EEG/MEG 3:

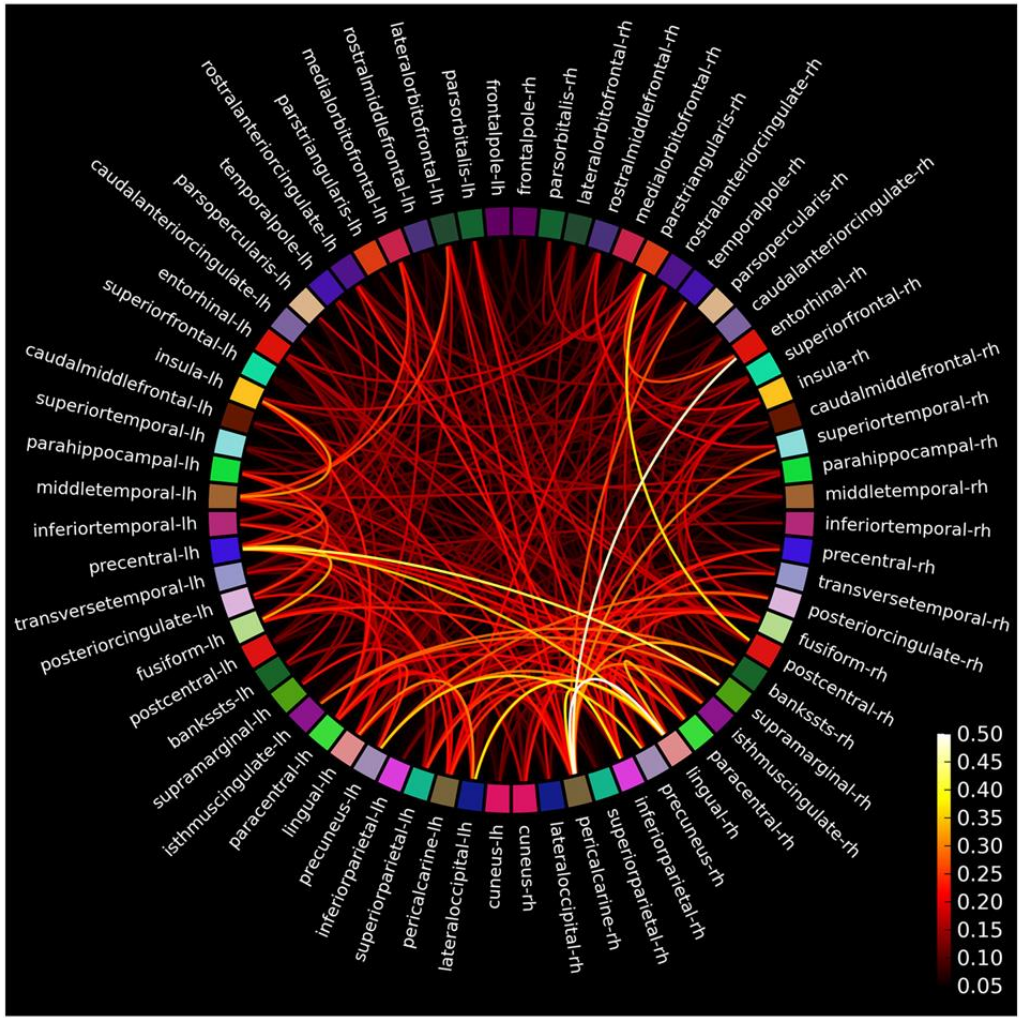
Functional Connectivity Analysis Cont'd

Olaf Hauk

olaf.hauk@mrc-cbu.cam.ac.uk

COGNESTIC 2023

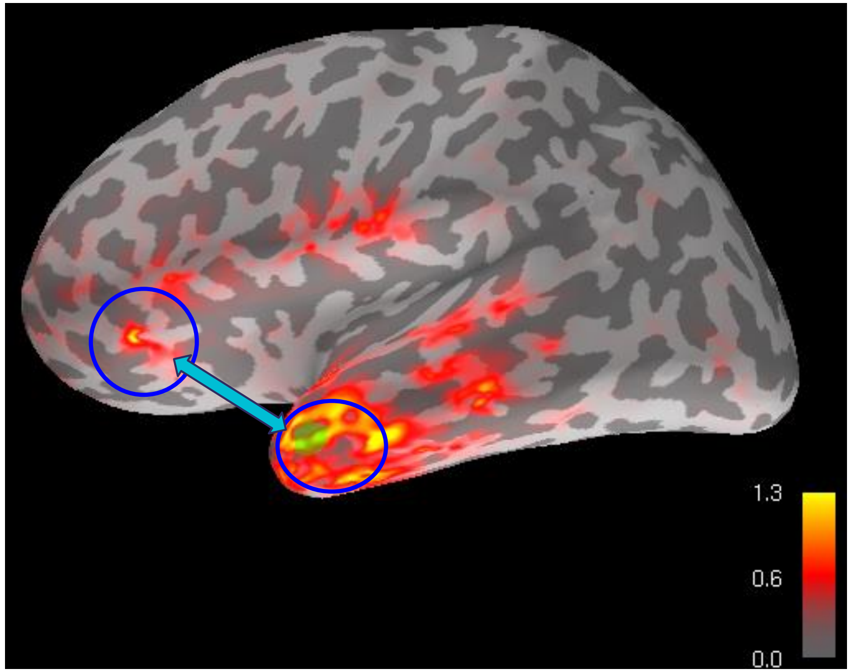
Bivariate Functional Connectivity Is Relatively Easy To Compute - And Therefore Suitable For Exploratory "All-To-All" Analyses



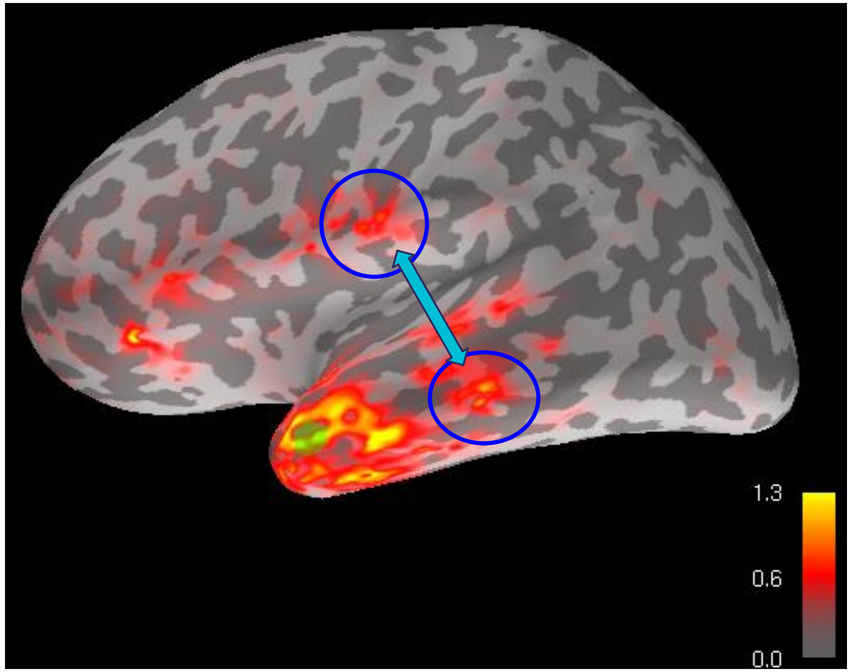
Gramfort et al., NI 2014
https://www.sciencedirect.com/science/article/pii/S1053811913010501

Field Spread / Point Spread

Connectivity between two regions may reflect cross-talk from one of the regions



Connectivity between two regions may reflect cross-talk from a third region

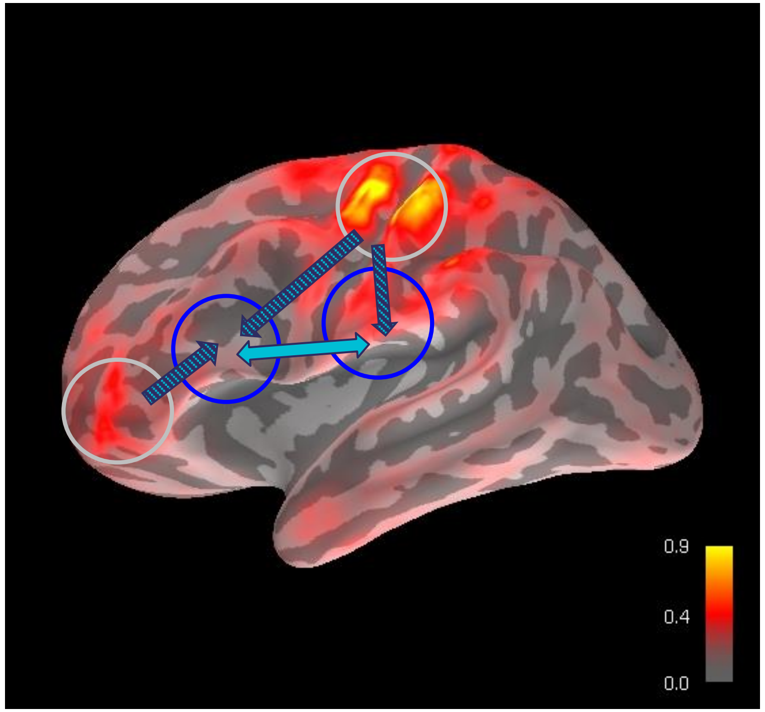


Some connectivity measures can rule out “zero-lag” connectivity

(but they are then also insensitive to real zero-lag connectivity)

Field Spread / Point Spread

Connectivity between two regions may reflect
cross-talk from several other regions

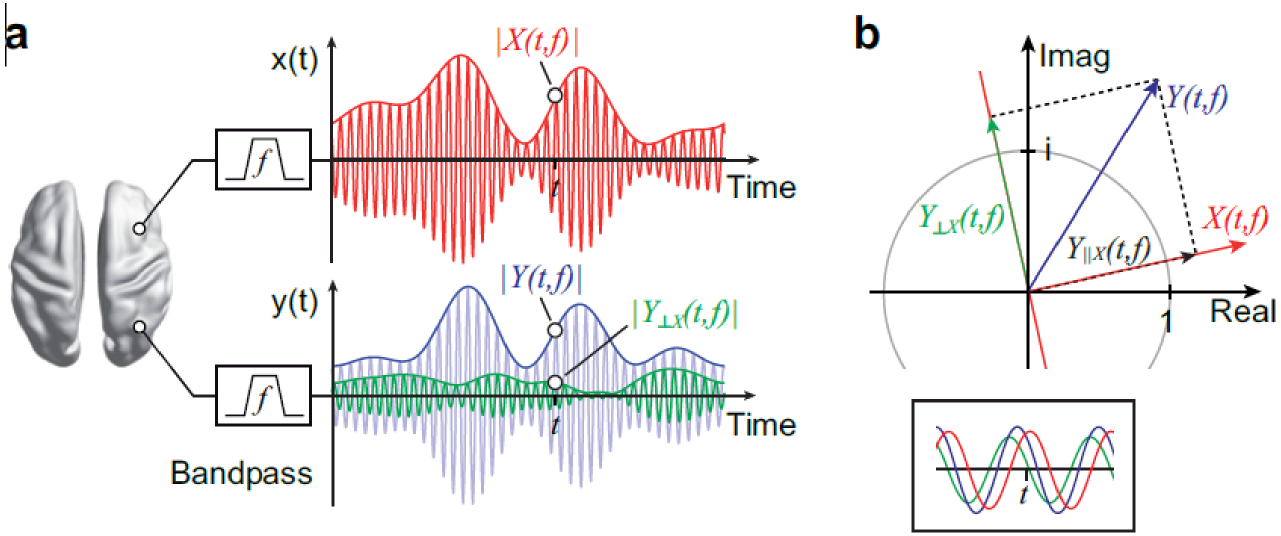


This is bad, and there is not much you can do –
except getting your model right in the first place, or use whole-brain analysis.

One Possibility: Remove Zero-Lag Connectivity

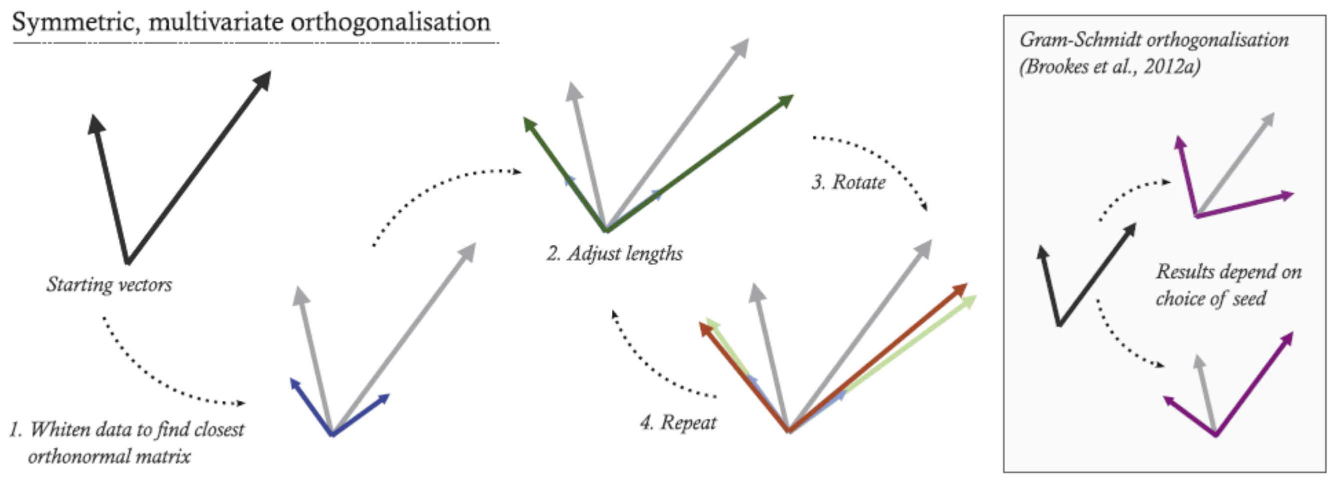
Orthogonalisation of time courses, Partial regression

Bivariate:



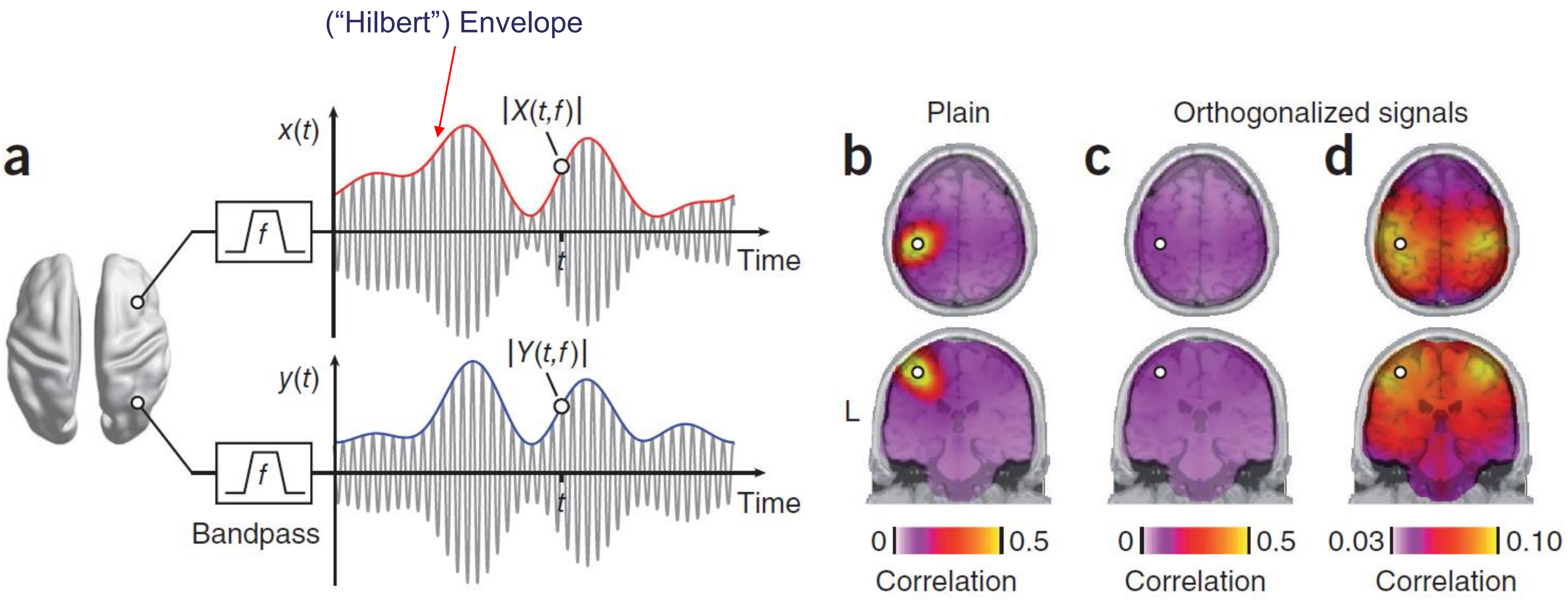
Hipp et al., Nat Nsc 2012, https://www.nature.com/articles/nn.3101

Multivariate:



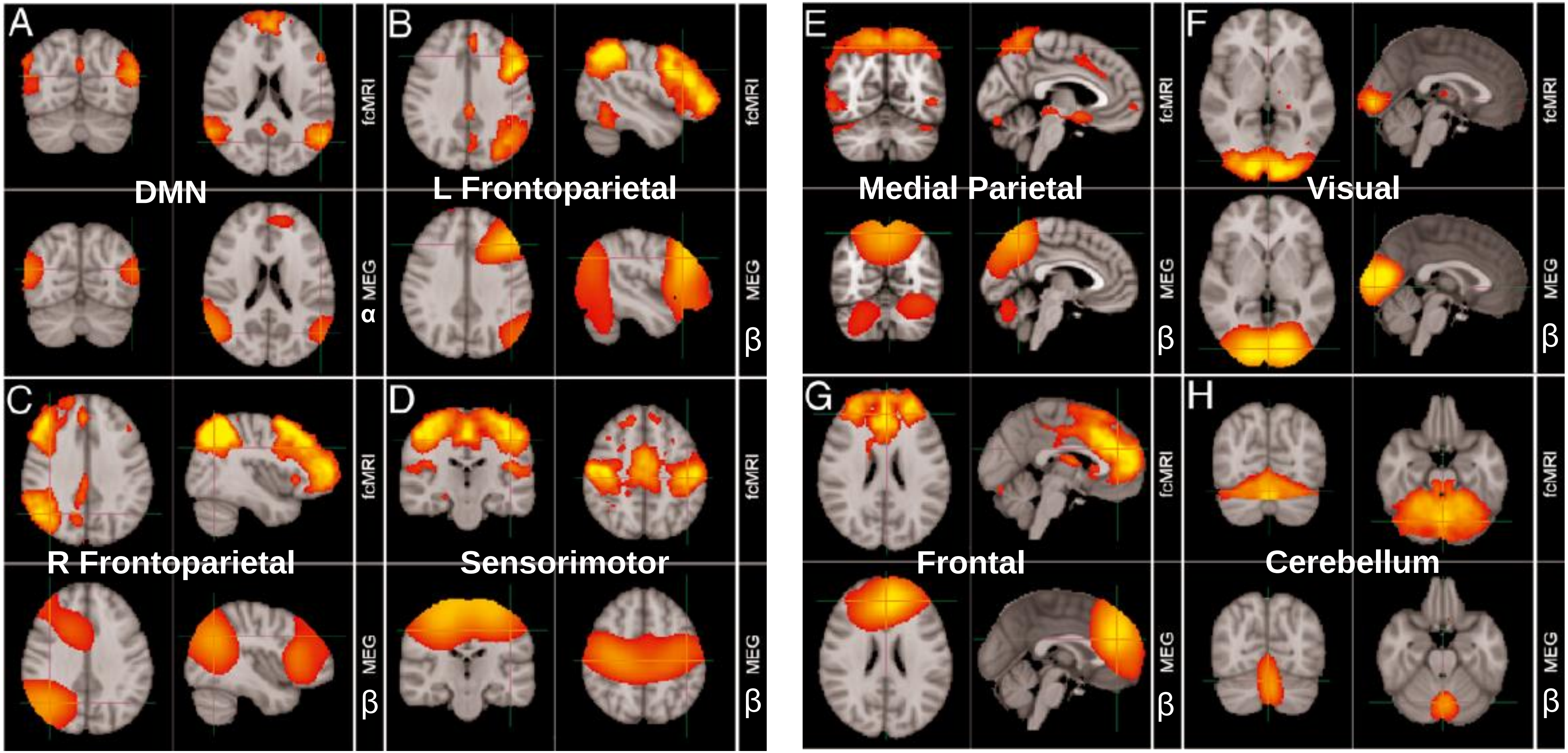
Colclough et al., NI 2015, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4528074/

Functional Connectivity of Resting State Activity



Hipp et al., Nat Nsc 2012, https://www.nature.com/articles/nn.3101

Functional Connectivity of Resting State Activity



Brooks et al., PNAS 2011, https://www.pnas.org/doi/10.1073/pnas.1112685108

One Possibility: Remove “Zero-Lag” Connectivity

E.g.: Imaginary Part of Coherency

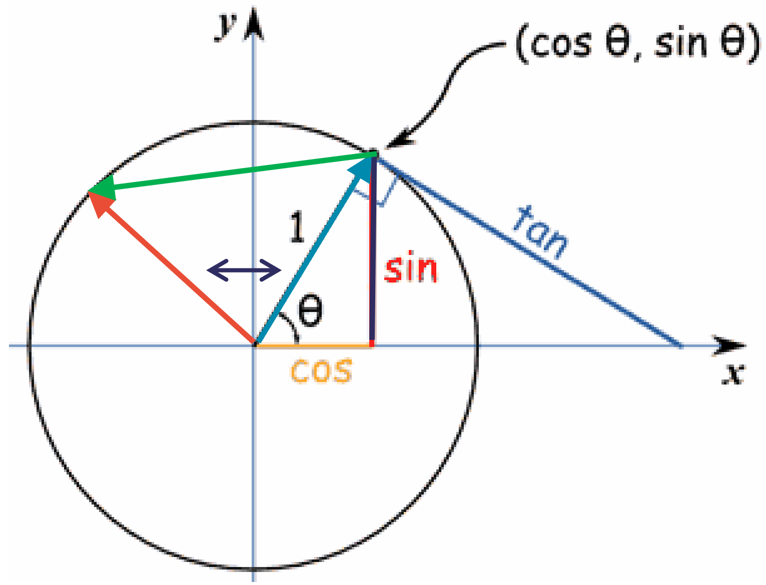
In spectral connectivity measures like Coherence, only use the imaginary part of the signal, which is unaffected by zero-lag connectivity (phase differences of zero are only represented in the real part).

Ewald et al., NI 2012, https://pubmed.ncbi.nlm.nih.gov/22178298/

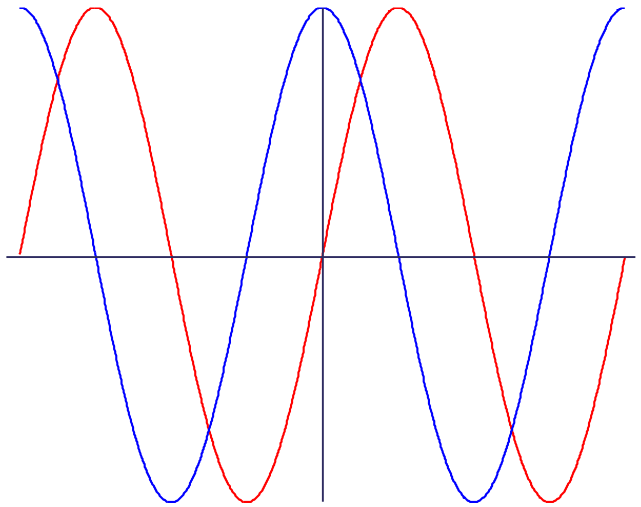
Pascqual-Marqui, arXiv 2007a and 2007b, https://arxiv.org/abs/0706.1776, https://arxiv.org/abs/0711.1455

Note: “Non-zero-lag methods” may also ignore true zero-lag connectivity, e.g. for bilateral sources – one may through out the child with the bath water.

Phase difference in frequency domain



Phase difference in time domain

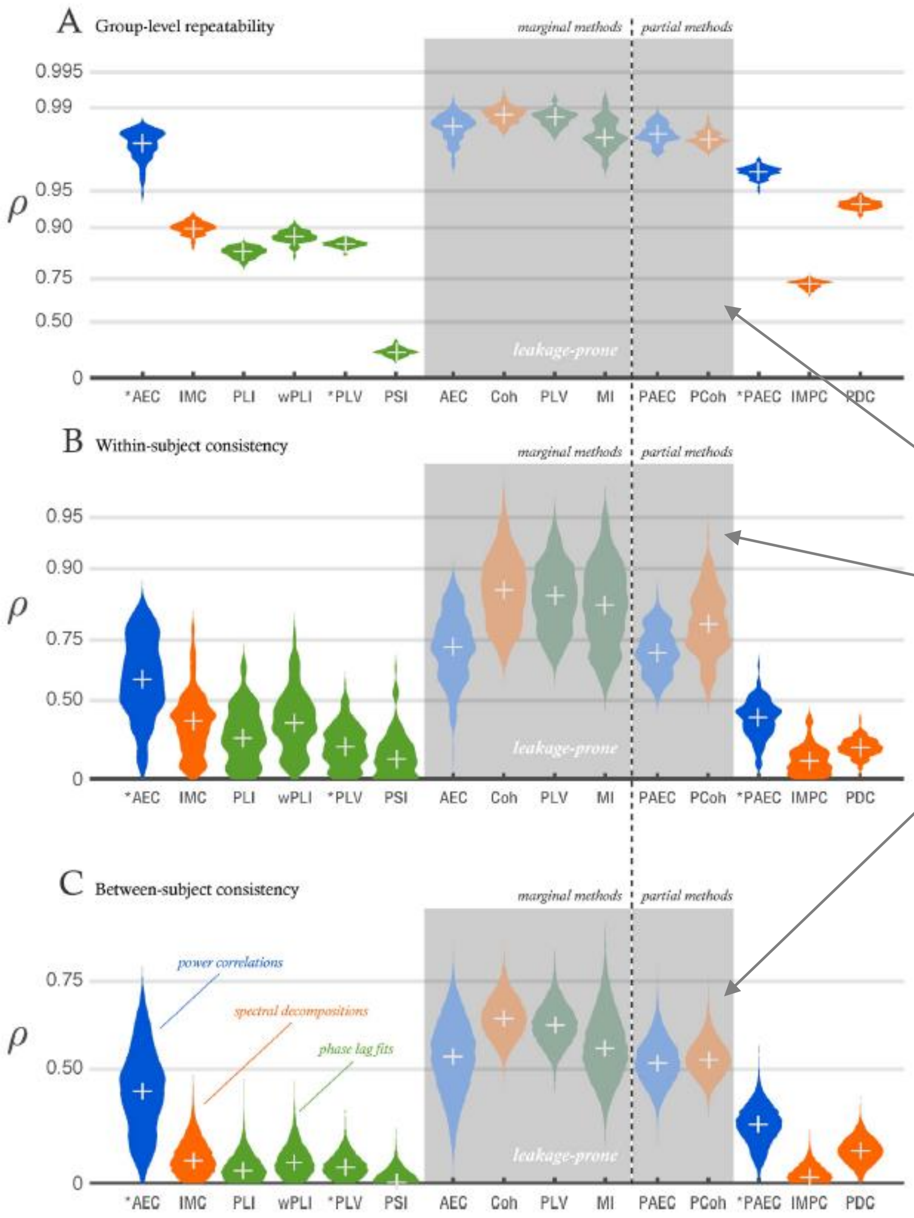


Leakage and Reliability of Functional Connectivity Methods

Group-level repeatability

Within-subject consistency

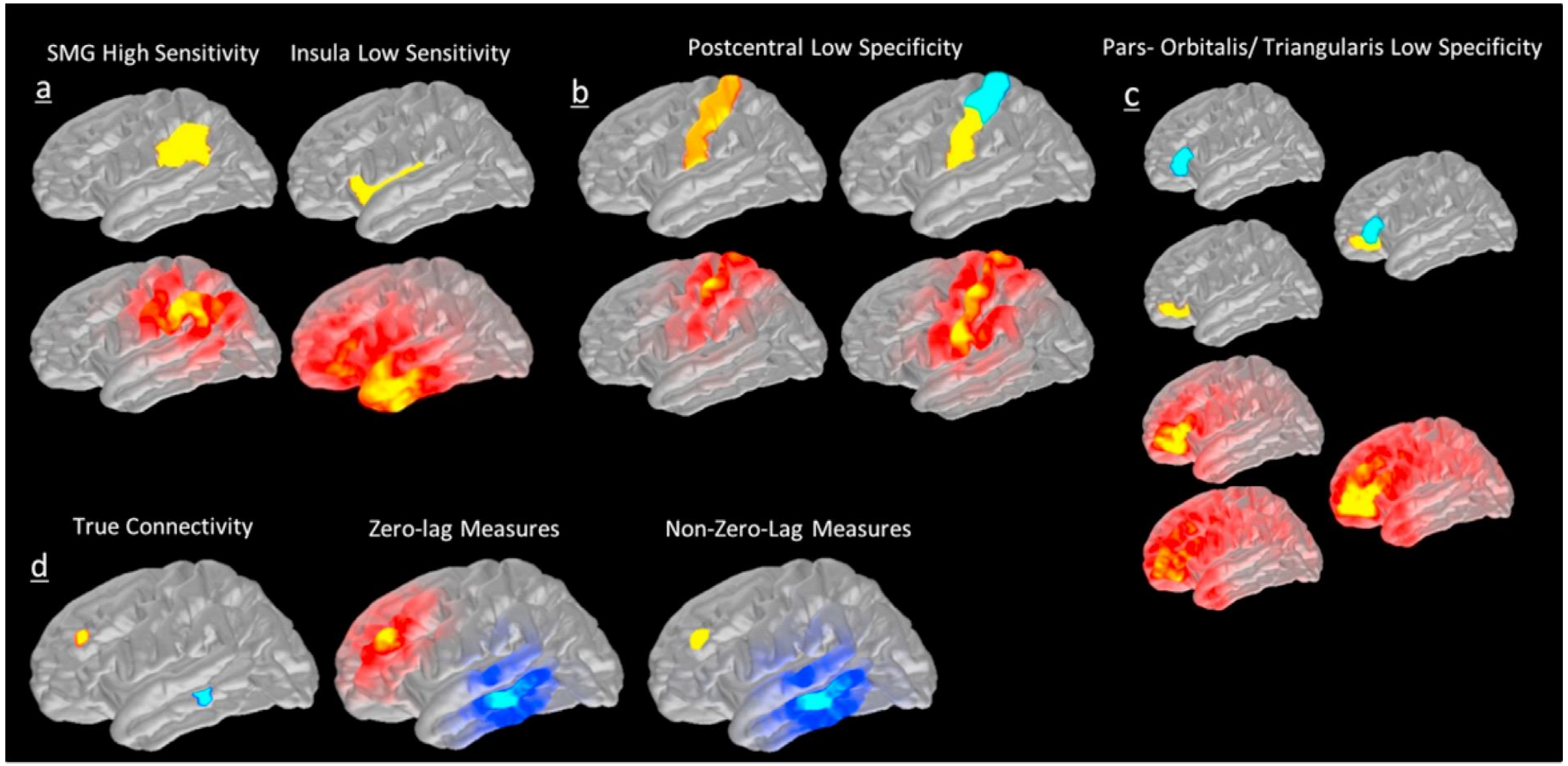
Between-subject consistency



leakage-prone

Colclough et al., Neuroimage, 2016
https://pubmed.ncbi.nlm.nih.gov/27262239/

Leakage Can Produce Spurious Connectivity
(also at zero-lag)



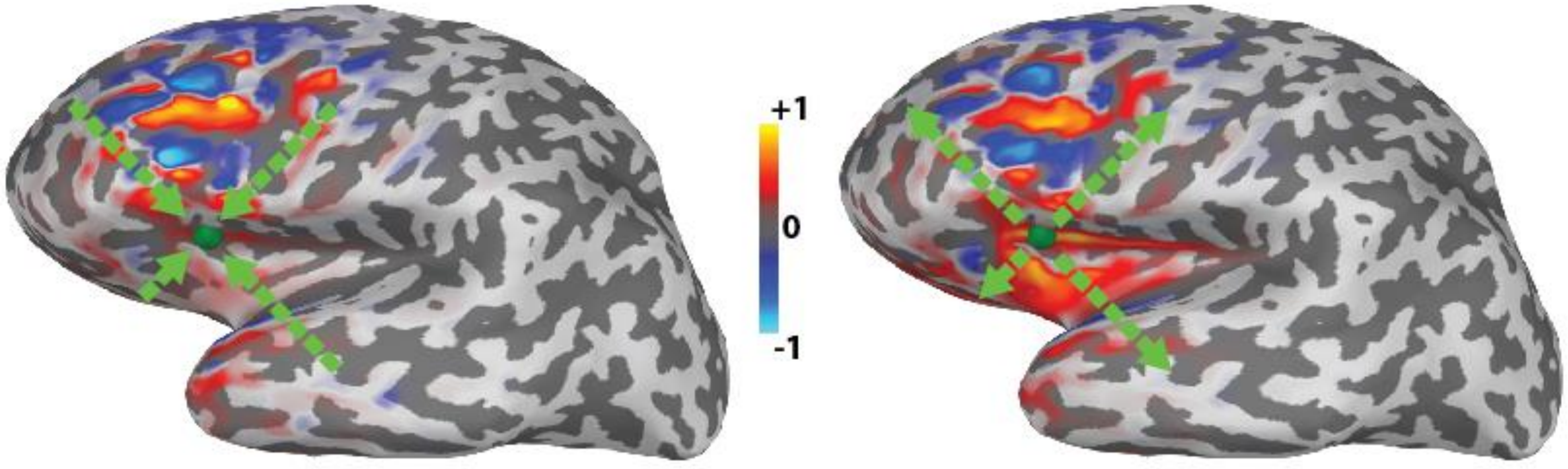
Farahibozorg, Henson, Hauk, NI 2018, https://pubmed.ncbi.nlm.nih.gov/28893608/
See also:
Palva et al., NI 2018, https://pubmed.ncbi.nlm.nih.gov/29477441/
Colclough et al. NI 2015, https://pubmed.ncbi.nlm.nih.gov/25862259/

Spatial Resolution / Leakage:

Point-Spread and Cross-Talk

Cross-Talk Function (CTF)

Point-Spread Function (PSF)



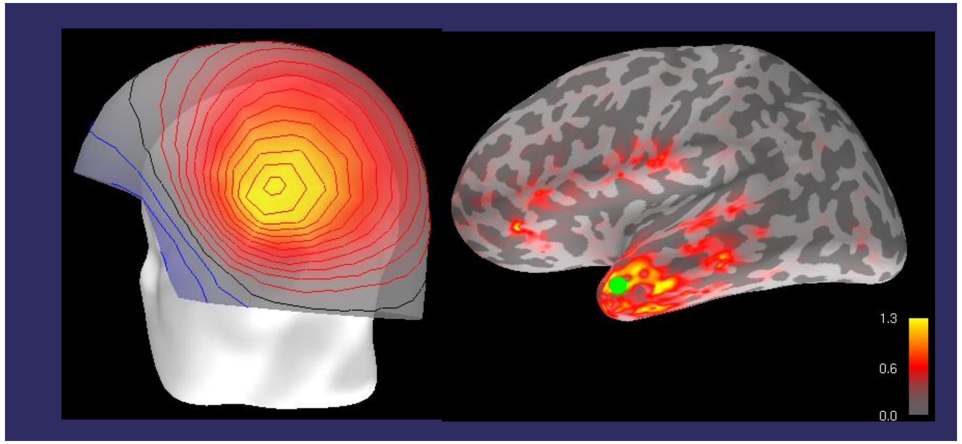
How other sources may affect the estimate for this source

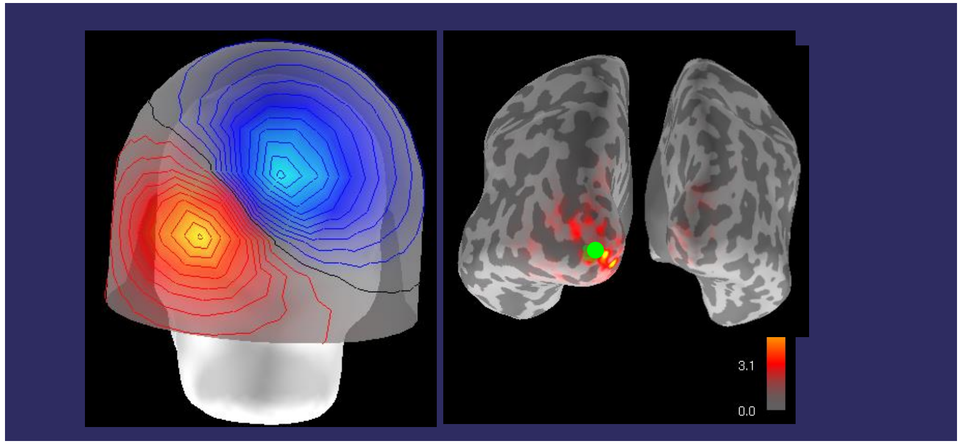
How this source affects estimates for other sources

Hauk, Stenroos, Treder, Neuroimage 2022
https://www.sciencedirect.com/science/article/pii/S1053811922002993

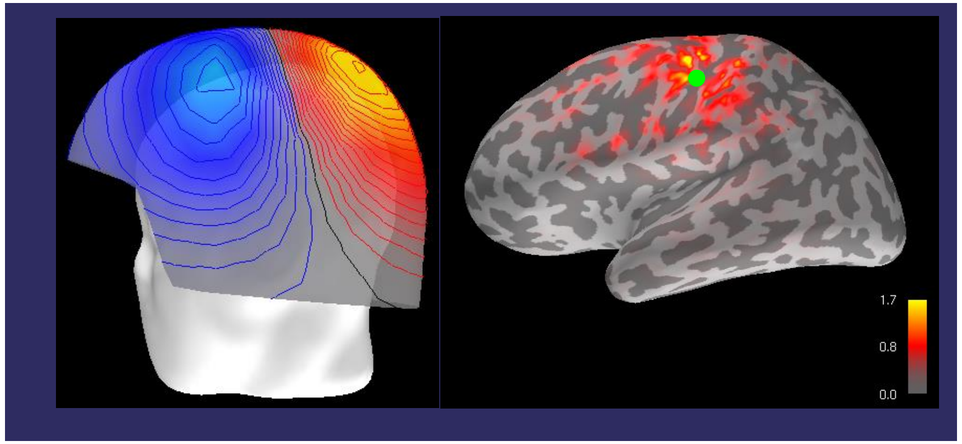
PSFs and CTFs for Some ROIs

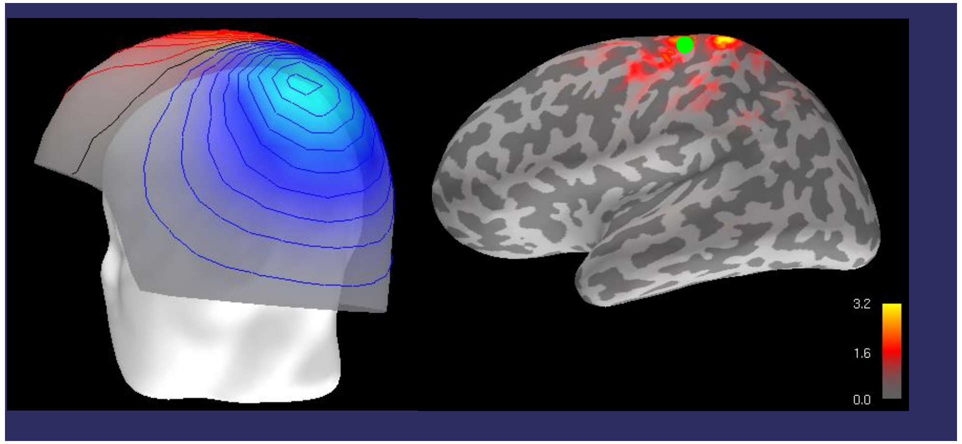
For MNE, PSFs and CTFs turn out to be the same





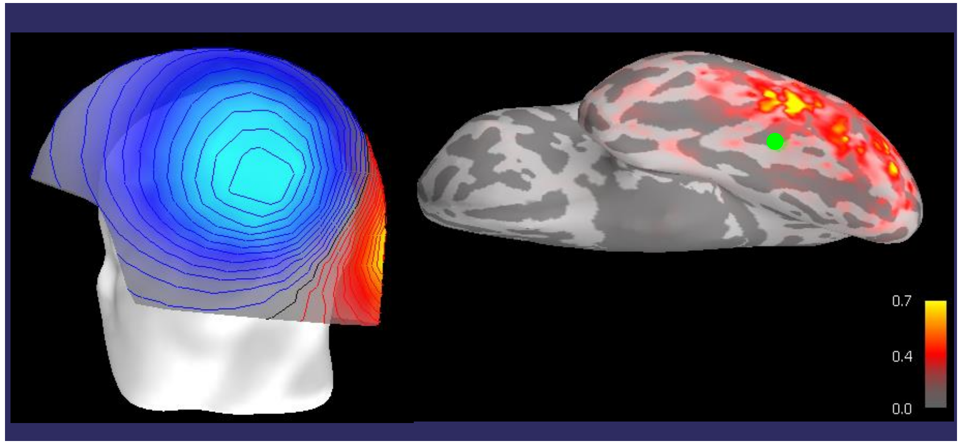
Good

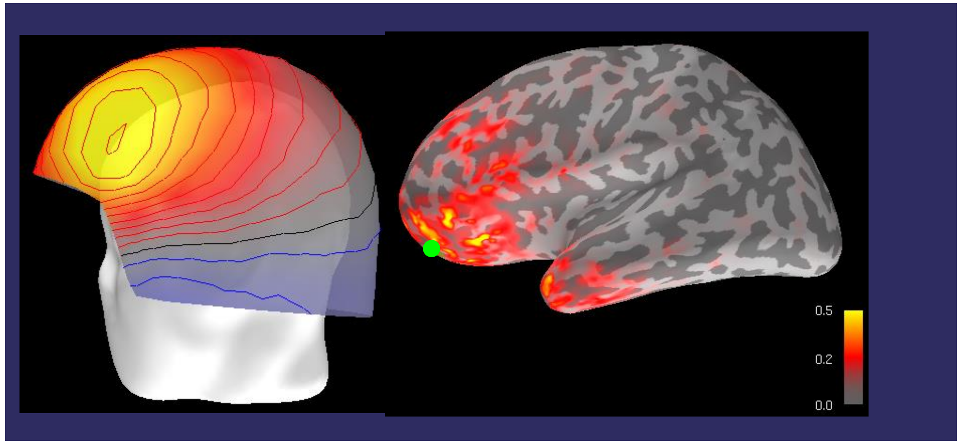




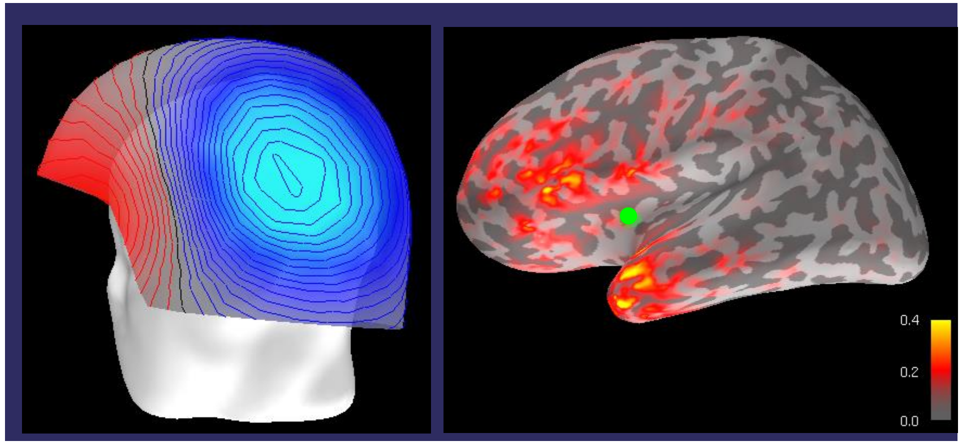
PSFs and CTFs for Some ROIs

For MNE, PSFs and CTFs turn out to be the same



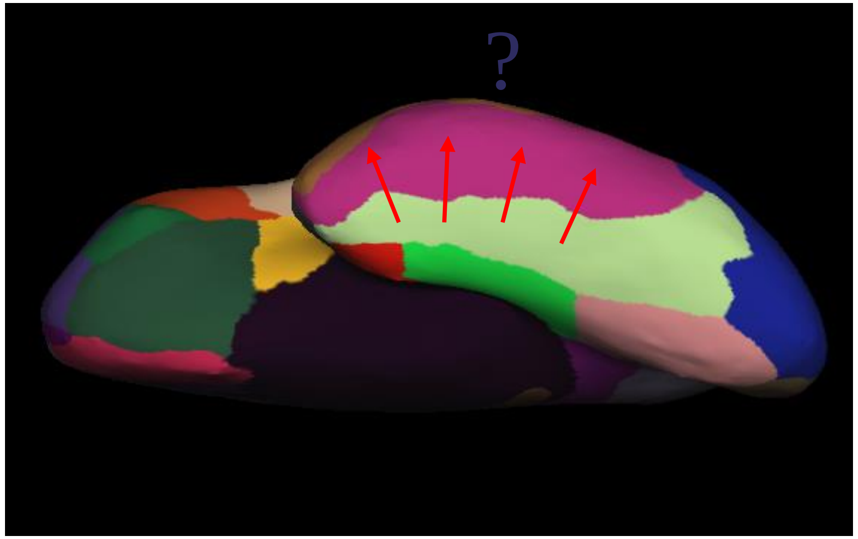


Less good

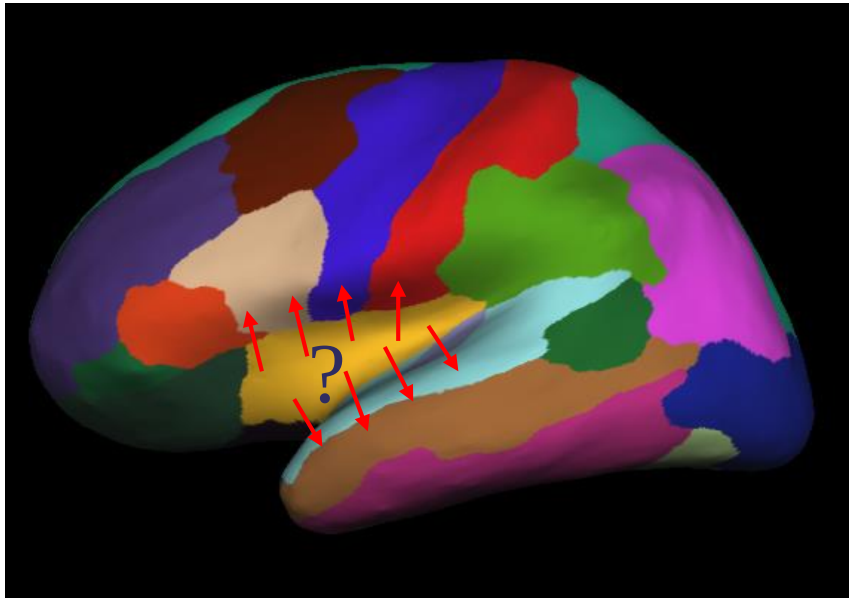


Localisation Bias Has Consequences for ROI analysis

PSFs/CTFs Can Tell You How It Looks Like

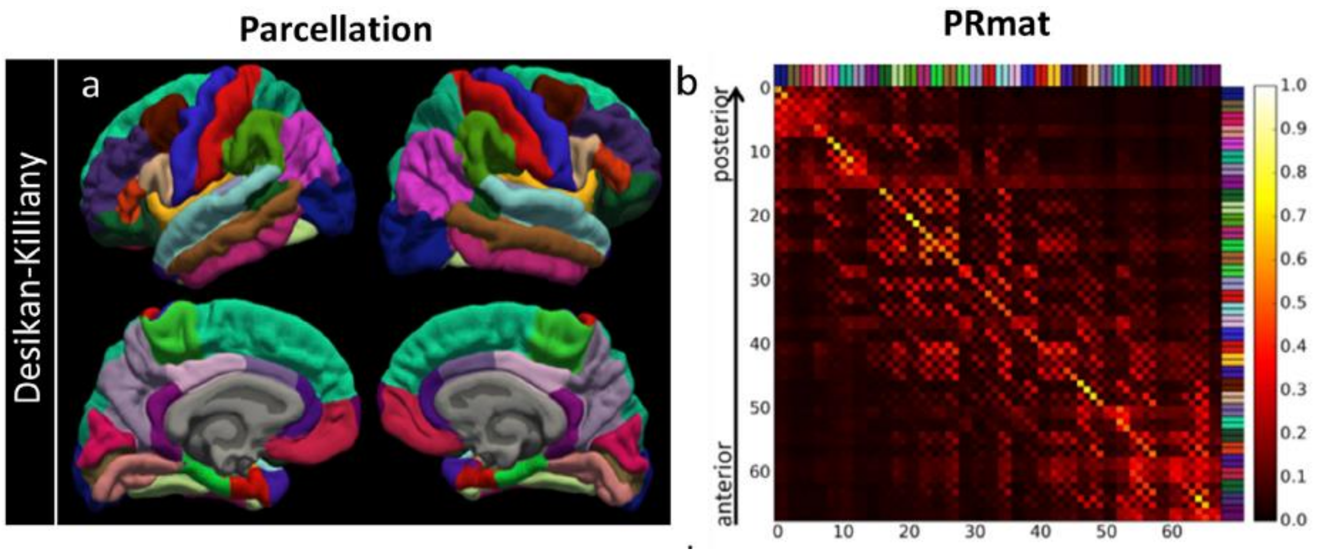


Desikan-Killiany Atlas parcellation

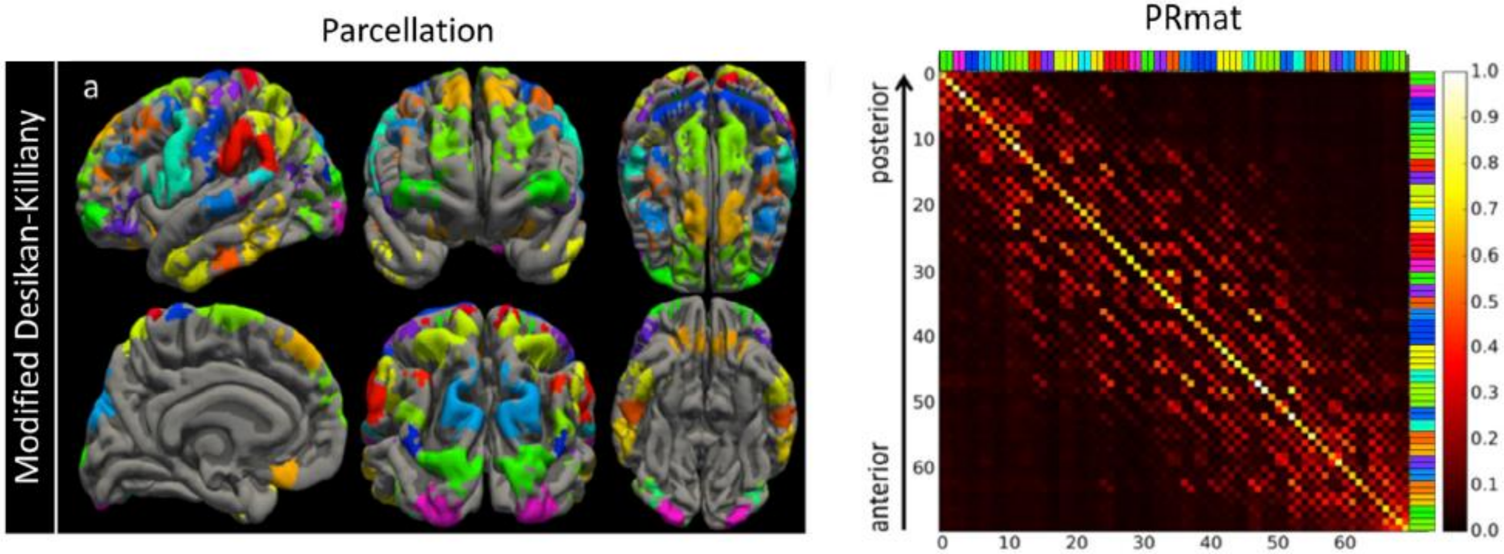


Adaptive cortical parcellation based on resolution matrix

Original Parcellation

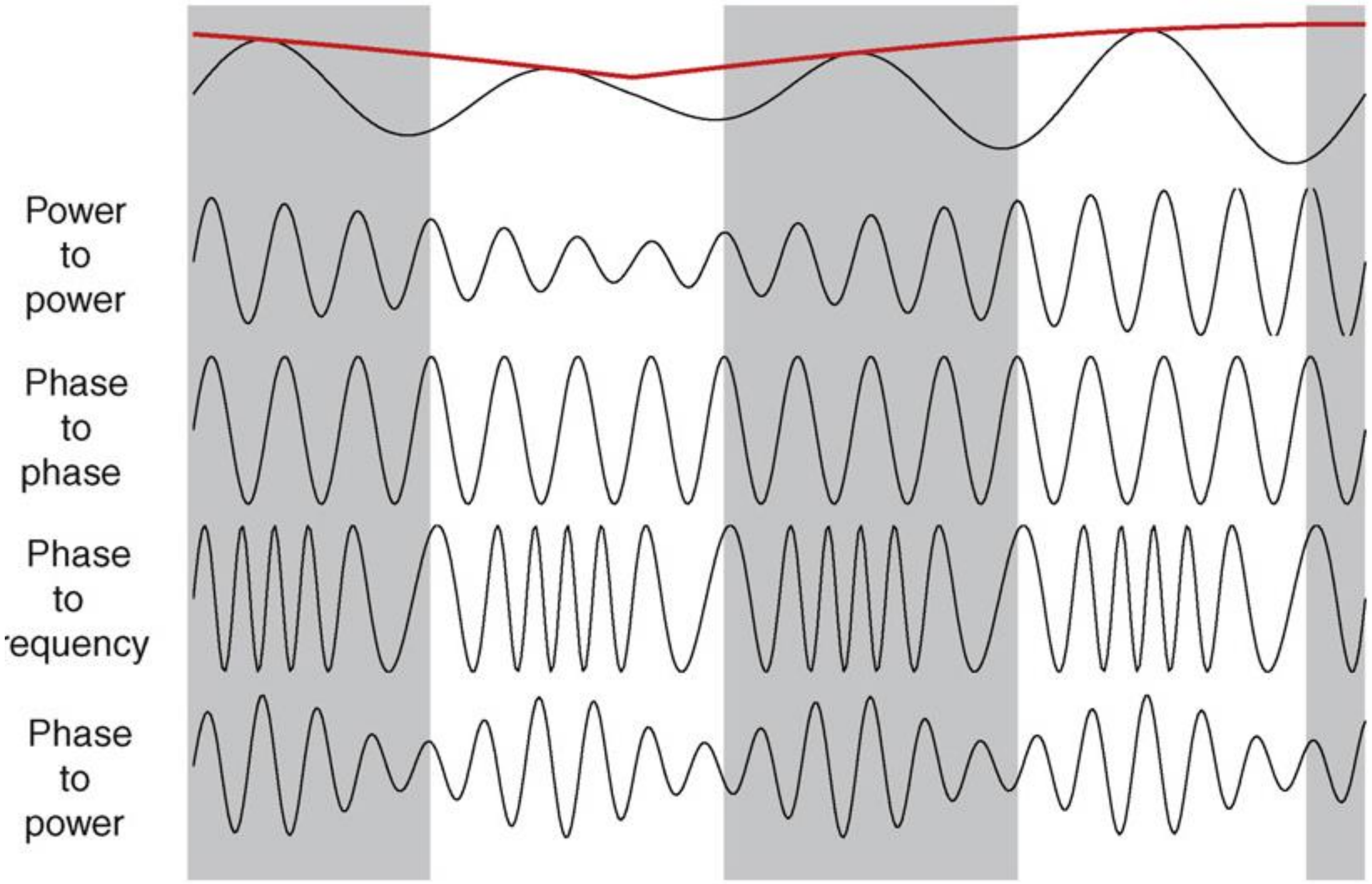


Modified Parcellation



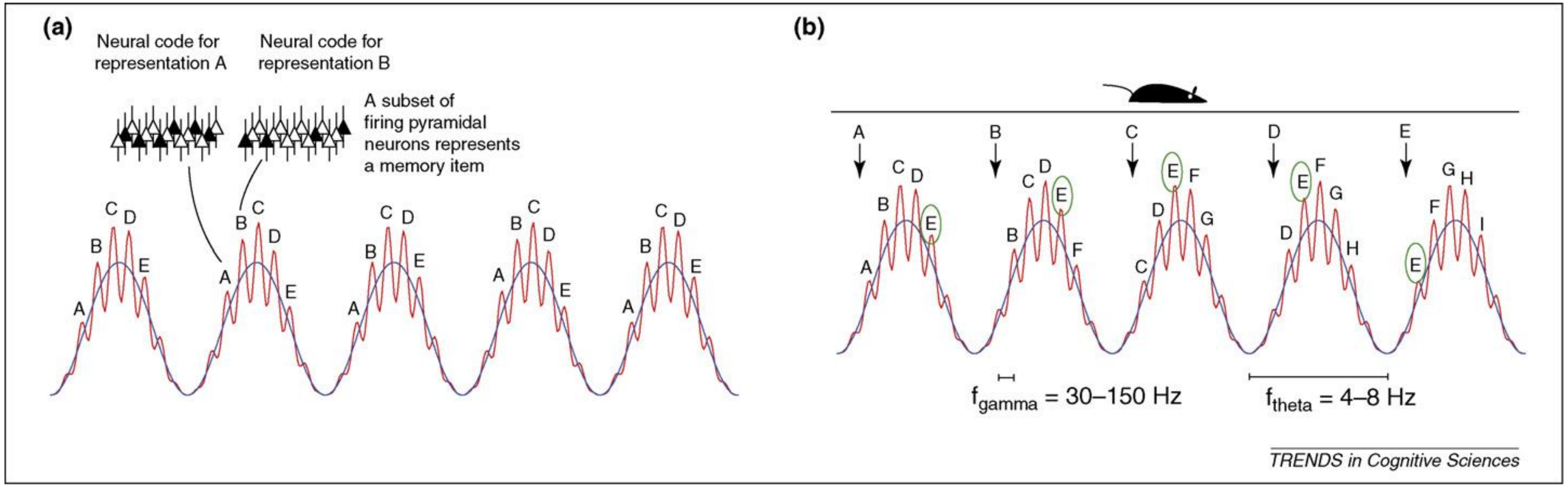
Farahibozorg/Henson/Hauk NI 2018
https://pubmed.ncbi.nlm.nih.gov/28893608/

Cross-Frequency Coupling



Jensen & Colgin, TICS 2007

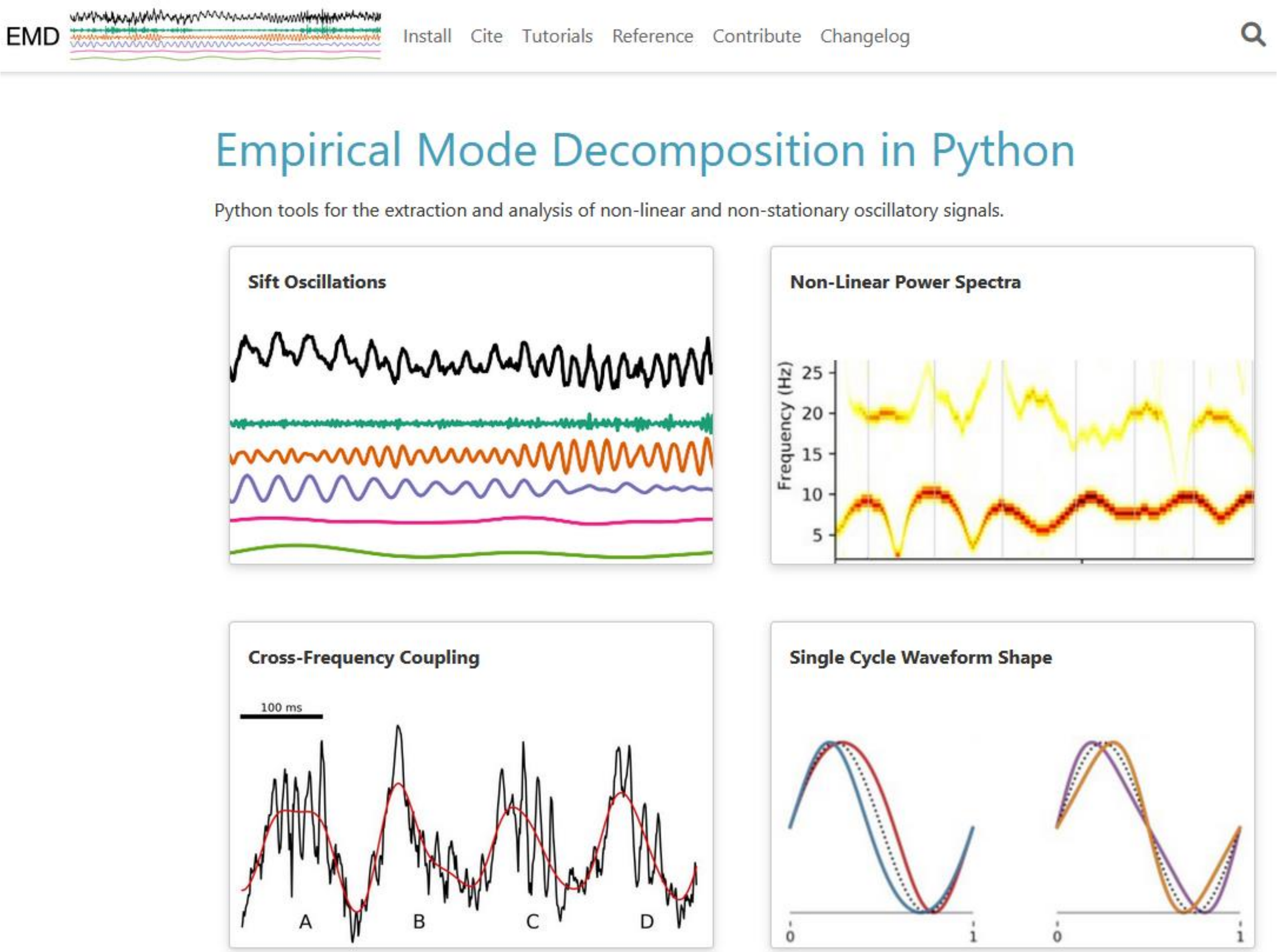
For Example: Theta-Gamma Coupling



Jensen & Colgin, TICS 2007

Figure 2. Models proposing computational roles for cross-frequency interactions between theta and gamma oscillations by means of phase coding. (a) In a model for working memory, individual memory representations are activated repeatedly in every theta cycle [10] (reviewed in Ref. [11]). Each memory representation is represented by a subset of neurons in the network firing synchronously. Because different representations are activated in different gamma cycles, the gamma rhythm serves to keep the individual memories segmented in time. The number of gamma cycles per theta cycle determines the span of the working memory. (b) A model accounting for theta phase precession in rats. As a rat advances through an environment, positional information is passed to the hippocampus. This activates the respective place cell representations, which provokes the prospective recall of upcoming positions. In each theta cycle, time-compressed sequences are recalled: one representation per gamma cycle. Consider the firing of a cell participating in representation E. As the rat advances, this cell fires earlier in the theta cycle, thus accounting for phase precession. According to this scheme, the number of gamma cycles per theta cycle is related quantitatively to the phase precession [13].

Python Toolbox for Cross-Frequency Coupling and more



https://emd.readthedocs.io/en/stable/index.html

More Python Toolboxes:

bycycle - cycle-by-cycle analysis of neural oscillations

repo status Active | pypi v1.1.0 | build passing | codecov 95% | license Apache License, 2.0 | python 3.6 | 3.7 | 3.8 | 3.9 | 3.10 | 3.11 | publication 10.1152/jn.00273.2019

ByCycle is a module for analyzing neural oscillations in a cycle-by-cycle approach.

Overview

`bycycle` is a tool for quantifying features of neural oscillations in the time domain, as opposed to the frequency domain, using a cycle-by-cycle approach. Rather than applying narrowband filters and other methods that use a sinusoidal basis, this approach segments a recording into individual cycles and directly measures each of their properties including amplitude, period, and symmetry.

This is most advantageous for analyzing the waveform shape properties of neural oscillations. It may also provide advantages for studying traditional amplitude and frequency effects, as well. Using cycle properties can also be used for burst detection.

A full description of the method and approach is available in the paper below.

https://bycycle-tools.github.io/bycycle/

FOOOF - fitting oscillations & one over f

repo status Active | pypi v1.1.0 | build passing | codecov 98% | license Apache License, 2.0 | python 3.6 | 3.7 | 3.8 | 3.9 | 3.10 | 3.11 | paper nn10.1038

FOOOF is a fast, efficient, and physiologically-informed tool to parameterize neural power spectra.

Overview

The power spectrum model conceives of a model of the power spectrum as a combination of two distinct functional processes:

- An aperiodic component, reflecting 1/f like characteristics, with
- A variable number of periodic components (putative oscillations), as peaks rising above the aperiodic component

This model driven approach can be used to measure periodic and aperiodic properties of electrophysiological data, including EEG, MEG, ECoG and LFP data.

The benefit of fitting a model in order to measure putative oscillations, is that peaks in the power spectrum are characterized in terms of their specific center frequency, power and bandwidth without requiring predefining specific bands of interest and controlling for the aperiodic component. The model also returns a measure of this aperiodic components of the signal, allowing for measuring and comparison of 1/f-like components of the signal within and between subjects.

https://fooof-tools.github.io/fooof/

More connectivity…

Most of the previously introduced measures are spectral measures, i.e. they are computed for specific frequencies (or frequency bands).

They rely on the assumption that brain signals can meaningfully be decomposed into “oscillations” or “frequency bands”.

This is a big assumption, and may not be the case for all modalities, stimuli, tasks etc., or may not even be true in general.

Therefore…

Non-Spectral and Effective Connectivity

Granger Causality: Is one time series useful to predict another?
x(t) Granger-causes y(t) if past values of x(t) add information to past values of y(t) for predicting future values of y(t).

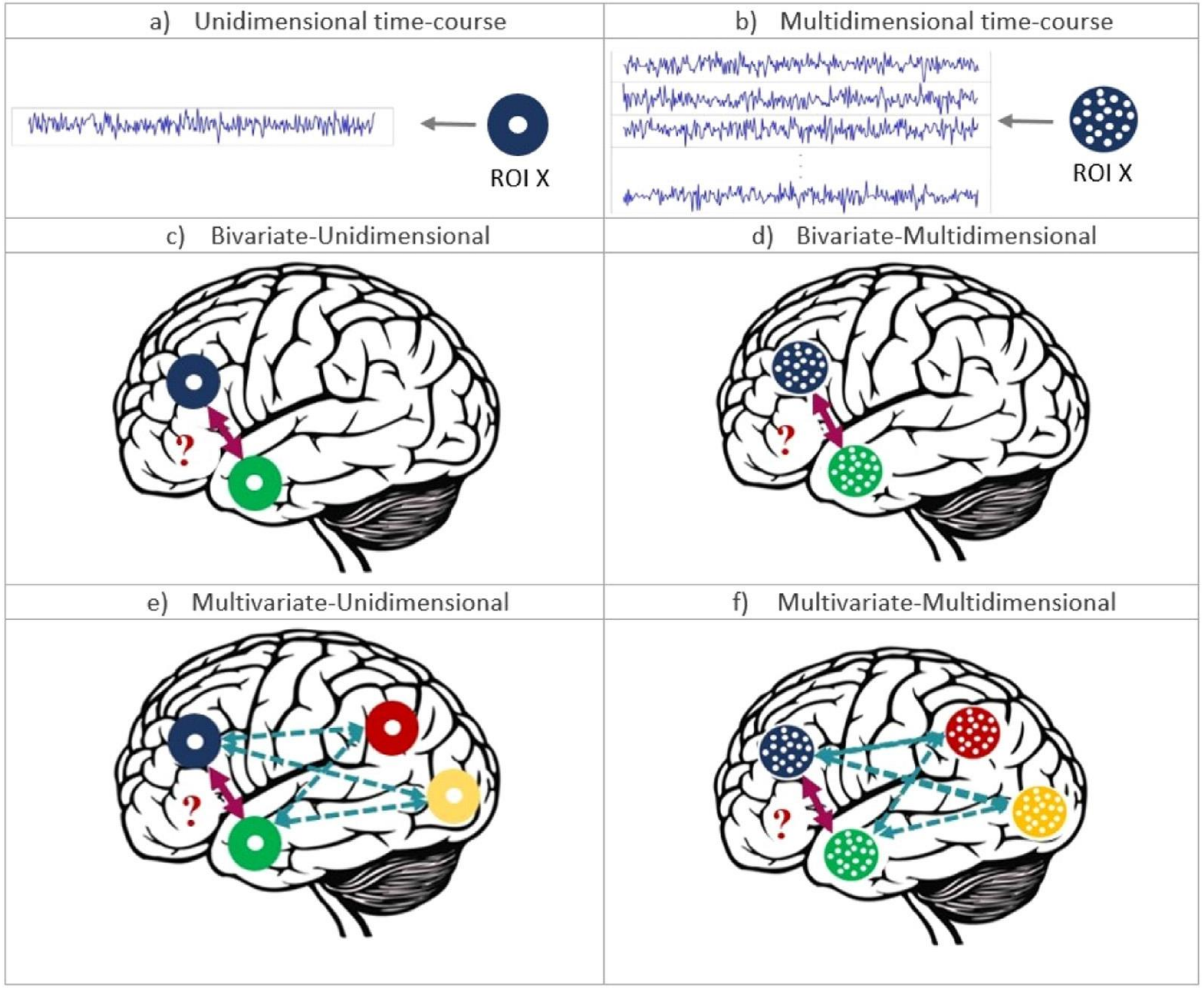
http://www.scholarpedia.org/article/Granger_causality
Multivariate Granger Toolbox: http://www.sussex.ac.uk/sackler/mvgc/
http://journal.frontiersin.org/article/10.3389/fnsys.2015.00175/full

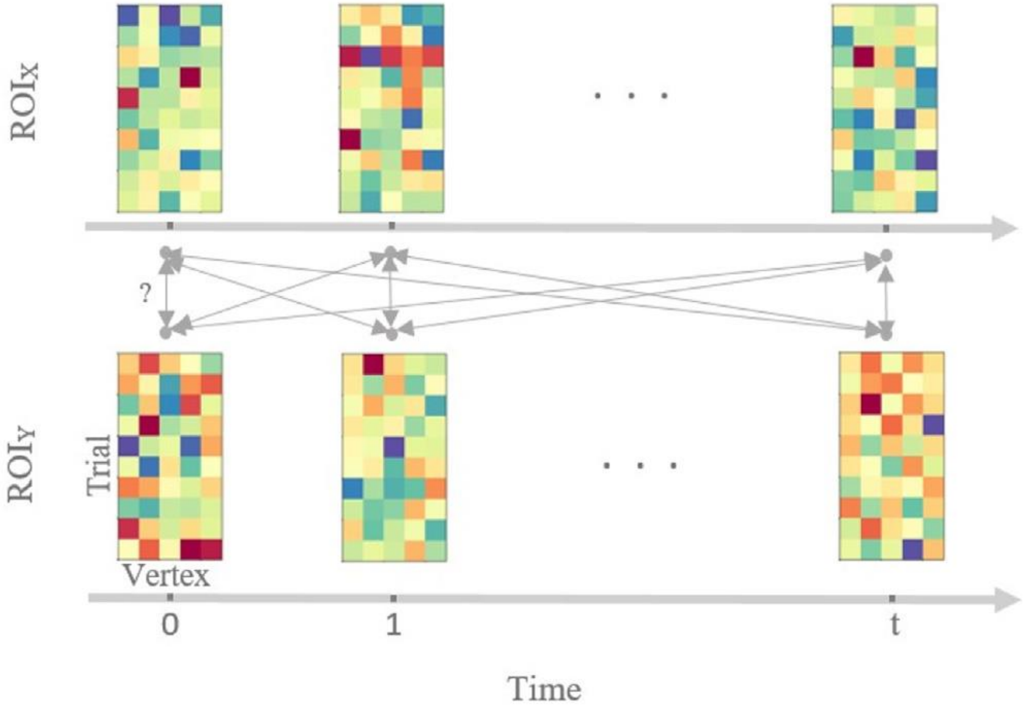
Structural Equation Modelling (SEM):
Models covariance structure of brain activation across brain regions (e.g. “path analysis”).

Dynamic Causal Modelling (DCM):
Models brain dynamics across regions as differential equations, in combination with Bayesian parameter/model estimation.

http://www.scholarpedia.org/article/Dynamic_causal_modeling

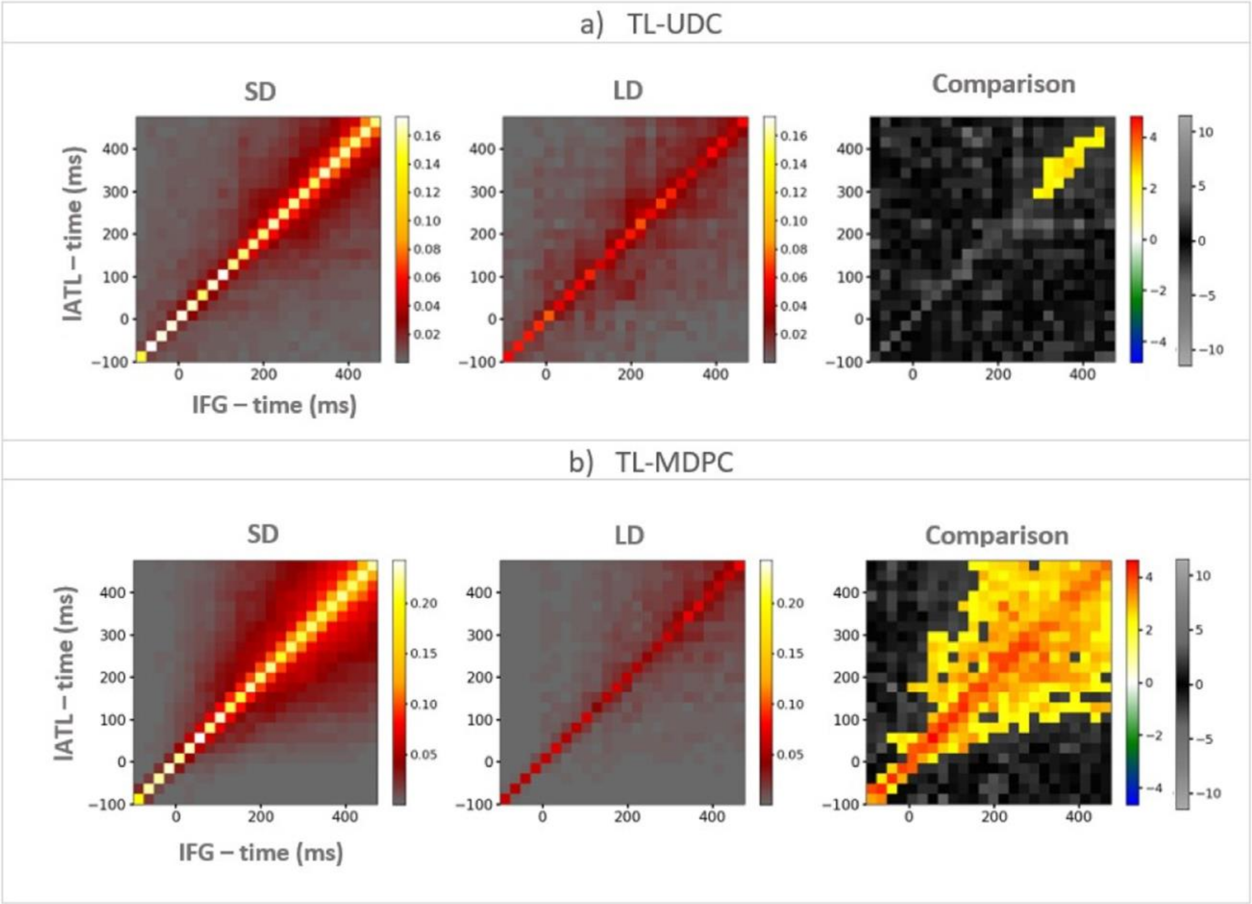
Multi-Variate and Multi-Dimensional Connectivity

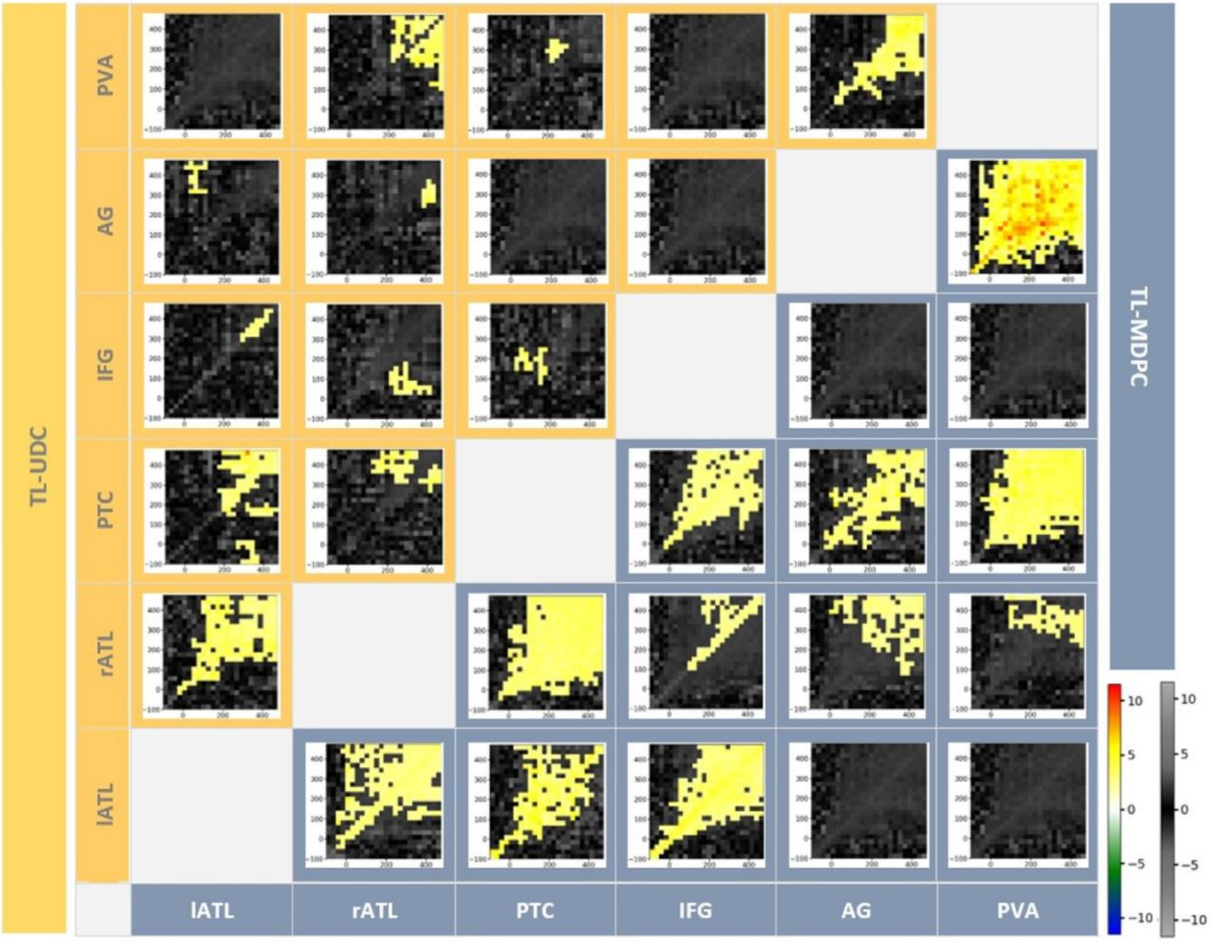




Rahimi et al., NI 2022, https://pubmed.ncbi.nlm.nih.gov/36813063/
Also:
Basti/Nili et al., NI 2020, https://www.sciencedirect.com/science/article/pii/S1053811920306650, Anzellotti & Coutanche, T Cogn Sci 2018, https://pubmed.ncbi.nlm.nih.gov/29305206/,
Basti et al., PLoS 2019, https://journals.plos.org/plosone/article/comments?id=10.1371/journal.pone.0223660

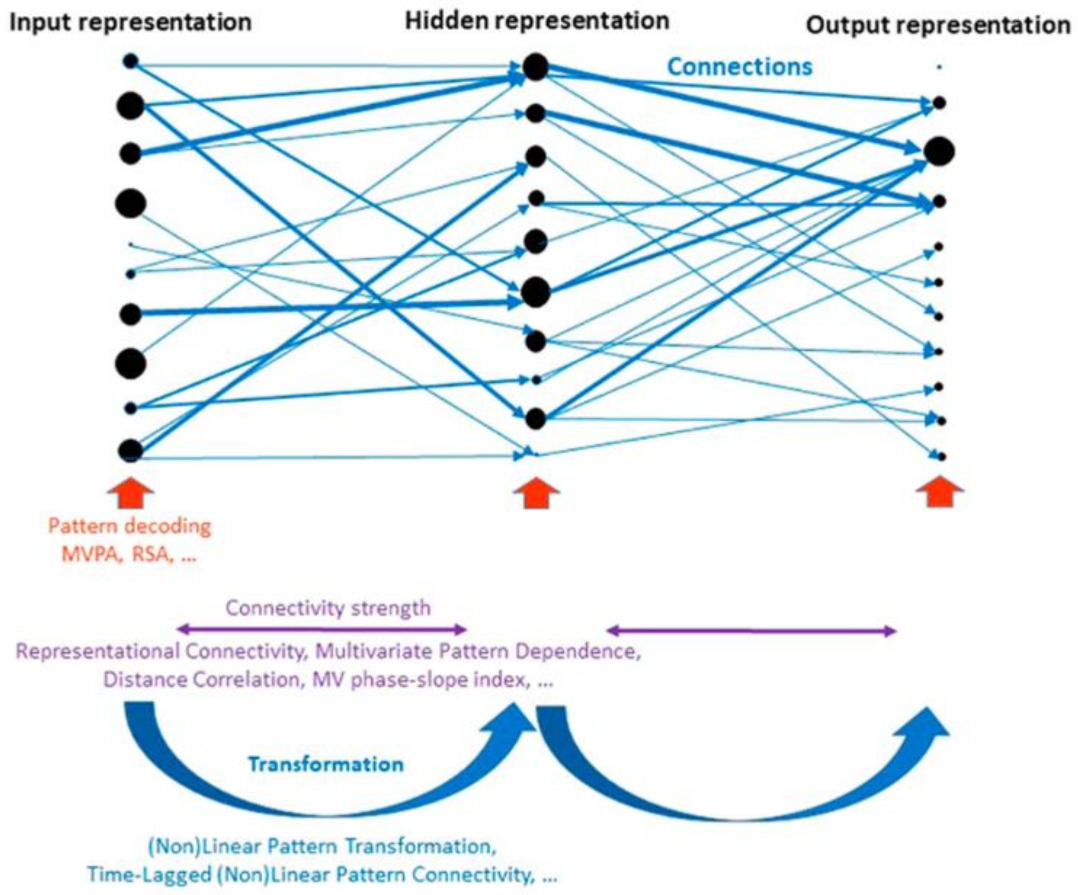
Multi-Dimensional Connectivity

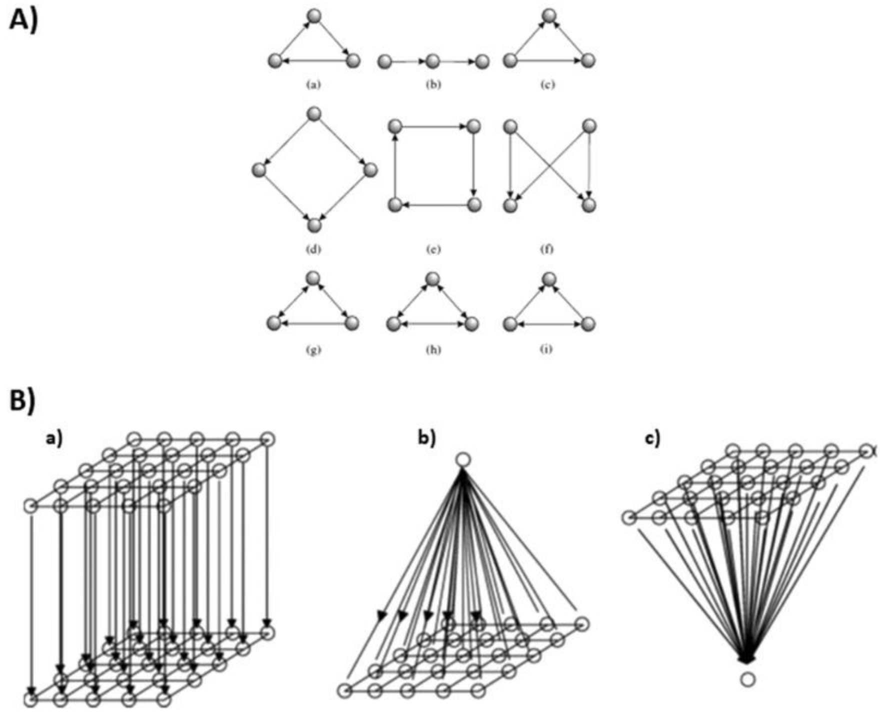




Rahimi et al., NI 2022, https://pubmed.ncbi.nlm.nih.gov/36813063/

“Transforming” Neuroscience





Hauk et al., Lang Cogn Nsc 2023, https://www.tandfonline.com/doi/pdf/10.1080/23273798.2023.2226268

Thank you