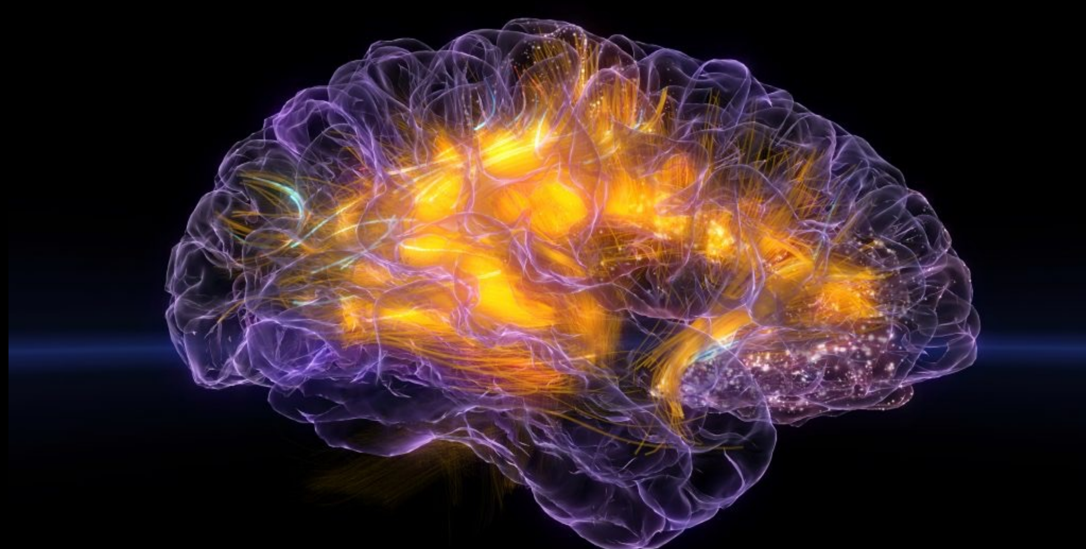
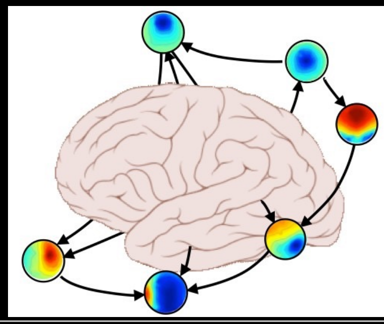
Connectivity analysis

Aspet, 2023



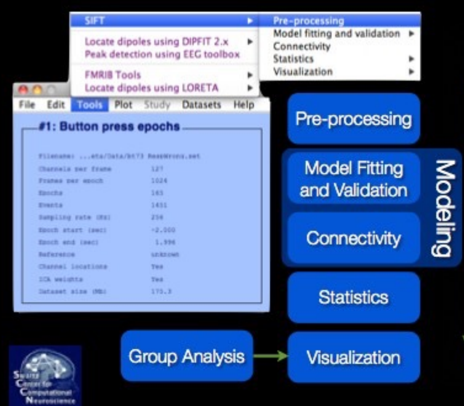
Tim Mullen

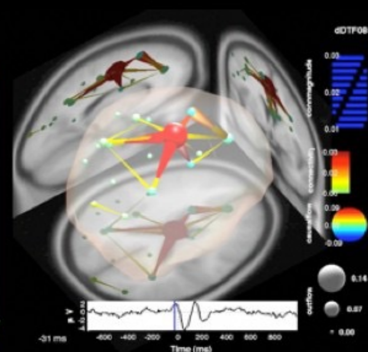


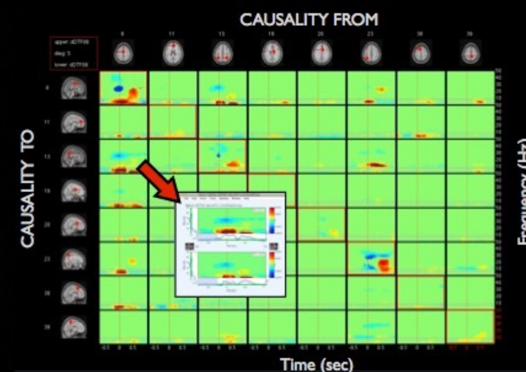
SIFT

Source Information Flow Toolbox

http://sccn.ucsd.edu/wiki/SIFT
Mullen, et al, *Journal of Neuroscience Methods* (in prep, 2012)
Mullen, et al, *Society for Neuroscience*, 2010
Delorme, Mullen, Kothe et al, *Computational Intelligence and Neuroscience*, vol 12, 2011







- A toolbox for (source-space) electrophysiological information flow and causality analysis (single- or multi-subject) integrated into EEGLAB
- Emphasis on vector autoregression and time-frequency domain approaches
- Standard and novel interactive visualization methods for exploratory analysis of connectivity across time, frequency, and spatial location

https://sccn.ucsd.edu/wiki/SIFT

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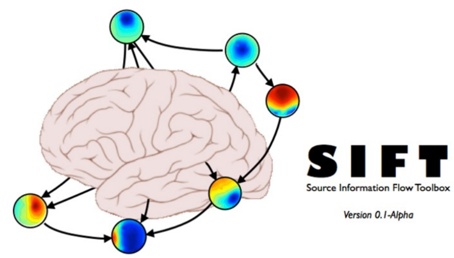
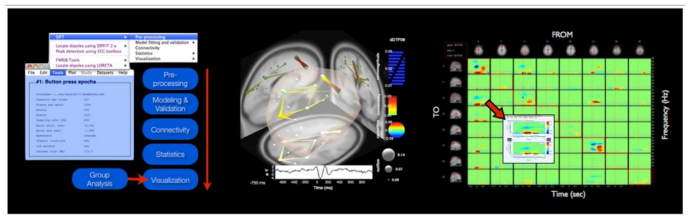
SIFT





Contents [hide]

Welcome to the repository for the Source Information Flow Toolbox (SIFT)

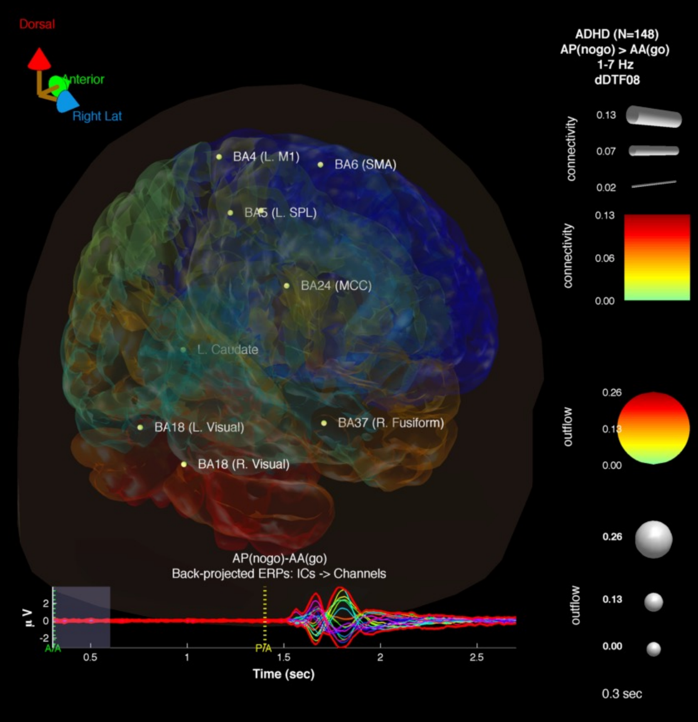
Developed and Maintained by: Tim Mullen (SCCN, INC, UCSD)
Web: http://www.antillipsi.net
Email: <Tim's first name> (at) sccn (dot) ucsd (dot) edu

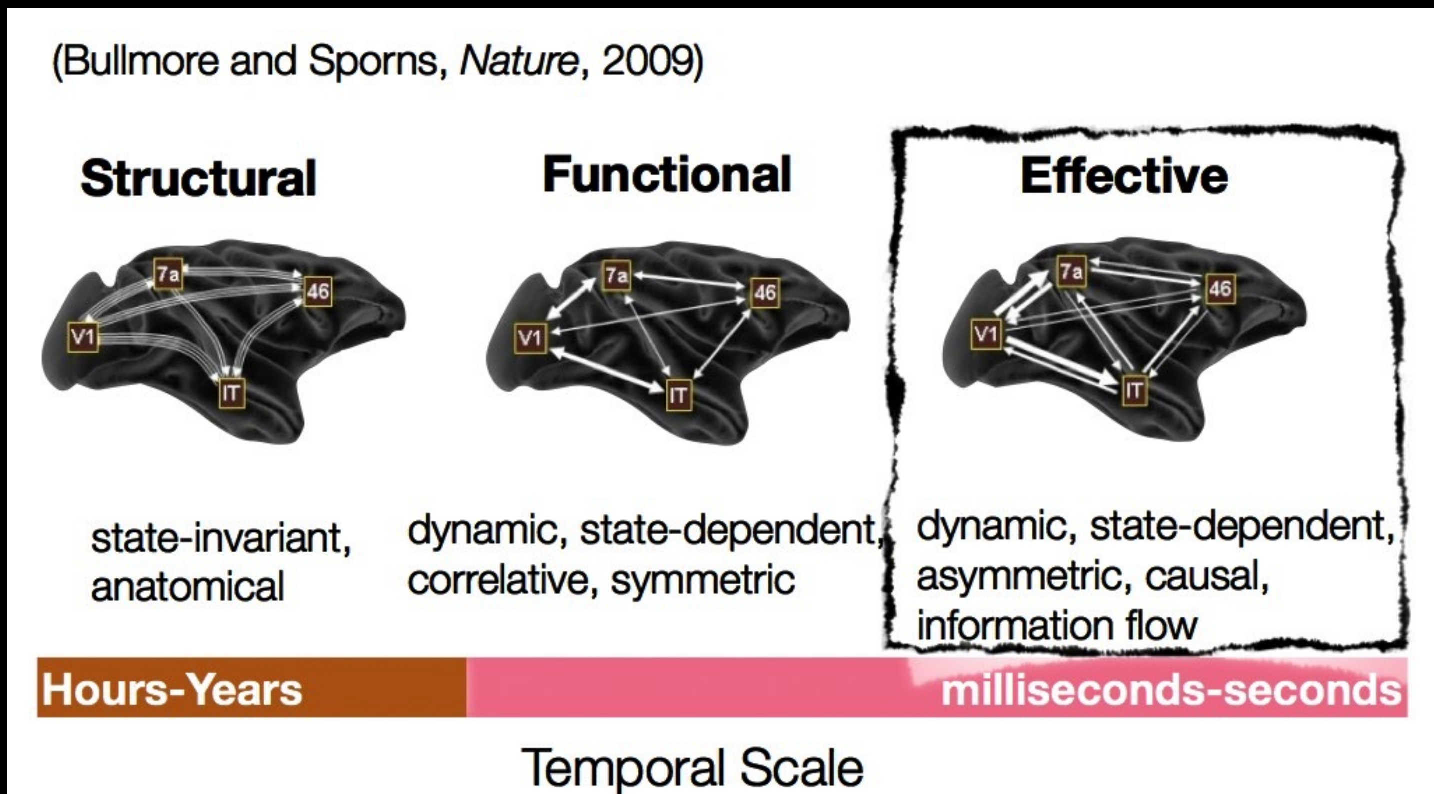
SIFT is an EEGLAB-compatible toolbox for analysis and visualization of multivariate causality and information flow between sources of electrophysiological (EEG/ECoG/MEG) activity. It consists of a suite of command-line functions with an integrated Graphical User Interface for easy access to multiple features. There are currently four modules: data preprocessing, model fitting and connectivity estimation, statistical analysis, and visualization.

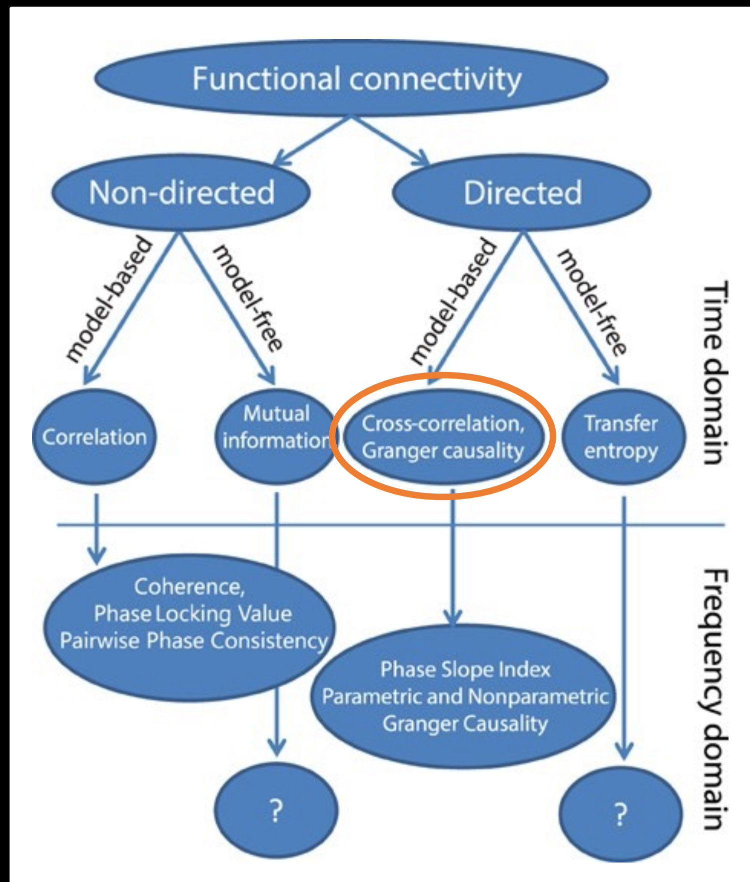
The Dynamic Brain

- A key goal: To model temporal changes in neural dynamics and information flow that index and predict task-relevant changes in cognitive state and behavior

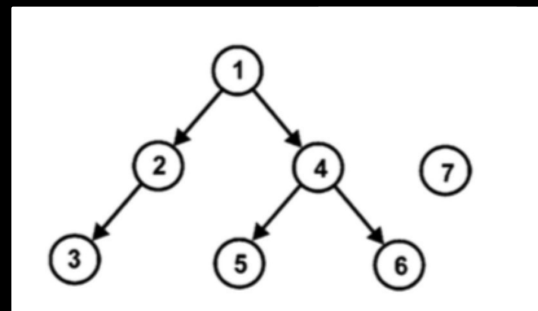
- Open Challenges:
  - Non-invasive measures (source inference)
  - Robustness and Validity (constraints   statistics)
  - Scalability (multivariate)
  - Temporal Specificity / Non stationarity / Single-trial (dynamics)
  - Multi-subject Inference
  - Usability and Data Visualization (software)




(Bullmore and Sporns, *Nature*, 2009)
Structural
Functional
Effective
7a
46
V1
IT
state-invariant,
anatomical
dynamic, state-dependent,
correlative, symmetric
dynamic, state-dependent,
asymmetric, causal,
information flow
Hours-Years
milliseconds-seconds
Temporal Scale



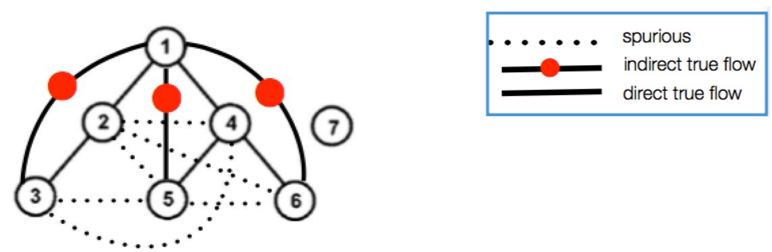
Bastos AM, Schoffelen J-M: **A Tutorial Review of Functional Connectivity Analysis Methods and Their Interpretational Pitfalls**. *Front Sys Neurosci* 2016, **9**:413.



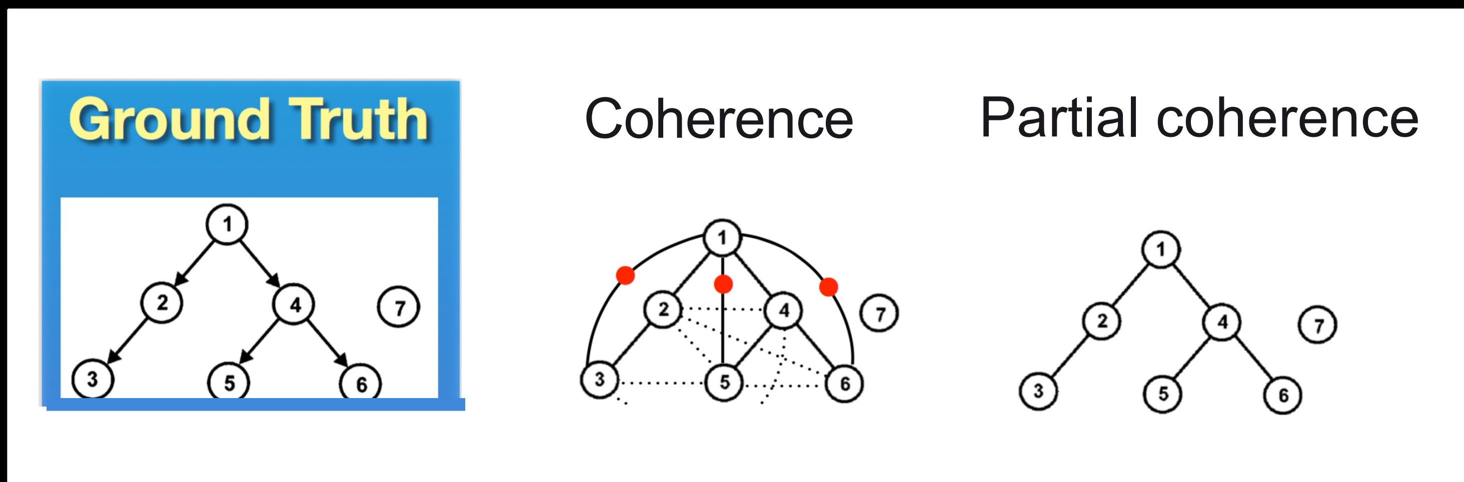
Coherency

$$C_{ij}(f) = \frac{S_{ij}(f)}{\sqrt{S_{ii}(f)S_{jj}(f)}}$$

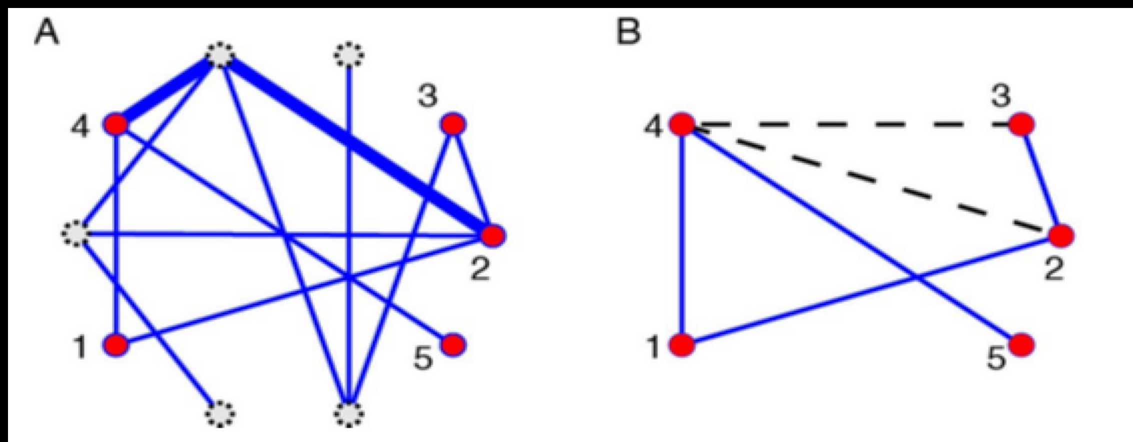
(Bendat and Piersol, 1986)



Bivariate measures such as coherence (but also original GC), find spurious connections between nodes if they share a common input.


Ground Truth
Coherence
Partial coherence
1
2
3
4
5
6
7

A deeper problem – unobserved nodes



With EEG, it's unavoidable that there will be contributing network nodes (e.g. thalamus) that we cannot observe.

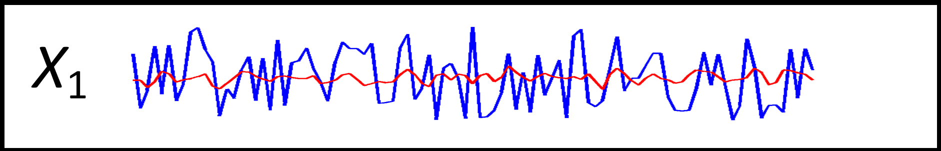
We also can't be sure ICA will identify all important sources…

Granger-causality

- A measure of *statistical* causality based on prediction.
- Widely used in time-series econometrics.
- Nobel Prize in economics, 2003.

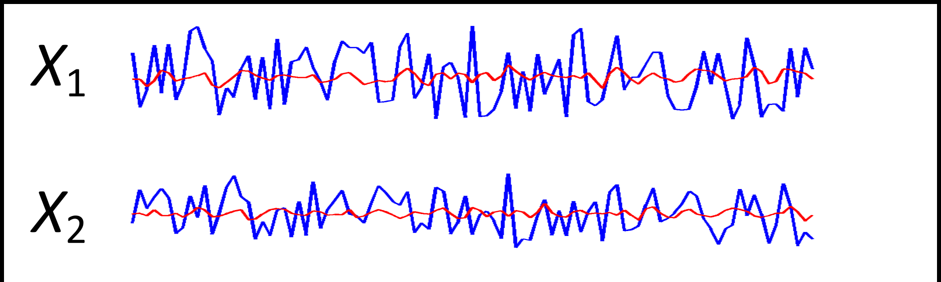
If a signal A causes a signal B, then knowledge of the past of both A and B should improve the predictability of B, as compared to knowledge of B alone.

AR Models (prediction of future of a signal by its past)

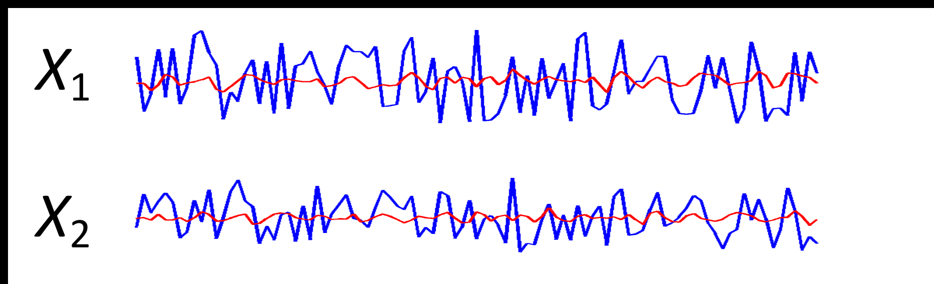


$$X_1(t) = -0.5X_1(t-1) + 0.3X_1(t-2) + 0.1X_1(t-3)\ldots$$

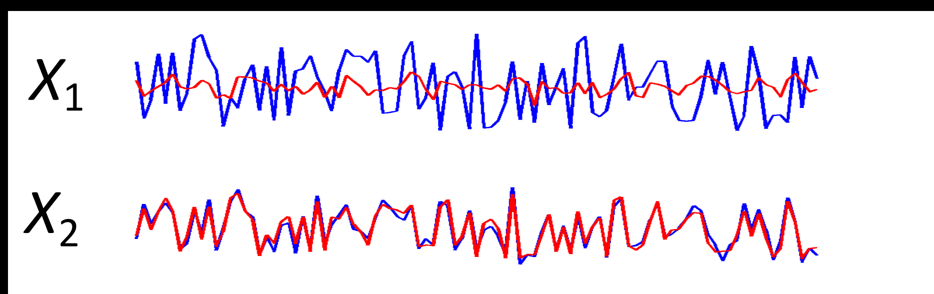
AR Models (prediction of future of a signal by its past)



AR Models (prediction of future of a signal by its past)

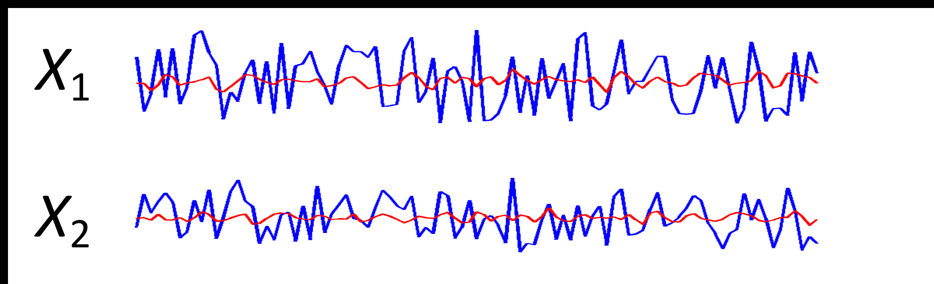


VAR Models (prediction of future of a signal by its past + the other signal's past)



Incorporating information about X_1 improves the prediction of X_2! We say "X_1 granger causes X_2"

AR Models (prediction of future of a signal by its past)



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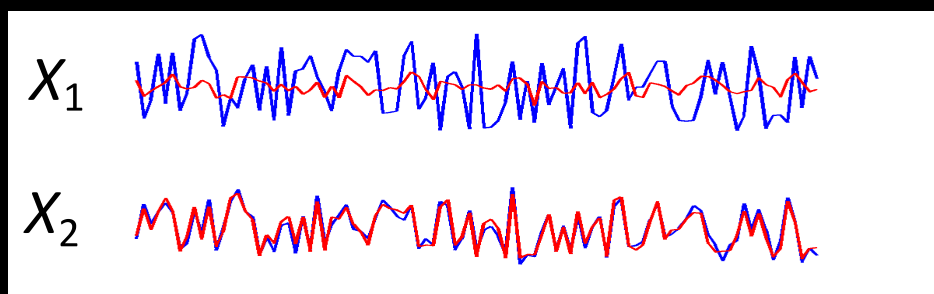
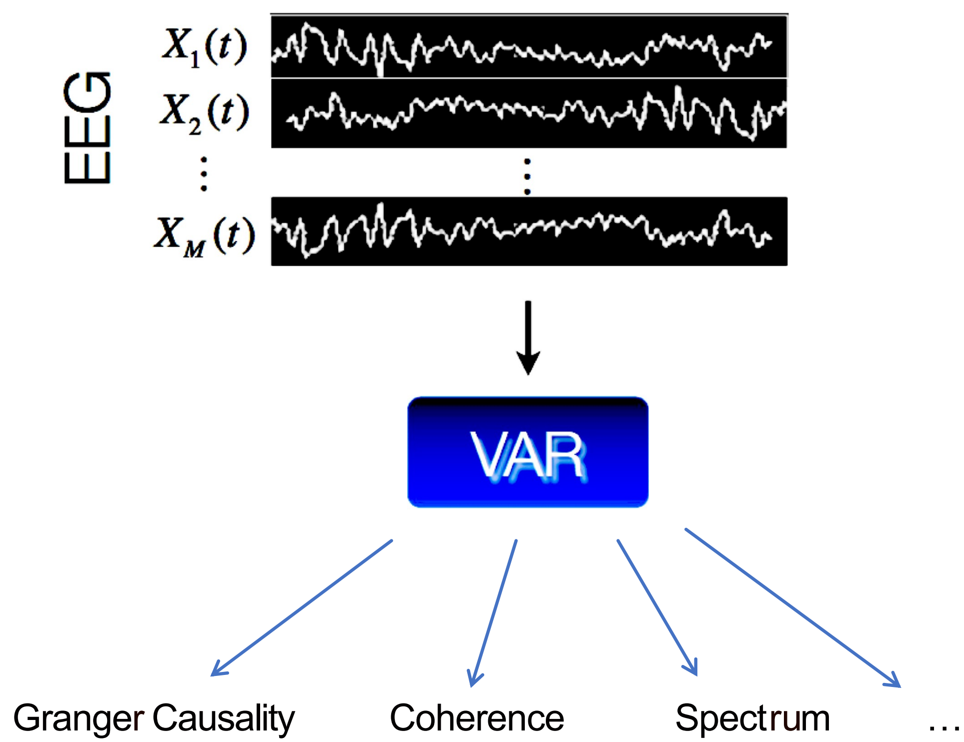


$X_1(t) = -0.5X_1(t-1) + 0.3X_2(t-1) + \ldots$

$X_2(t) = -5X_1(t-1) - 0.1X_2(t-1) + \ldots$

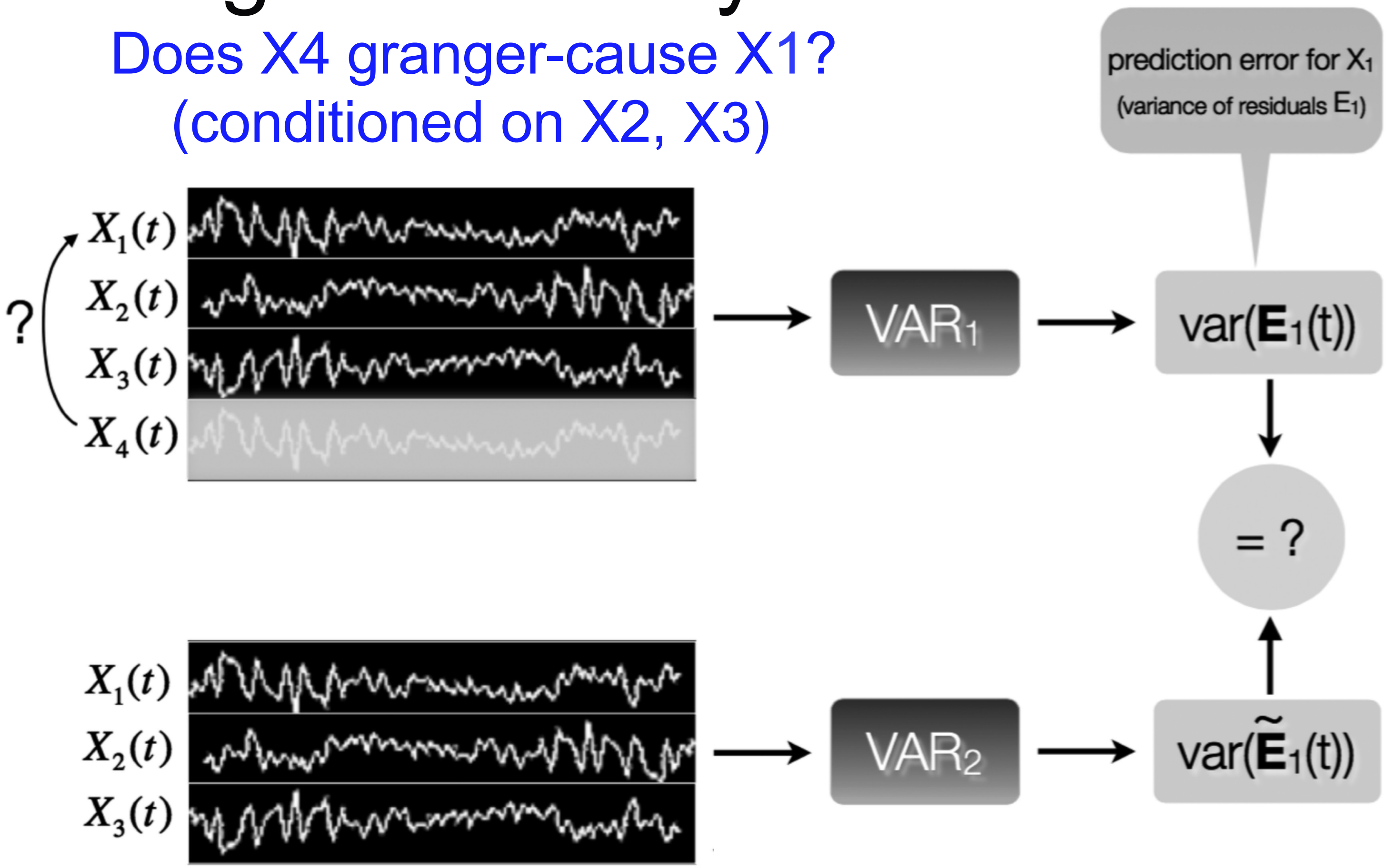
Incorporating information about X_1 improves the prediction of X_2! We say "X_1 granger causes X_2"

Vector Autoregressive (VAR / MAR / MVAR) Modeling



Granger Causality

Does X4 granger-cause X1?
(conditioned on X2, X3)



Granger-causality quiz

$$X_1(t) = -0.5X_1(t-1) + \boxed{0X_2(t-1)} + E_1(t)$$

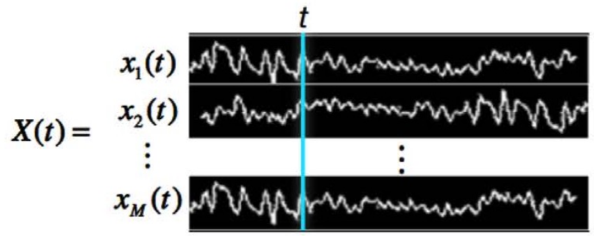
$$X_2(t) = \boxed{0.7X_1(t-1)} + 0.2X_2(t-1) + E_2(t)$$

Which causal structure does this model correspond to?

a) $1 \longrightarrow 2$ b) $1 \longleftarrow 2$ c) $1 \longleftrightarrow 2$

The Linear Vector Auto-regressive (VAR) Model

Ordinary Least-Squares



VAR[p] model

$$\mathbf{X}(t) = \sum_{k=1}^{p} \mathbf{A}^{(k)}(t)\mathbf{X}(t-k) + \mathbf{E}(t)$$

model order

random noise process

M-channel data vector at current time *t*

M x M matrix of (possibly time-varying) model coefficients indicating variable dependencies at lag *k*

multichannel data *k* samples in the past

$$\mathbf{A}^{(k)}(t) = \begin{pmatrix} a_{11}^{(k)}(t) & \cdots & a_{1M}^{(k)}(t) \\ \vdots & \ddots & \vdots \\ a_{M1}^{(k)}(t) & \cdots & a_{MM}^{(k)}(t) \end{pmatrix} \qquad \mathbf{E}(t) = N(0, \mathbf{V})$$

Selecting a VAR Model Order

- Model order is typically determined by minimizing information criteria such as Akaike Information Criterion (AIC) for varying model order (p):

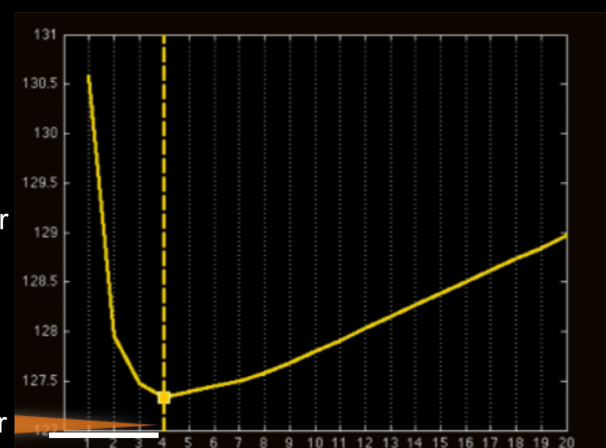
$$AIC(p) = 2\log(\det(V)) + M2p/N$$

Penalizes high model orders (parsimony)

entropy rate (amount of prediction error)

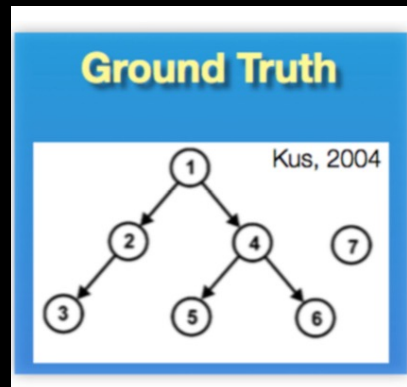
- Optimal model order depends on sampling rate (higher sampling rate often requires higher model orders)

Error



optimal order

model order


Ground Truth
Kus, 2004
1
2
3
4
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6
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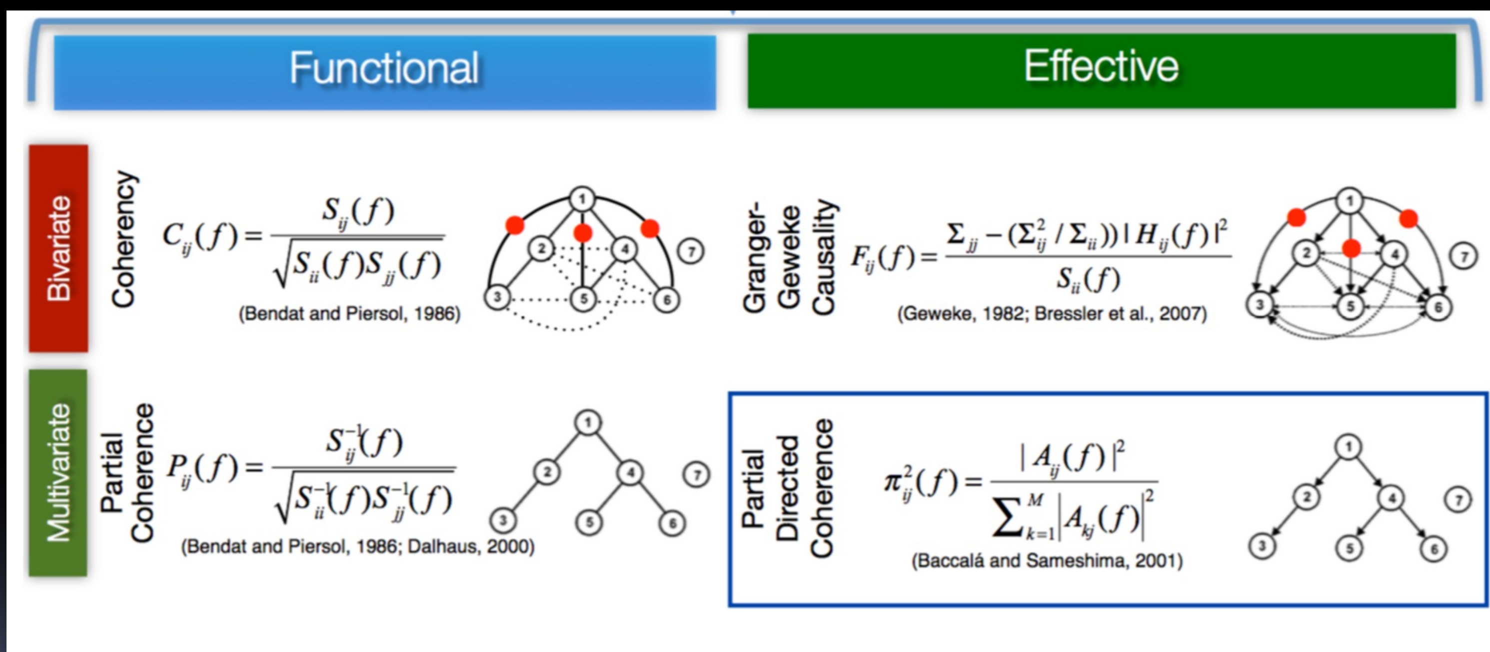
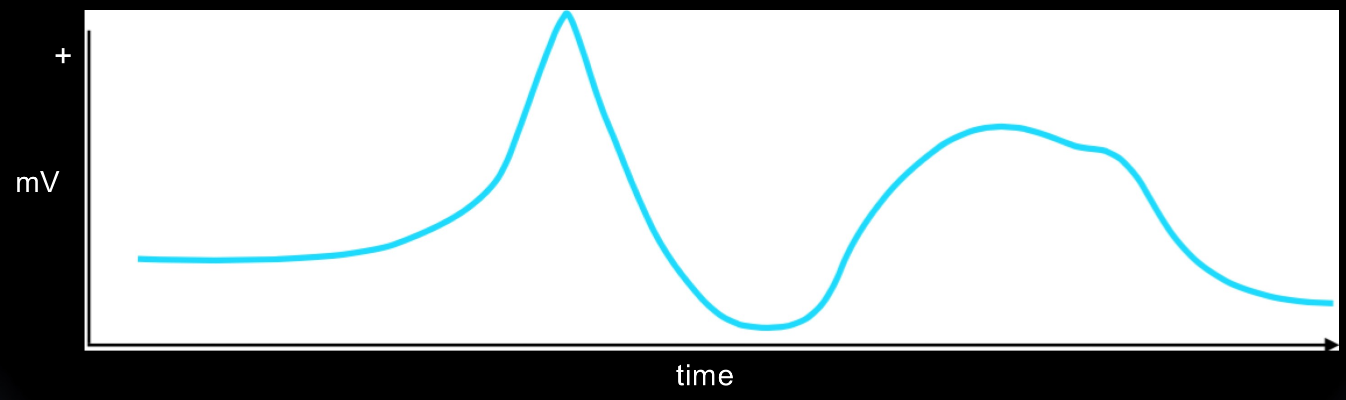

Functional
Effective
Bivariate
Multivariate
Coherency
$C_{ij}(f)=\frac{S_{ij}(f)}{\sqrt{S_{ii}(f)S_{jj}(f)}}$
(Bendat and Piersol, 1986)
Granger-Geweke Causality
$F_{ij}(f)=\frac{\Sigma_{jj}-(\Sigma_{ij}^2/\Sigma_{ii})|H_{ij}(f)|^2}{S_{ii}(f)}$
(Geweke, 1982; Bressler et al., 2007)
Partial Coherence
$P_{ij}(f)=\frac{S_{ij}^{-1}(f)}{\sqrt{S_{ii}^{-1}(f)S_{jj}^{-1}(f)}}$
(Bendat and Piersol, 1986; Dalhaus, 2000)
Partial Directed Coherence
$\pi_{ij}^2(f)=\frac{|A_{ij}(f)|^2}{\sum_{k=1}^{M}|A_{kj}(f)|^2}$
(Baccalá and Sameshima, 2001)

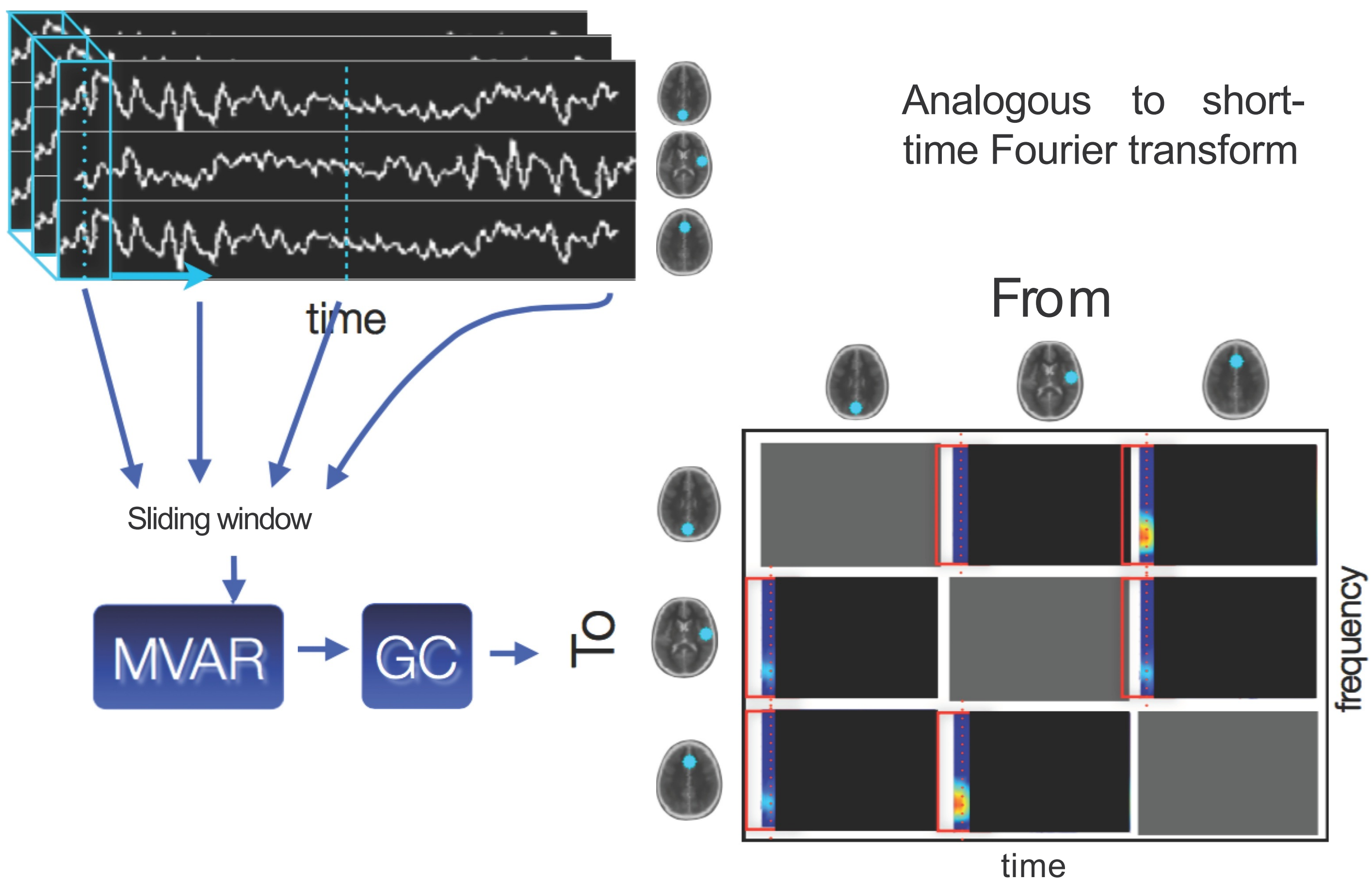
Adapting to Non-Stationarity

- The brain is **a dynamic system** and measured brain activity and coupling can change rapidly with time (non-stationarity)
  - event-related perturbations (ERSP, ERP, etc)
  - structural changes due to learning/feedback
- How can we adapt to non-stationarity?



Segmentation-based VAR

(Jansen et al., 1981;Florian and Pfurtscheller, 1995; Ding et al,2000)



Analogous to short-time Fourier transform

Segmentation-based VAR

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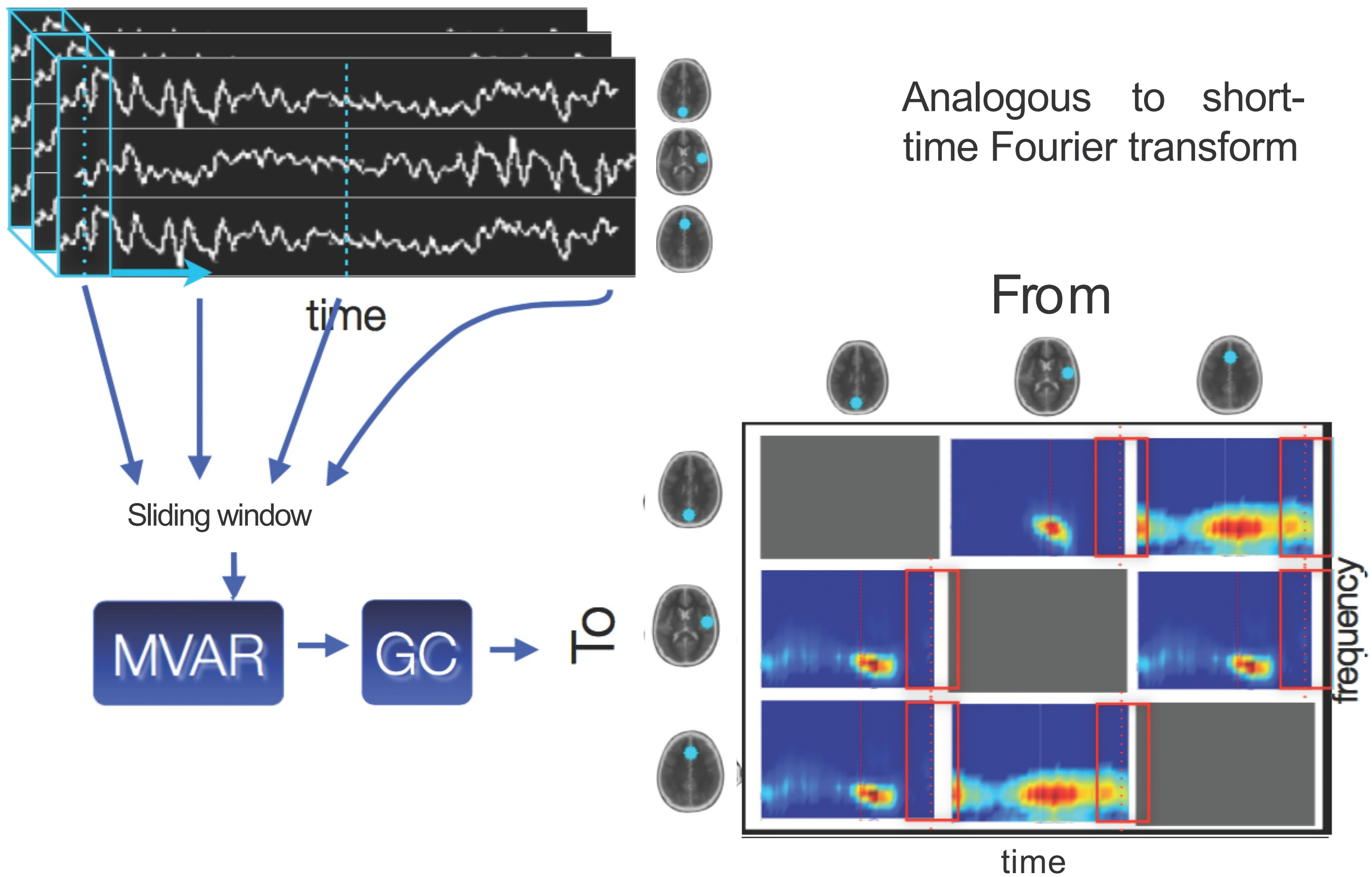
Analogous to short-time Fourier transform

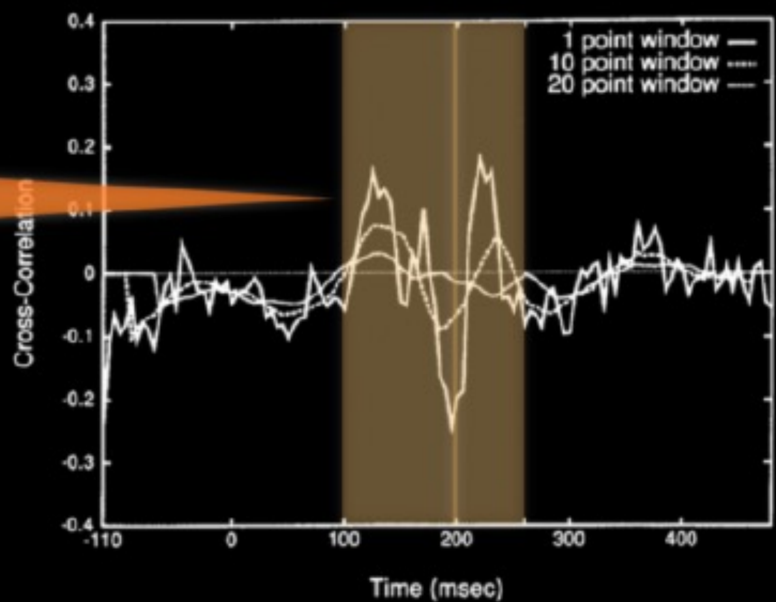


Important Choices

- Model Order
  - Determines complexity of spectrum you can model
  - Larger orders need more data
- Window Length
  - Window must be long enough to contain sufficient data for your chosen model order
  - Must be long enough to encompass the time-scale of interactions
  - Yet not too long as to smear temporal dynamics or include non-stationary data
  - *If trials are present, can optimize AR model over trials*

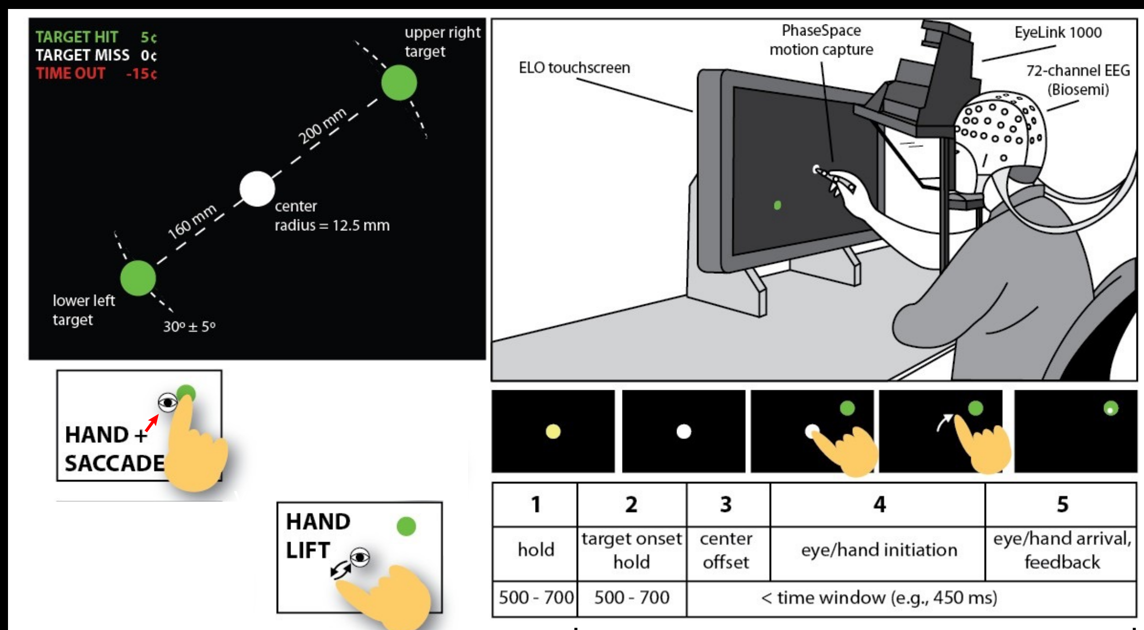
Consideration: Local Stationarity

Too-large, windows may not be locally-stationary



How does brain plan visually guided movements?

- Pointing Task (Park, et al. 2014, *IEEE Trans Neural Syst Rehabil Eng)*



N=10 (right-handed, mean age=21) 70 channel EEG (Biosemi) 512 Hz; 128Hz for connectivity

Planning | Execution

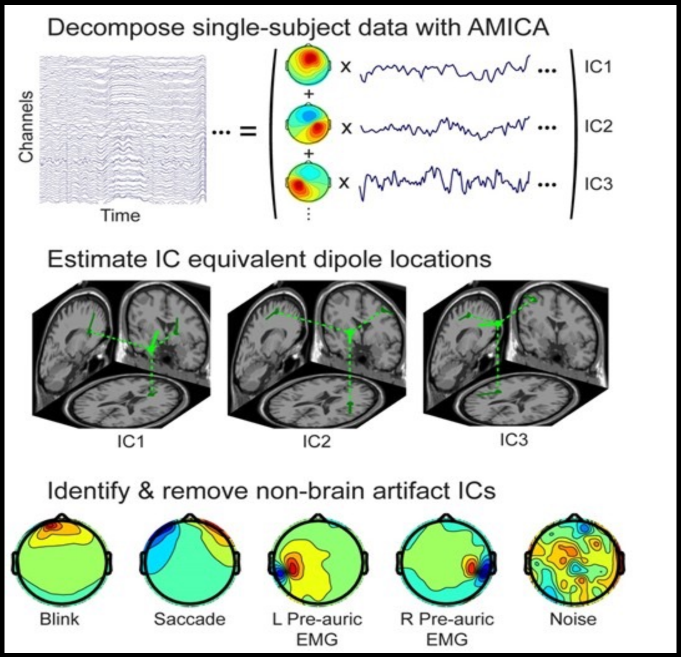
0 0.5 1.0

Time (s)

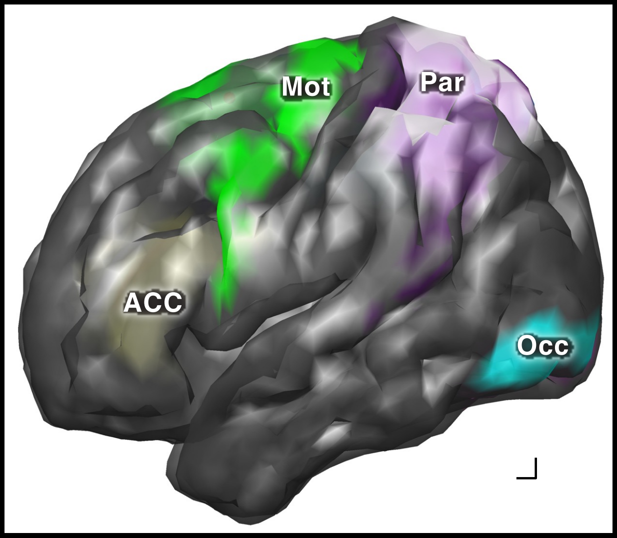
John R. Iversen, Alejandro Ojeda, Tim Mullen, Markus Plank, Joseph Snider, Gert Cauwenberghs, Howard Poizner (2014) EMBC

ICA source space analysis

Independent Component Analysis

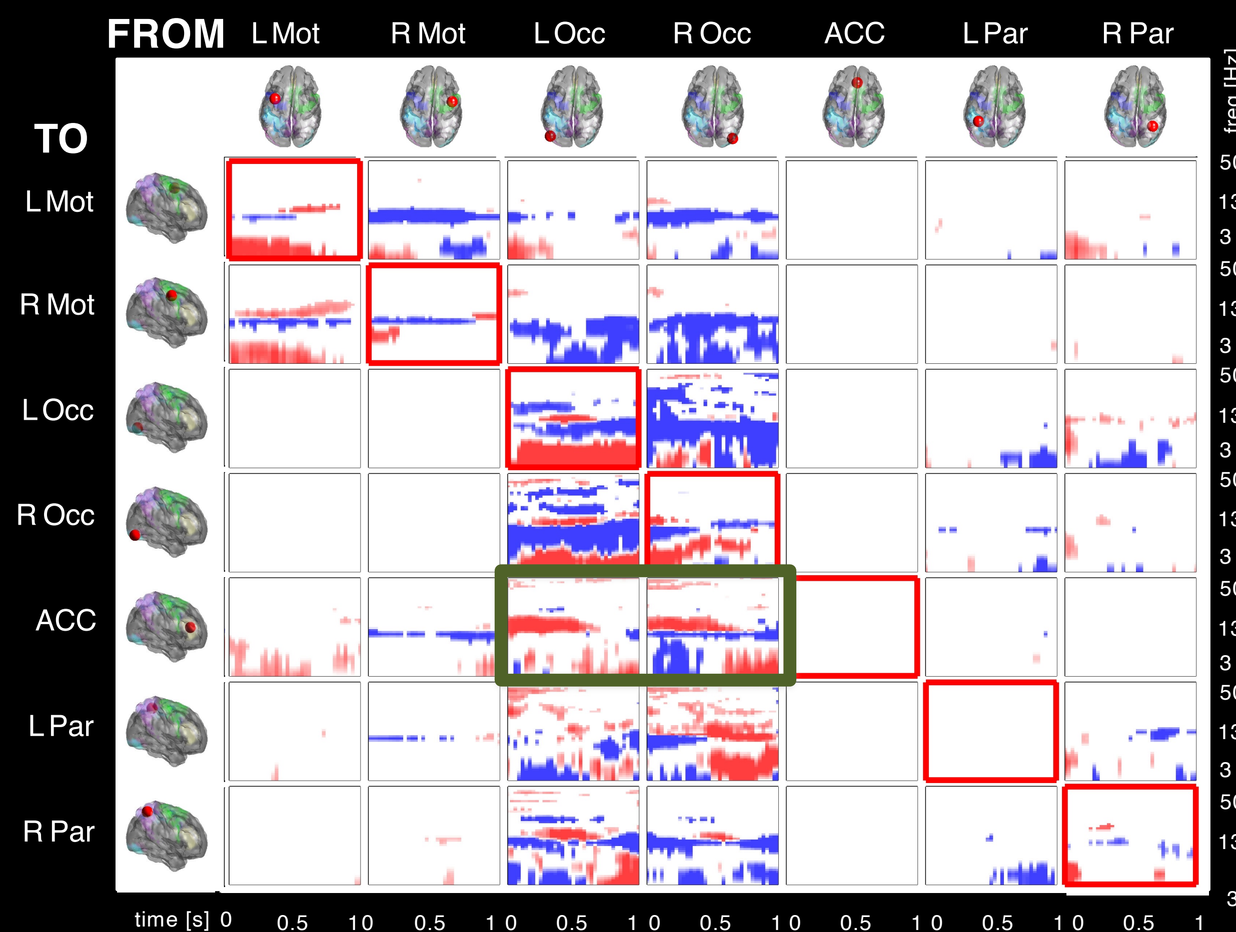


Cortical Regions of Interest



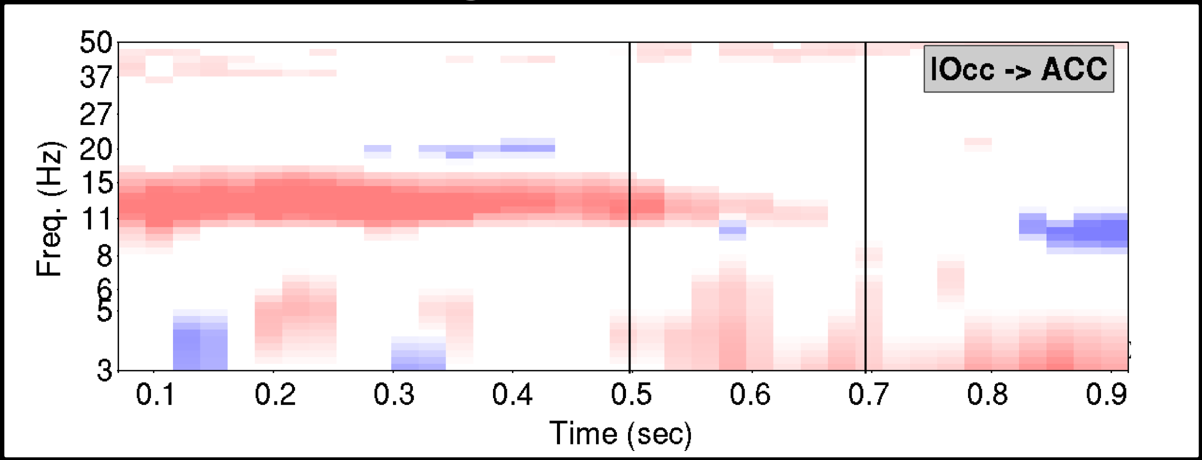
Group SIFT: Project ICs onto cortical surface using LORETA; extract ROI time series. Advantage: Same ROIs for all subjects enables statistical comparison. (*Use BCILAB srcpot*)

Changed causal flow during reaching

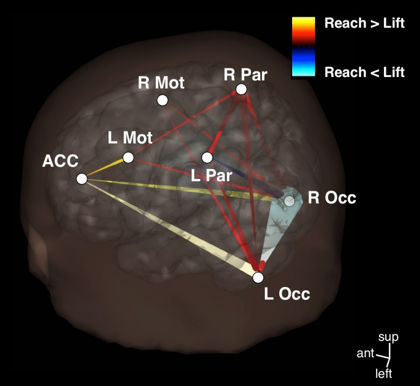


Occipital -> ACC

Planning | Execution

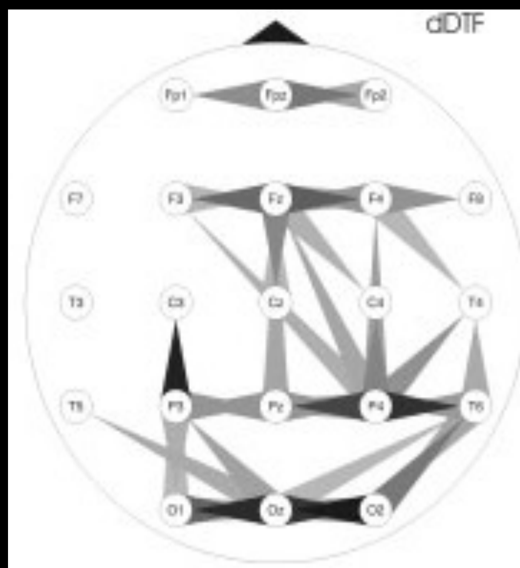


Result discussion

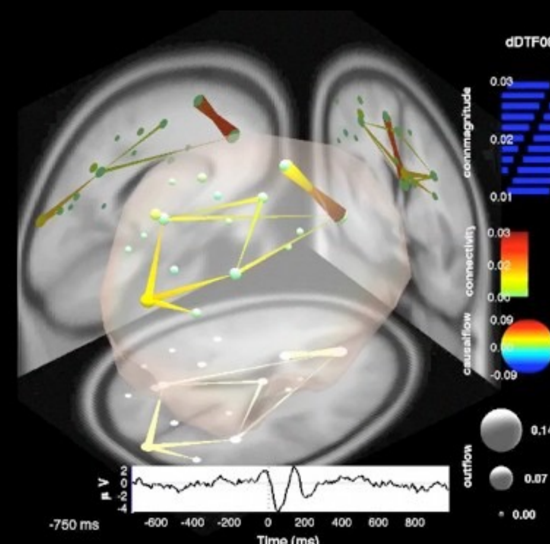


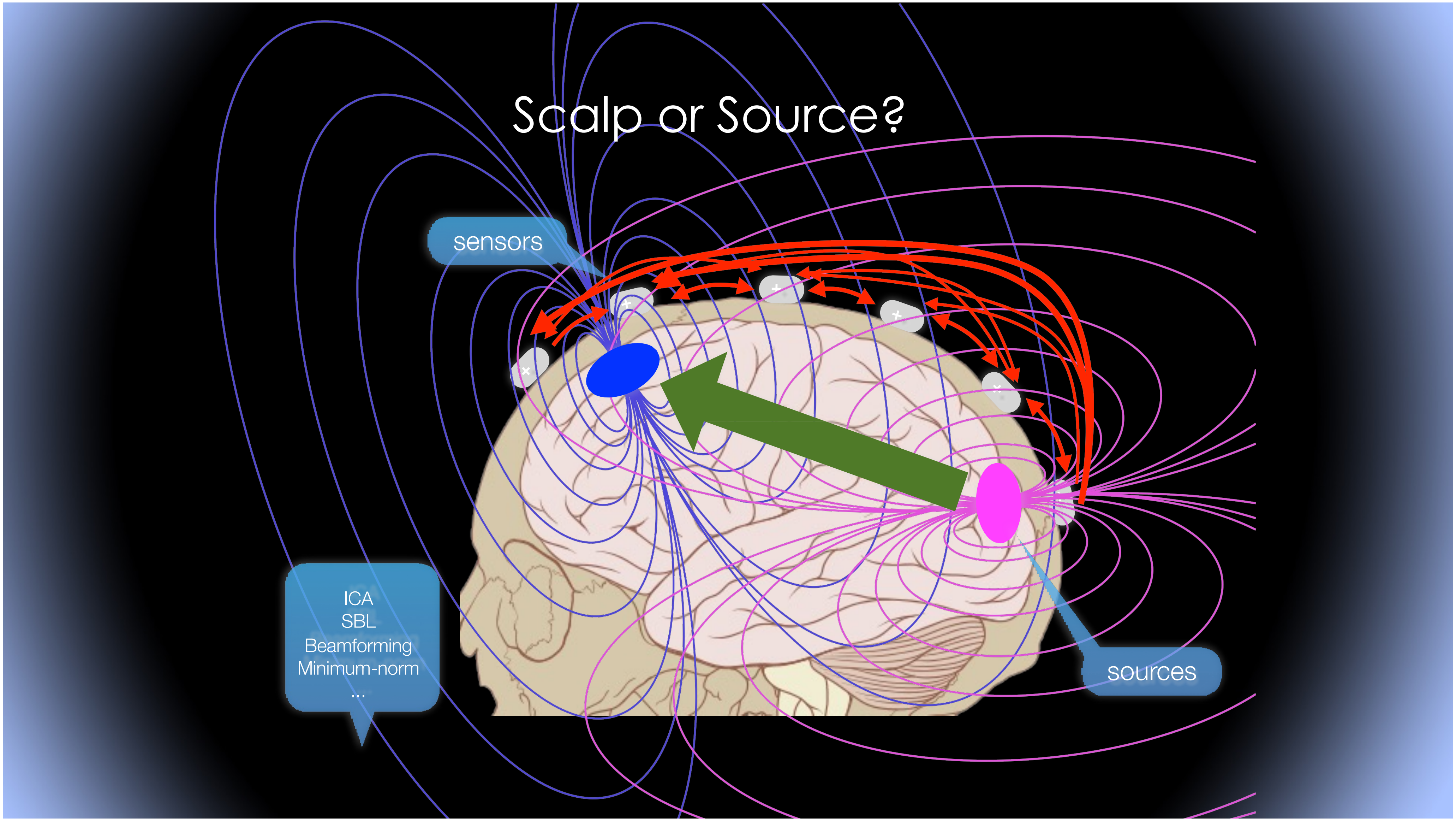
- SIFT is a capable toolkit for causal dynamical analysis at source level
- Parietal network expected for visually guided action (e.g. Heider, et al., 2010)
- ACC more strongly driven by Occipital Motor. Locus for translation of intention into action (Paus, 2001; Srinivasan, et al. 2013). ACC drives SMA (not shown).
- Causal network results depend on the number of nodes
  - E.g. Occipital " ACC could be mediated by region not included in model
  - There will always be a tradeoff between network size and amount of data needed to fit the model.
  - Regularization

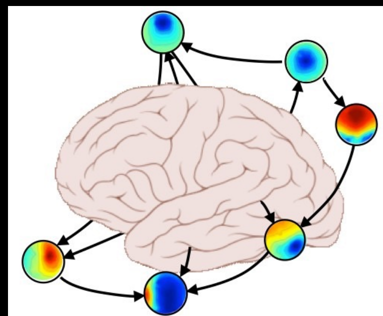
Scalp or Source?



or




Scalp or Source?
sensors
ICA
SBL
Beamforming
Minimum-norm
...
sources



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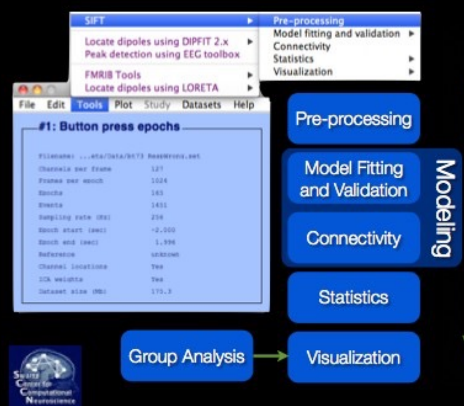
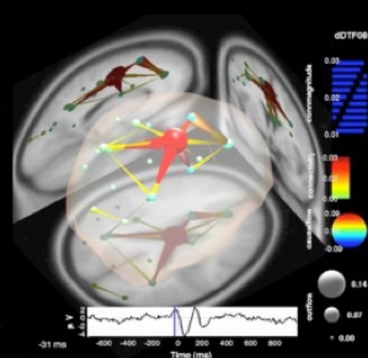
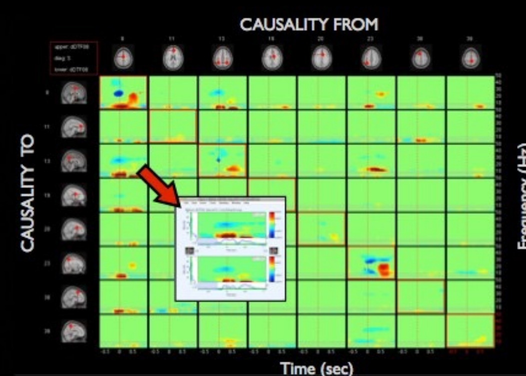
Delorme, Mullen, Kothe et al, *Computational Intelligence and Neuroscience*, vol 12, 2011







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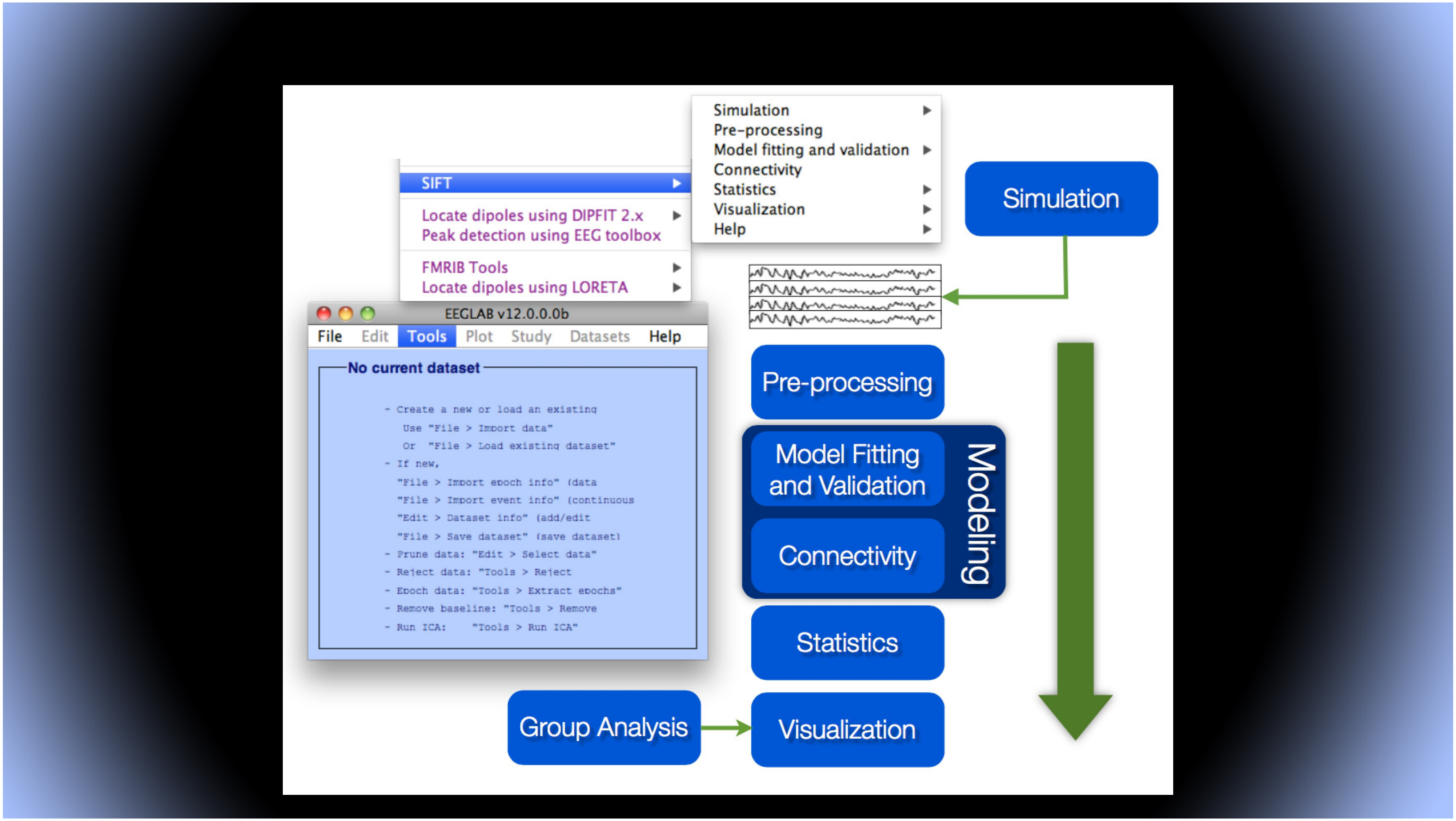
- Emphasis on vector autoregression and time-frequency domain approaches
- Standard and novel interactive visualization methods for exploratory analysis of connectivity across time, frequency, and spatial location



Simulation
Pre-processing
Model fitting and validation
Connectivity
Statistics
Visualization
Help
SIFT
Locate dipoles using DIPFIT 2.x
Peak detection using EEG toolbox
FMRIB Tools
Locate dipoles using LORETA
EEGLAB v12.0.0.0b
File Edit Tools Plot Study Datasets Help
No current dataset
- Create a new or load an existing
Use "File > Import data"
Or "File > Load existing dataset"
- If new,
"File > Import epoch info" (data
"File > Import event info" (continuous
"Edit > Dataset info" (add/edit
"File > Save dataset" (save dataset)
- Prune data: "Edit > Select data"
- Reject data: "Tools > Reject
- Epoch data: "Tools > Extract epochs"
- Remove baseline: "Tools > Remove
- Run ICA: "Tools > Run ICA"
Simulation
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Group Analysis
Visualization

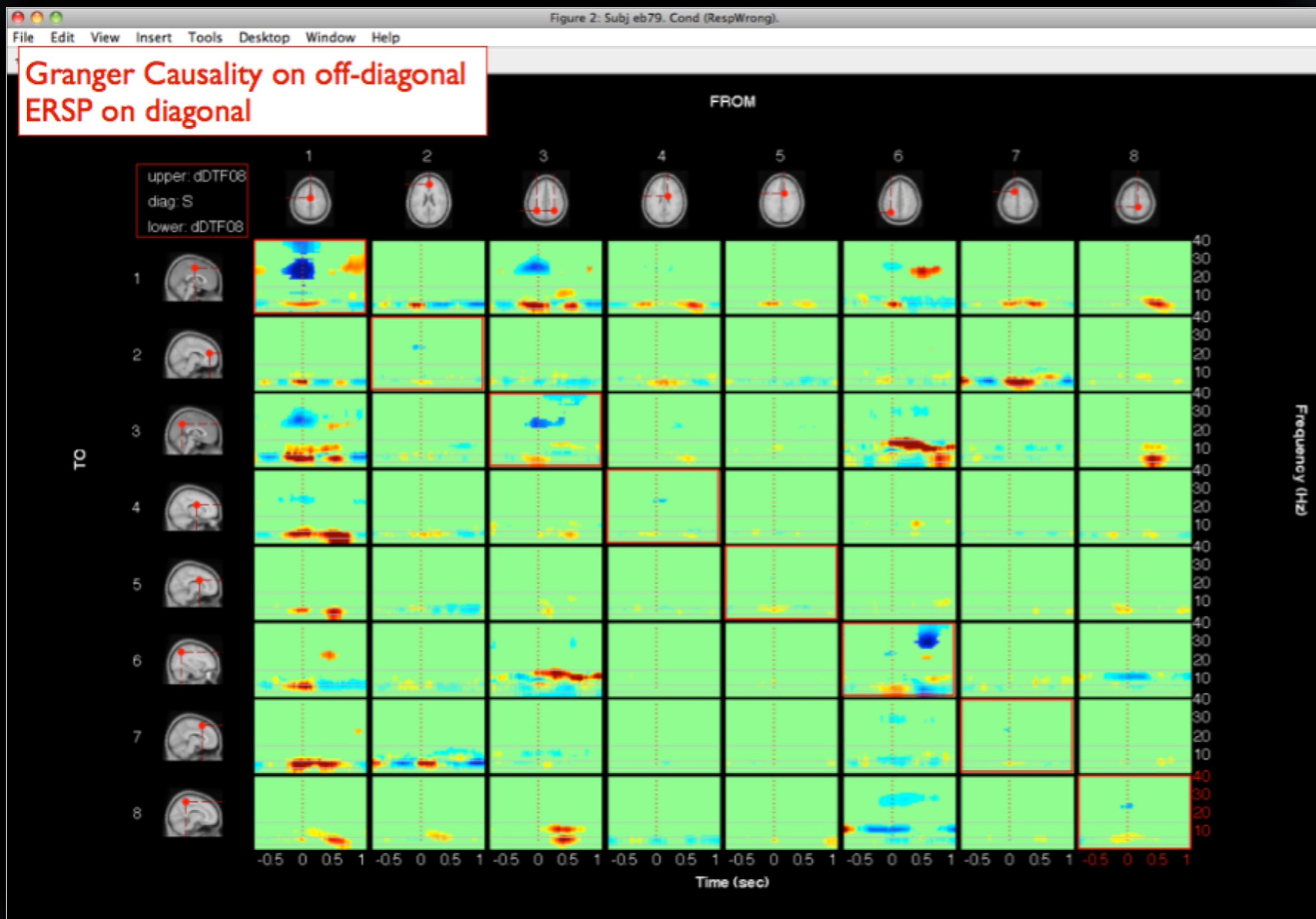
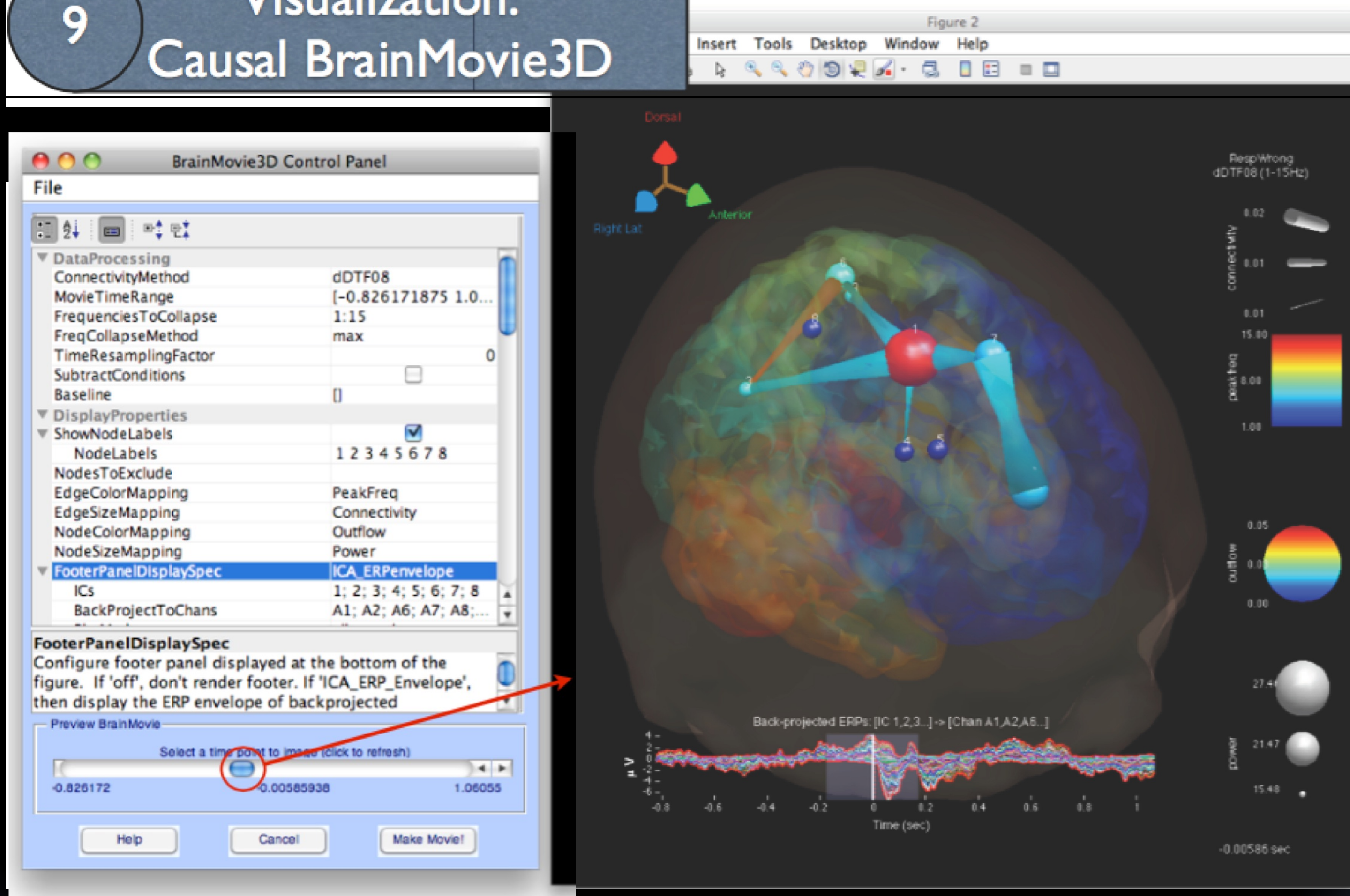


Figure 2: Subj eb79. Cond (RespWrong).
File Edit View Insert Tools Desktop Window Help
Granger Causality on off-diagonal
ERSP on diagonal
FROM
TO
upper: dDTF08
diag: S
lower: dDTF08
1 2 3 4 5 6 7 8
40 30 20 10
-0.5 0 0.5 1
Time (sec)
Frequency (Hz)

9

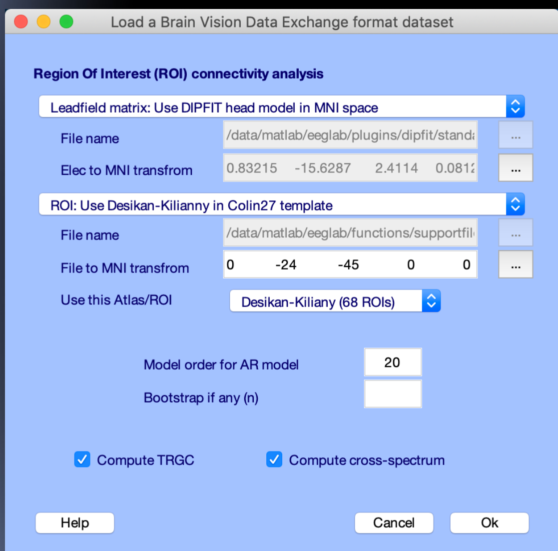
Visualization: Causal BrainMovie3D



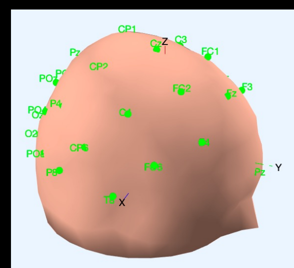
Time-Frequency Analysis of
EEG Time series

More Connectivity analysis

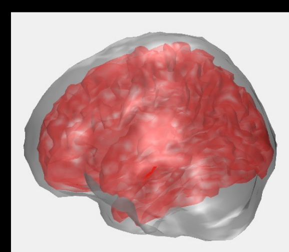
EEGLAB ROI connectivity plugin



Align electrodes with scalp model

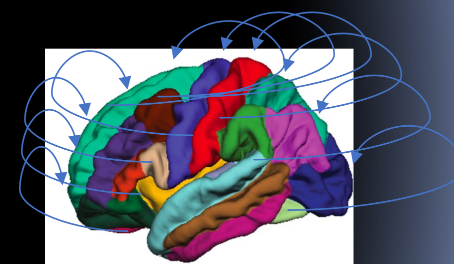


Align atlas with cortex model



Distributed source modeling

Group voxels in regions and compute connectivity



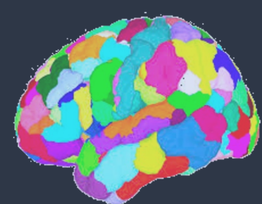
Measures TRGC, GC, TRPDC, PDC, TRDTF, DTF and CS

Haufe, S., Nikulin, V. V., Miller, K. R., & Nolte, G. (2013). A critical assessment of connectivity measures for EEG data: a simulation study. Neuroimage, 64, 120-133.

Connectivity analysis using EEG

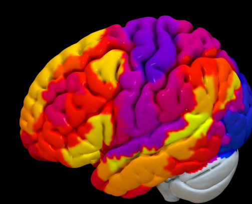
Volumetric atlases

AFNI MNI



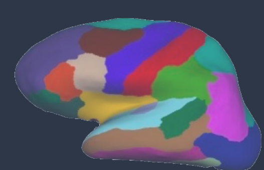
Brainnetome

Schaefer 2018

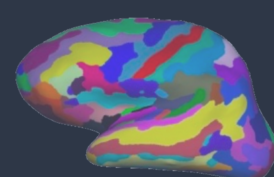


Surface atlases

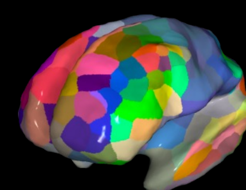
Desikan Kiliany



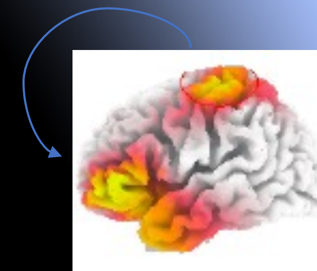
Destrieux



PrAGMATiC

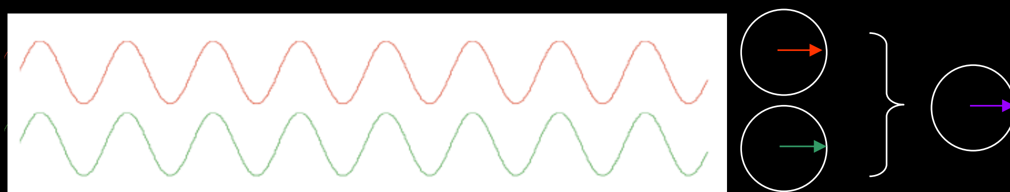


Cross-coherence amplitude and phase



2 areas, comparison on the same trials

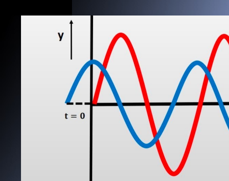
Trial 1

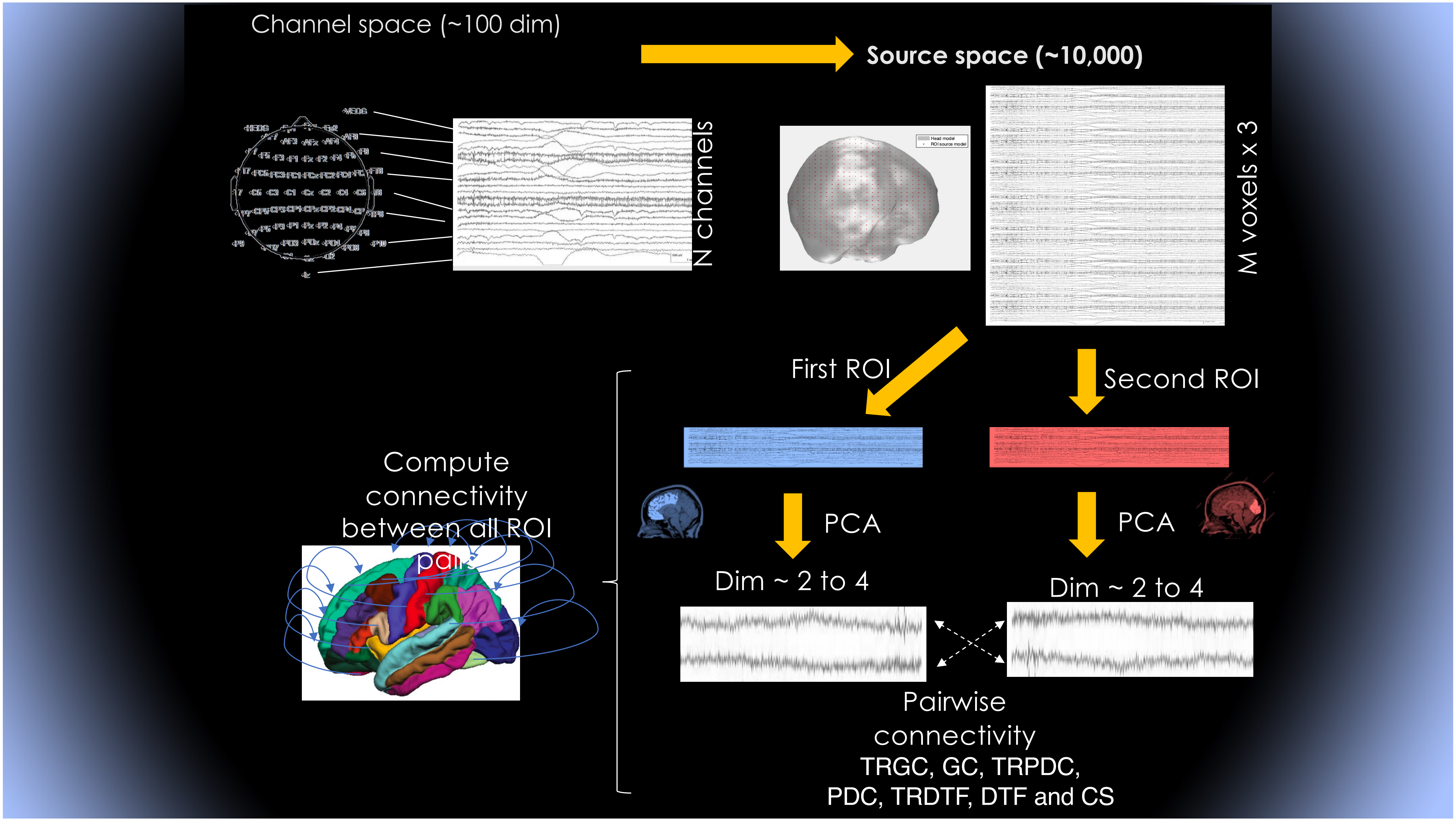


Coherence amplitude 1
Phase coherence 0

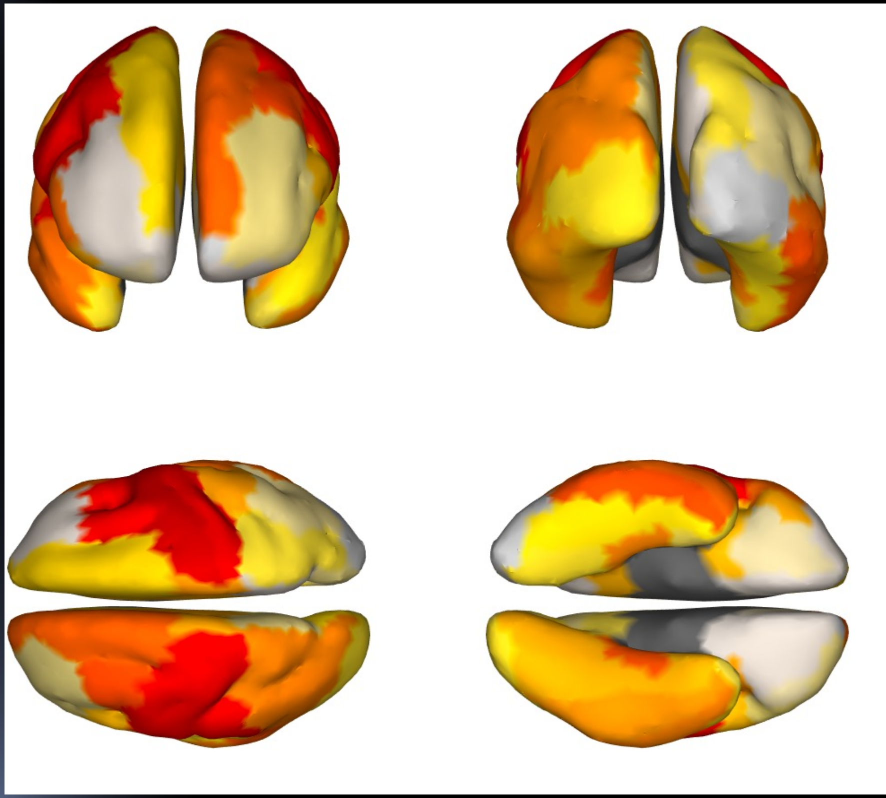
COHERENCE = mean(phase vector)

Norm 0.33
Phase 90 degree

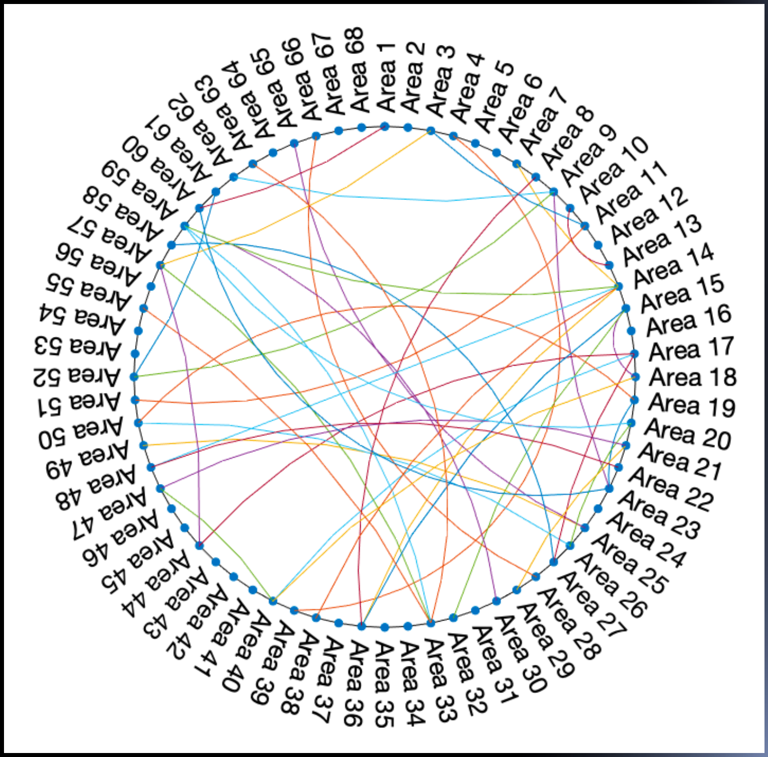



Channel space (~100 dim)
Source space (~10,000)
N channels
M voxels x 3
First ROI
Second ROI
Compute connectivity between all ROI pairs
PCA
PCA
Dim ~ 2 to 4
Dim ~ 2 to 4
Pairwise connectivity
TRGC, GC, TRPDC, PDC, TRDTF, DTF and CS

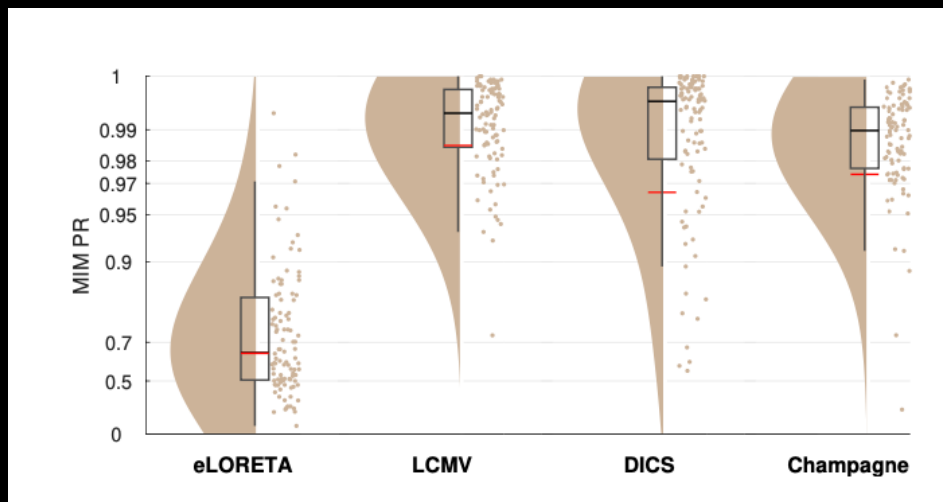
Red regions are highly interacting



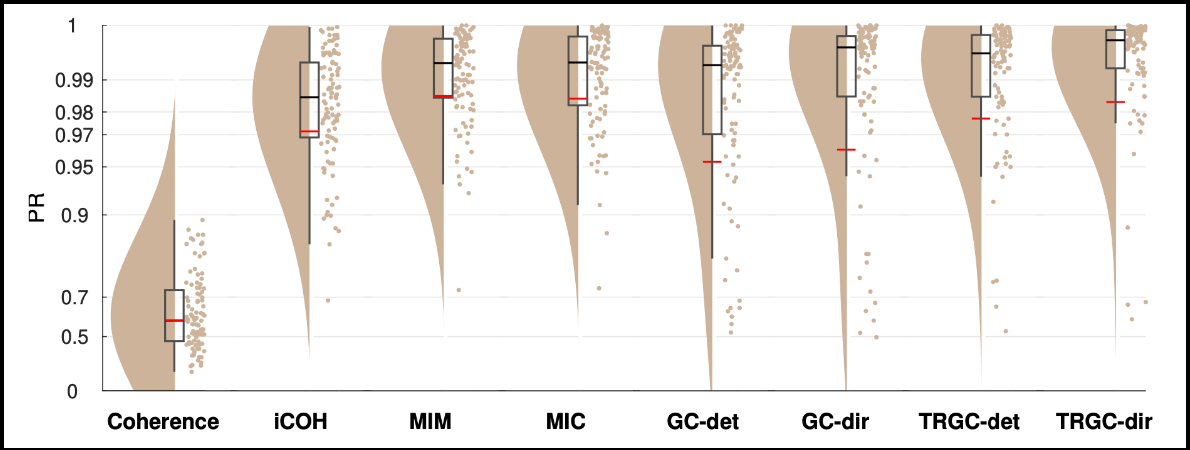
Connectivity matrix between 68 ROIs



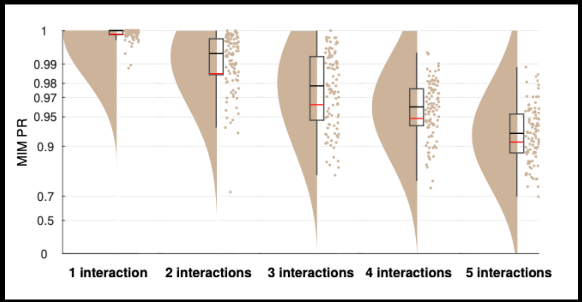
Inverse method



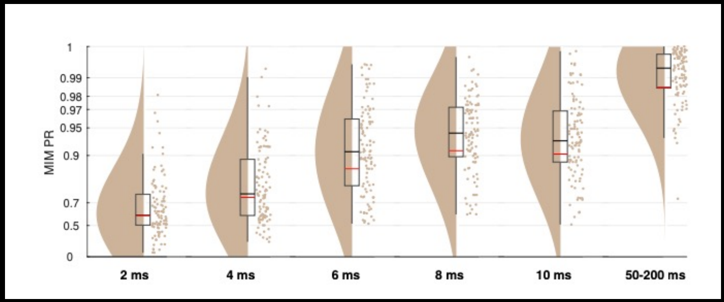
Connectivity method



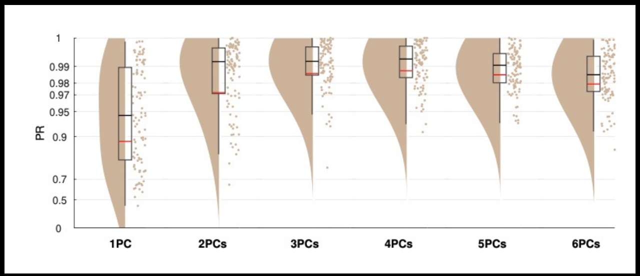
Number of interactions



Delay between sources



Number of PCA comp.



Data intake

- Stationary continuous data
- About 100 Hz
- 2 second data chunks (or epochs)
- Same length of data for each condition
- No dynamics – static image

The end/La fin