

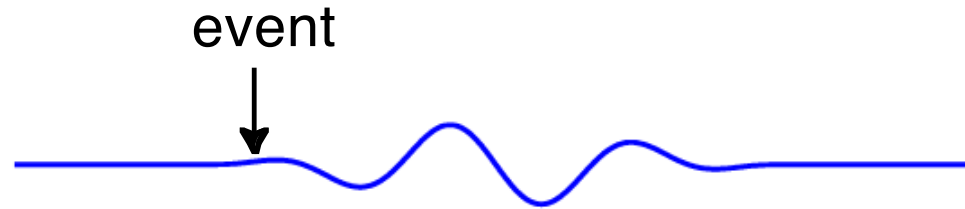
Fundamentals of neuronal oscillations and synchrony

Jan Mathijs Schoffelen, MD PhD

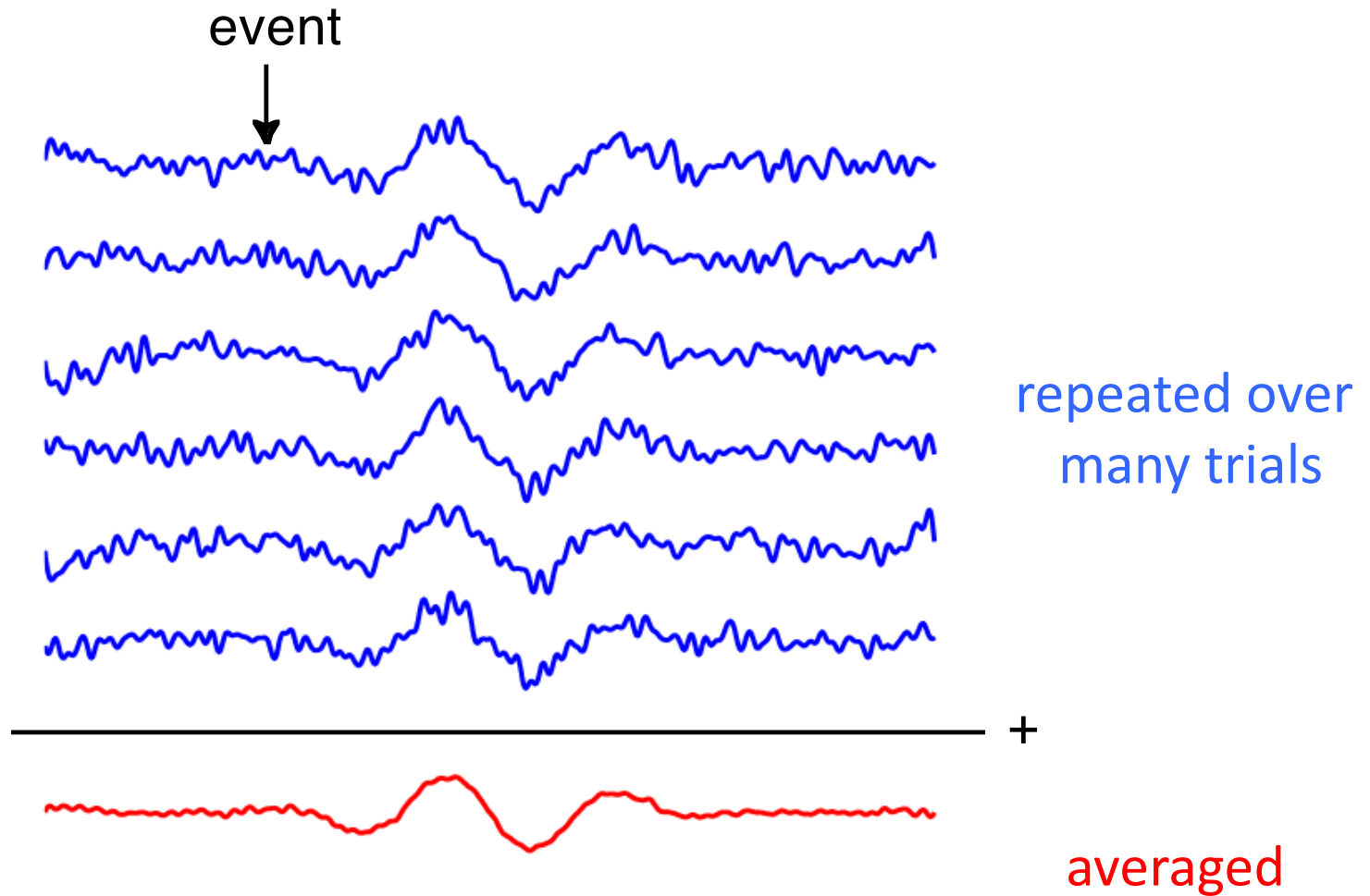
j.schoffelen@donders.ru.nl

Donders Institute, Radboud University, Nijmegen, NL

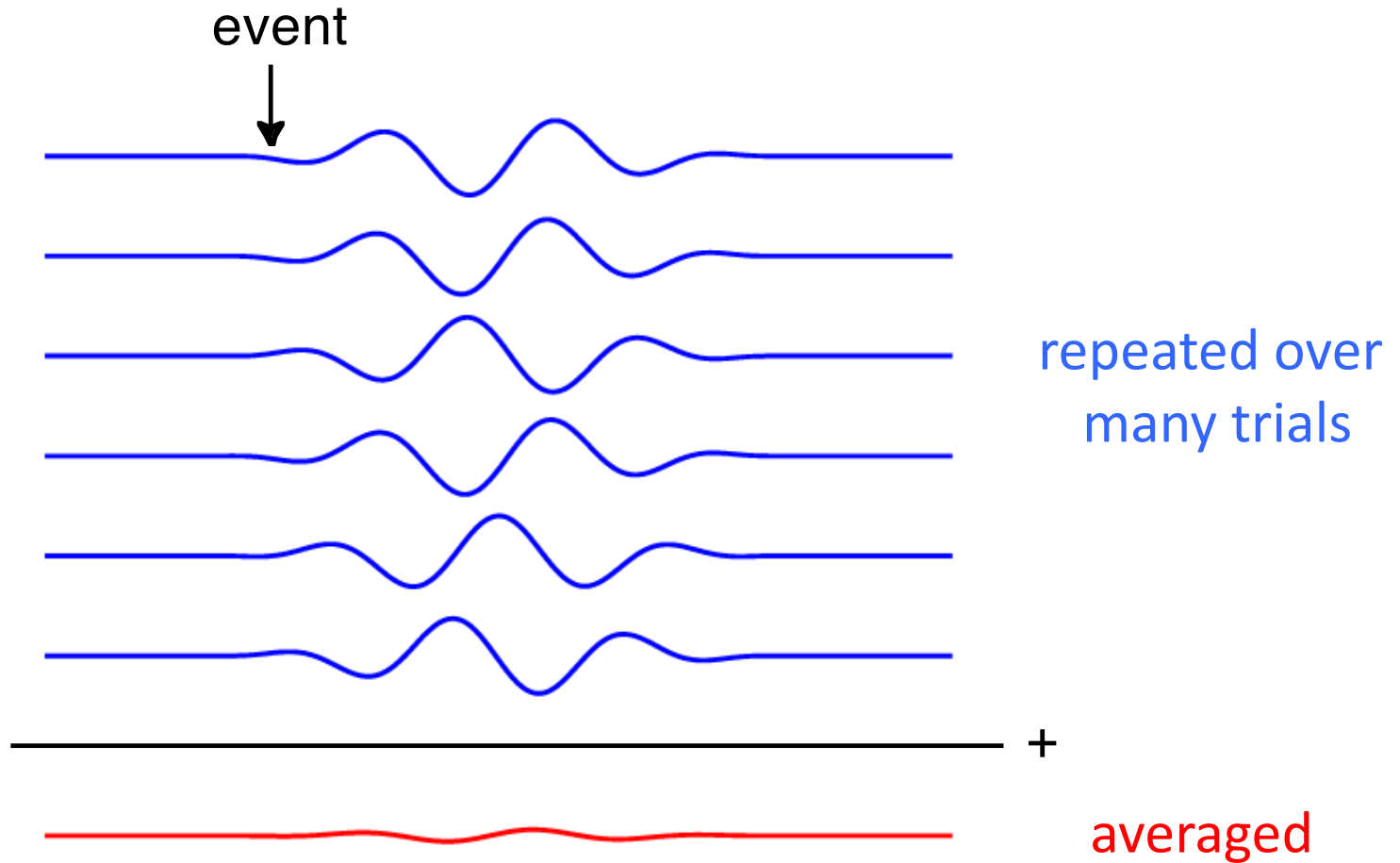
Let's recap evoked activity



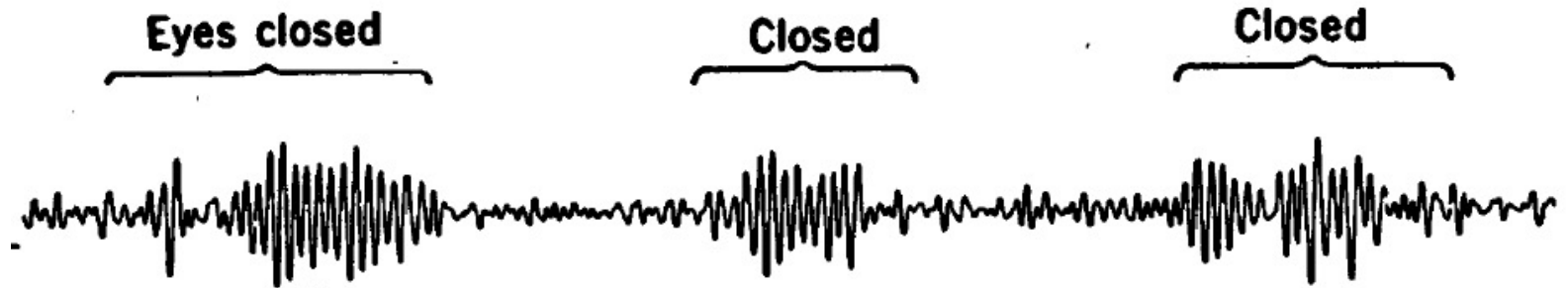
Let's recap evoked activity



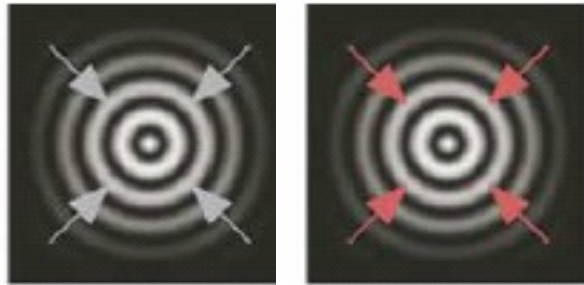
What now?



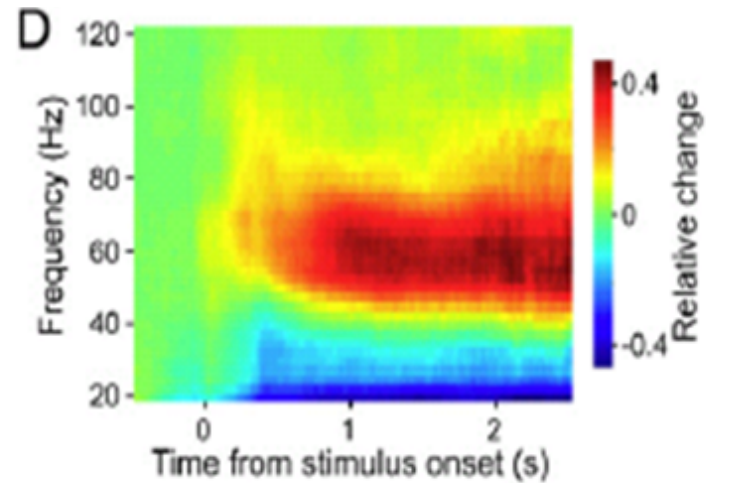
Or what if the brain signal contains oscillatory components?



Cohen, 1972



Hoogenboom et al, 2006



M/EEG signal characteristics considered during analysis

timecourse of activity

-> ERP

spectral characteristics

-> power spectrum

temporal changes in power

-> time-frequency response (TFR)

spatial distribution of activity over the head

-> source reconstruction

Outline

Spectral analysis: going from time to frequency domain

Spectral leakage and (multi-)tapering

Time-frequency analysis

Outline

Spectral analysis: going from time to frequency domain

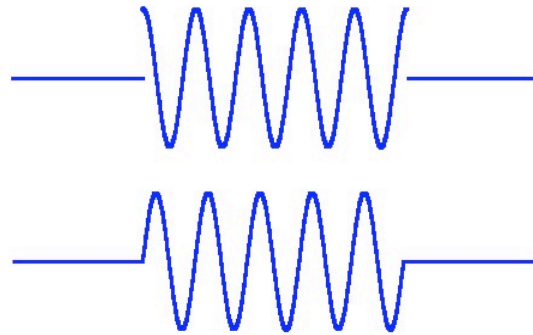
Spectral leakage and (multi-)tapering

Time-frequency analysis

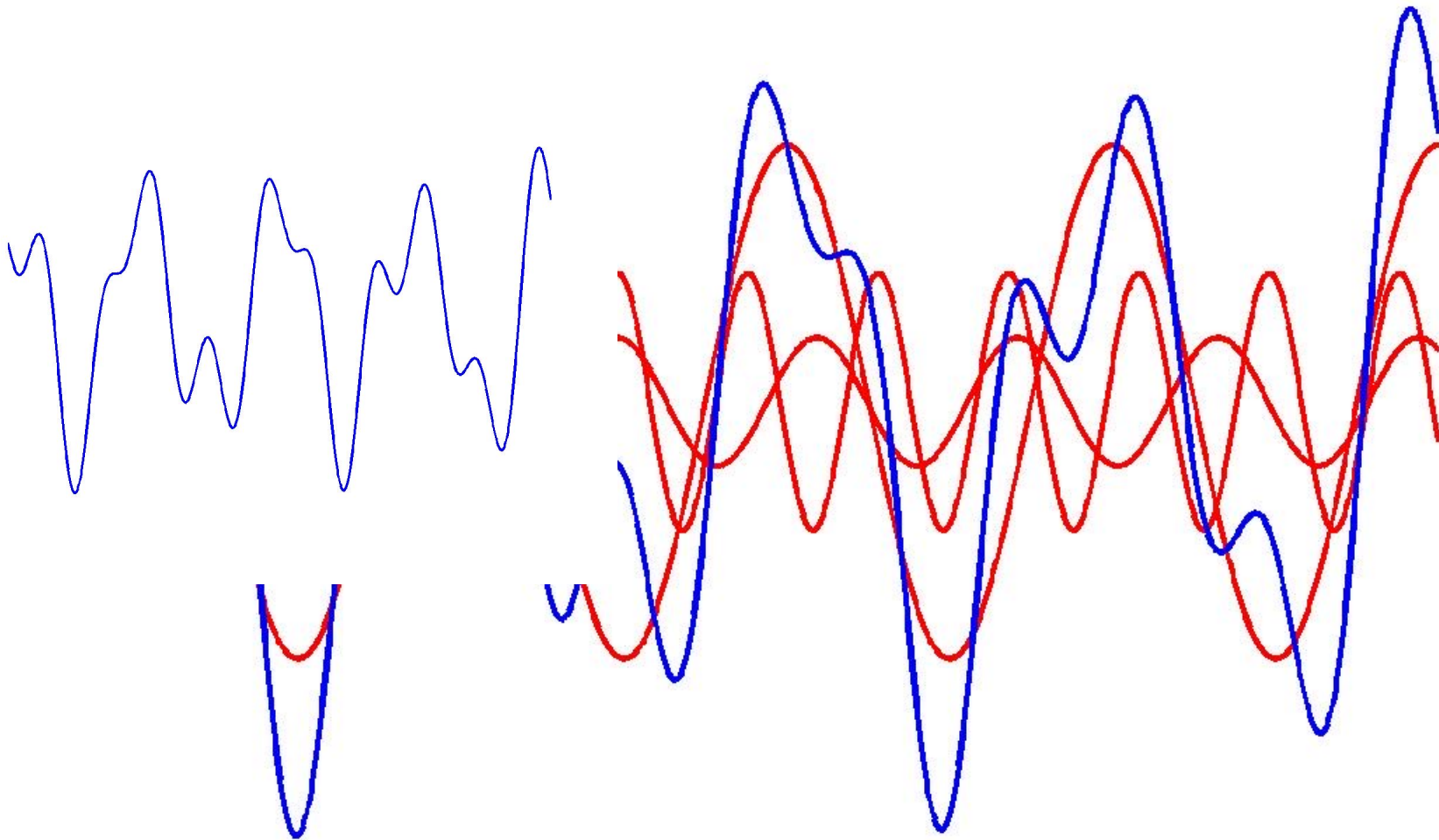
Spectral analysis

Deconstructing a time domain signal into its constituent oscillatory components, a.k.a. Fourier analysis

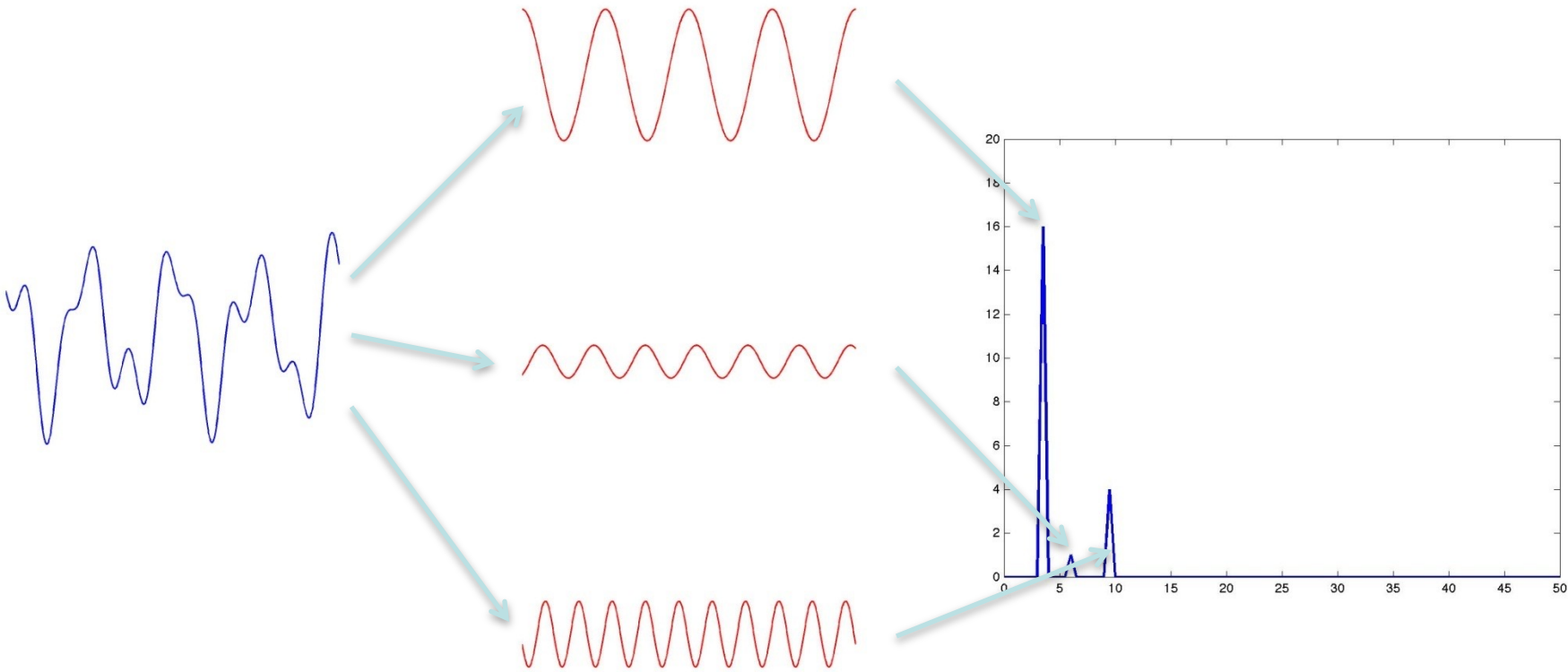
Using simple oscillatory functions: cosines and sines



Spectral decomposition: the principle



Spectral decomposition: the power spectrum



Spectral analysis

Deconstructing a time domain signal into its constituent oscillatory components, a.k.a. Fourier analysis

Using simple oscillatory functions: cosines and sines

Express signal as function of frequency, rather than time

Technique: Fourier transform

Concept: linear regression using oscillatory basis functions

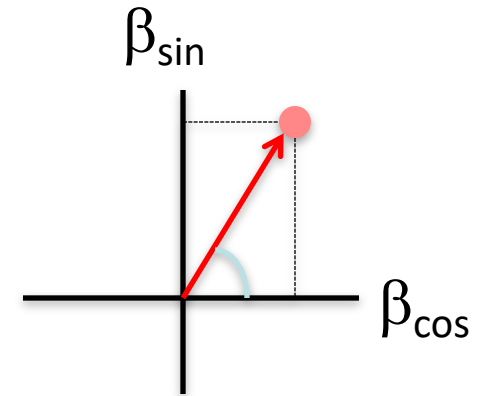
Spectral analysis ~ GLM

$$Y = \beta * X$$

X set of (orthogonal) basis functions

β_i contribution of basis function i to the data.

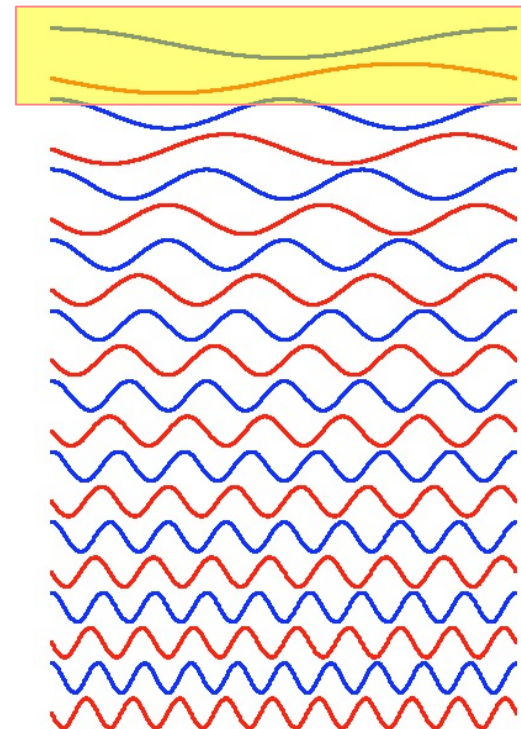
β for cosine and sine components for a given frequency
map onto amplitude and phase estimate.



Going from N time points
to N cosine/sine components

Each cosine/sine pair reflects 1 frequency bin
so $\sim N/2$ frequencies can be estimated

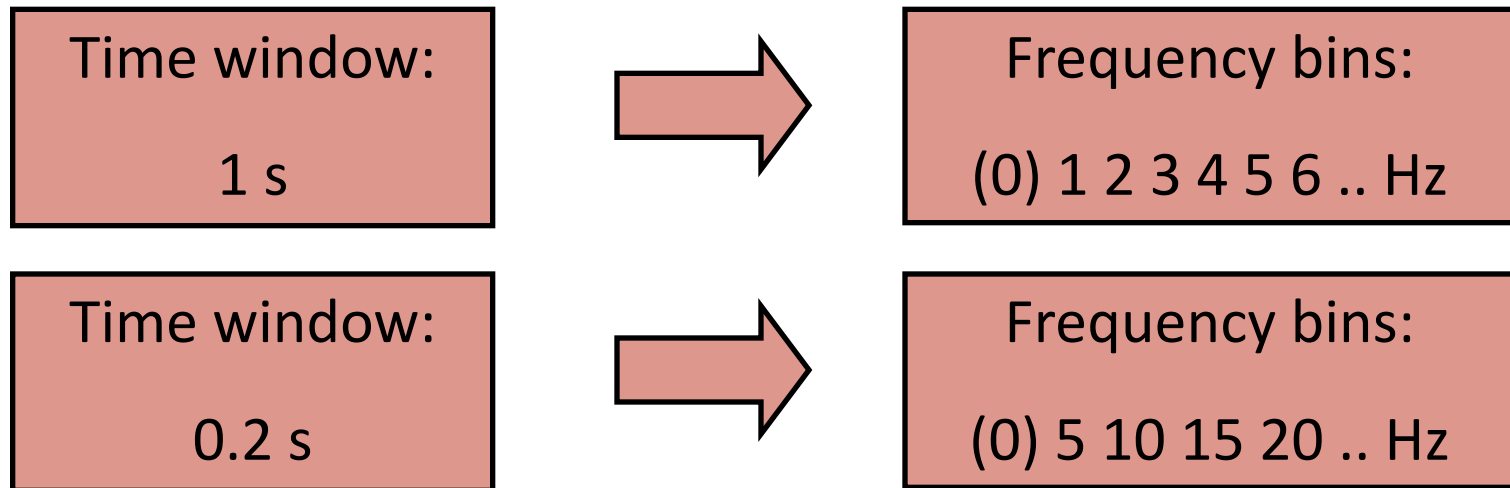
Frequencies correspond to integer number of
cycles of basis functions in time window



Time-frequency relation

Frequencies correspond to basis functions with integer number of cycles in time window (T), sampled in N discrete time steps of length Δt (i.e. with sampling frequency $1/\Delta t$)

Rayleigh frequency = $1/T = \Delta f$ = frequency resolution



Time-frequency relation

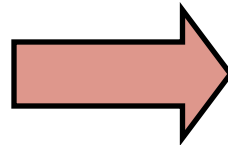
N basis functions -> N/2 frequencies

Frequency bins are spaced with $1/T = 1/(N*\Delta t)$

The highest frequency that can be resolved thus depends on the sampling frequency $1/\Delta t$

Nyquist frequency = $1/(2*\Delta t)$

Sampling freq 1 kHz
Time window 1 s



Frequencies:
(0) 1 2 ... 499 500 Hz

Sampling freq 400 Hz
Time window 0.25 s



Frequencies:
(0) 4 8... 196 200 Hz

Spectral analysis

Deconstructing a time domain signal into its constituent oscillatory components, a.k.a. Fourier analysis

Using simple oscillatory functions: cosines and sines

Express signal as function of frequency, rather than time

Technique: Fourier transform

Concept: linear regression using oscillatory basis functions

Each oscillatory component has an amplitude and phase

Discrete and finite sampling constrains the frequency bins

-> spectral leakage

Outline

Spectral analysis: going from time to frequency domain

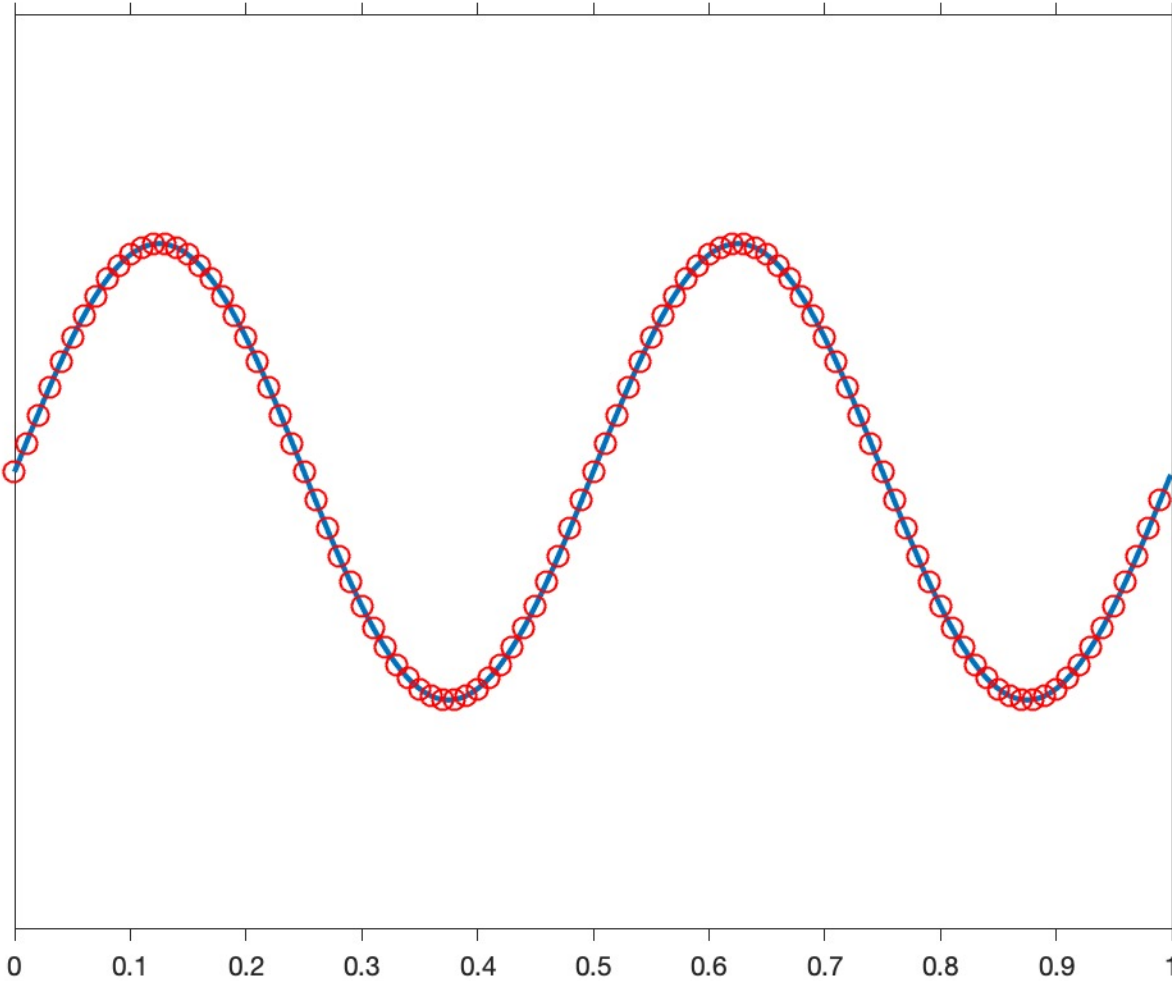
Spectral leakage and (multi-)tapering

Time-frequency analysis

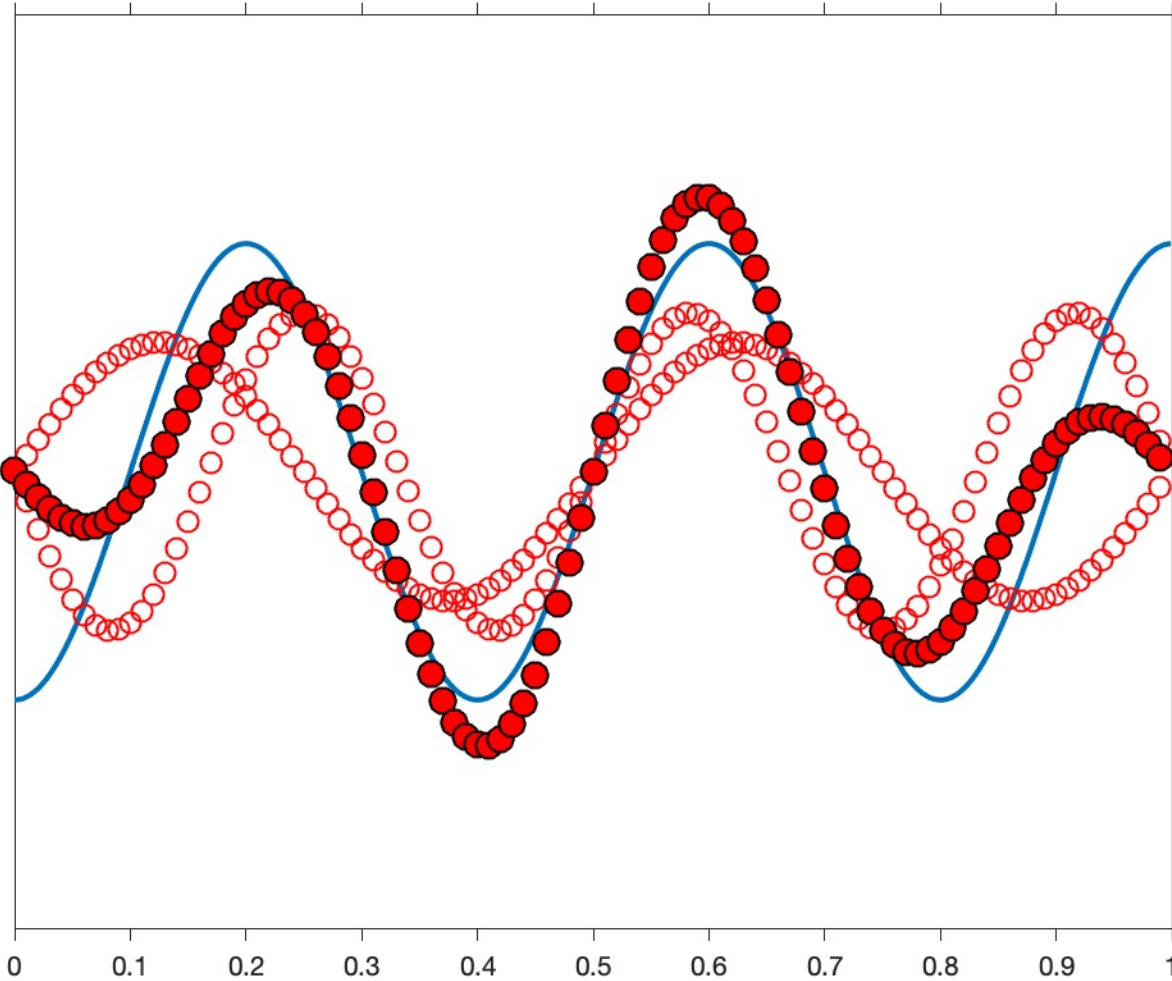
Spectral leakage and tapering

- Signal components at frequencies not sampled with Fourier transform spread their energy to the sampled frequencies

Spectral leakage

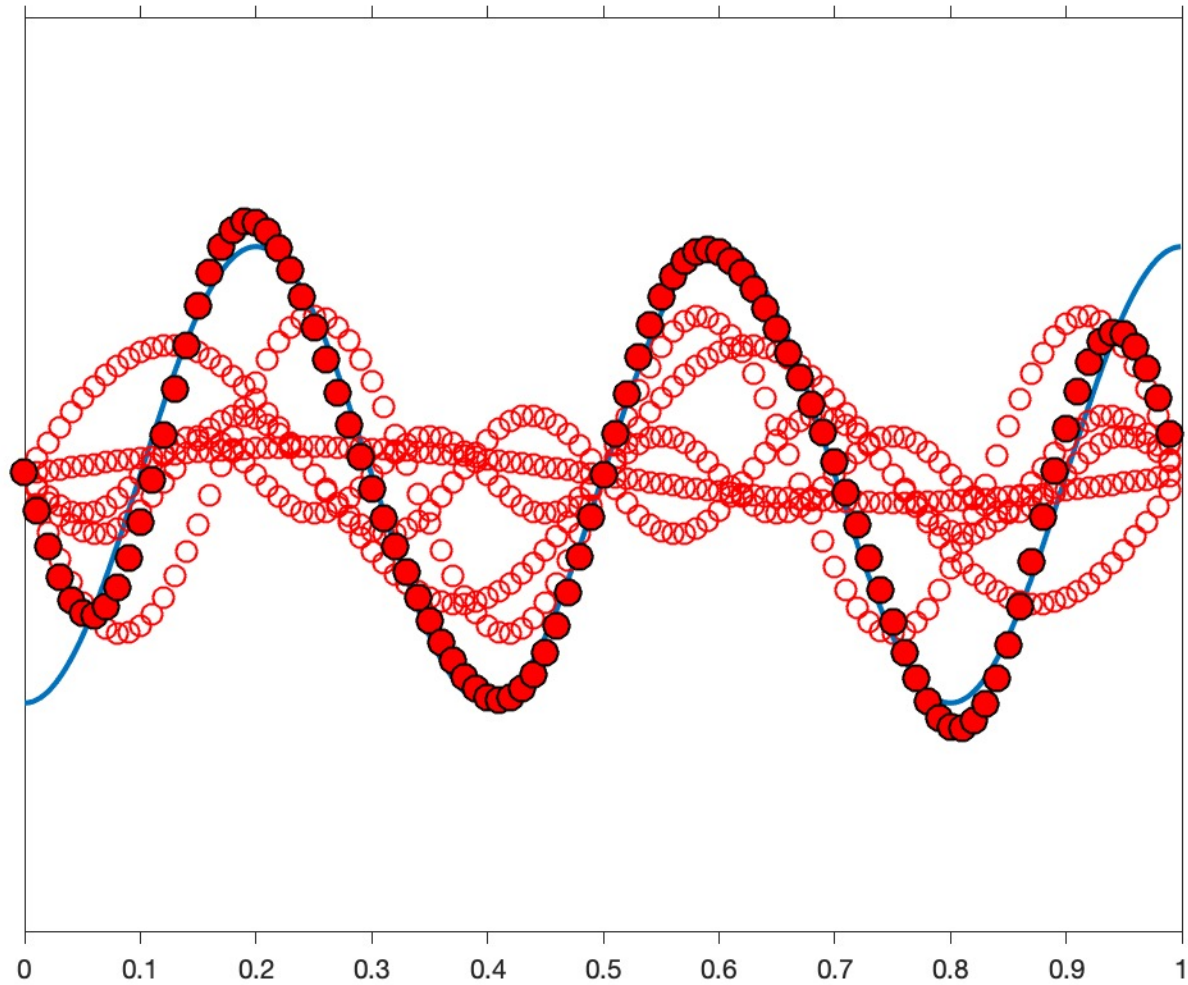


Spectral leakage



Leakage can be 'local'

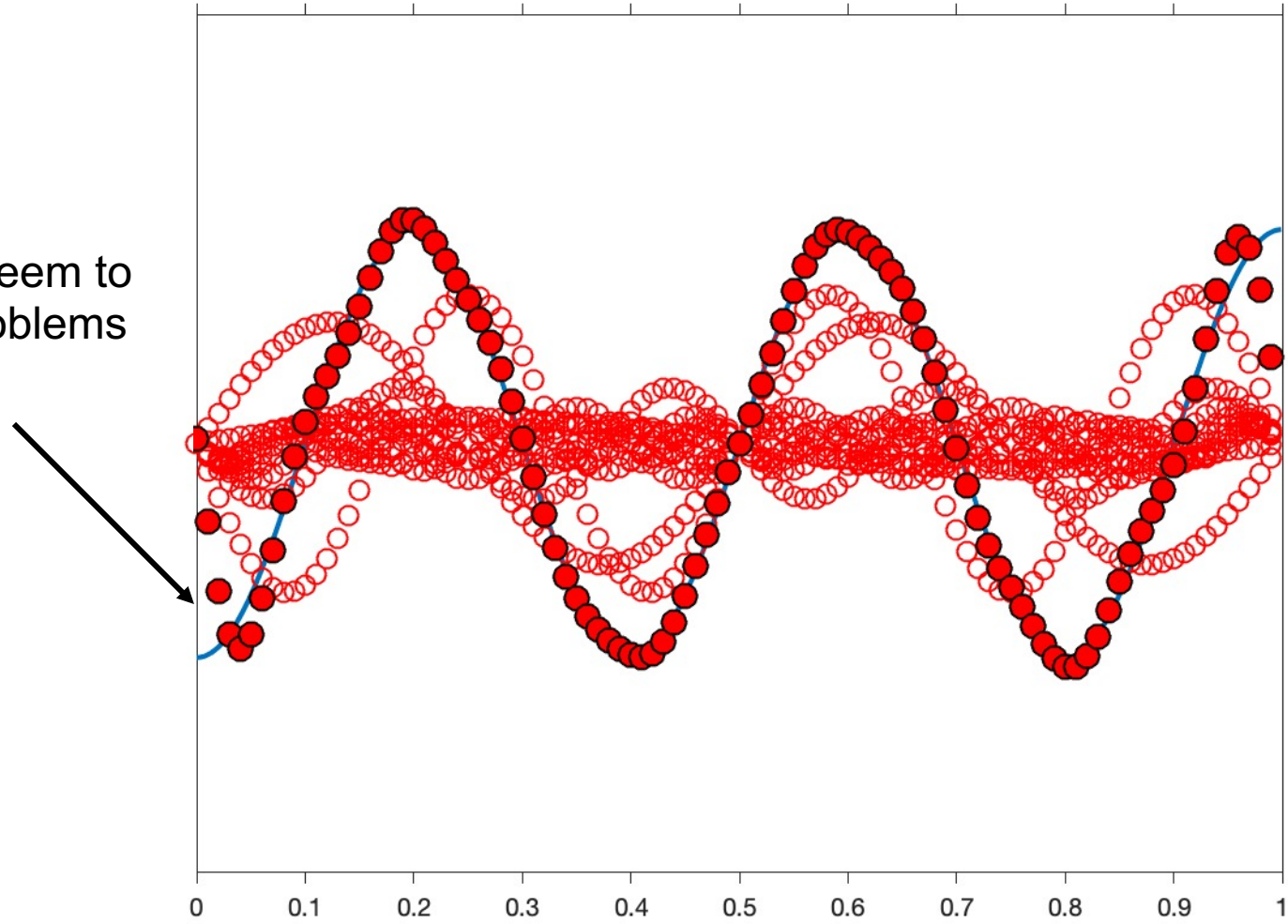
Spectral leakage



Leakage is also 'distant'

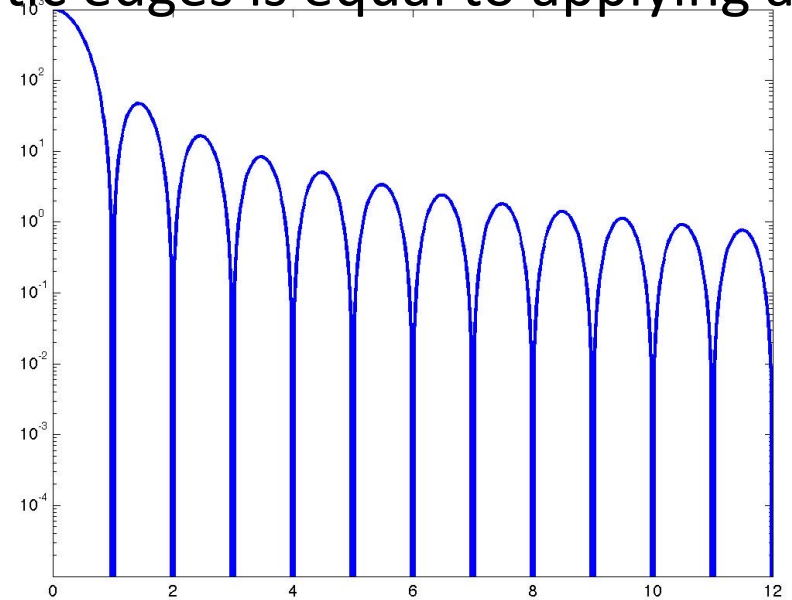
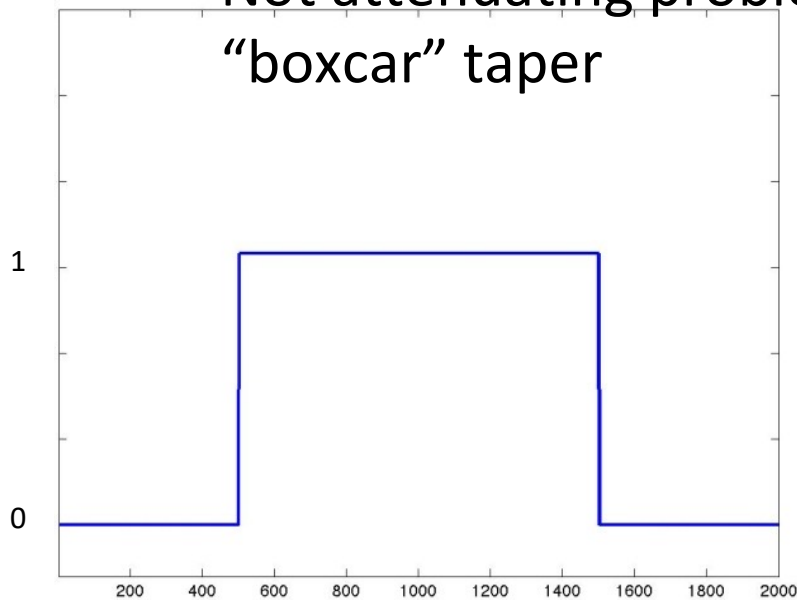
Spectral leakage

Edges seem to pose problems

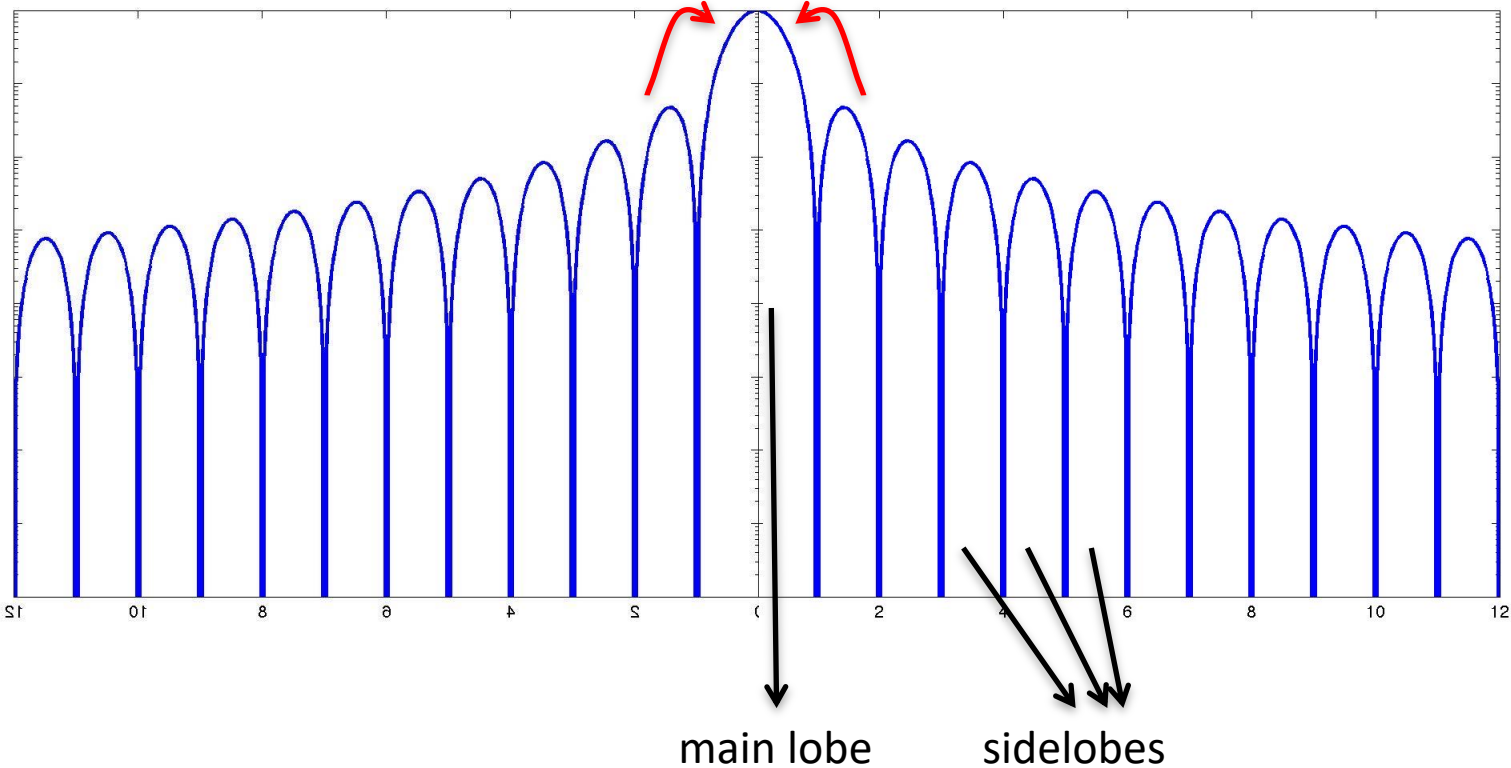


Spectral leakage in the frequency domain

- Signal components at frequencies not sampled with Fourier transform spread their energy to the sampled frequencies
- To fit edges, many basis functions may be needed (lot of distant spectral leakage)
- Not attenuating problematic edges is equal to applying a

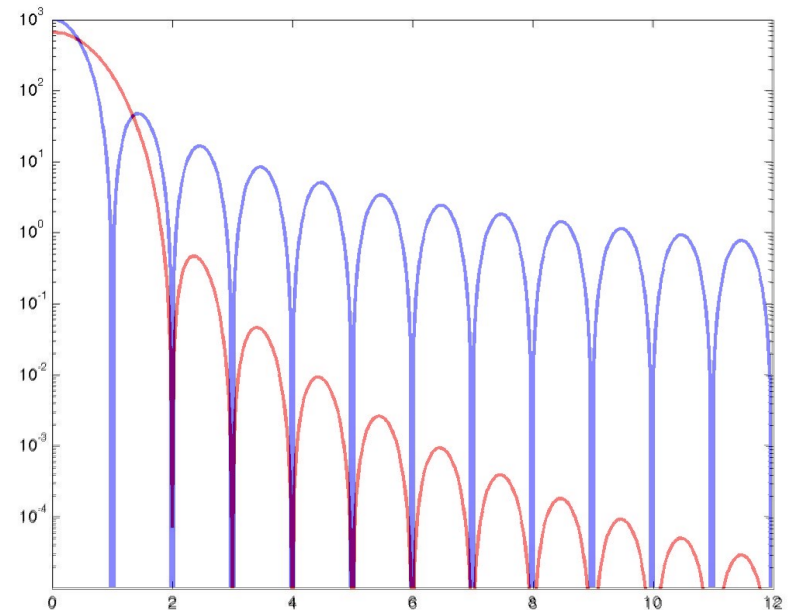
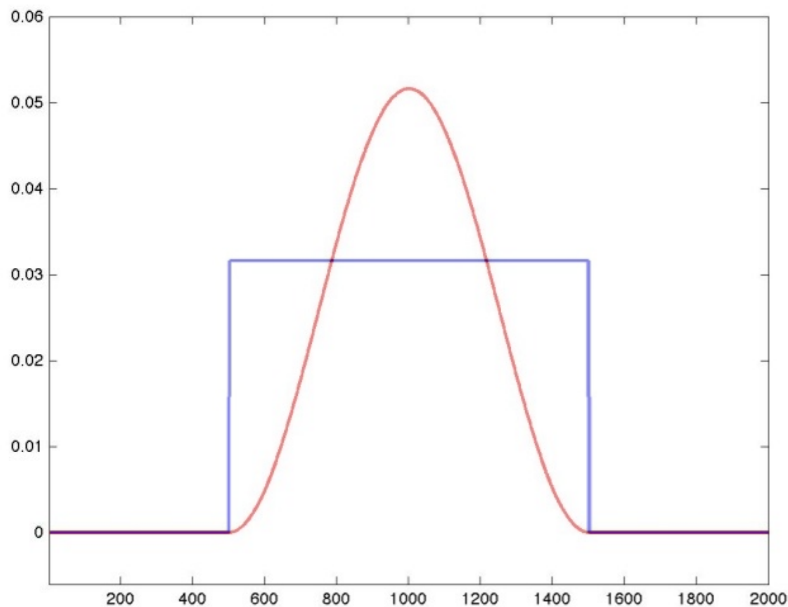


Spectral leakage in the frequency domain

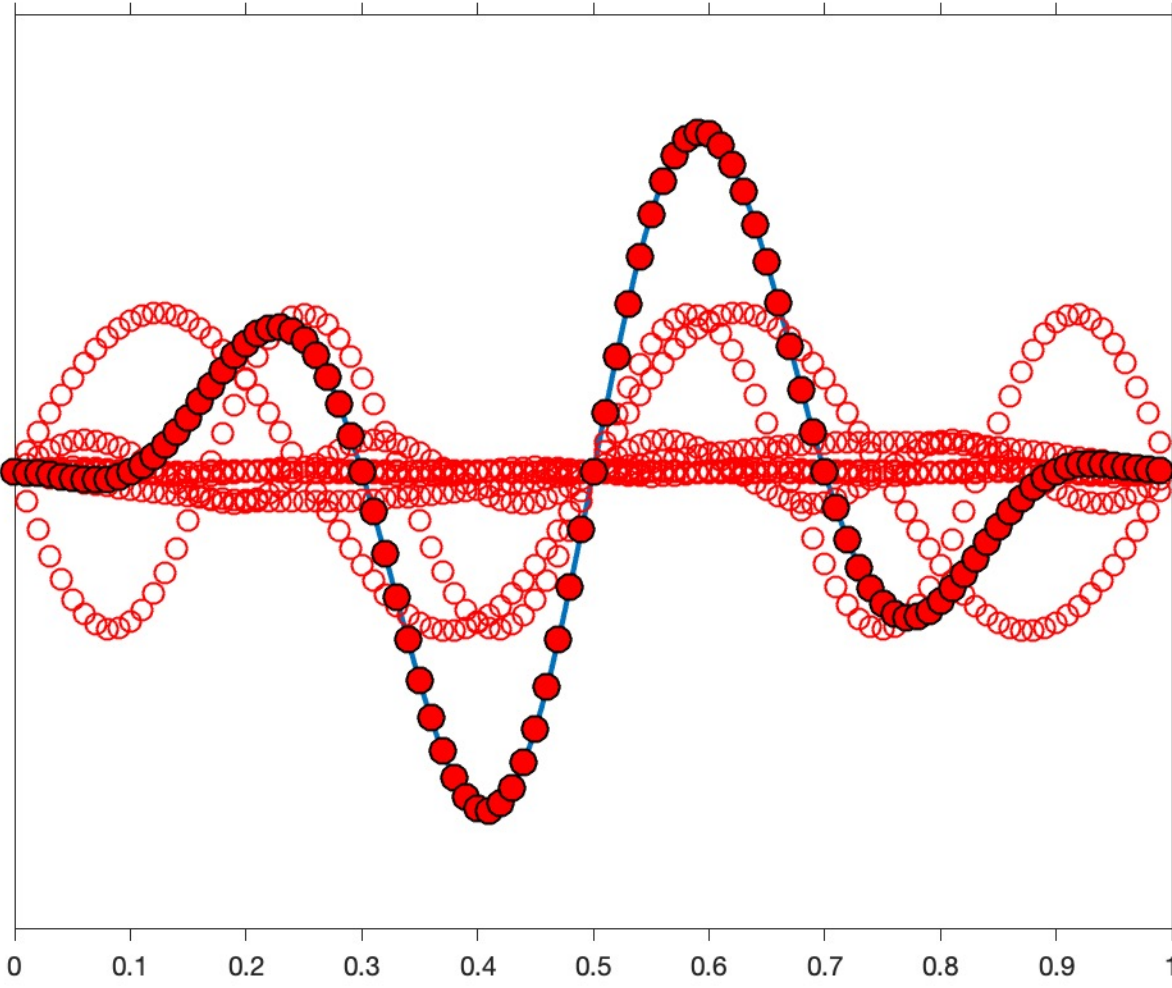


Spectral leakage and tapering

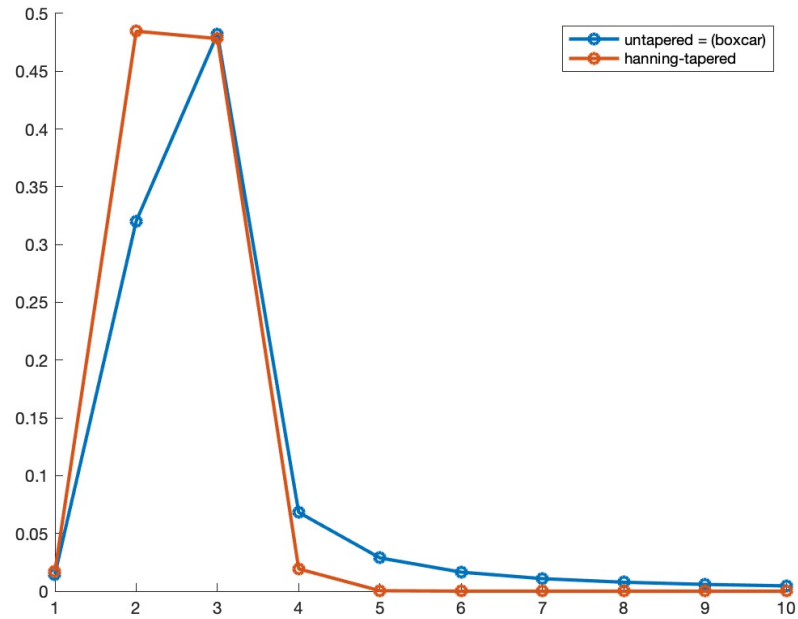
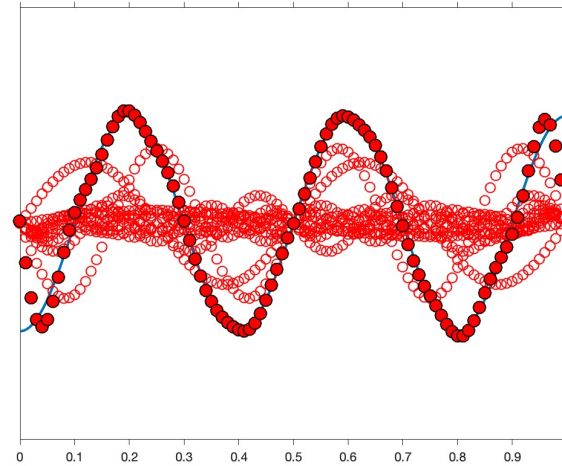
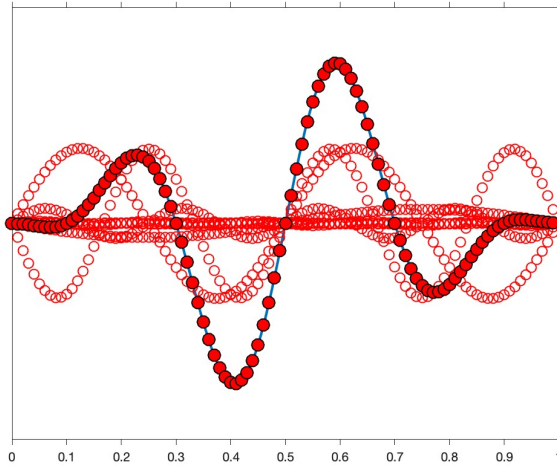
- Tapering = attenuating potentially problematic edges of the signal by multiplication with a 'taper function'



Spectral leakage and tapering



Spectral leakage and tapering



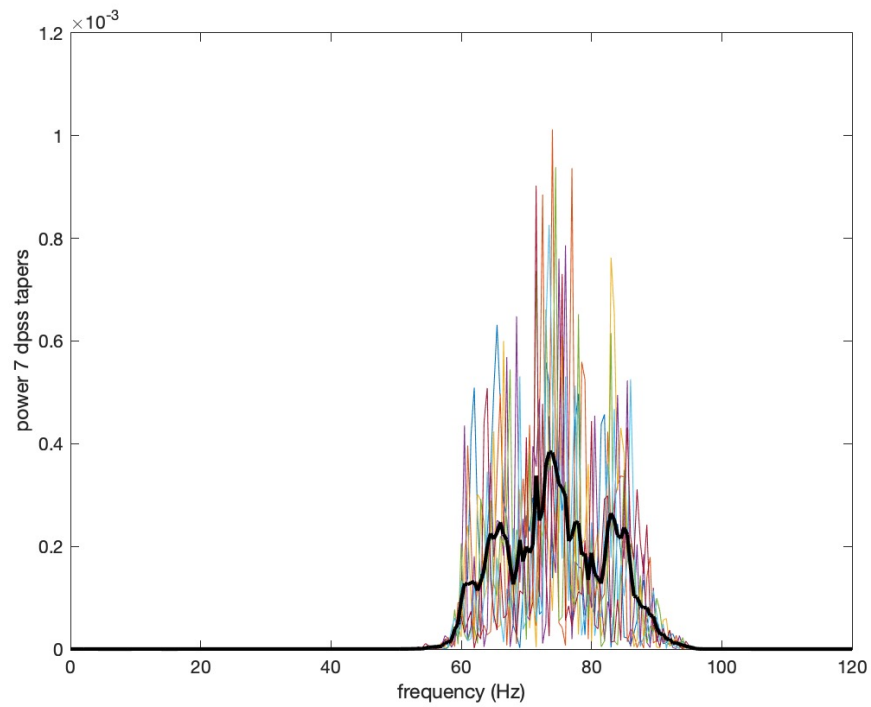
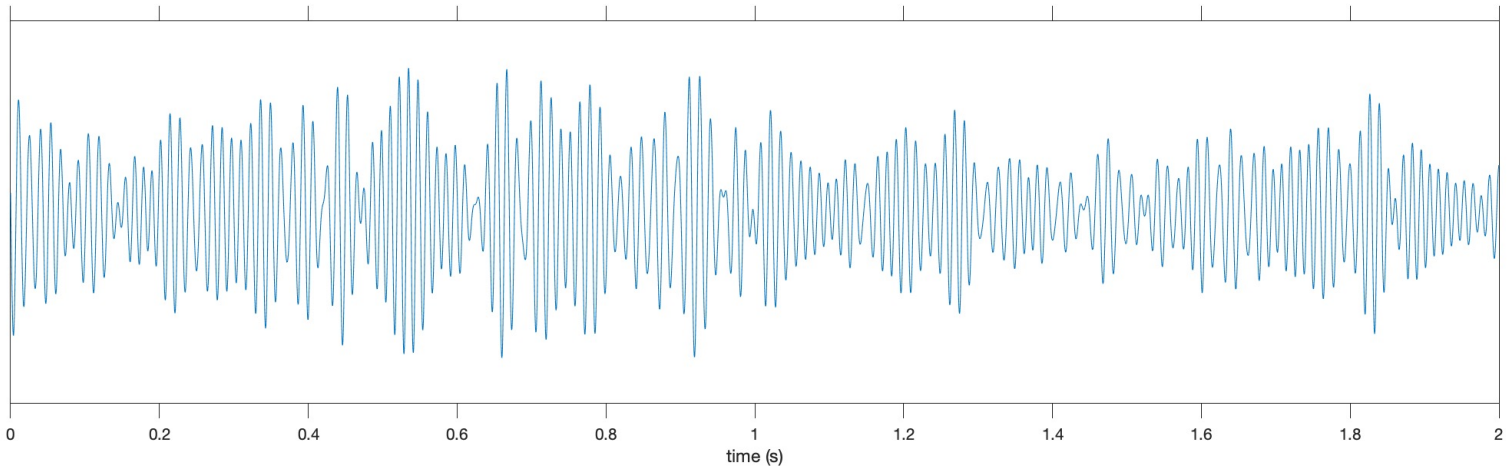
Multitapers

Make use of more than one taper and combine their leakage properties

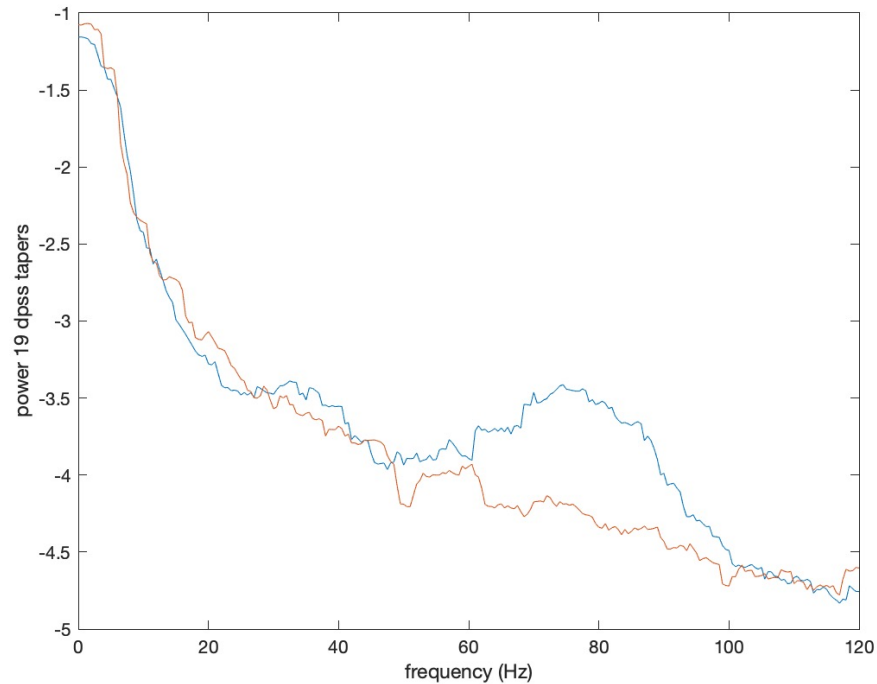
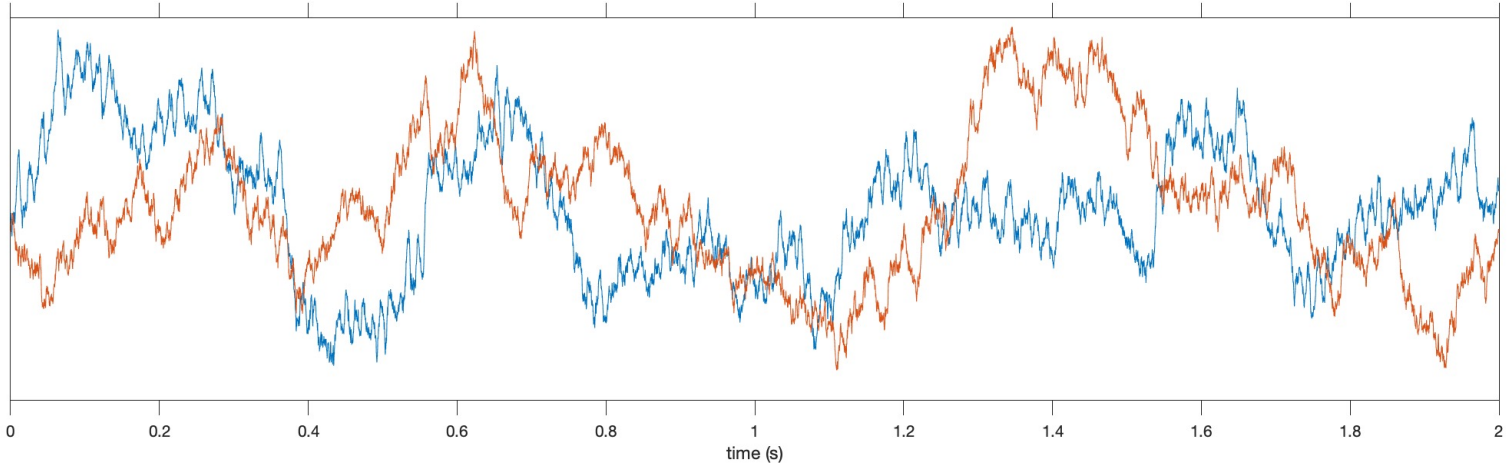
Used for smoothing in the frequency domain

Instead of “smoothing” one can also say “controlled leakage”

Multitapered spectral analysis



Multitapered spectral analysis



Multitapers

Multitapers are useful for reliable estimation of frequency components with a bandwidth $>$ spectral resolution

Low frequency components are better estimated using a single (Hanning) taper

```
%estimate low frequencies
```

```
cfg = [];  
cfg.method = 'mtmfft';  
cfg.foylim = [1 30];  
cfg.taper = 'hanning';  
.  
.  
.  
freq=ft_freqanalysis(cfg, data);
```

```
%estimate high frequencies
```

```
cfg = [];  
cfg.method = 'mtmfft';  
cfg.foylim = [30 120];  
cfg.taper = 'dpss';  
cfg.tapsmofrq = 8;  
.  
.  
freq=ft_freqanalysis(cfg, data);
```

Outline

Spectral analysis: going from time to frequency domain

Spectral leakage and (multi-)tapering

Time-frequency analysis

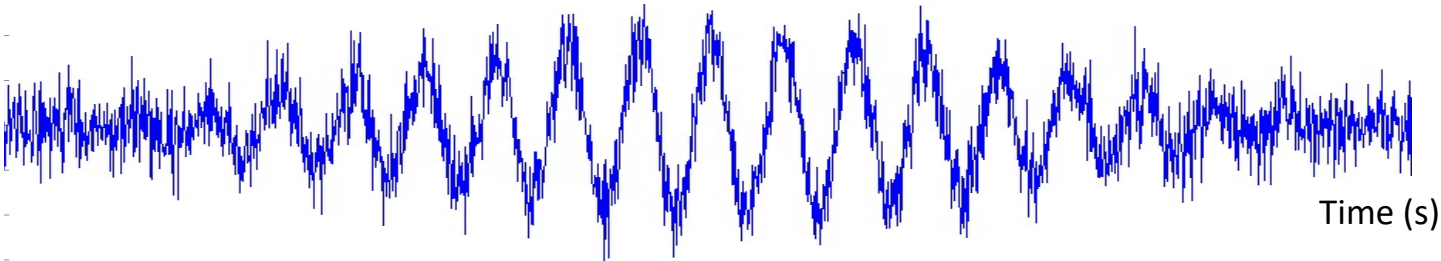
Time-frequency analysis

Typically, brain signals are not ‘stationary’

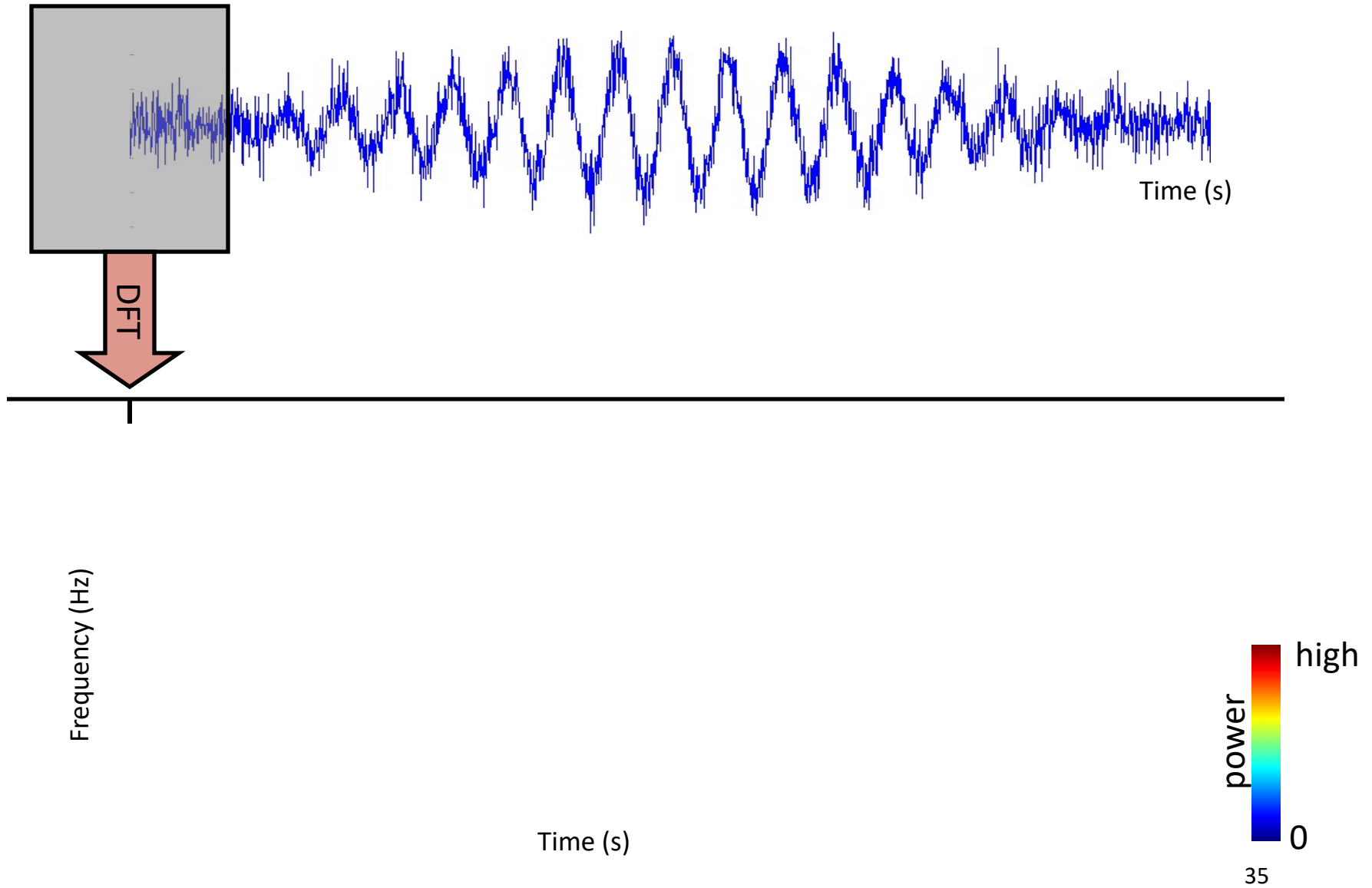
- Divide the measured signal in shorter time segments and apply Fourier analysis to each signal segment

```
cfg = [];  
cfg.method = 'mtmconvol';  
.  
.  
.  
freq = ft_freqanalysis(cfg, data);
```

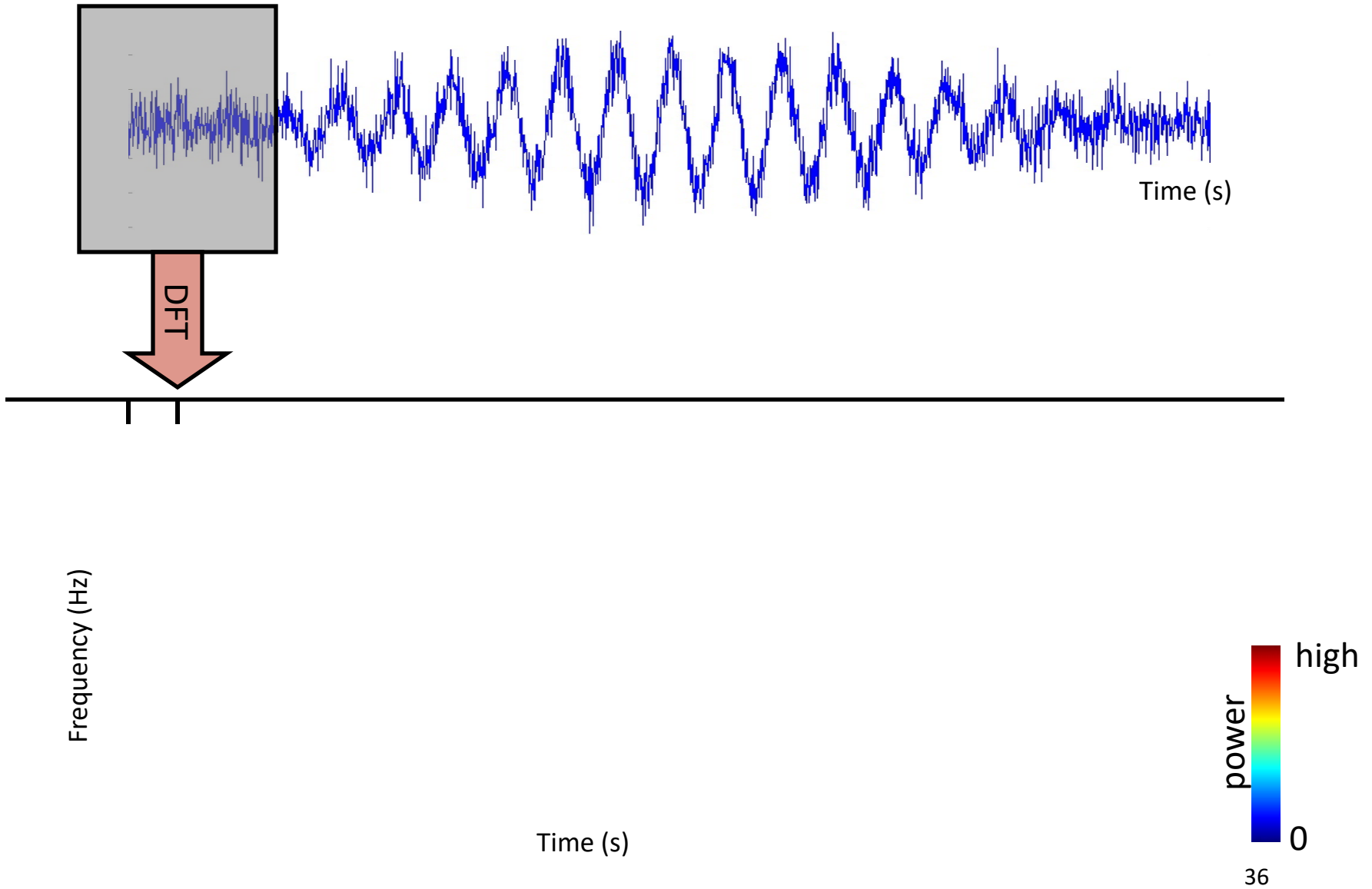
Time frequency analysis



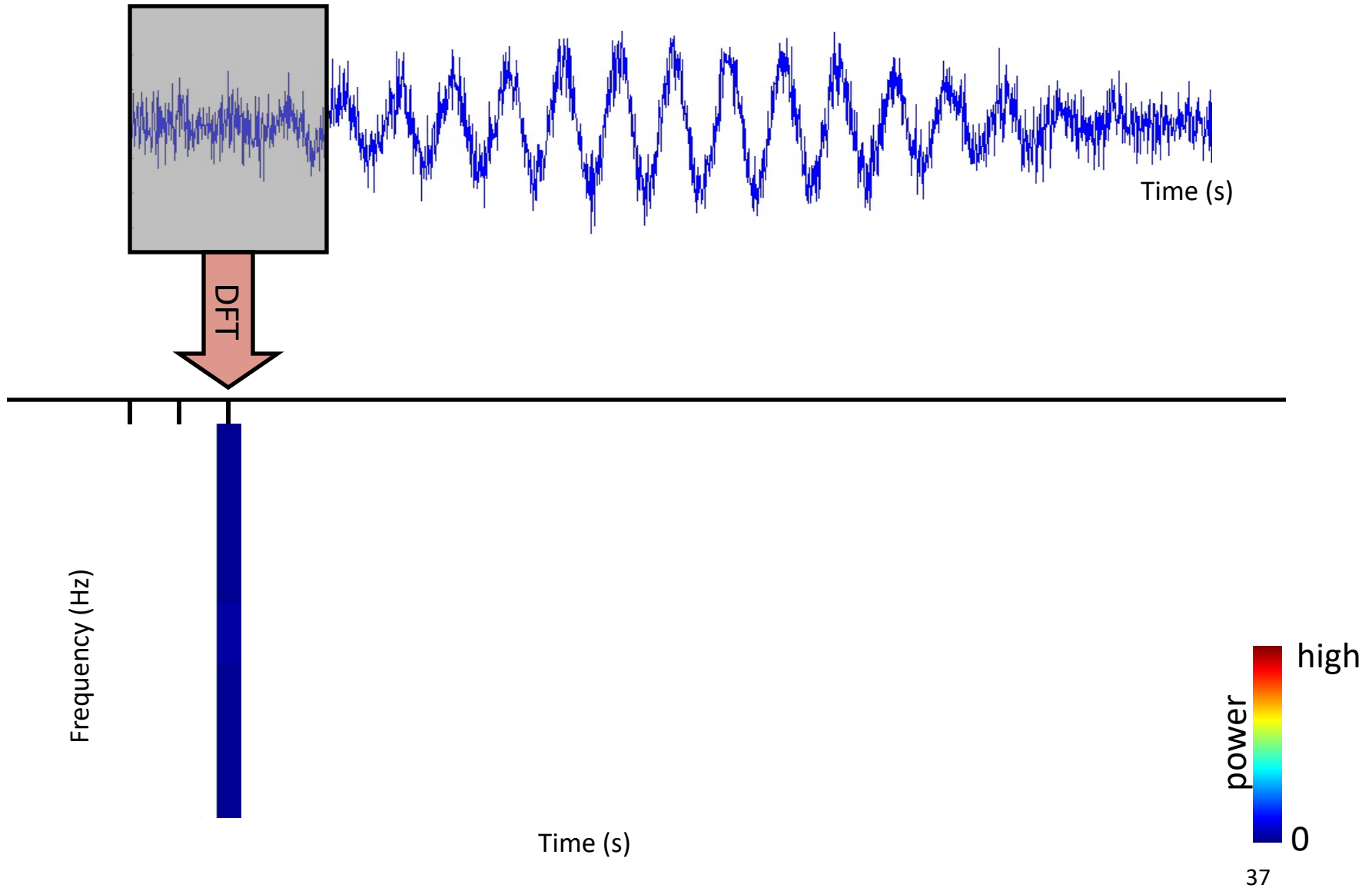
Time frequency analysis



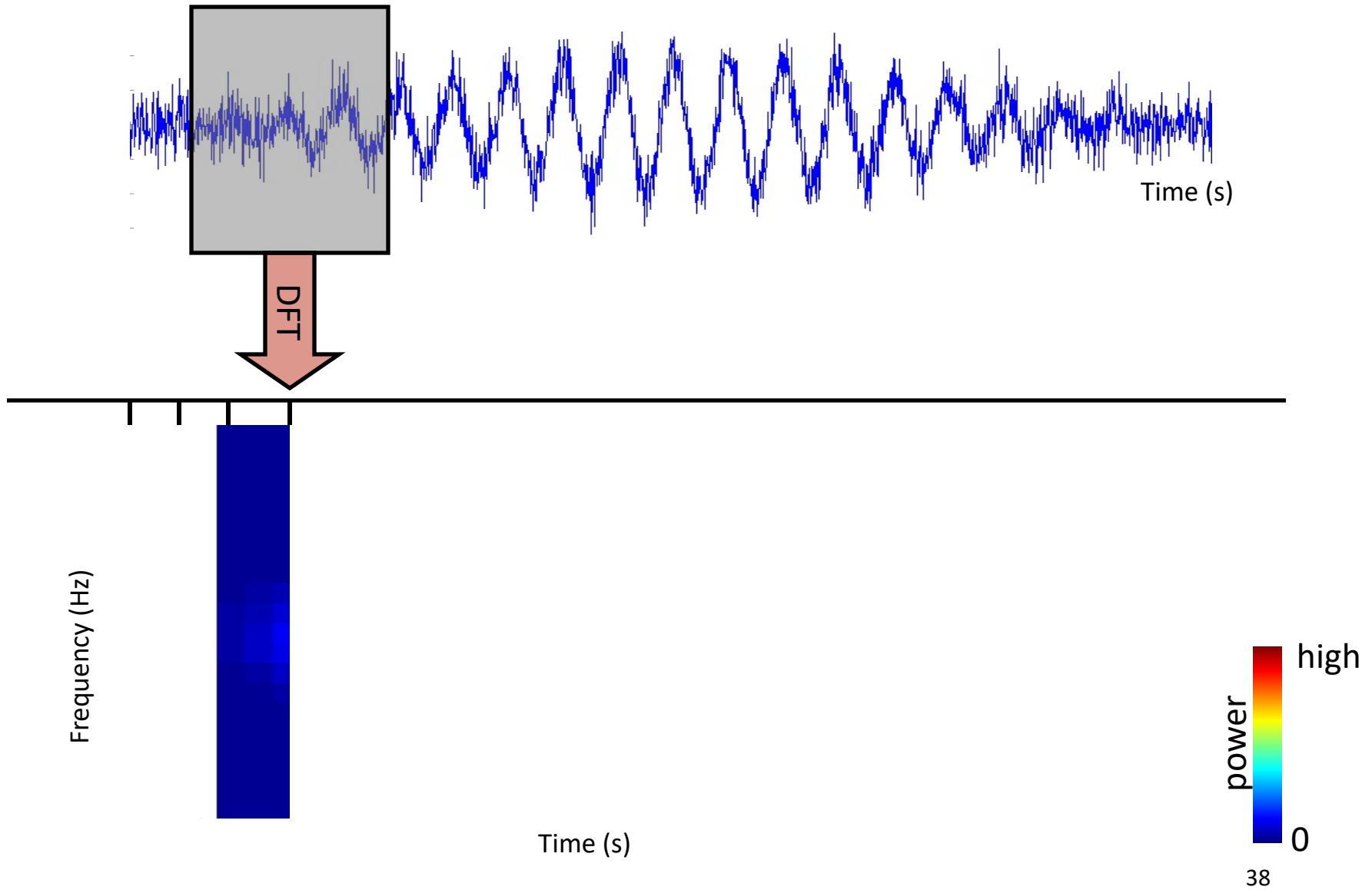
Time frequency analysis



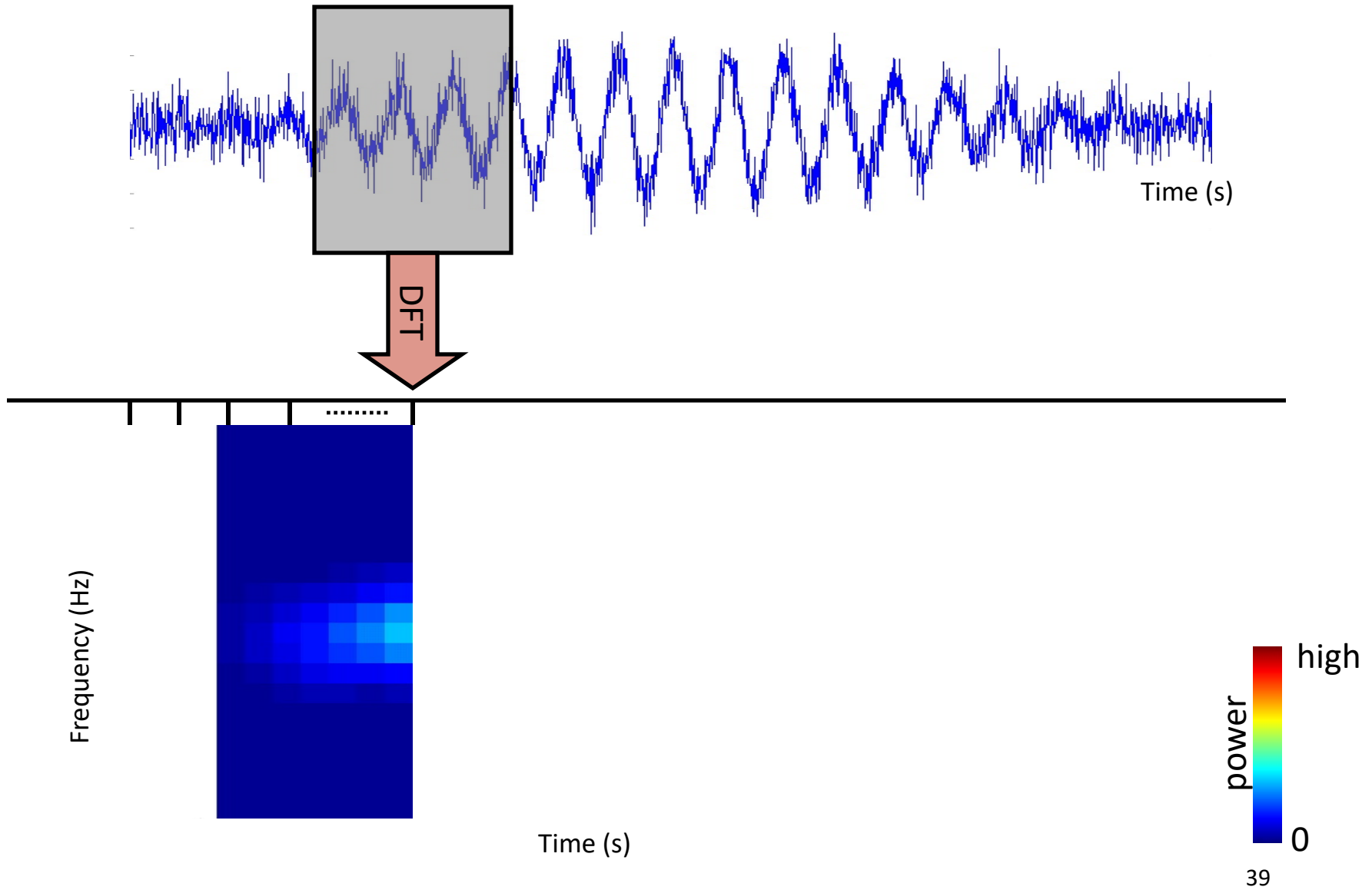
Time frequency analysis



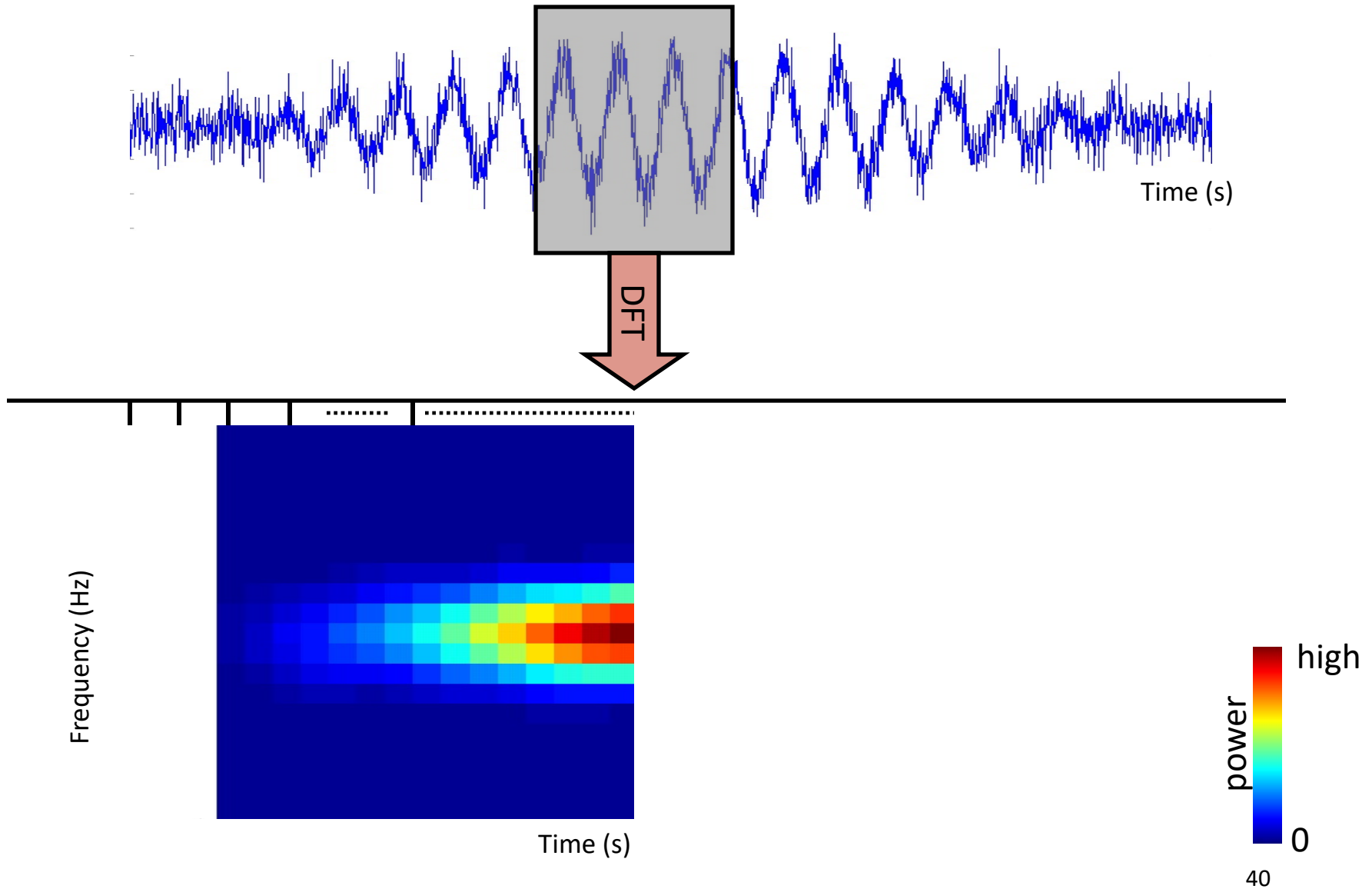
Time frequency analysis



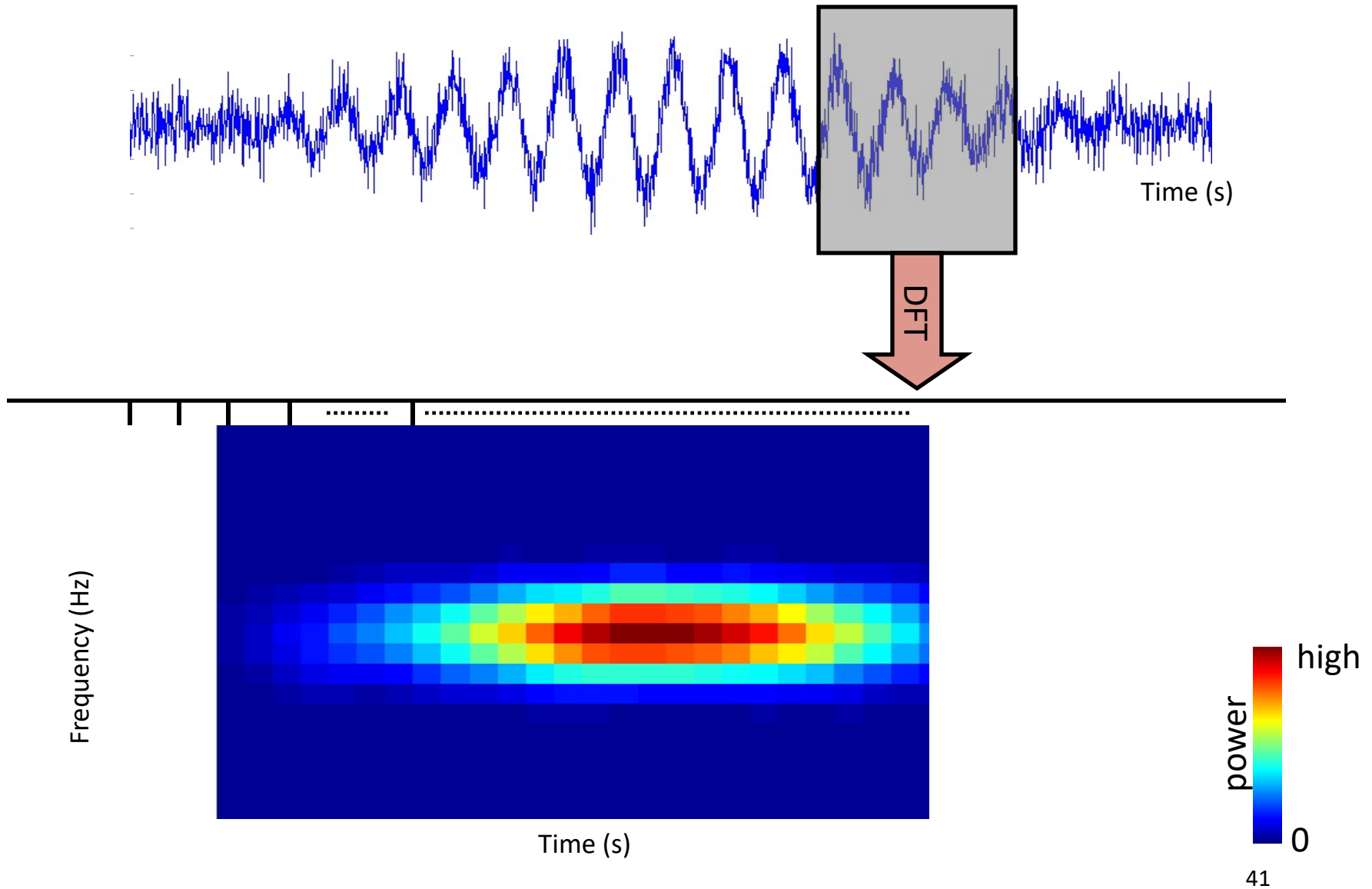
Time frequency analysis



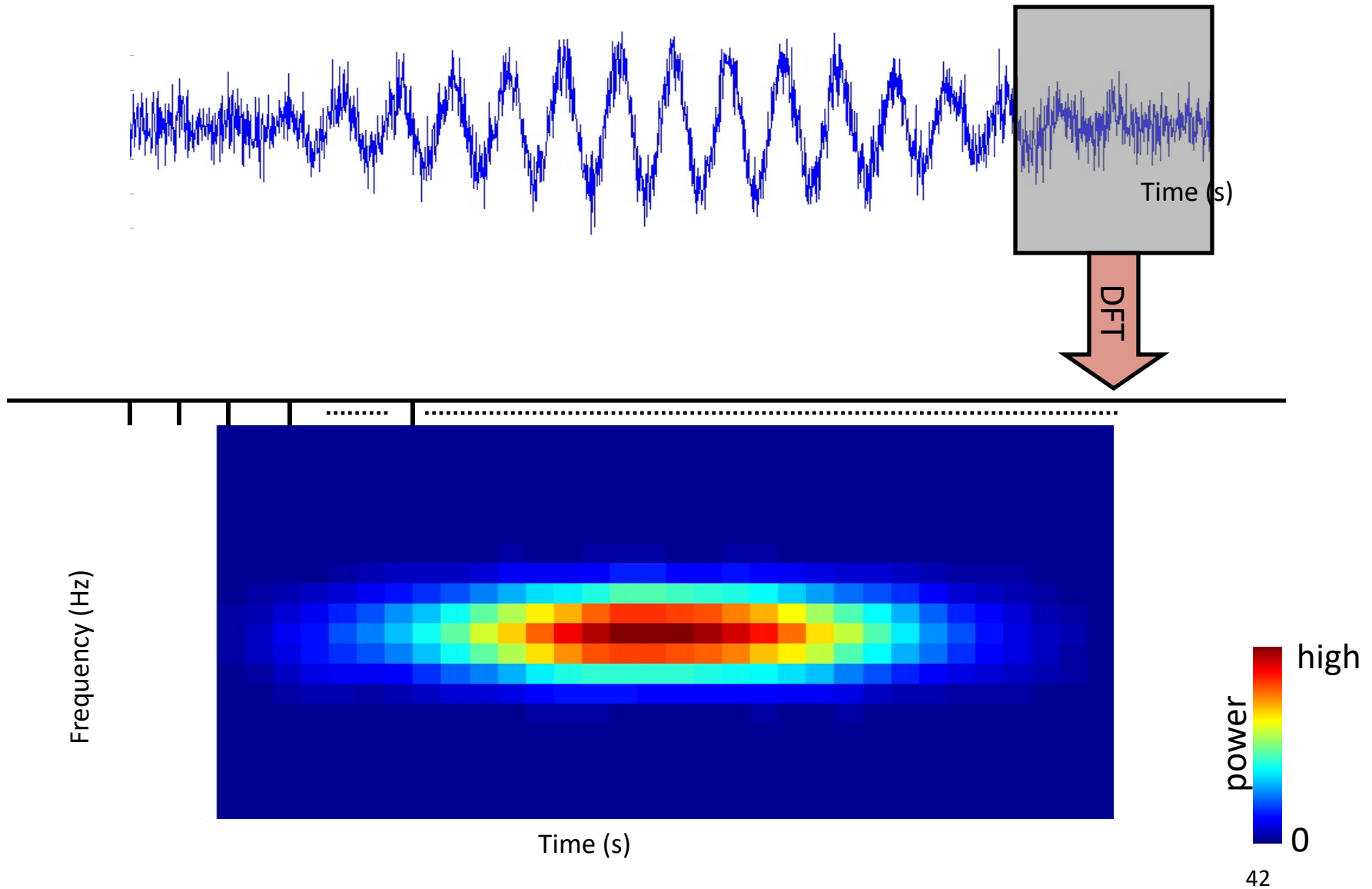
Time frequency analysis



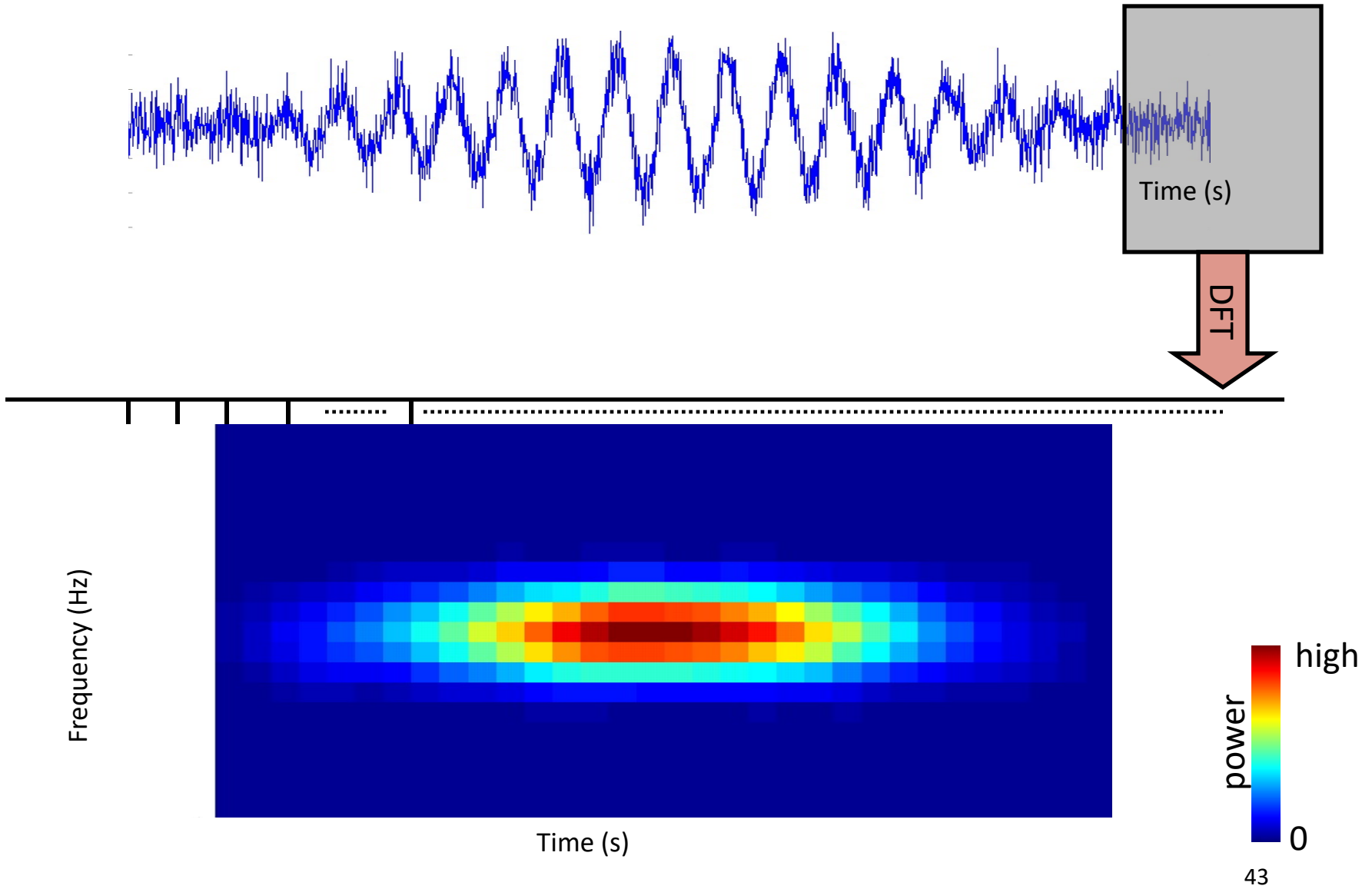
Time frequency analysis



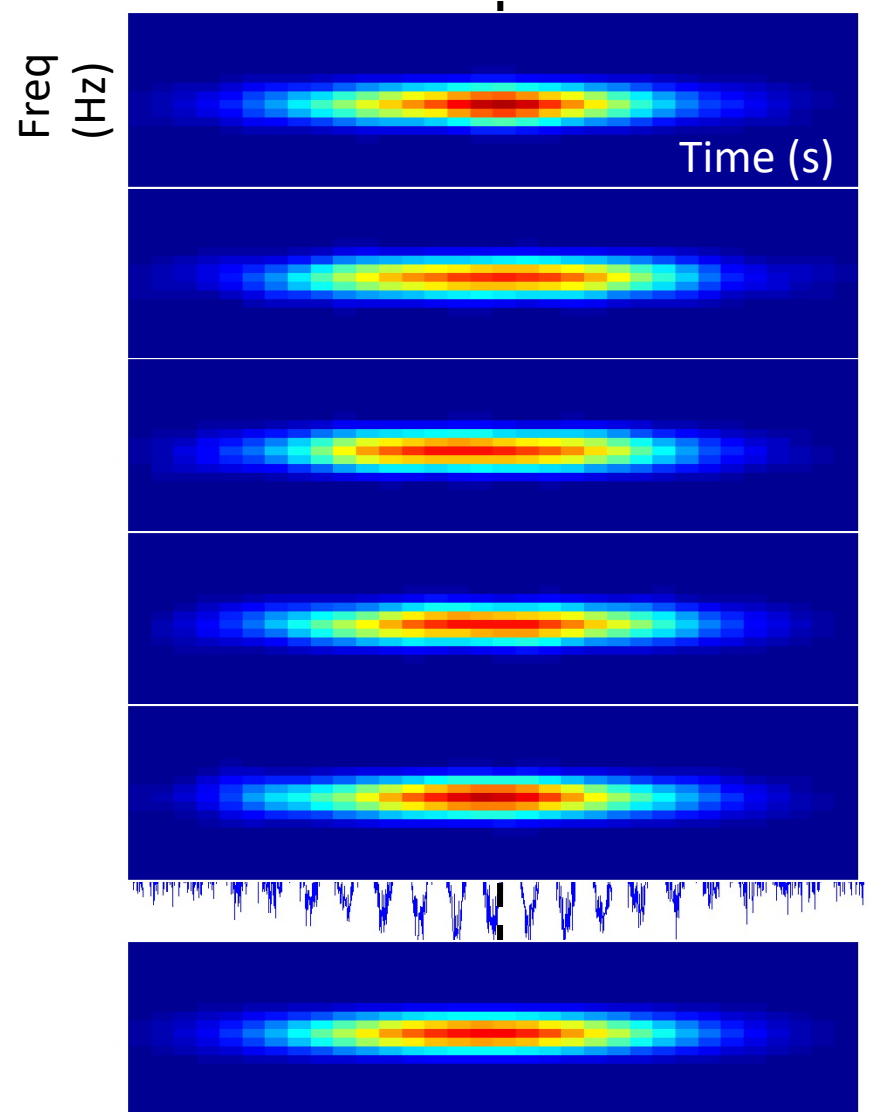
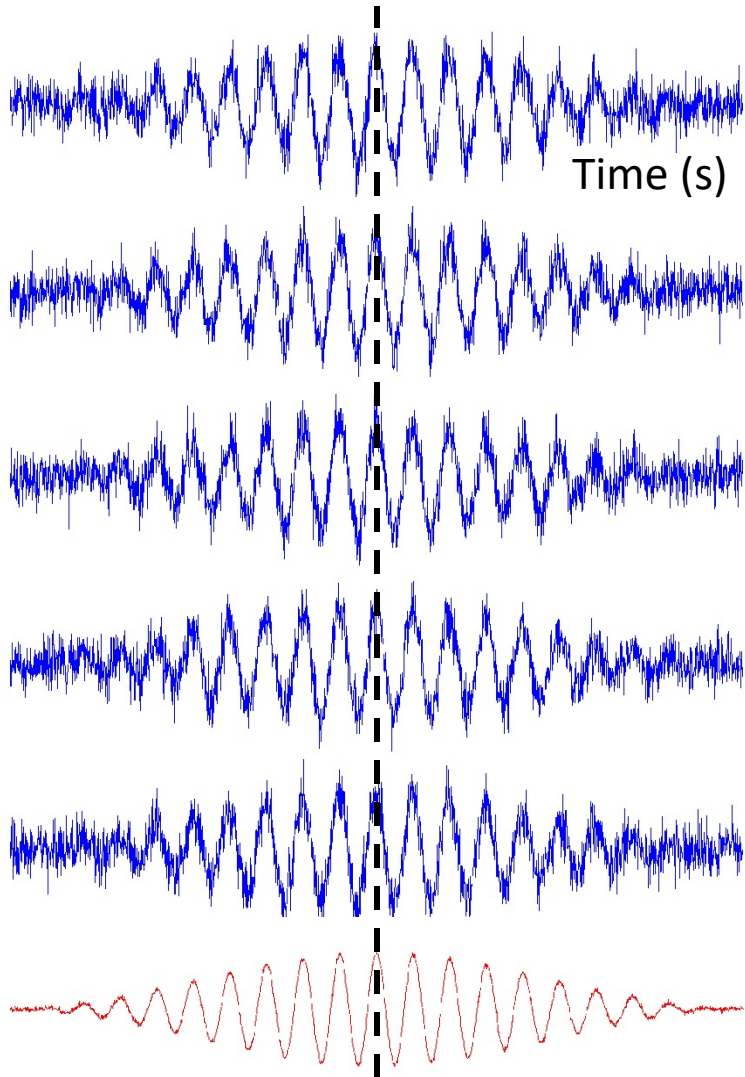
Time frequency analysis



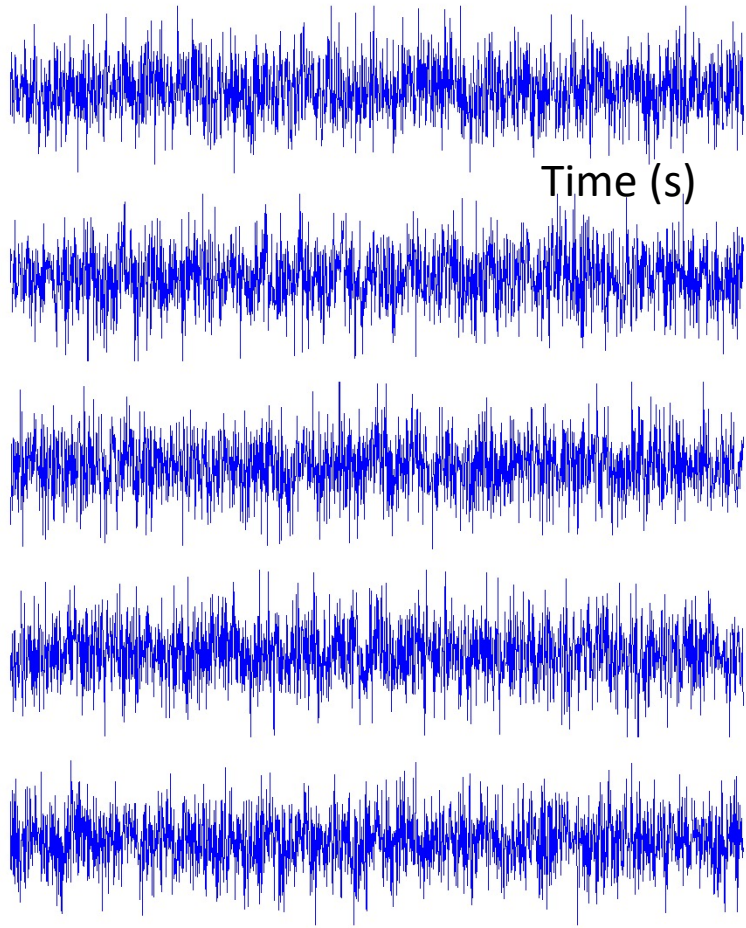
Time frequency analysis



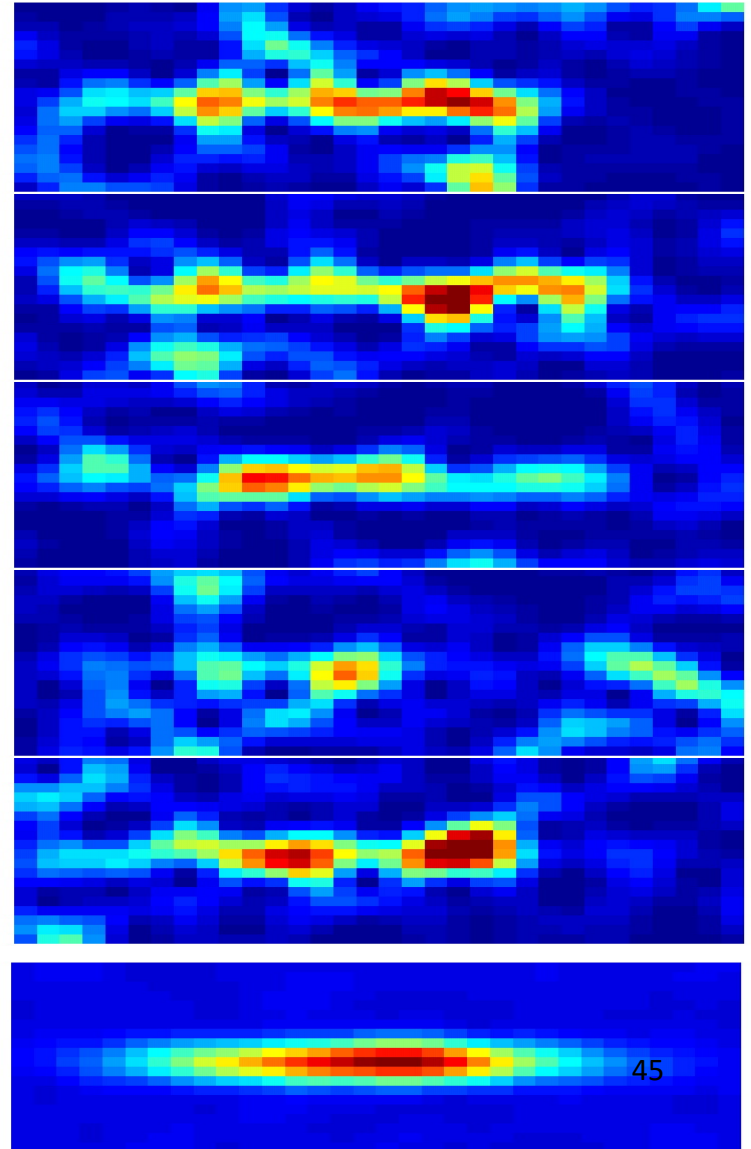
Evoked versus induced activity



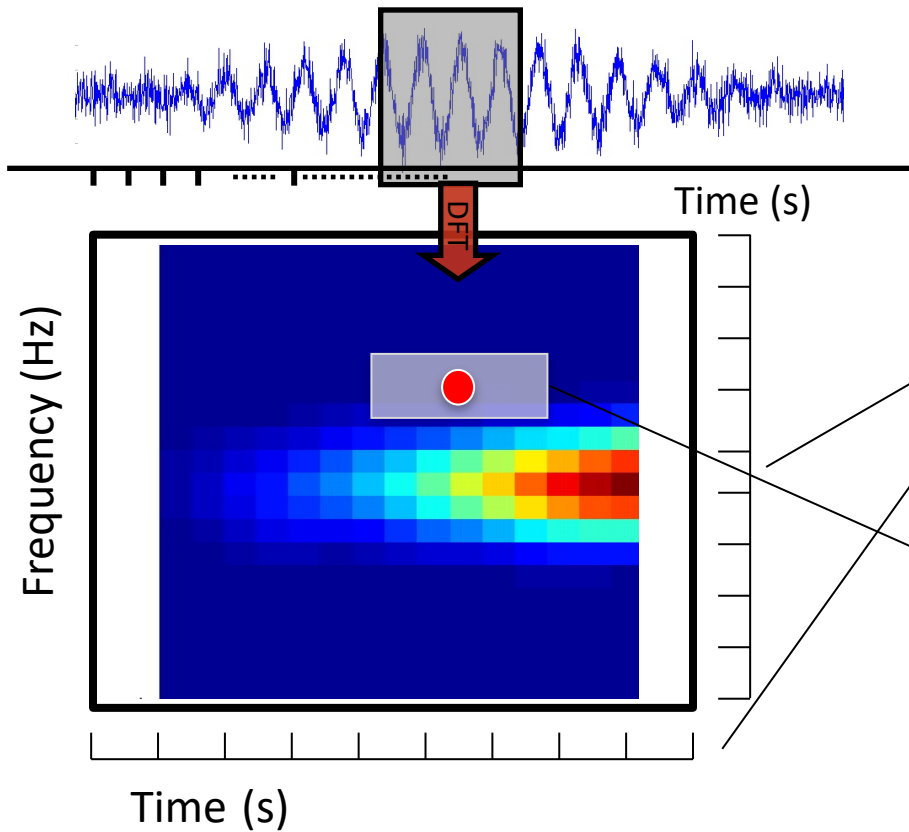
Noisy signal -> many trials needed



Freq
(Hz)



The time-frequency plane



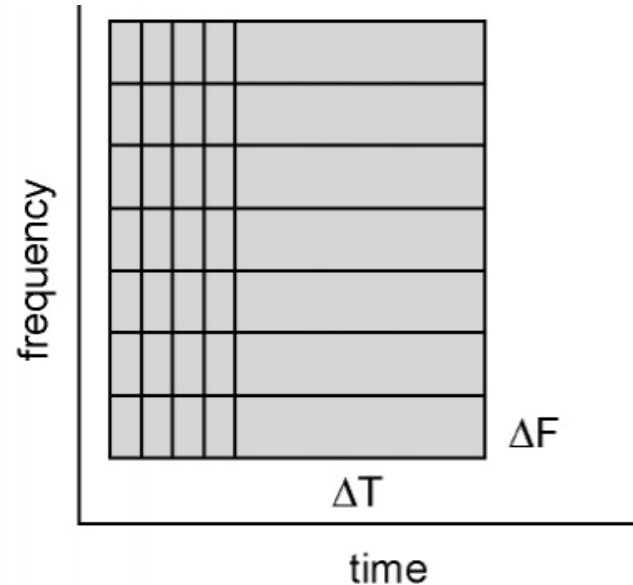
```
cfg          = [];  
cfg.method   = 'mtmconvol';  
  
freq = ft_freqanalysis(cfg,data)
```

The time-frequency plane

The division is ‘up to you’

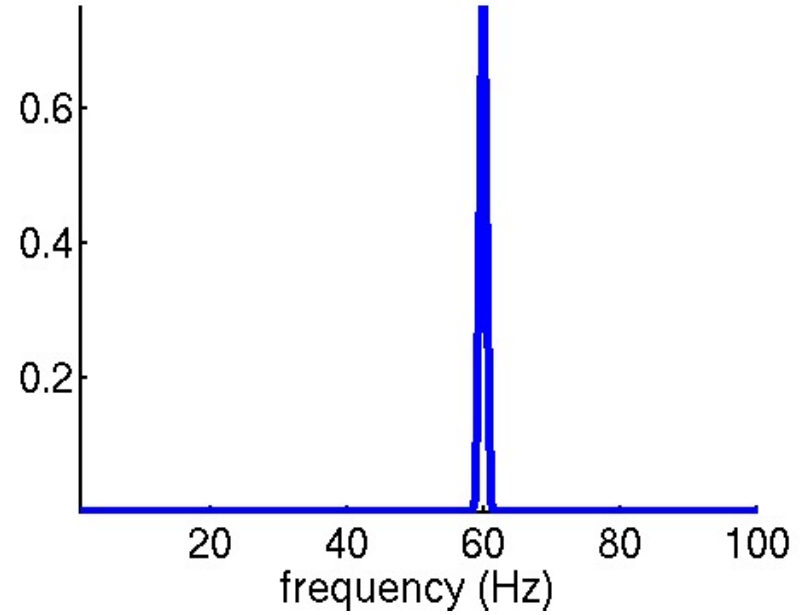
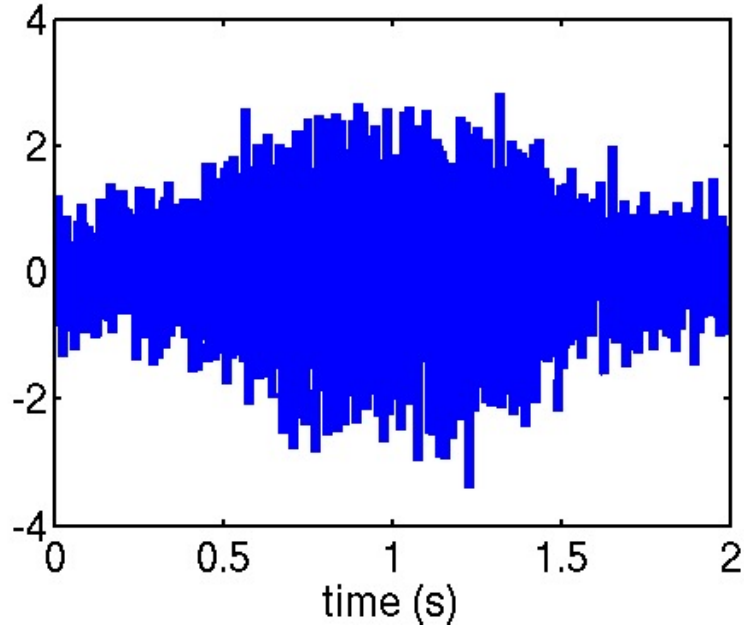
Depends on the phenomenon
you want to investigate:

- Which time scale?
- Bandwidth?



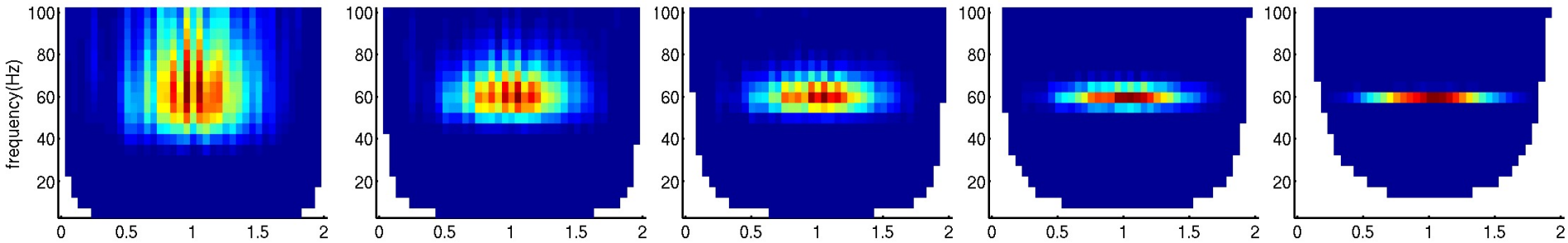
```
cfg = [];  
cfg.method      = 'mtmconvol';  
cfg.foi         = [2 4 ... 40];  
cfg.toi         = [0:0.050:1.0];  
cfg.t_ftimwin   = [0.5 0.5 ... 0.5];  
cfg.tapsmofrq   = [ 4  4 ... 4 ];  
.  
.  
freq = ft_freqanalysis(cfg,data);
```

Time versus frequency resolution



short timewindow

long timewindow



Wavelet analysis

Popular method to calculate time-frequency representations

Is based on convolution of signal with a family of 'wavelets' which capture the different frequency components in the signal

Convolution \sim local correlation

Wavelet analysis

```
cfg = [];  
cfg.method = 'wltconvol';  
.  
.  
.  
freq=ft_freqanalysis(cfg, data);
```

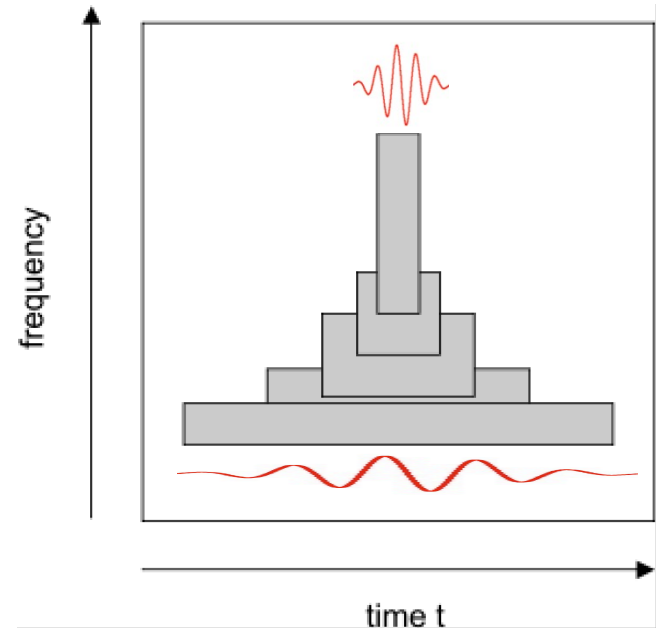
Wavelet analysis

Wavelet width determines the time-frequency resolution

Width is a function of frequency (often 5 cycles)

‘Long’ wavelet at low frequencies leads to relatively narrow frequency resolution but poor temporal resolution

‘Short’ wavelet at high frequencies leads to broad frequency resolution but more accurate temporal resolution



Summary

Spectral analysis: going from time to frequency domain

Spectral leakage and (multi-)tapering

Time-frequency analysis

This afternoon: hands-on

- Time-frequency analysis on real data

- Different methods

- Parameter tweaking

- Power versus baseline

- Visualization

