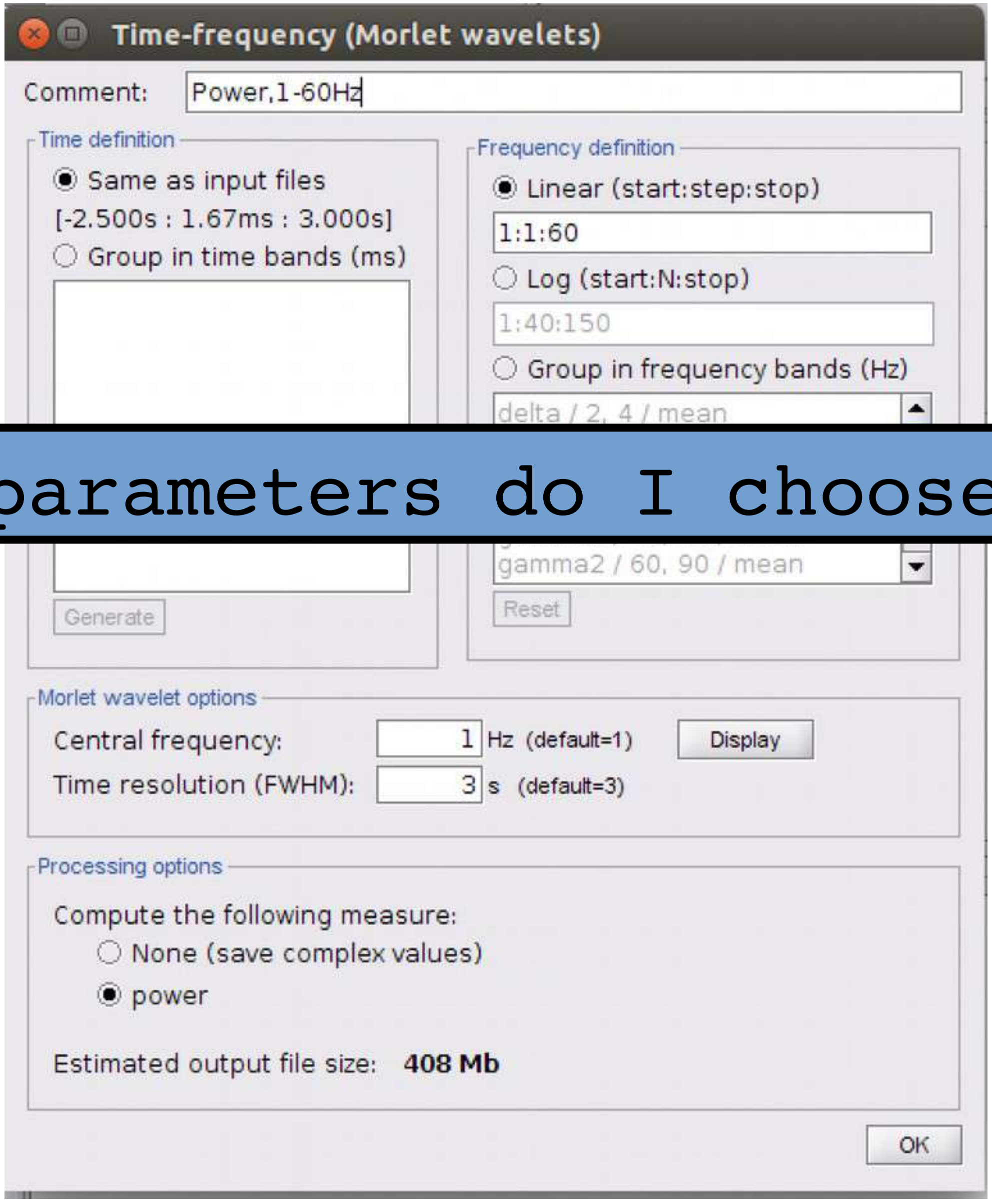


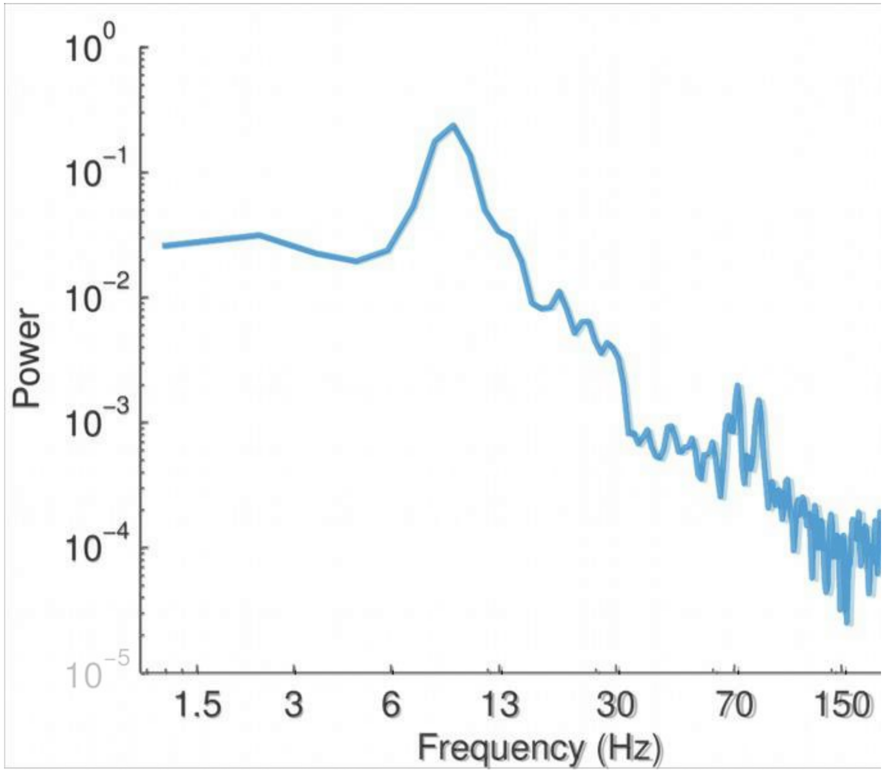


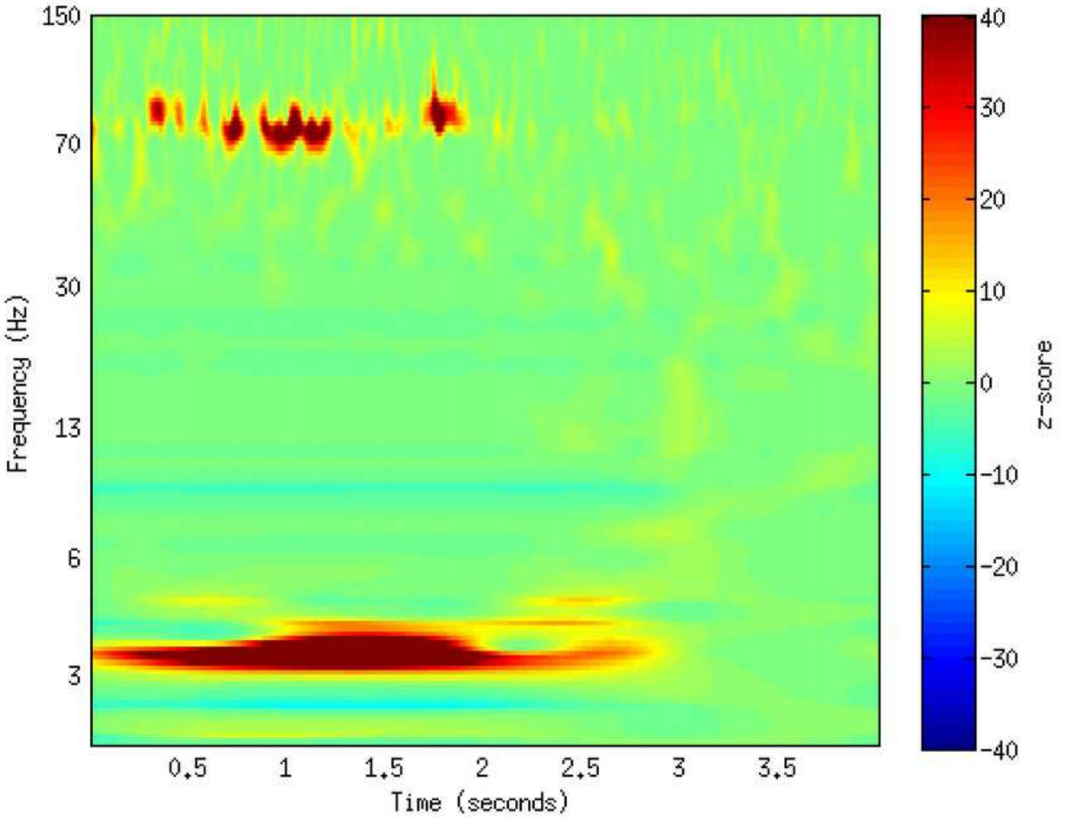
Which methods, which parameters do I choose?

Methods covered today

Two main groups:

- Estimation of spectral power (stationary) vs.
- Localization of Power in time & frequency





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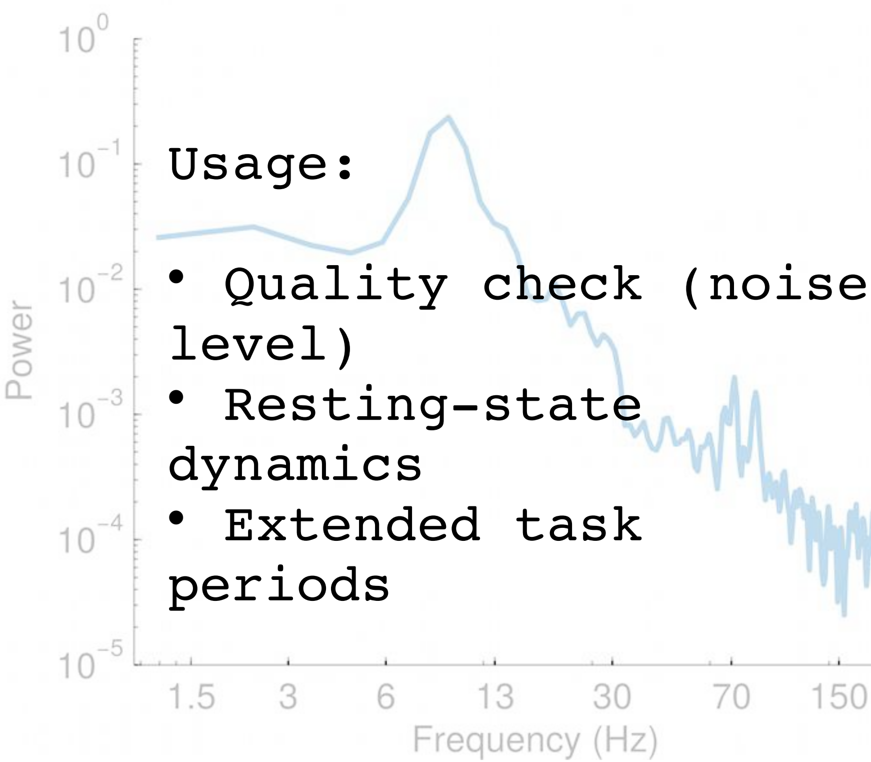
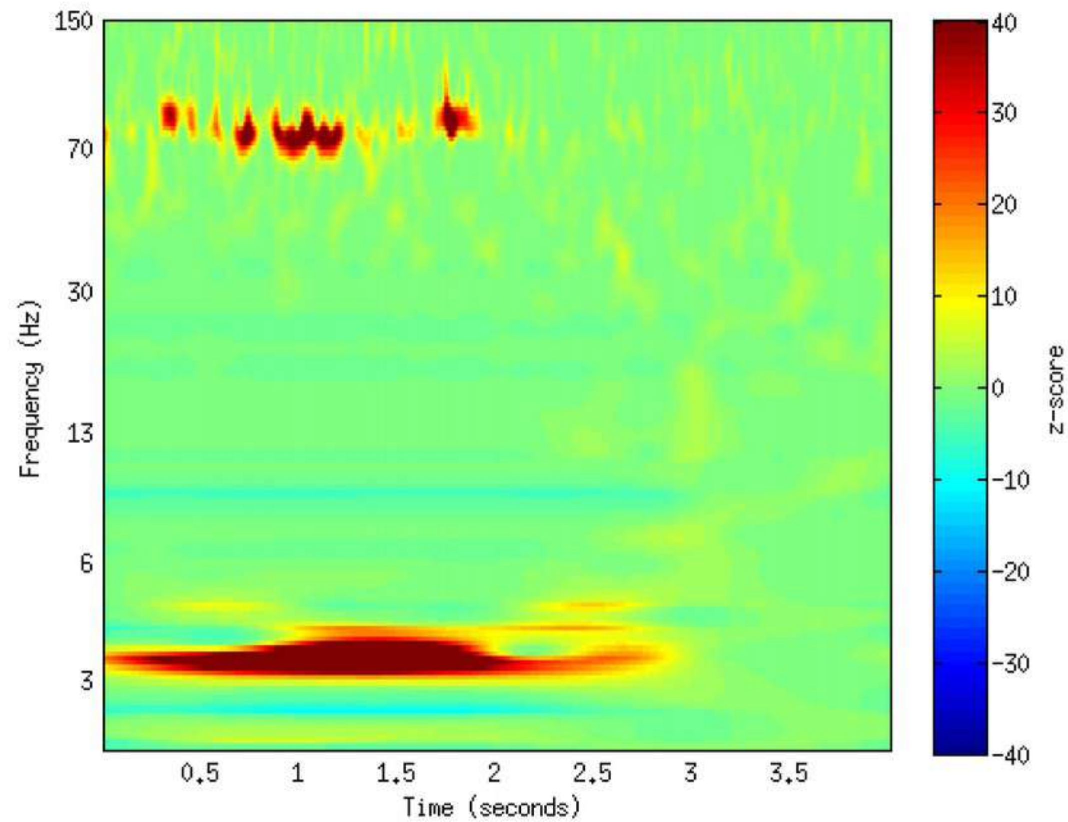


Usage:

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



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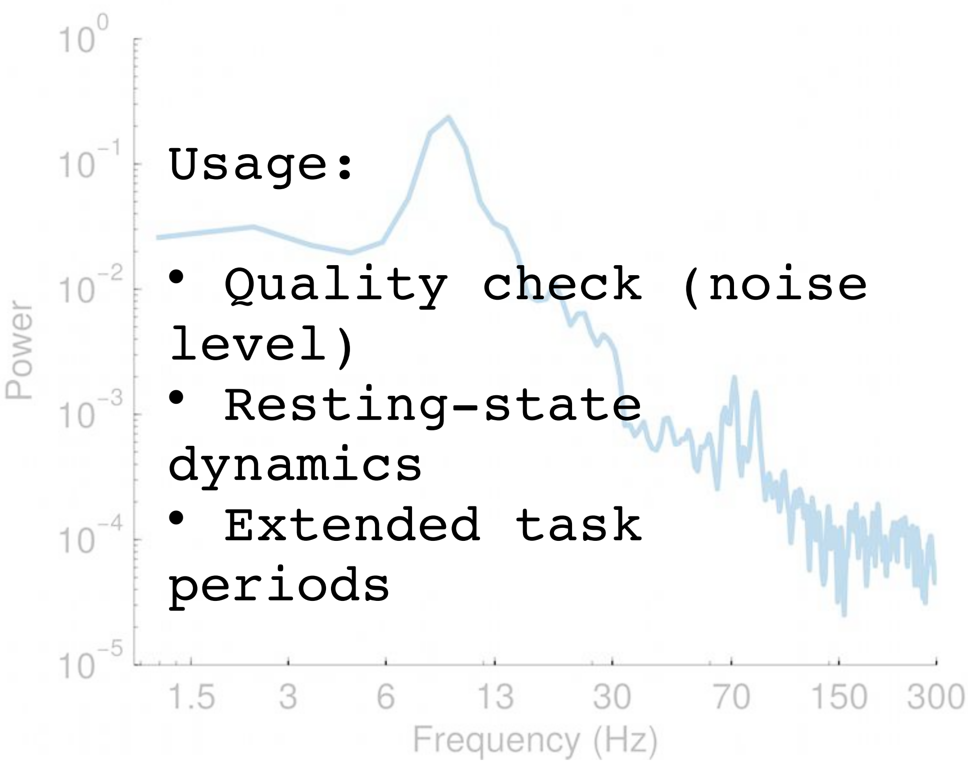

Usage:

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

Usage:

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

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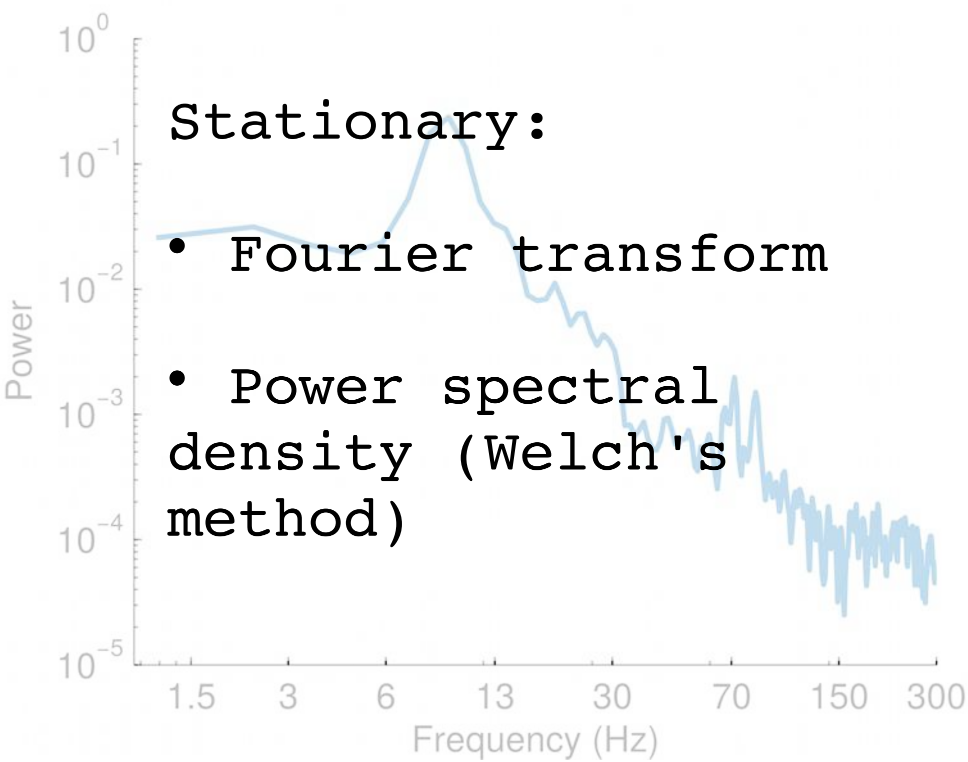

Stationary:

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- Power spectral density (Welch's method)

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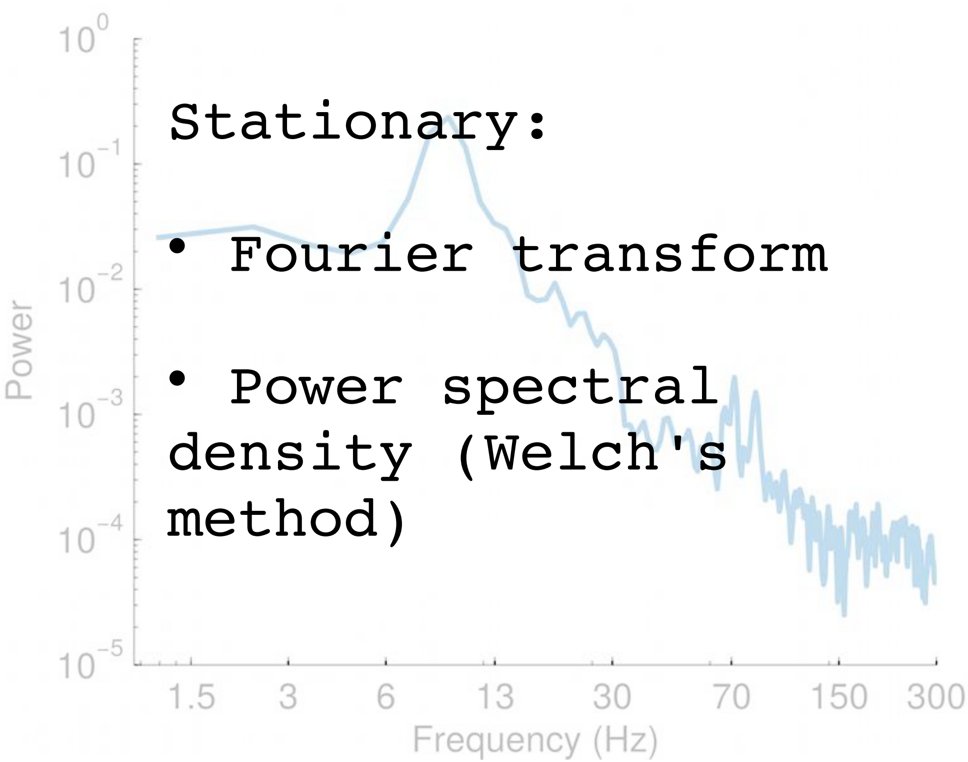

Stationary:

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Time-resolved:

- Wavelet transform
- Filtering & Hilbert transform

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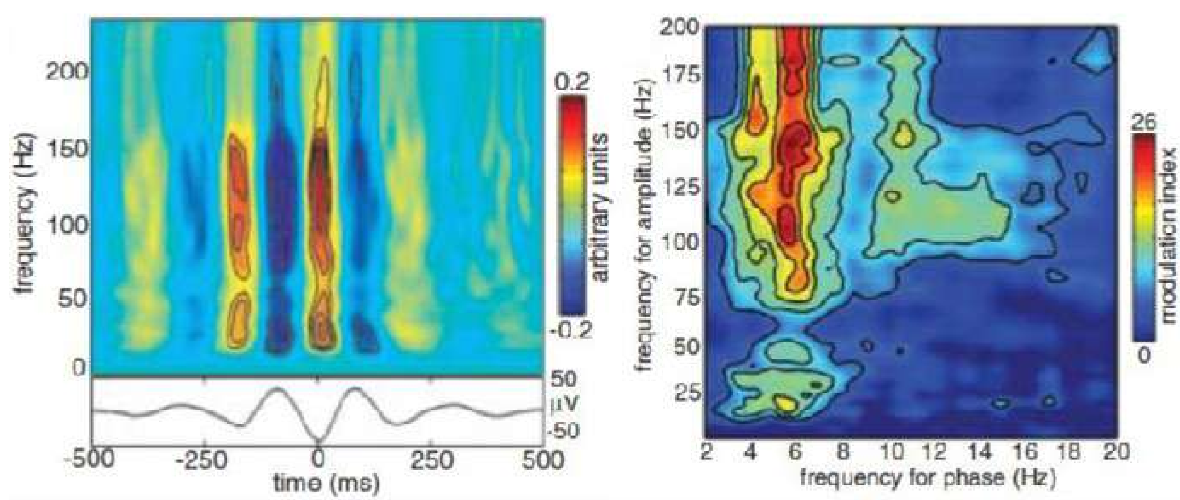
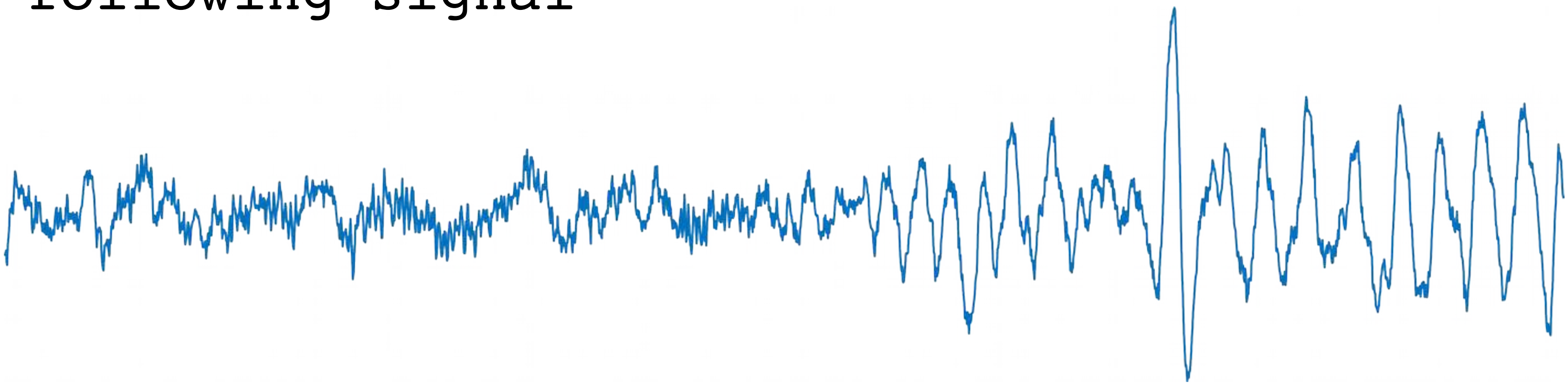
Short introduction to cross-frequency coupling measures



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

Example signal

- Concepts will be illustrated using the following signal



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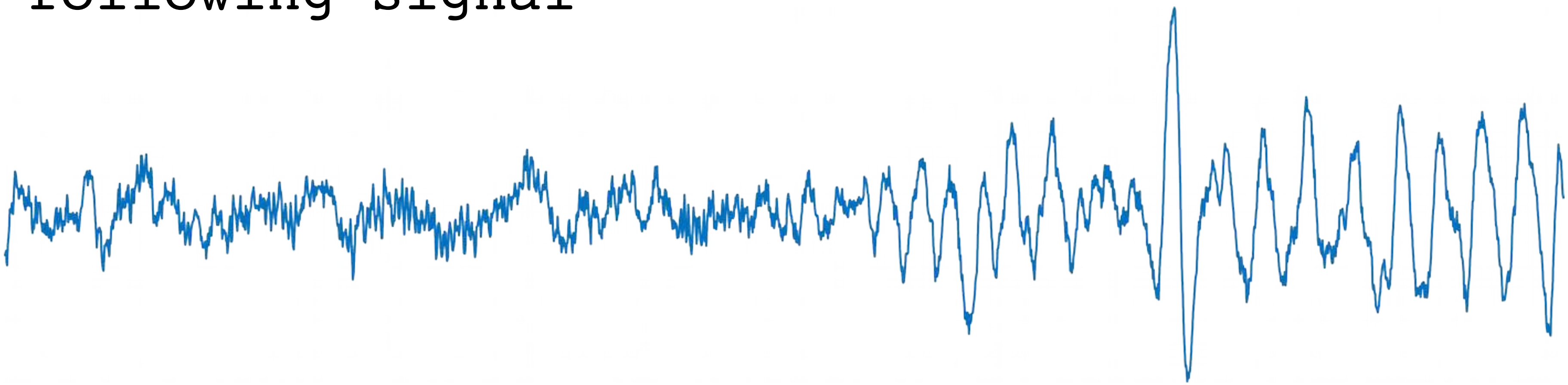

- MEG source signal from visual cortex
- 4 seconds
- Sampling frequency: 600 Hz

Example signal

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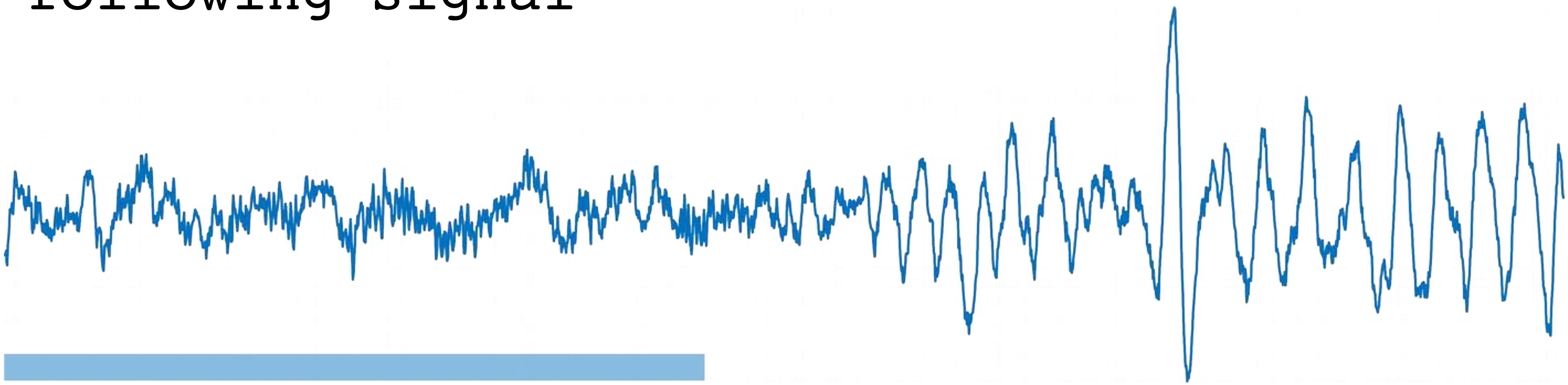

- MEG source signal from visual cortex
- 4 seconds
- Sampling frequency: 600 Hz
- Visual stimulus

Contents

Stationary:

- Fourier transform
- Power spectral density (Welch's method)

Time-resolved:

- Wavelet transform
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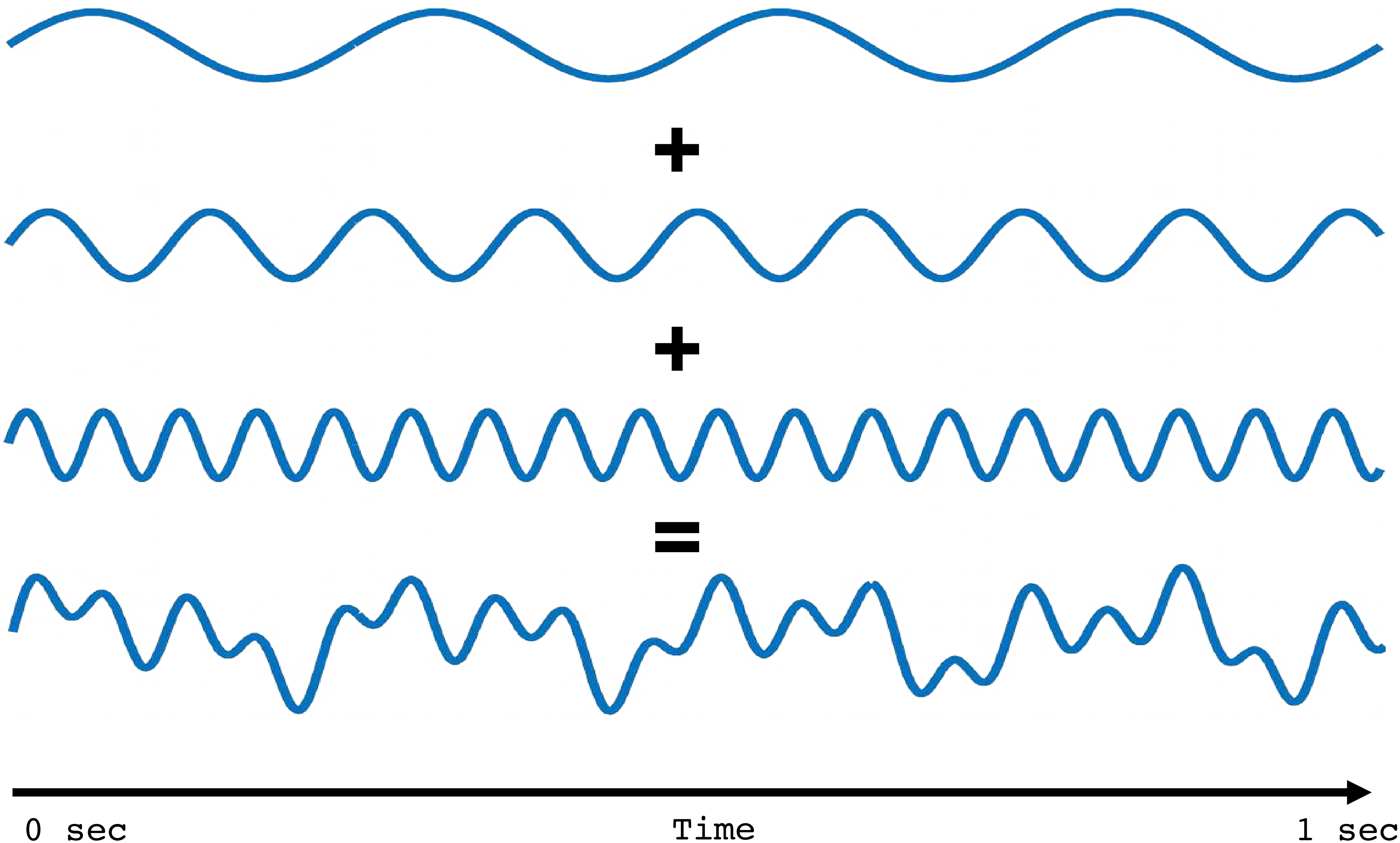
(Fast) Fourier Transform, FFT

- 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



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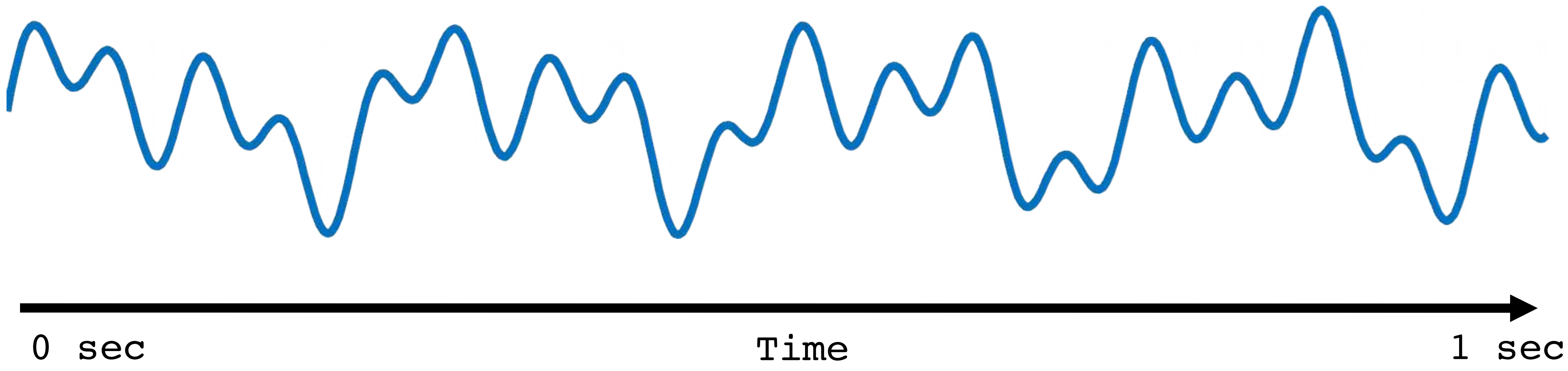

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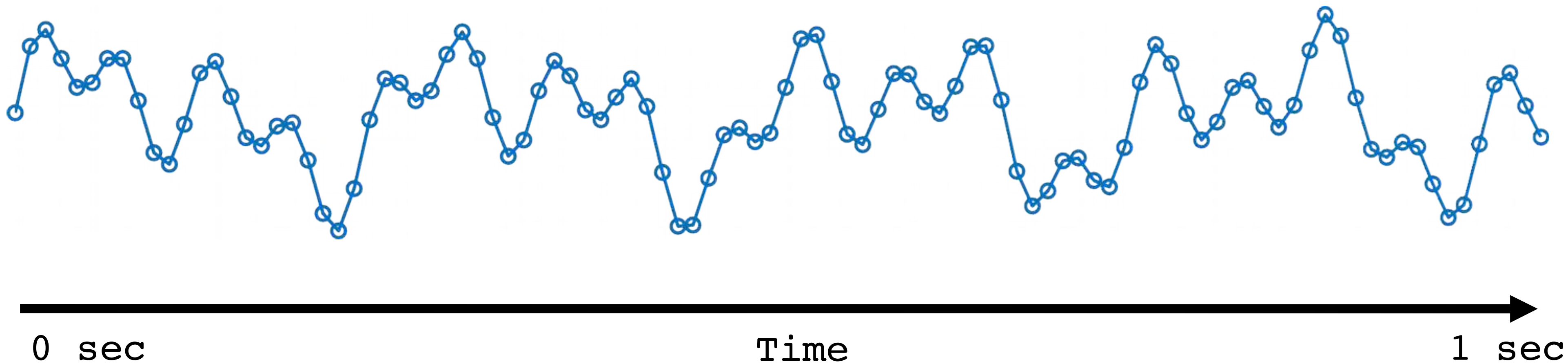

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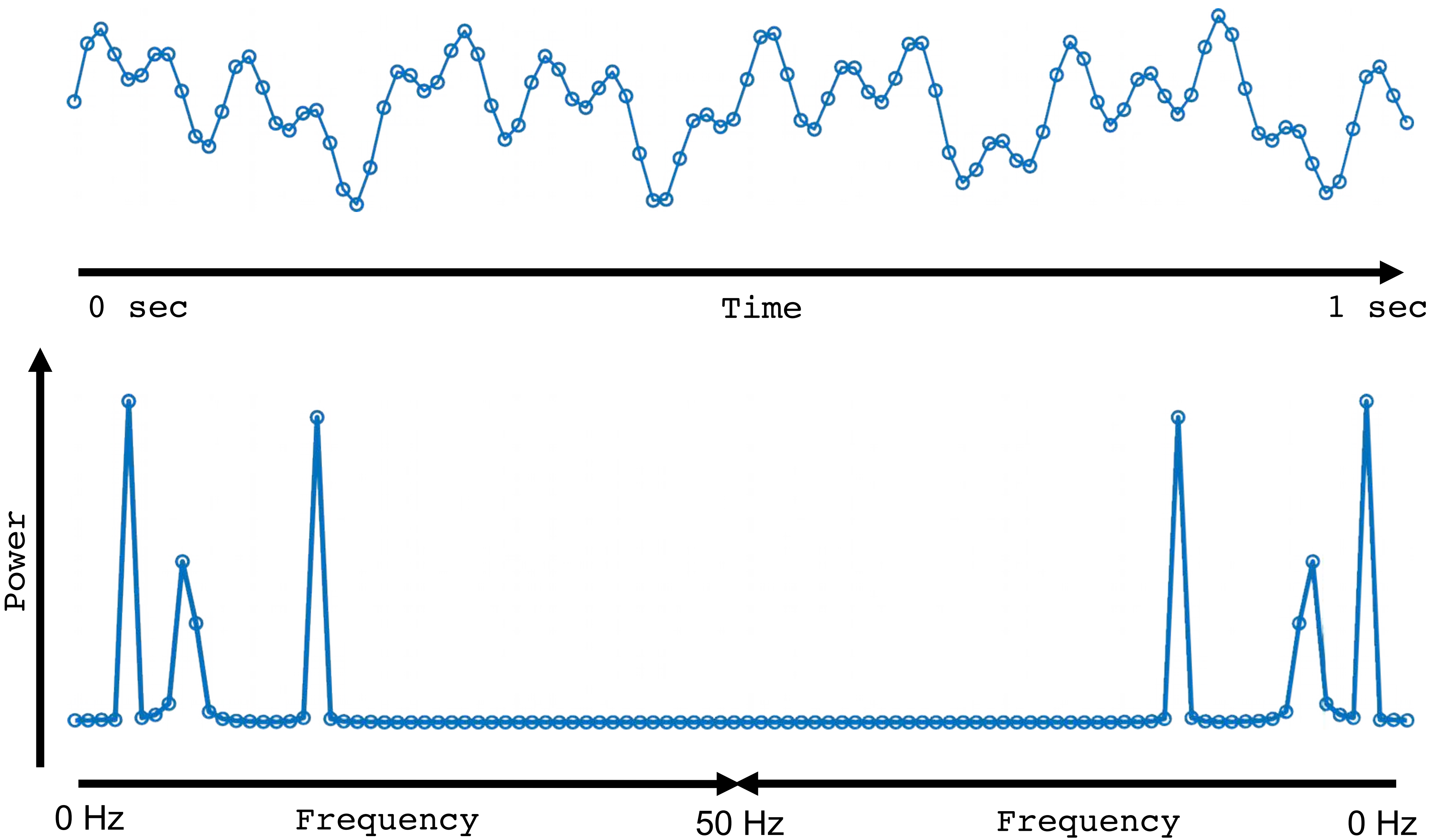

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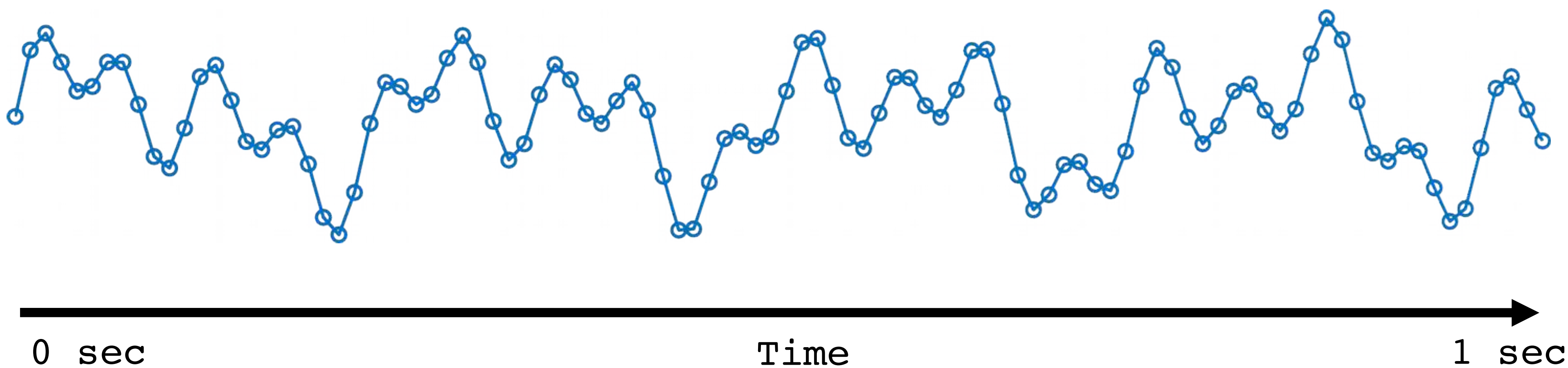

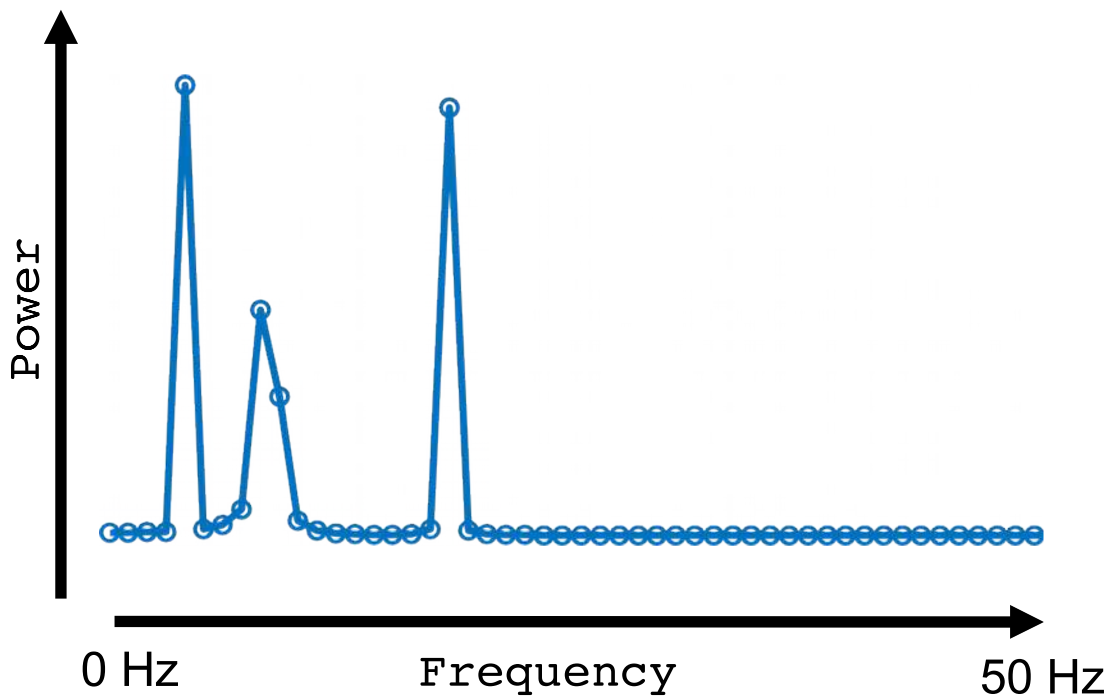

- FFT output is symmetric, second half usually removed
- Peaks in frequency domain correspond to an oscillatory component in time domain

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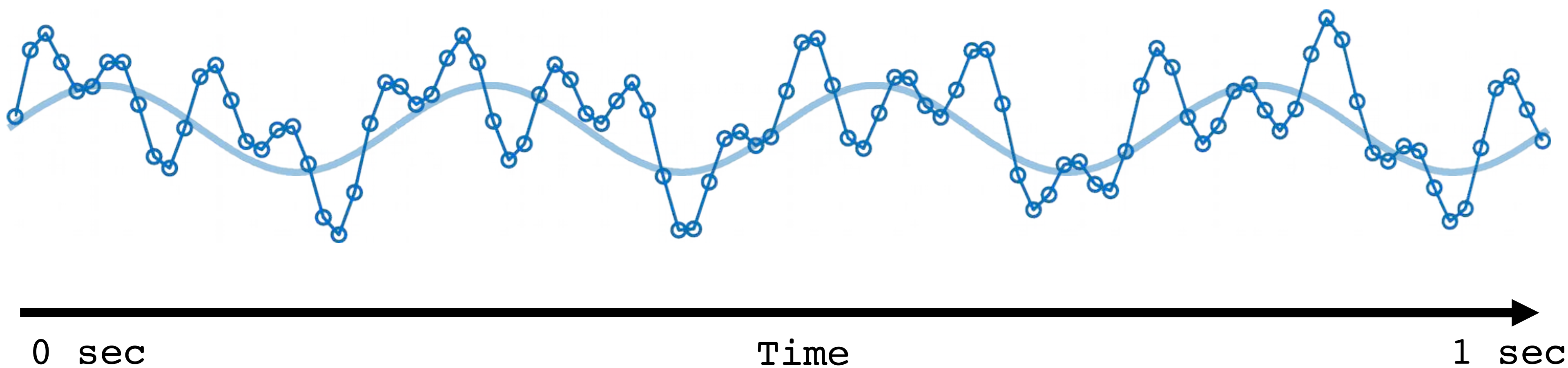

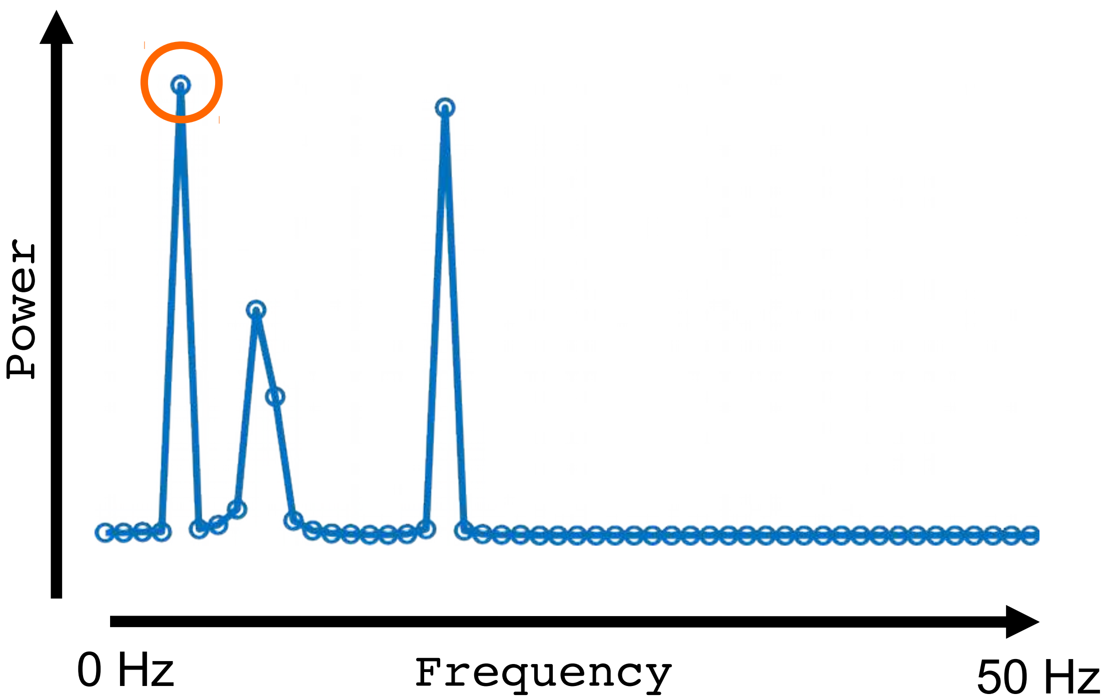

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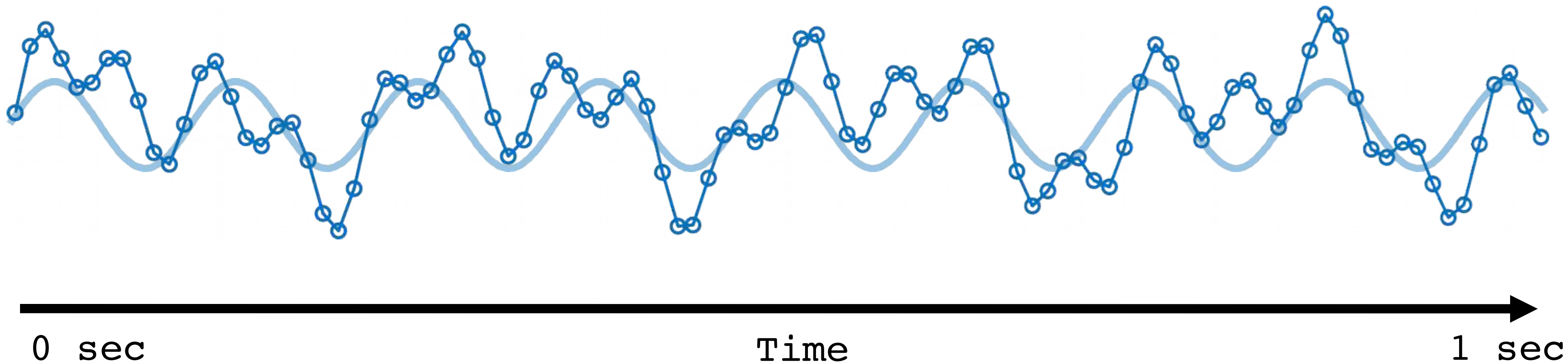

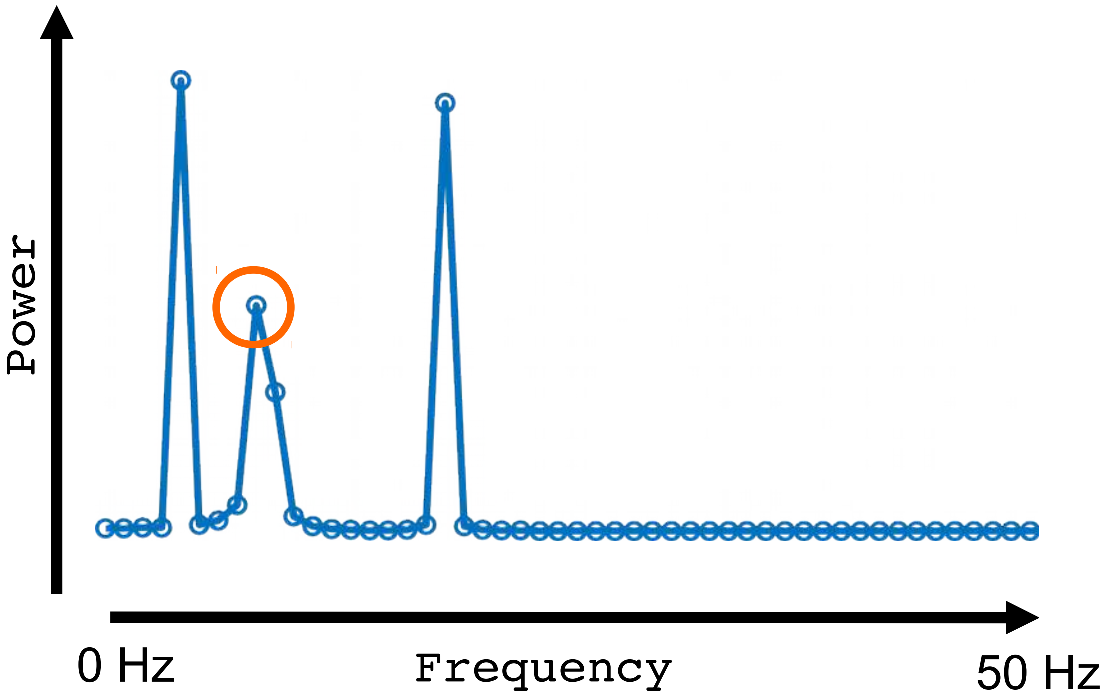

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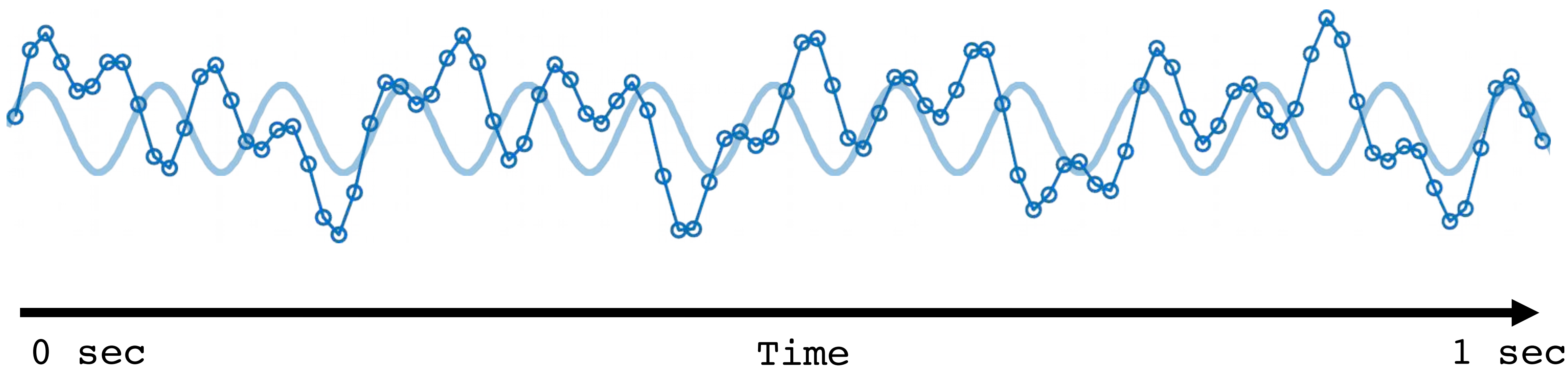

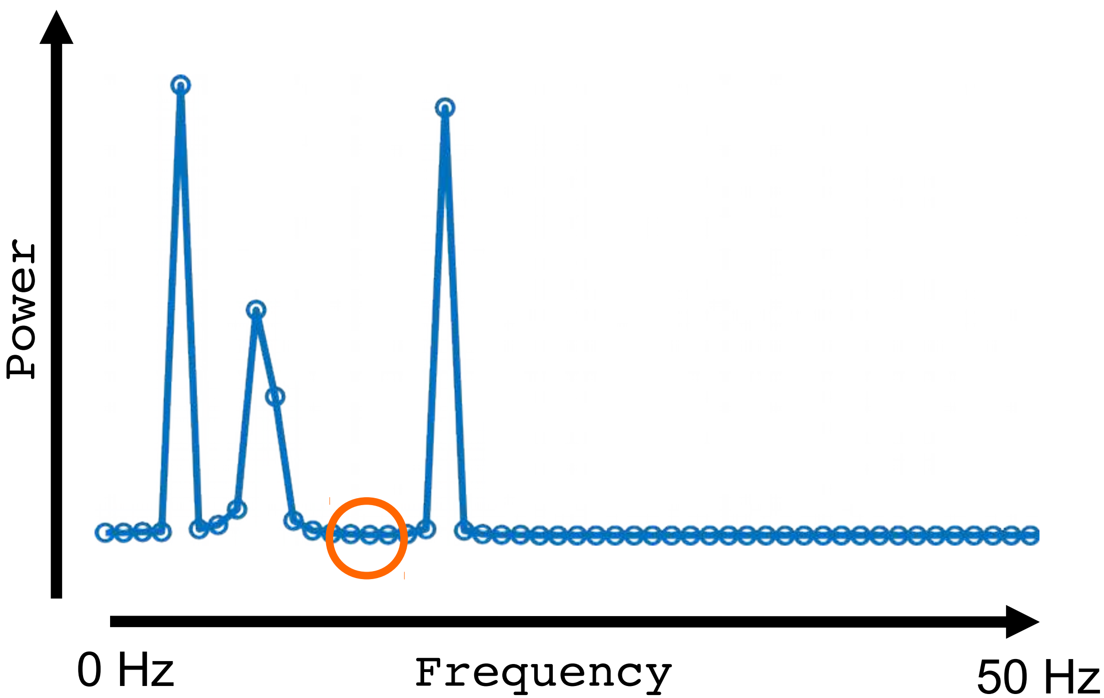

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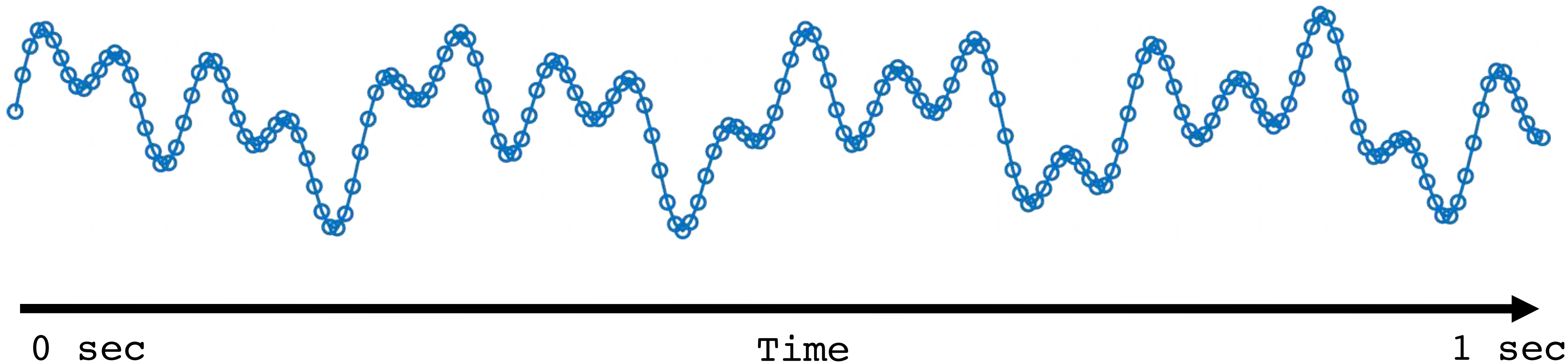
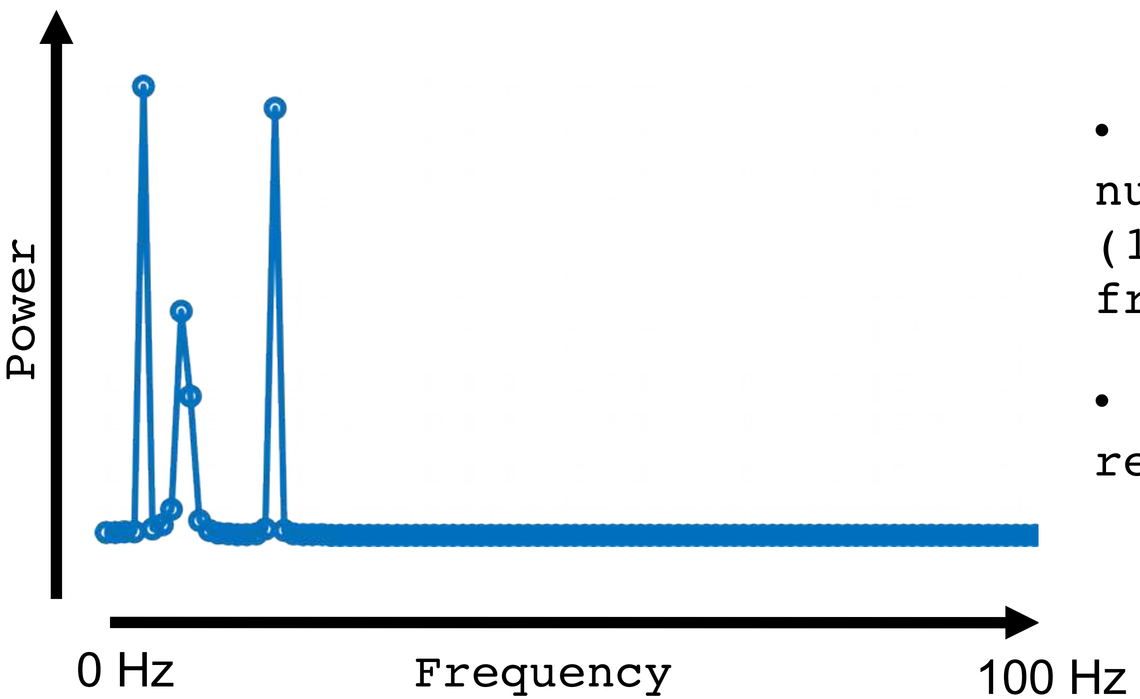
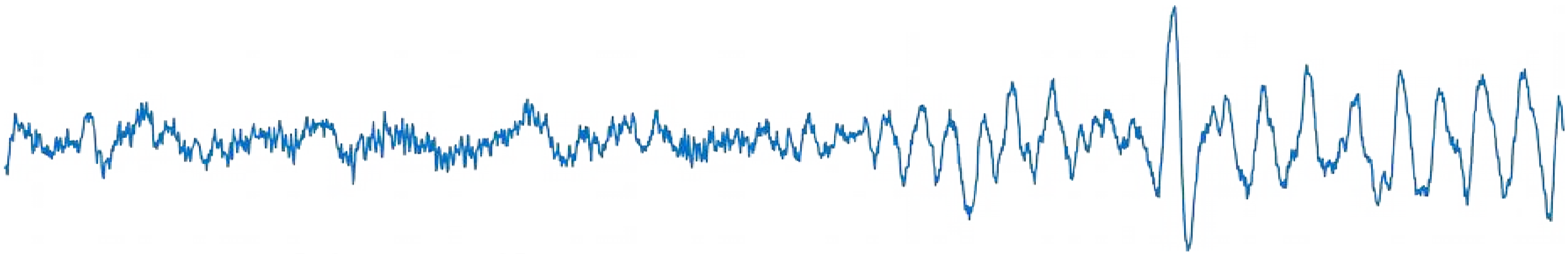
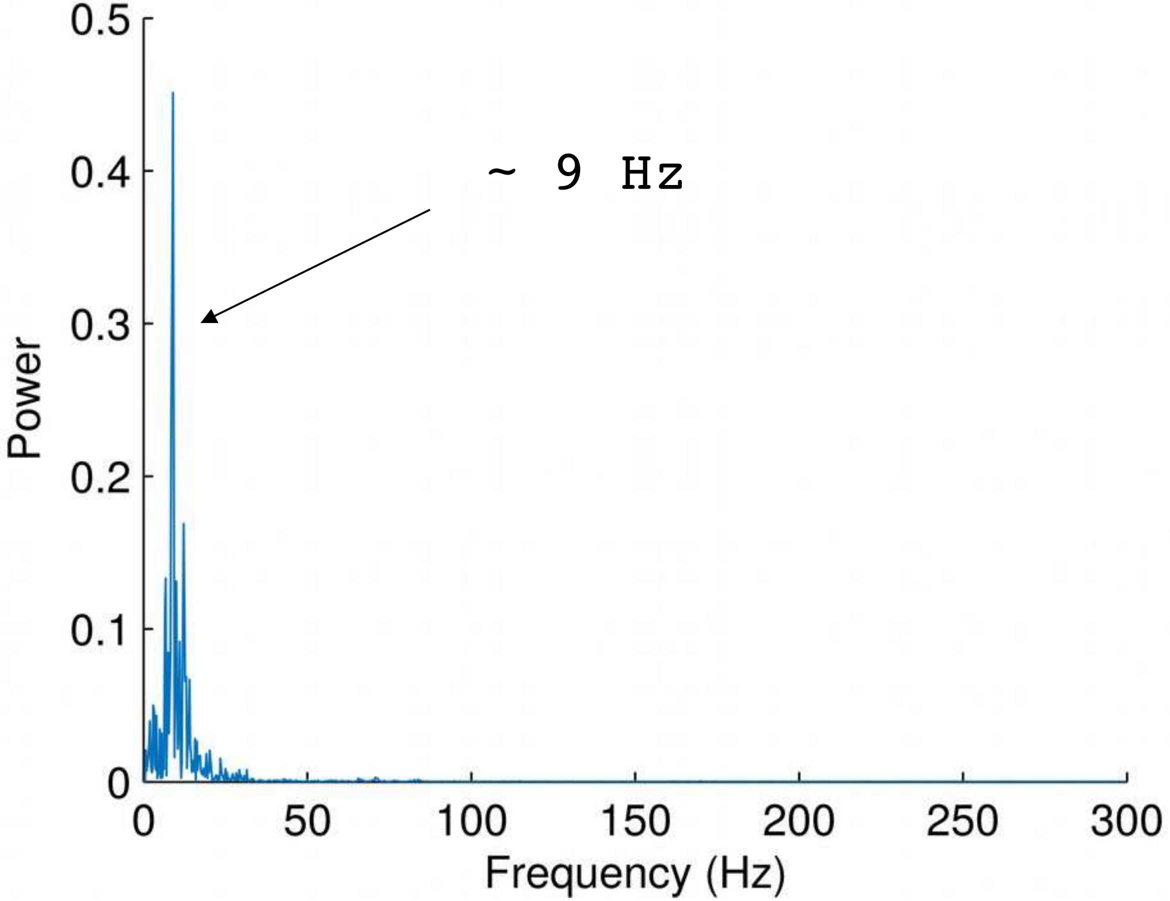




- Number of samples in time = number of samples in frequency (1/2 without 'negative frequencies')
- Higher sampling rate can resolve higher frequencies

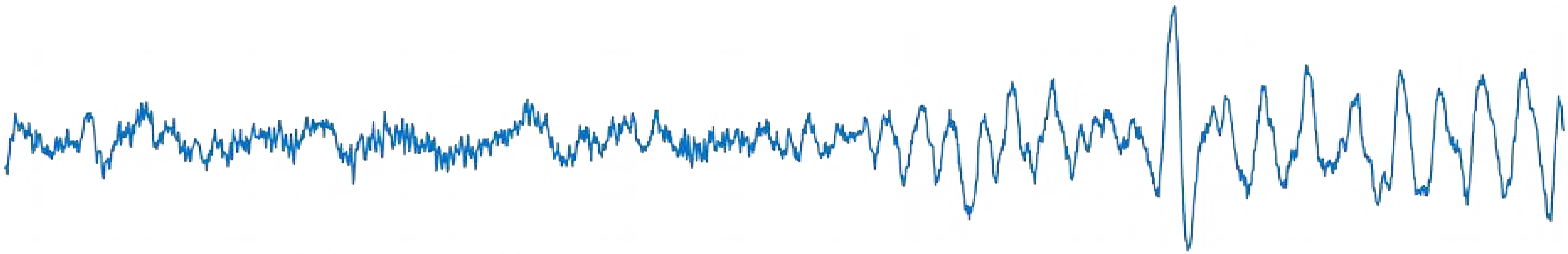
Fourier Transform

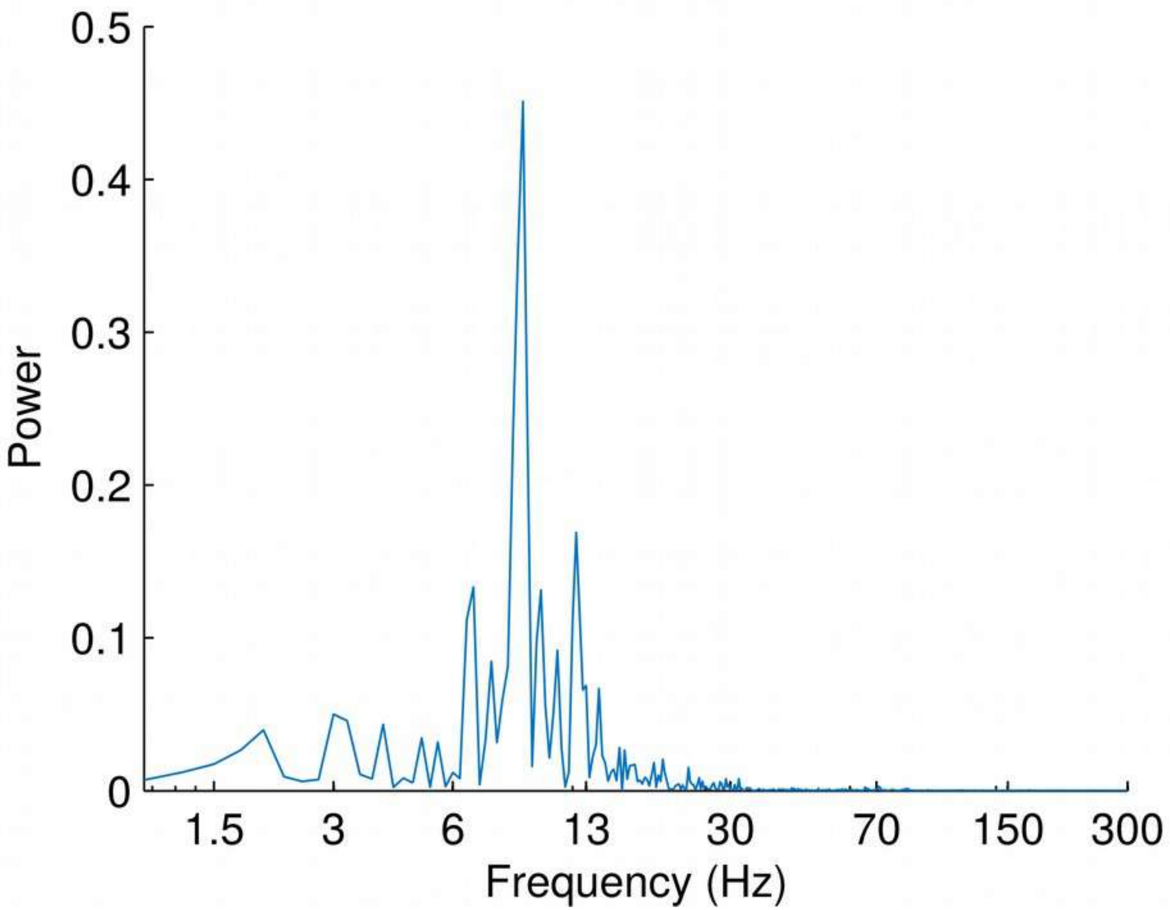




- We can see a peak in the alpha band (8-12 Hz)

Fourier Transform





- We can see a peak in the alpha band (8-12 Hz)
- Sometimes helpful to display frequency axis in log-scale (see next)

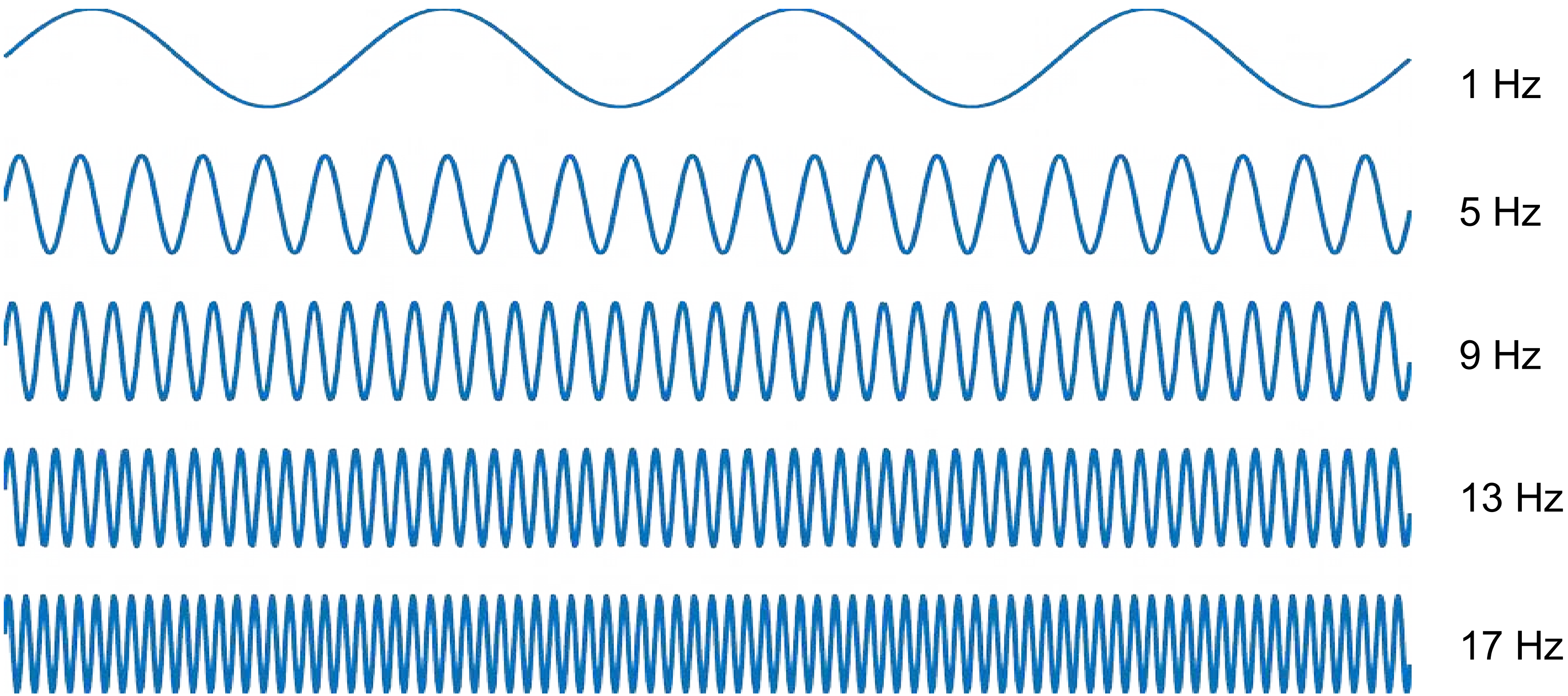
Linear- vs. Log-scaled spectrum

Compare:

1 or 2 cycles per second

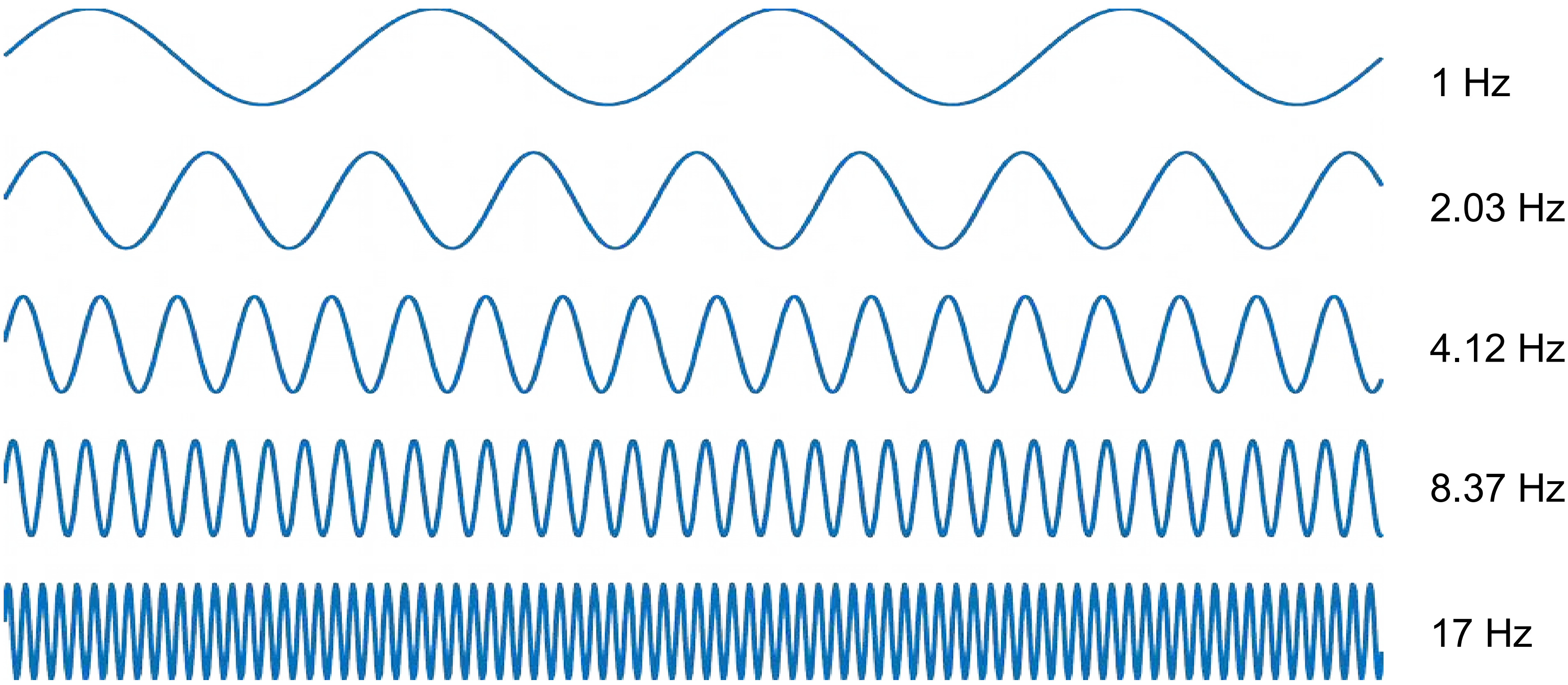
50 or 51 cycles per second

Linear- vs. Log-scaled spectrum



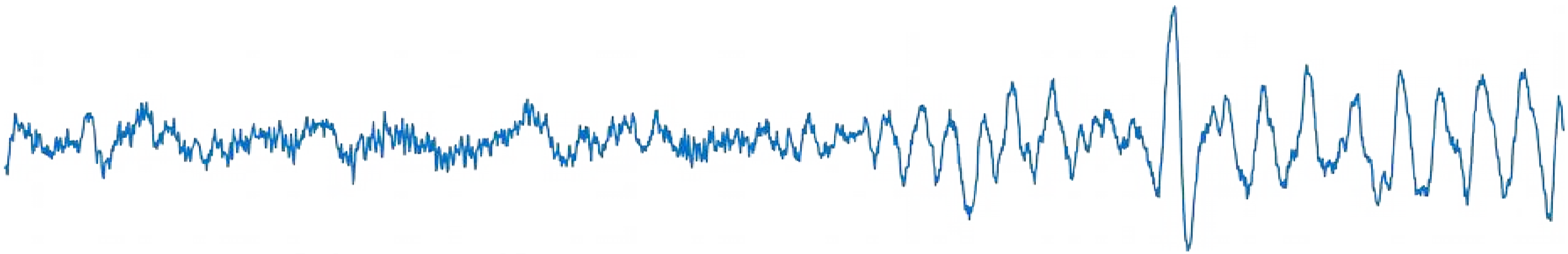
Sinusoids linearly spaced from 1 Hz to 17 Hz

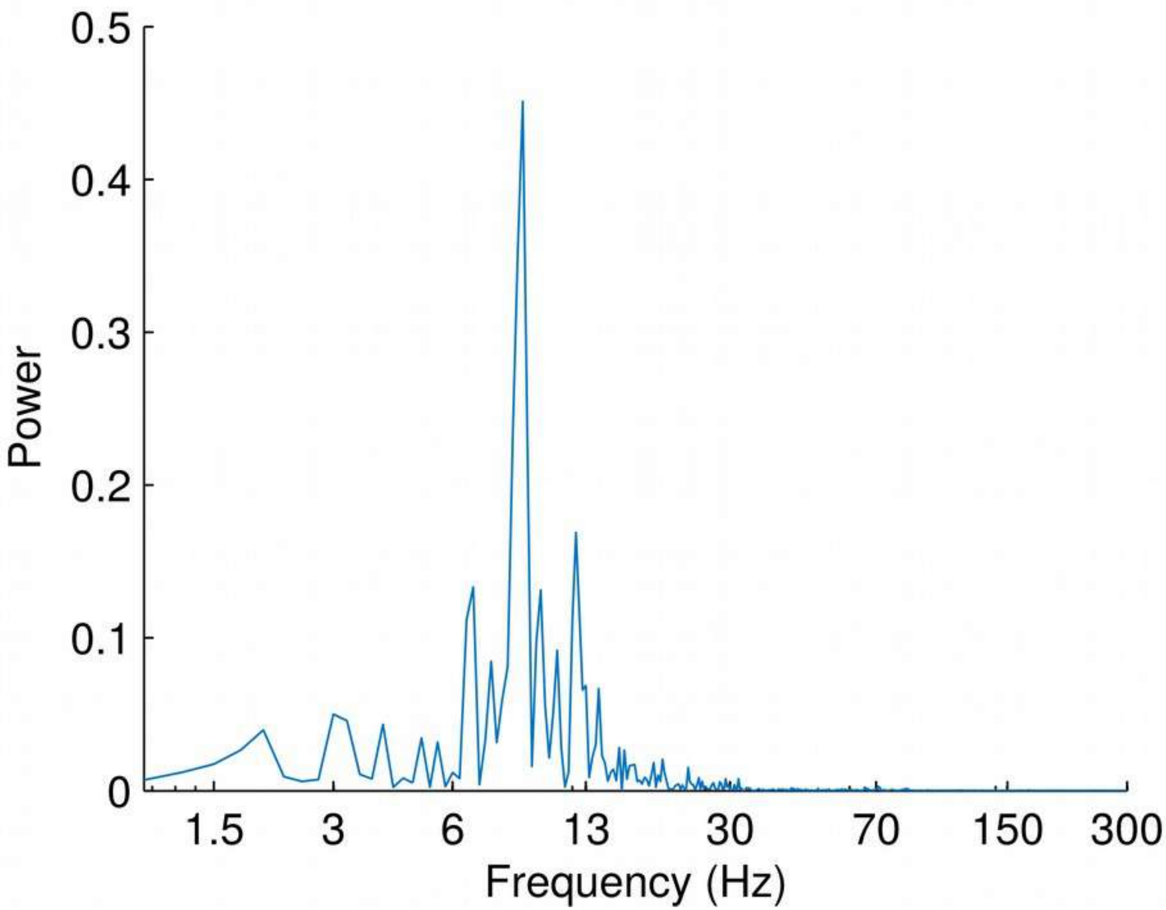
Linear- vs. Log-scaled spectrum



Sinusoids log spaced from 1 Hz to 17 Hz

Fourier Transform





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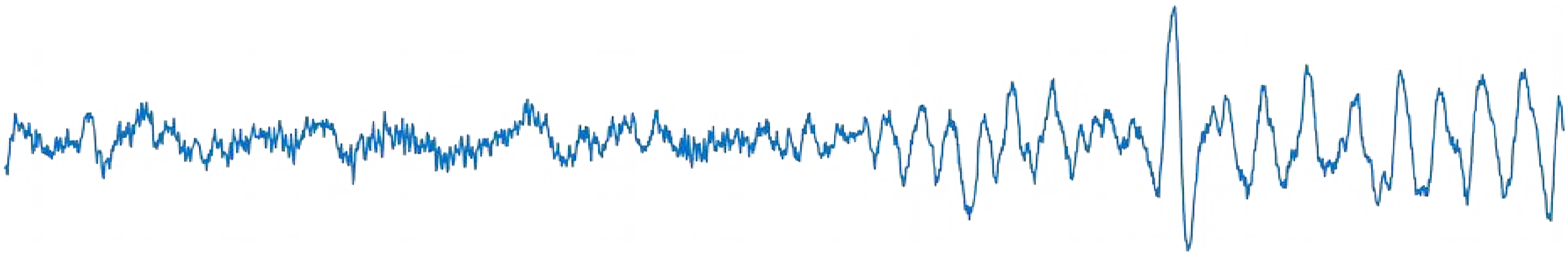

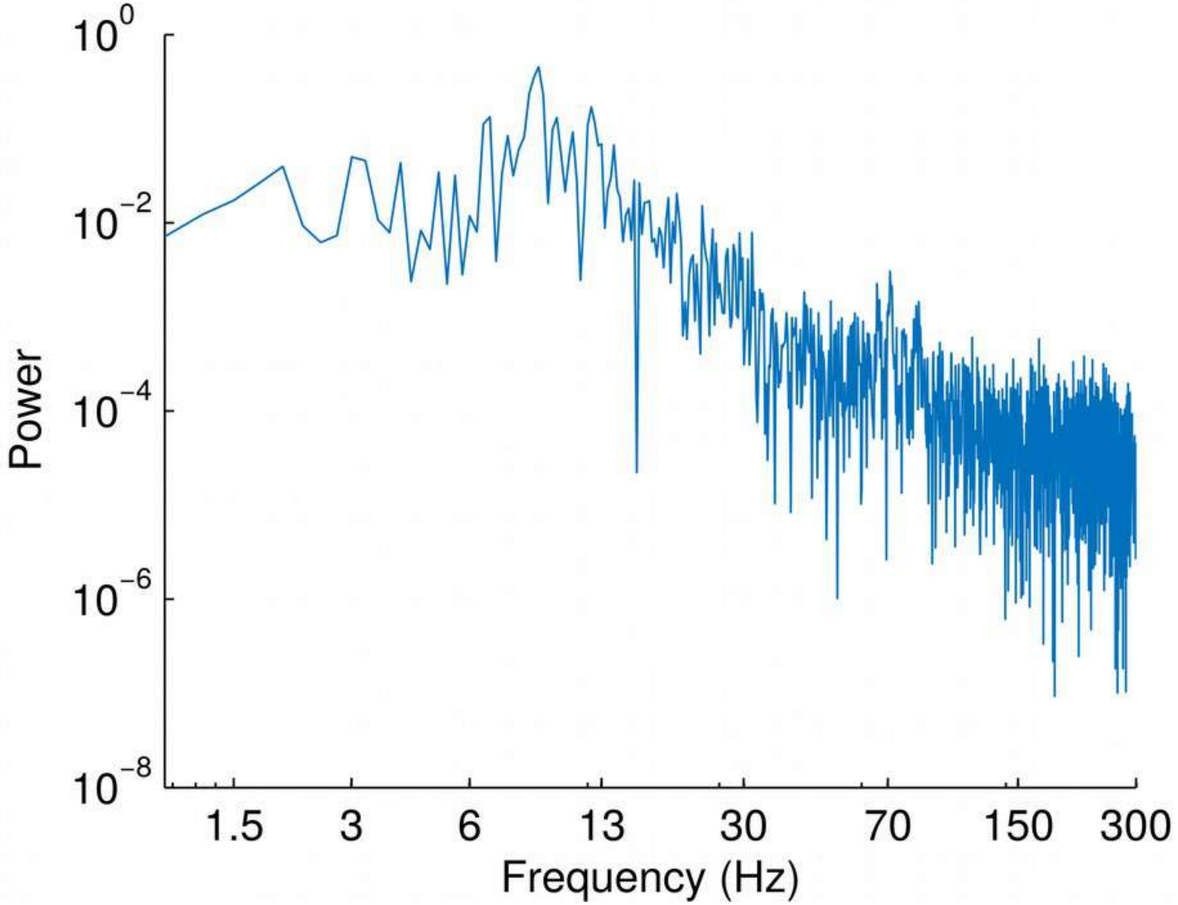

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- Power usually decreases at higher frequencies
  - 1/f phenomenon
  - Log-scaling the power axis

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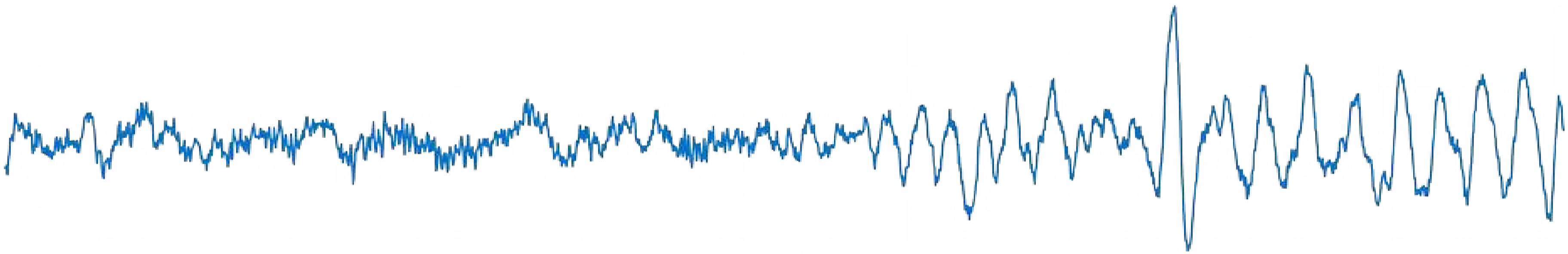

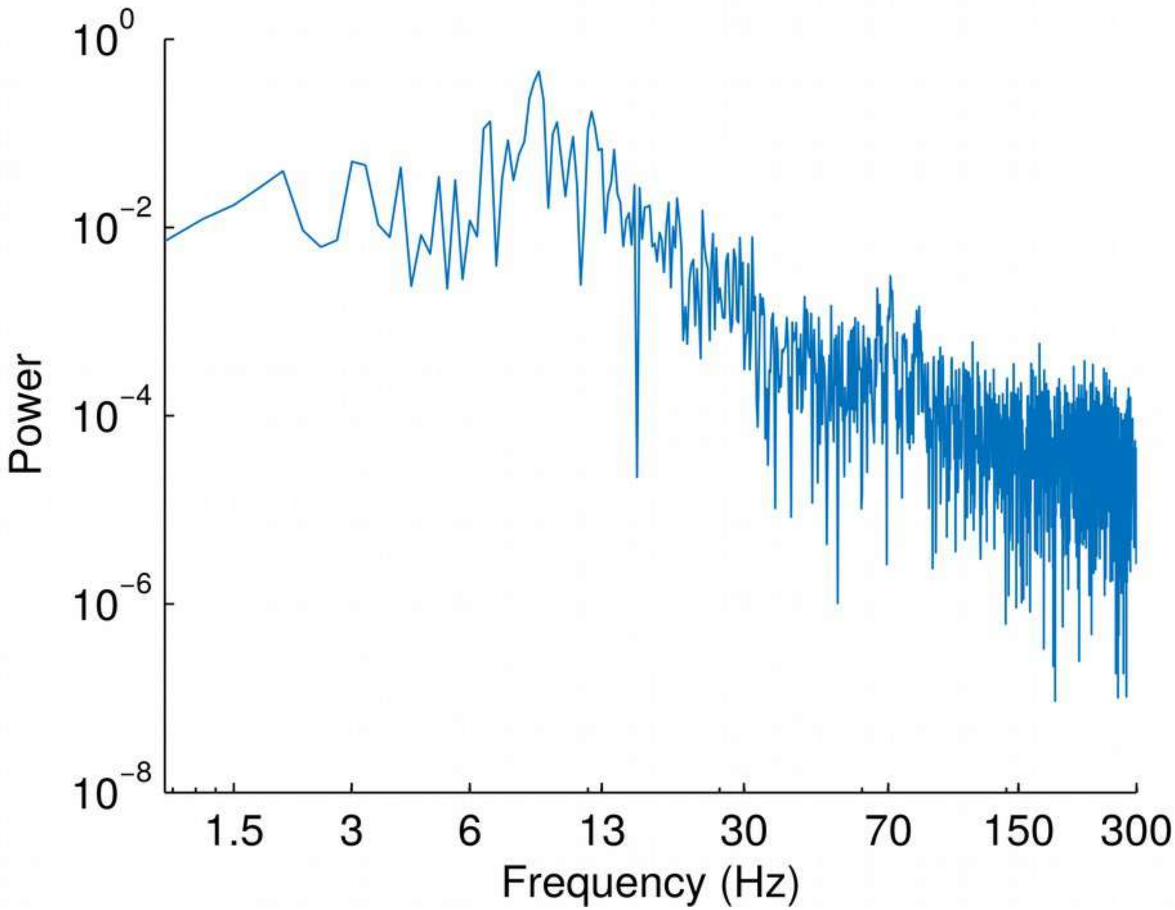

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  - Log-scaling the power axis
- Raw FFT can be very noisy
  - see next

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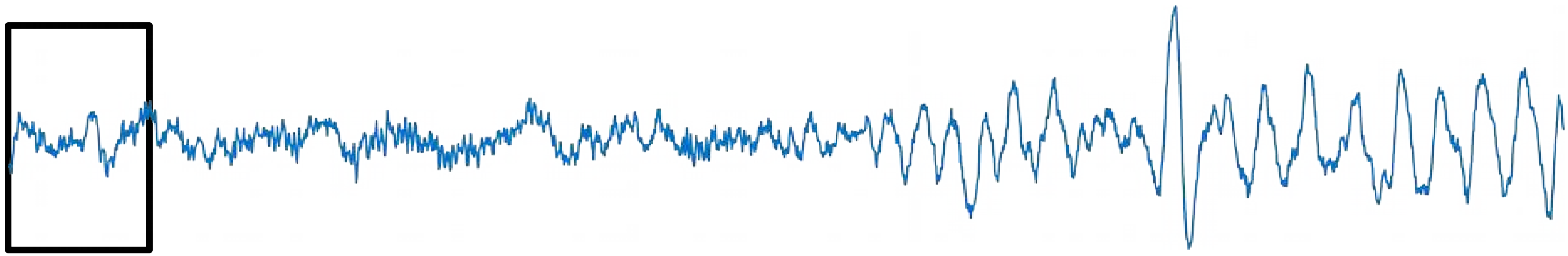
Power spectral density



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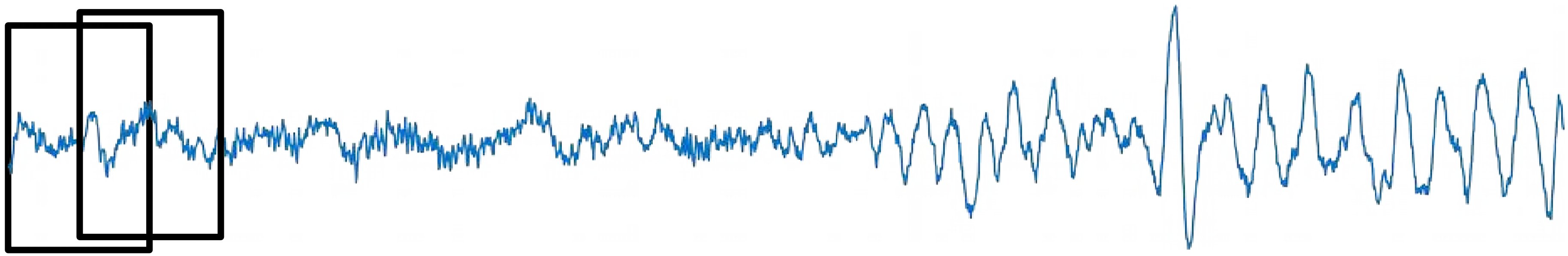

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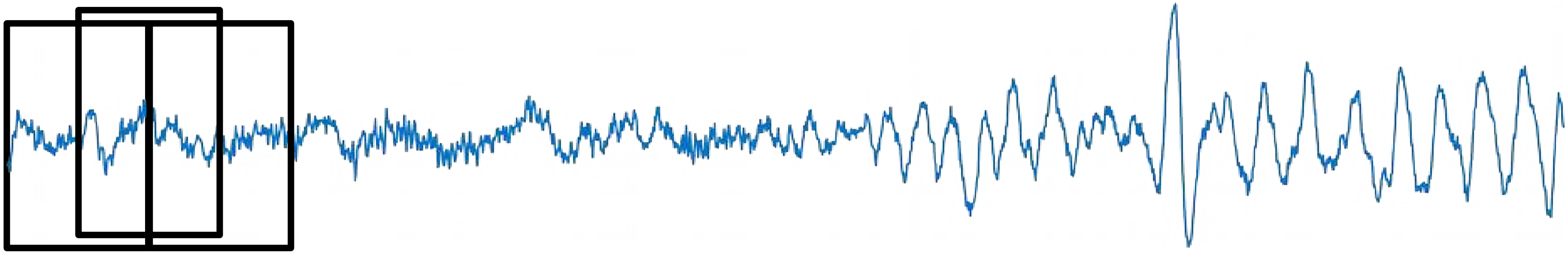

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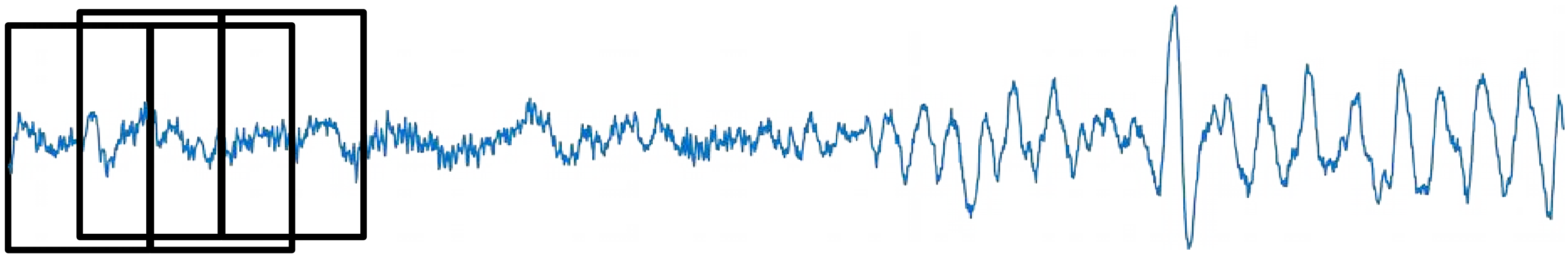

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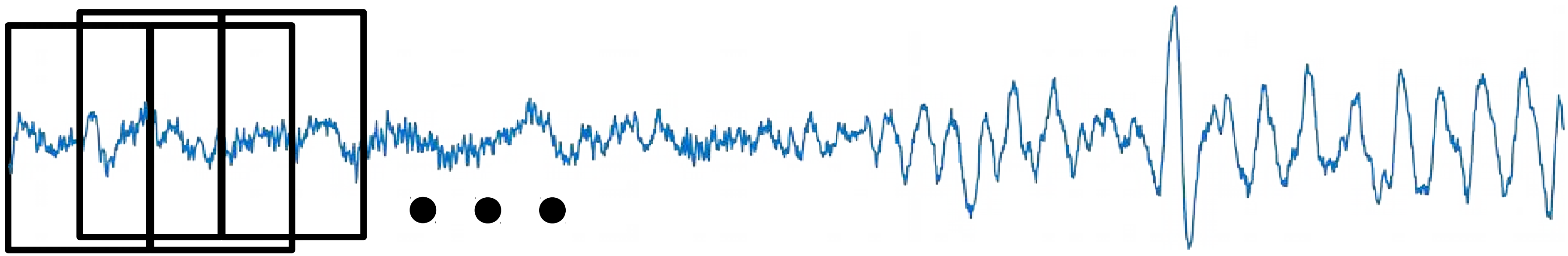

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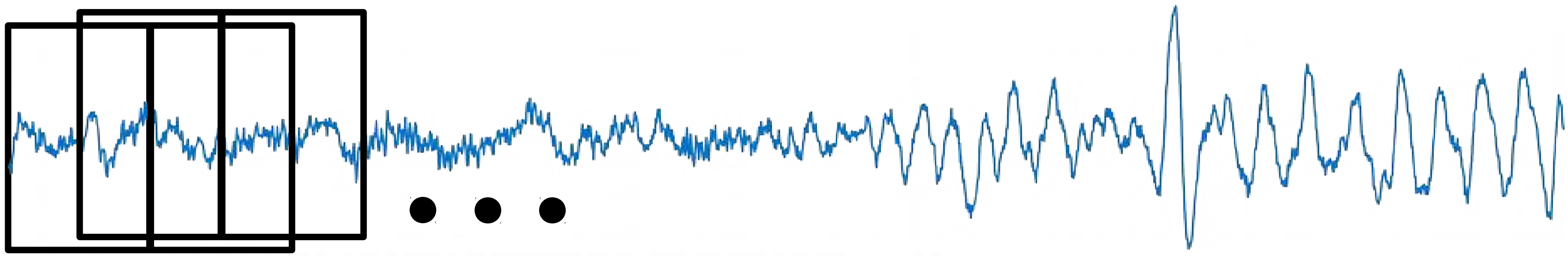
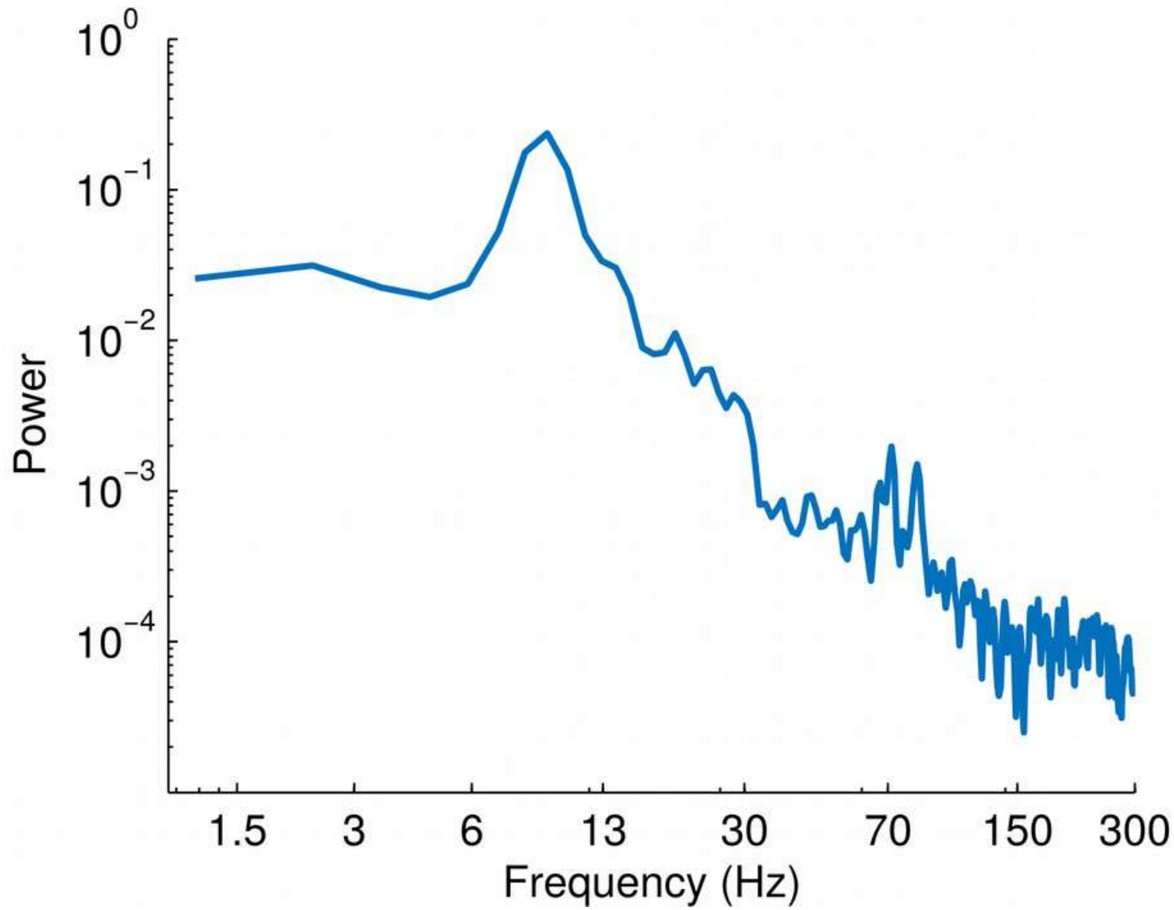
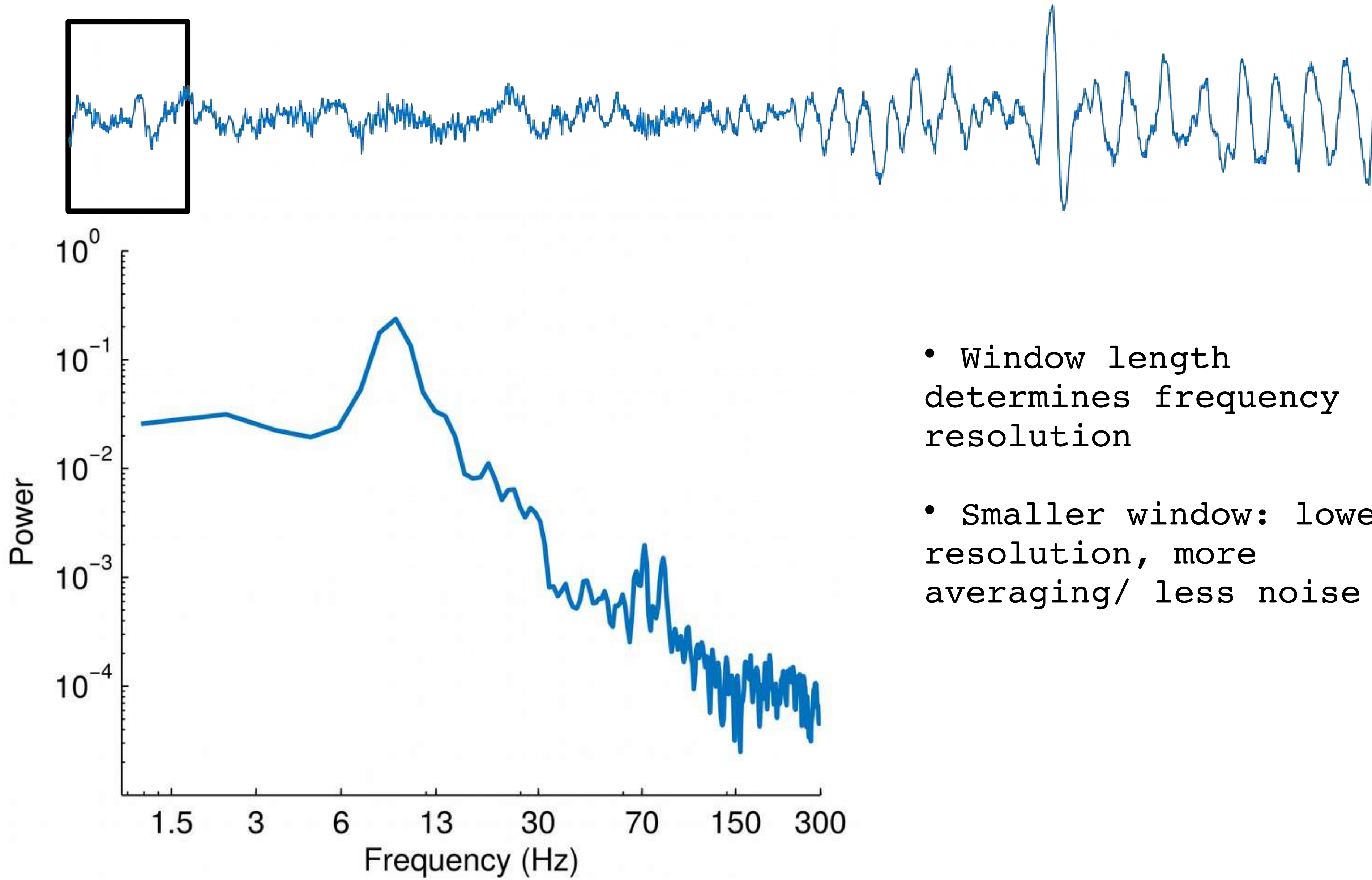




- Repeated averaging over sliding windows decreases noise in the estimation

- 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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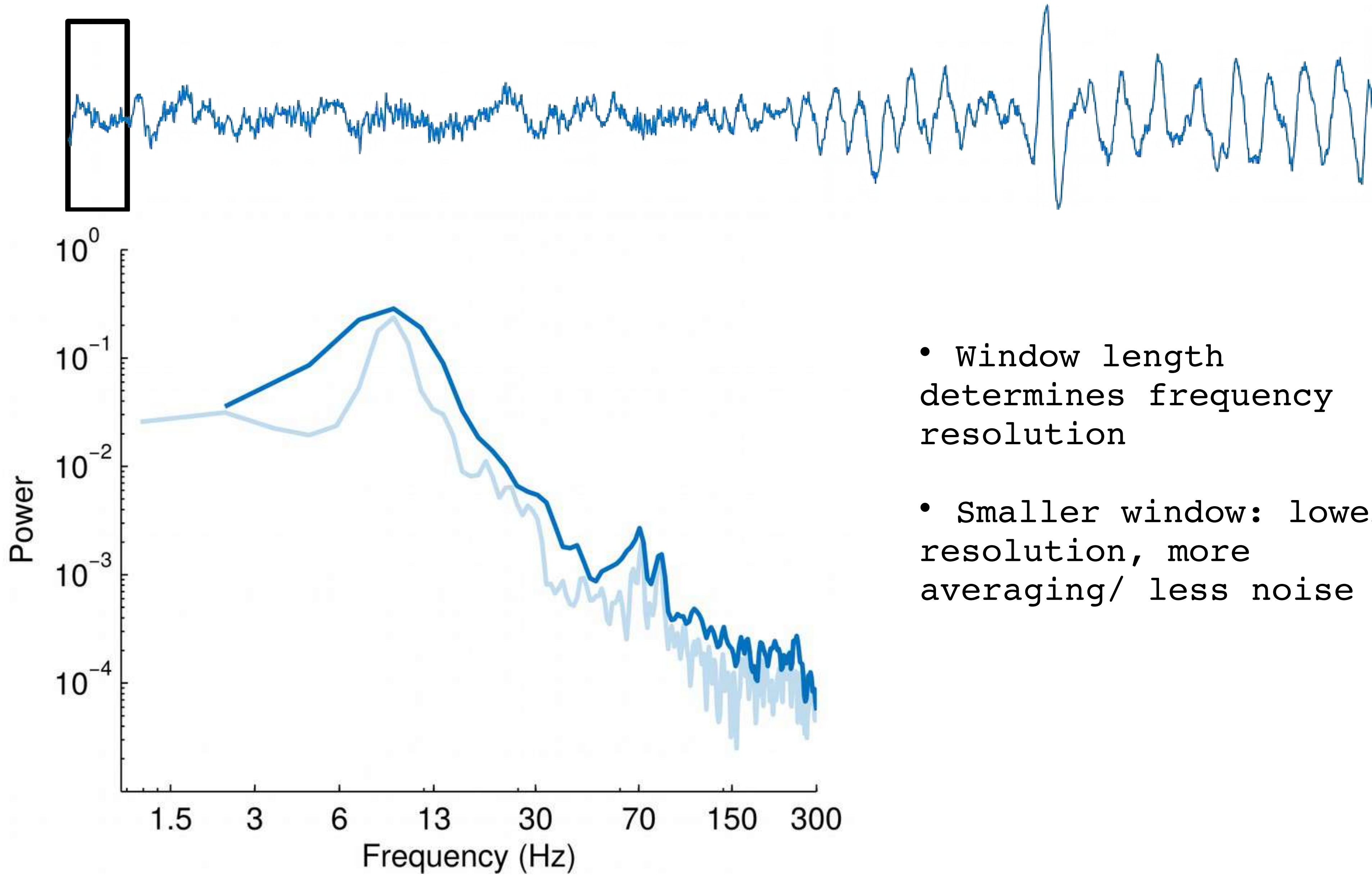

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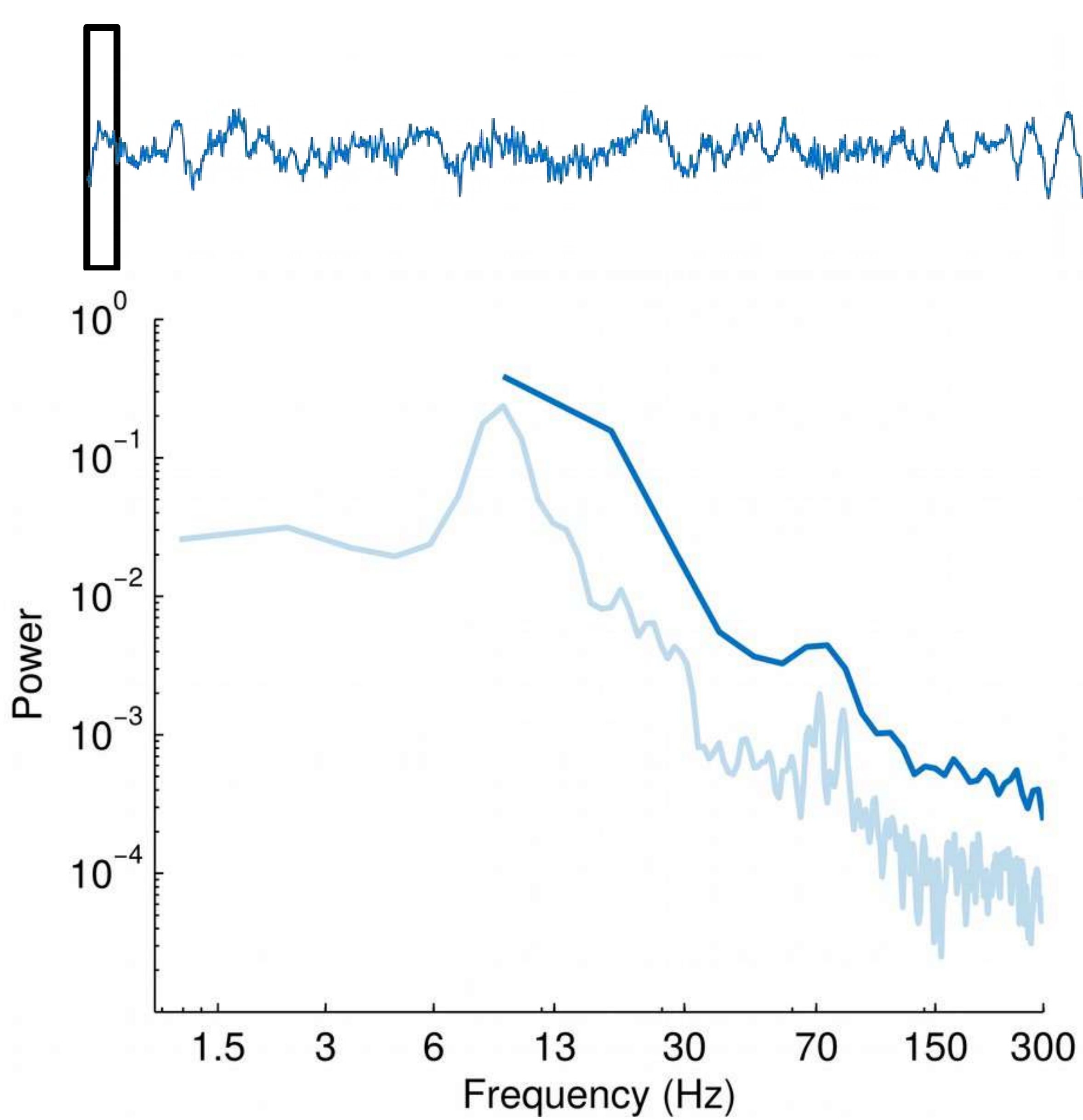

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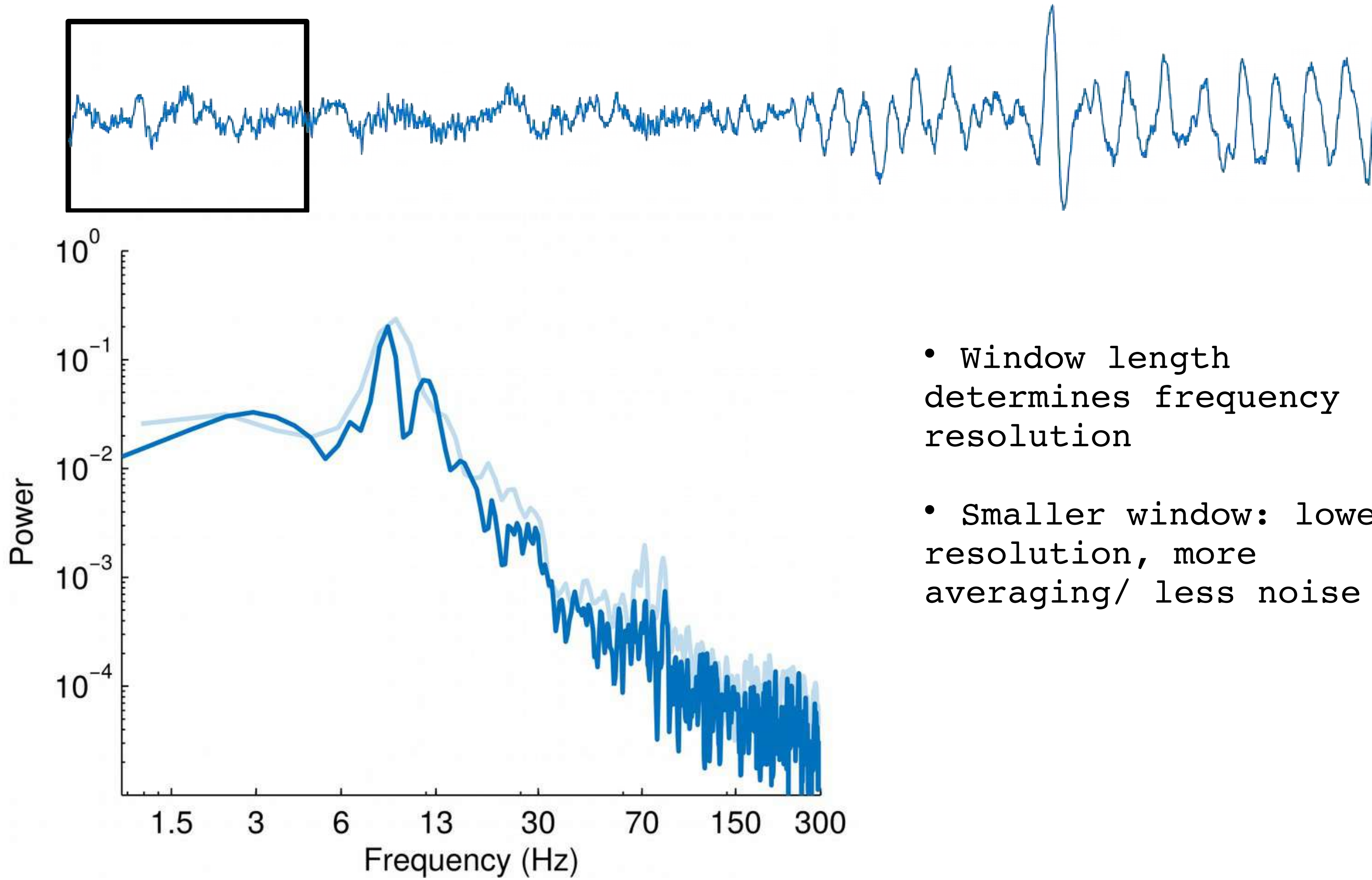

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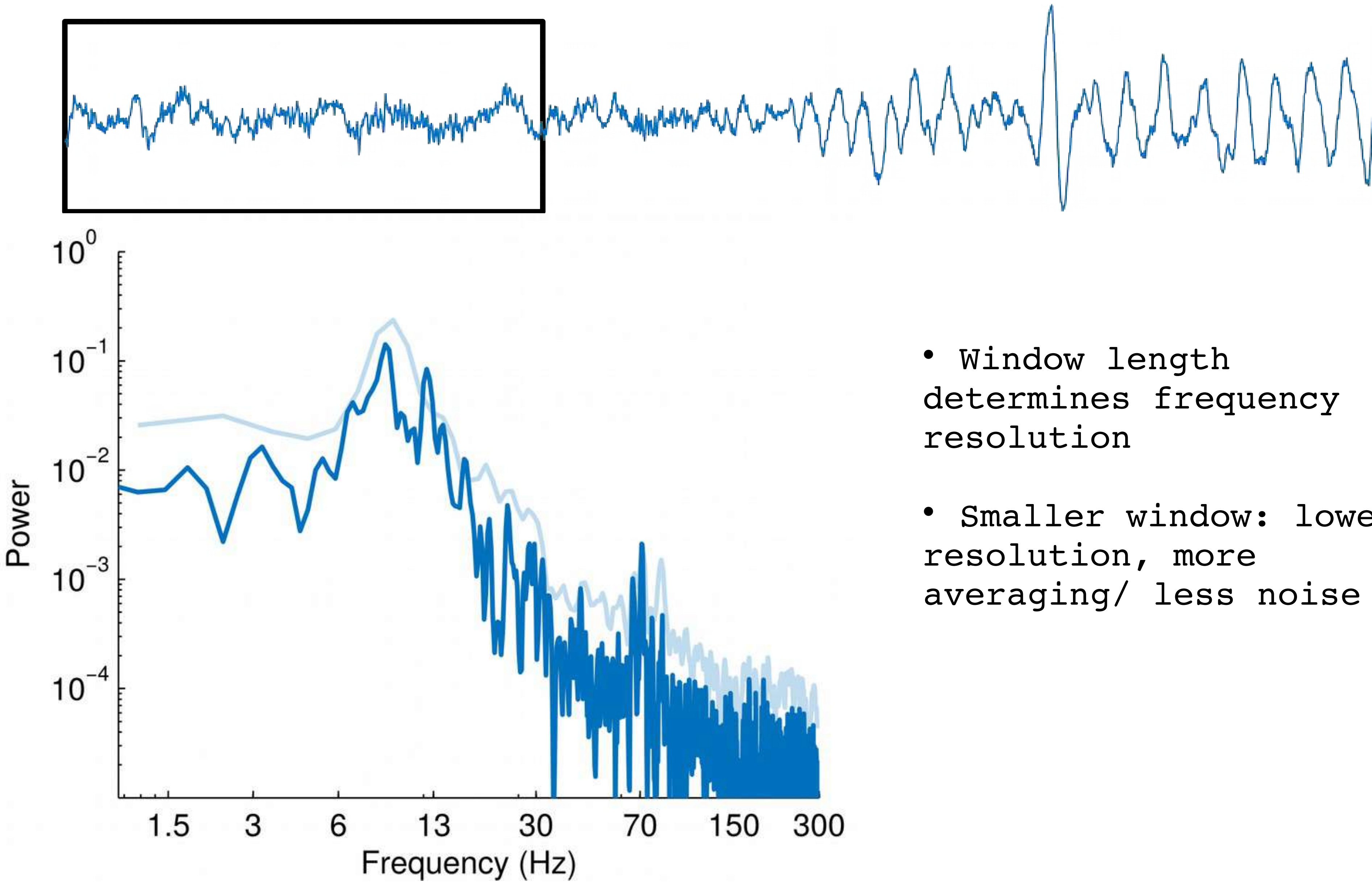

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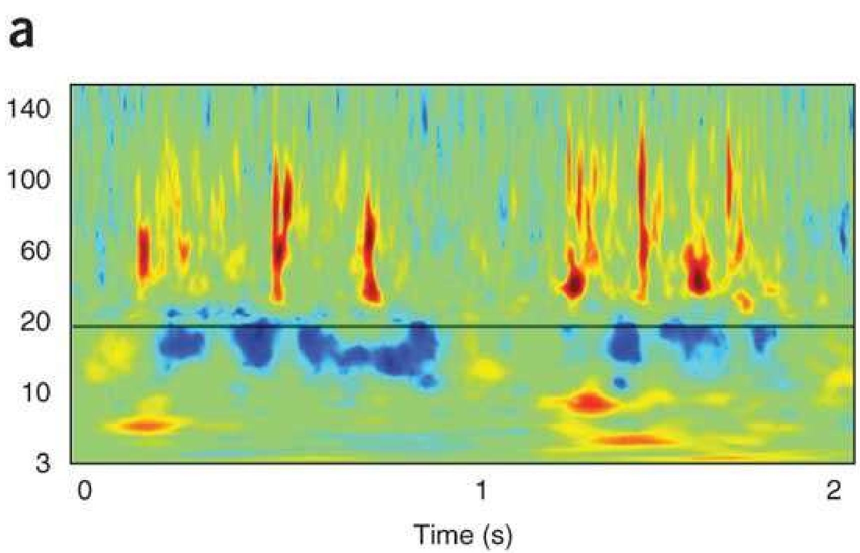
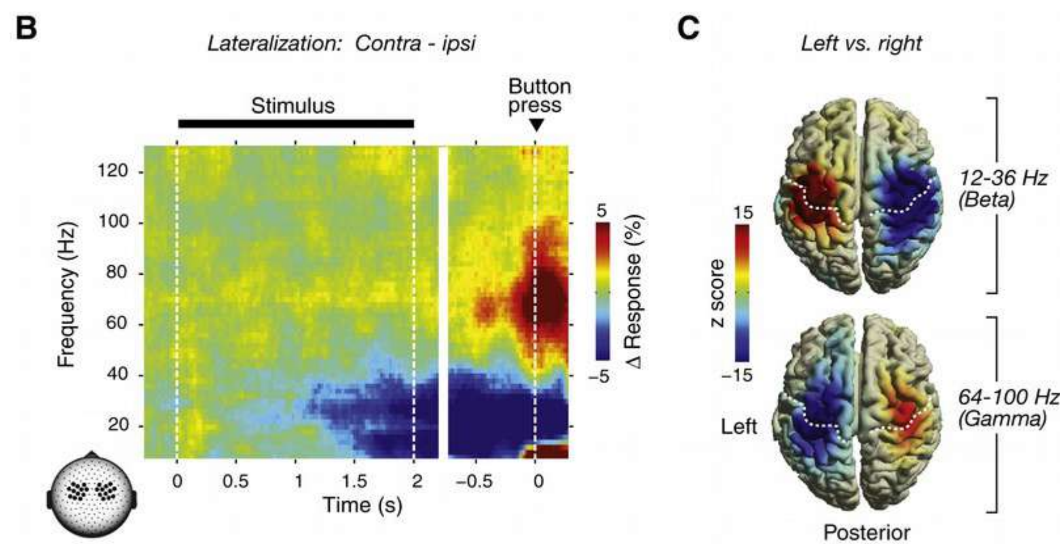
Time-frequency analysis

- Analysis of transient oscillatory activity
- Examples: auditory cortex / motor cortex
- Event-related synchronization vs. desynchronization

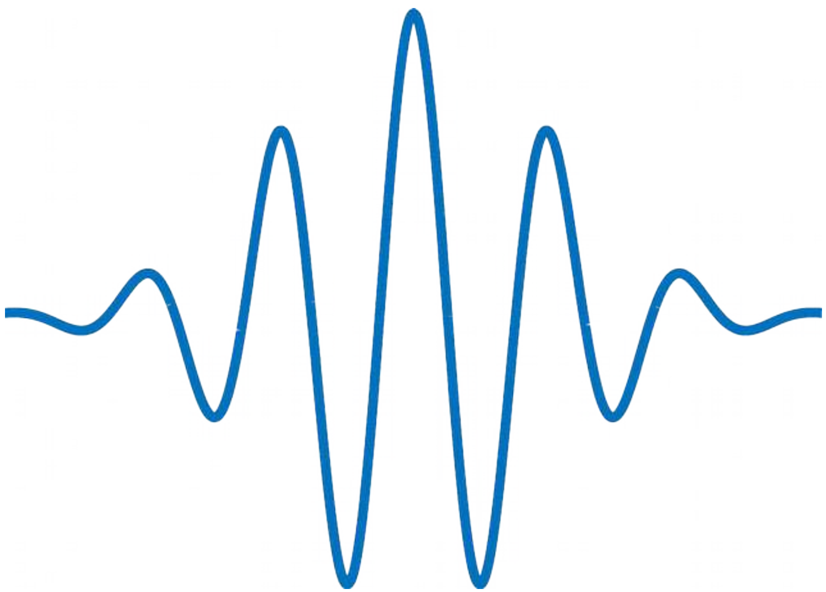


Spoken sentence, auditory cortex responses (Fontolan, Morillon et al, 2014)



Build-up of choice predictive activity in motor cortex (Donner et al., 2009)

Wavelet transform

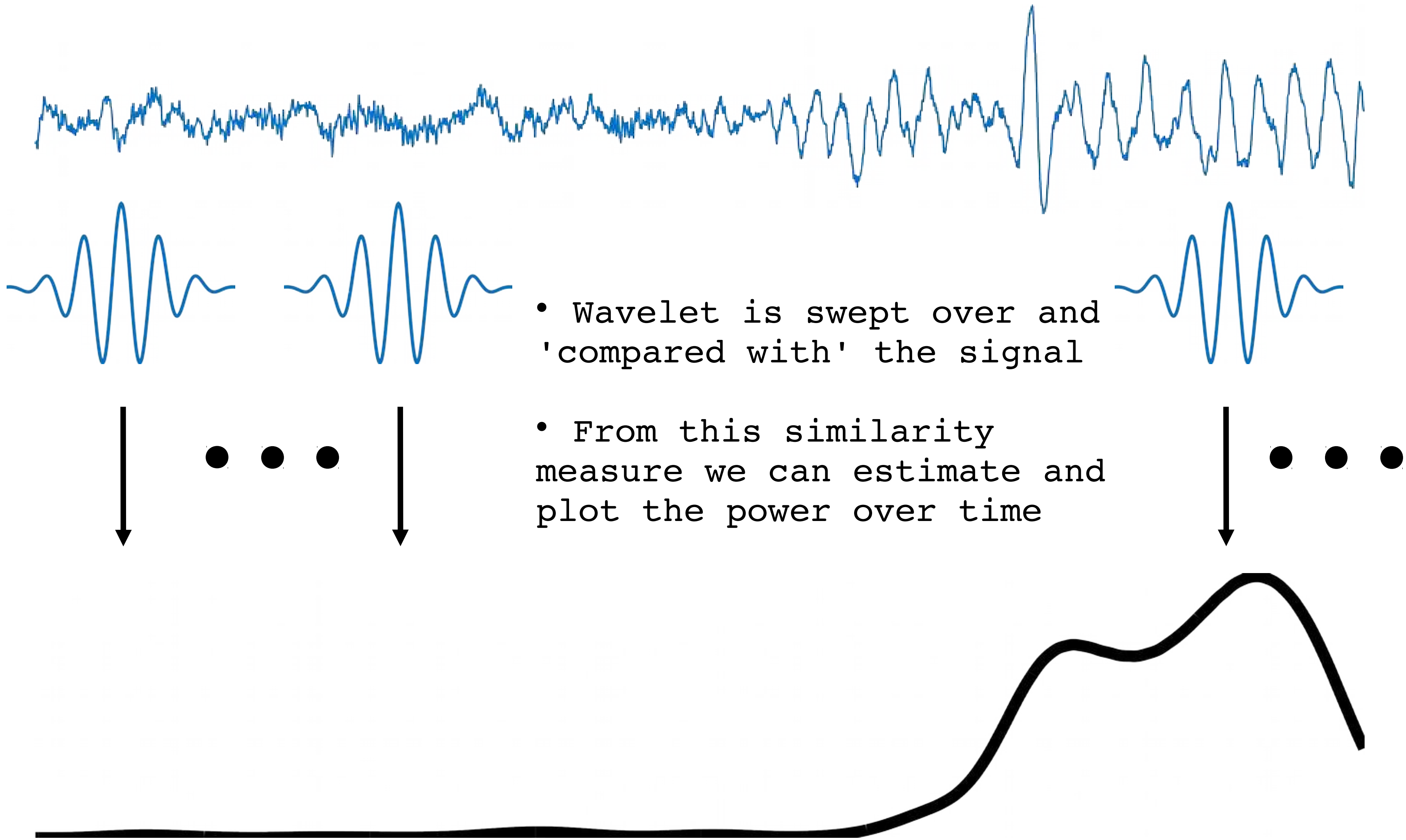


Morlet wavelet (used in Brainstorm):

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

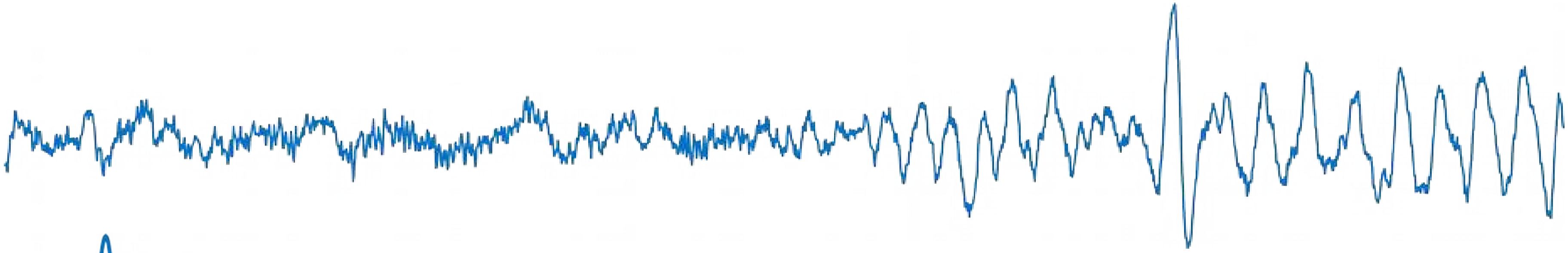
- Serves as a 'template'

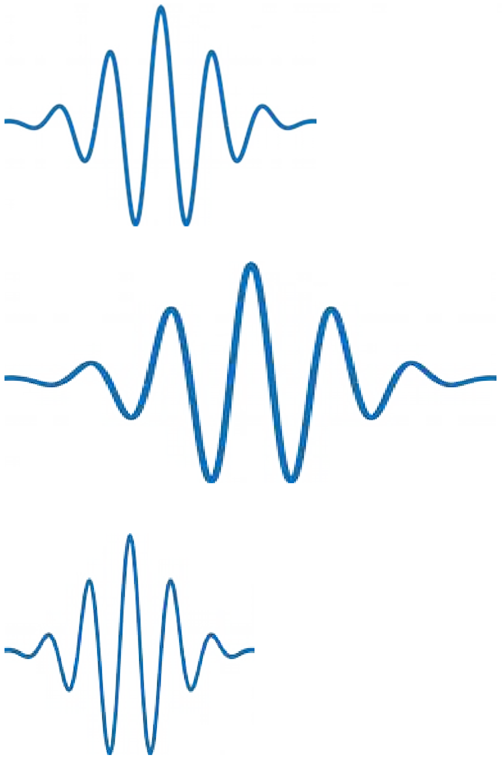
Wavelet transform



- Wavelet is swept over and 'compared with' the signal
- From this similarity measure we can estimate and plot the power over time

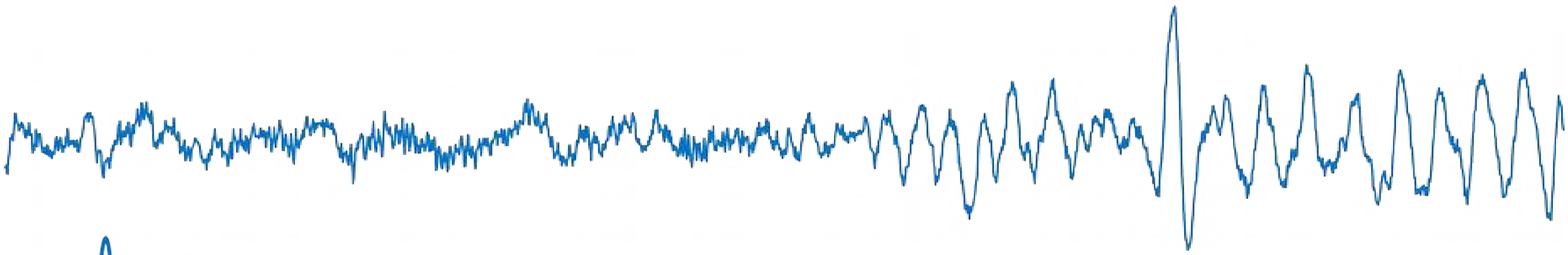
Wavelet transform

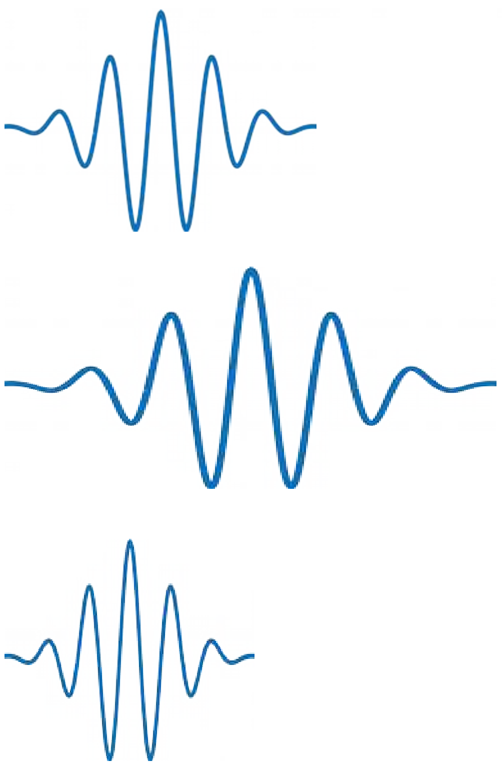




- Wavelet is contracted and expanded to estimate power over different center frequencies

Wavelet transform



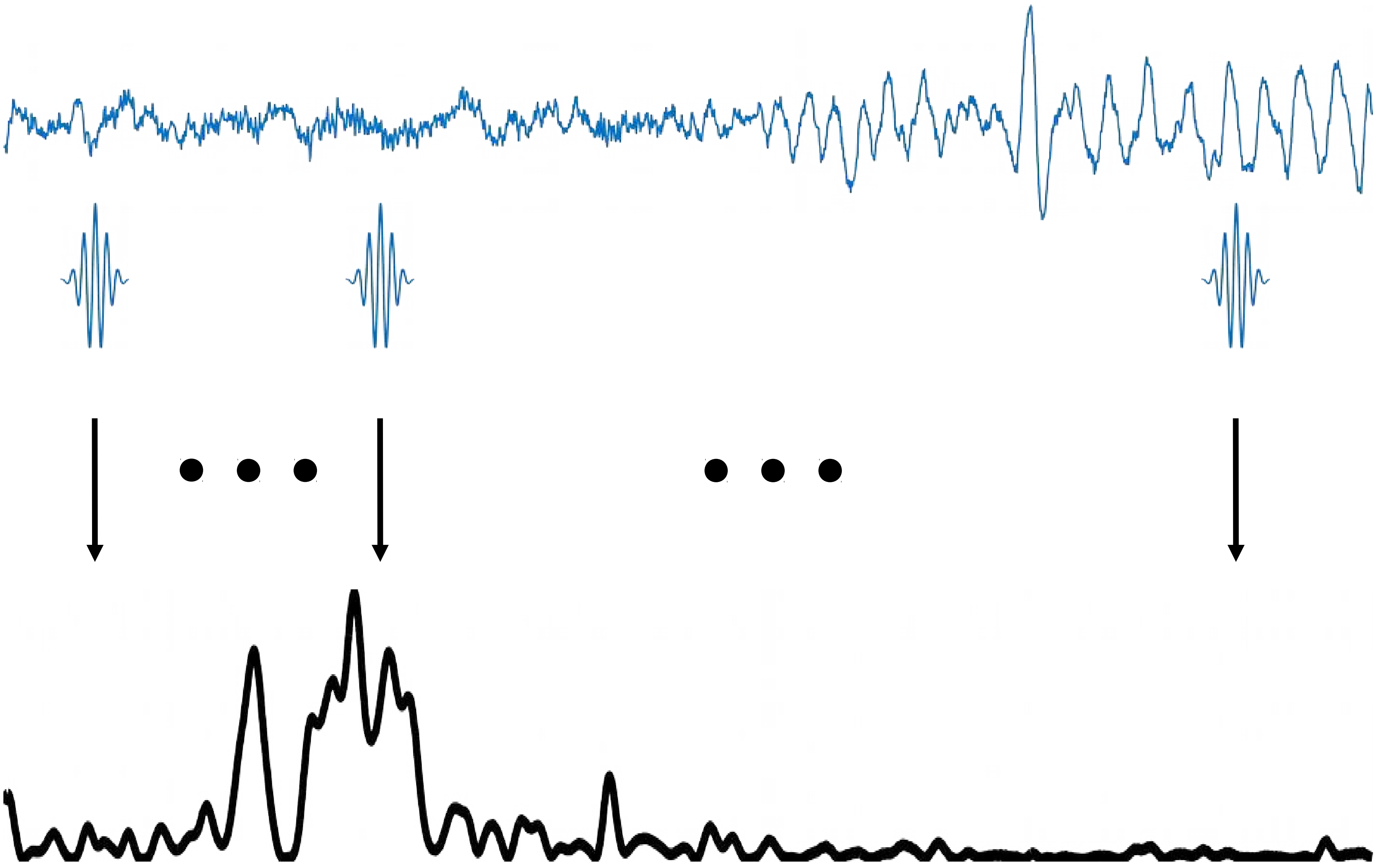


- Wavelet is contracted and expanded to estimate power over different center frequencies

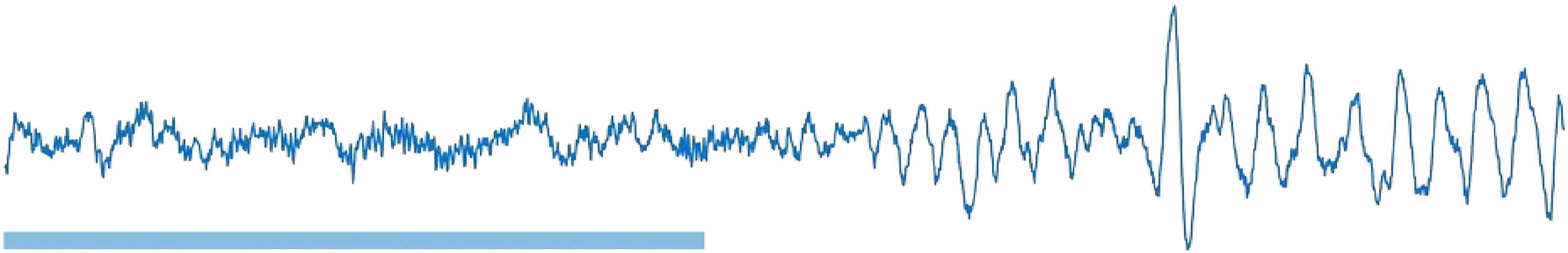
- Important: time and frequency resolution changes for different frequencies

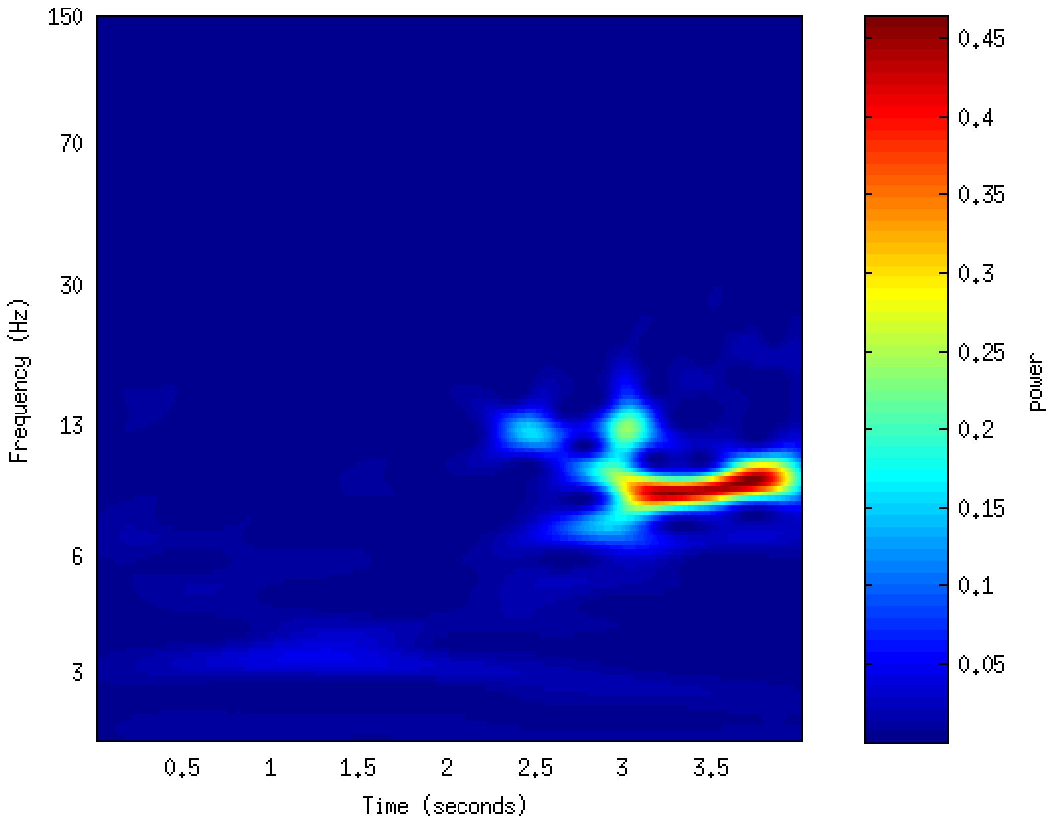
  - ➔ Compare with PSD window length

Wavelet transform



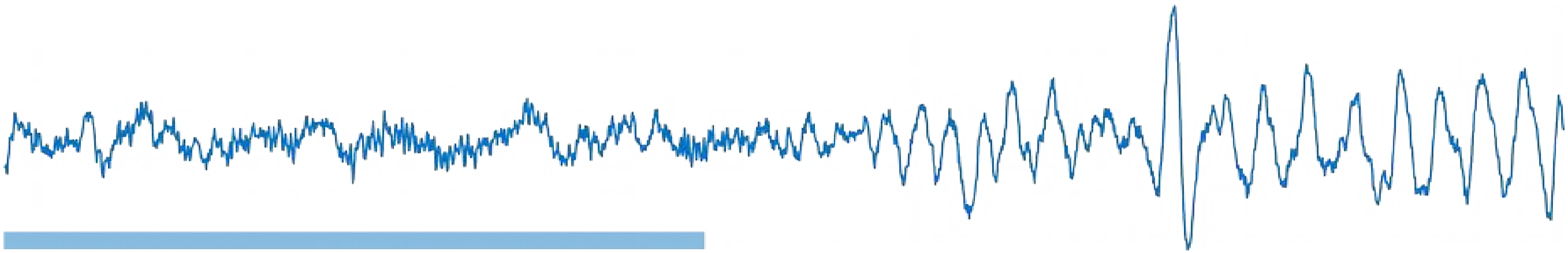
Wavelet transform

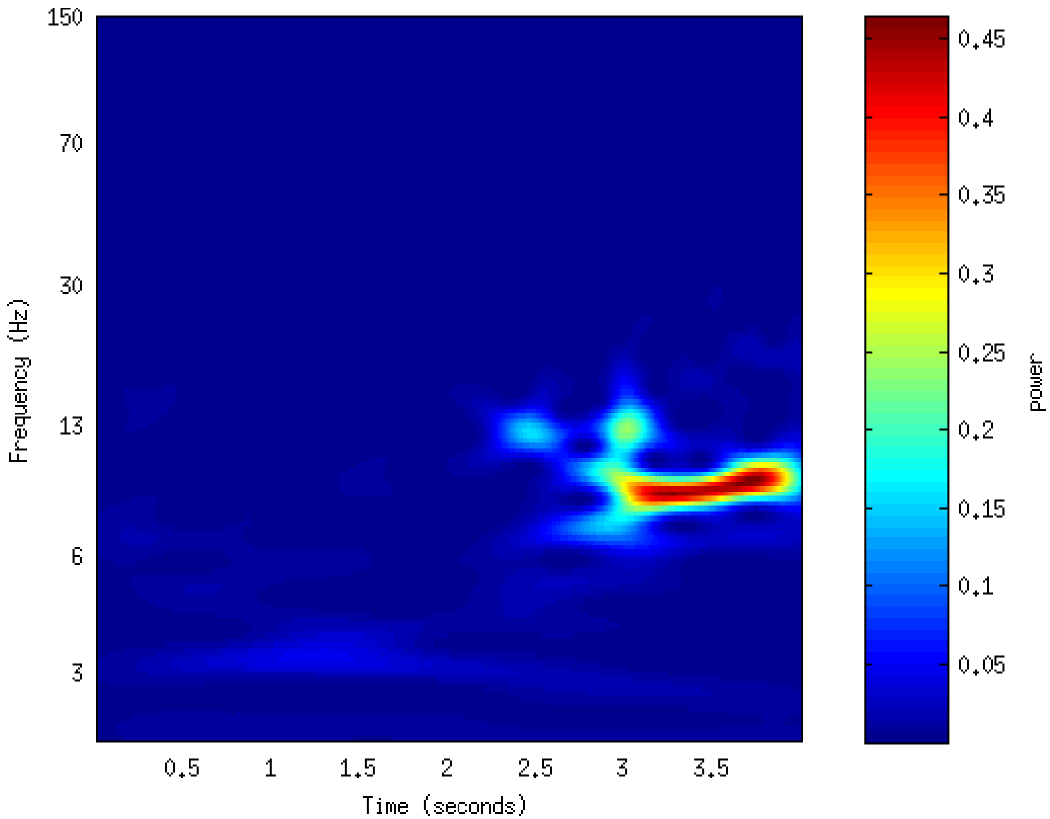




- Repeating this over a range of center frequencies produces a time-frequency map

Wavelet transform





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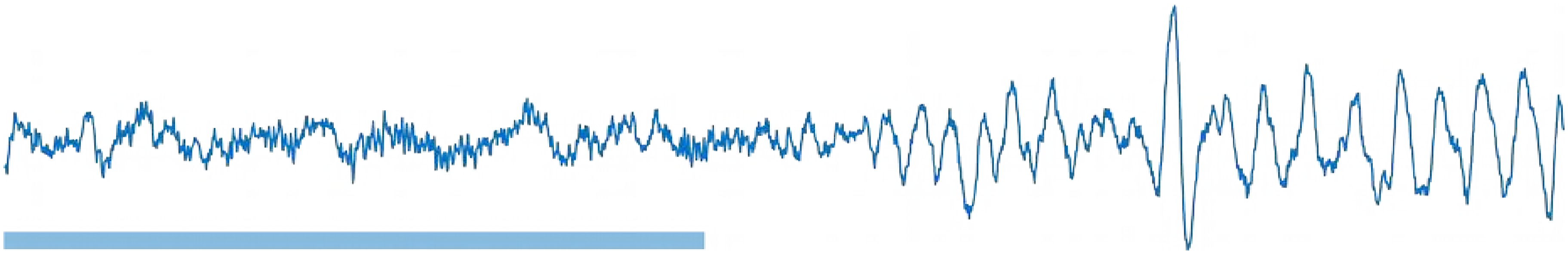
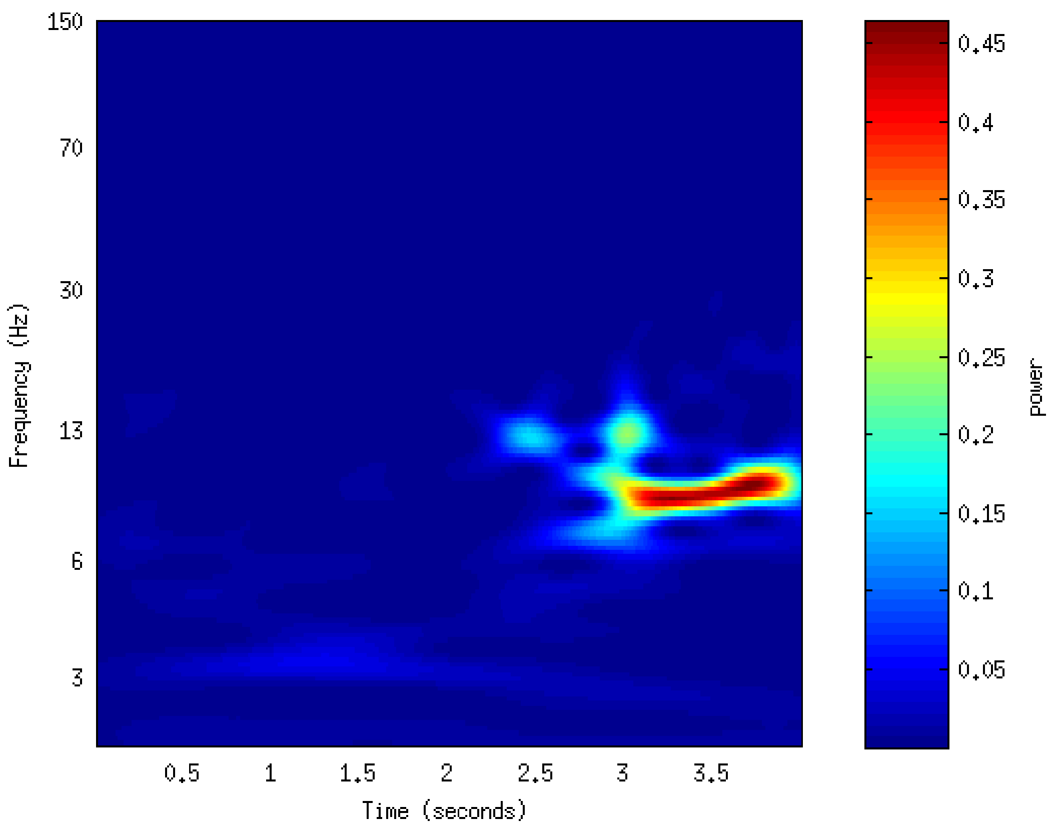
- Remember the 1/f phenomenon: high frequencies tend to have less power

Wavelet transform





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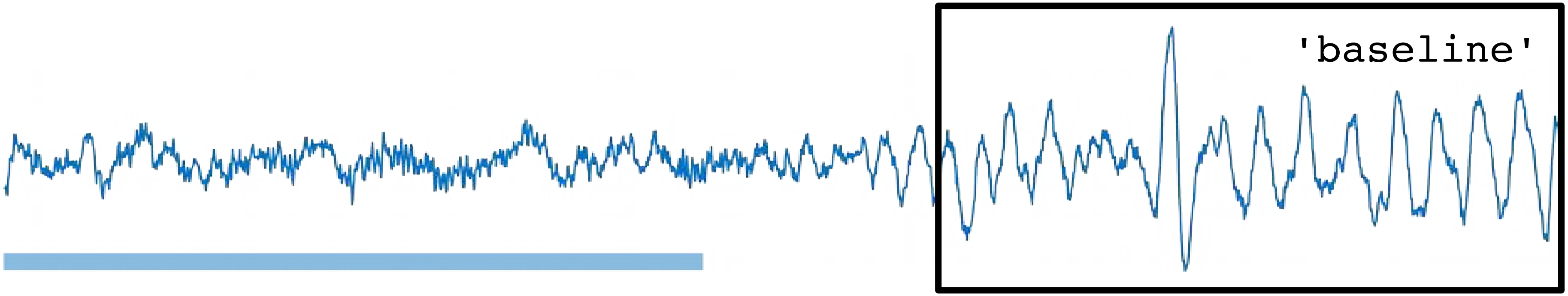
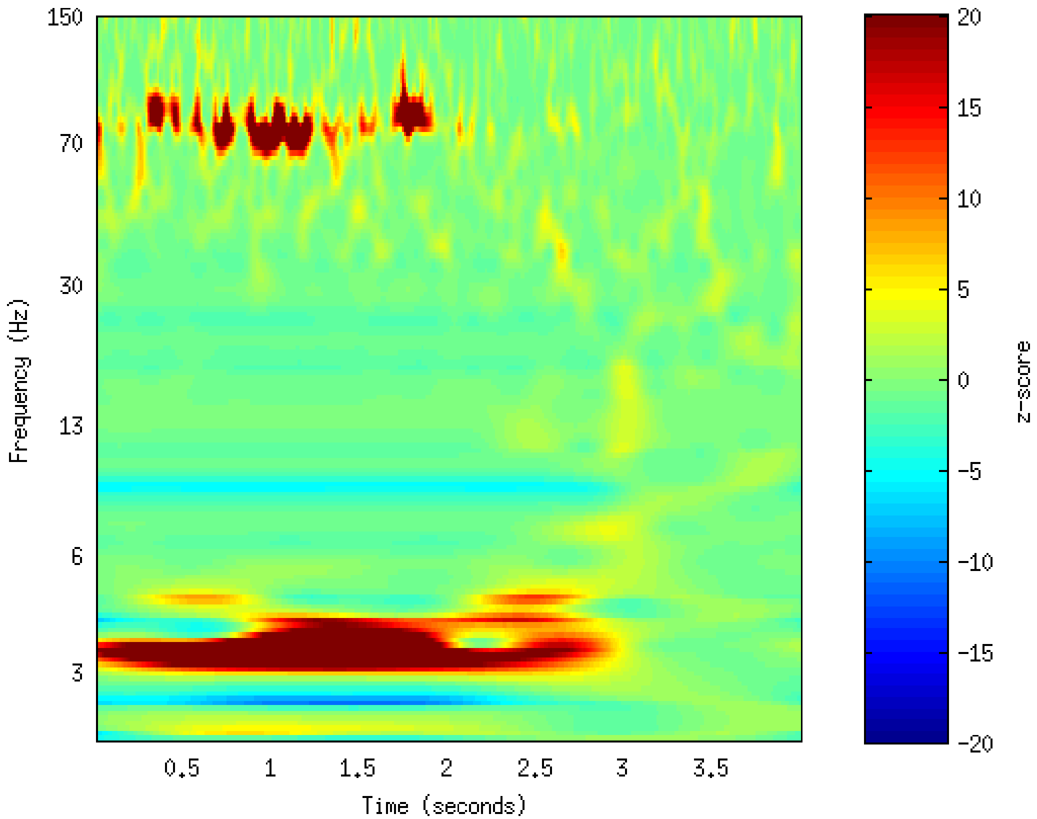
- Map can be normalized using a z-score based on the mean and std of a 'baseline period'

Wavelet transform





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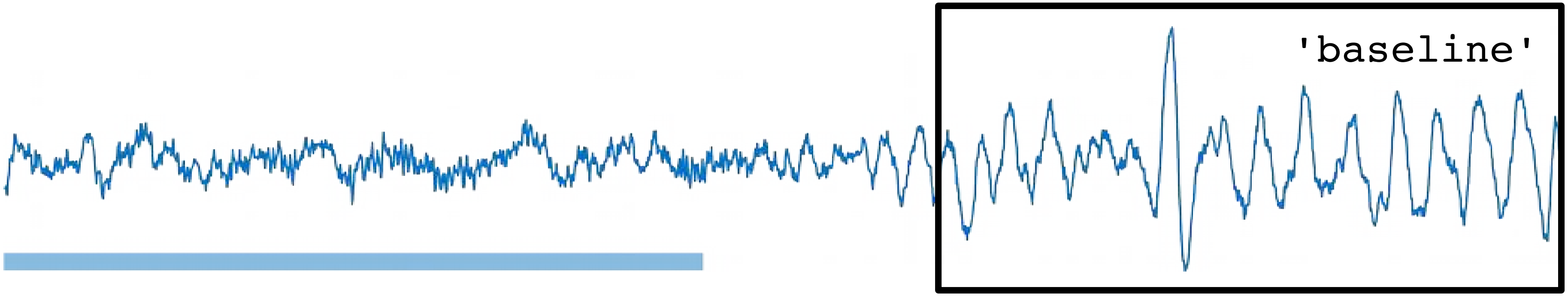
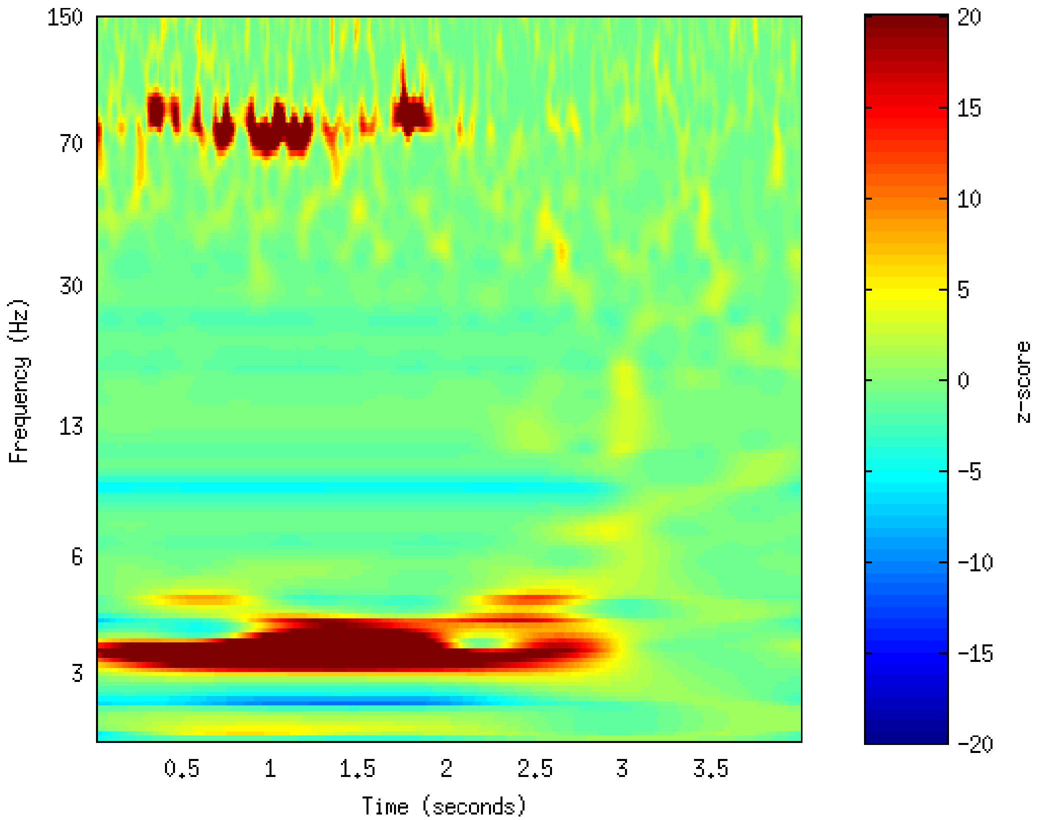
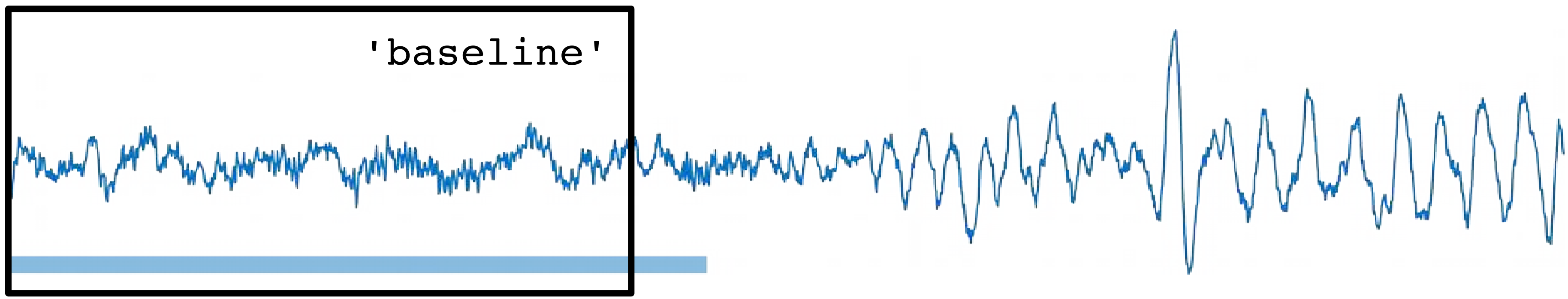
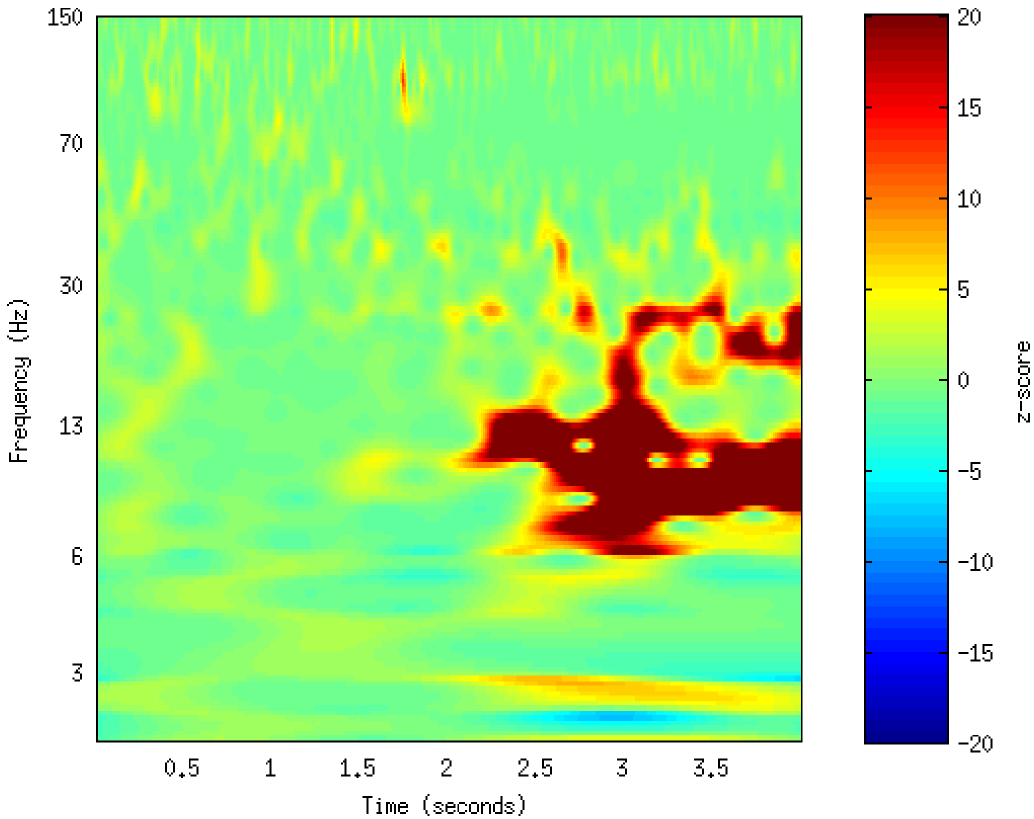




- Map can be normalized using a z-score based on the mean and std of a 'baseline period'
- What is the right baseline?!?

Wavelet transform





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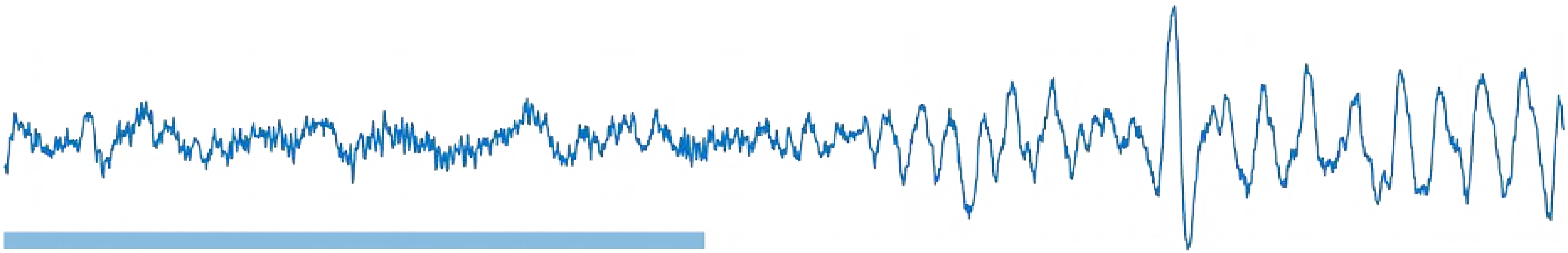
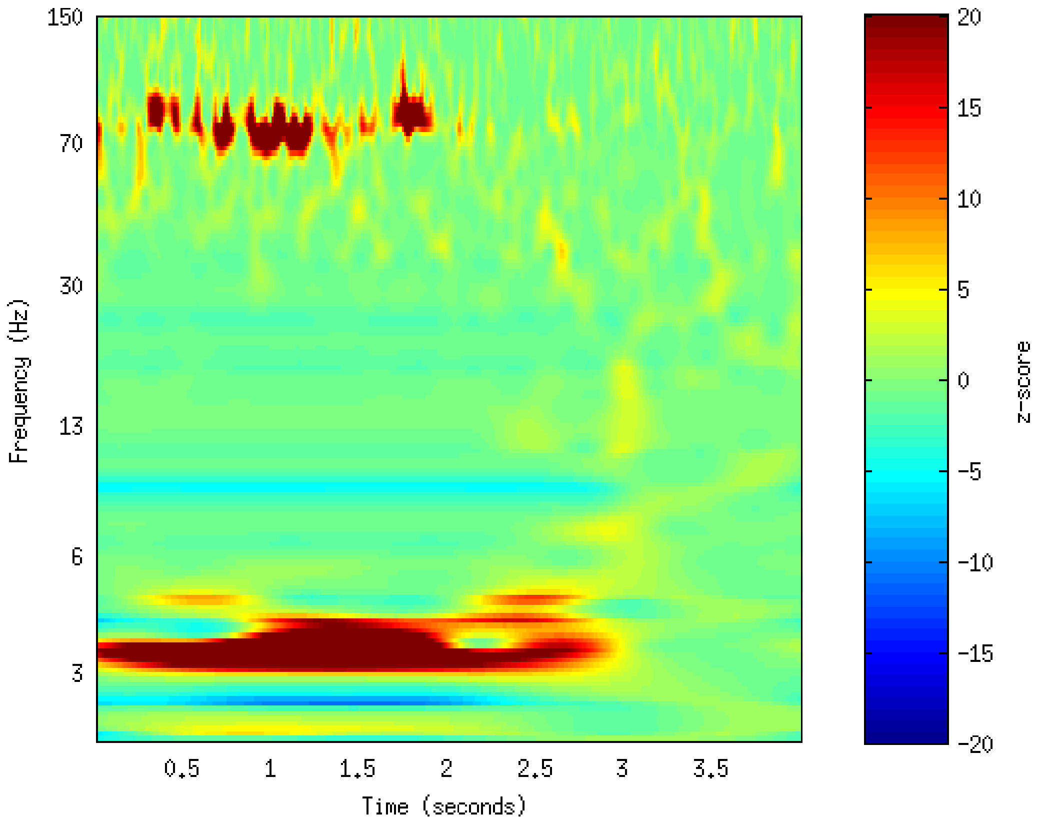
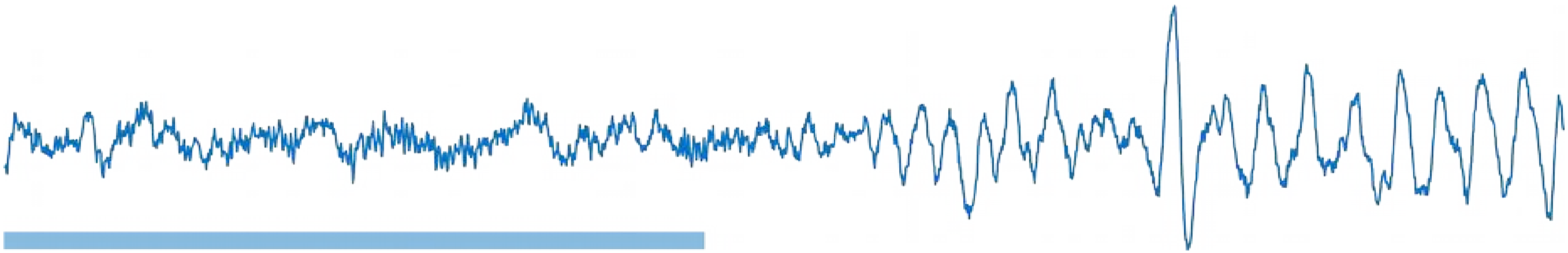
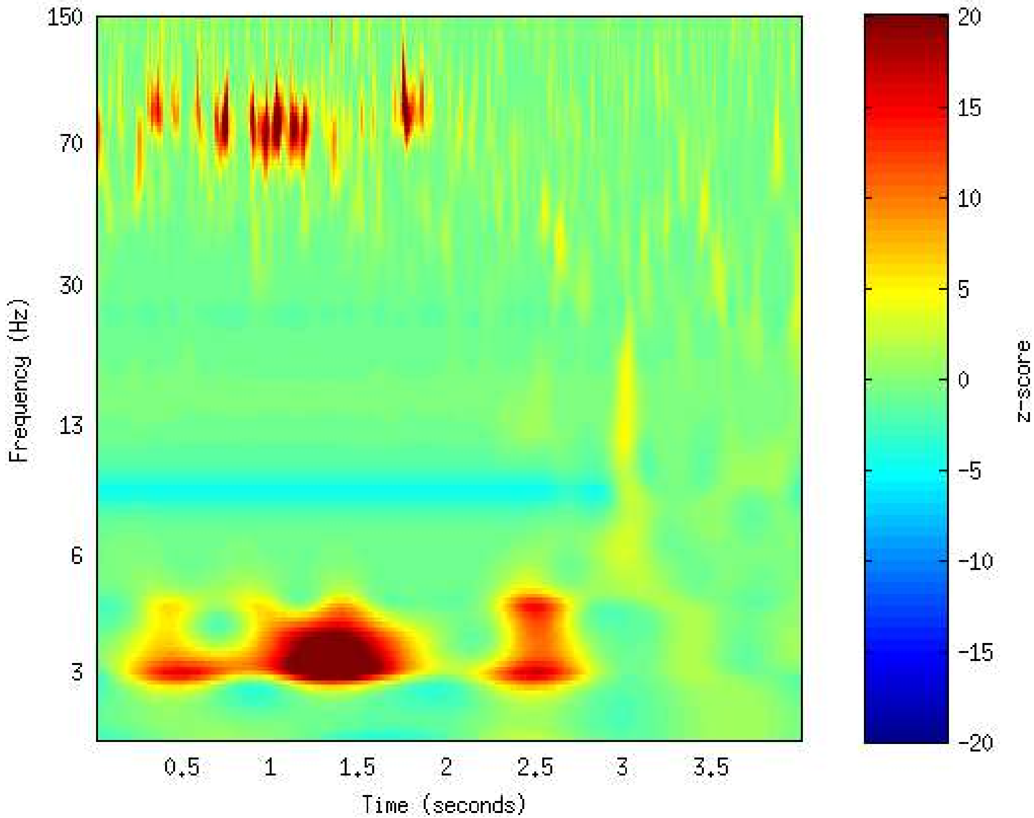




- Changing the parameters of the 'mother wavelet' affects time vs. Frequency resolution of the results

Wavelet transform





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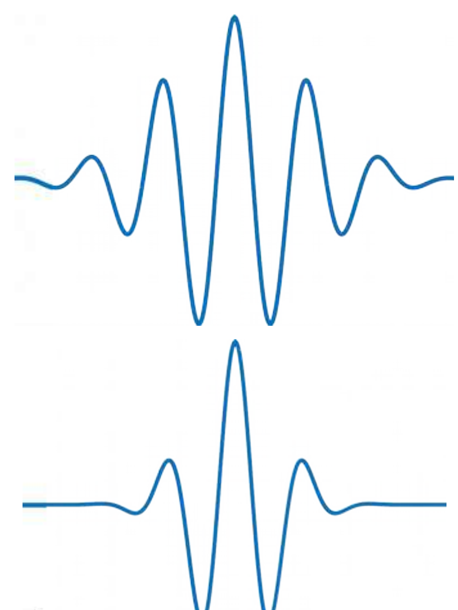
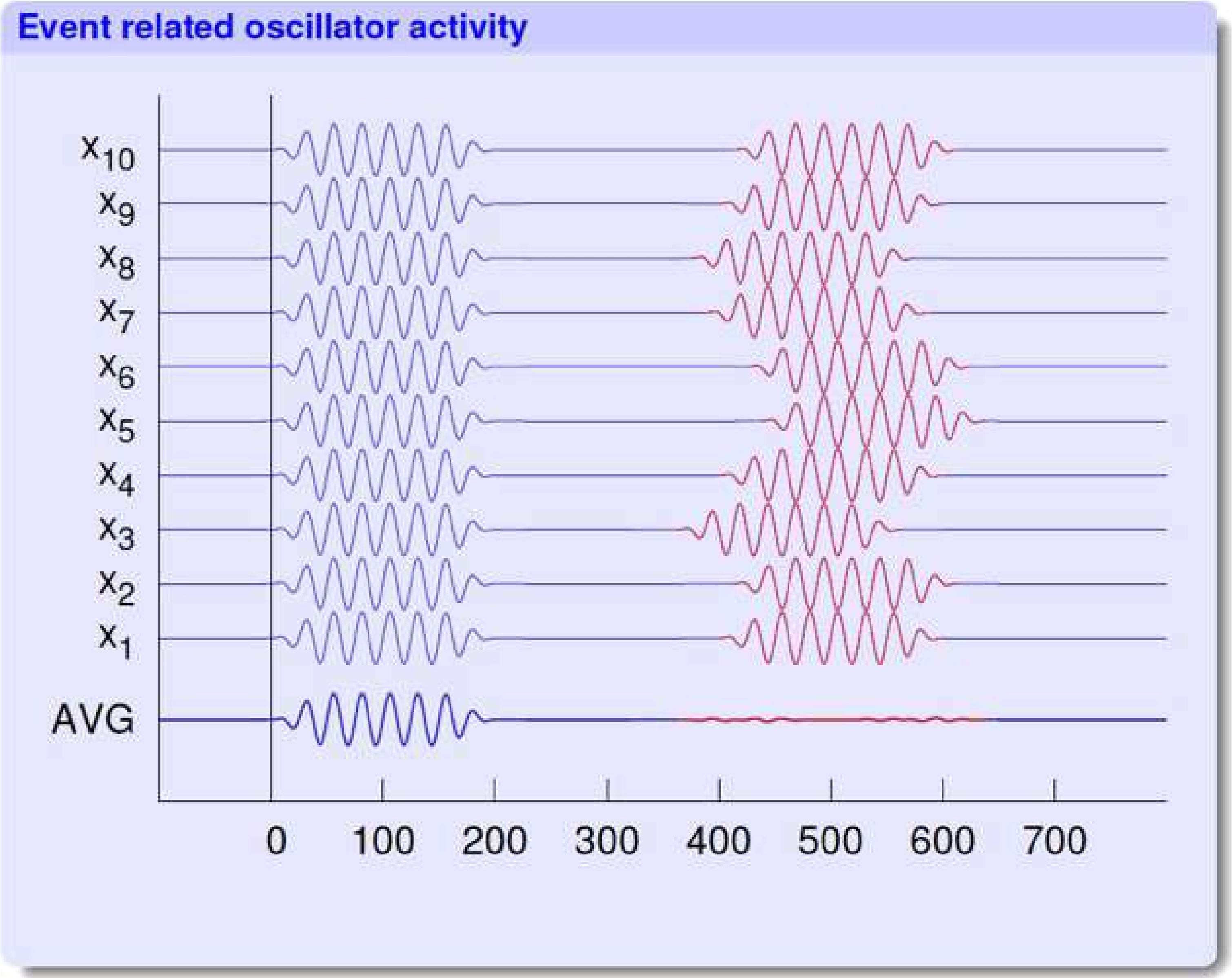


Evoked vs induced responses



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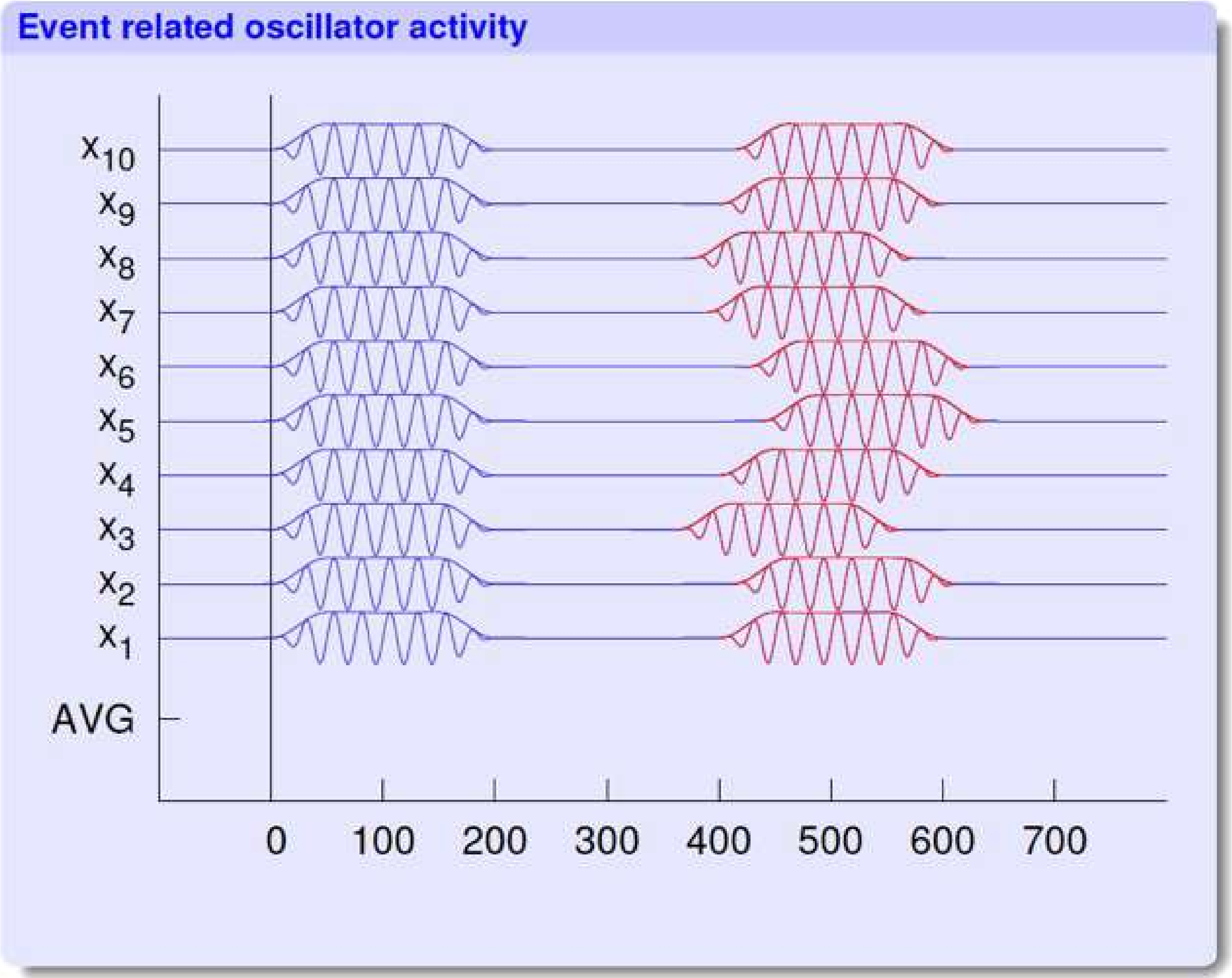

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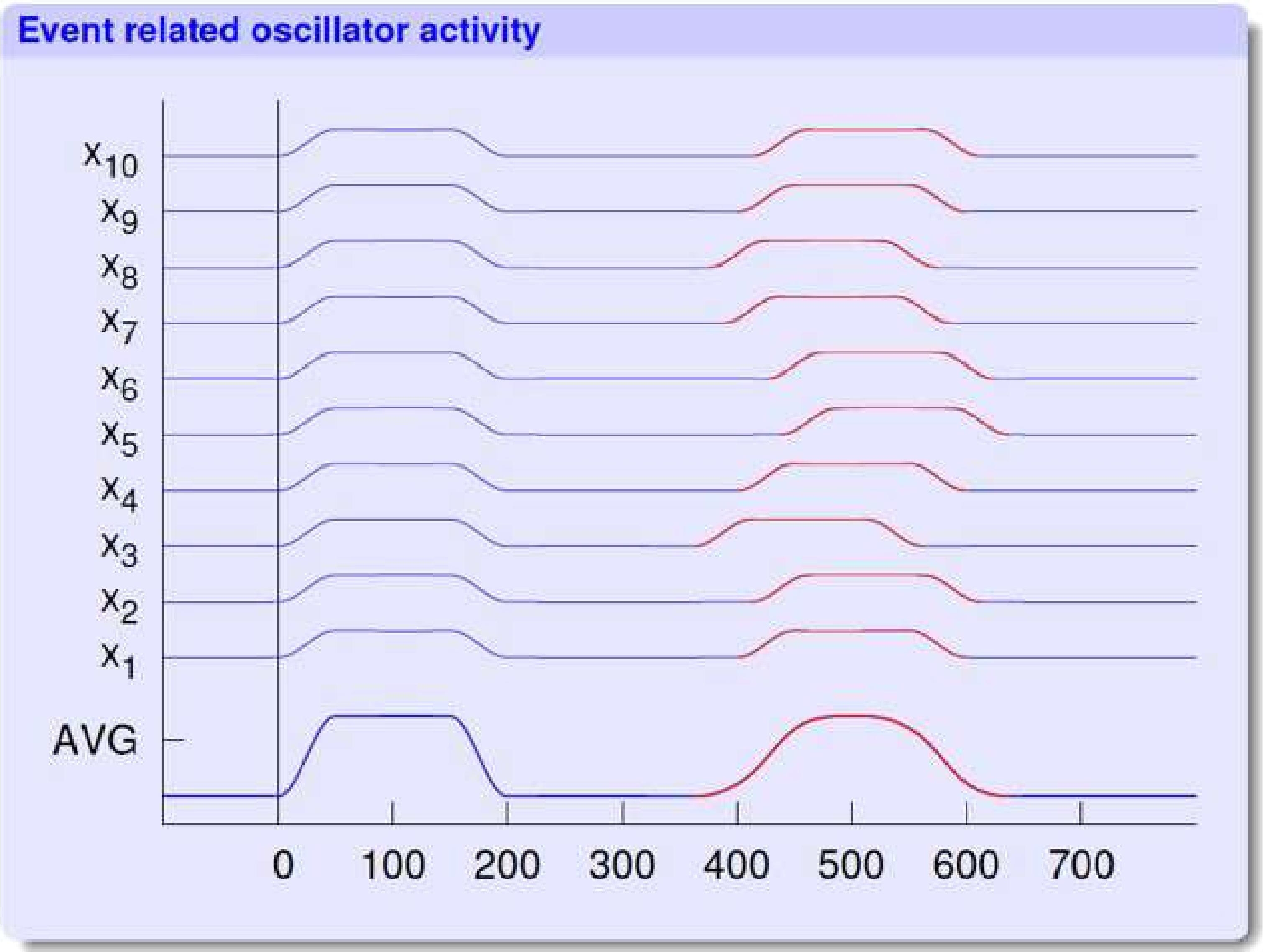

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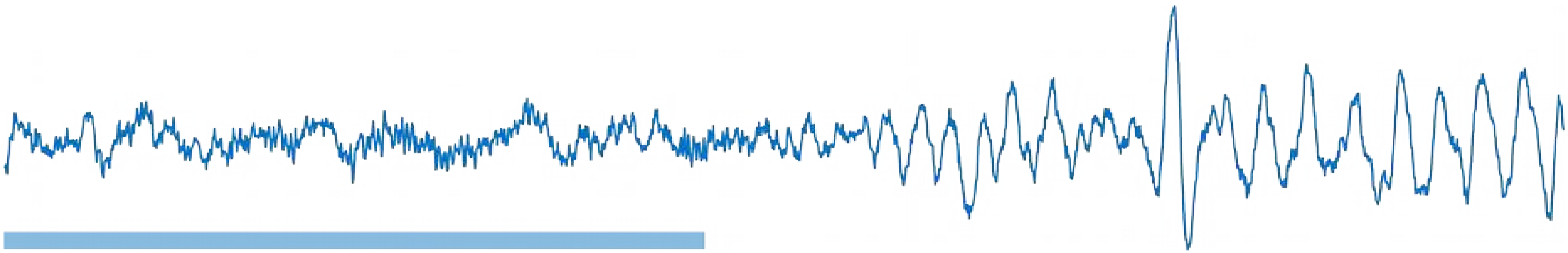
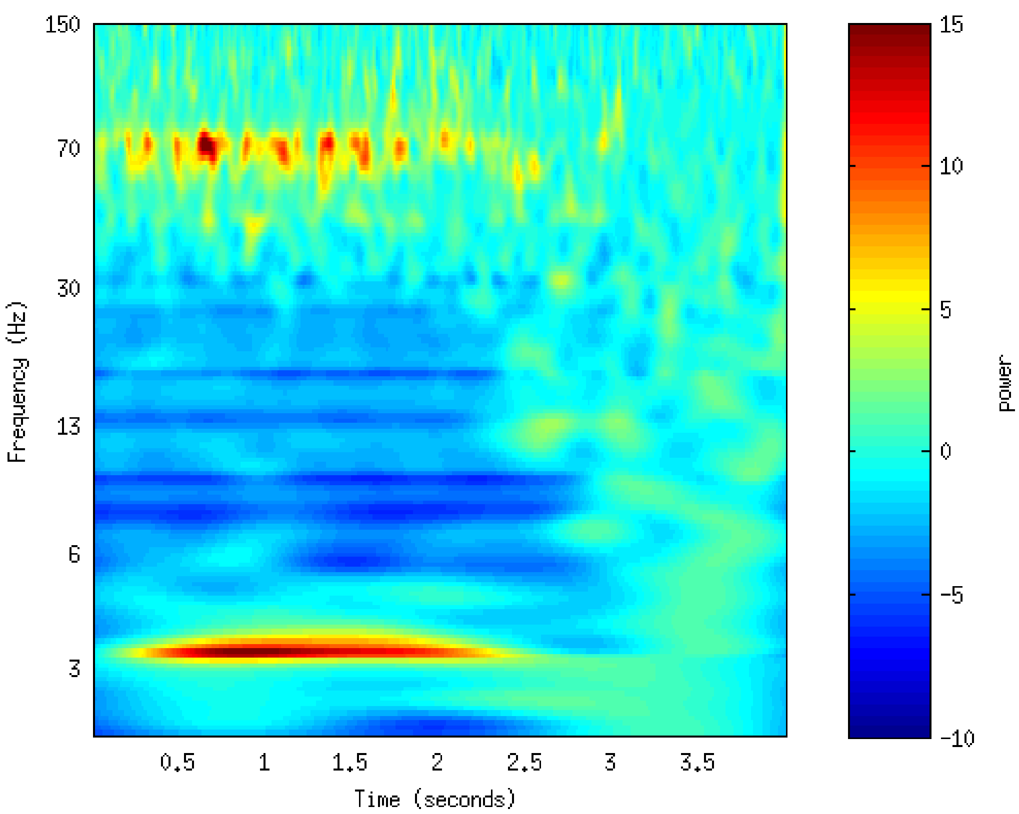
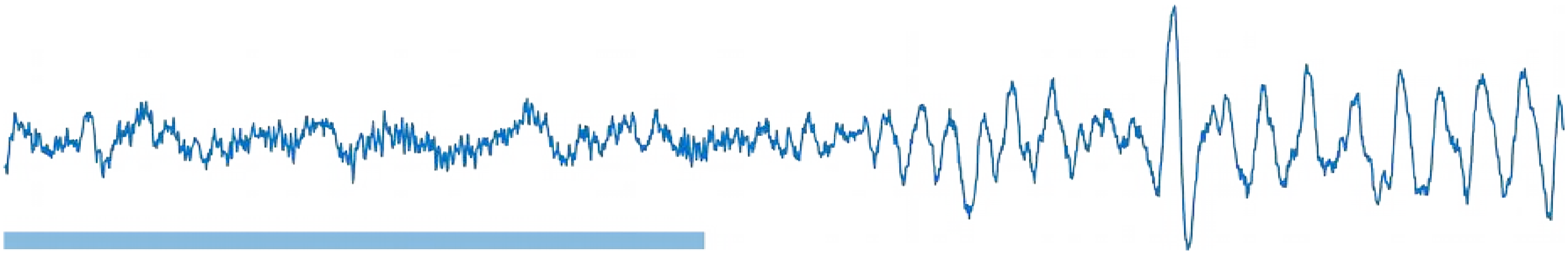
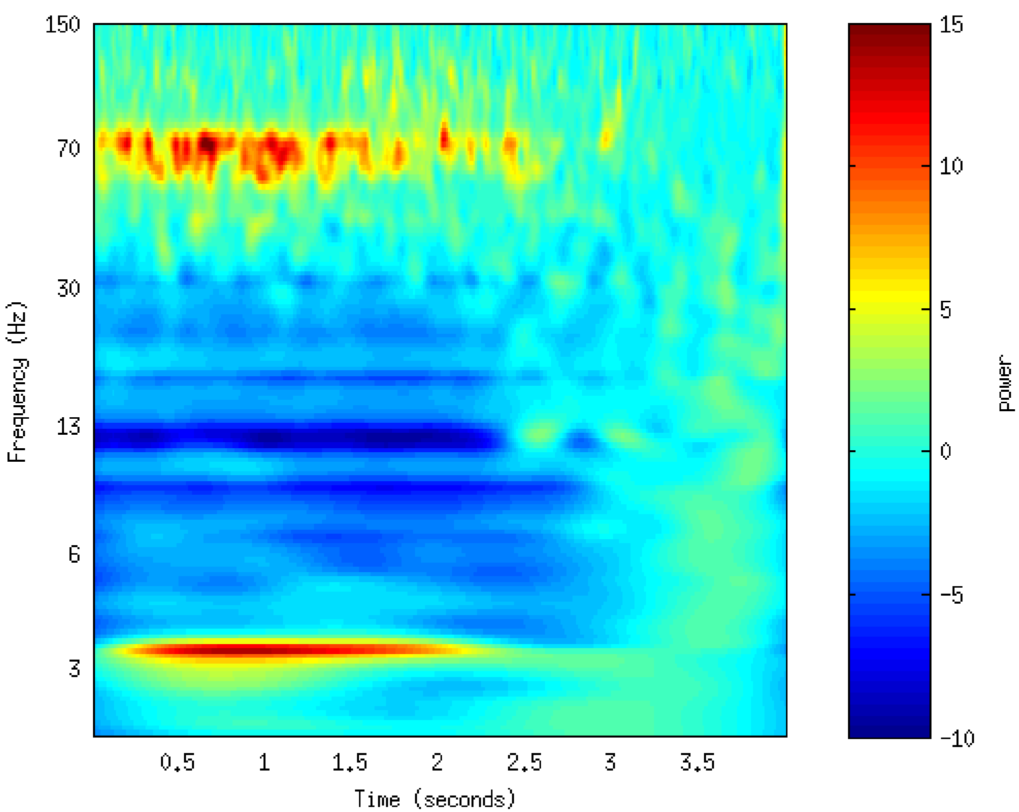




- Averaging
  - 10 trials

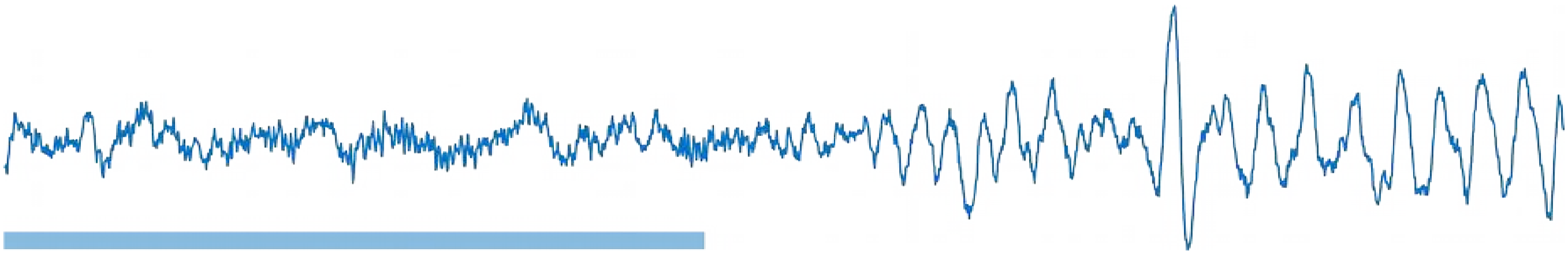
Evoked vs induced responses

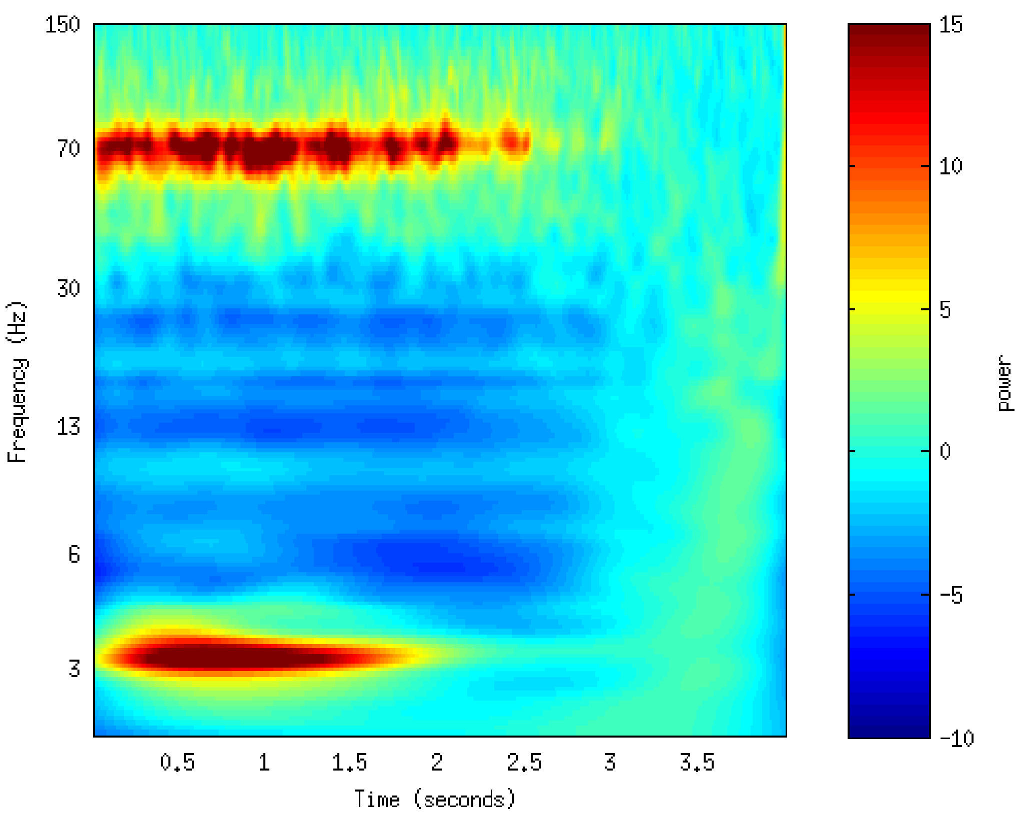




- Averaging
  - 10 trials
  - 20 trials

Evoked vs induced responses





- Averaging
  - 10 trials
  - 20 trials
  - 100 trials

Contents

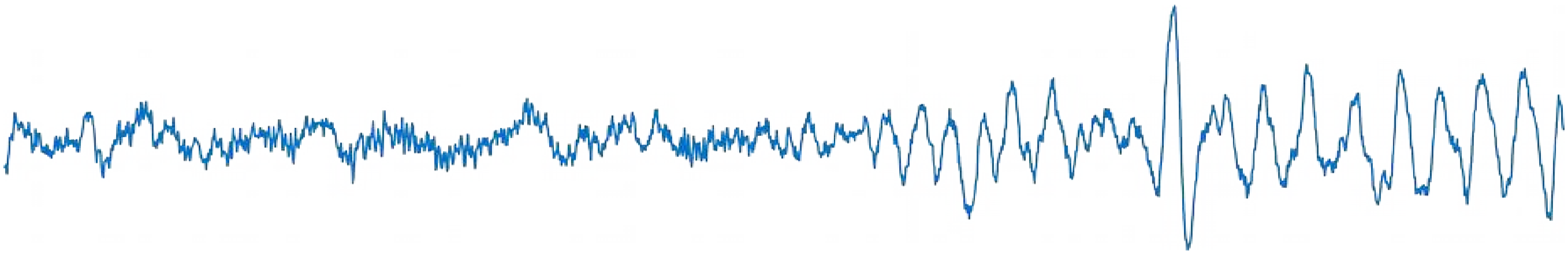
Stationary:

- Fourier transform
- Power spectral density (Welch's method)

Time-resolved:

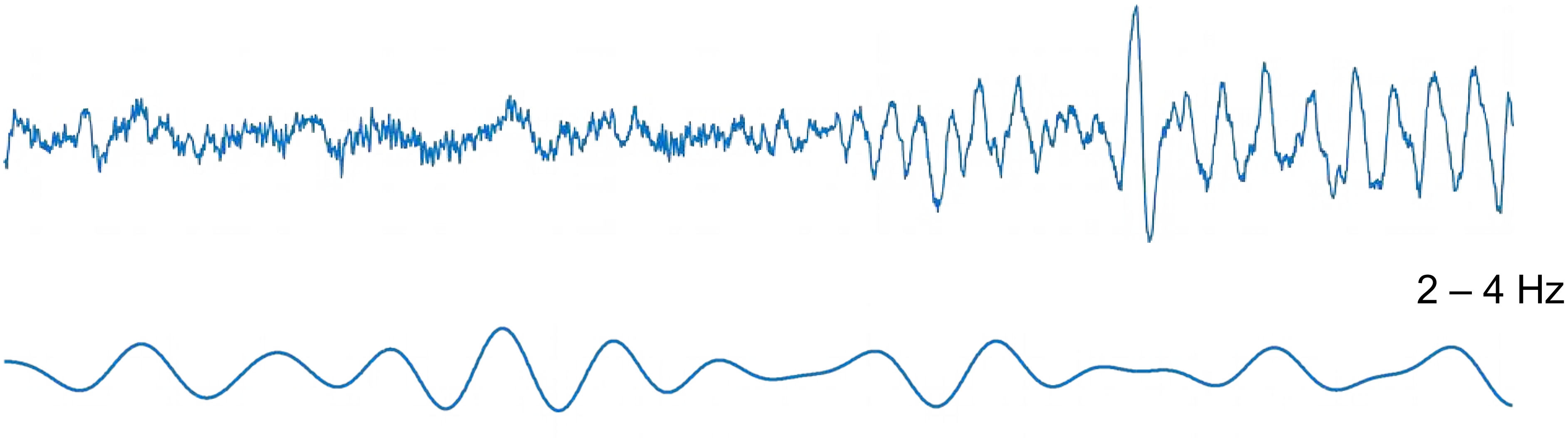
- Wavelet transform
- Filtering & Hilbert transform

Hilbert transform



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

Hilbert transform



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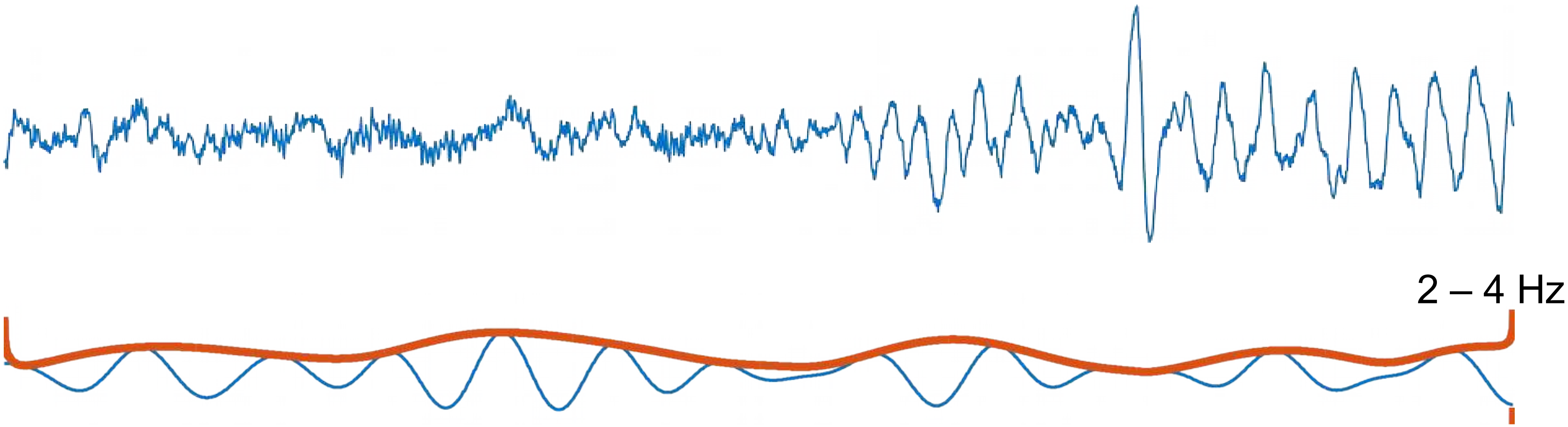
- Signal is first filtered in the specified band

Hilbert transform

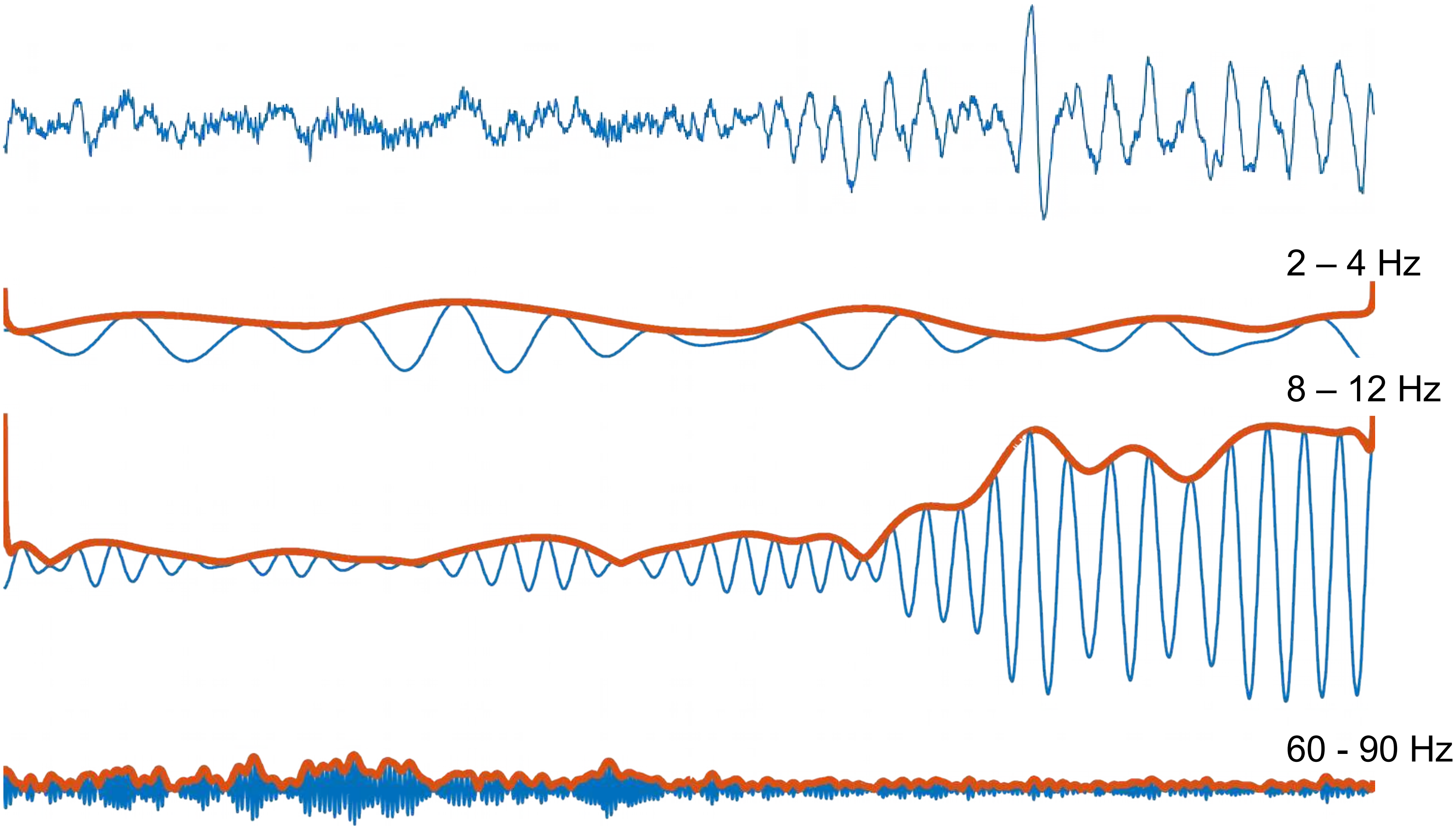


- Useful for estimating time-resolved power (or phase) in a pre-defined frequency band (e.g. Delta: 2-4 Hz)

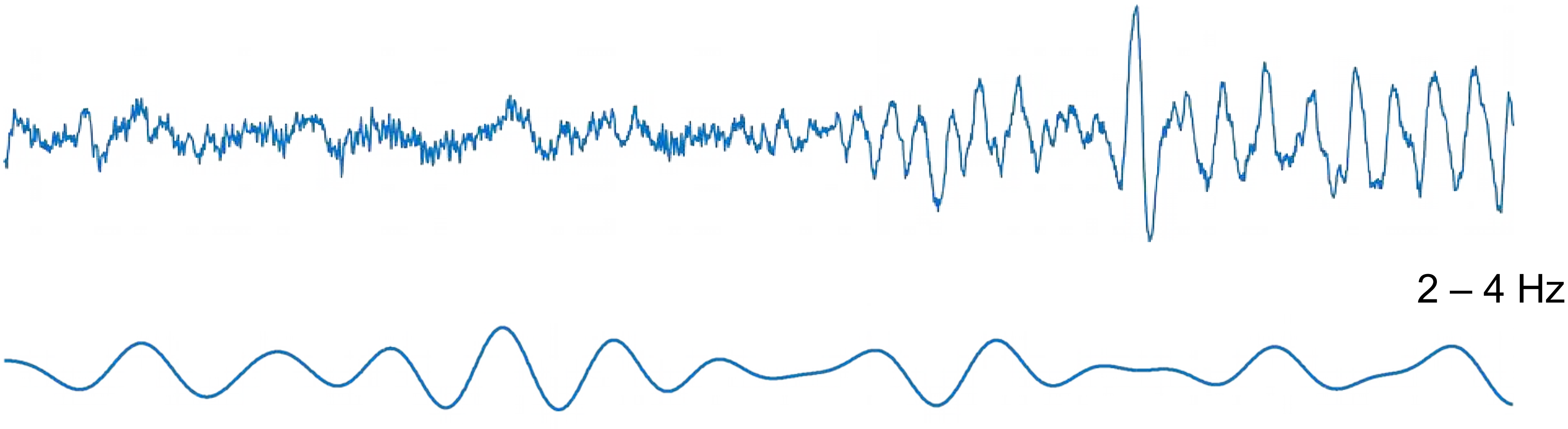
- Signal is first filtered in the specified band

- Envelope (power) is computed using the Hilbert transform

Hilbert transform

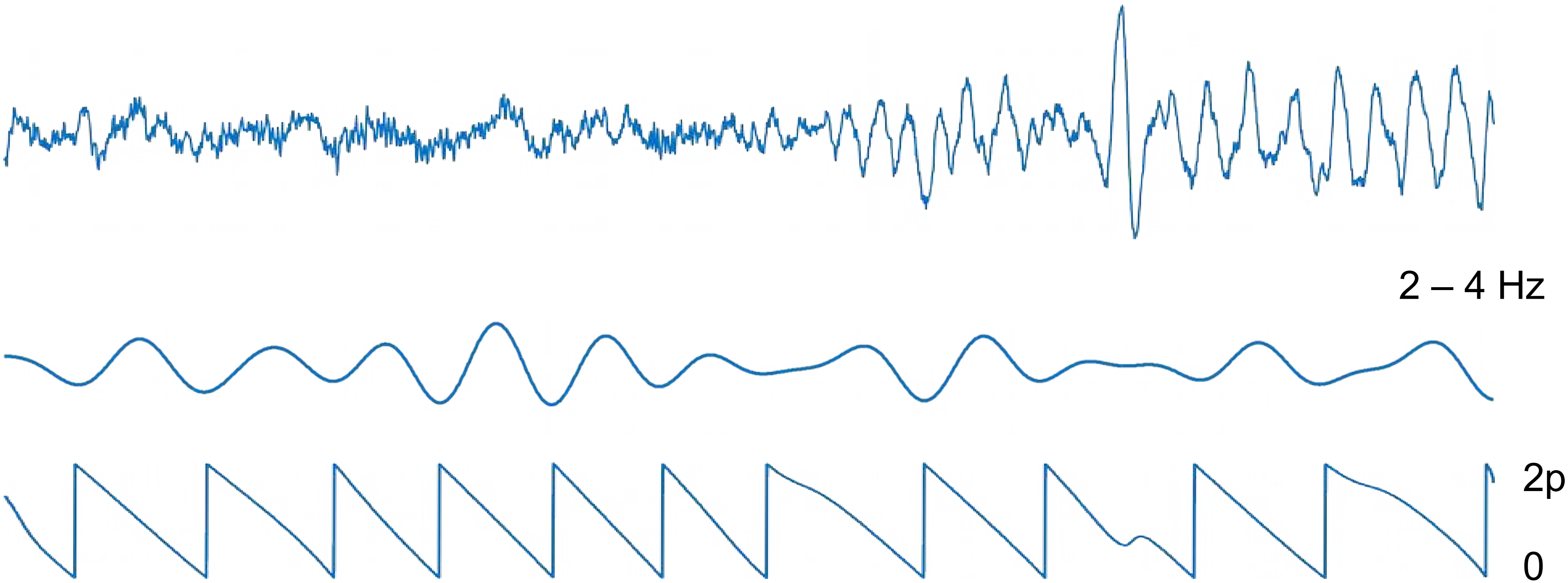


Hilbert transform



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

Hilbert transform



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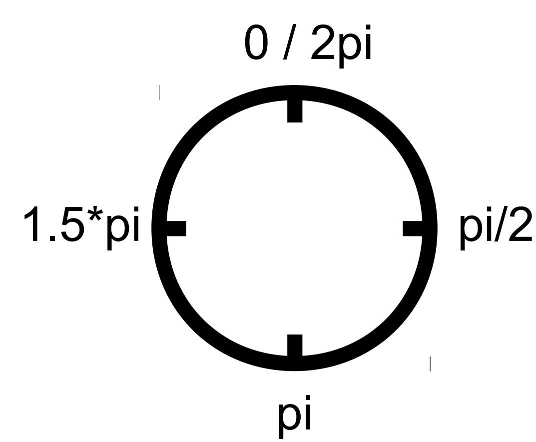
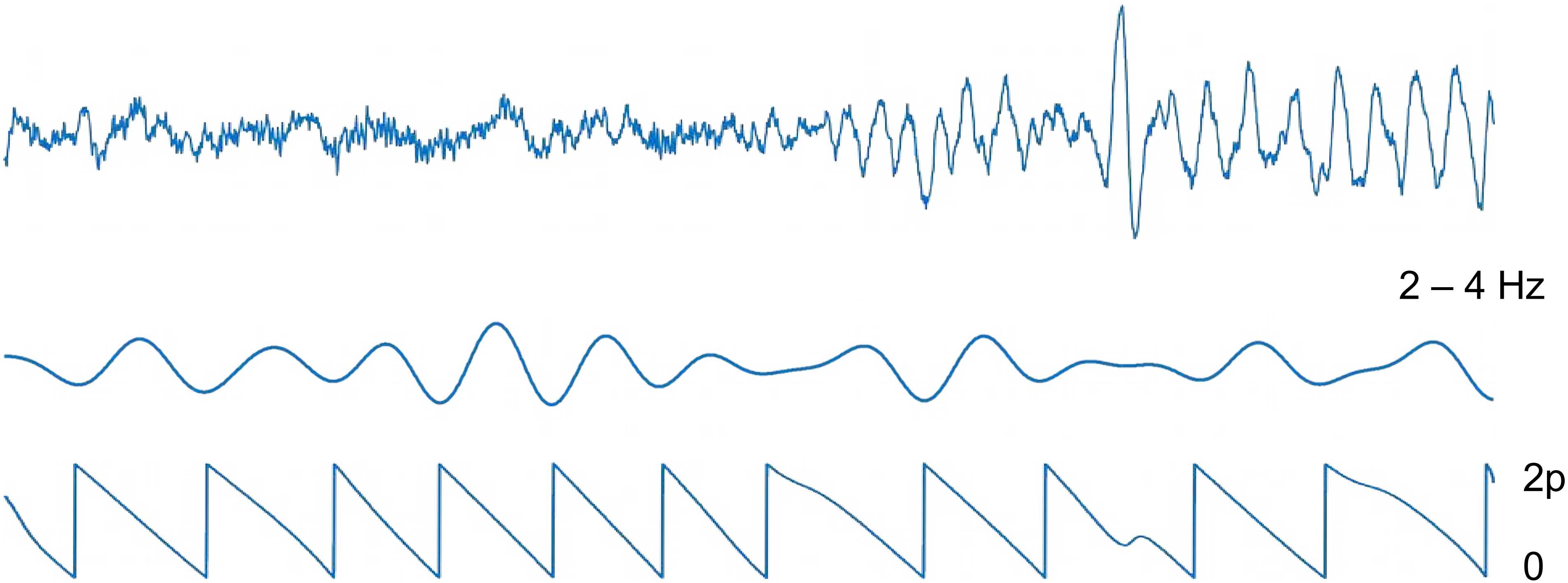


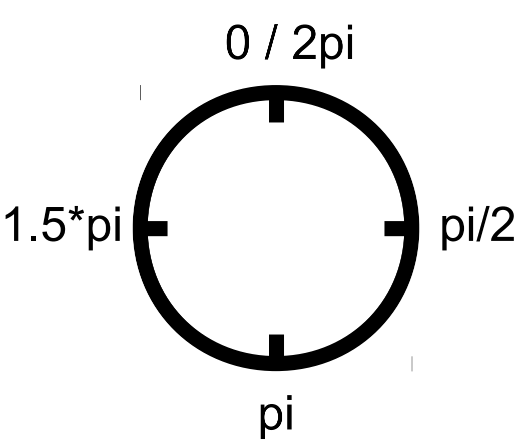
Hilbert transform



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

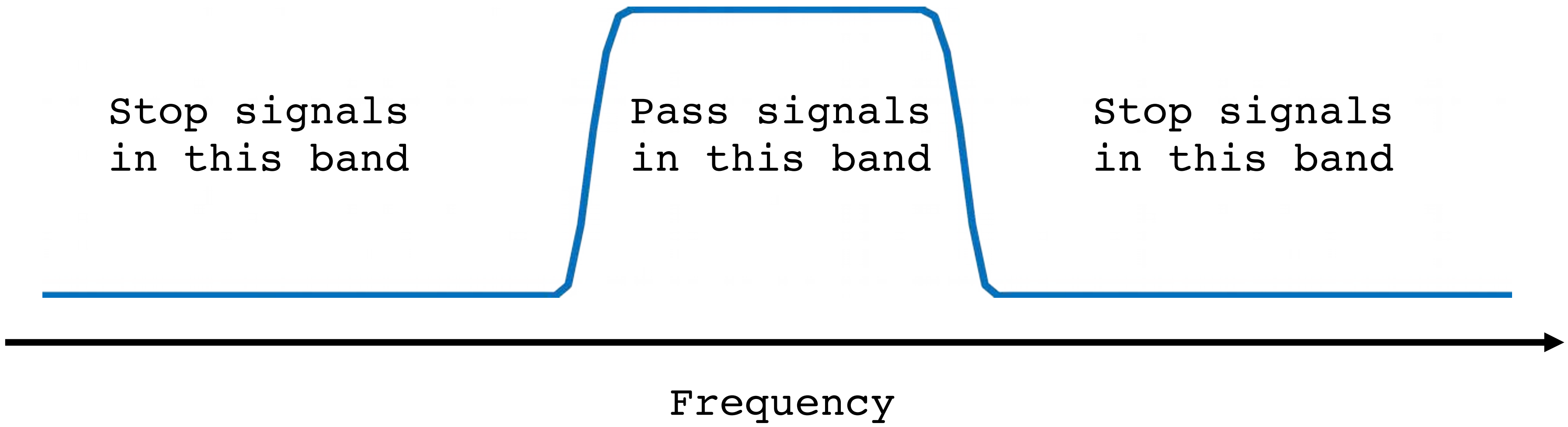
- Usage: phase-locking value, stimulus-brain coupling, phase-amplitude coupling

  ➔ All of that later in the day



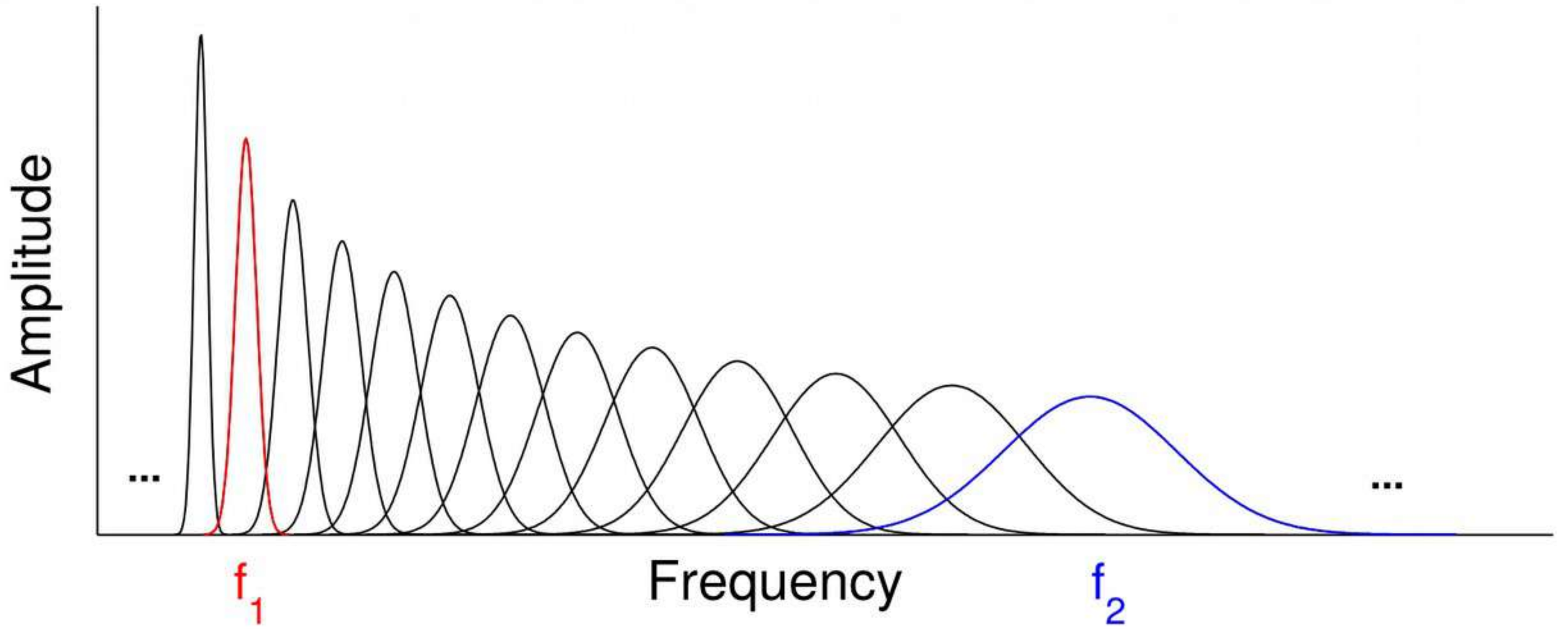
Hilbert vs. Wavelet

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



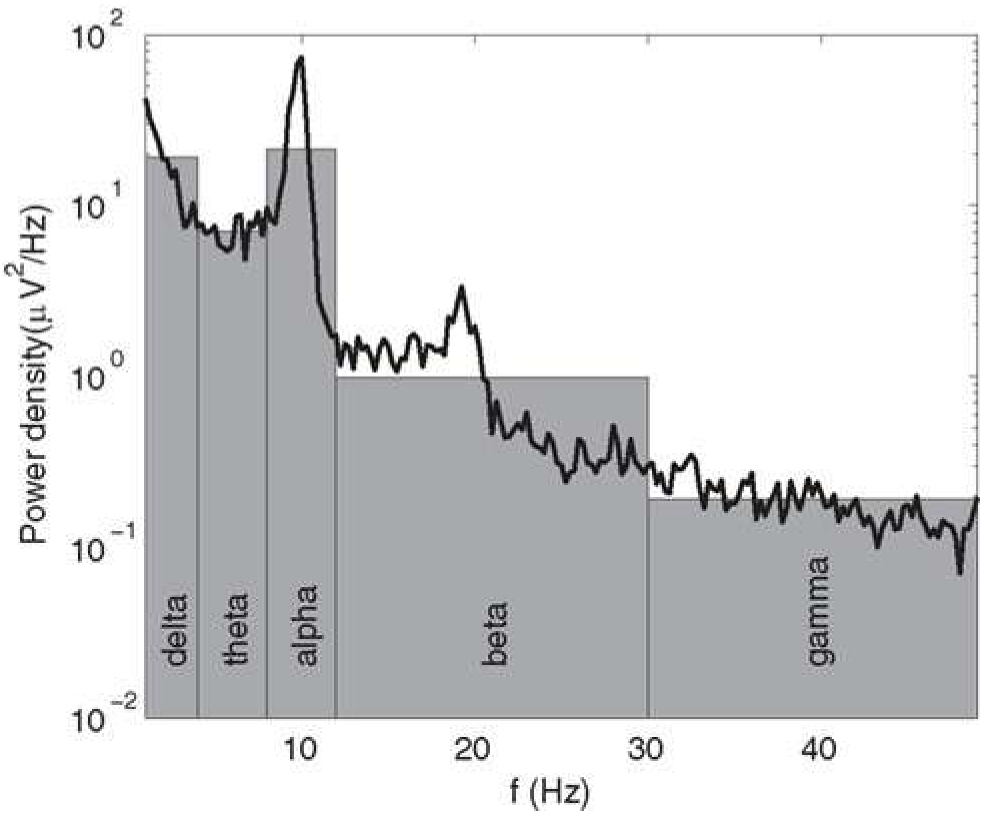
Hilbert vs. Wavelet

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



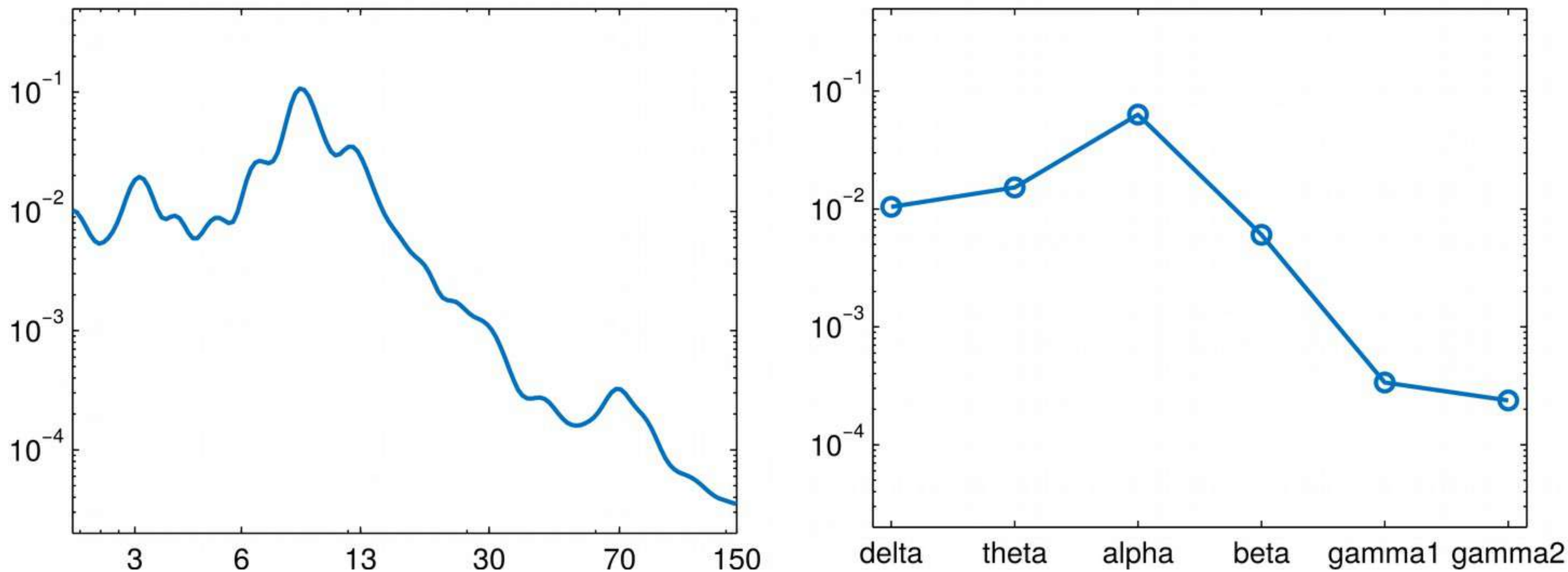
Defining frequency bands

- 'Based on the literature': many definitions



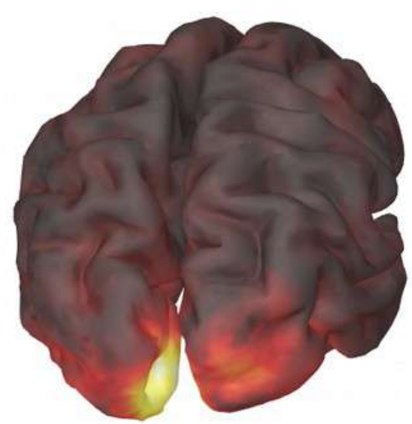
Defining frequency bands

- 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

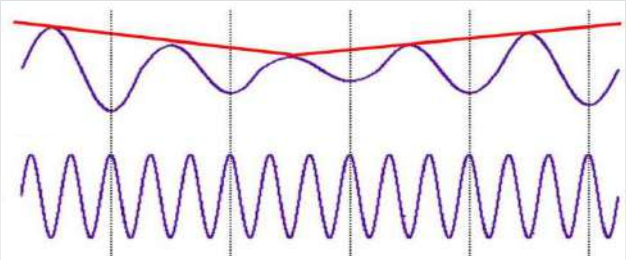
- Several synchronized neuronal assemblies in the brain:
  - Each supports a frequency band of the network rhythm

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

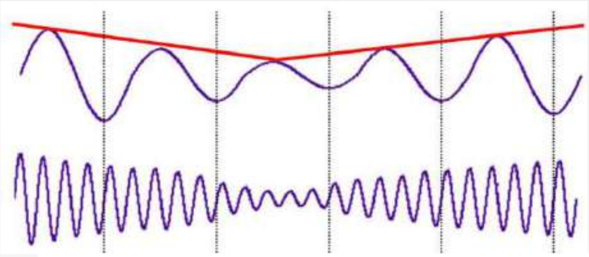
- G. Buzsaki. Cerebral Cortex, 1996
- A. Bragin, et al., The Journal of Neuroscience, 1995.
- A. Roopun, et al., Frontiers in Neuroscience, 2008.

Types of CFC

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



Jirsa et al., Front. Neurosci. , 2013



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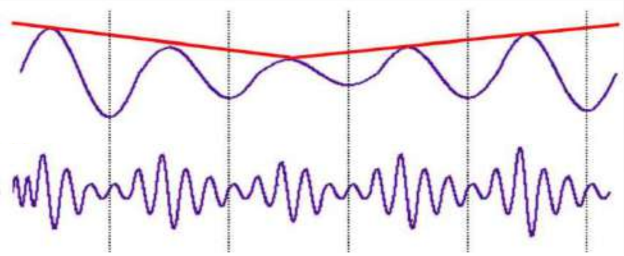
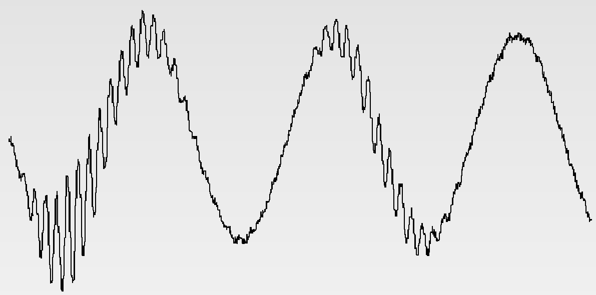
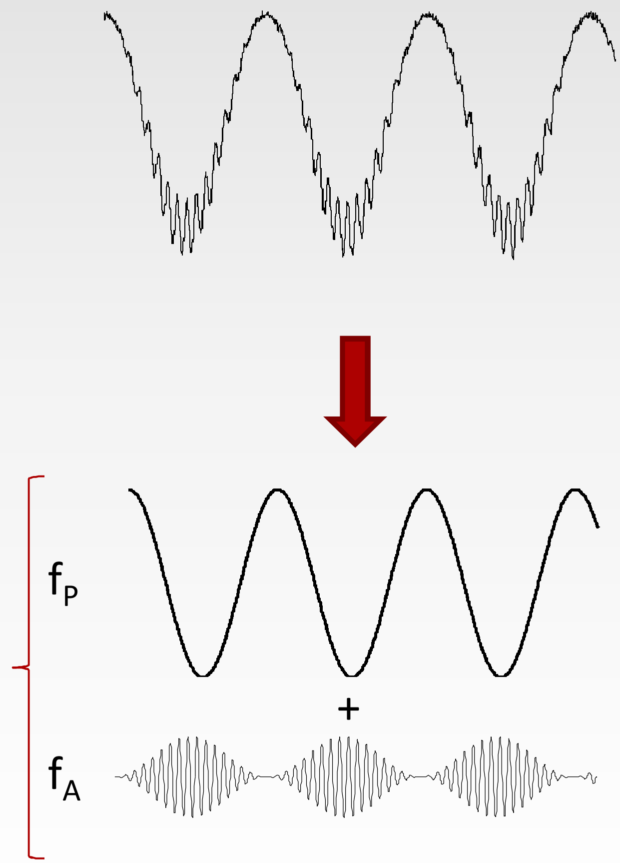


Jirsa et al., Front. Neurosci. , 2013

Cross-frequency Phase-amplitude Coupling

- Phase-amplitude coupling

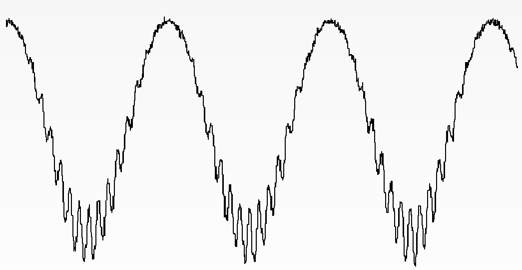


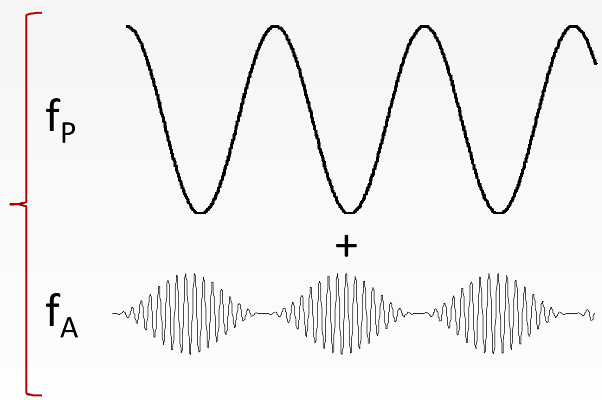


- Canolty and Night, Trends Cogn Sci, 2010

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

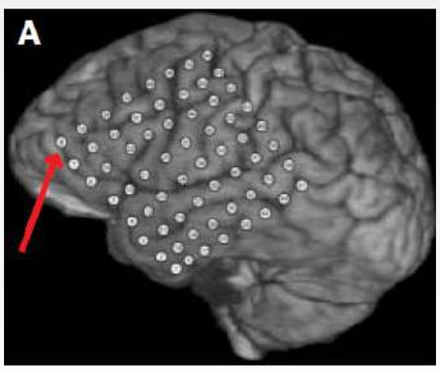


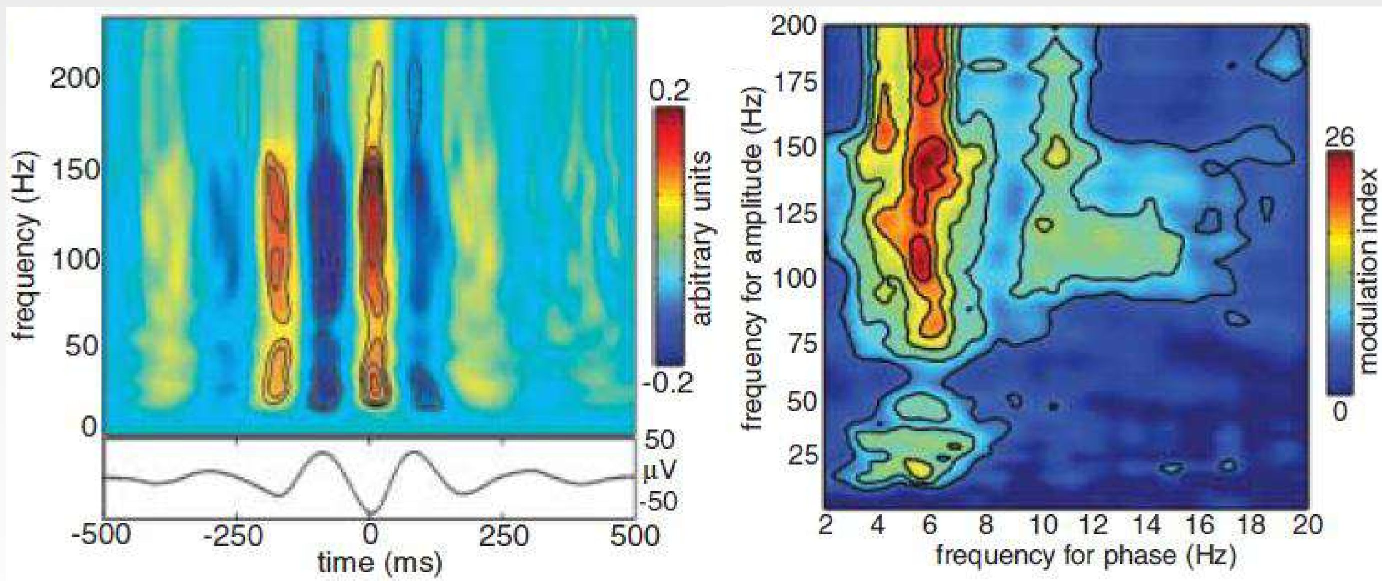


- Canolty and Night, Trends Cogn Sci, 2010

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





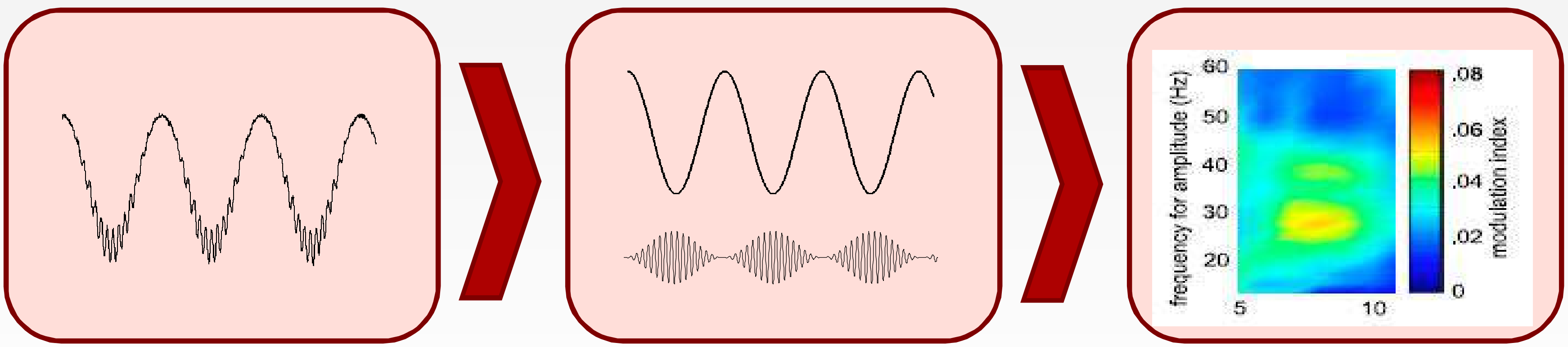
- R. Canolty, et al., Science, 2006.

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]	★ (blue-grey) ★ (dark red)
2	PLV	Phase-locking value	[Vanhatalo et al., 2004]	★ (dark red)
3	MVL	Mean vector length	[Canolty et al., 2006]	★ (tan)
4	GLM	The general linear model measure	[Penny et al., 2008]	★ (dark red)
5	APSD	Amplitude power spectral density	[Cohen, 2008]	★ (dark red)
6	CV	Coherence Value	[Colgin et al., 2009]	★ (dark red)
7	KL-MI	Kullback-Leibler based modulation index	[Tort et al., 2010]	★ (tan)
8	ERPAC	Event related phase amplitude coupling	[Voytek et al., 2012]	★ (green) ★ (dark red)

★ (blue-grey) Sensitive to coupling phase (Negative feature)

★ (tan) Need long data length

★ (green) Only works on event-related datasets

★ (dark red) Potentially not capable of calculating coupling intensity

Summary

Stationary:

- Fourier transform
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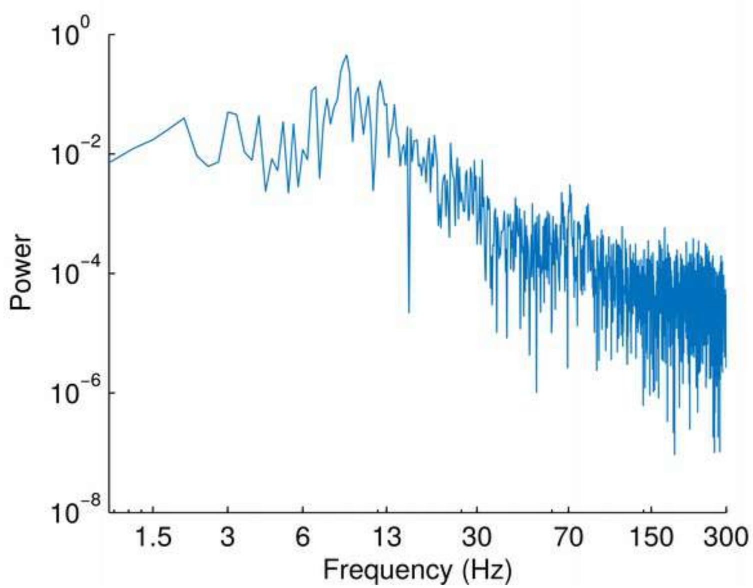


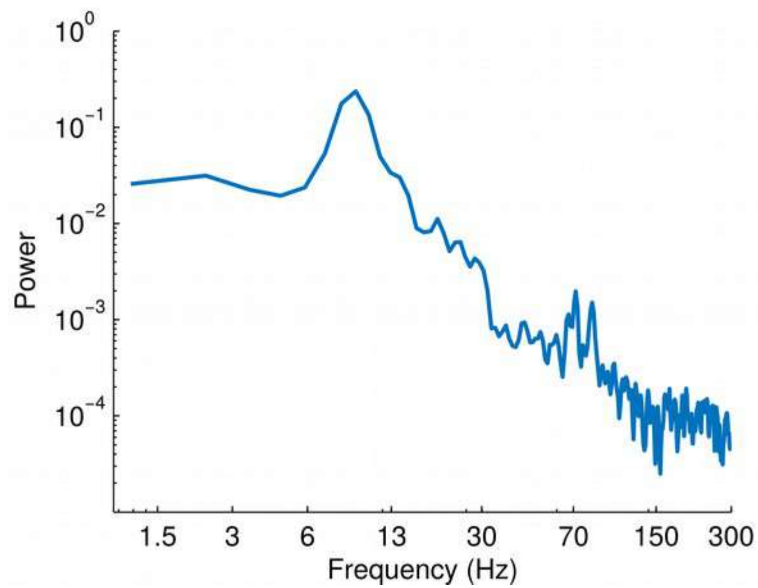
Summary

Stationary:

- Fourier transform
- Power spectral density (Welch's method)

Time-resolved:

- Wavelet transform
- Filtering & Hilbert transform



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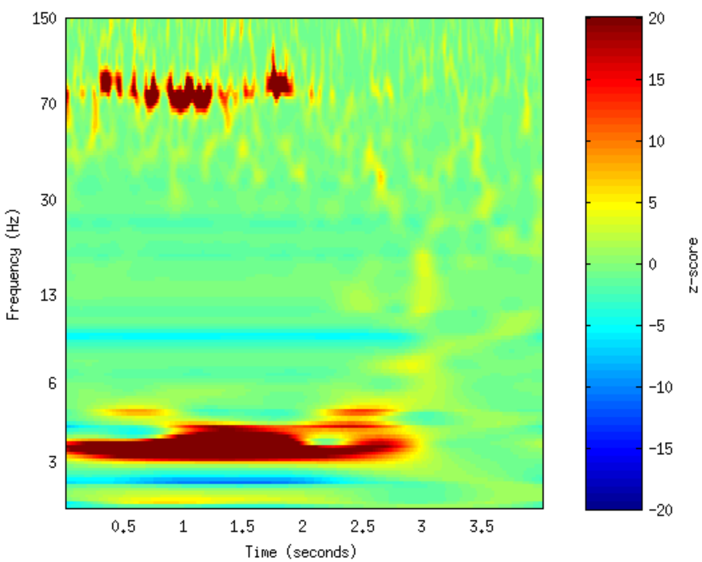

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