Spectral analysis...

...Why?

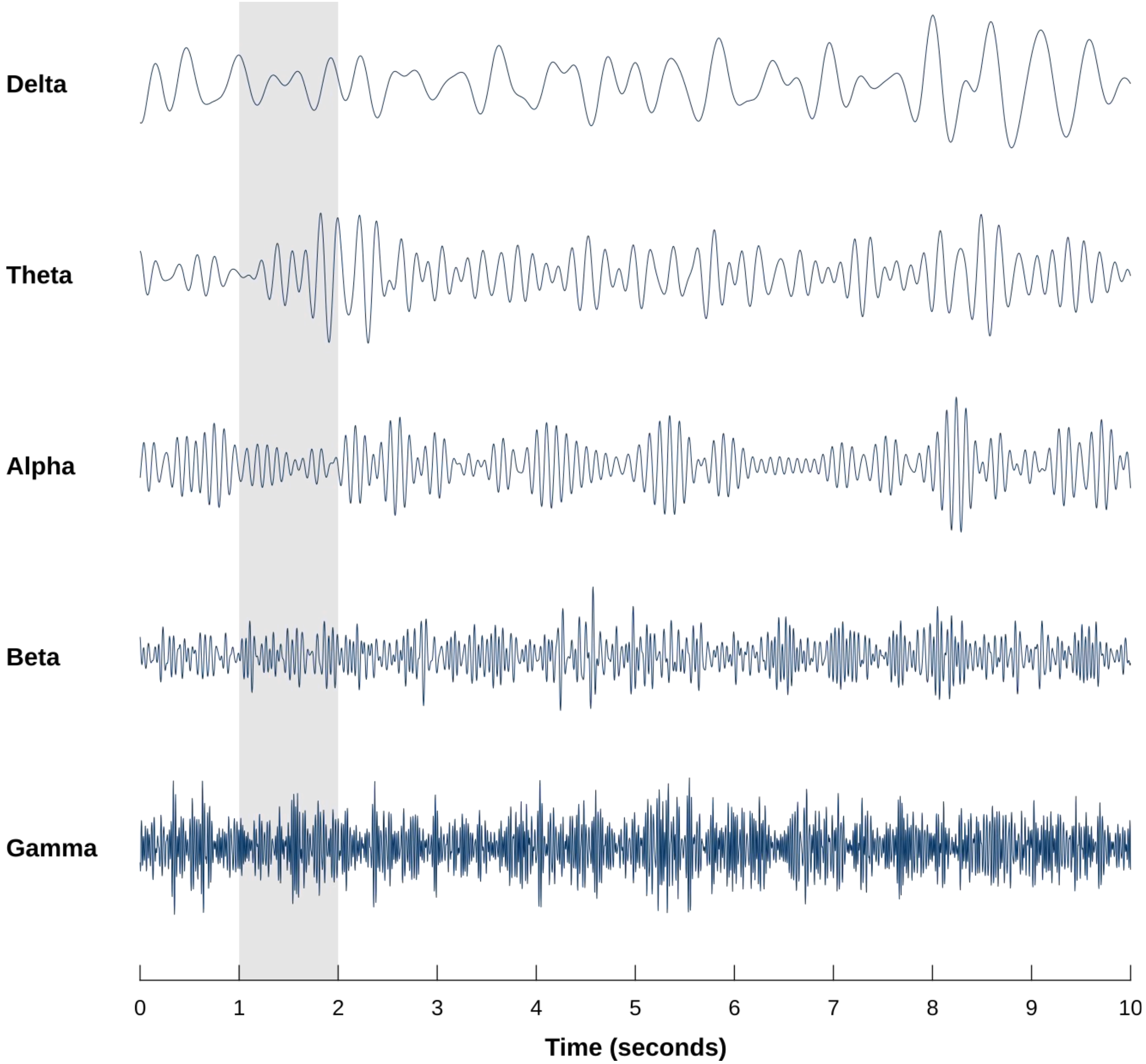
originally from ANDA2021 G-Node Advanced Neural Data Analysis Course given by U.E. in 2021

Neural signals contain oscillatory activity

Oscillations emerge in all kinds of neural signals:
EEG, MEG, LFPs, ESA, population rates, VSD, ...

Emergence and decay of oscillatory/rhythmic activity have been linked to, e.g., **stimulus configuration**[1], **cognitive state**[2], and **behaviour**[3].

[1] Gray, C., König, P., Engel, A. et al. Nature 338, 334–337 (1989).
[2] Bosman CA, Schoffelen JM, Brunet N, et al. (2012);75(5):875-888.
[3] Lewandowski & Schmidt (2011), J. Neurosci. 31 (39) 13936-13948.



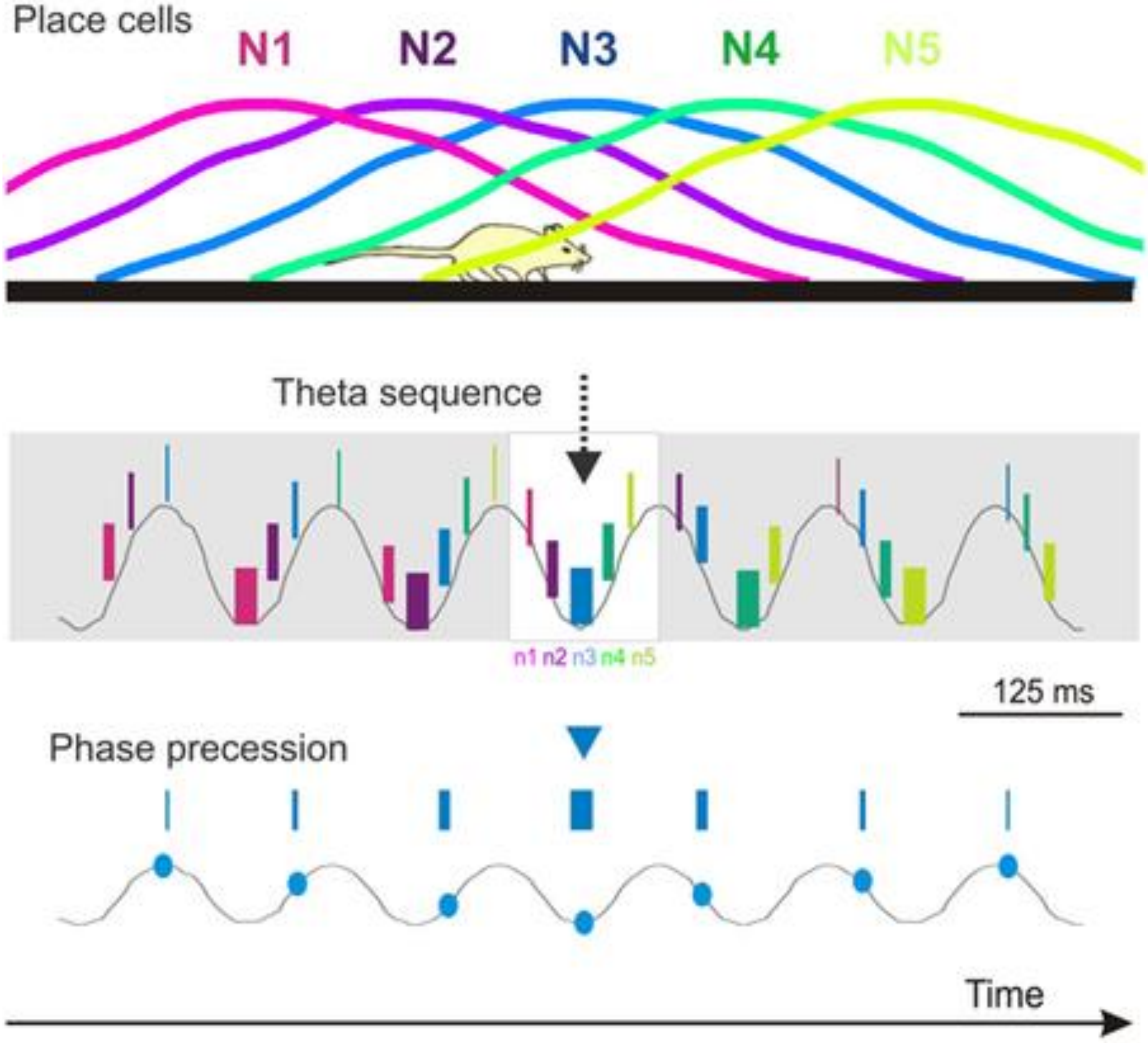
EEG example, looted from Wikipedia

Oscillations can play important functional roles

Oscillations and synchrony can play an important functional roles in information processing:

- stronger or more reliable activation of postsynaptic targets
- information integration in time domain, phase coding
- coordination of processing among different neural populations or brain areas
- multiplexing and time-sharing between different functional processes

Phase precession in the Hippocampus



Dragoi G. (2013), Internal operations in the hippocampus: single cell and ensemble temporal coding, Frontiers in Systems Neuroscience 7, 46ff.

Oscillations are a collective phenomenon

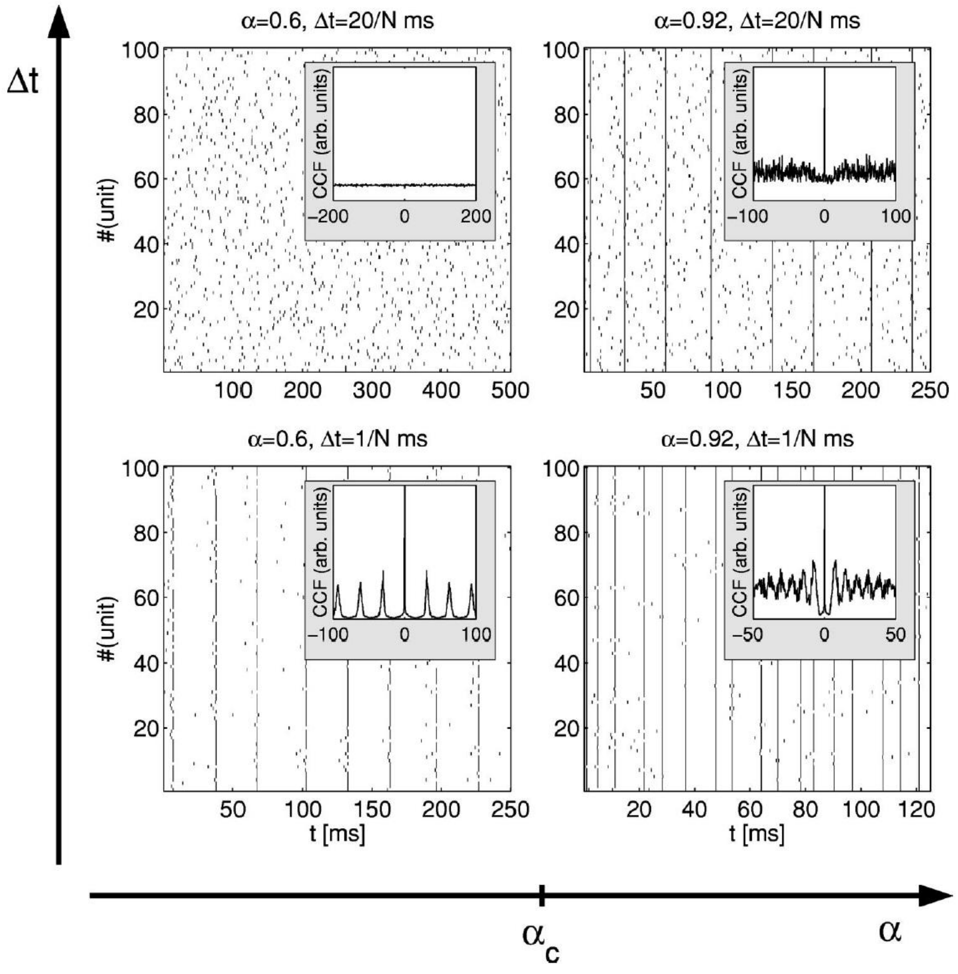
Oscillations are one particular example for a
more general phenomenon: neural synchronization:

- regular sync. (oscillations → focus of this Lecture!)
- irregular synchronization (spike avalanches, criticality)
- detailed spike patterns (→ Sonja!)

Oscillations are a signature of **collective dynamics**; it is hard to build a recurrent neural network which does not exhibit synchronization and oscillations.

Investigating spectral content in signals **provides information about interactions**, the **nature of collective dynamics** in a neural system, and yields **clues about network mechanisms**.

Criticality and Oscillations



Eurich, Herrmann, Ernst (2002), Phys. Rev. E.

…a quick reminder:

Fourier Facts

Fourier facts: Definition

Signal s(t) can be described by a **superposition of periodic functions** with different frequencies $\omega=2\pi f$ and amplitudes $|S(\omega)|$. Transform is invertible:

$$S(\omega) = F[s] \quad \propto \quad \int_{-\infty}^{+\infty} s(t) \exp(-i\omega t) dt$$

$$s(t) = F^{-1}[S] \quad \propto \quad \int_{-\infty}^{+\infty} S(\omega) \exp(i\omega t) d\omega$$

Euler's identity, relation to Fourier sin/cos transform:

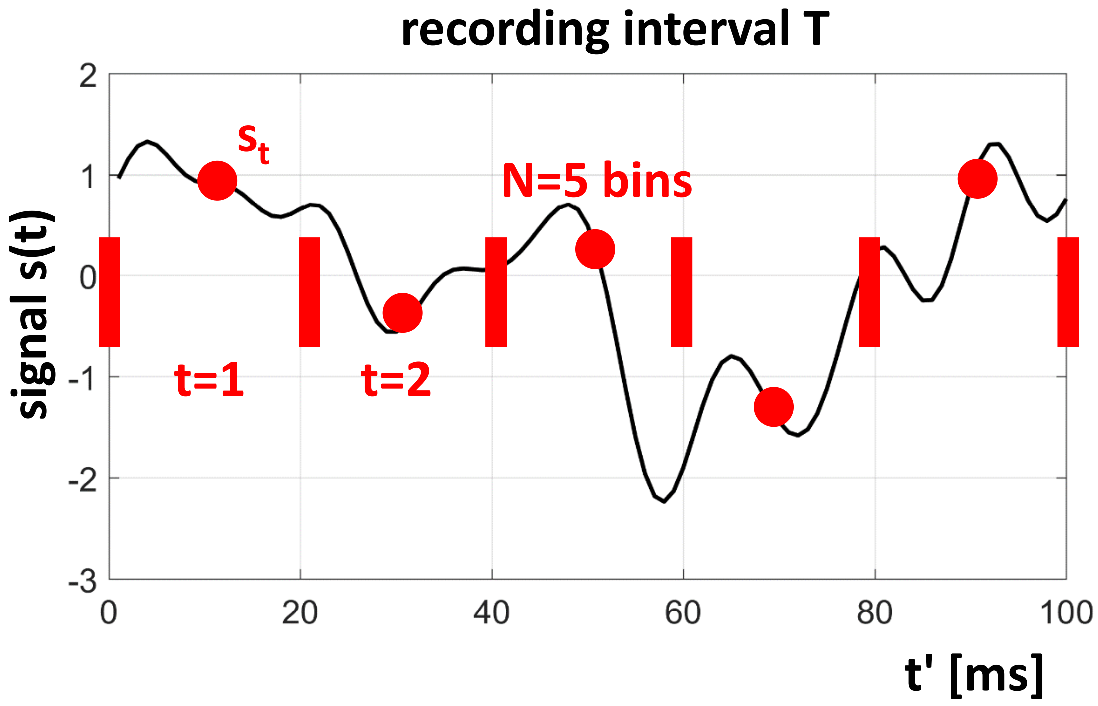
$$\exp(i\phi) = \cos(\phi) + i \sin(\phi)$$

Python tools: FFT, IFFT (numpy, scipy)

Fourier facts: Sampling

In practice, we have to deal with **discrete signals** s_t :

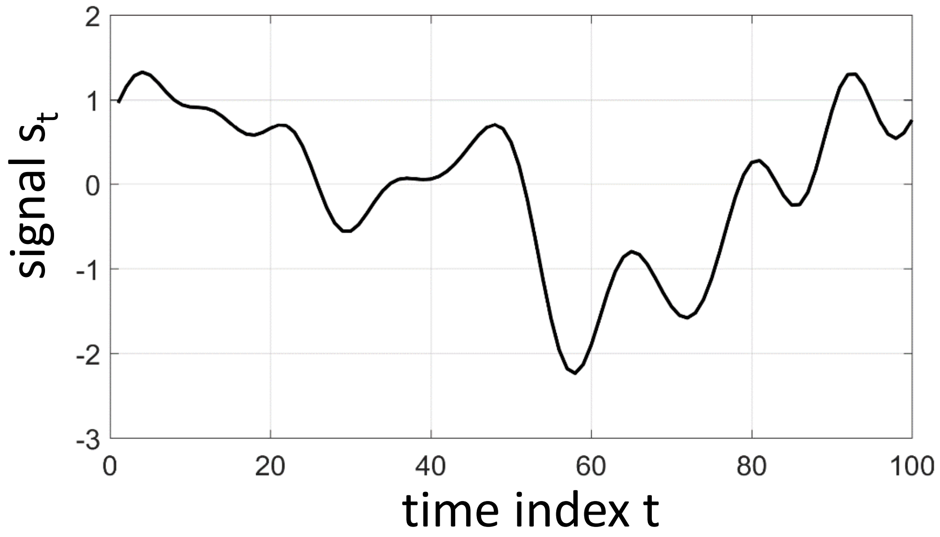
$$S(f) \quad = \quad \sum_t^N s_t \exp(-2\pi i f t)$$



Convention: 'time' t is an index, thus time resolution $\Delta t=1$, and 'frequency' f expressed in cycles/(unit time interval).

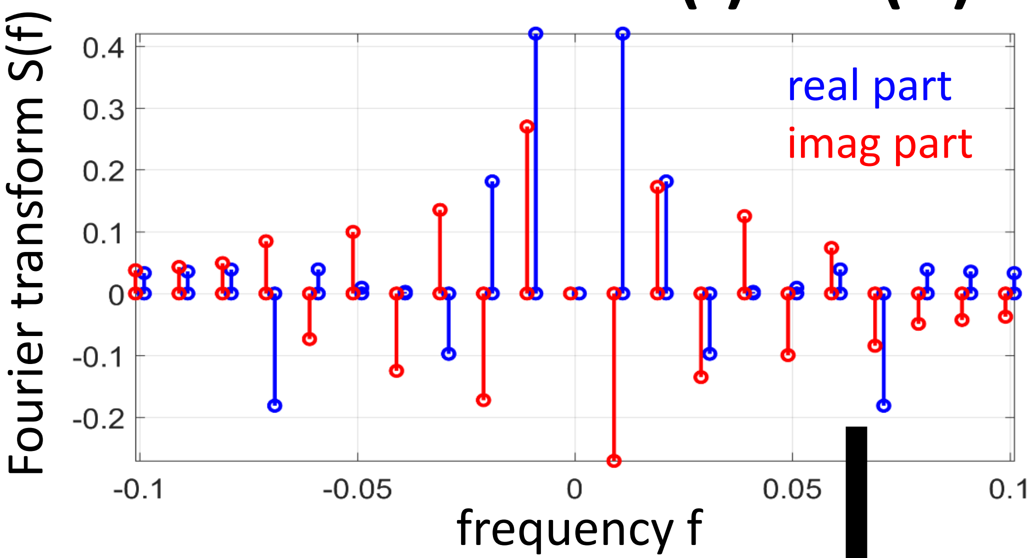
Relation to real time t' via t'=t (T/N), where T is 'recording time', and to real frequency via f'=f (N/T). The factor $f_s=(N/T)$ is the sampling frequency.

Fourier facts: an example...



F[...]

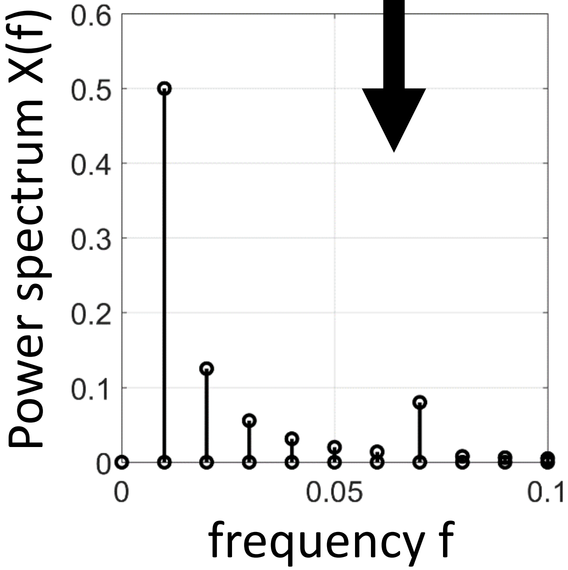
$$S(f) = S^*(-f)$$



For each frequency: One amplitude and phase as the absolute value $|S|$ and argument $\arg(S)$ of the complex-valued result S.

The amplitude spectrum shows how strongly each frequency is expressed in the signal.

Power spectrum for f>0: $X(f) = 2|S(f)|^2$, and $X(0)=|S(0)|^2$. Total power without X(0) equivalent to variance of s_t (**Parseval's theorem**).



Fourier facts: an example...

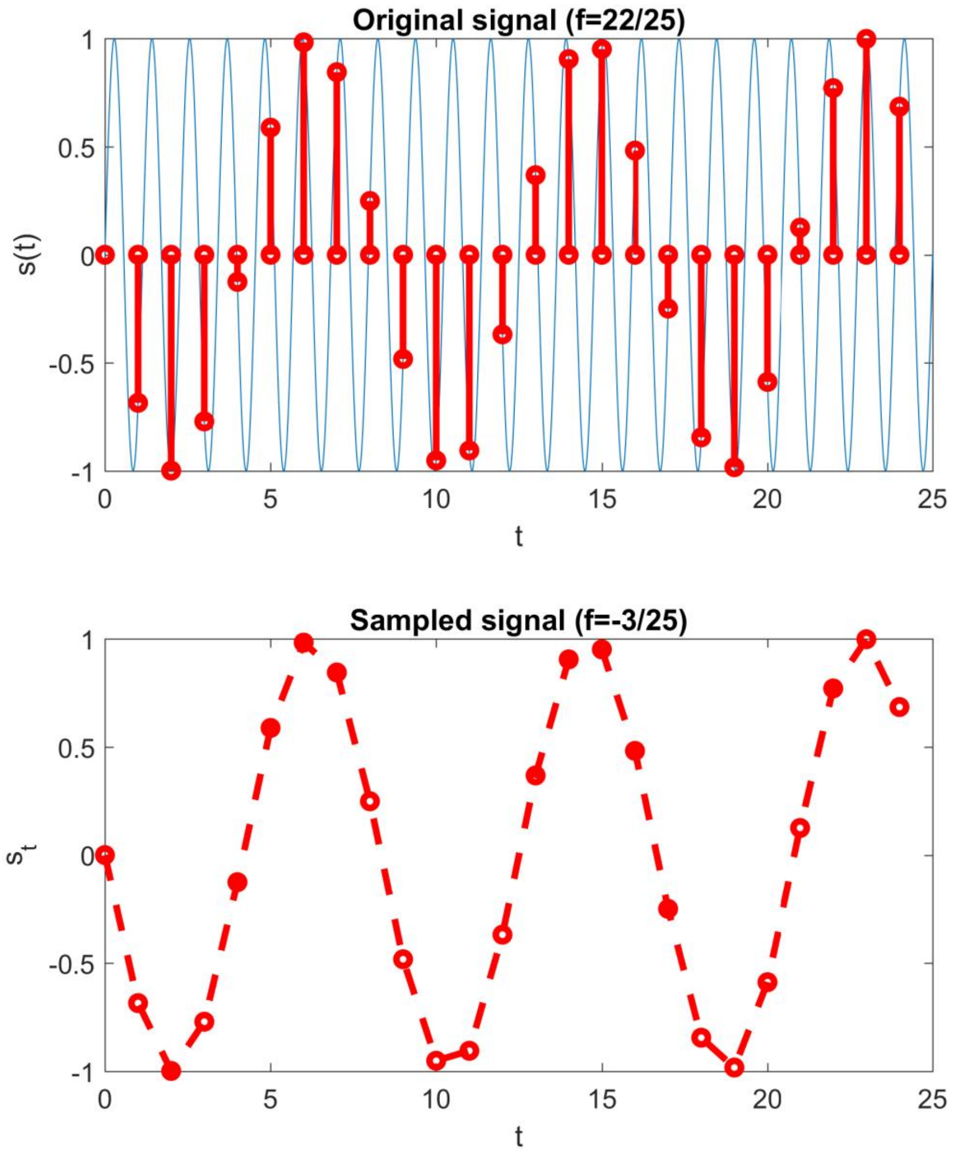
Sampling induces **finite frequency resolution**: the Nyquist frequency

$$\begin{aligned} f'_{Ny} &= f_s/2 \\ \text{i.e., } f_{Ny} &= 1/2 \end{aligned}$$

Aliasing: Higher frequencies are mapped to lower frequencies

$$f \longrightarrow \mod(f, f_{Ny})$$

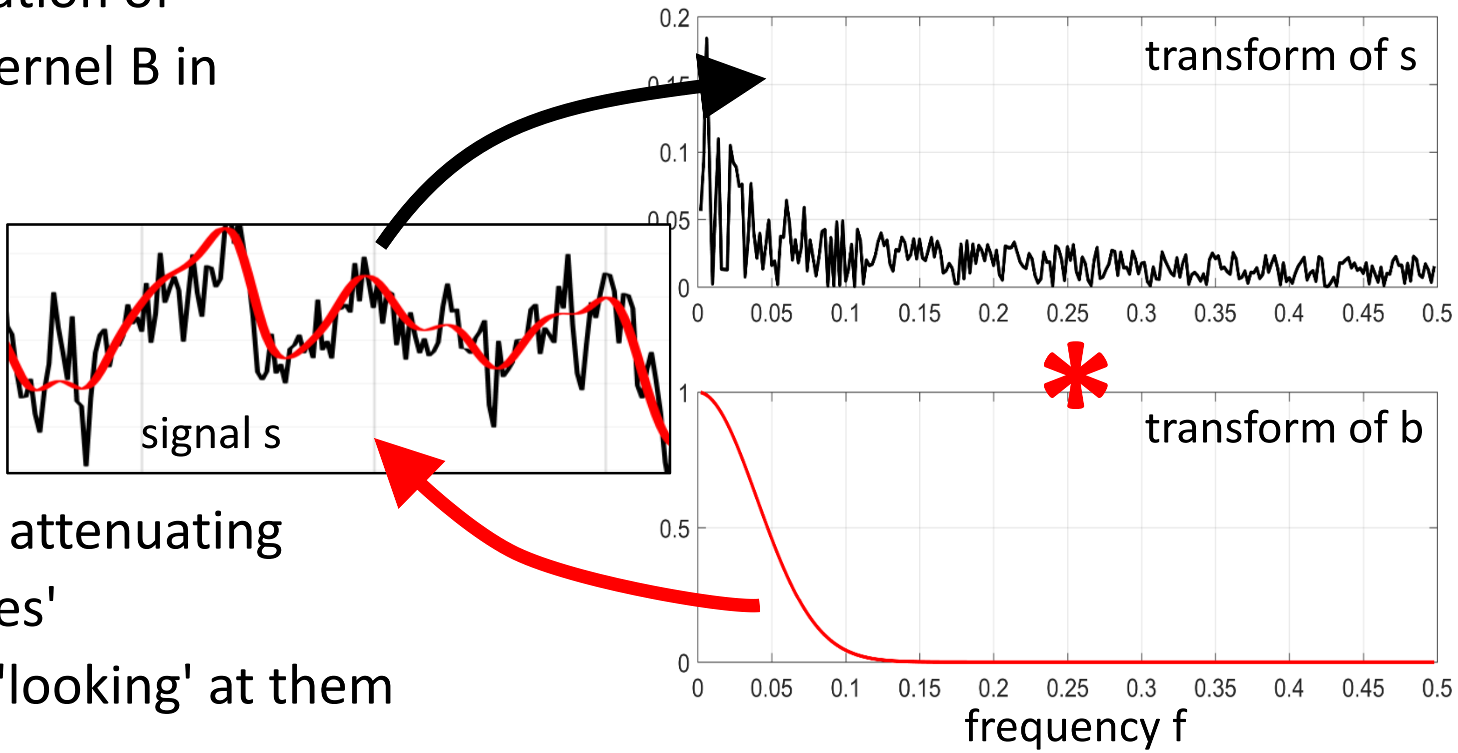
Take care! First filter, then downsample, but never downsample, then filter (high frequency traces will still be inside!)



Fourier facts: convolutions in frequency space

Convolution Theorem: Convolution in time-domain is equivalent to (element-wise) multiplication of transformed signal with transformed kernel B in frequency domain:

$$\begin{aligned}(s * b)(t) &= F^{-1}[S(f)B(f)] \\ &= F^{-1}[F[s(t)]F[b(t)]]\end{aligned}$$



- simple filters can be constructed by attenuating coefficients of 'undesired frequencies'
- convolutions can be interpreted by 'looking' at them in frequency space

Take care! Convolution theorem assumes periodic boundary conditions - for neural signals, don't trust your signal 'edges'.

...obtaining the "good vibrations"

Multitapering

Which problems do we have in estimating spectra?

Vanilla Fourier is only ideal for noiseless infinite signals, but...

- ...physiological data is subject to noise
- ...physiological data is finite

a) So, we have an **unknown spectrum S(f)** which is related to samples s_t via:

$$s_t = \int_{-1/2}^{1/2} S(f) \exp(i2\pi f t) df$$

b) **Estimate** computed via DTFT:

$$\hat{S}(f) = \sum_t^N s_t \exp(-i2\pi f t)$$

c) These equations relate the estimate to the real spectrum by means of a kernel K.
The **spectral estimate turns out to be a mixture of components** from 'correct' spectrum:

$$K(f-f',N) = \exp(-2\pi i(f-f')(N+1)/2)\frac{\sin(N\pi(f-f'))}{\sin(\pi(f-f'))}$$

The solution: Multitapering - the method

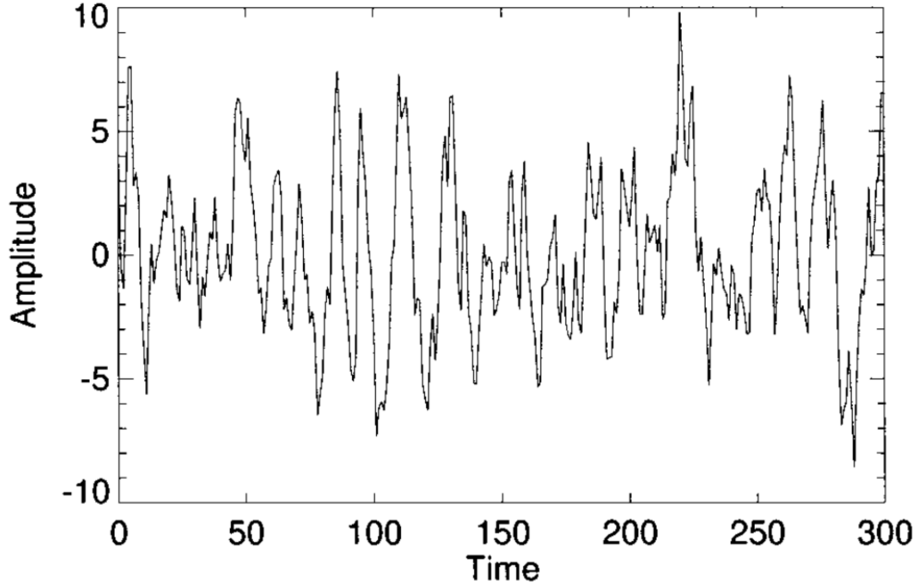
Multitapering: **Average spectral estimates from different "regions"** of a time series (regions = tapers)

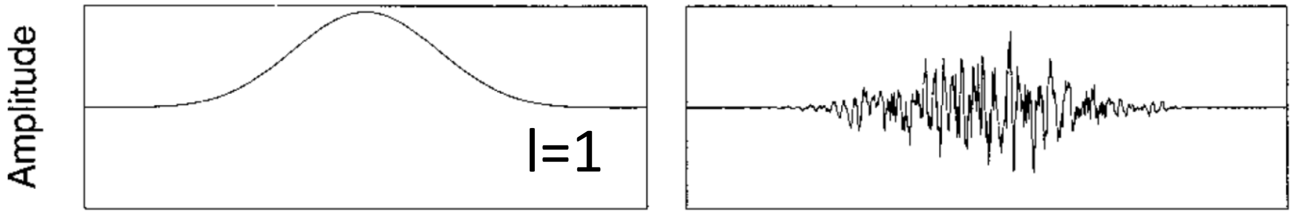
- **Idea:** Use taper functions/envelopes $w^{(l)}$ implying kernels $K^{(l)}$ which are more localized in frequency space...

$$\hat{S}^{(l)}(f) = \sum_{t}^{N} s_t w_t^{(l)} \exp(-i2\pi f t)$$

Multitapering: Examples

signal s_t





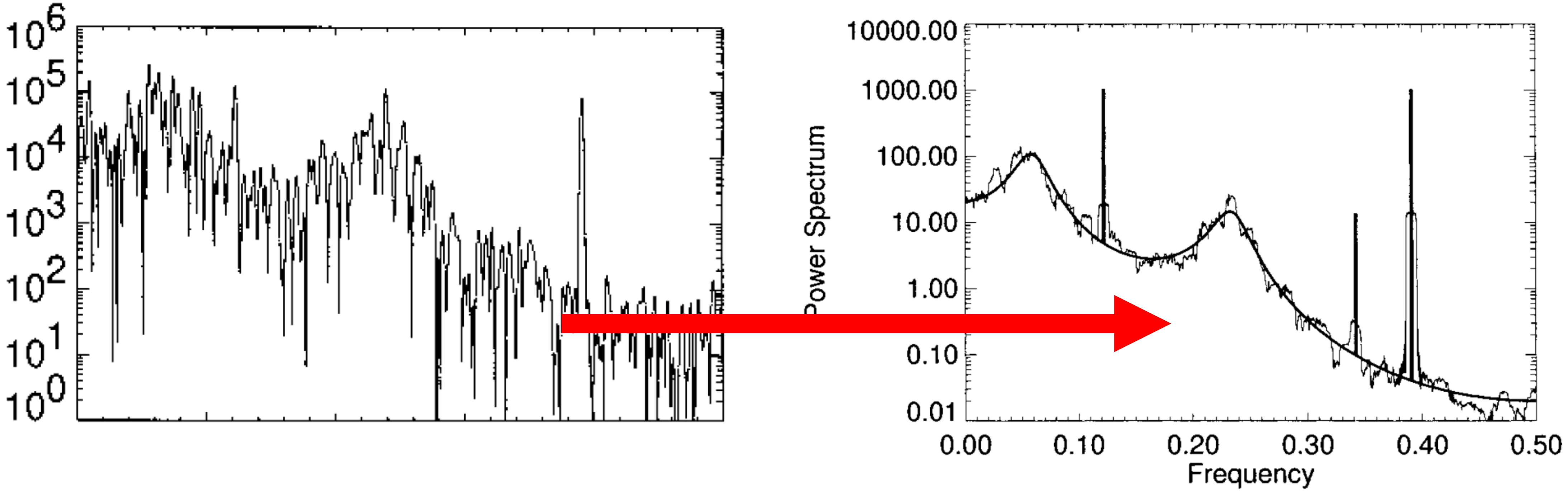
Which tapers to use? For example:
DPSS: discrete prolate spheroidal functions
(constitutes local eigenbasis in frequency space)

Python tools: scipy.signal.windows.dpss

Spectral estimates are improved

Spectrum estimated from one taper

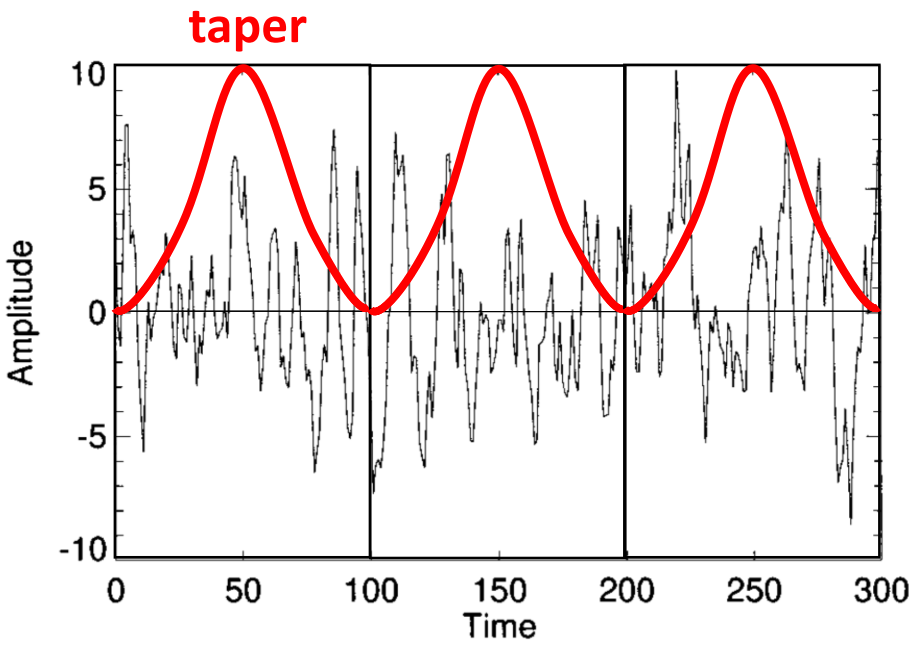
Spectrum estimated from multiple tapers



…a dynamic brain requires dynamic methods

Time-resolved spectral analysis

Extend Fourier to windowed Fourier...

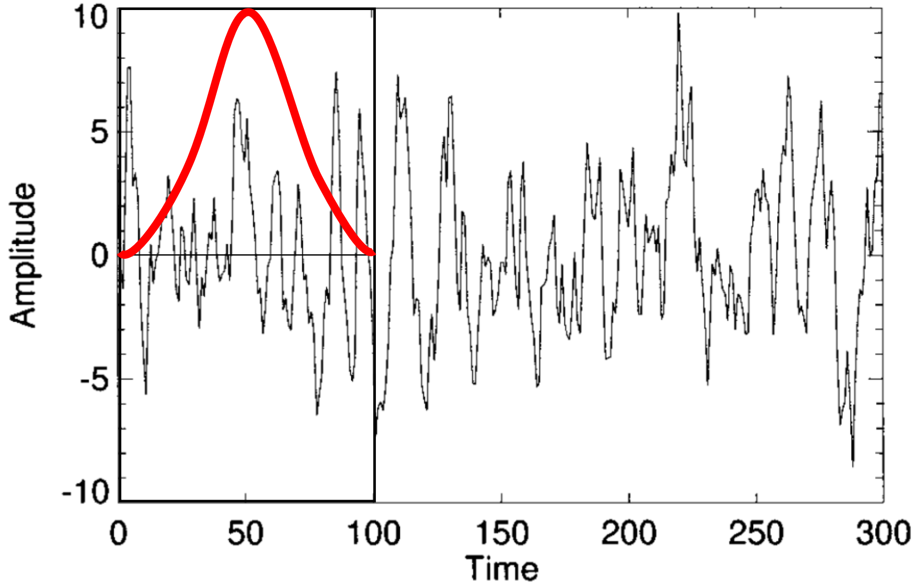


...or **move analysis window over time series**: can be written as a convolution (marked as *)

(but does NOT increase temporal resolution, just gives smoother curves)

Split time series into chunks, size of taper determines temporal resolution...

$$\hat{S}^{(l)}(f,t) = s(t) \star \left(w^{(l)}(t) \exp(i2\pi f(t - T/2)) \right)$$



Bruns A. (2004), J Neurosci Methods 30;137(2):321-32.

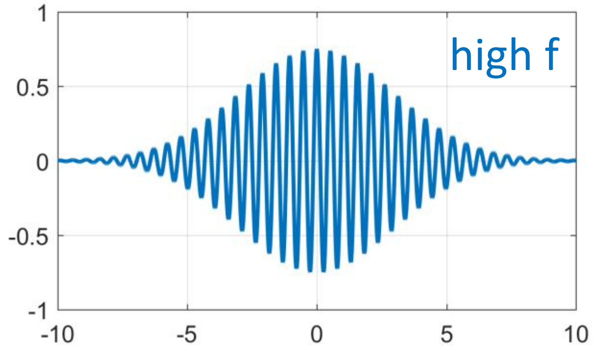
A similar idea: the continuous Wavelet transform

$$\hat{S}_F^{(l)}(f,t) = s(t) \star \left(w_F^{(l)}(t) \exp(i2\pi f(t - T/2)) \right)$$ ...windowed Fourier

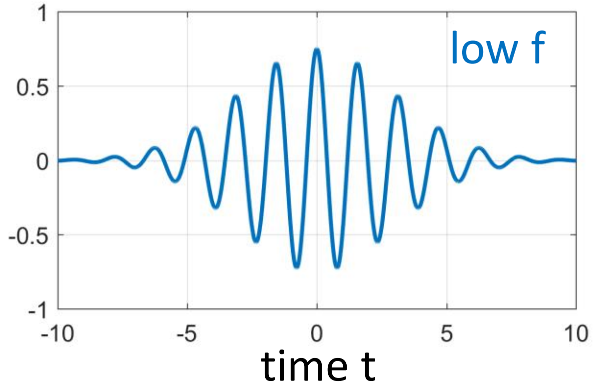
$$\hat{S}_W(f,t) = s(t) \star \left(w_W(f,t) \exp(i2\pi f t) \right)$$ ...Wavelet transform

Windowed Fourier:

$w_F^{(l)}(t)$

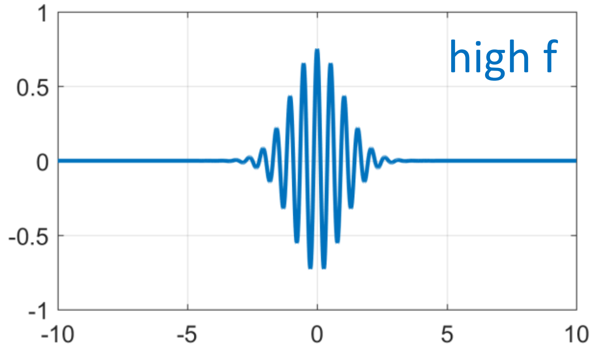


$$\Delta f = const.$$

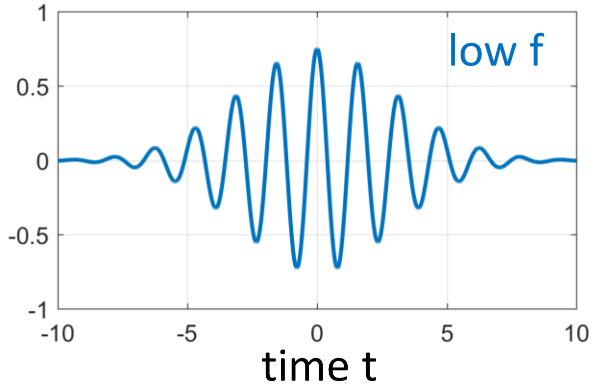


Wavelet transform:

$w_W(f,t)$



$$\frac{\Delta f}{f} = const.$$



Wavelet Demo Matlab

Example: Morlet-(mother)-Wavelet

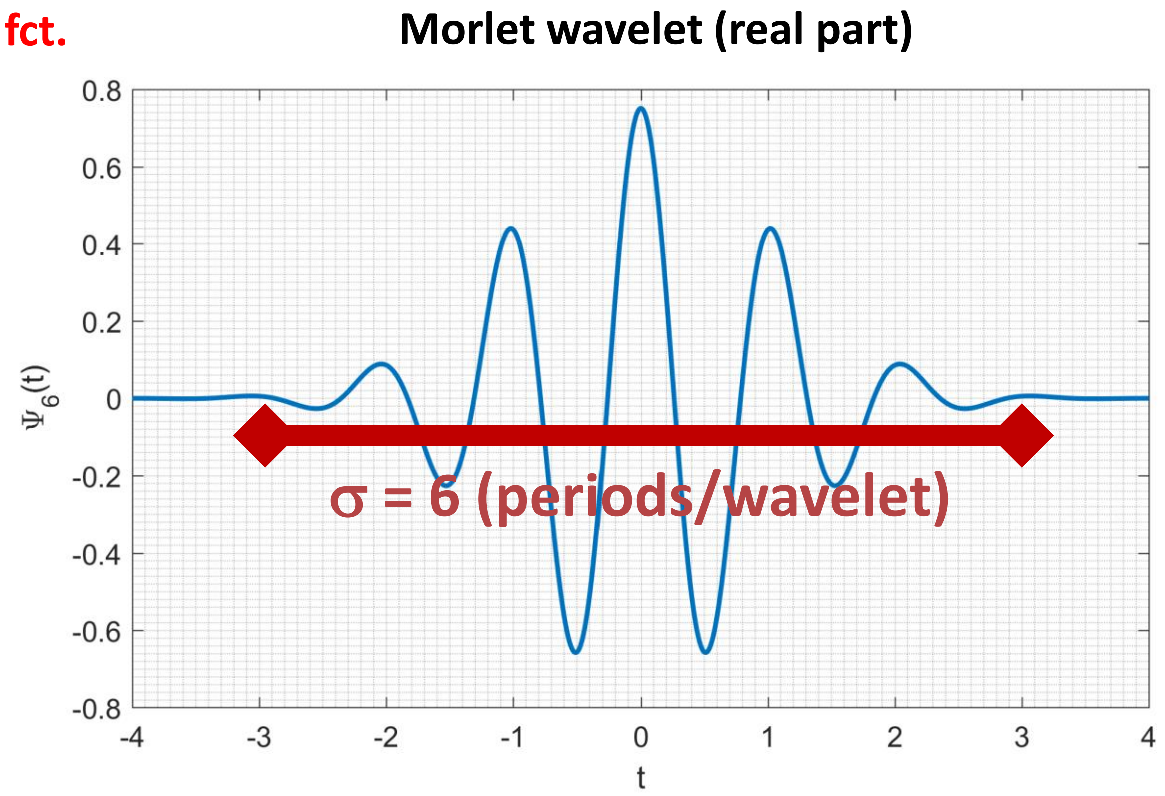
Envelope

Periodic fct.

$$\Psi_\sigma(t) = c_\sigma \pi^{-\frac{1}{4}} \exp\left(-\frac{1}{2}t^2\right)\left(\exp(-i\sigma t) - k_\sigma\right)$$

$$c_\sigma = \sqrt{1 + \exp(-\sigma^2) - 2\exp\left(-\frac{3}{4}\sigma^2\right)}$$

$$k_\sigma = \exp\left(-\frac{1}{2}\sigma^2\right)$$

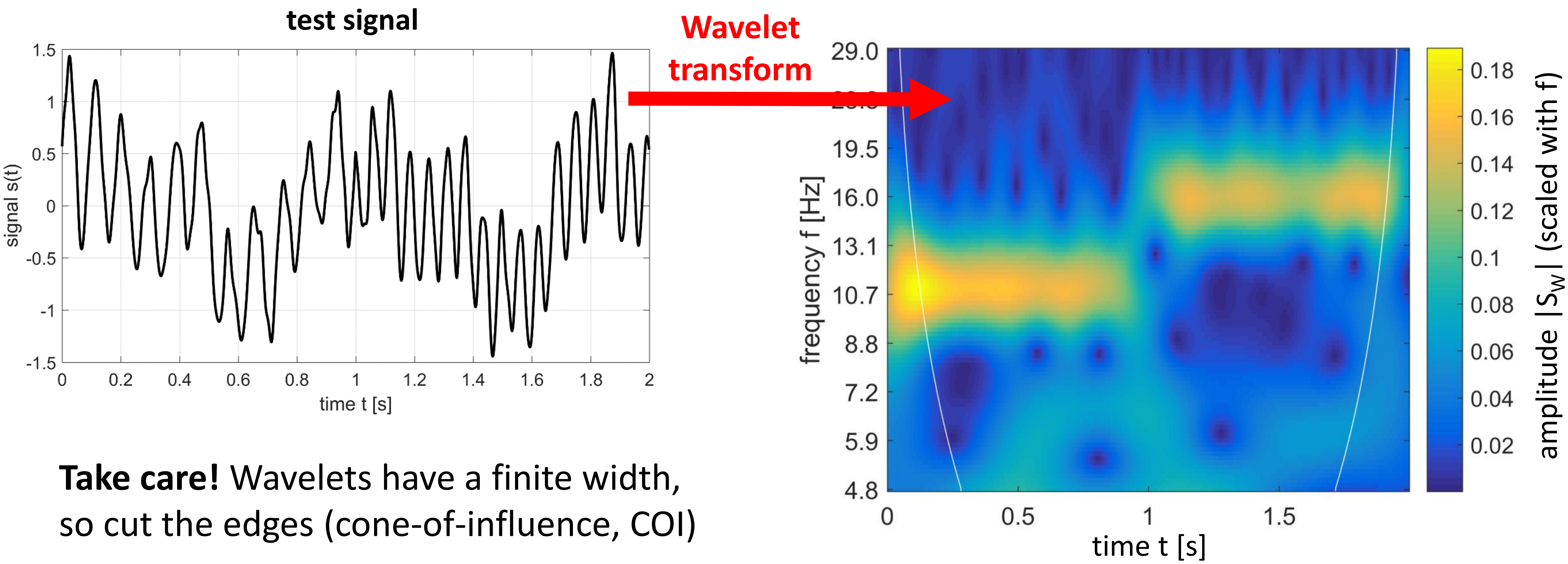


Morlet-Wavelet has a parameter σ which controls how many periods are squeezed into the envelope.

To obtain wavelets for analyzing different frequencies, the mother wavelet is scaled accordingly:

$$w_W(f,t) := \Psi_\sigma\left(\frac{2\pi}{\sigma} f t\right)$$

Example: Wavelet amplitude spectrum



Take care! Wavelets have a finite width, so cut the edges (cone-of-influence, COI)

for Morlet: $$t_{COI} \approx \frac{\sigma}{2\pi} \frac{\sqrt{2}}{f}$$ (power has to decay to 1/exp(2), it's a bit too permissive for my taste...)

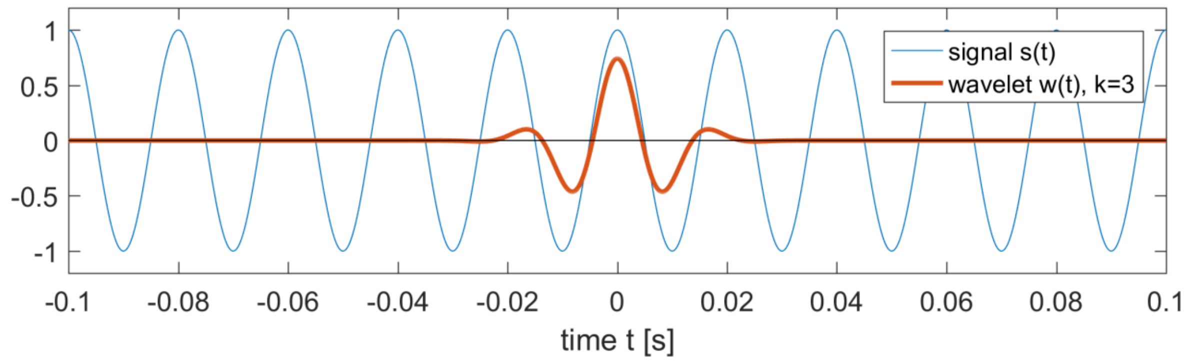
Torrence, C. and Compo, G.P. (1998) A practical guide to wavelet analysis. Bulletin of the American Meteorological Society, 79: 61--78.

Tradeoff between temporal and spectral resolution

Frequency and time (of change) can not be assessed independently with arbitrary precision!

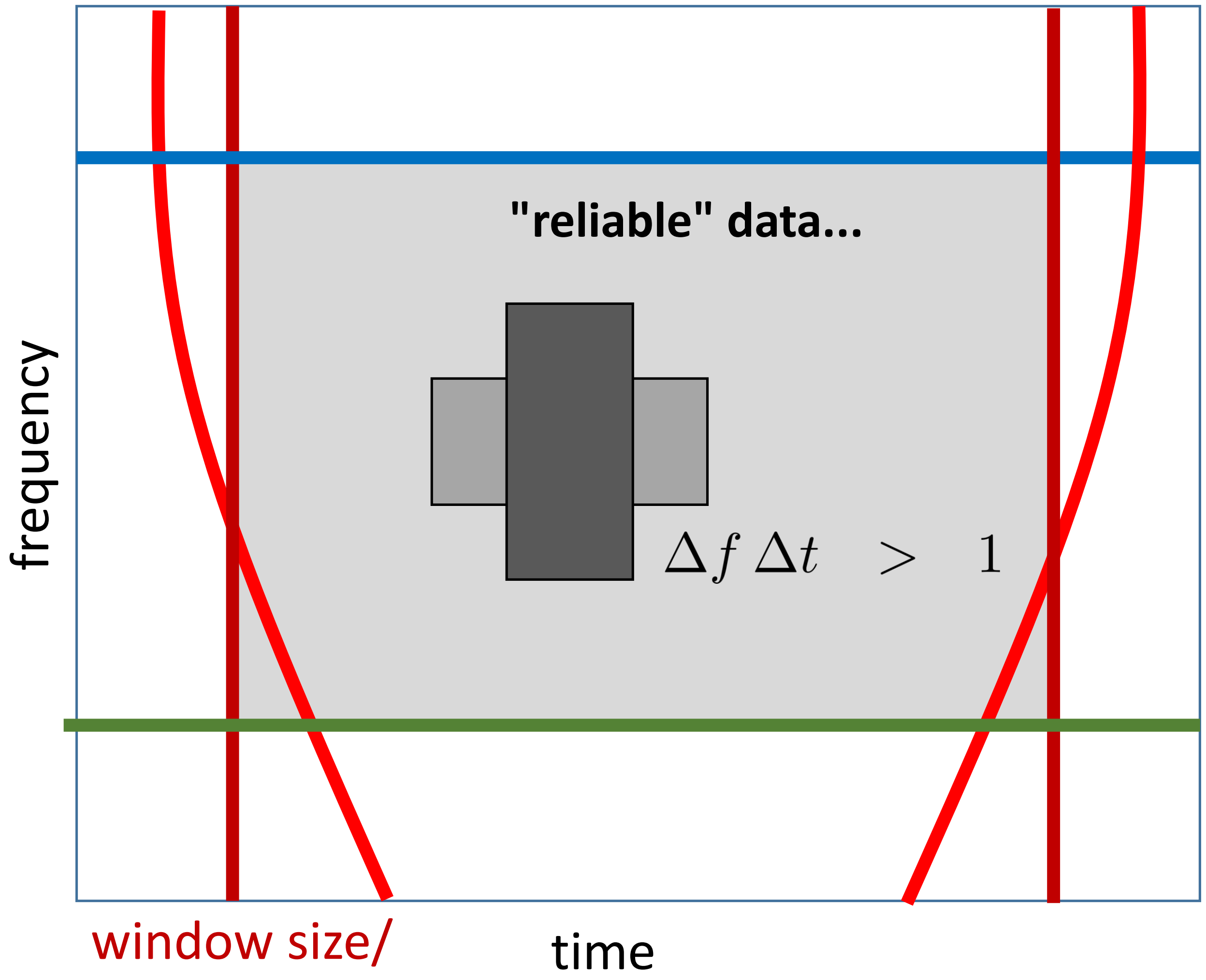
$$\Delta f \, \Delta t \quad > \quad 1$$

Matlab: WAVELET_UncertaintyRelation



looks good!

Time-resolved analysis: Limits on temporal/spectral resolution



sampling rate (Nyquist)+ preprocessing filter properties (i.e. lowpass) imply an appropriate upper threshold

recording time/size of trial implies lower threshold

window size/ envelope provide left/right cutoff

…going beyond power

Extracting the phase

How do we obtain the phase?

Remember: $S(f,t) = A(f,t)\exp(i\phi(f,t))$

From a time-varying spectral estimate S(f, t), the current phase of the signal can simply be obtained as its **argument** (**Python:** 'angle' function)

Windowed Fourier: $\hat{\phi}_F(f,t) = \arg[\hat{S}_F(f,t)]$

Wavelet: $\hat{\phi}_W(f,t) = \arg[\hat{S}_W(f,t)]$

The phase is fragile: filtering before spectral analysis should use **phase-preserving filters** (e.g. forward/backward filtering, **Python:** filtfilt)

Filter Demo Matlab

...and there's yet another transform: the **Hilbert transform**!

The Hilbert transform

The idea: from real-valued signal s(t), construct a complex analytic signal by adding a complex-valued function h(t):

$$c(t) = s(t) + ih(t)$$

The Hilbert transform h(t) is obtained by **applying a phase shift of -π/2** to all spectral components, via multiplication with exp(i Δϕ):

$$A \exp(i\phi) \exp(i\Delta\phi)$$
$$= A \exp(i(\phi + \Delta\phi))$$

(...for example, cos(wt) gives sin(wt), thus arg[h(t)]=wt gives the time-varying phase)

Phase shift of π/2 is multiplication with i in frequency space: $H(f) = -i\,\mathrm{sgn}(f) S(f)$

Using the Heaviside-Function θ, the **analytic signal in frequency space** becomes:

$$C(f) = S(f) + i\,H(f) = 2S(f)\Theta(f)$$

Interpreting the Hilbert transform I

Neurophysiological (and other) signals typically have a broad spectrum. Before applying the Hilbert transform, it makes sense to **bandpass-filter the signal** around frequency of interest f_0 , via bandpass $b_{f_0}(t)$:

$$s_{f_0}(t) = s(t) \star b_{f_0}(t)$$

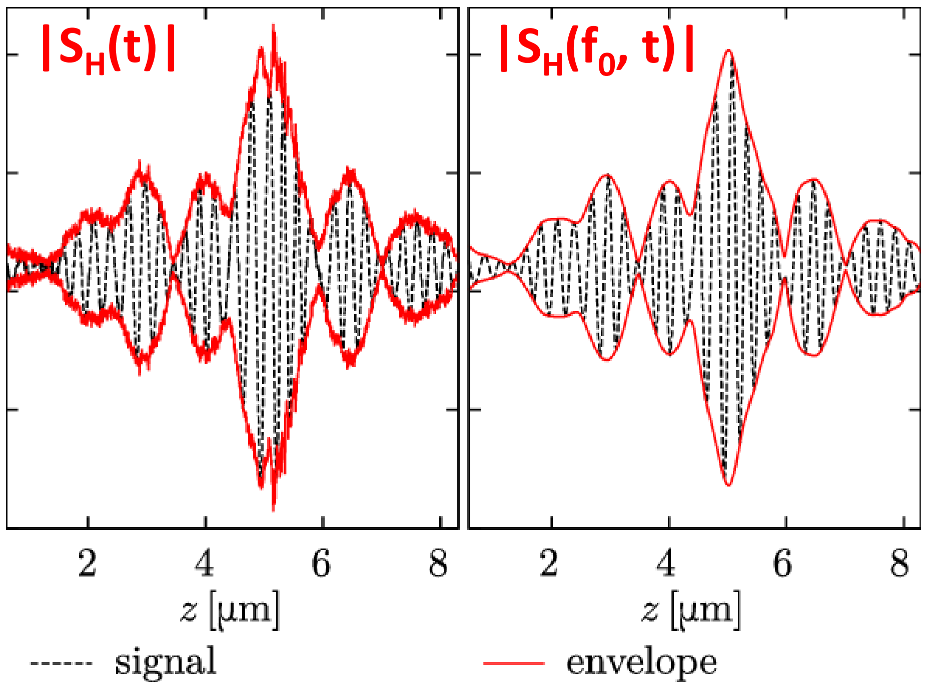
Filtering and Hilbert transform can both be performed by multiplication in frequency space:

$$\hat{S}_H(f,t) = F^{-1}[S(f)B_{f_0}(f)2\Theta(f)]$$

Interestingly, this operation can be described by convolution of the signal with an **equivalent lowpass filter**, multiplied by a periodic function!

$$\hat{S}_H(f,t) = s(t) \star (b_T(t)\ \exp(i2\pi f t))$$

(Convolution: $a(t) \star b(t) = \int a(t')b(t-t')dt'$)



Interpreting the Hilbert transform II

a) Bandpass filter in frequency space:

$$B_{f_0}(f)$$

b) Equivalent lowpass:

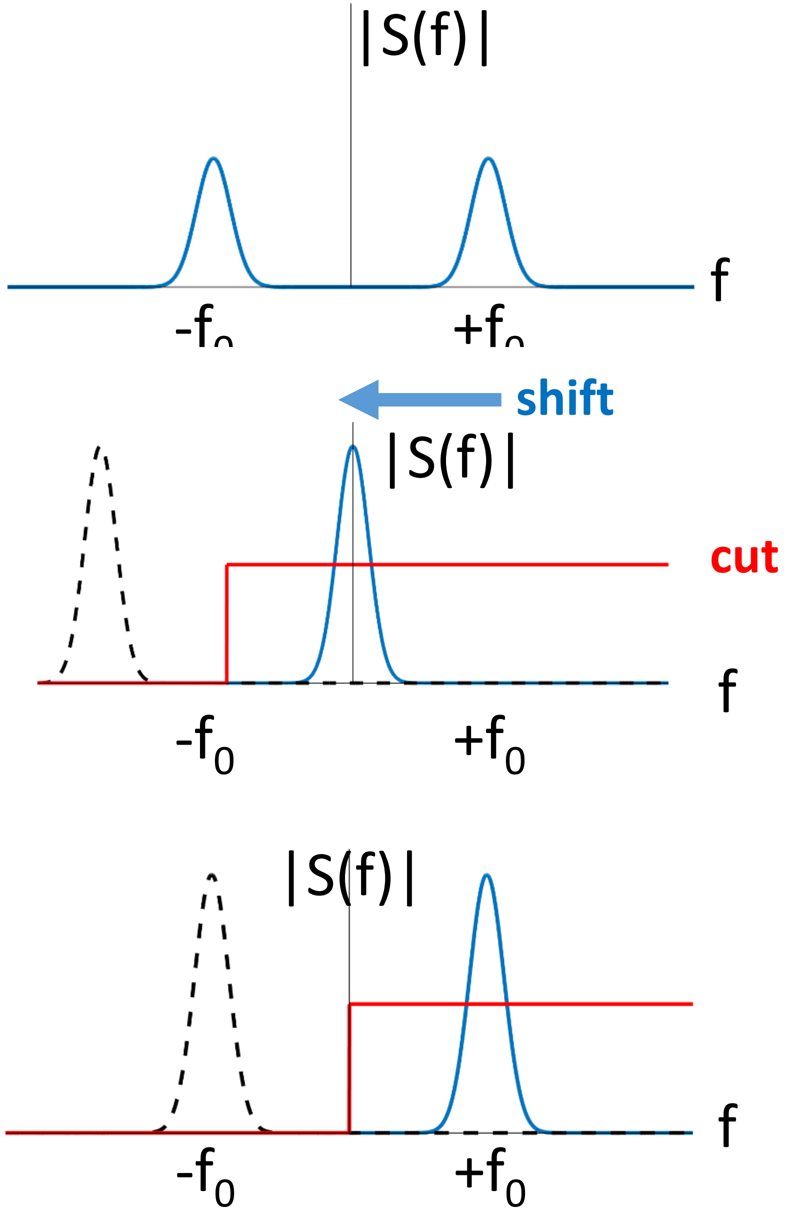
$$B_T(f) = 2B_{f_0}(f + f_0)\Theta(f + f_0)$$

c) Turn it around...:

$$\begin{aligned} 2B_{f_0}(f)\Theta(f) &= B_T(f - f_0) \\ &= B_T(f) \star \delta(f - f_0) \end{aligned}$$

$$F^{-1}[B_T(f) \star \delta(f - f_0)] = b_T(t)\ \exp(i2\pi f_0 t)$$

$$\longrightarrow \hat{S}_H(f,t) = s(t) \star (b_T(t)\ \exp(i2\pi f t))$$



Which one is the best? Fourier, Wavelet or Hilbert?

They are all equivalent! Can be written as convolution of the signal with a temporal kernel multiplied by a complex periodic function:

$$\begin{aligned}
\hat{S}_F^{(l)}(f,t) &= s(t) \star \left(w_F^{(l)}(t) \exp(i2\pi f(t - T/2)) \right) \\
\hat{S}_W(f,t) &= s(t) \star (w_W(f,t) \exp(i2\pi f t))) \\
\hat{S}_H(f,t) &= s(t) \star (b_T(t)\ \exp(i2\pi f t))
\end{aligned}$$

Bruns A. Fourier-, Hilbert- and wavelet-based signal analysis: are they really different approaches? J Neurosci Methods. 2004 Aug 30;137(2):321-32. doi: 10.1016/j.jneumeth.2004.03.002. PMID: 15262077.

...relating signals across sites and frequency bands

Spectral coherence and cross-frequency coupling

Relating spectral content across sites

Spectral coherence is defined **similar to a 'normal' correlation function**, but operates on the complex-valued spectral coefficients of two (Wavelet/Hilbert/Fourier)-transformed time series from two (recording) sites A and B:

Take care! Averaging before or after taking absolute value matters!

$$\left|\sum_t \sum_i C_i\right|^2 \neq \sum_t \left|\sum_i C_i\right|^2$$

Time delay: i.e., compensates for synaptic transmission, internal dynamics

Summation: e.g. over trial repetitions r. In addition, one can collapse e.g. over time:

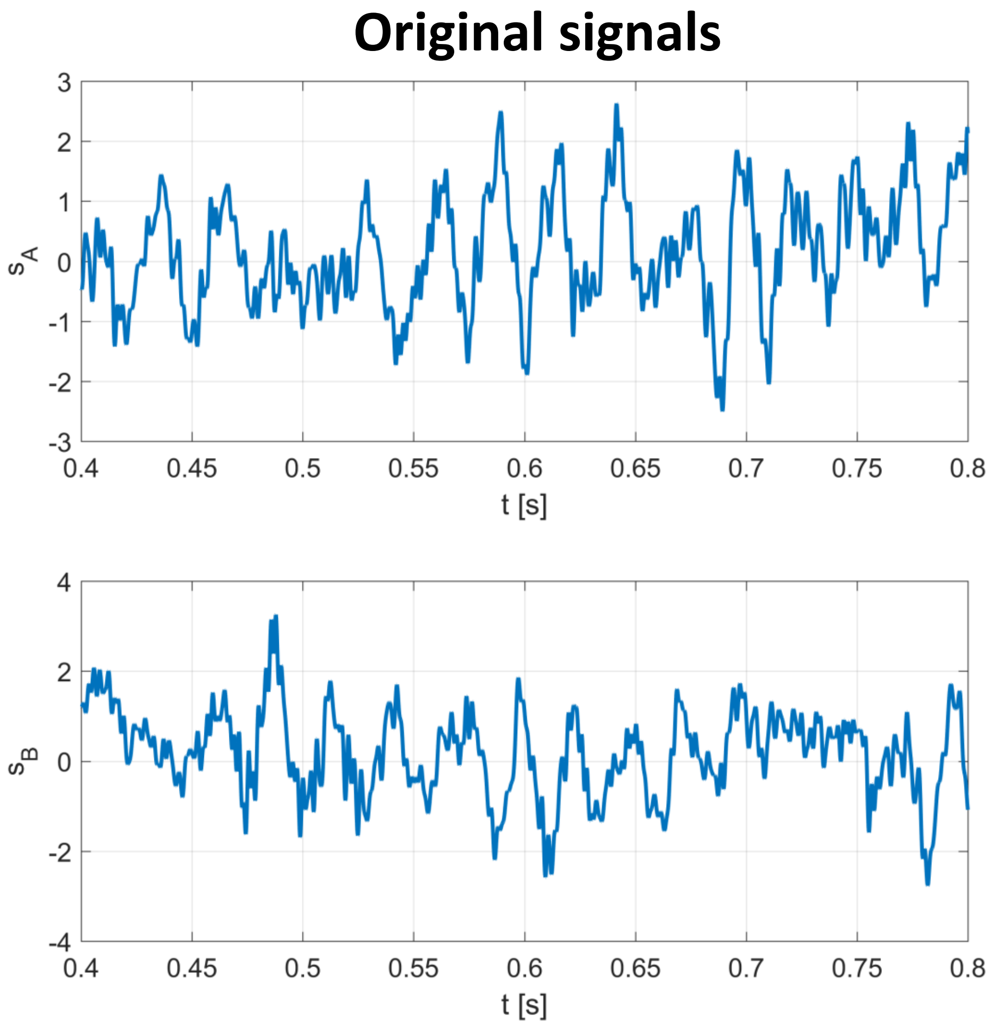
$$\sum_r \longrightarrow \sum_{r,t}$$

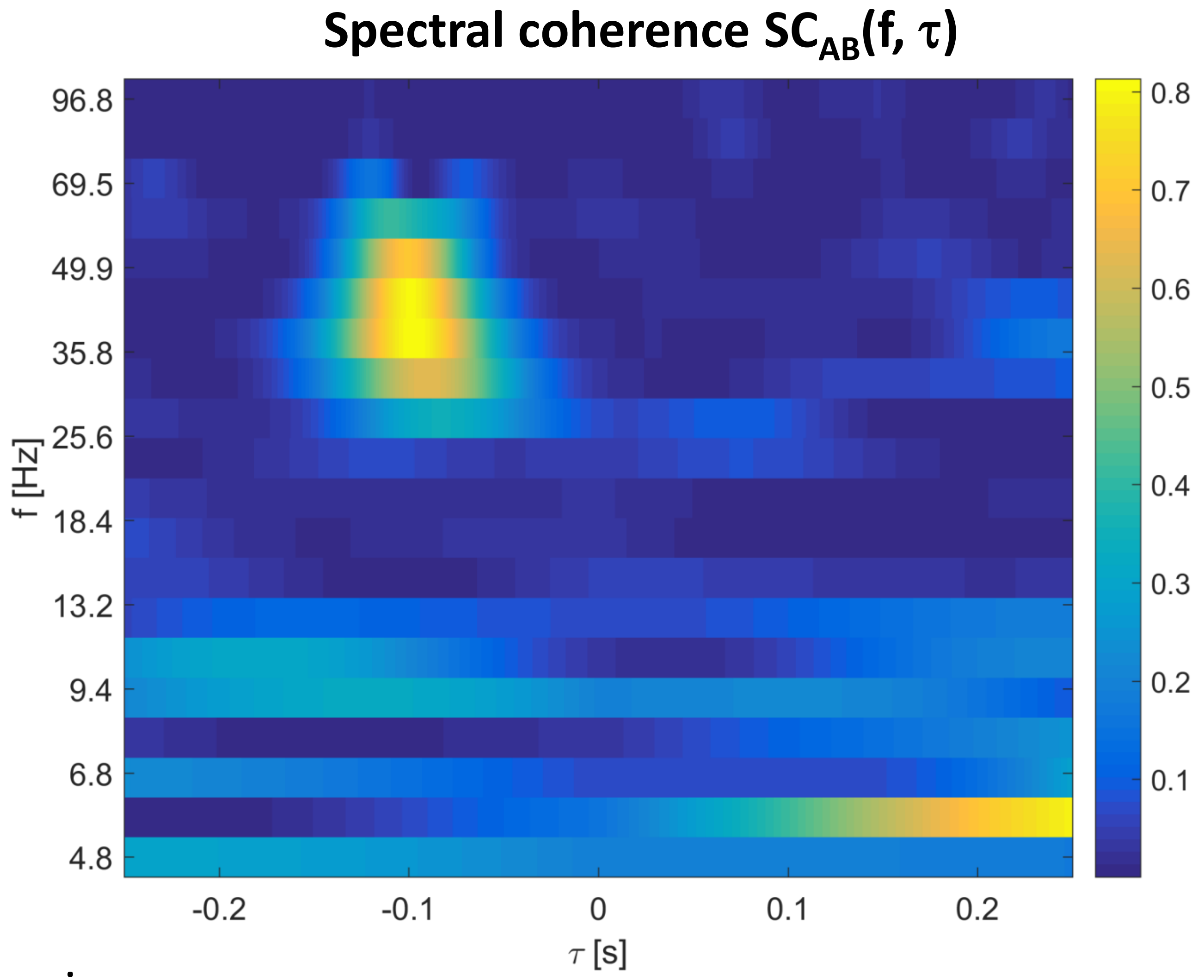
$$SC(f,t,\tau) \longrightarrow SC(f,\tau)$$

$$SC(f,t,\tau) = \frac{\left|\sum_r^N S_r^A(f,t+\tau)\overline{S}_r^B(f,t)\right|^2}{\sum_r^N \left|S_r^A(f,t+\tau)\right|^2 \sum_r^N \left|S_r^B(f,t)\right|^2}$$

Normalization: ensures result is between 0 and 1.

Example: Spectral coherence





Two signals s_A and s_B, both broadband 1/f-noise.

Common, superimposed f_0=42 Hz oscillation, delayed in signal A.

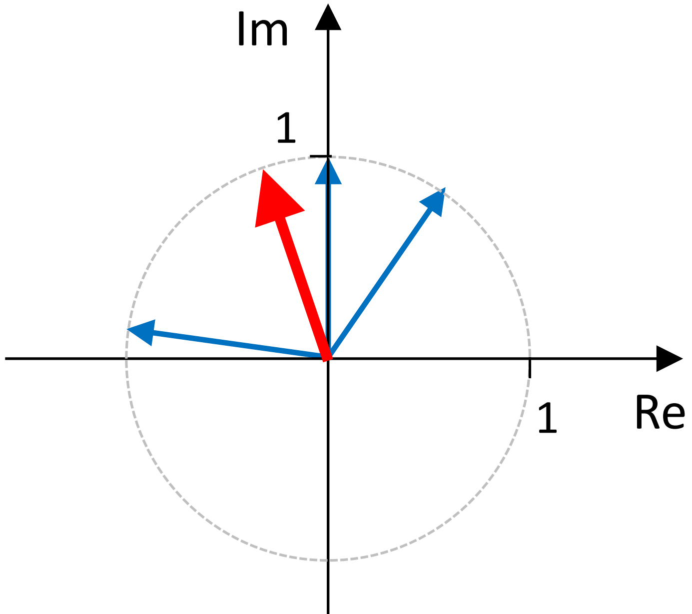
What is computed?

Inside sum: Product of amplitudes, and difference of phases:

$$S_A \overline{S}_B = |S_A||S_B| \exp(i(\phi_A - \phi_B))$$

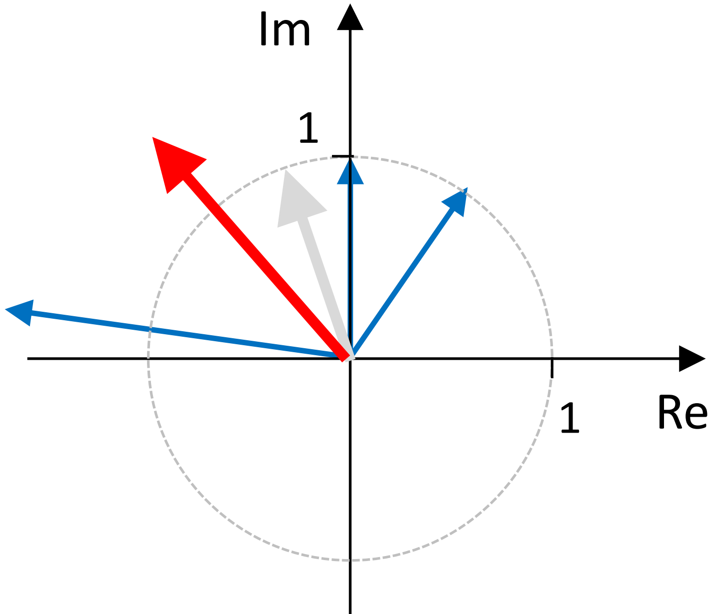
(Vector) Summation: Complex average of phase differences... (weighted by amplitudes)

all amplitudes 1:



--> phase locking value (PLV)

amplitudes different:



--> mean vector length (MVL)

The phase-locking value (PLV) or phase consistency (PCO)

Ignore the amplitudes:

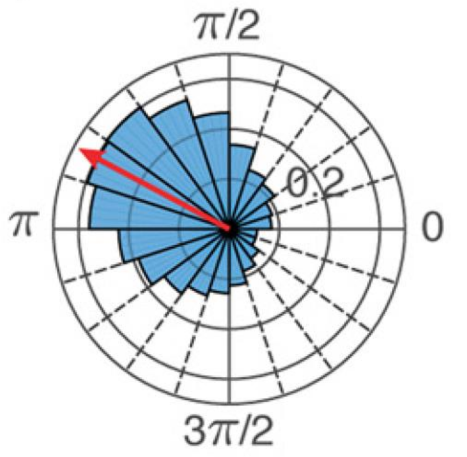
PLV/PCO is one, if A and B are coherent, and 0 if phase diffs are uniformly distributed.

$$PCO = \frac{\left|\sum_r^N \exp(i(\phi_r^A - \phi_r^B))\right|^2}{\sum_r^N \left|\exp(i\phi_r^A)\right|^2 \sum_r^N \left|\exp(i\phi_r^B)\right|^2}$$

$$= \frac{1}{N^2}\left|\sum_r^N \exp(i(\phi_r^A - \phi_r^B))\right|^2$$

$$PLV = \sqrt{PCO}$$

Example:



Silversmith et al. (2020), J. Neurosci. 40(24):4673–4684

However, the measure has a bias!

$$PCO_{bias} = \frac{\pi}{4N}$$

Sun T, Yang ZJ (1992) How far can a random walker go? Phys A Stat Mech Appl 182:599–606.

$$PCO_{corr} = PCO - \frac{1 - PCO}{N}$$

Benignus VA. Estimation of the coherence spectrum and its confidence interval using the fast Fourier transform. IEEE Trans Aud Electroacoust 1969; AU-17:145–50.

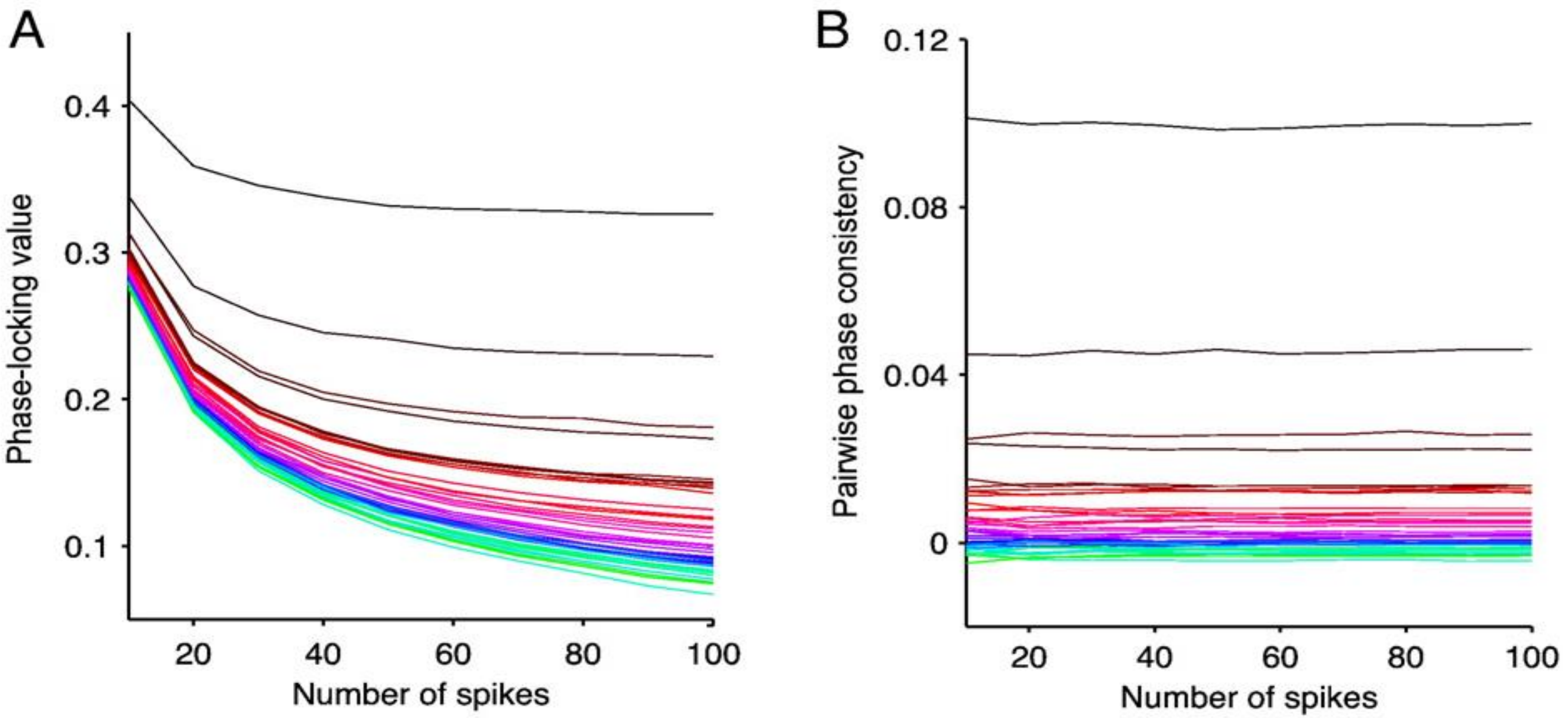
Removing the bias: pairwise phase consistency (PPC)

The idea: Consider differences of phase differences!

$$PPC = \frac{2}{N(N-1)} \sum_{r=1}^{N-1} \sum_{r'=r+1}^{N} \cos\left(\Delta\phi_r^{AB} - \Delta\phi_{r'}^{AB}\right)$$

$$\Delta\phi_r^{AB} := \phi_r^A - \phi_r^B$$

Bias for the two measures:



Vinck, van Wingerden, Womelsdorf, Fries, Pennartz, The pairwise phase consistency: A bias-free measure of rhythmic neuronal synchronization, NeuroImage, 51 (1), 2010, 112-122, https://doi.org/10.1016/j.neuroimage.2010.01.073.

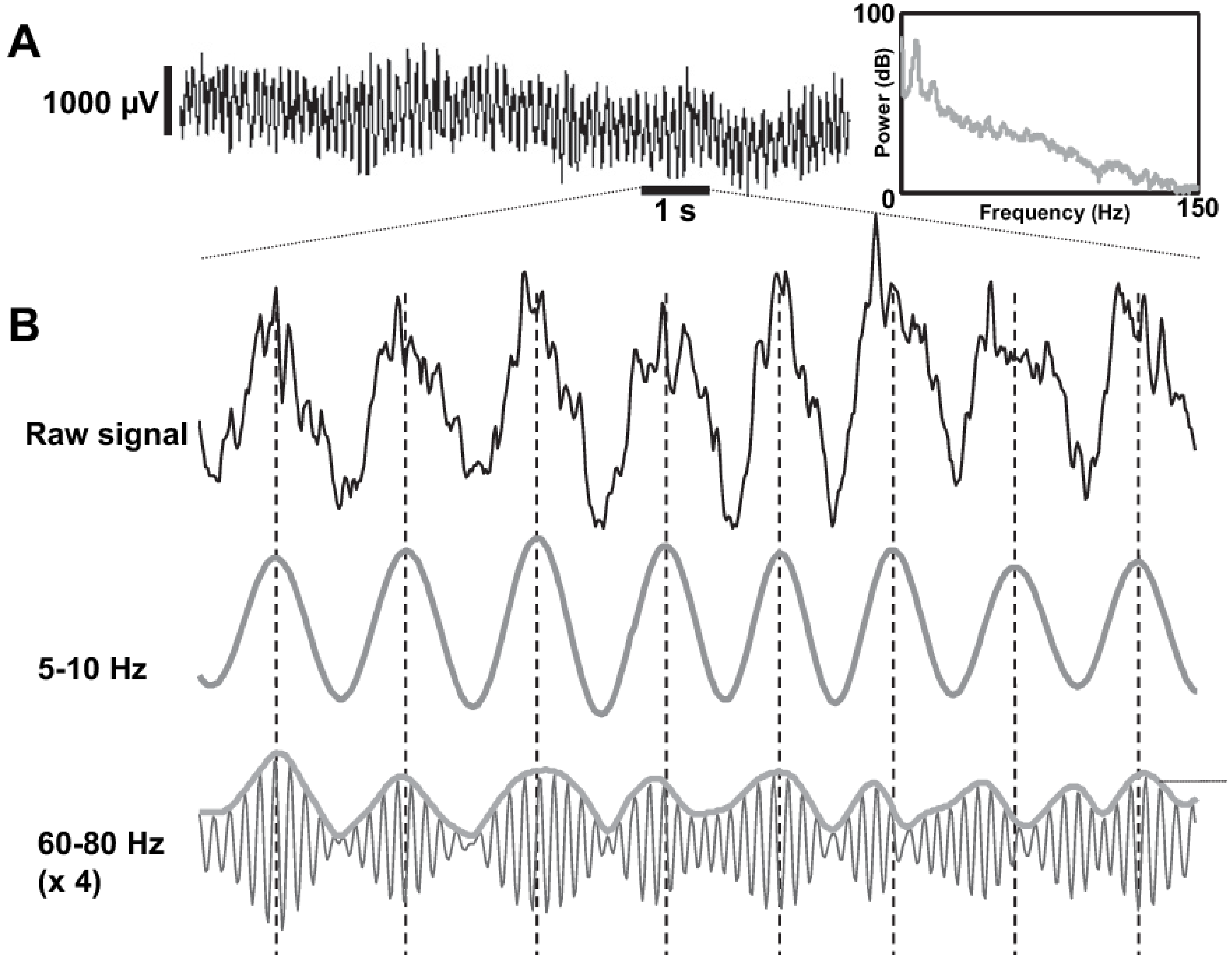
Relating spectral content across frequencies (and sites...)

Phase-amplitude coupling (PAC):
Several measures, for example cross-frequency coherence (CFC), envelope-to-signal correlation (ESC) or modulation index (MI).

MI: computation similar to MLV; use equation for SC, replace:

$$S^A(f) \longrightarrow |S^A(f_{amp})|$$
$$S^B(f) \longrightarrow \exp\left(i\phi^B(f_{phase})\right)$$

Angela C.E. Onslow, Rafal Bogacz, Matthew W. Jones, Prog. Biophys. and Molec. Biol., 105 (1–2), 2011, 49-57, https://doi.org/10.1016/j.pbiomolbio.2010.09.007.

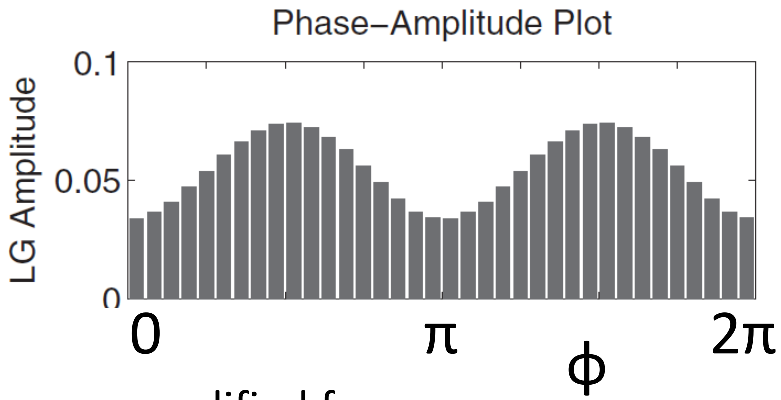


Various other aspects...

a) More complex forms of phase-amplitude coupling (bi-modality, cross-frequency coupling):

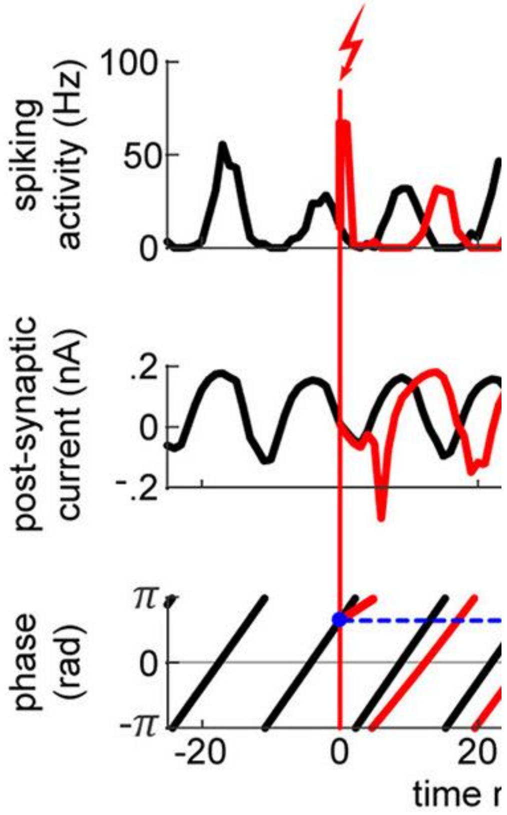
$\rightarrow$ use Kullback-Leibler distance

(measures devations from equidistribution)



modified from:

Tort et al., J. Neurophys. 2010



b) Closed-loop scenarios:

$\rightarrow$ use autoregressive methods to predict phase advance into the future

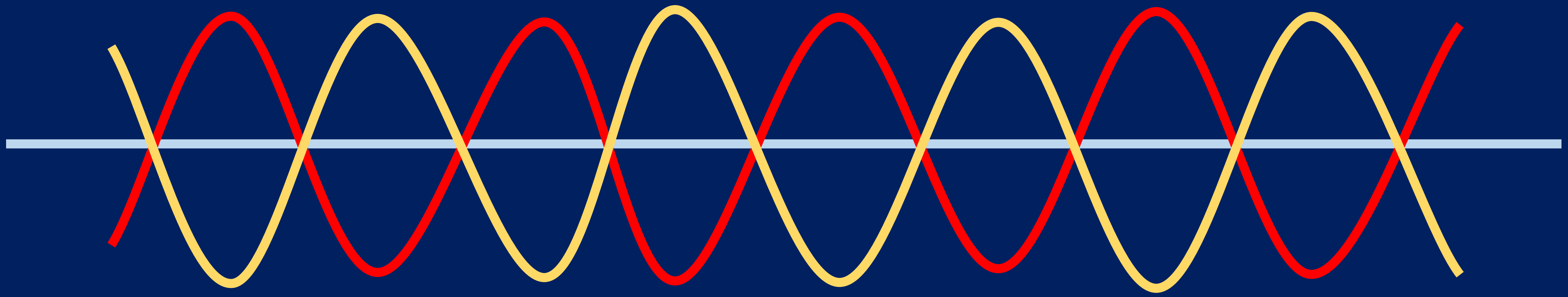
Lisitsyn & Ernst, Frontiers Comp. Neurosci. 2019

c) Linking/correlating continuous signals to spikes

$\rightarrow$ spike-triggered averaging, e.g. spike-field coherence

...the End:

Guess - what's this?



(of course, a superposition of two extremely strong gamma oscillations in perfect antiphase)

ANDA2021

G-Node Advanced Neural Data Analysis Course

Spectral analysis of neural signals:

Opportunities and pitfalls in characterizing oscillations and synchrony in brain activity

Udo Ernst

Computational Neurophysics Lab,
Institute for Theoretical Physics

University of Bremen

ZKW Zentrum für Kognitionswissenschaften

Universität Bremen

neuron Network of European Funding for Neuroscience Research

Bernstein Award in Computational Neuroscience Udo Ernst

IRIS UND HARTMUT JÜRGENS STIFTUNG CHANCE AUF EIN NEUES LEBEN

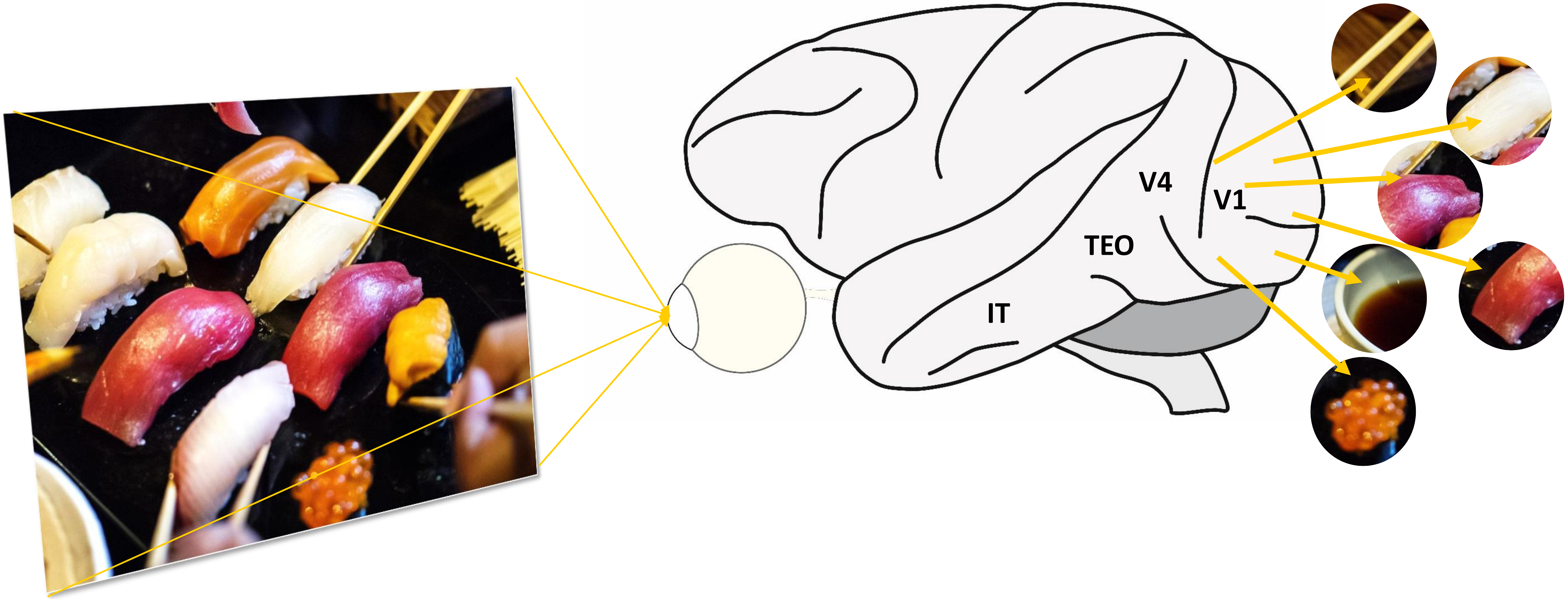
SPP 2205 Evolutionary optimization of neuronal processing

...an example:

Selective processing in the visual system

(aka: the "Sushi challenge")

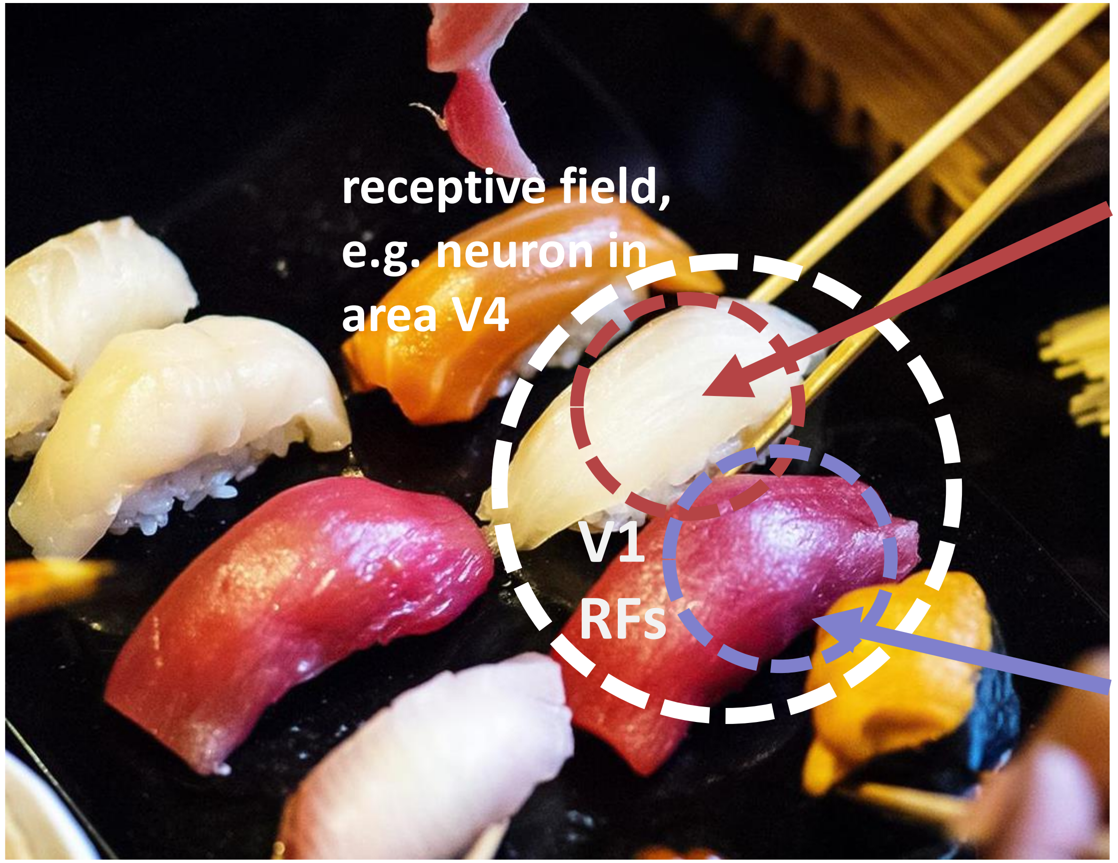
The visual system has to integrate distributed information



[modified from A. Kreiter]

With increasing RF size, selection becomes necessary

Signal integration creates a challenge for selective processing



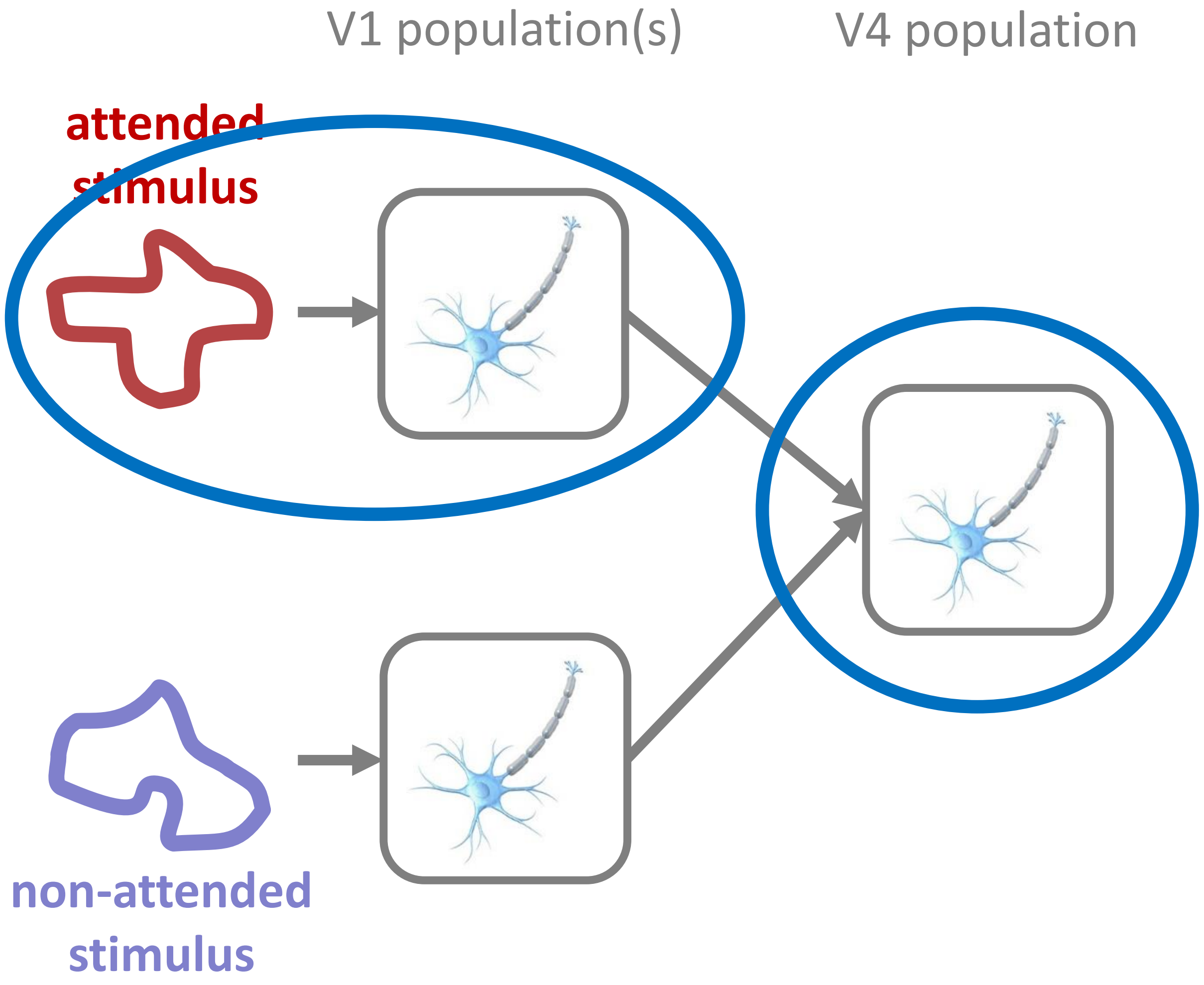
behaviorally relevant, attend!

irrelevant, ignore (...maybe becomes important later!)

In such a situation, neurons in area V4 seem to respond as **if only the attended stimulus would be present**...

Moran J and Desimone R (1985). Selective attention gates visual processing in extrastriate cortex. *Science*, *229*, 782–784.
Reynolds JH, Chelazzi L and Desimone R (1999). Competitive mechanisms subserve attention in macaque areas V2 and V4. *J.Neurosci.*, *19*(5), 1736–1753.

How could selective processing work?



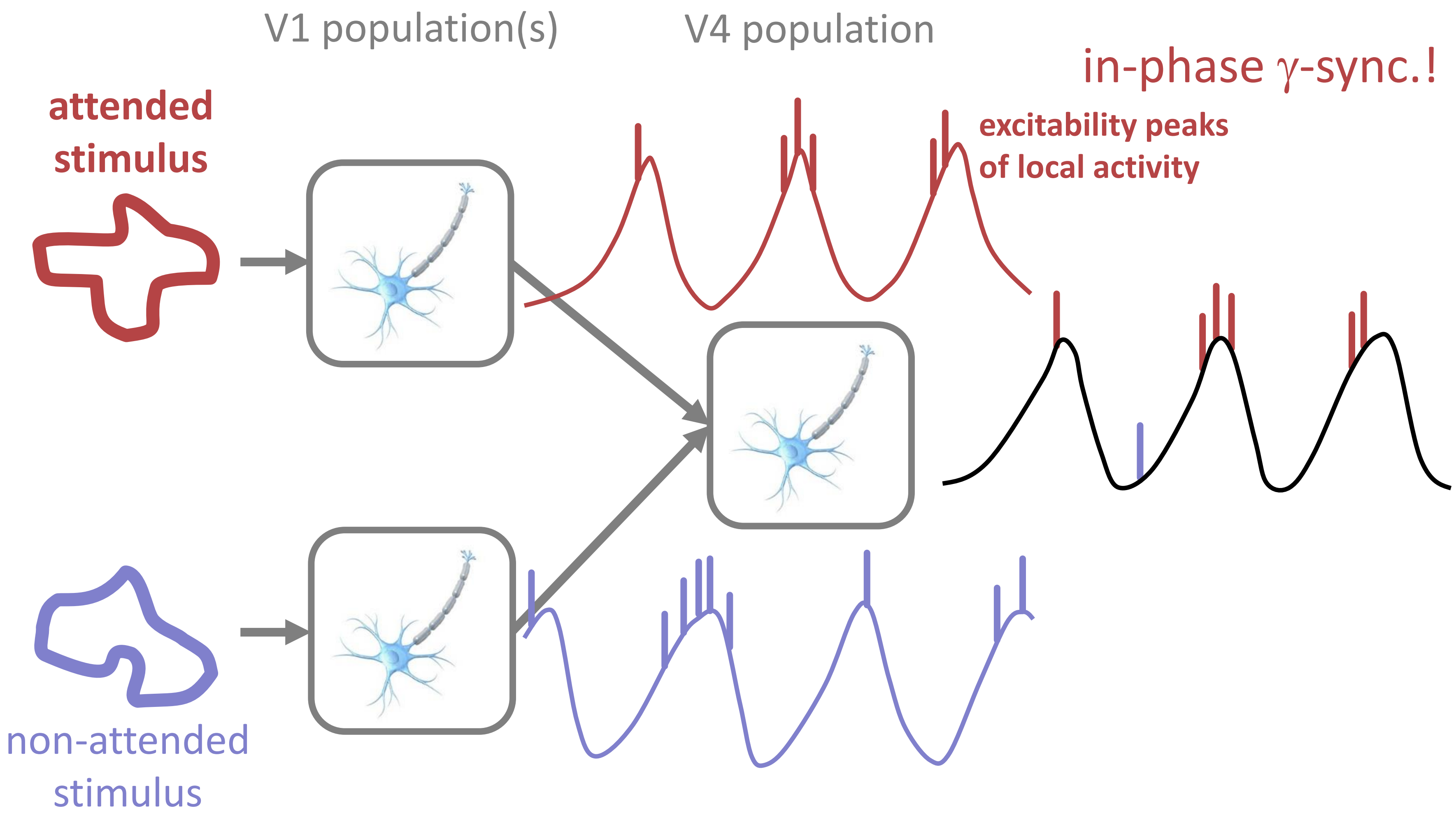
1. Enhancement of output of V1 population representing attended stimulus?

No, not observed, both V1 populations carry about the same stimulus information!

2. Enhancement of output of V4 ?

Not a good idea, this would enhance the signal representation of both stimuli

How could selective processing work?



3. Enhance effective interactions! But how?

Communication-through-coherence (CTC)

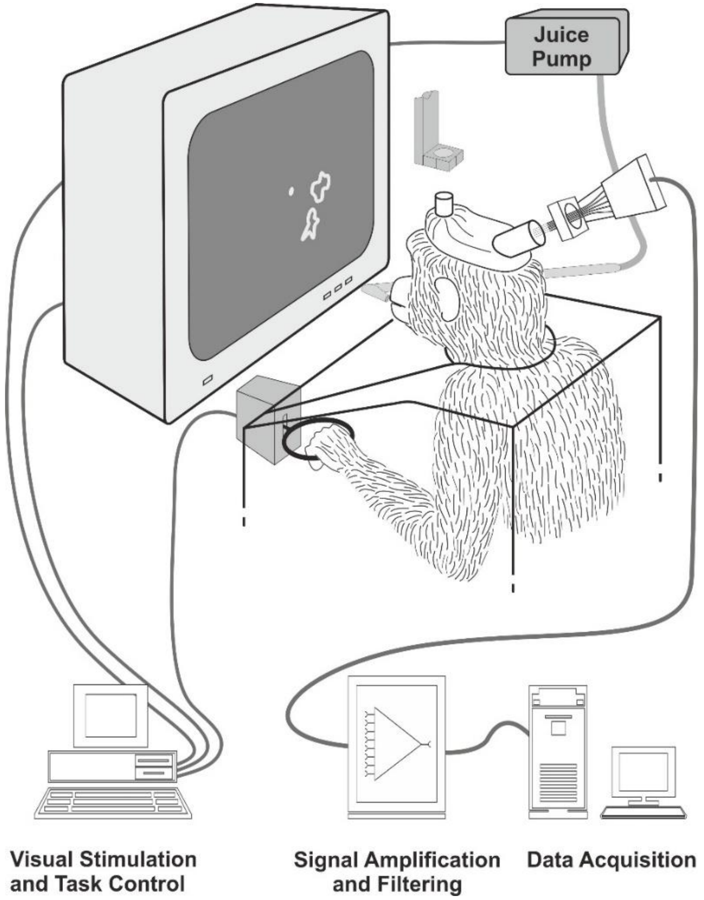
Fries P (2005) A mechanism for cog-nitive dynamics: neuronal communi-cation through neuronal coherence. *Trends Cogn Sci.* 9(10):474-80.

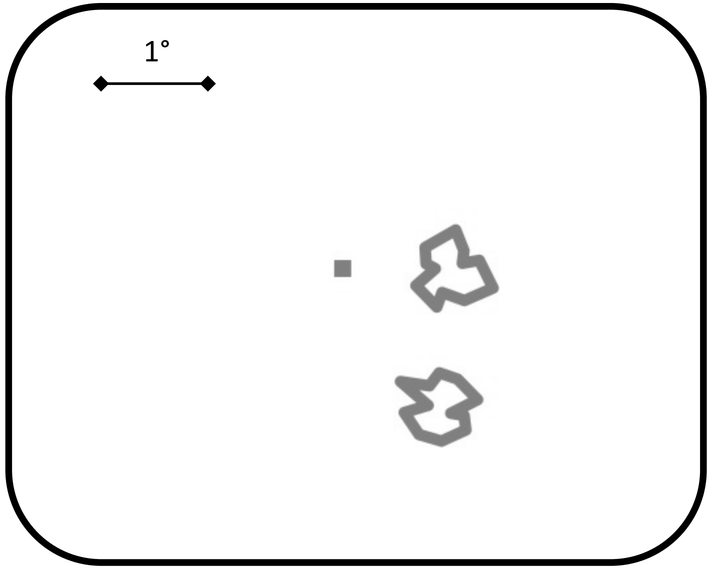
Routing-by-synchrony (RBS)

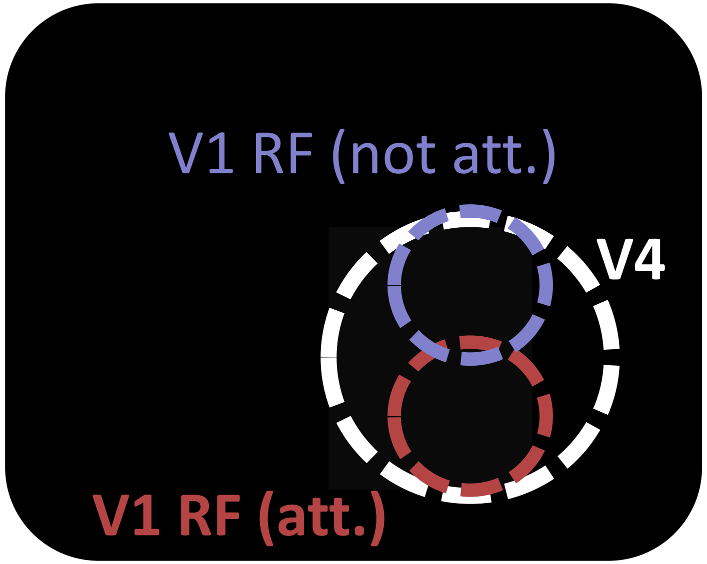
Kreiter AK (2006) How do we model attention-dependent signal routing? *Neural Networks* 19: 1443-1444

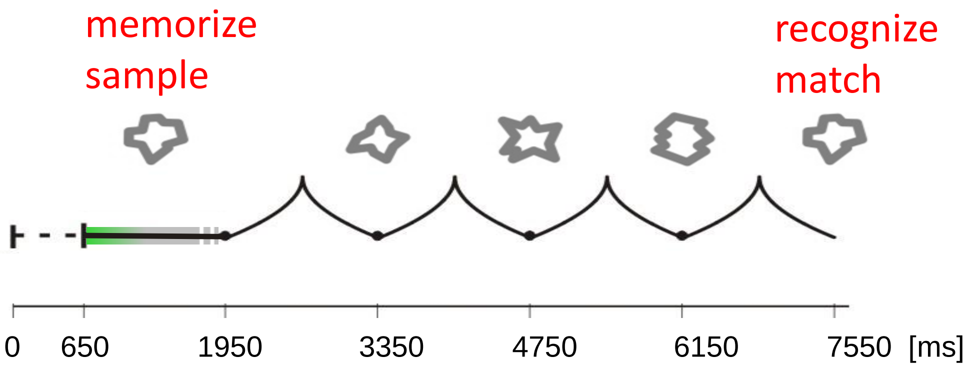
Kreiter AK (2020) Synchrony, flexible network configuration, and linking neuralevents to behavior. Cur. Op. Physiol. 16: 98–108

An experimental paradigm for investigating selective processing









Taylor K, Mandon S, Freiwald WA and Kreiter AK (2005). Coherent oscillatory activity in monkey area v4 predicts successful allocation of attention. *Cereb. Cortex* 15(9), 1424-37.

[modified from A. Kreiter]

a) Is selective attention accompanied by selective (phase) synchronization?

Is selective attention accompanied by selective synchronization?

Hypothesis: V1 attended synchronizes with V4. How do we investigate?

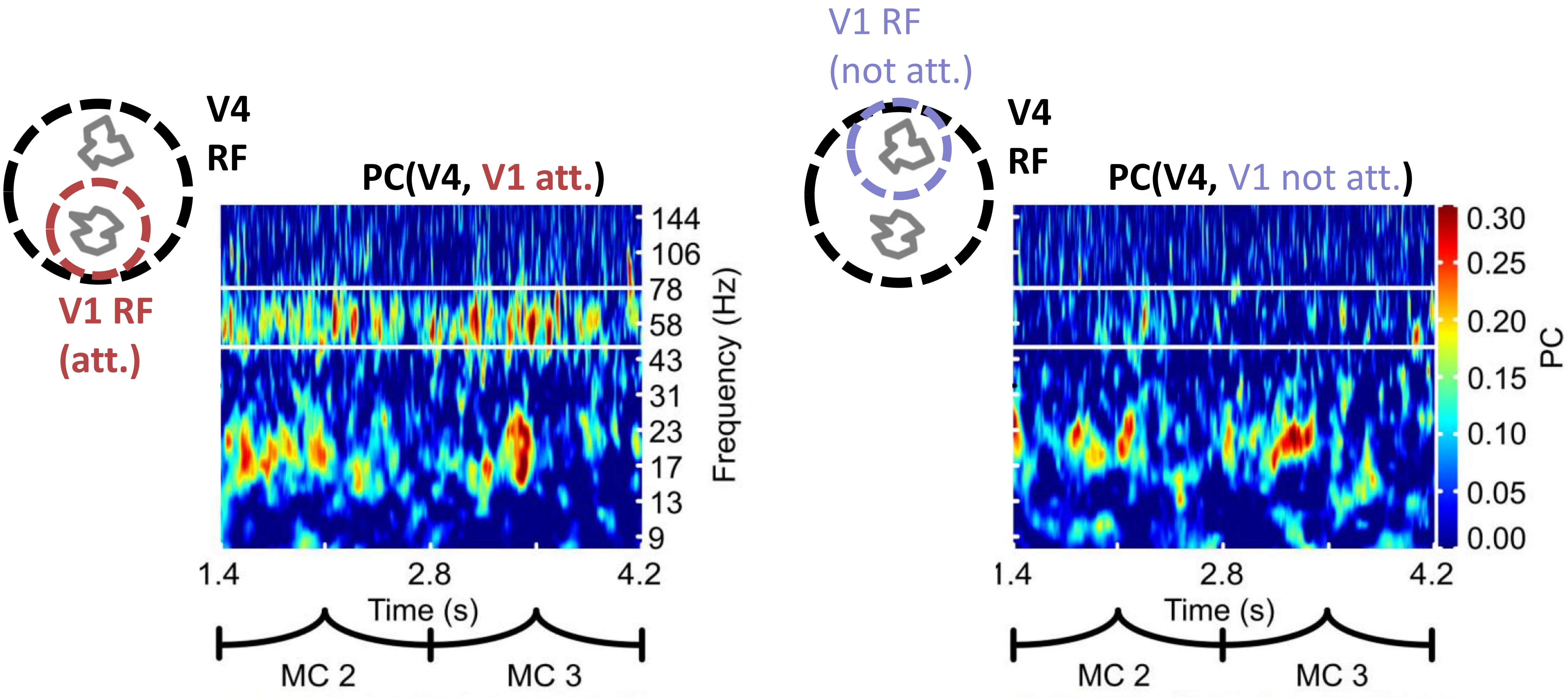
- stimulus is dynamic over time, neural signals are subject to considerable noise, thus oscillatory dynamics (if present) is not "stationary":
  use Wavelet transform

- identify **frequency band of interest**

- amplitude of wavelet transforms is not very important:
  compute phase coherence (PC, PLV!)

$$PLV_{AB} = \frac{1}{N}\left|\sum_{r}^{N} \exp(i(\phi_r^A - \phi_r^B))\right|$$

Phase coherence (PC) between V1 and V4 supports RBS



b) Does selective attention/synchronization modulate effective interactions?

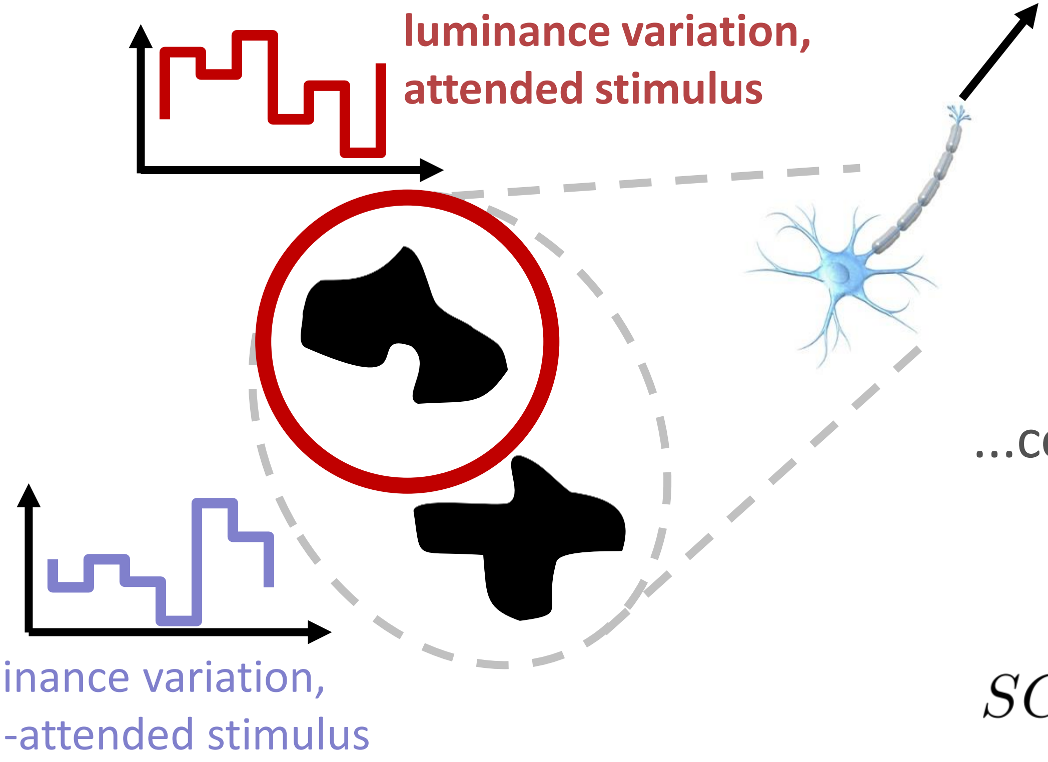
Is selective processing accompanied by enhanced signal transfer?

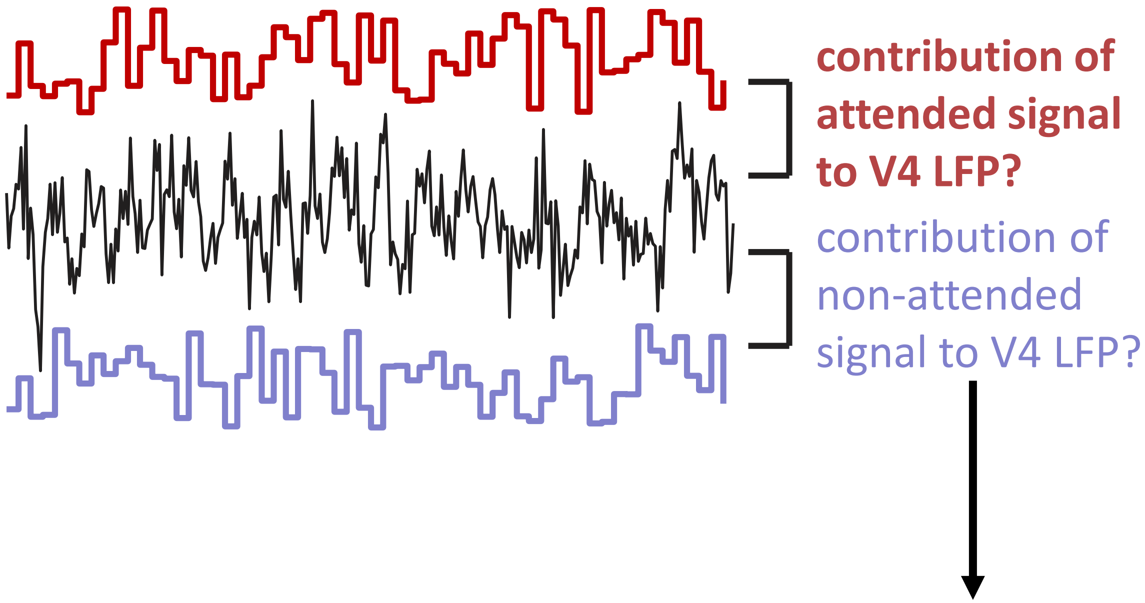
Hypothesis: We know V1 attended synchronizes with V4.
Does it open a 'gate' for visual information?

- Detecting correlations between V1 and V4 does not give us the answer. We do not know their contribution to signal processing or signal transfer...
- We need a **causal method**: here **we have to specify the signals** the visual system has to select by constructing the visual stimuli appropriately!
  (...alternatively: by activating the 'sending' populations, e.g. by electric/optogenetic stimulation

Tracking visual information with flickering stimuli

Tag visual stimuli with independent, random luminance fluctuations :





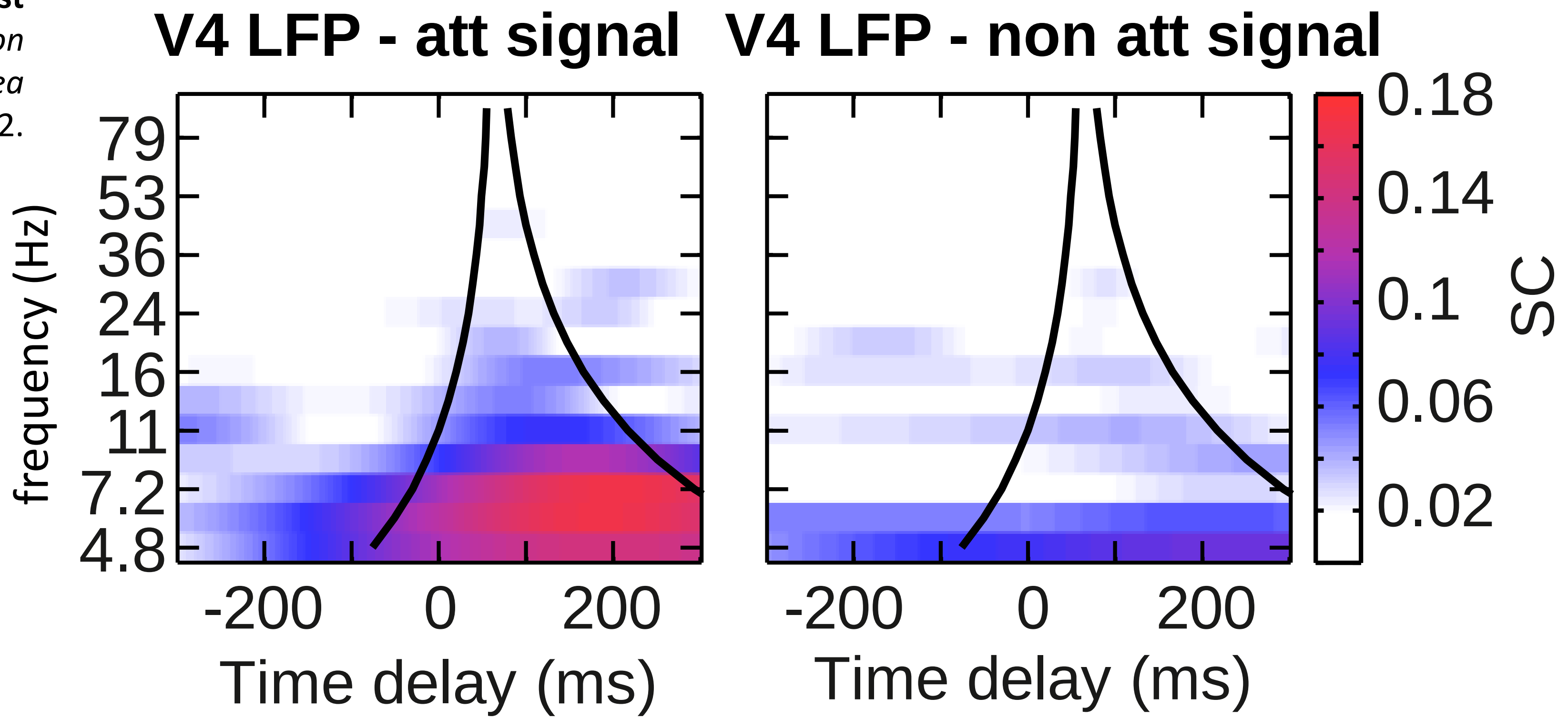
...compute frequency-resolved correlation between visual signal and LFP (spectral coherence)

$$SC(f,\tau) = \frac{\left|\sum_t^N S^A(f,t+\tau)\overline{S}^B(f,t)\right|^2}{\sum_t^N \left|S^A(f,t+\tau)\right|^2 \sum_t^N \left|S^B(f,t)\right|^2}$$

Modified from Grothe, Rotermund, Neitzel, Mandon, Ernst, Kreiter and Pawelzik K (2018)., J. Neurosci.,38:3441-3452.

Attended signal is enhanced relative to non-attended signal

Grothe I, Rotermund D, Neitzel SD, Mandon S, Ernst UA, Kreiter AK and Pawelzik K (2018). *Attention Selectively Gates Afferent Signal Transmission to Area V4*, J. Neurosci., 38 (14):3441-3452.



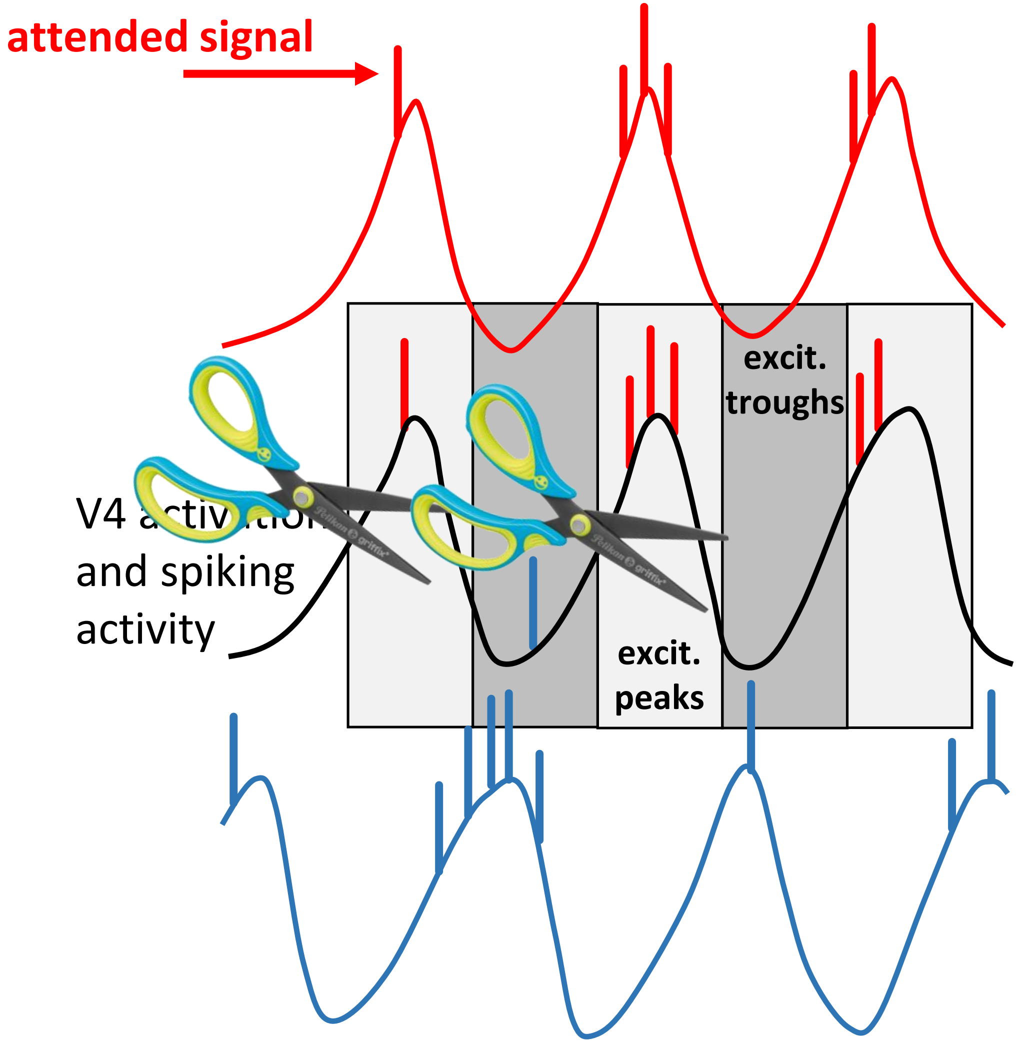
Computing a **delayed correlation** is important:

e.g. transmission delays, finite response times of neural system

Good to have **f-dependence**. Obtain a transmission characteristics instead of a single value...

c) Do effective interactions rely on a pulsed-package transmission scheme?

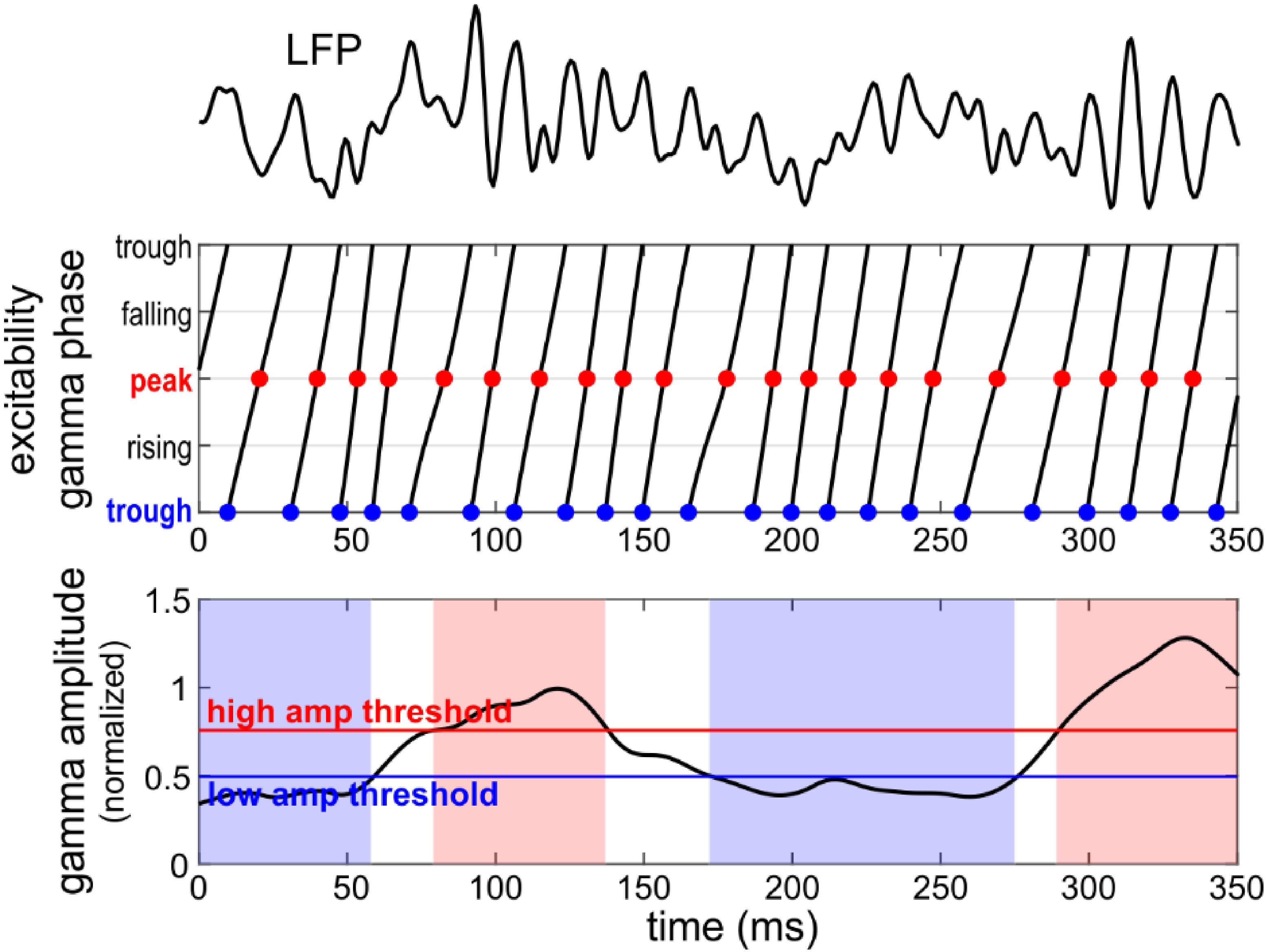
Routing-by-synchrony makes a specific prediction...



- Transfer of attended signal is **Gamma-phase-specific:**
  high near peaks, low near troughs
- Routing occurs through
  pulsed information packages
- The **higher the LFP amplitude** of the receiving population in V4, the **larger is signal content**.

Quantify visual signal content at specific γ-phases and amplitudes

1. **Extract γ-activity** from LFP (by bandpass filter)
2. **Determine γ-phase and γ-amplitude** (by Hilbert transform)

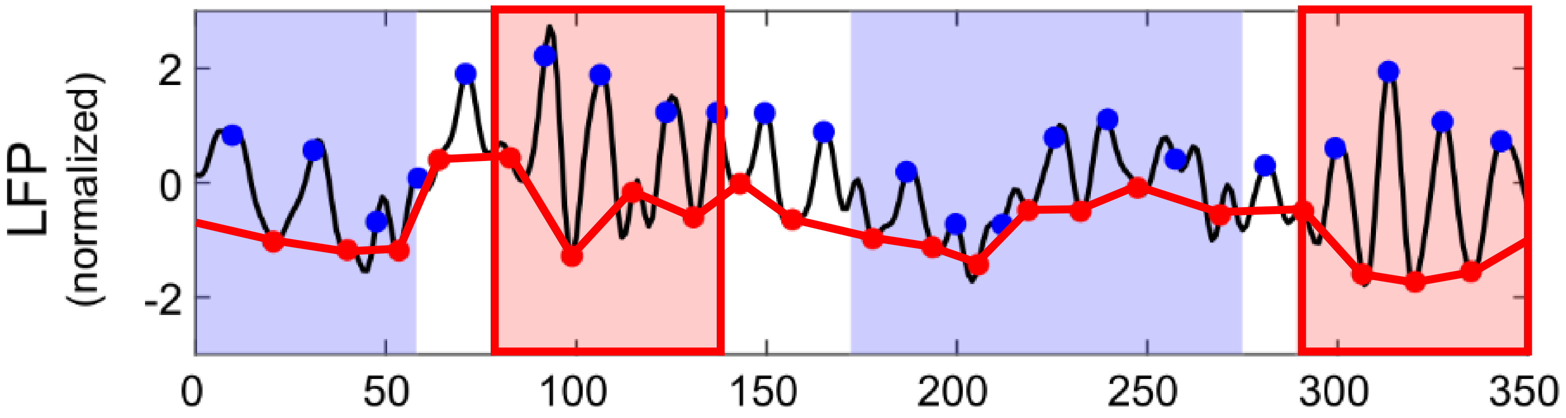


Extracting phase- and amplitude-specific neural signals

We **use the marked phases and tagged intervals as selectors** to pick the corresponding signal content from the recorded data:

Phase-specific analysis:

Resample LFPs or multi-unit activity (MUA) at excitability peaks (red dots) or troughs (blue dots) or ***ANY other phase of interest...***

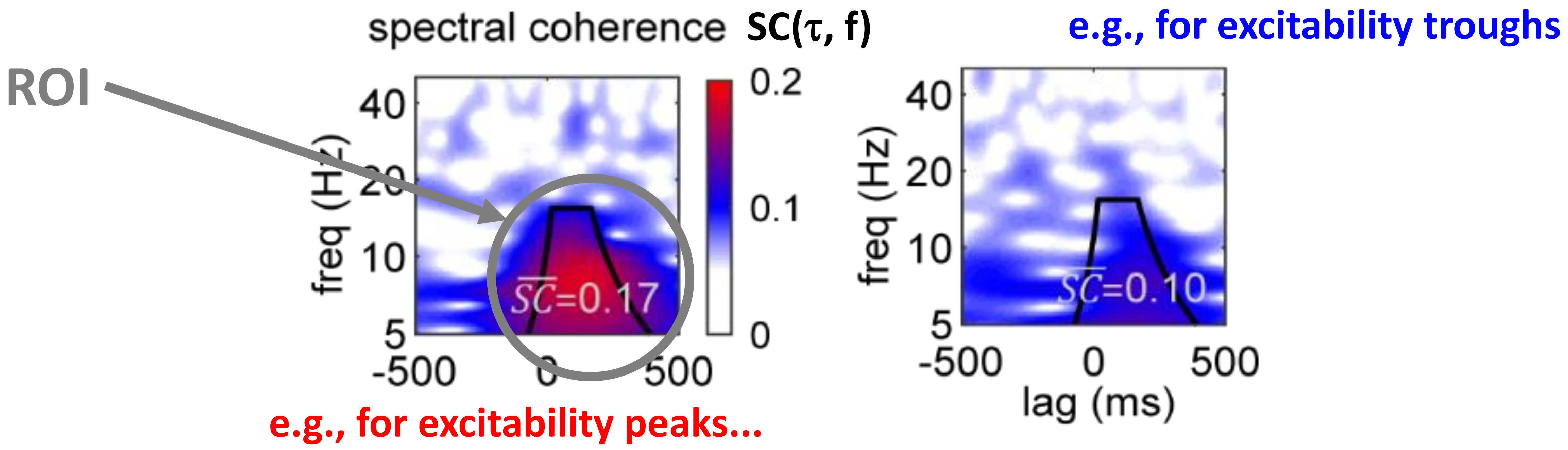


Amplitude-specific analysis:

Extract periods of high γ-activity (red regions) or low γ-activity (blue regions)

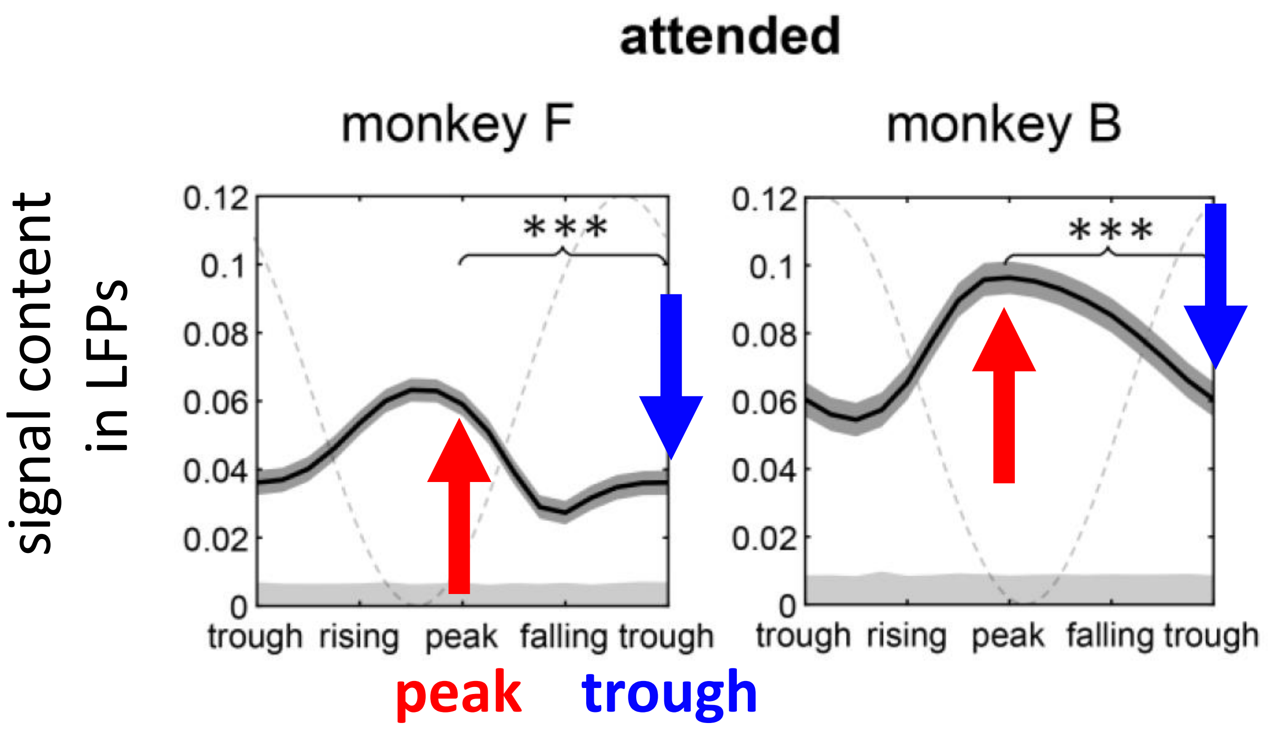
Collapsing the spectra to single numbers

Average spectral coherence over **region-of-interest (ROI)** in time and frequency to obtain just one number $\overline{\textbf{SC}}$...



Signal content is higher at excitability peaks

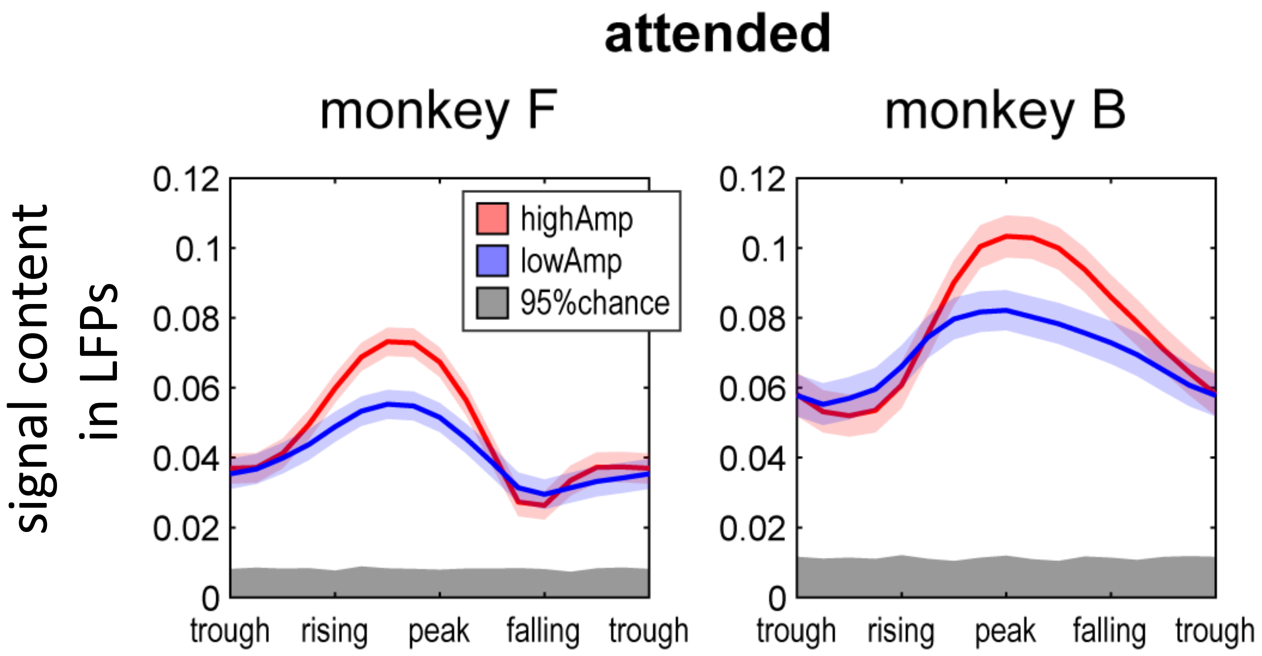
Quantify **attended/non-attended** stimulus signal content in **phase-specific signals extracted from LFPs:**



D. Lisitsyn, I. Grothe, A.K. Kreiter, U.A. Ernst (2020). Visual Stimulus Content in V4 Is Conveyed by Gamma-Rhythmic Information Packages J. Neurosci., 40 (50) 9650-9662.

Signal content is higher during high-γ-amplitude periods

Split analysis into **low/high** gamma amplitude intervals, and analyze separately



red curve: high-amplitude gamma activity

blue curve: low-amplitude gamma activity

Thanks to *YOU* and to...:


Andreas Kreiter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Iris Grothe


Sunita Mandon


Katja Taylor


Maik Schünemann

Your tutor for today and tomorrow!


Dmitriy Lisitsyn


David Rotermund


Klaus Pawelzik

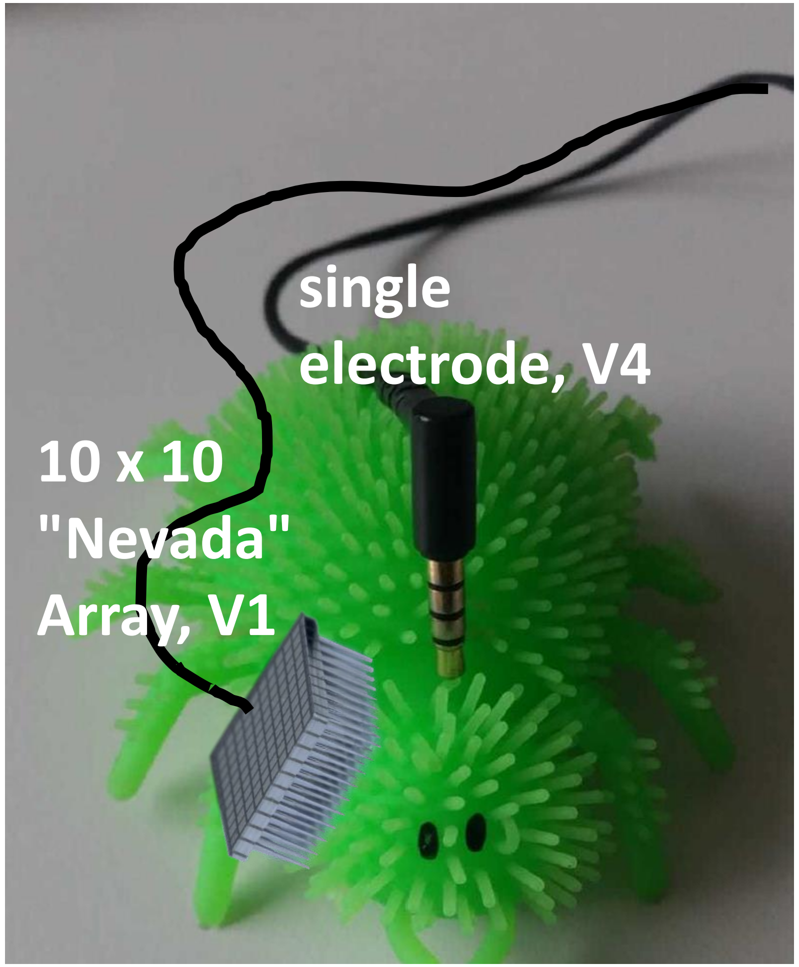

Daniel Harnack

Exercises for this Lecture

Your gamma-challenge

The experiment!

a North German spider monkey



All groups:

- implement (i.e., find out how to use) Wavelet transform

Group A:

- implement spectral coherence (SC)
- compute SC between flicker signals A, B and V4 local field potential (LFP)
- find out which stimulus was attended (i.e. is 'routed')!

Group B:

- implement computing the phase-locking-value (PLC)
- compute PLVs between V4 LFP and all V1 sites
- find out which V1 site is maximally synchronized with V4!