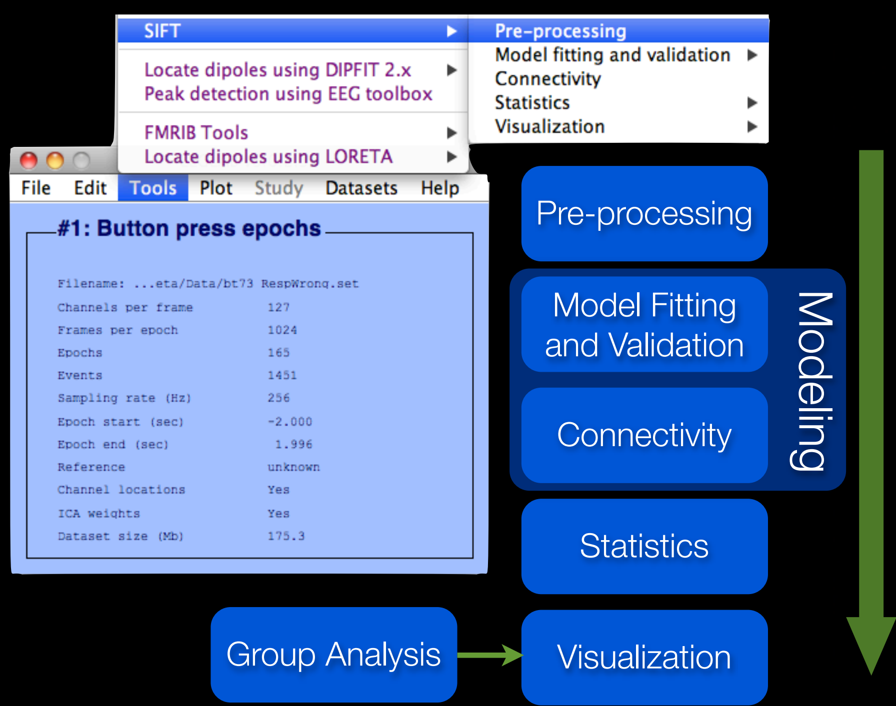
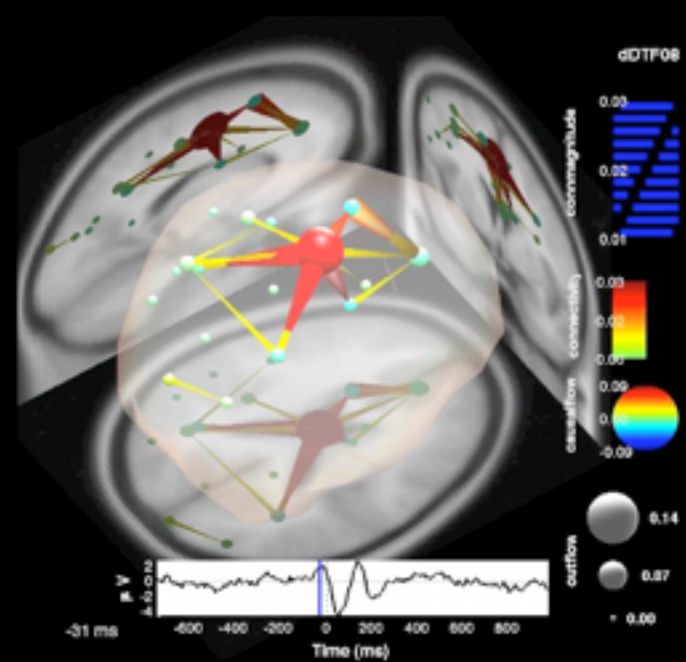
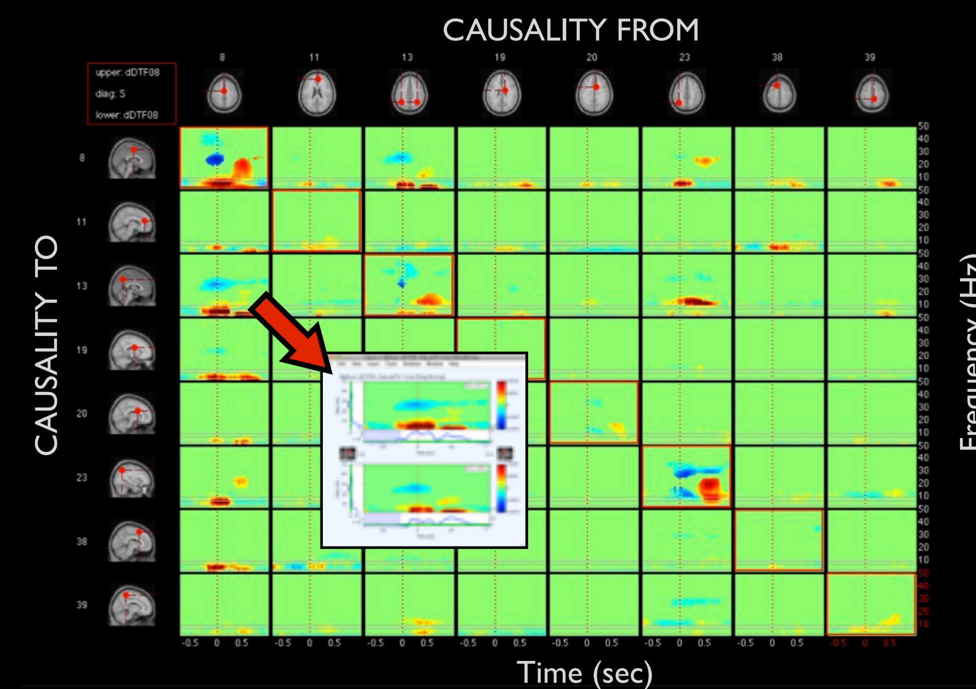
The Source Information Flow Toolbox

An Electrophysiological Information Flow Toolbox for EEGLAB







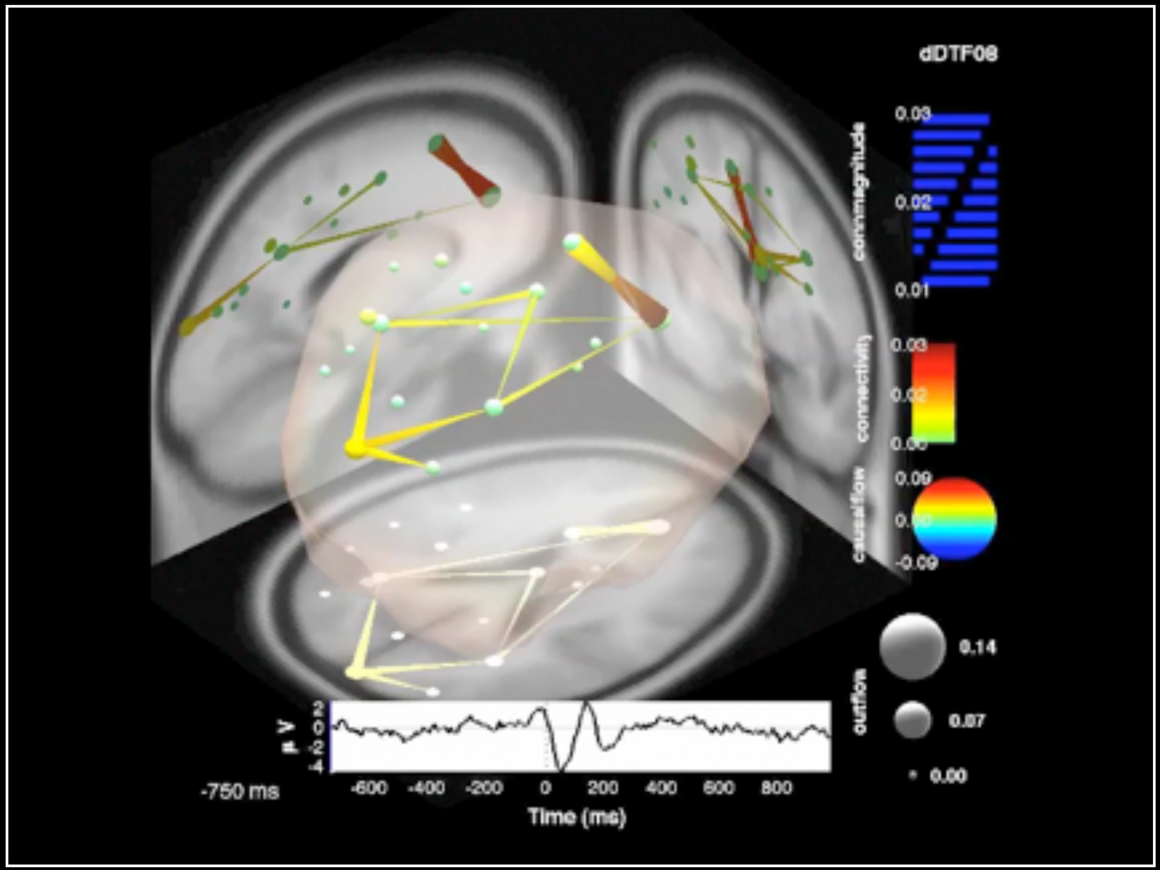
Tim Mullen

15^{th} EEGLAB Workshop
June 16, 2012
Tsinghua University, Beijing, China

Outline

The Dynamic Brain

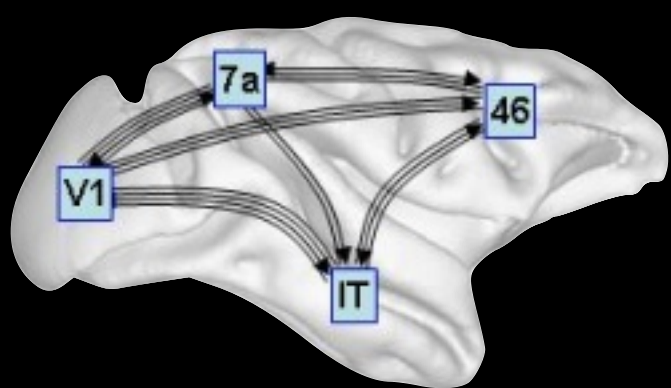
- A key goal: To measure temporal changes in neural dynamics and information flow that index and predict task-relevant changes in cognitive state and behavior
- Important factors:
  - Accuracy and Validity
  - Temporal Specificity
  - Non-invasive measures



Categorizations of Large-Scale Brain Connectivity Analysis

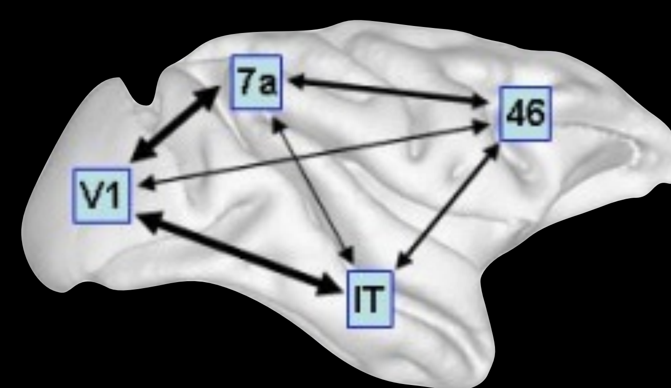
(Bullmore and Sporns, *Nature*, 2009)

Structural



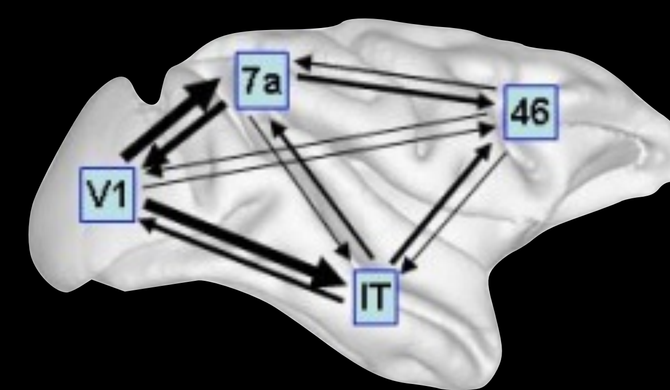
state-invariant, anatomical

Functional



dynamic, state-dependent, correlative, symmetric

Effective



dynamic, state-dependent, asymmetric, causal, information flow

Hours-Years | **milliseconds-seconds**

Temporal Scale

Modeling Brain Connectivity

- Model-based approaches mitigate the ‘curse of dimensionality’ by making some assumptions about the structure, dynamics, or statistics of the system under observation

Box and Draper (1987):

> “Essentially, all models are wrong, but some are useful [...] the practical question is how wrong do they have to be to not be useful”

“The map is not the territory”

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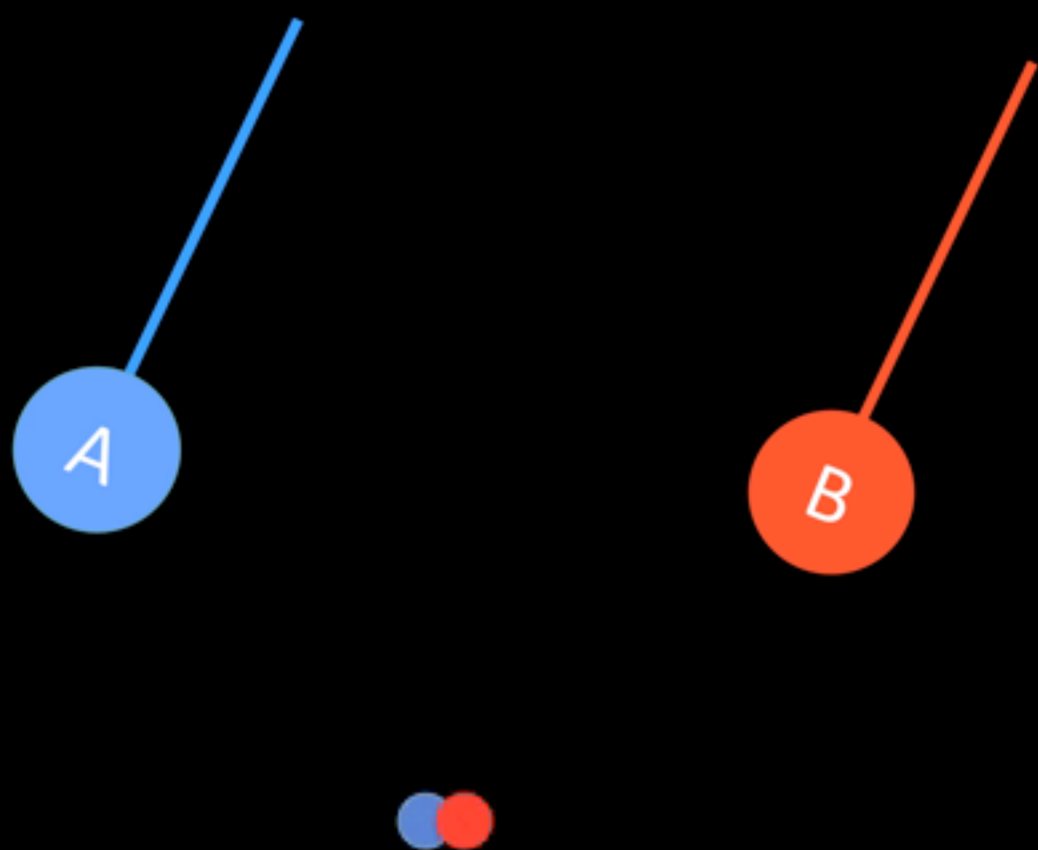
Estimating Functional Connectivity

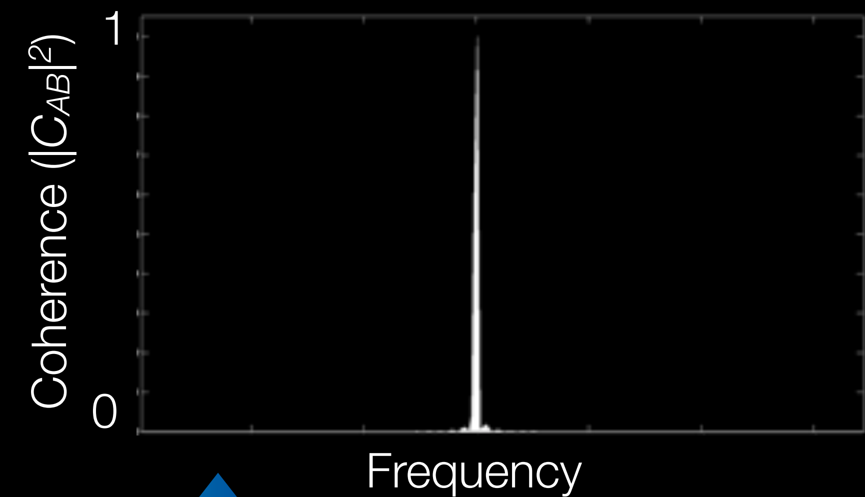
Popular measures

- Cross-Correlation
- Coherence
- Phase-Locking Value
- Phase-amplitude coupling

...

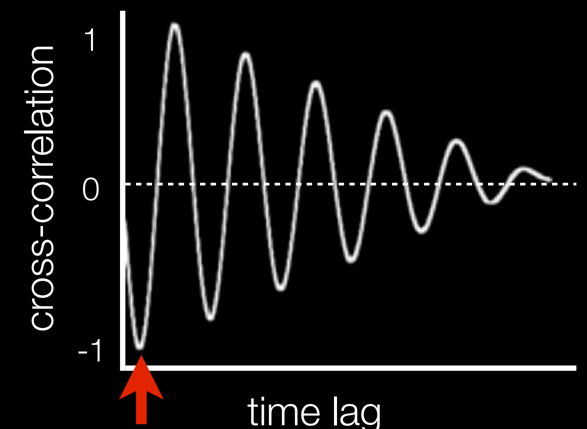
Cross-Correlation and Linear Coherence





FFT

$$C_{AB}(f) = \sum_{k=0}^{p} \rho_{AB}(k) e^{-i2\pi fk} = \frac{S_{AB}(f)}{\sqrt{S_A(f)S_B(f)}}$$



$$\rho_{AB}(k)$$

Coherence/CC/PLV indicate ***functional***, but not ***effective*** connectivity

Estimating Effective Connectivity

Non-Invasive

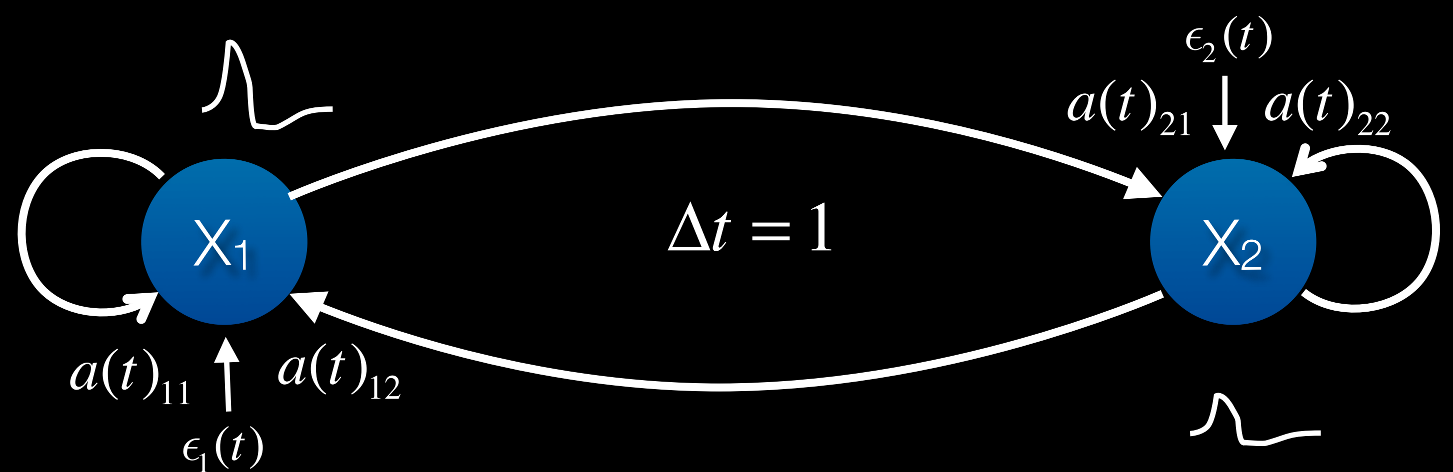
- *Post-hoc* analyses applied to measured neural activity
- Confirmatory
  - Dynamic Causal Models
  - Structural Equation Models
- Exploratory
  - Granger-Causal methods

- Data-driven
- Rooted in *conditional predictability*
- Scalable (Valdes-Sosa, 2005)
- Extendable to nonlinear and/or non-stationary systems (Freiwald, 1999; Ding, 2001; Chen, 2004; Ge, 2009)
- Extendable to non-parametric representations (Dhamala, 2009a,b)
- Can be (partially) controlled for (unobserved) exogenous causes (Guo, 2008a,b; Ge, 2009)
- Equivalent to Transfer Entropy for Gaussian Variables (Seth, 2009)
- Flexibly allows us to examine **time-varying** (dynamic) multivariate causal relationships in either the **time** or **frequency** domain

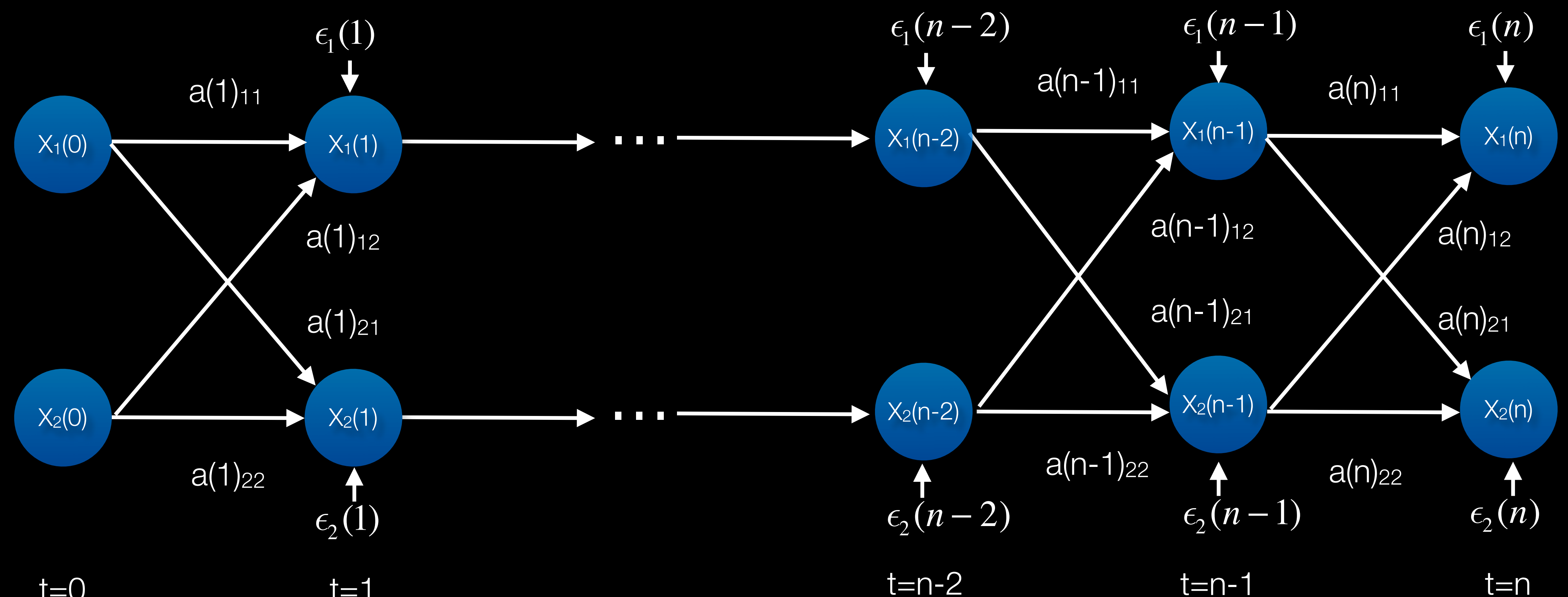
Linear Dynamical Systems

Stochastic Linear Dynamical System

$$X_1(t) = a(t)_{11} X_1(t-1) + a(t)_{12} X_2(t-1) + \epsilon_1(t)$$
$$X_2(t) = a(t)_{22} X_2(t-1) + a(t)_{21} X_1(t-1) + \epsilon_2(t)$$

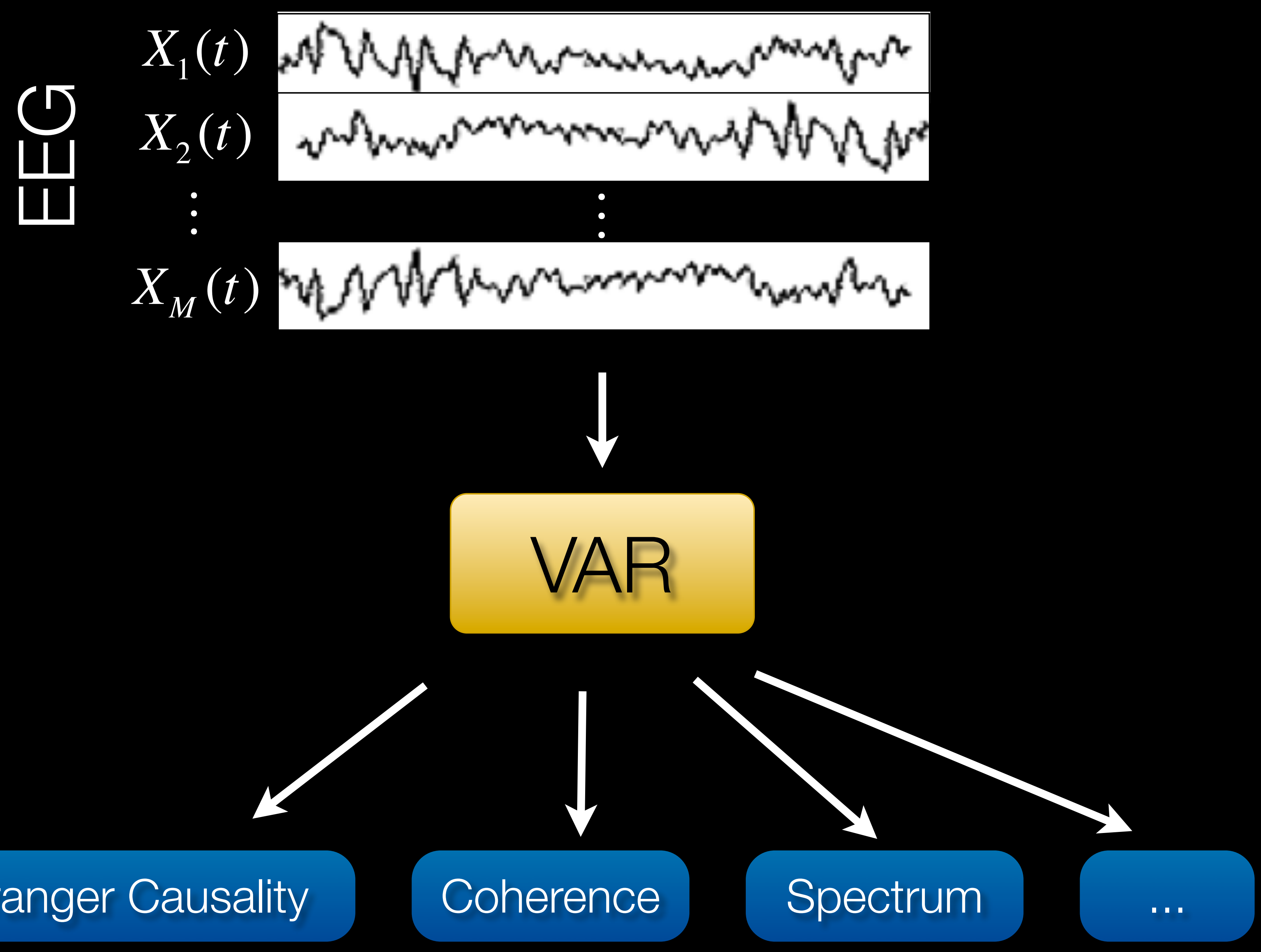


Order 1 Markov Process (VAR[1])



time step

Vector Autoregressive (VAR / MAR / MVAR) Modeling



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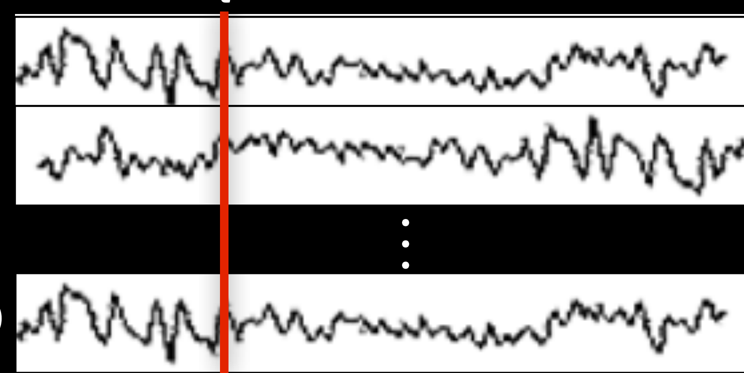
VAR Modeling: Assumptions

- **“Weak” stationarity of the data**
  - mean and variance do not change with time
  - An EEG trace containing prominent evoked potentials is a classic example of a non-stationary time-series
- **Stability**
  - A stable process will not “blow up” (diverge to infinity)
  - Importantly, stability implies stationarity

The Linear Vector Auto-regressive (VAR) Model

t

$$X(t) = \begin{matrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_M(t) \end{matrix}$$



Ordinary Least-Squares
Lattice Filters
Kalman Filtering
Bayesian Methods
Sparse methods
...

VAR[p] model

model order

random noise process

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

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

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

$$\mathbf{E}(t) = N(0, \mathbf{V})$$

Selecting a VAR Model Order

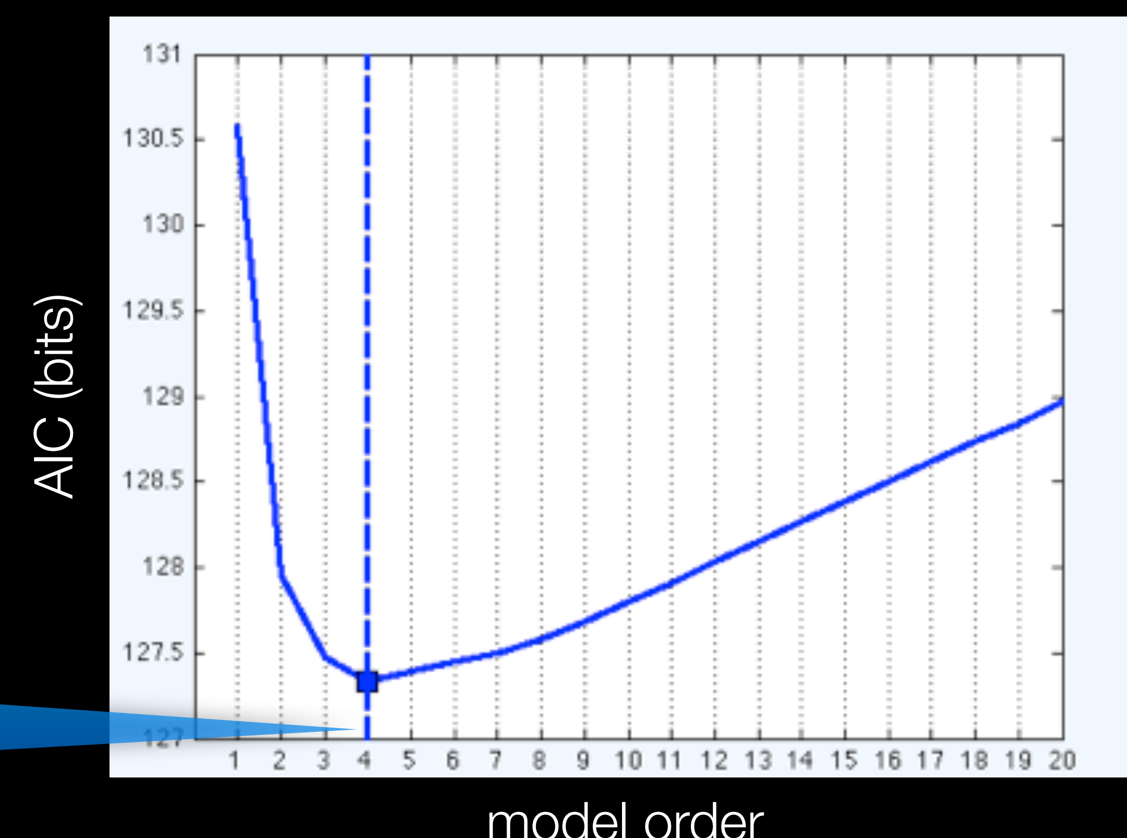
- Model order is typically determined by minimizing information criteria such as Akaike Information Criterion (AIC) for varying model order (p):

$$AIC(p) = 2\log(\det(\mathbf{V})) + M^2p/N$$

Penalizes high model orders (parsimony)

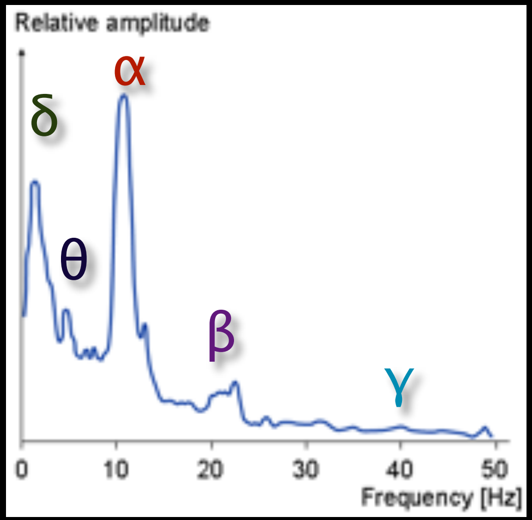
entropy rate (amount of prediction error)

optimal order



Selecting a VAR Model Order

- Other considerations:
  - A M-dimensional VAR model of order *p* has at most *Mp/2* spectral peaks distributed amongst the *M* variables. This means we can observe at most *p/2* peaks in each variables' spectrum (or in the causal spectrum between each pair of variables)



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

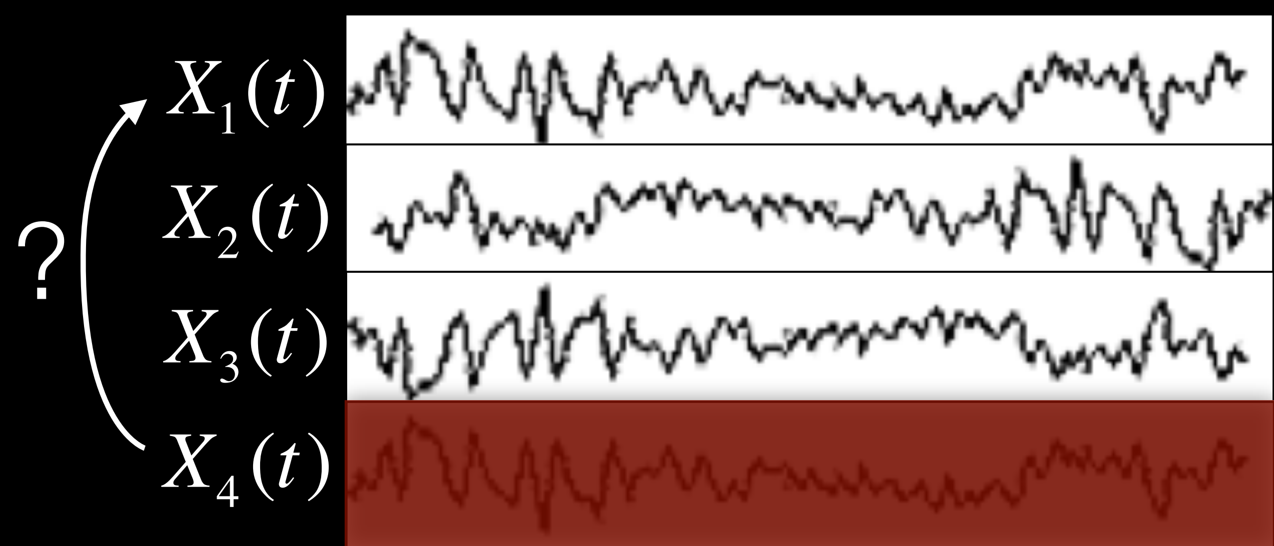
Granger Causality

- First introduced by Wiener (1958). Later reformulated by Granger (1969) in the context of linear stochastic autoregressive models
- Relies on two assumptions:

Granger Causality Axioms
1. Causes should precede their effects in time (Temporal Precedence)
2. Information in a cause's past should improve the prediction of the effect, above and beyond the information contained in past of the effect (and other measured variables)

Granger Causality

Does $\mathbf{X}_4$ granger-cause $\mathbf{X}_1$?
(conditioned on $\mathbf{X}_2$, $\mathbf{X}_3$)

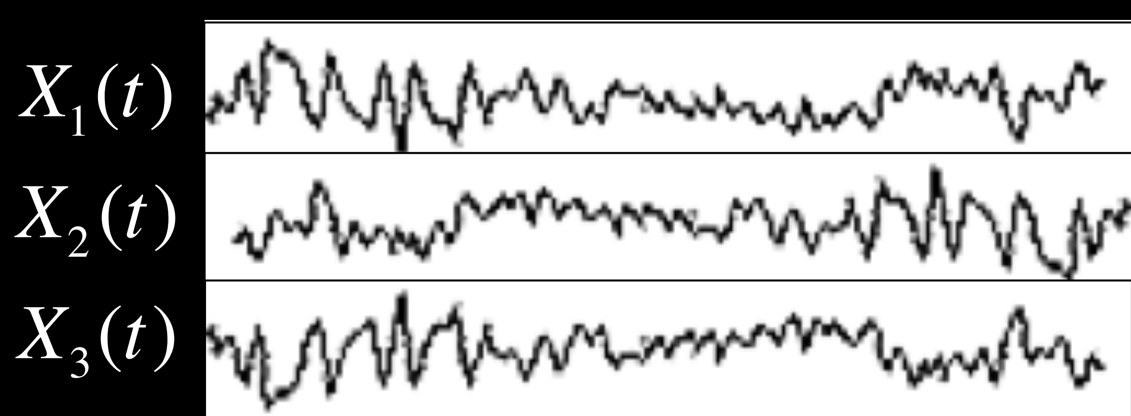


→ VAR$_1$ → var($\mathbf{E}_1$(t))

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

prediction error for X_1
(variance of residuals E_1)

= ?



→ VAR$_2$ → var($\tilde{\mathbf{E}}_1$(t))

$$\mathbf{X}_{-4}(t) = \sum_{k=1}^{p} \tilde{\mathbf{A}}^{(k)} \mathbf{X}_{-4}(t-k) + \tilde{\mathbf{E}}(t)$$

Granger Causality

- Granger (1969) quantified this definition for **bivariate** processes in the form of an F-ratio:

reduced model

$$F_{X_1 \leftarrow X_2} = \ln\left(\frac{var(\tilde{E}_1)}{var(E_1)}\right) = \ln\left(\frac{var(X_1(t) \mid X_1(\cdot))}{var(X_1(t) \mid X_1(\cdot), X_2(\cdot))}\right)$$

full model

- Alternately, for a **multivariate interpretation** we can fit a single MVAR model to all channels and apply the following definition:

Definition 1

X_j granger-causes X_i conditioned on all other variables in **X**

<u>if and only if</u> $\mathbf{A}_{ij}(k) >> 0$ for some lag $k \in \{1, \ldots, p\}$

Granger Causality Quiz

- Example: 2-channel MVAR process of order 1

$$\begin{pmatrix} X_1(t) \\ X_2(t) \end{pmatrix} = \begin{pmatrix} -0.5 & 0 \\ 0.7 & 0.2 \end{pmatrix} \begin{pmatrix} X_1(t-1) \\ X_2(t-1) \end{pmatrix} + \begin{pmatrix} E_1(t) \\ E_2(t) \end{pmatrix}$$

$$X_1(t) = -0.5X_1(t\text{ - }1) + \boxed{0X_2(t\text{ - }1)} + E_1(t)$$
$$X_2(t) = \boxed{0.7X_1(t\text{ - }1)} + 0.2X_2(t\text{ - }1) + E_2(t)$$

Which causal structure does this model correspond to?

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

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Granger Causality – Frequency Domain

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

Fourier-transforming **A**$^{(k)}$ we obtain

Likewise, **X**(*f*) and **E**(*f*) correspond to the fourier transforms of the data and residuals, respectively

$$\mathbf{A}(f) = -\sum_{k=0}^{p} \mathbf{A}^{(k)} e^{-i2\pi fk}; \mathbf{A}^{(0)} = I$$

We can then define the spectral matrix **X**(*f*) as follows:

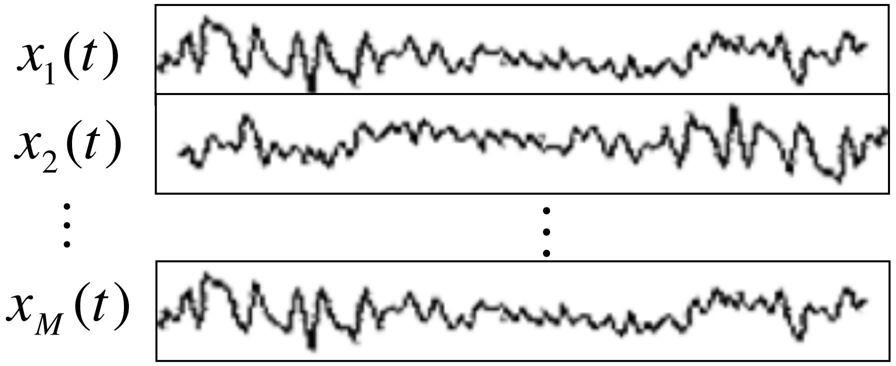
$$\mathbf{X}(f) = \mathbf{A}(f)^{-1}\mathbf{E}(f) = \mathbf{H}(f)\mathbf{E}(f)$$

Where **H**(*f*) is the *transfer matrix* of the system.

Definition 2

X_j granger-causes X_i conditioned on all other variables in **X**
<u>if and only if</u> |$\mathbf{A}_{ij}(f)$| >> 0 for some frequency *f*

leads to PDC

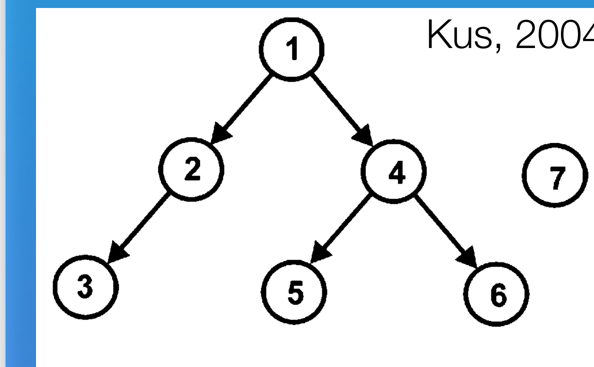


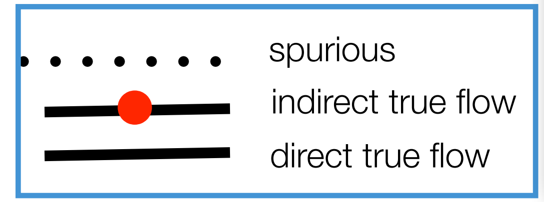
$$\mathbf{X}(t) = \sum_{k=1}^{p} \mathbf{A}^{(k)}(t)\mathbf{X}(t-k) + \mathbf{E}(t)$$

$$\mathbf{A}(f,t) = -\sum_{k=0}^{p} \mathbf{A}^{(k)}(t)e^{-i2\pi fk}; \quad \mathbf{A}^{(0)} = I$$

$$\mathbf{X}(f,t) = \mathbf{A}(f,t)^{-1}\mathbf{E}(f,t) = \mathbf{H}(f,t)\mathbf{E}(f,t)$$

Ground Truth

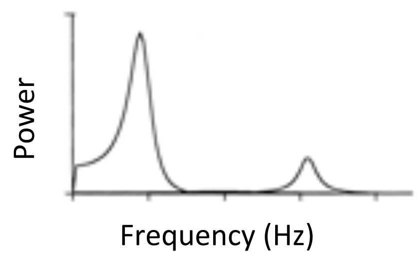




Spectrum

$$S(f) = \mathbf{X}(f)\mathbf{X}(f)^* = \mathbf{H}(f)\Sigma\mathbf{H}(f)^*$$

(Brillinger, 2001)



NOTE: time index (t) dropped for convenience

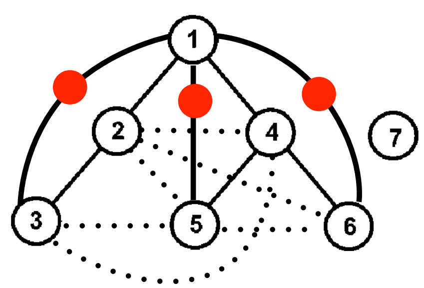
	Functional	Effective
Bivariate	**Coherency**	**Granger-Geweke Causality**
Multivariate	**Partial Coherence**	**Partial Directed Coherence**

Bivariate

Coherency

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

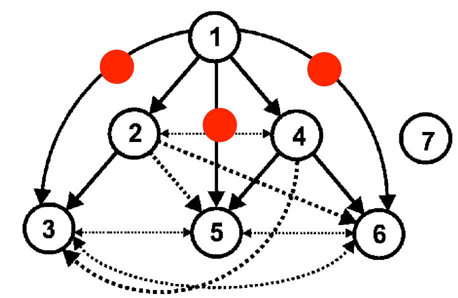
(Bendat and Piersol, 1986)



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)

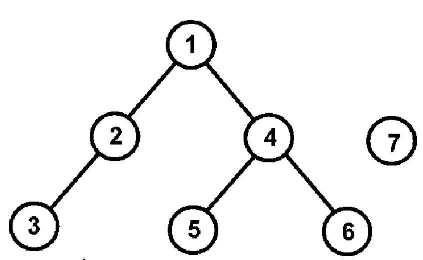


Multivariate

Partial Coherence

$$P_{ij}(f) = \frac{S_{ij}^{-1}(f)}{\sqrt{S_{ii}^{-1}(f)S_{jj}^{-1}(f)}}$$

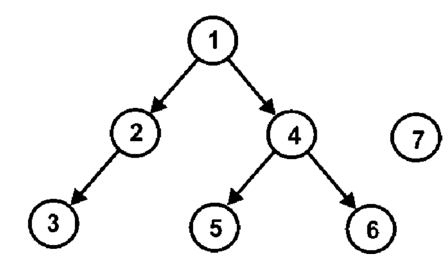
(Bendat and Piersol, 1986; Dalhaus, 2000)



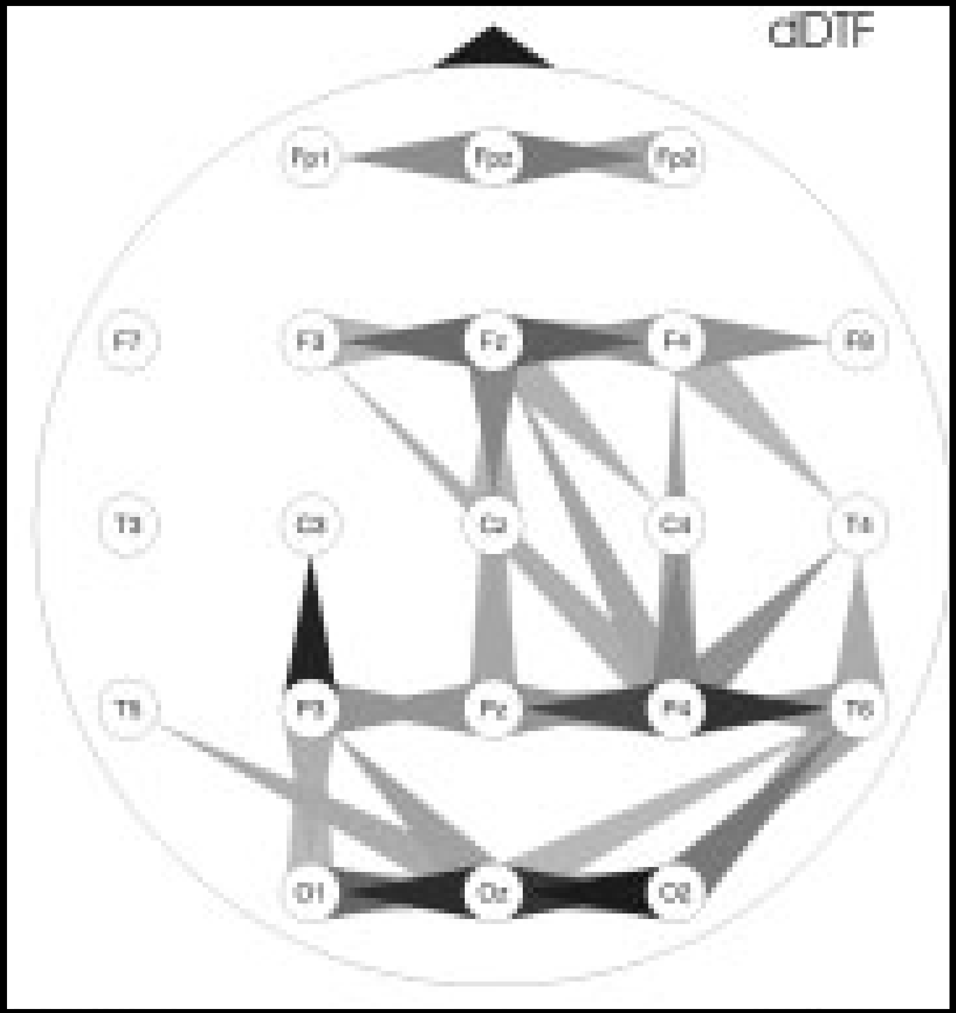
Partial Directed Coherence

$$\pi_{ij}^2(f) = \frac{|A_{ij}(f)|^2}{\sum_{k=1}^{M} \left|A_{kj}(f)\right|^2}$$

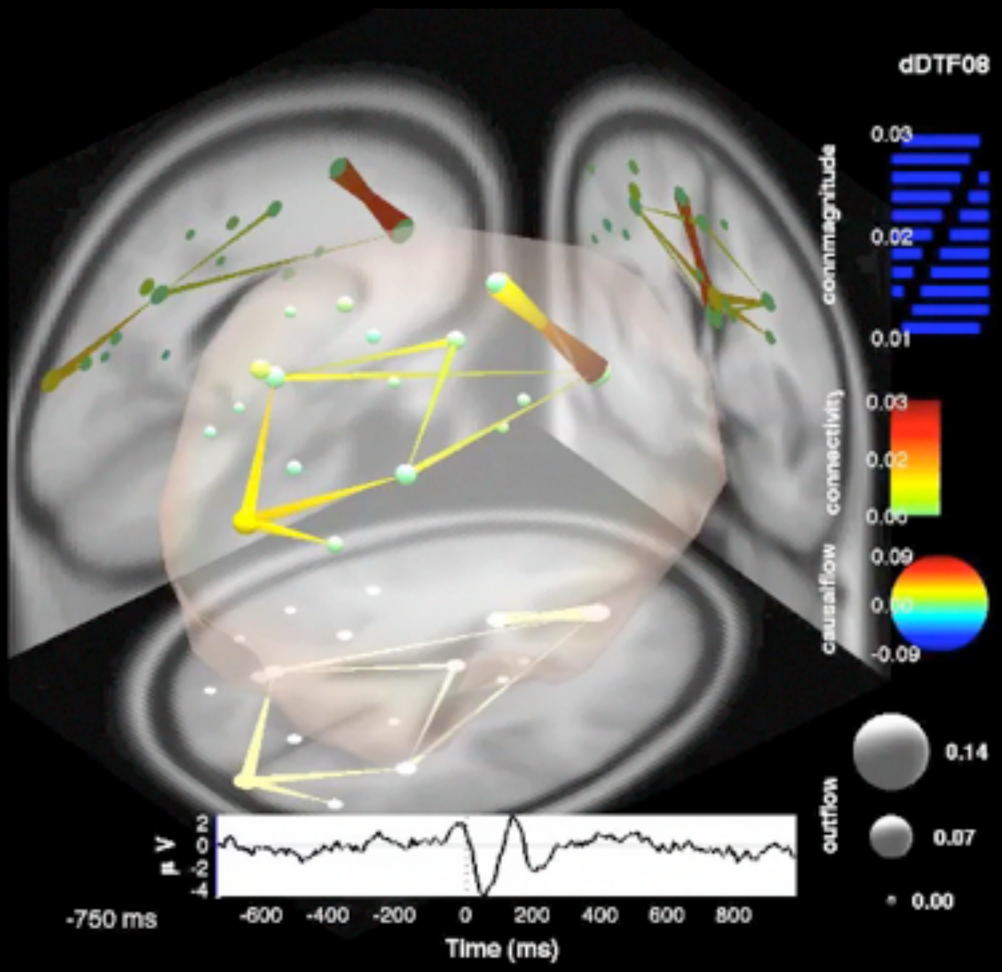
(Baccalá and Sameshima, 2001)



Scalp or Source?



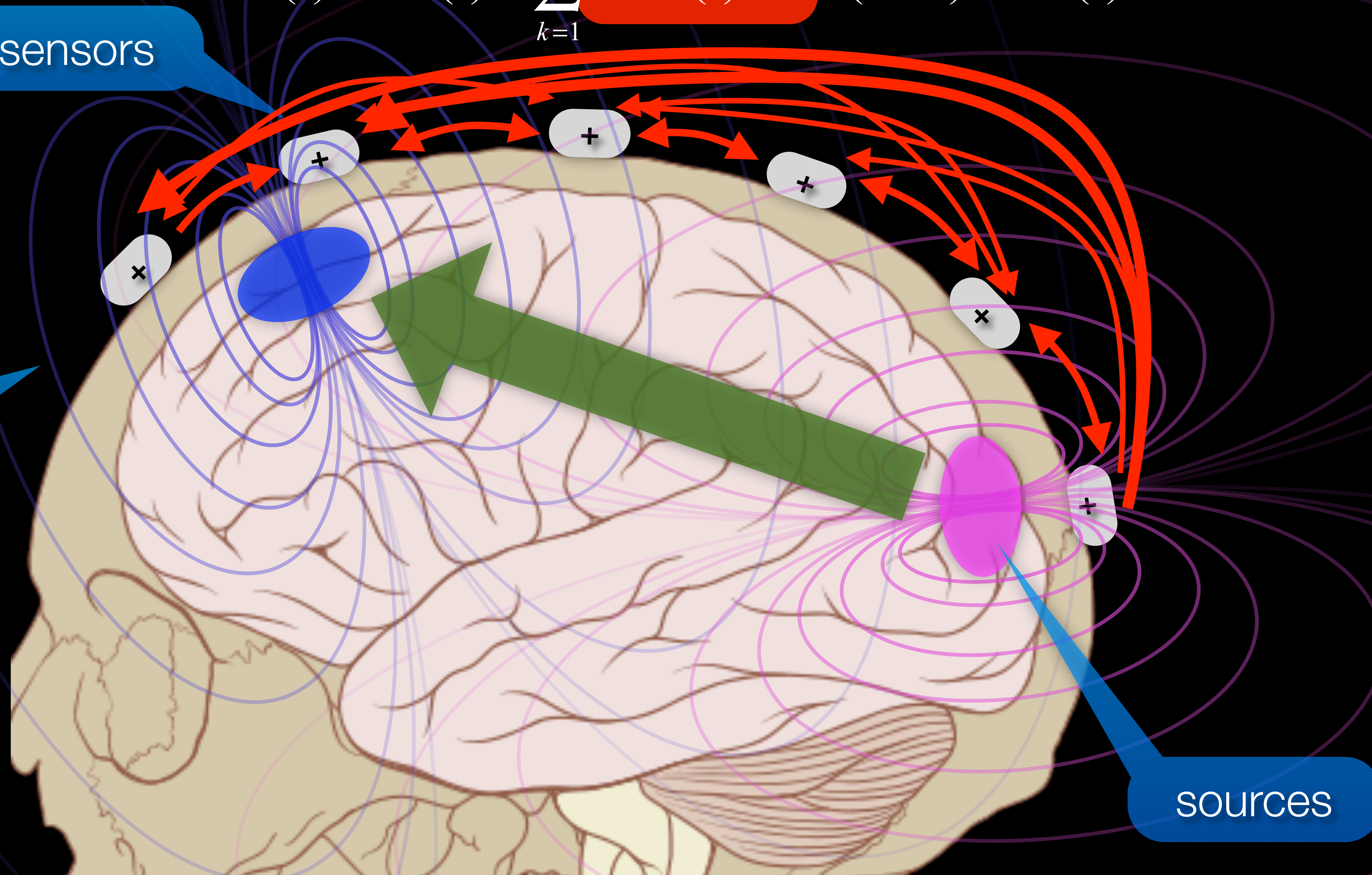
or



Scalp or Source?

Volume conduction exists for ECoG too!
(c.f. Whitmer, Worrell, ... , Makeig, *Frontiers in Neuro*. 2010

$$X(t) = HS(t) = \sum_{k=1}^{p} \boxed{HA^{(k)}(t)H^{-1}} X(t-k) + HE(t)$$



$$X(t) = \overset{H^{-1}}{H}S(t)$$

Volume Conduction

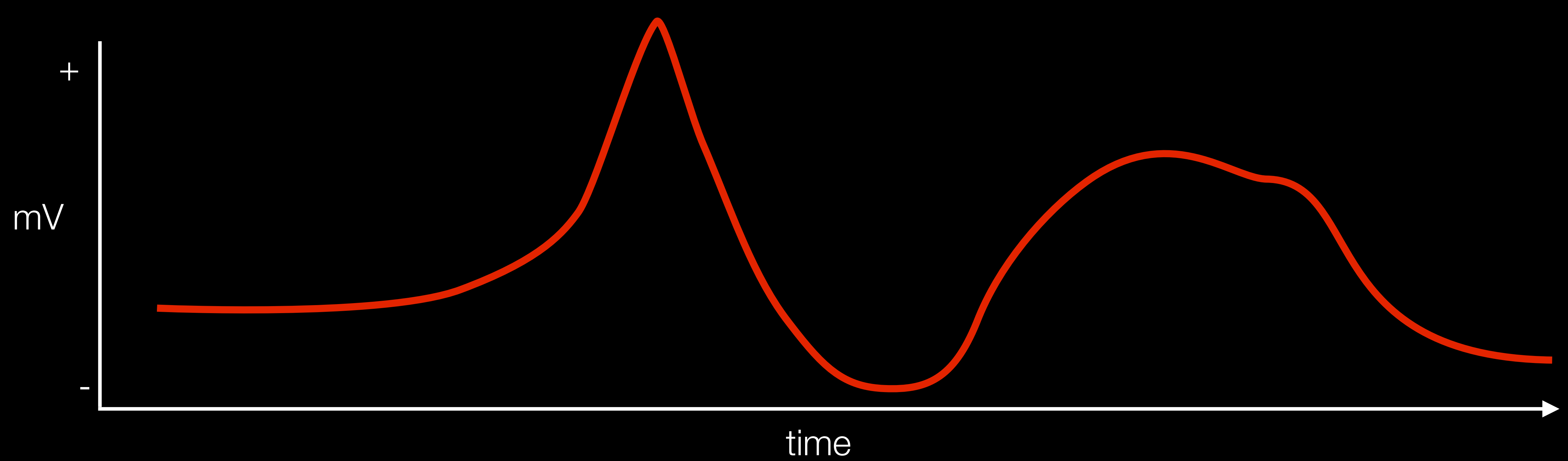
ICA
SBL
Beamforming
Minimum-norm
...

Solution? Source Separation

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

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?

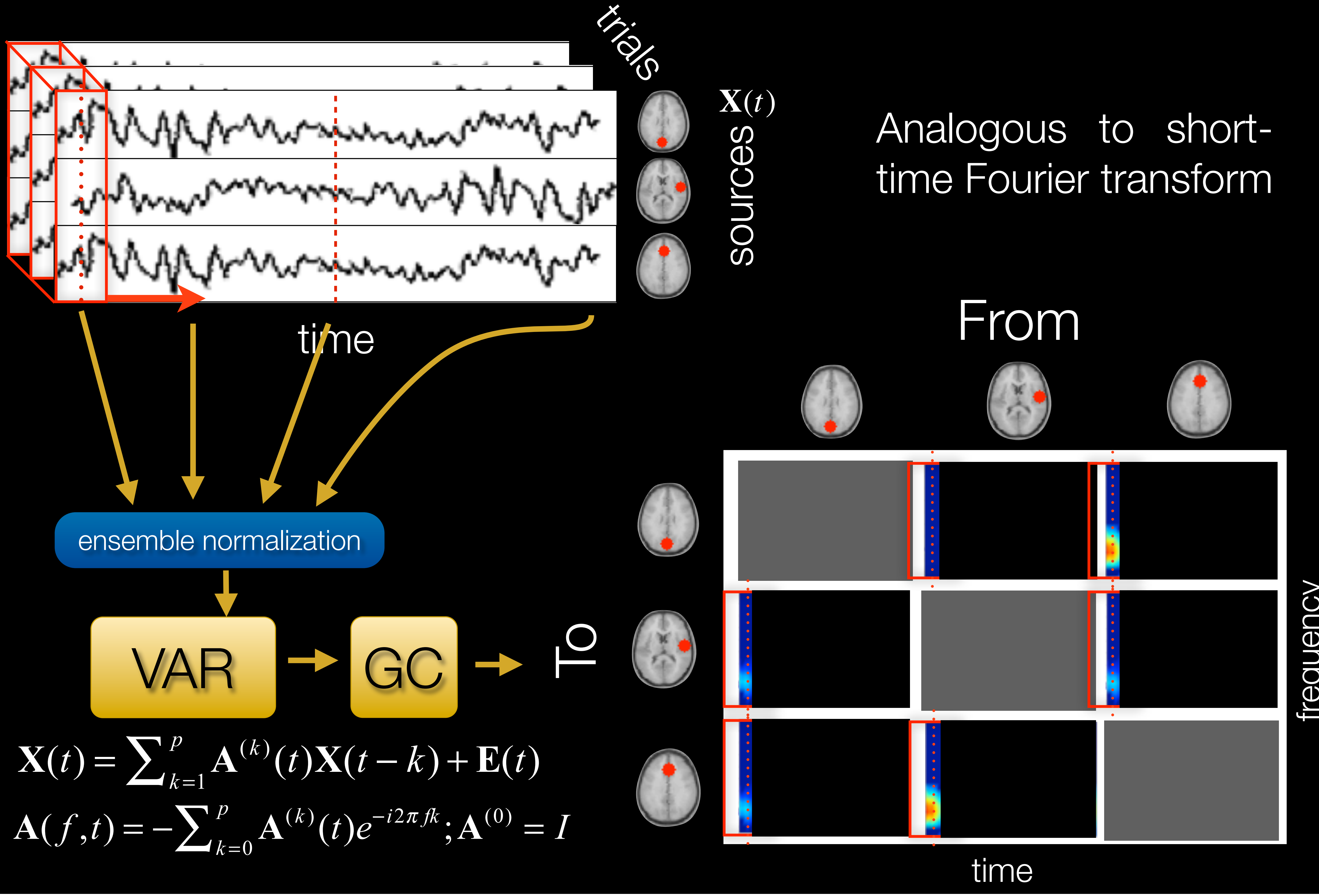


Adapting to Non-Stationarity

- **Many ways to do adaptive VAR estimation**
  - Segmentation-based adaptive VAR estimation
  - Factorization of time-varying spectral density matrices (e.g. from STFTs, Wavelets, etc)
  - State-Space Modeling
  - ...

Segmentation-based VAR

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



Analogous to short-time Fourier transform

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

$$\mathbf{A}(f,t) = -\sum_{k=0}^{p} \mathbf{A}^{(k)}(t)e^{-i2\pi fk}; \mathbf{A}^{(0)} = I$$

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Time-Frequency GC

- **What is a good window length?**
- Considerations:
  - Temporal smoothing
  - Local stationarity
  - Sufficient amount of data
  - Process dynamics

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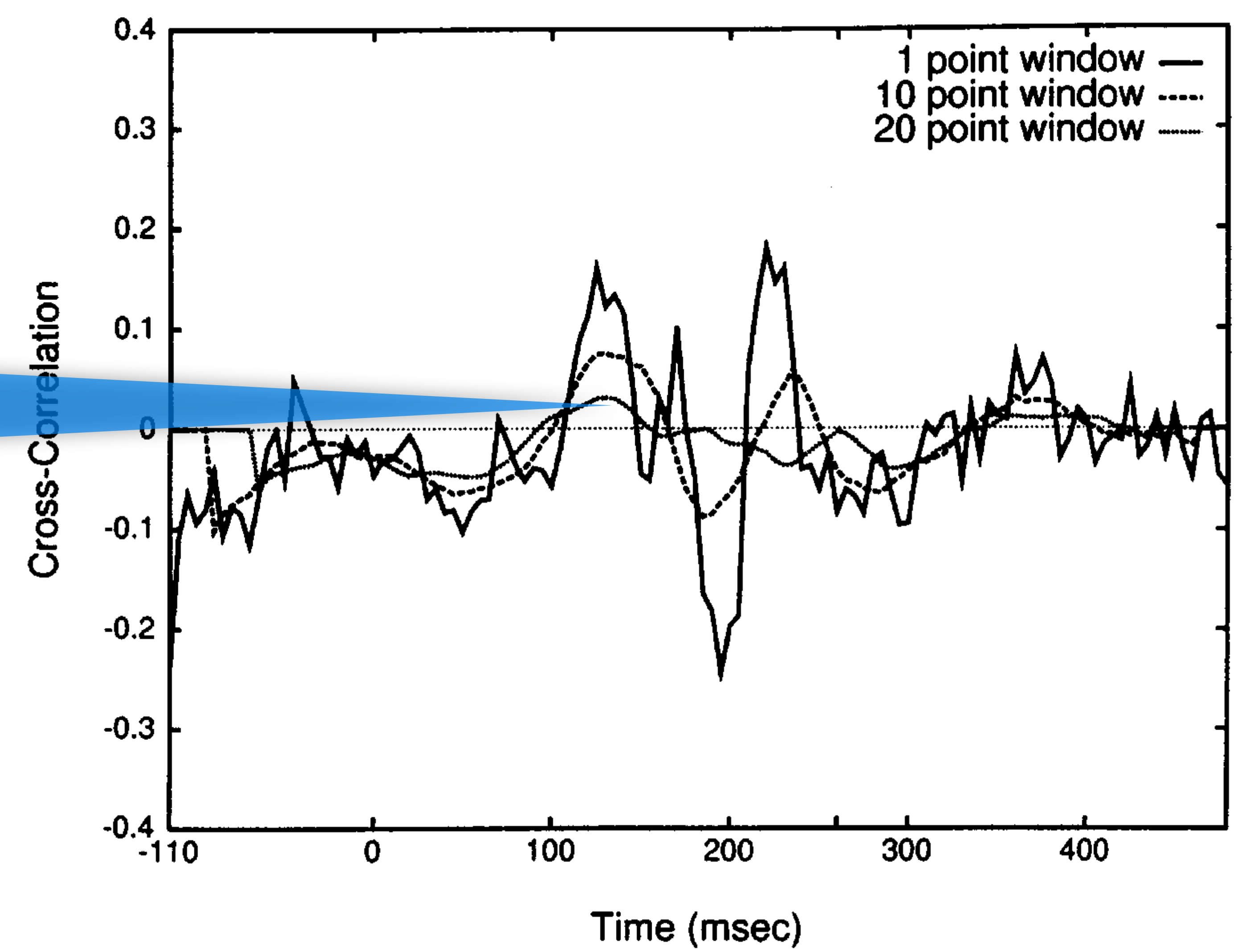
Time-Frequency GC

Consideration: Temporal Smoothness

Too-large windows may smooth out interesting transient dynamic features.

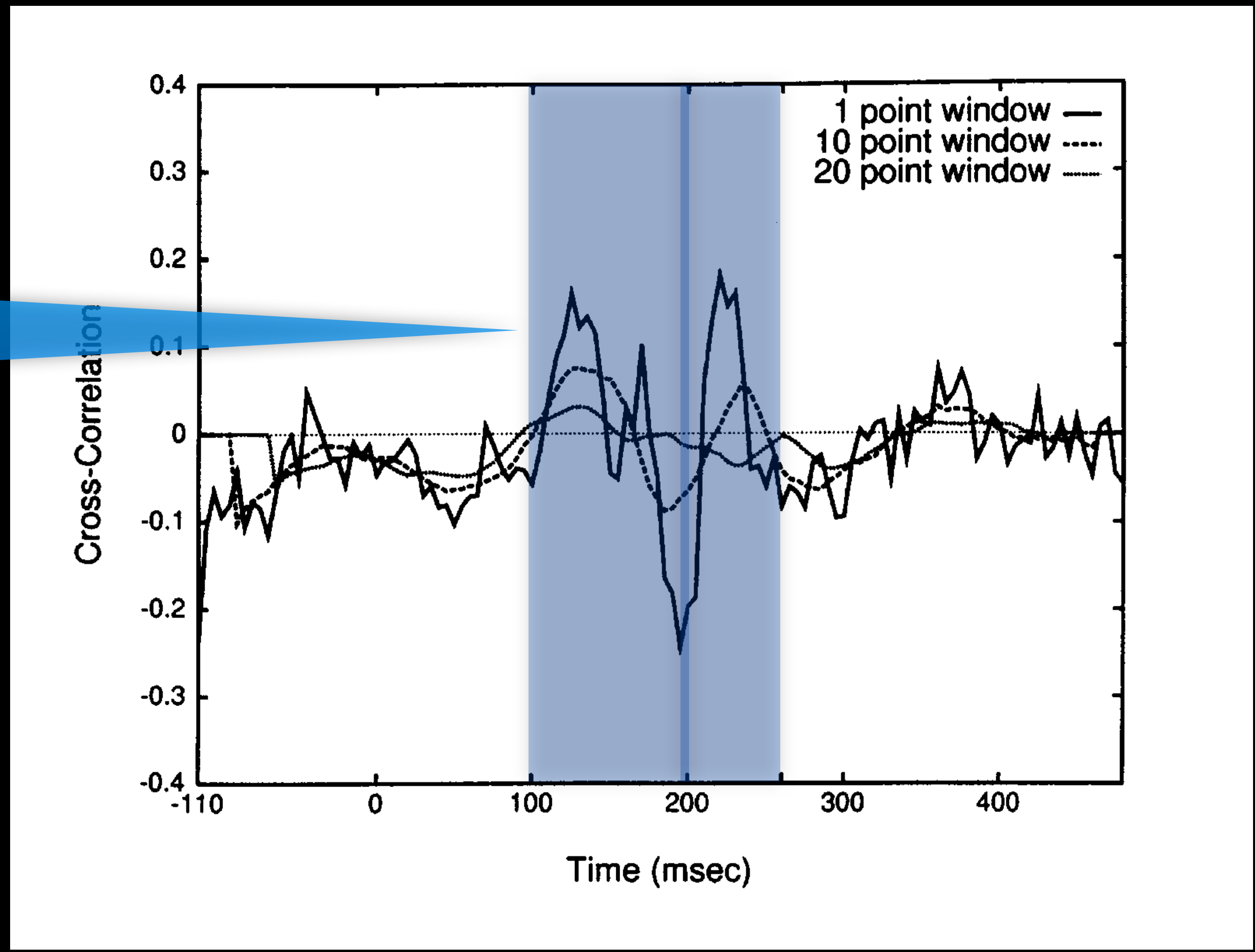


Ding et al, 2000

Time-Frequency GC

Consideration: Local Stationarity

Too-large windows may not be locally-stationary



Time-Frequency GC

Consideration: Sufficient data

M = number of variables

p = model order

N_{tr} = number of trials

W = length of each window (sample points)

We have M^2p model coefficients to estimate. This requires a minimum of M^2p independent samples.
So we have the constraint $M^2p <= N_{tr} W$.
In practice, however, a better heuristic is $M^2p <= (1/10)N_{tr} W$.

Or: **$W >= 10(M^2p/N_{tr})$**

10x more data points than parameters to estimate

SIFT will let you know if your window length is not optimal

Time-Frequency GC

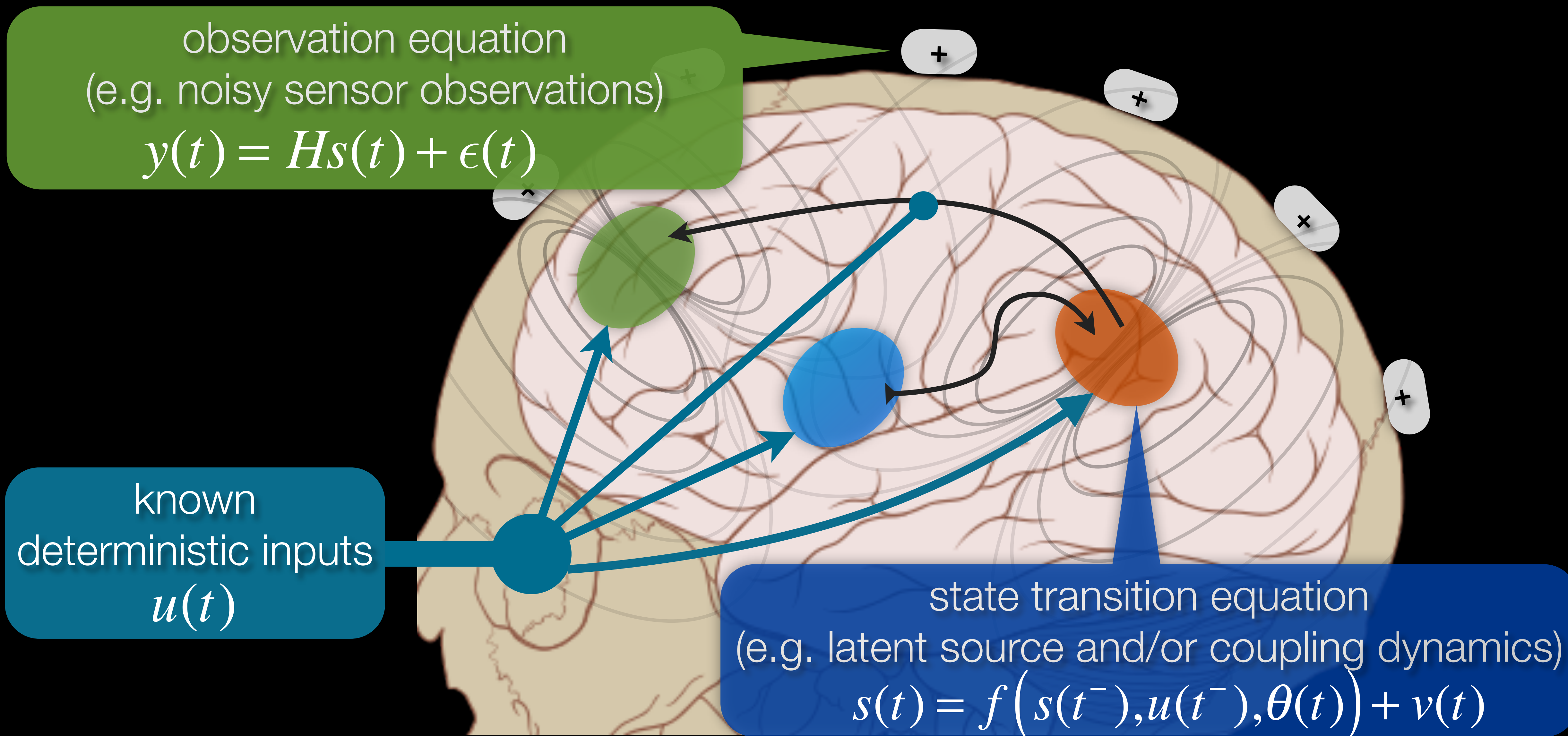
Consideration: Process dynamics

- Your window must be larger than the maximum expected interaction time lag between any two processes.
- Your window should be large enough to span ~1 cycle of the lowest frequency of interest (remember the Heisenberg uncertainty principle)

Time-Frequency GC

- **Many ways to do time-varying VAR estimation**
  - Segmentation-based adaptive VAR estimation
  - Factorization of time-varying spectral density matrices (e.g. from STFTs, Wavelets, etc)
  - State-Space Modeling
  - ...

Discrete State-Space Model (SSM) for Electrophysiological Dynamics

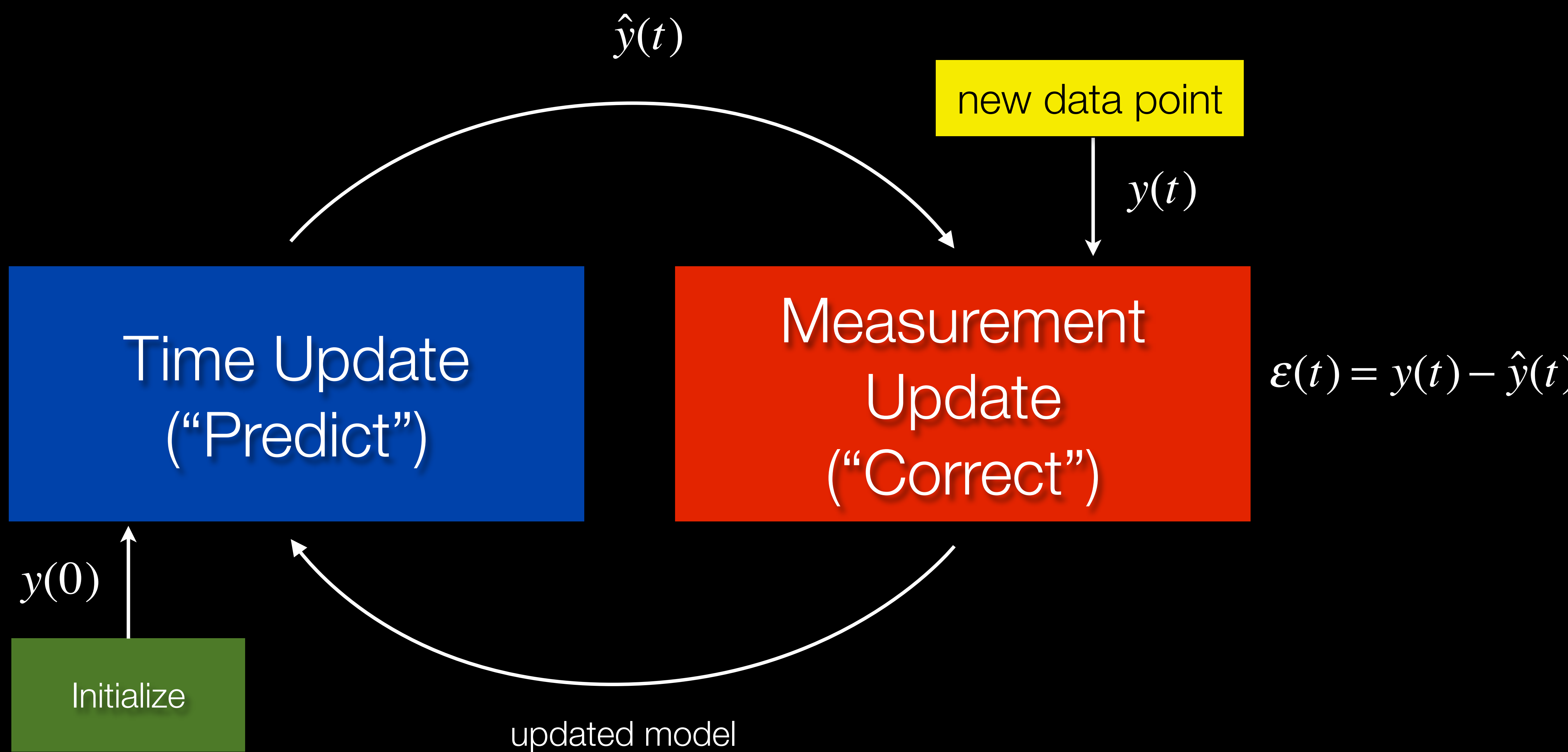


Linear VAR[1] $\Rightarrow$ $s(t) = \mathbf{A}(t)s(t-1) + v(t)$

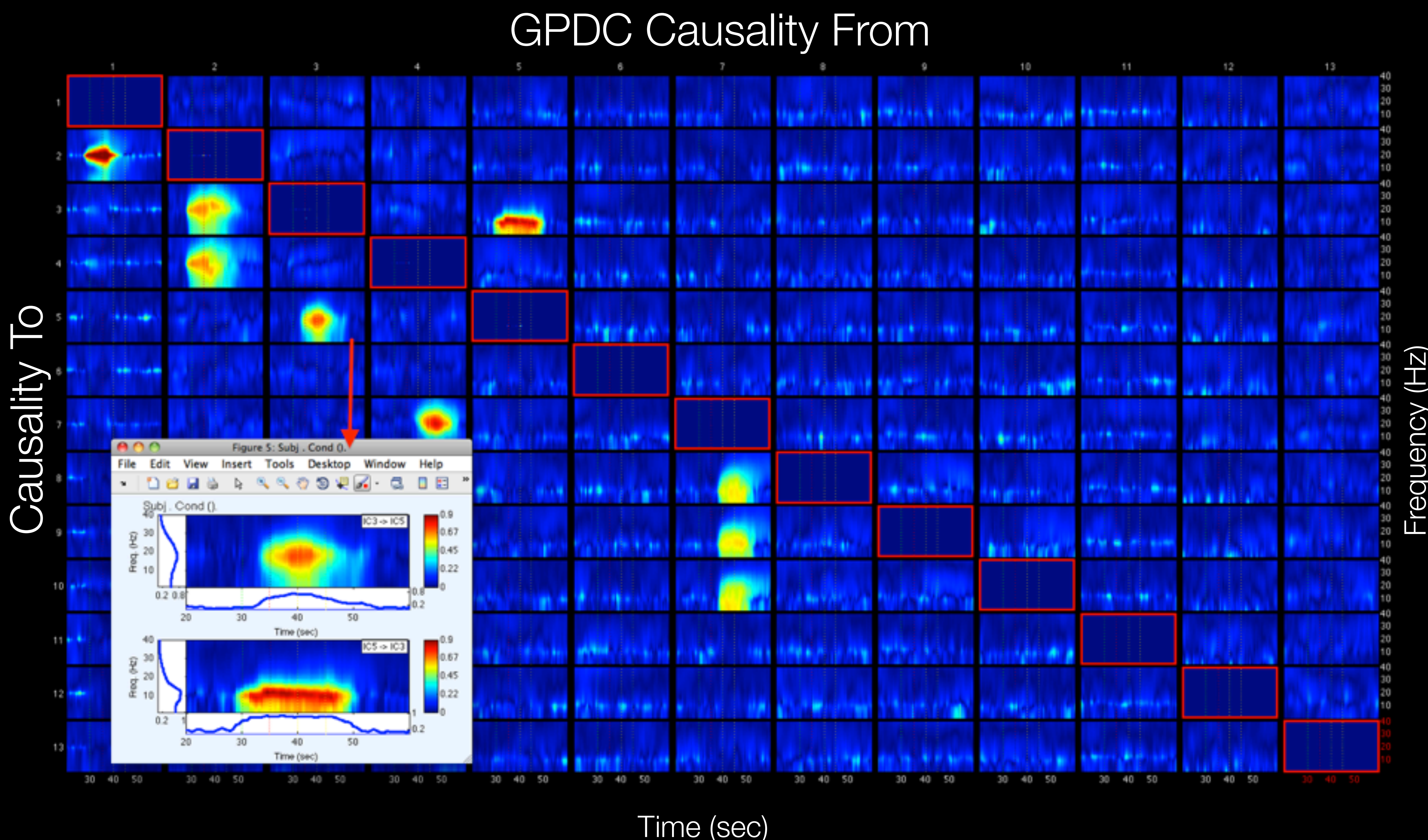
- Dynamical system may be linear or nonlinear, dense or sparse, non-stationary, high-dimensional, partially-observed, and stochastic
- Subsumes discrete Delay Differential Equation (DDE) and Vector Autoregressive (VAR) methods and closely related to Dynamic Causal Modeling (DCM)

Kalman Filtering

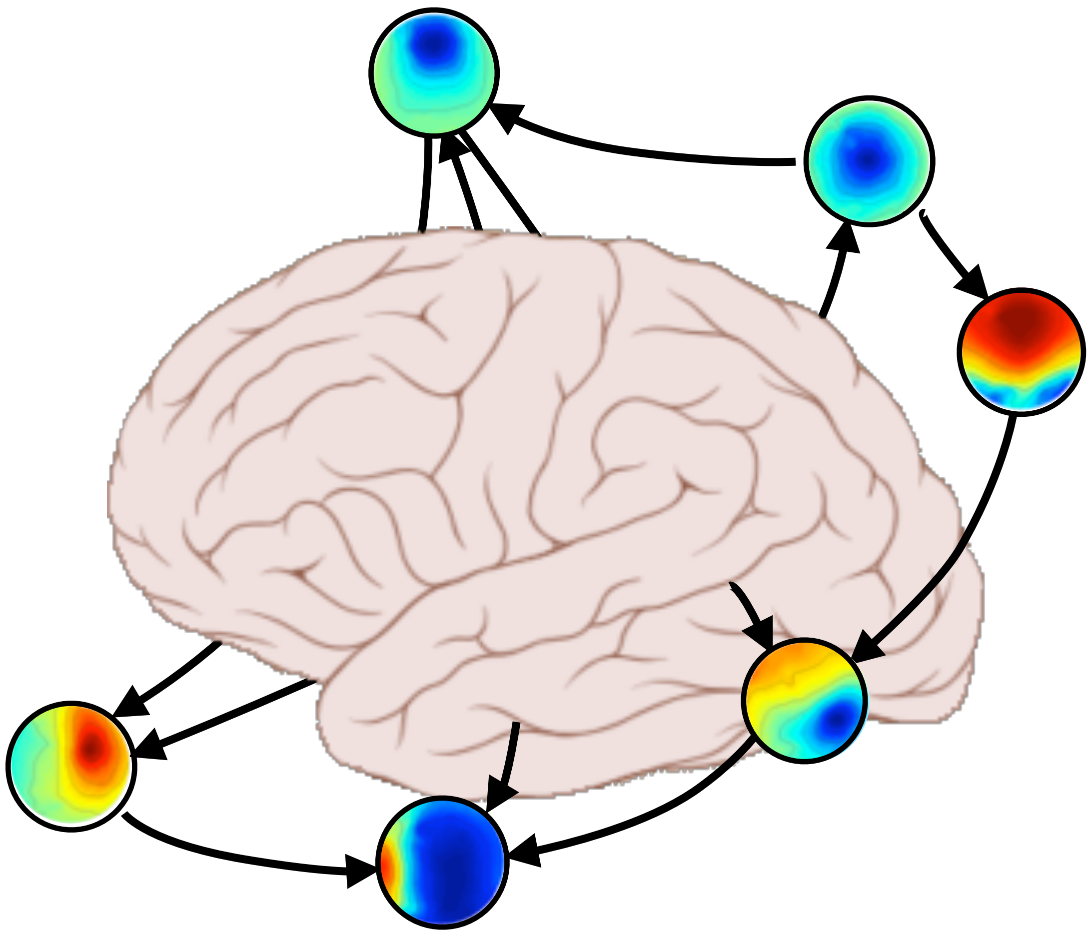
optimal estimator (in terms of minimum variance) for the state of a linear dynamical system

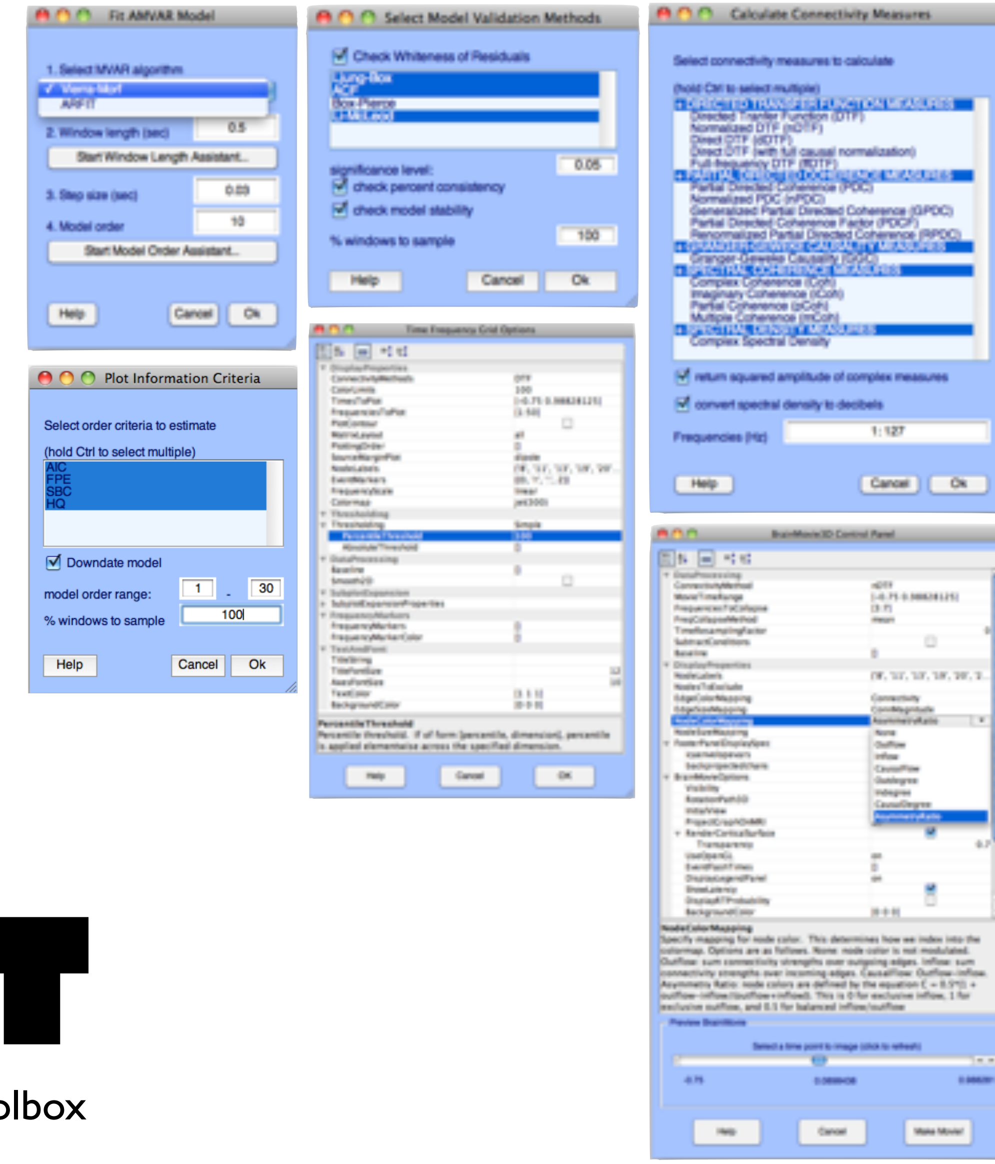


Kalman Filtering



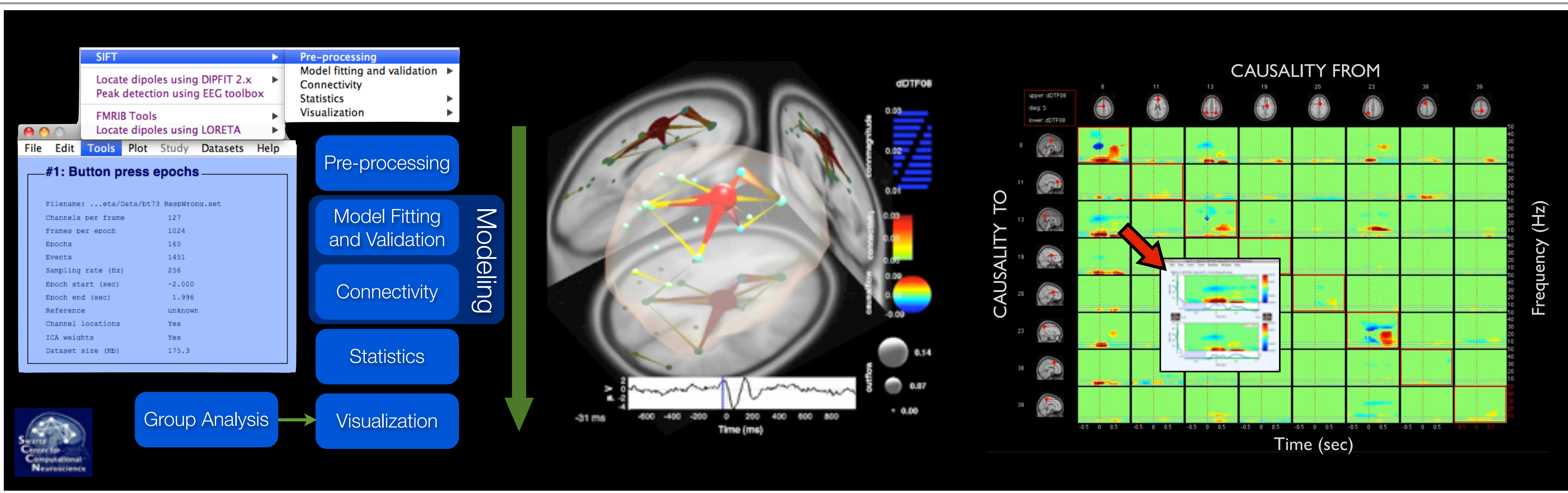
http://sccn.ucsd.edu/wiki/SIFT
Mullen, et al, *Journal of Neuroscience Methods* (in prep, 2012)
Mullen, et al, *Society for Neuroscience*, 2010
Delorme, Mullen, Kothe et al, *Computational Intelligence and Neuroscience*, vol 12, 2011



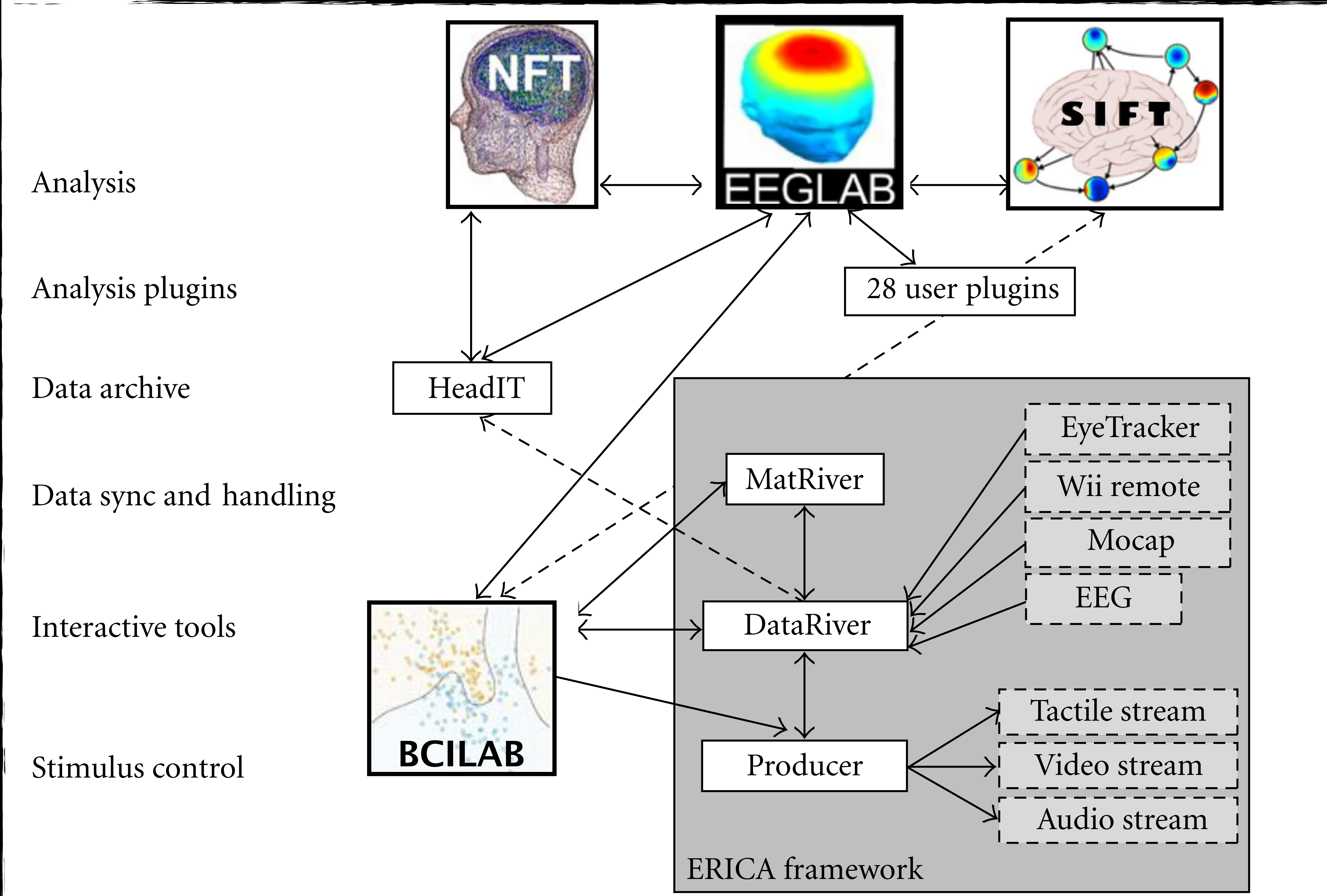


SIFT

Source Information Flow Toolbox



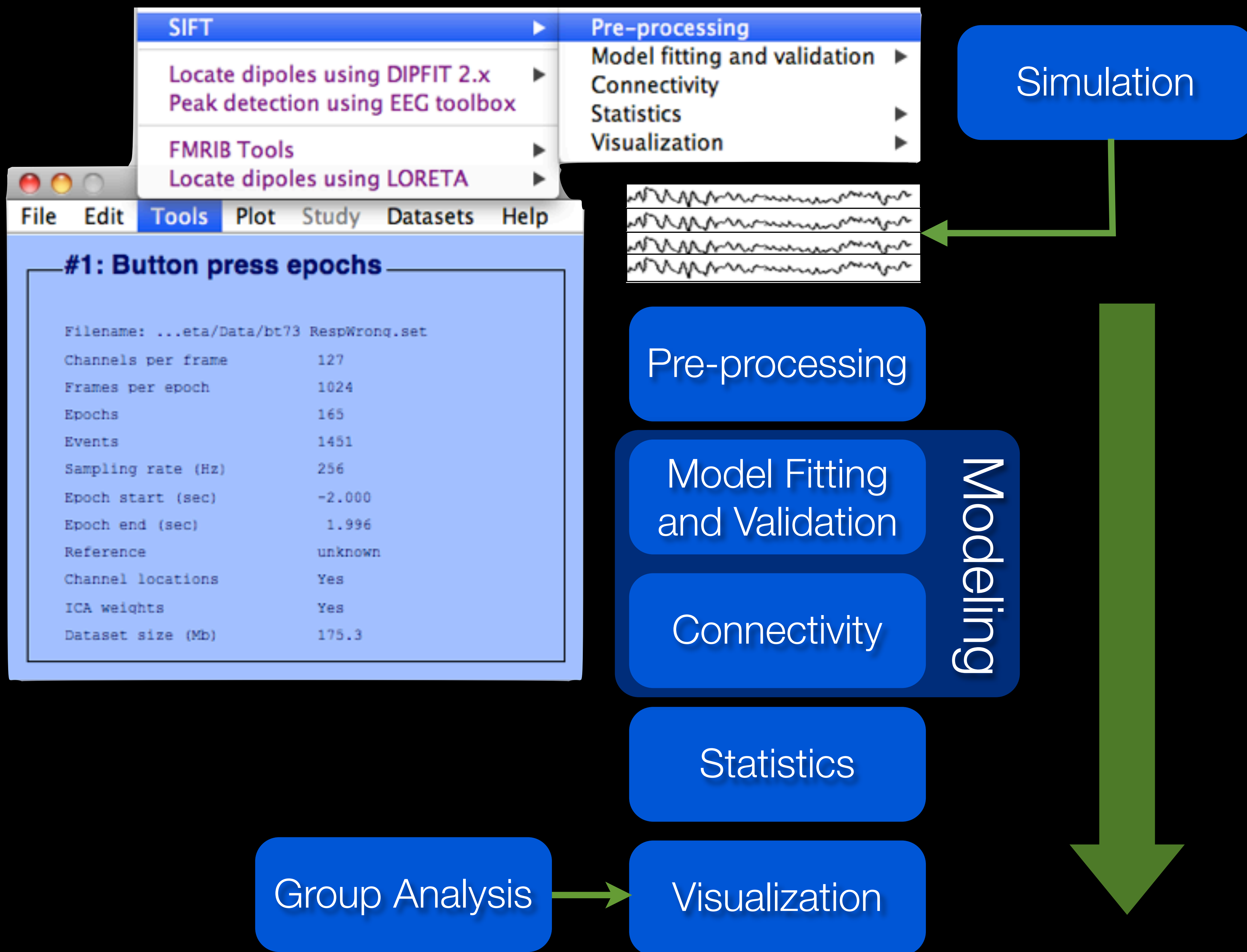
EEGLAB Software framework



Delorme, Mullen, Kothe, Akalin Acar, Bigdely-Shamlo, Vankov, Makeig, *Computational Intelligence and Neuroscience*, 2011

Source Information Flow Toolbox (SIFT)

- A toolbox for (source-space) electrophysiological information flow and causality analysis (single- or multi-subject) integrated into the EEGLAB software environment.
- Modular architecture intended to support multiple modeling approaches
- Emphasis on vector autoregression and SSMs and time-frequency domain approaches
- Standard and novel interactive visualization methods for exploratory analysis of connectivity across time, frequency, and spatial location
- **Requirements**: EEGLAB, MATLAB™ 2008a+, Signal Processing Toolbox, Statistics Toolbox (for some functions -- may be removed in the future)


SIFT
Locate dipoles using DIPFIT 2.x
Peak detection using EEG toolbox
FMRIB Tools
Locate dipoles using LORETA
Pre-processing
Model fitting and validation
Connectivity
Statistics
Visualization
File Edit Tools Plot Study Datasets Help
#1: Button press epochs
Filename: ...eta/Data/bt73 RespWrong.set
Channels per frame 127
Frames per epoch 1024
Epochs 165
Events 1451
Sampling rate (Hz) 256
Epoch start (sec) -2.000
Epoch end (sec) 1.996
Reference unknown
Channel locations Yes
ICA weights Yes
Dataset size (Mb) 175.3
Simulation
Pre-processing
Model Fitting and Validation
Connectivity
Modeling
Statistics
Group Analysis
Visualization

Preprocessing | Modeling | Statistics | Visualization

SIFT | Apps | To-Do | Fin

Source reconstruction
(performed externally using EEGLAB or other toolboxes)

Filtering or Local Detrending

Downsampling

Differencing

Normalization (temporal or ensemble)

Trial balancing

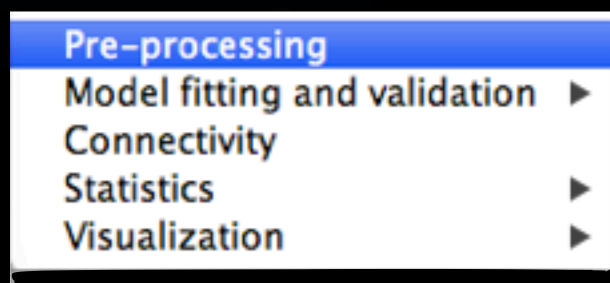
Preprocessing | Modeling | Statistics | Visualization

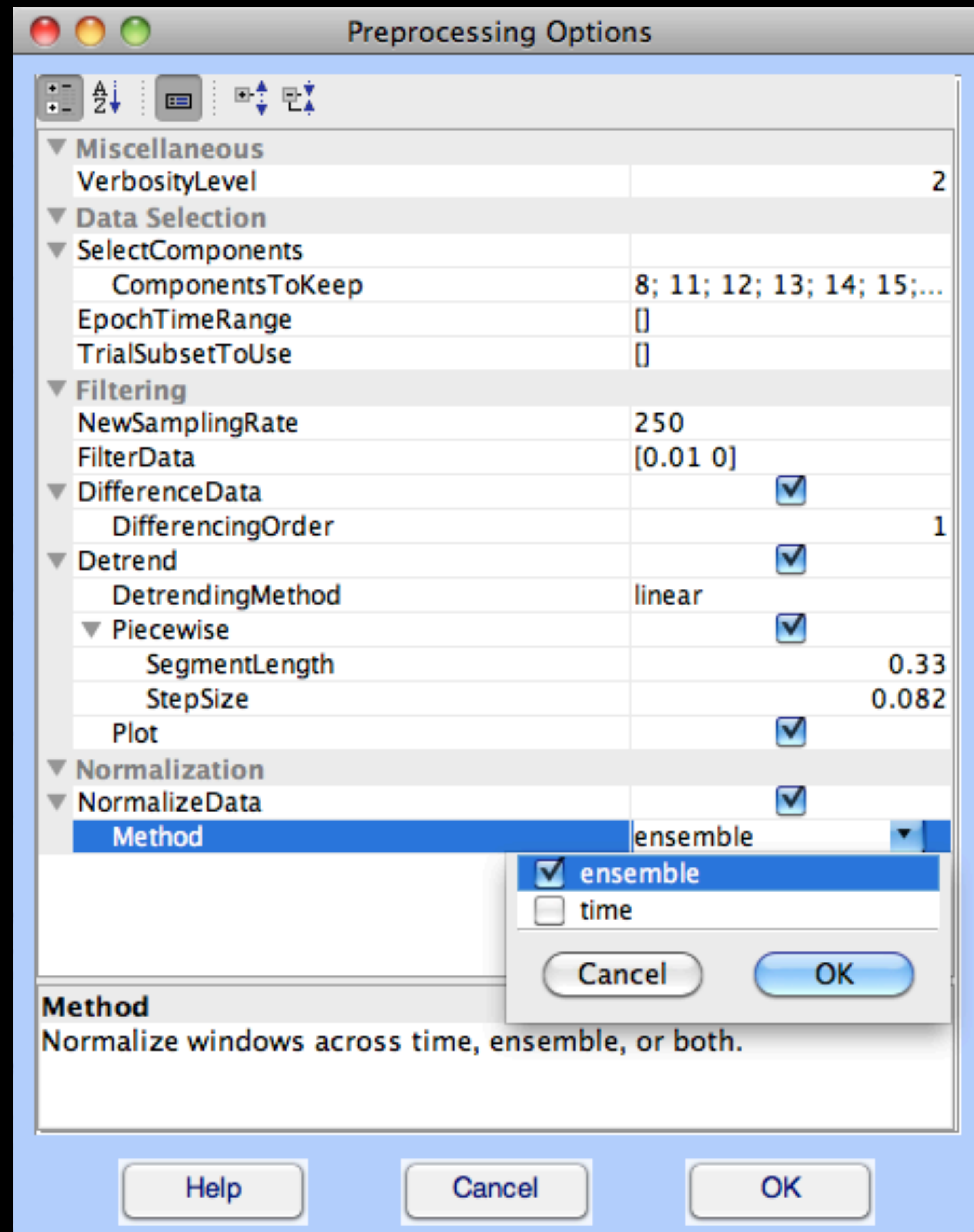
SIFT

Apps

To-Do

Fin





Preprocessing

Modeling

Statistics

Visualization

Model Fitting

Validation

Connectivity

SIFT

Apps

To-Do

Fin

SIFT | Apps | To-Do | Fin

Preprocessing | **Modeling** | Statistics | Visualization

Model Fitting | Validation | Connectivity

Linear	Linear+Nonlinear
VAR Modeling Vieira-Morf, ARFIT	Dual Extended Kalman Filtering
Sparse VAR Group Lasso ($L_{1,2}$), TSBL (L_p)	Cubature Kalman Filtering
Linear Kalman Filtering	Transfer Entropy (TRENTOOL interface)
Nonparametric VAR (minimum-phase spectral matrix factorization)	

fully implemented — alpha-testing — coming soon

Preprocessing | Modeling | Statistics | Visualization

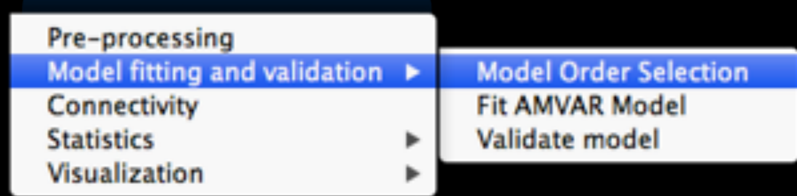
Model Fitting | Validation | Connectivity

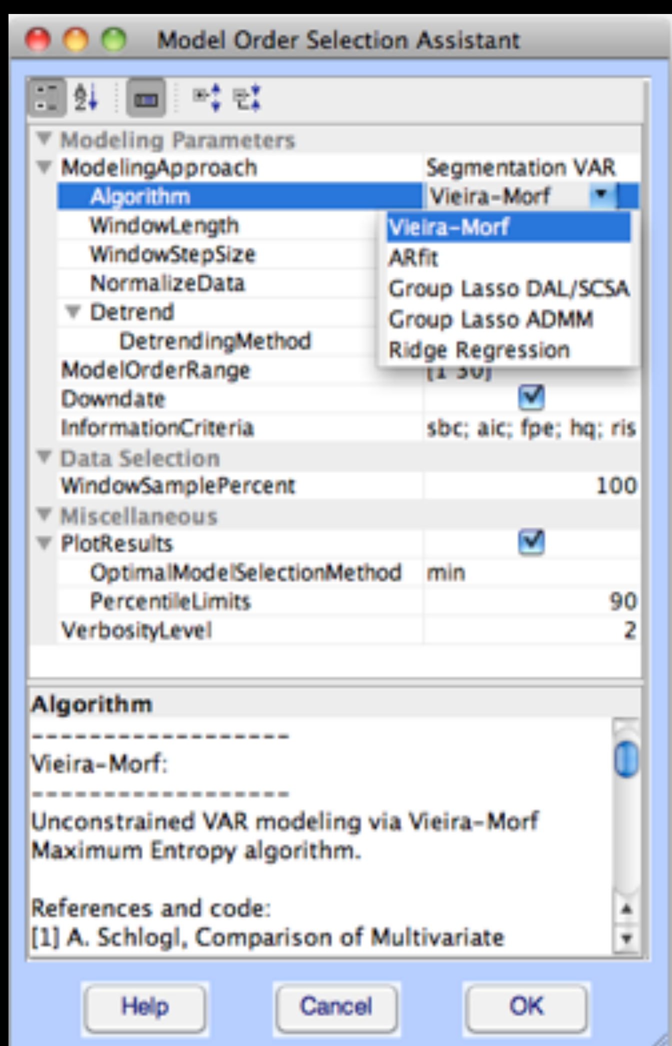
SIFT

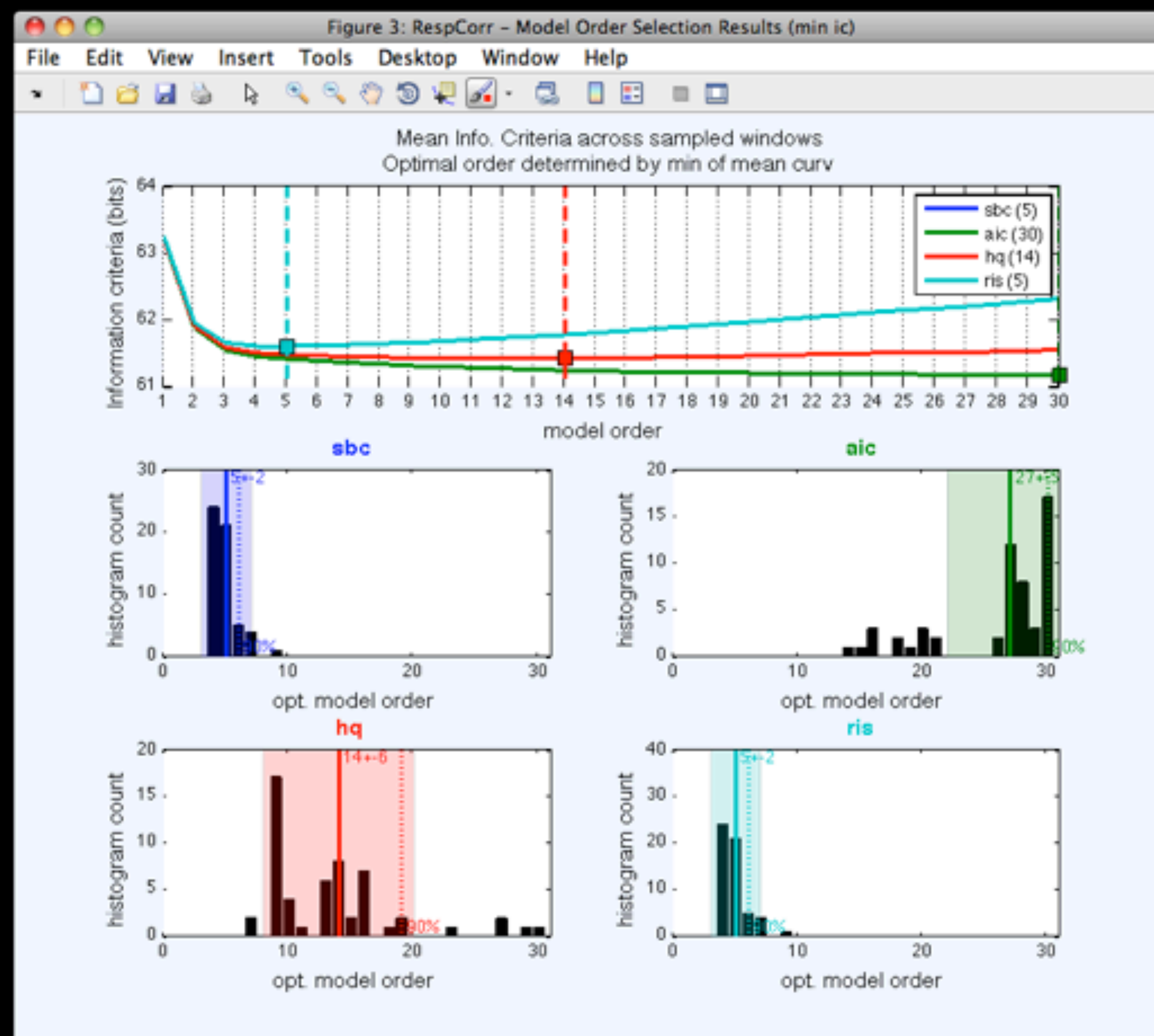
Apps

To-Do

Fin







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Preprocessing

Modeling

Statistics

Visualization

Model Fitting

Validation

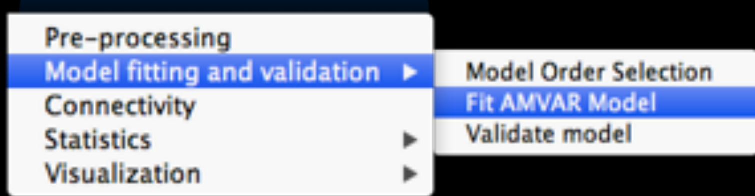
Connectivity

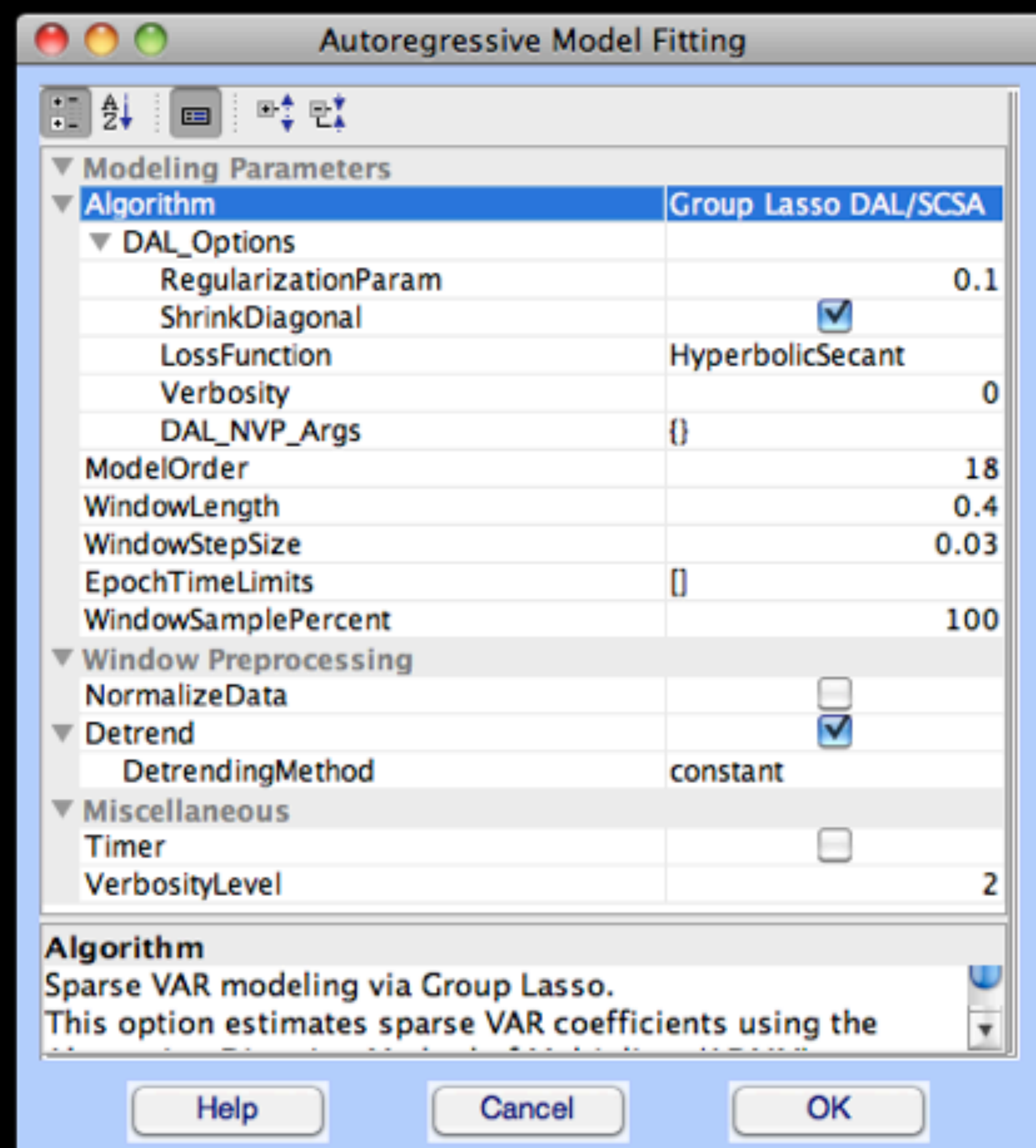
SIFT

Apps

To-Do

Fin





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Preprocessing | Modeling | Statistics | Visualization

Model Fitting | Validation | Connectivity

SIFT | Apps | To-Do | Fin

VAR Model Validation
Residual 'Whiteness' Tests
Multivariate portmanteau tests
Residual autocorrelation probability test
Model Consistency
Model Stability
Nonparametric Spectral/Coherence Correlation

fully implemented | alpha-testing | coming soon

Preprocessing

Modeling

Statistics

Visualization

Model Fitting

Validation

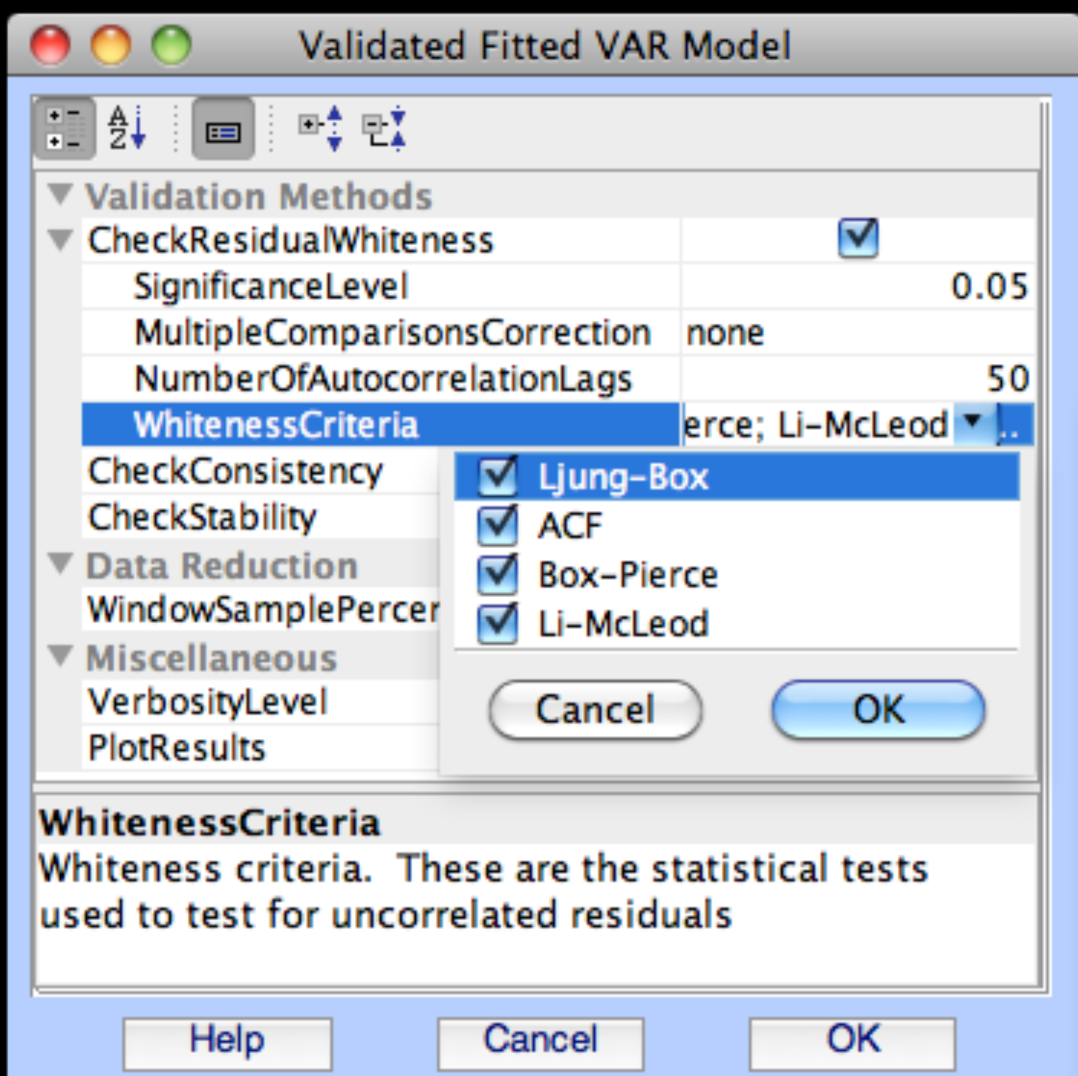
Connectivity

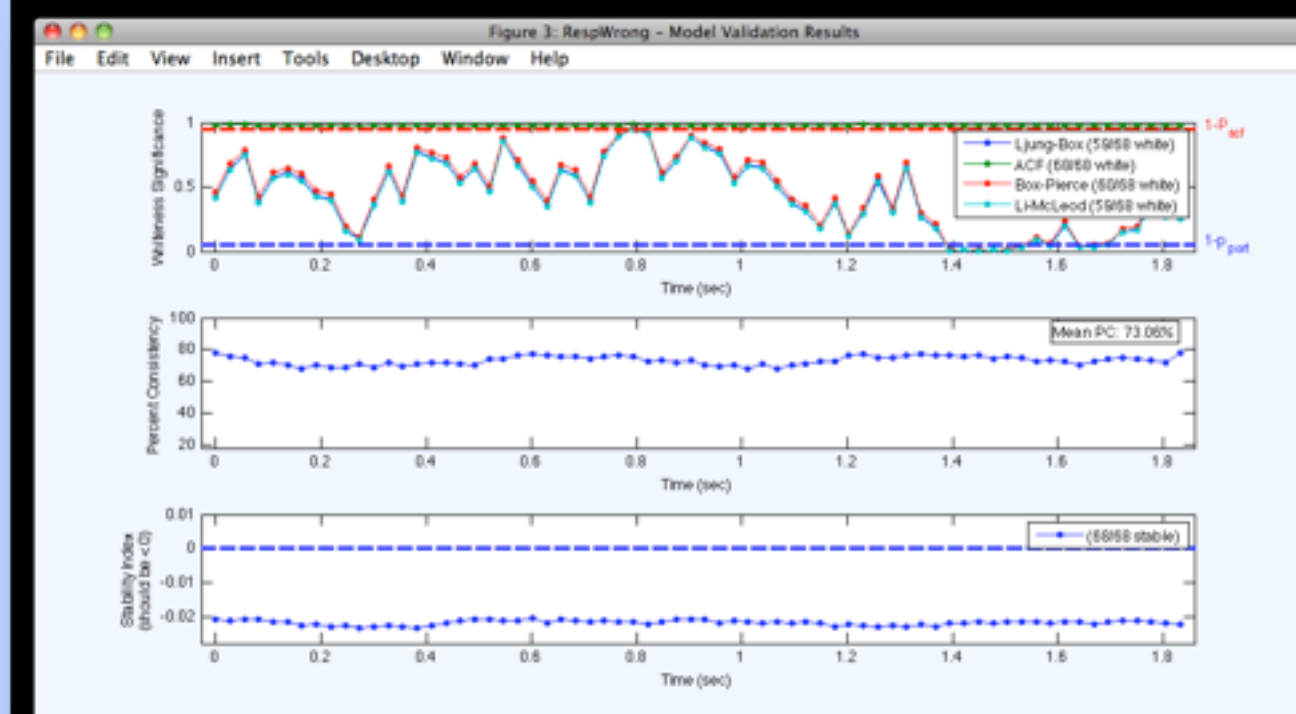
SIFT

Apps

To-Do

Fin





Preprocessing

Modeling

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Connectivity

SIFT

Apps

To-Do

Fin

VAR-based Measures
Power spectrum (ERSP)
Coherence (Coh), Partial Coherence (pCoh), Multiple Coherence (mCoh)
Partial Directed Coherence (PDC)
Generalized PDC (GPDC)
Partial Directed Coherence Factor (PDCF)
Renormalized PDC (rPDC)
Directed Transfer Function (DTF)
Direct Directed Transfer Function (dDTF)
Bivariate Granger-Geweke Causality (GGC)
Conditional GGC
Blockwise GGC

fully implemented

alpha-testing

coming soon

Preprocessing

Modeling

Statistics

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Model Fitting

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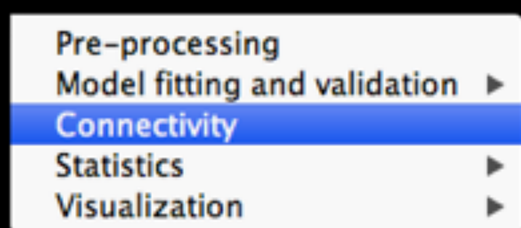
Connectivity

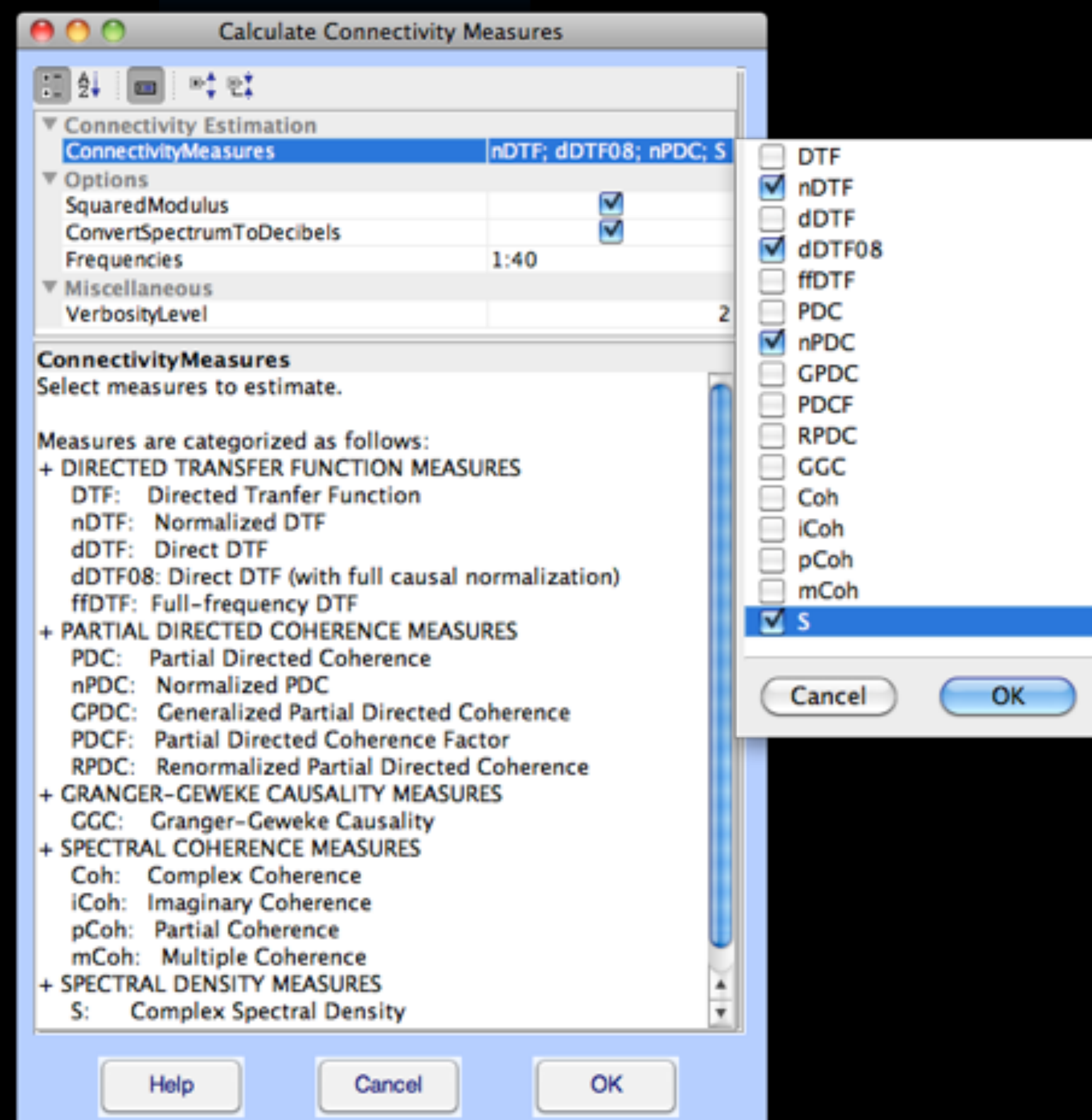
SIFT

Apps

To-Do

Fin





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Preprocessing | Modeling | **Statistics** | Visualization

SIFT | Apps | To-Do | Fin

Parametric	Non-parametric
Asymptotic analytic estimates of confidence intervals Applies to: PDC, nPDC, DTF, nDTF, rPDC Tests: H_{null}, H_{base}, H_{AB} Confidence intervals using Bayesian smoothing splines Applies to: all Tests: H_{base}, H_{AB}	Phase-randomization Applies to: all Tests: H_{null} Bootstrap, Jacknife, Cross-Validation Applies to: all Tests: H_{AB}, H_{base}

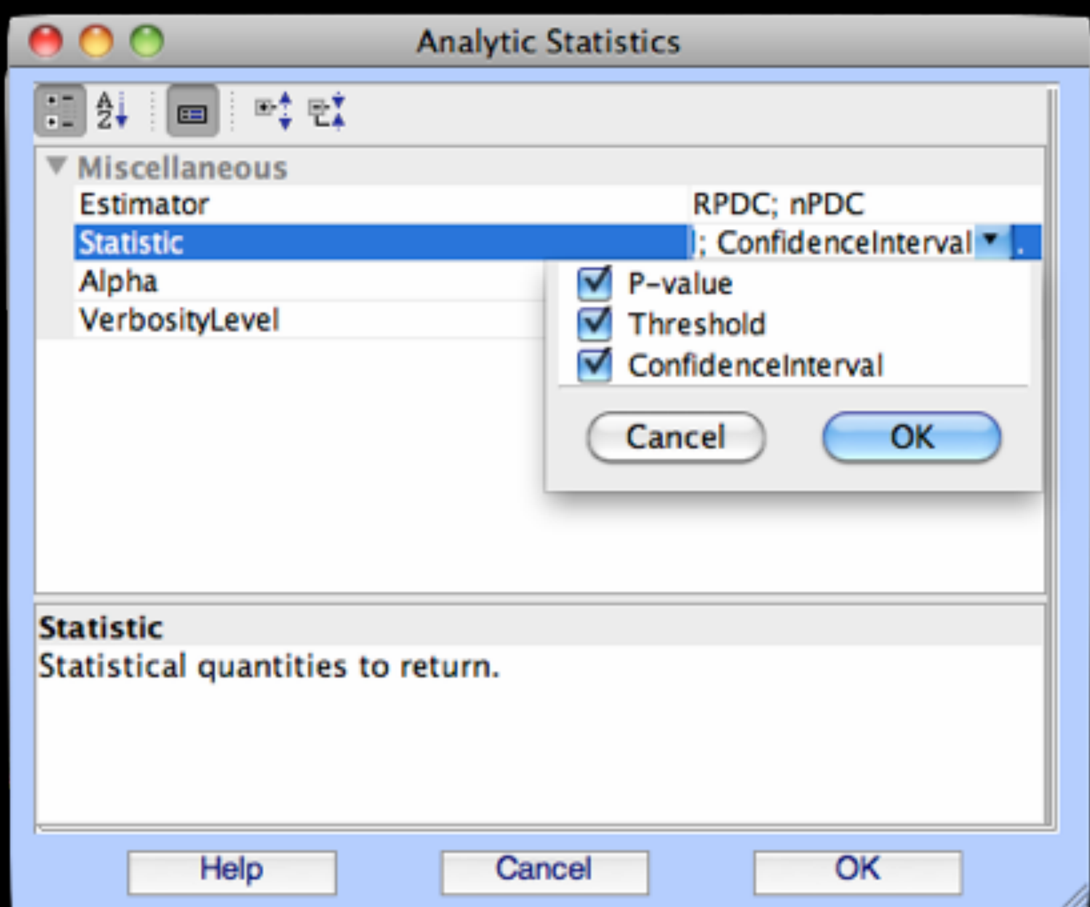
H_{null} : $\mathbf{C}_{ij} \leq \mathbf{C}_{null}$ H_{base}: $\mathbf{C}_{ij} \leq \mathbf{C}_{baseline}$ H_{AB}: $\mathbf{C}^{A}_{ij} = \mathbf{C}^{B}_{ij}$

fully implemented   alpha-testing   coming soon

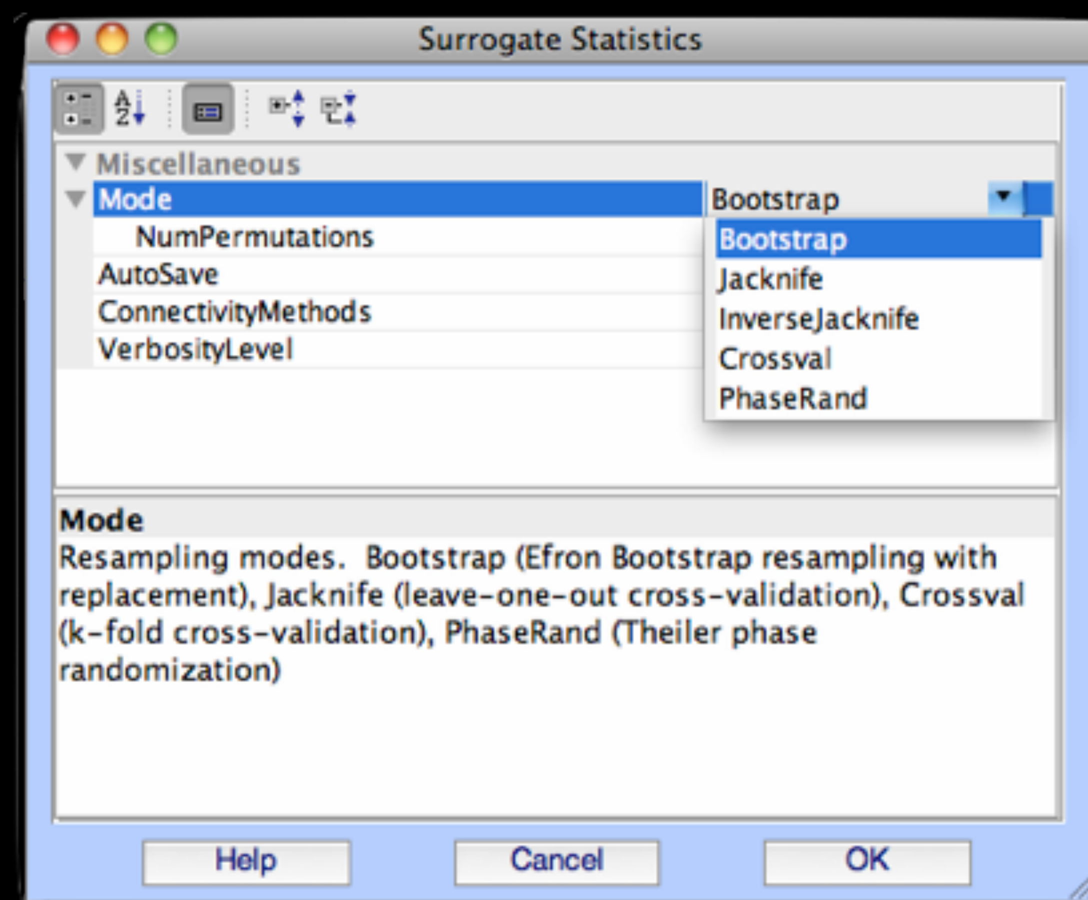
Preprocessing | Modeling | **Statistics** | Visualization

SIFT | Apps | To-Do | Fin

Parametric



Non-parametric



fully implemented | alpha-testing | coming soon

Preprocessing | Modeling | Statistics | **Visualization**

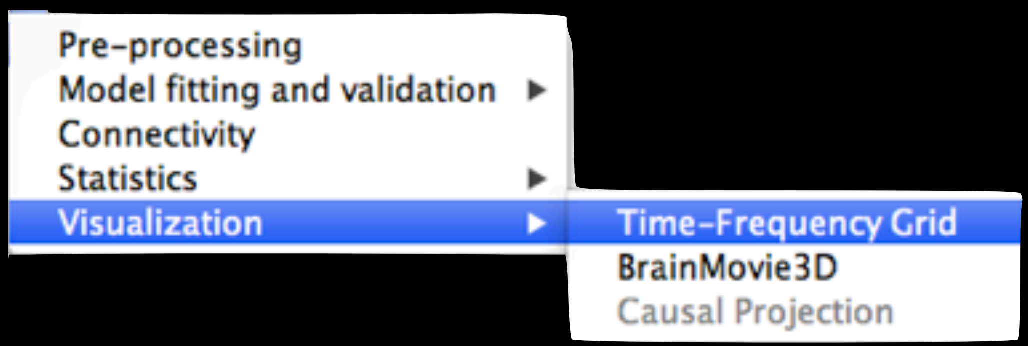
SIFT | Apps | To-Do | Fin

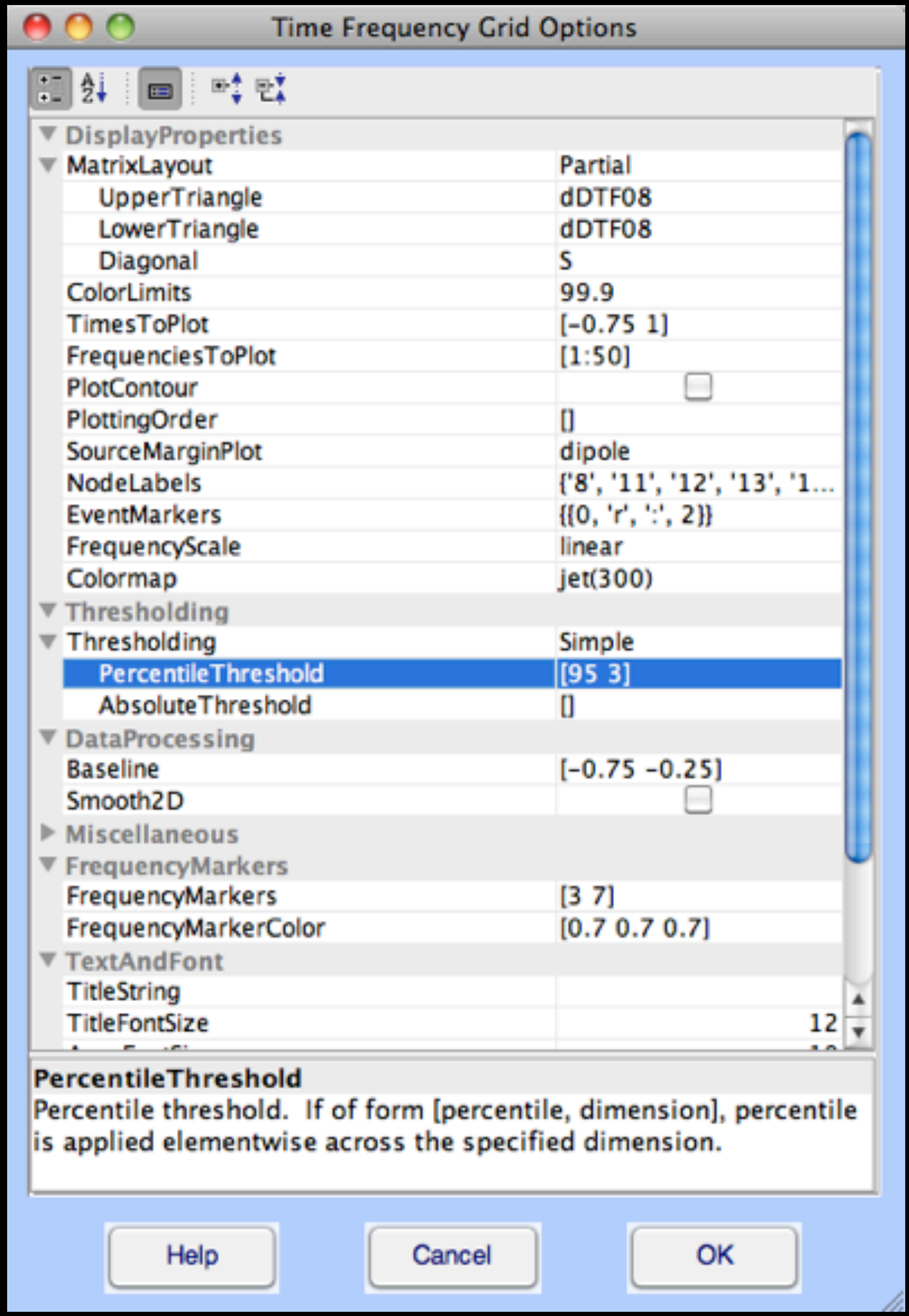
Interactive Visualizers

Interactive Visualizers
Interactive Time-Frequency Grid
Interactive 3D Causal Brainmovie
Causal Projection Movie
Directed Graphs and Graph Theoretic Analysis (Bioinformatics Toolbox Interface)
and more ...

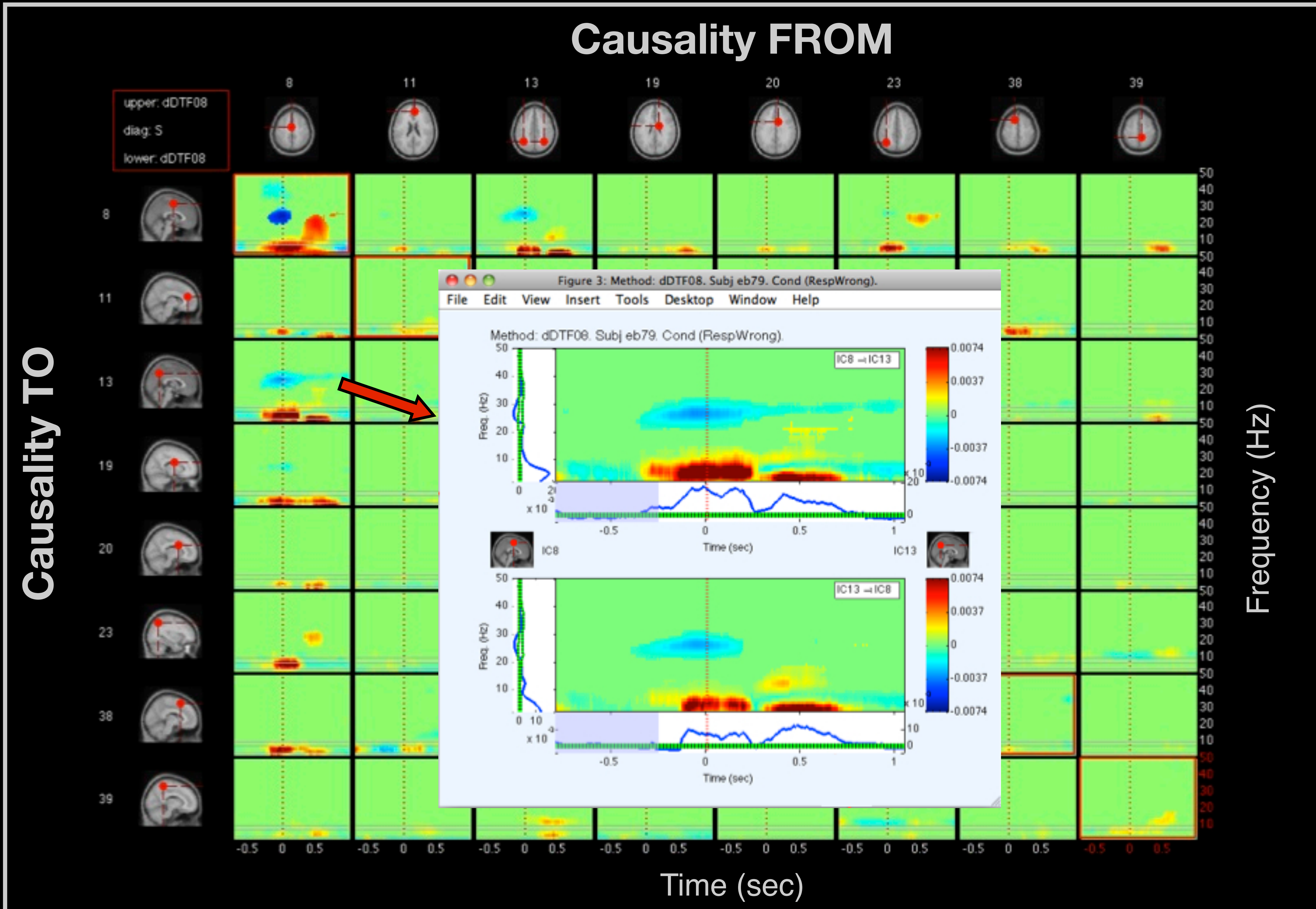
fully implemented   alpha-testing   coming soon

Interactive Time-Frequency Grid

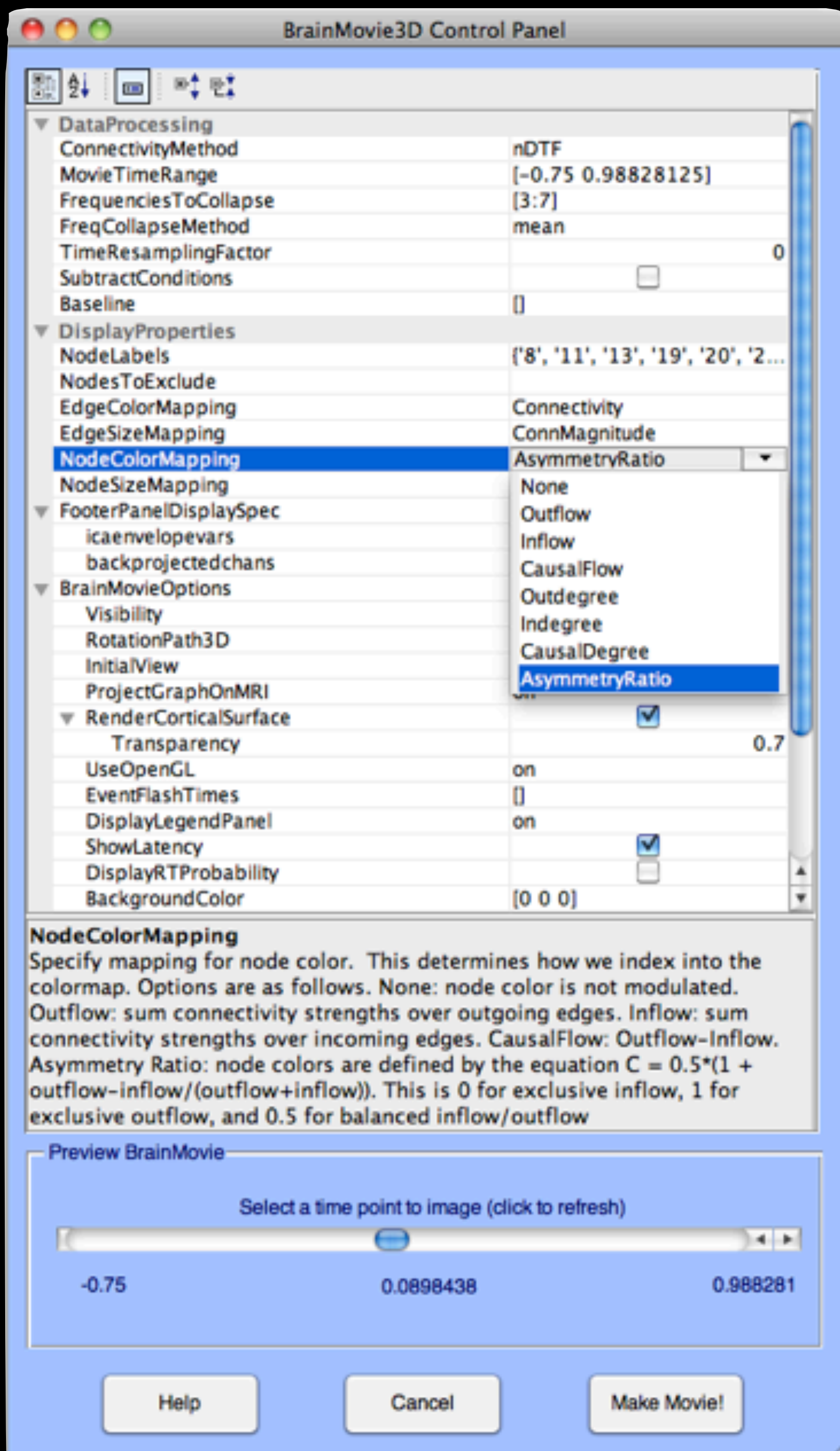


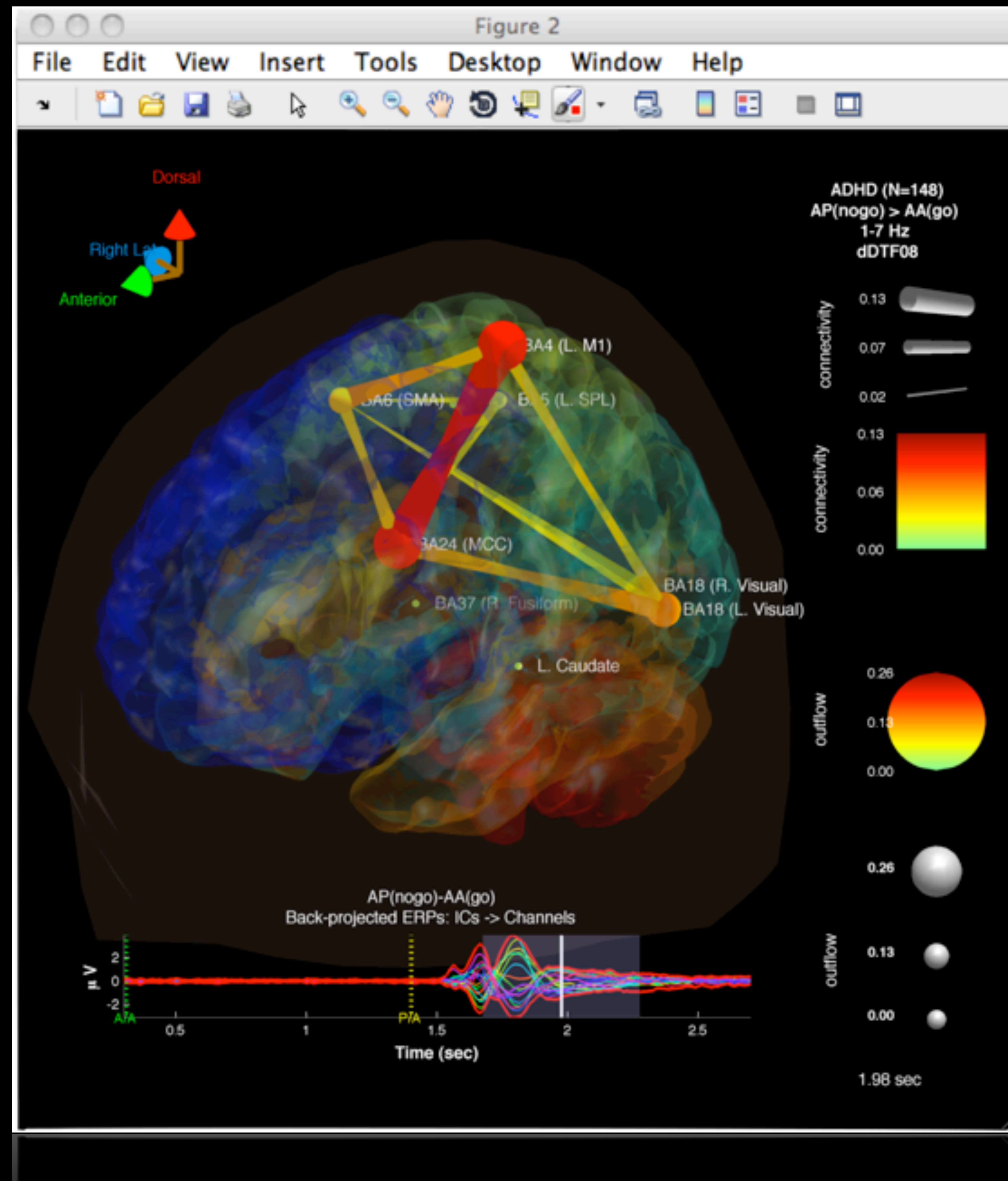


Interactive Time-Frequency Grid

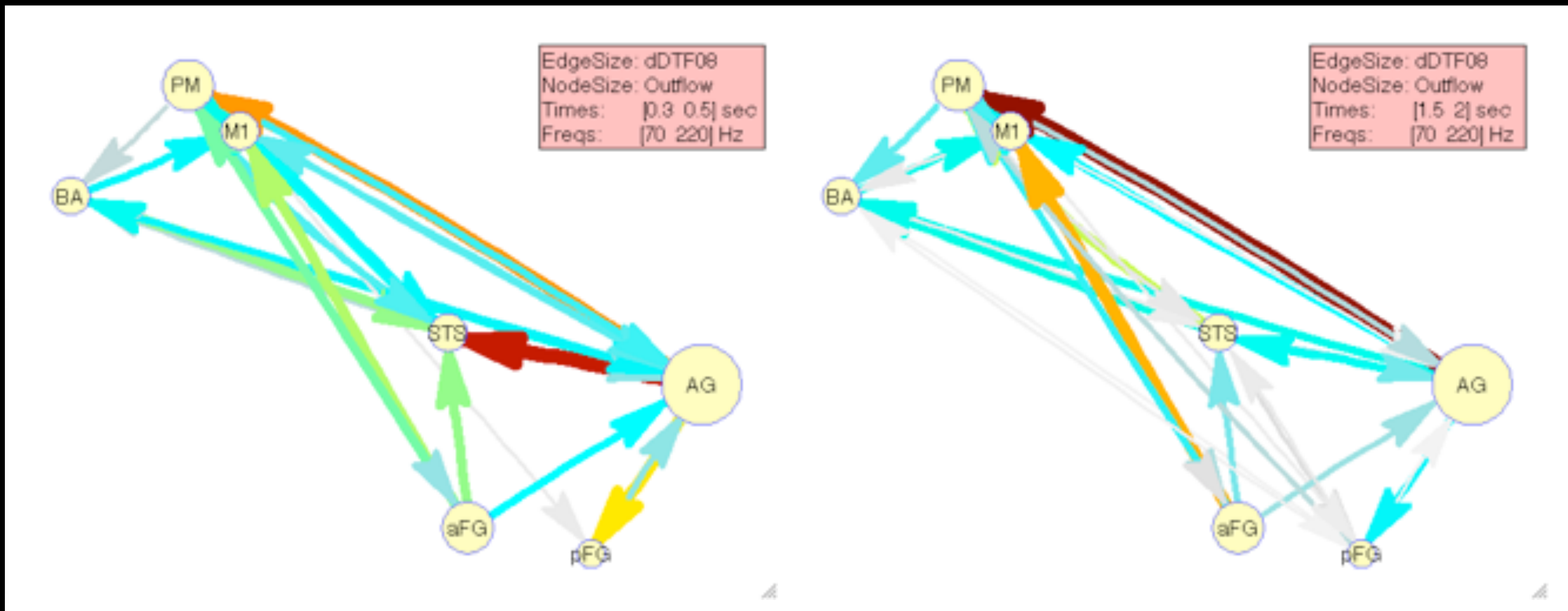


Interactive Causal BrainMovie3D

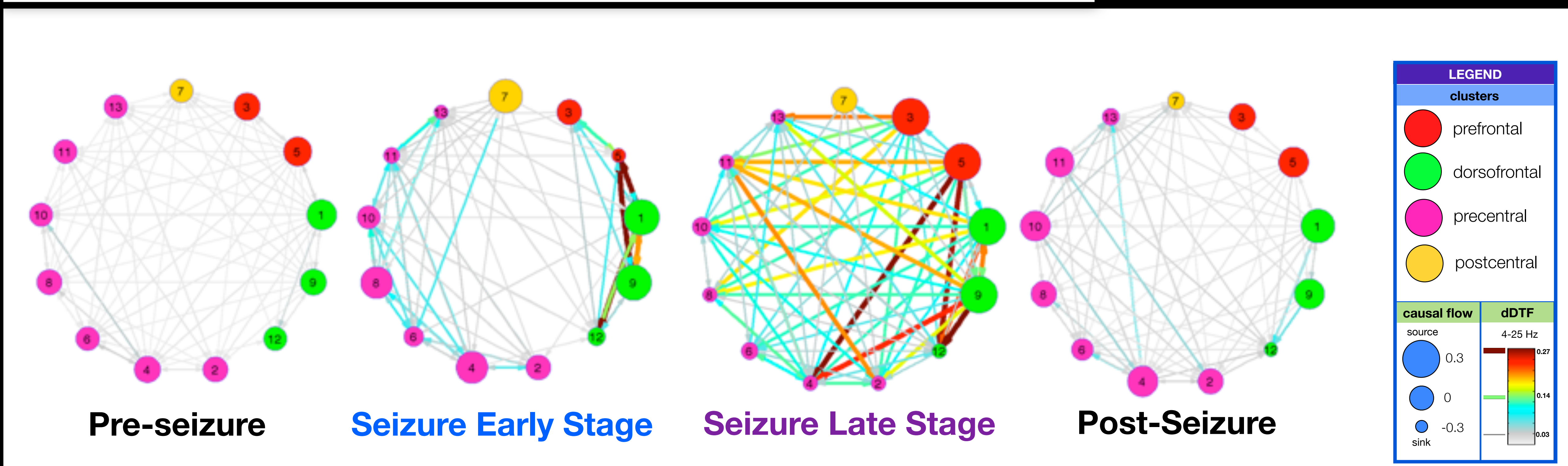




Bioinformatics Toolbox IFace



- Interactive Directed Graphs
- Radial, Hierarchical, or Customized Node Layout
- Graph-Theoretic Analysis (SCCs, Shortest-Path, MaxFlow, etc)
- Assignment of useful quantities to Node and Edge size/color

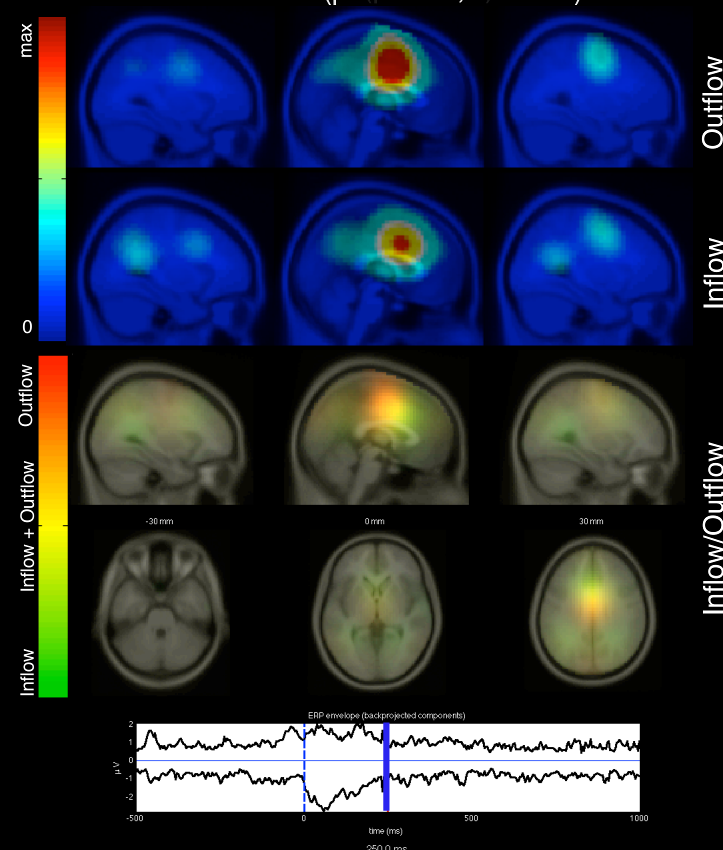


Mullen et al, 2011

alpha-testing

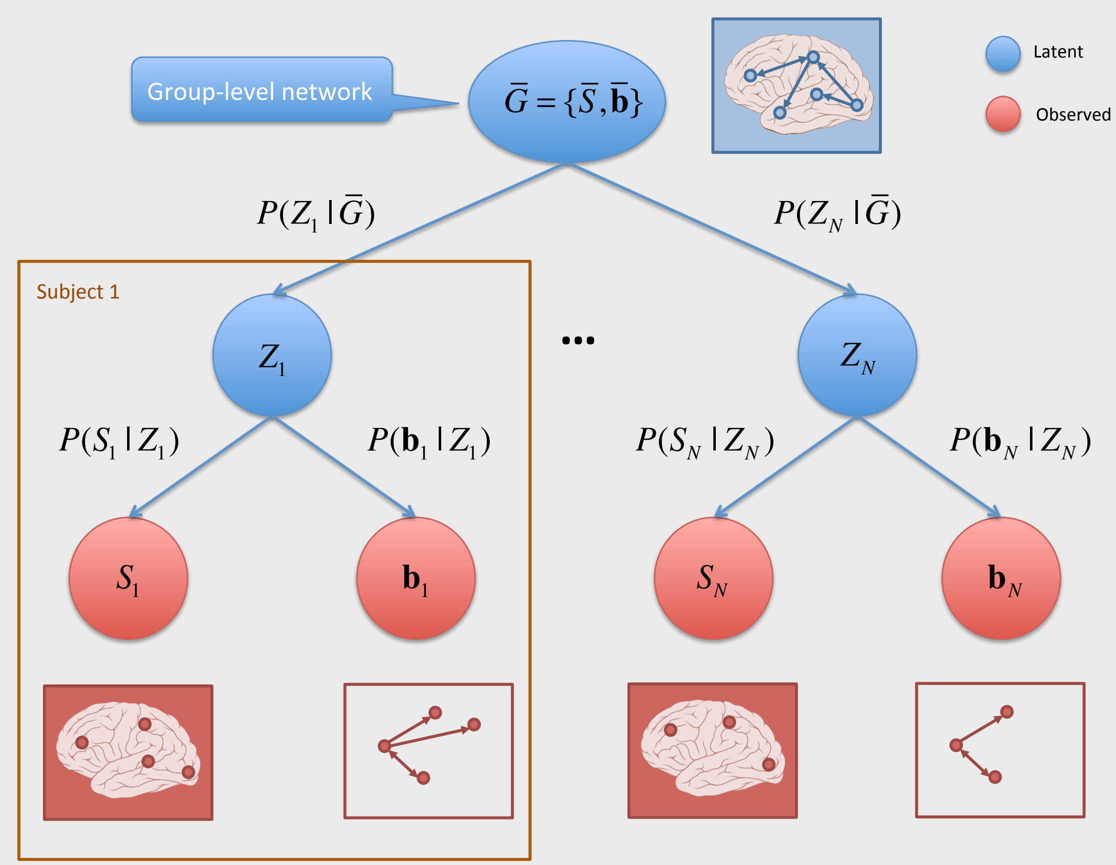
Group Analysis

Causal/Measure Projection



Mullen, Onton, et al, 2010, HBM, Barcelona
Bigdely-Shamlo, Mullen, et al, 2012, *in review*

Bayesian Hierarchical Model



Thompson, Mullen, Makeig, 2011, ICONXI
Thompson, Mullen, Makeig, 2012, *in prep*

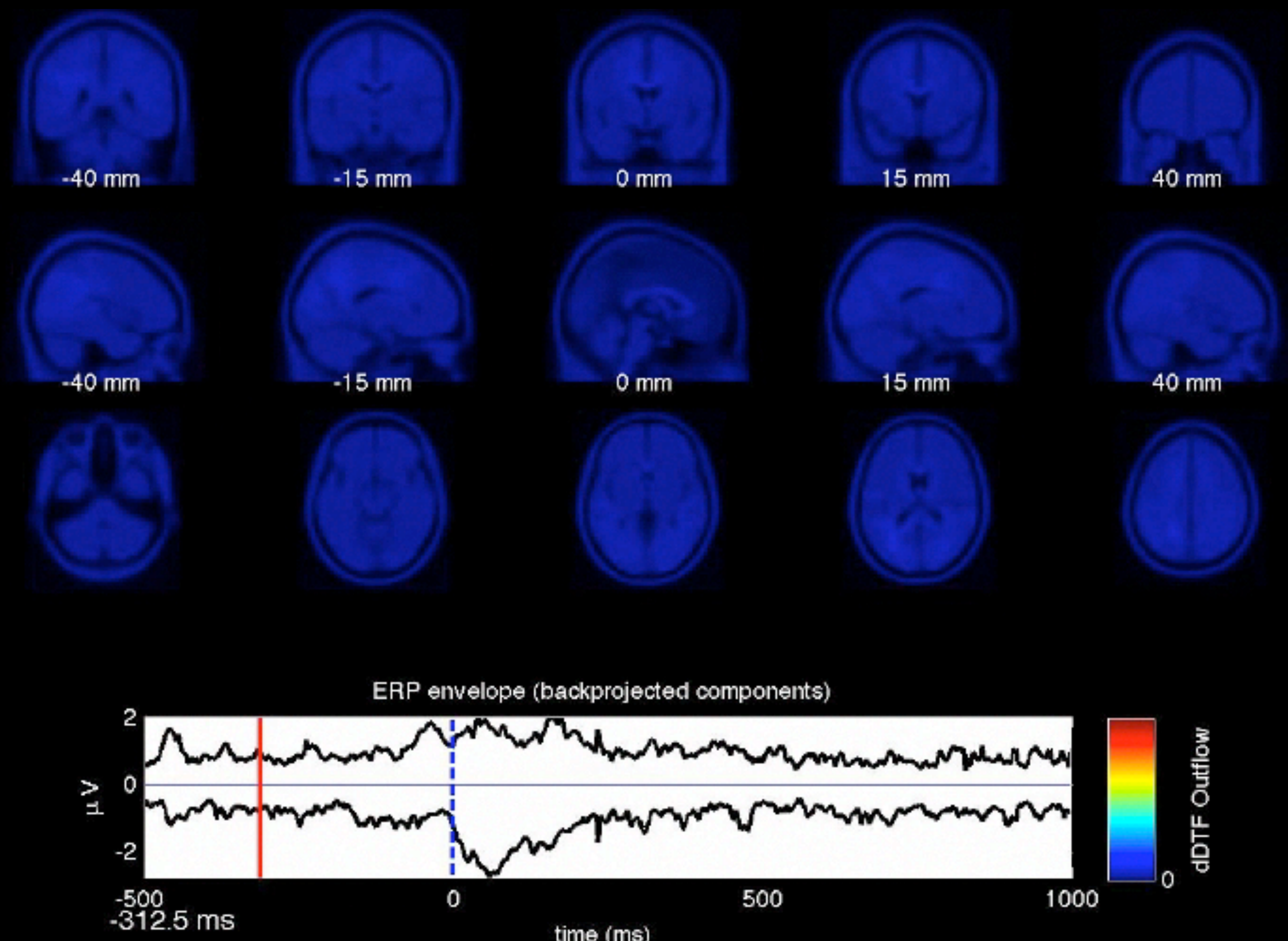
alpha-testing

Causal Projection

Error > Correct ($p < 0.05$, N=24)

dDTF

3-7 Hz

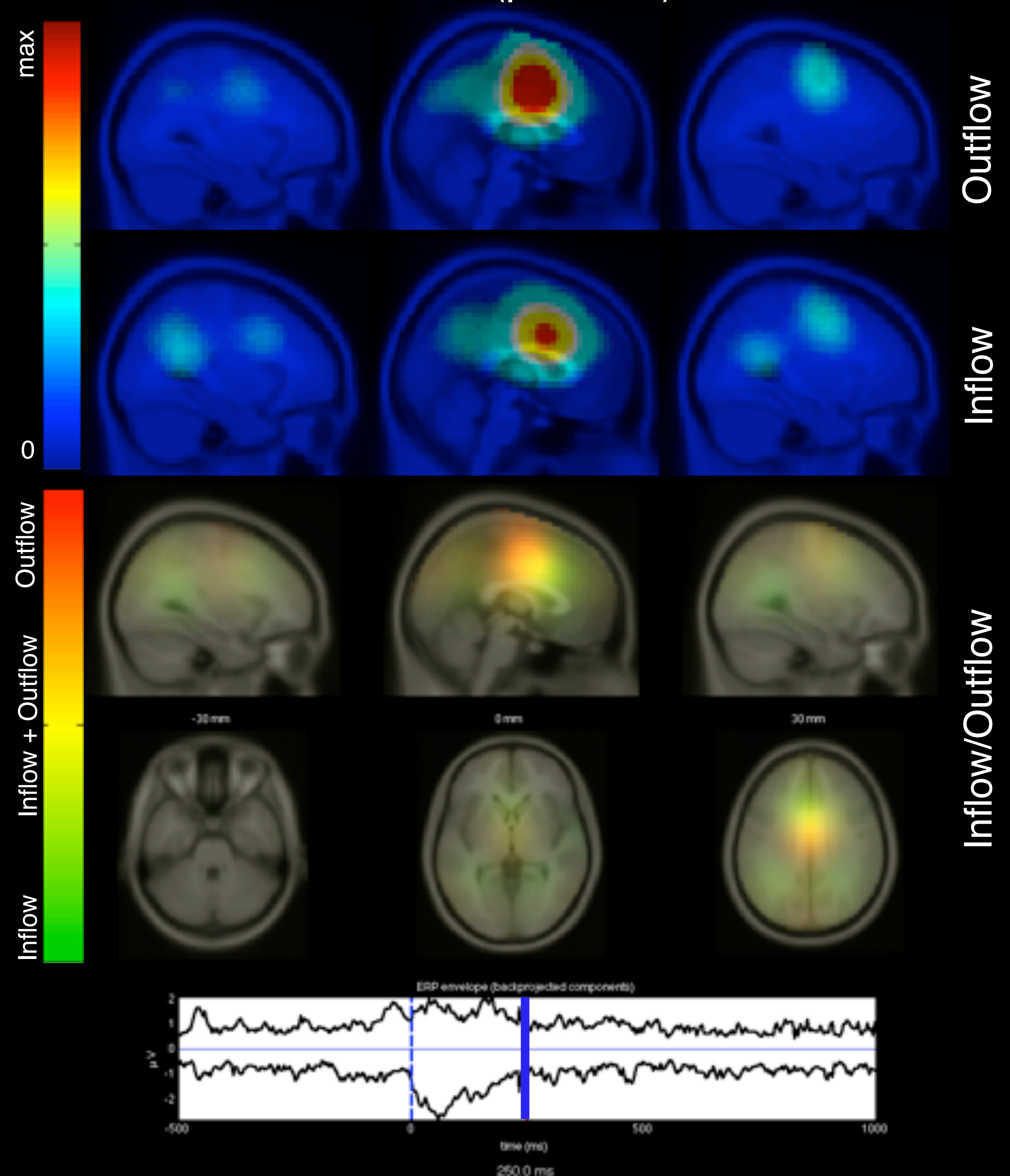


Mullen, et al, 2010, HBM, Barcelona

alpha-testing

Causal Projection

Error > Correct ($p < 0.05$) 3-7 Hz

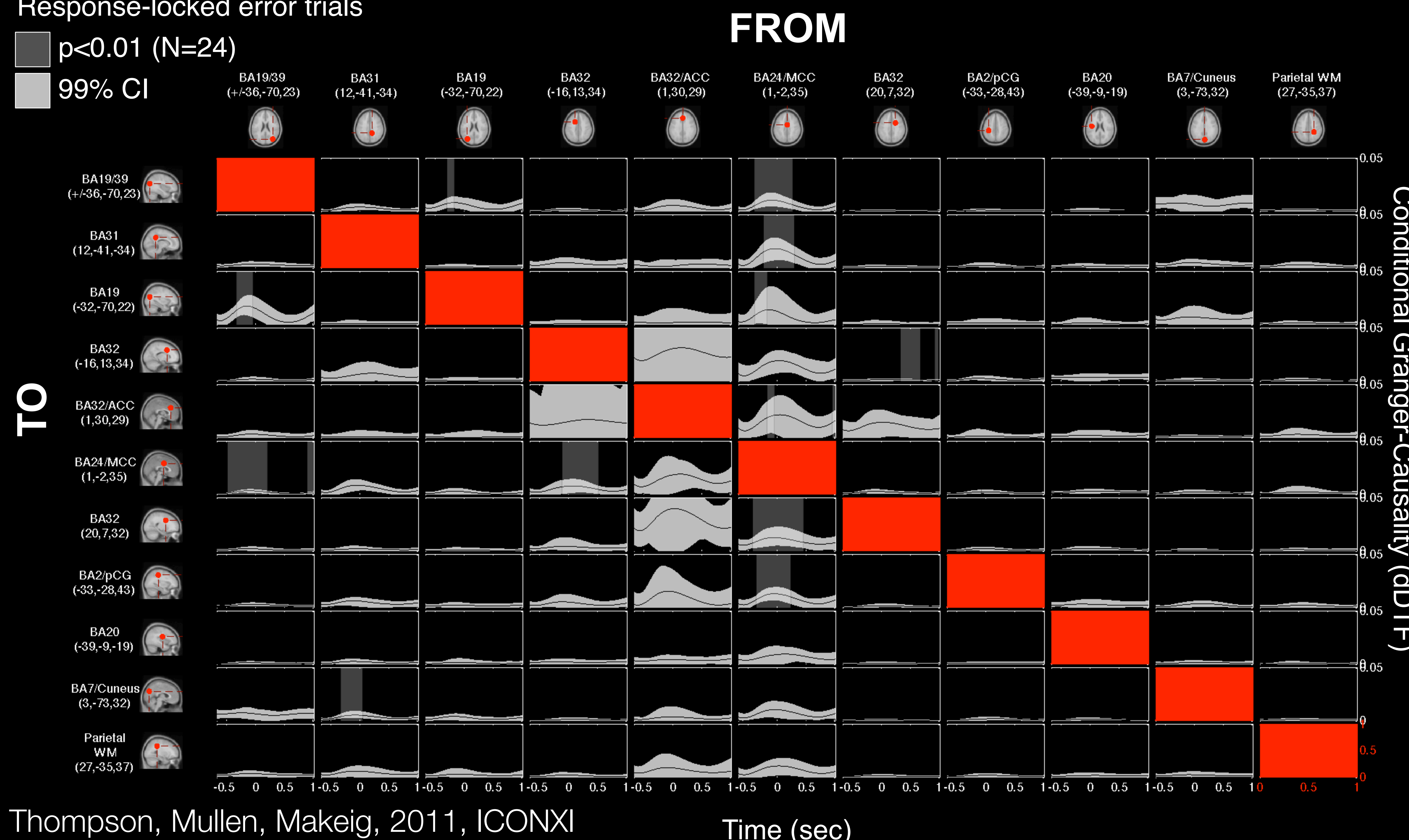


alpha-testing

Mullen, et al, 2010, HBM, Barcelona

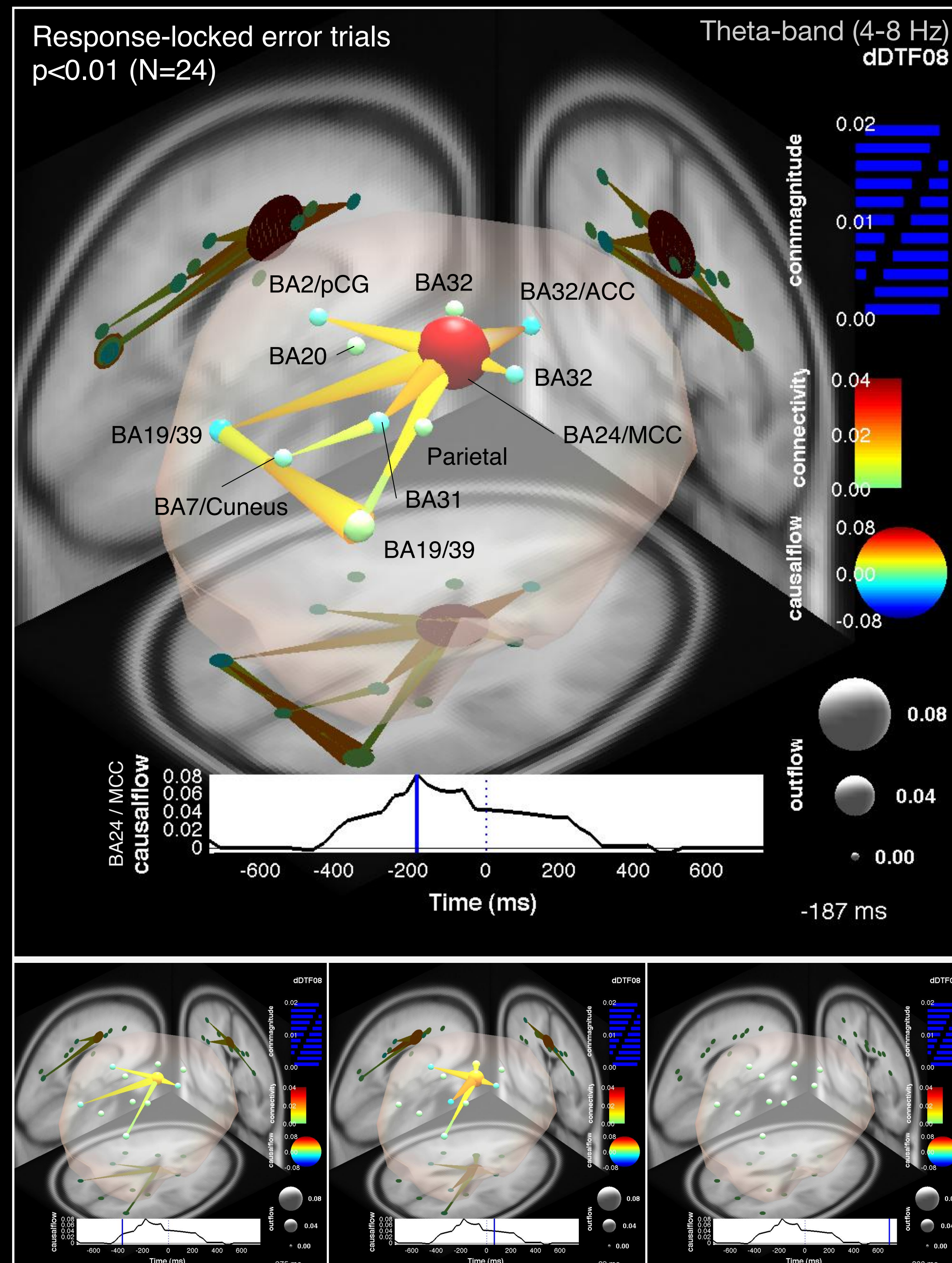
Bayesian Multi-Subject Inference

Theta-band (4-8 Hz) dDTF
Response-locked error trials
p<0.01 (N=24)
99% CI



Thompson, Mullen, Makeig, 2011, ICONXI
Thompson, Mullen, Makeig, 2012, *in prep*

Bayesian Multi-Subject Inference



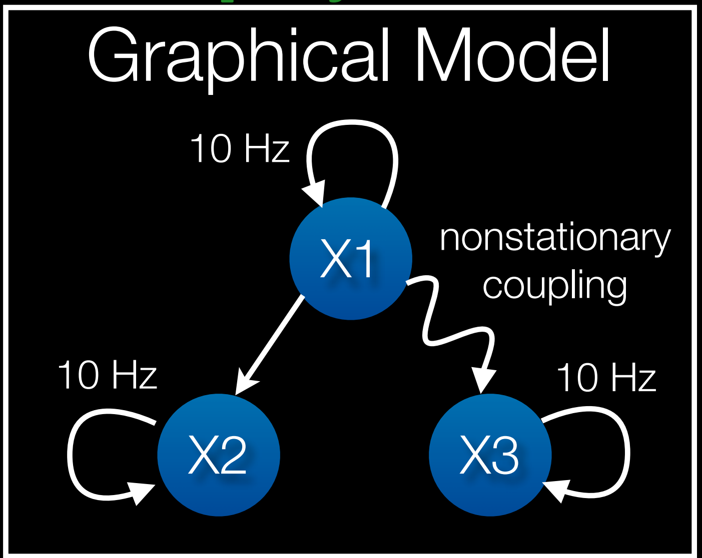
Thompson, Mullen, Makeig, 2011, ICONXI
Thompson, Mullen, Makeig, 2012, *in prep*

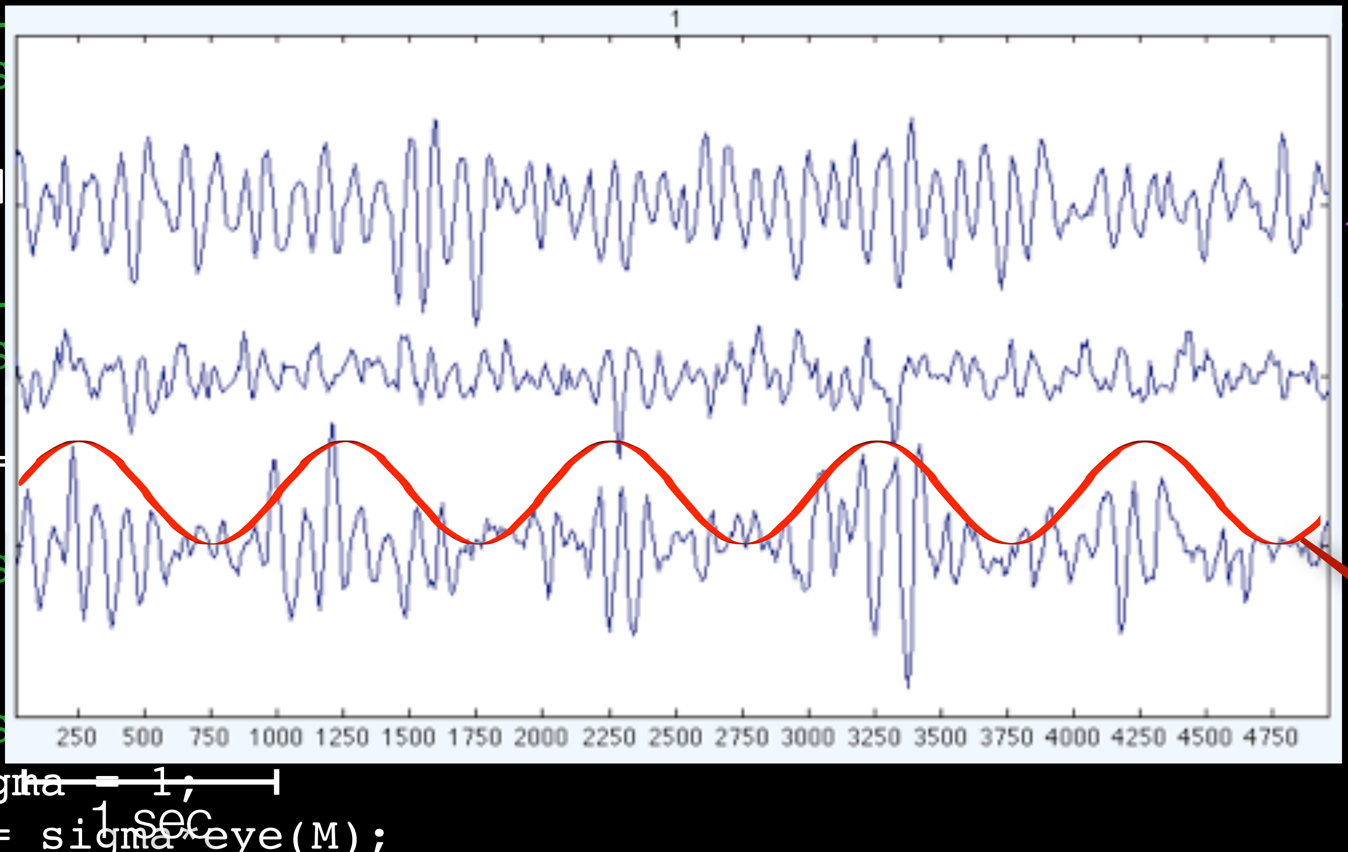
Simulation

Dynamical System Simulation Workbench
Systems of linear stochastically-forced damped coupled oscillators
Support for arbitrary time-varying (non-stationary) coupling dynamics
Intuitive equation-based scripting environment
Support for generalized gaussian or hyperbolic secant innovations
Nonlinear Dynamical Systems
Rössler and Lorenz Systems

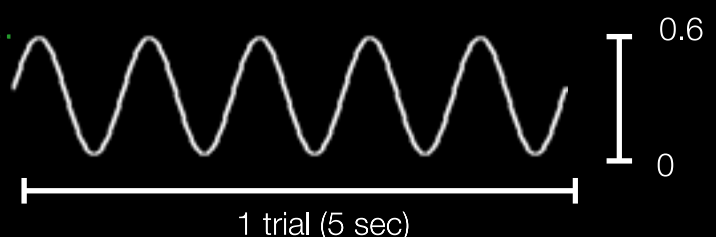
fully implemented — alpha-testing — coming soon

```
% Example: Trivariate damped coupled oscillators with sinusoidally-modulated coupling
% ------------------------------------------------------------------------------------
% STEP 1: create prototype VAR structure

Fs = 100;                    % Sampling Rate (Hz)
Nl = 500;                    % length of each epoch (samples)
Nr = 100;                    % number of trials (realizations)
ndisc = 1000;                % number of startup samples to discard
ModelOrder = 2;              % model order
f0 = 10;                     % central oscillation frequency (Hz)

expr = {...
    ['x1(t) = ' sim_dampedOscillator(f0,9,Fs,1) '                                          + e1(t)'] ...
    ['x2(t) = ' sim_dampedOscillator(f0,2,Fs,2) ' + -0.1*x1(t-2)                           + e2(t)'] ...
    ['x3(t) = ' sim_dampedOscillator(f0,2,Fs,3) ' + {0.3*sin(2*pi*t/100)+0.3}*x1(t-2) + e3(t)'] ...
};

Aproto = sim_genVARModelFromEq(expr,ModelOrder);

% -
% S
[A]
                                     Verbose',true);
% -
% S
M =

% S
Mu

% S
sigma = 1;
E = sigma*eye(M);

% generate simulated data with laplacian (supergaussian) innovations
data = sim_tvarsim(Mu,A,E,[Nl Nr],ndisc,1,1,'gengauss');
```



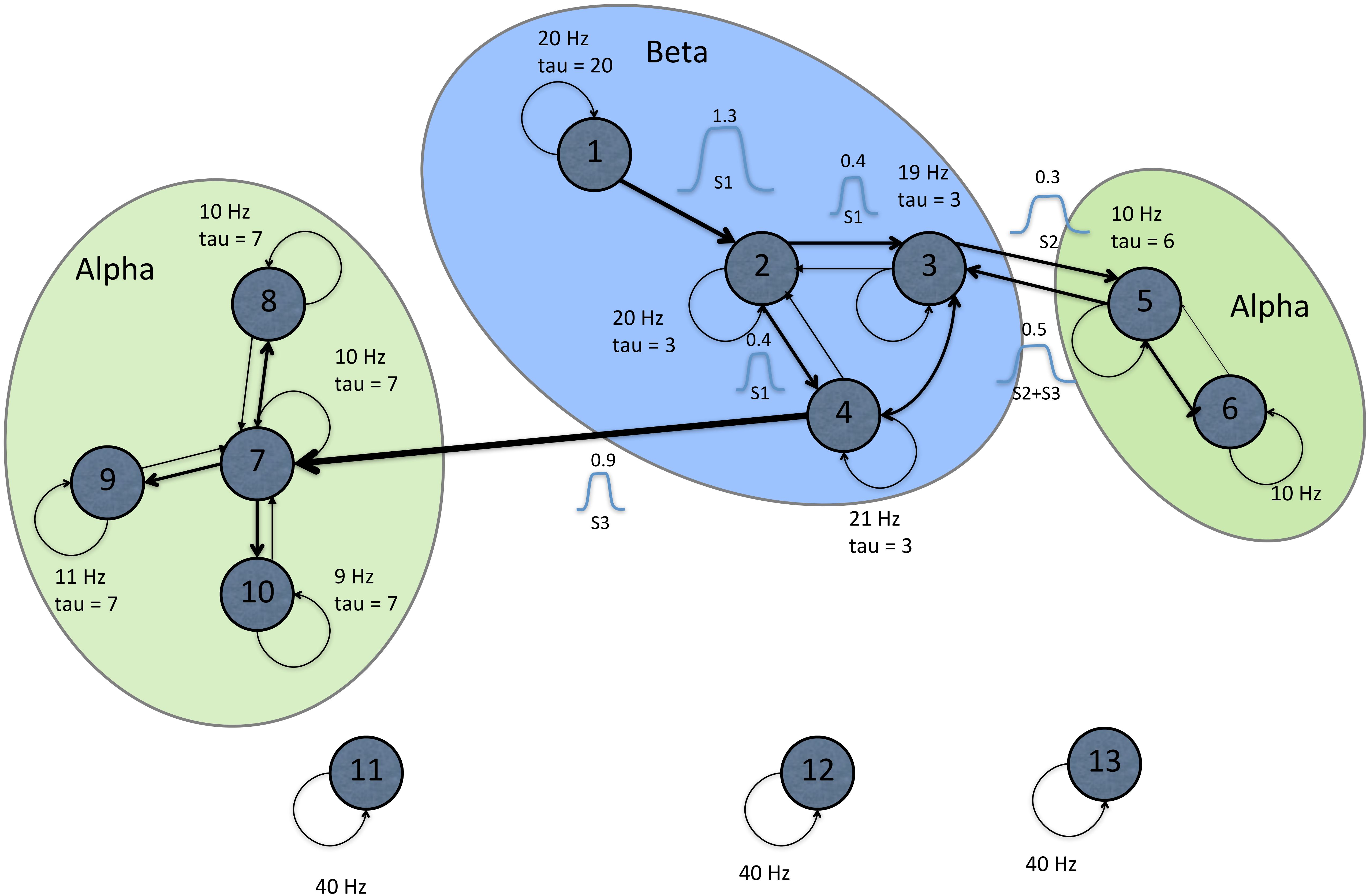


Time-varying X1→X3 coupling (1 Hz modulation)

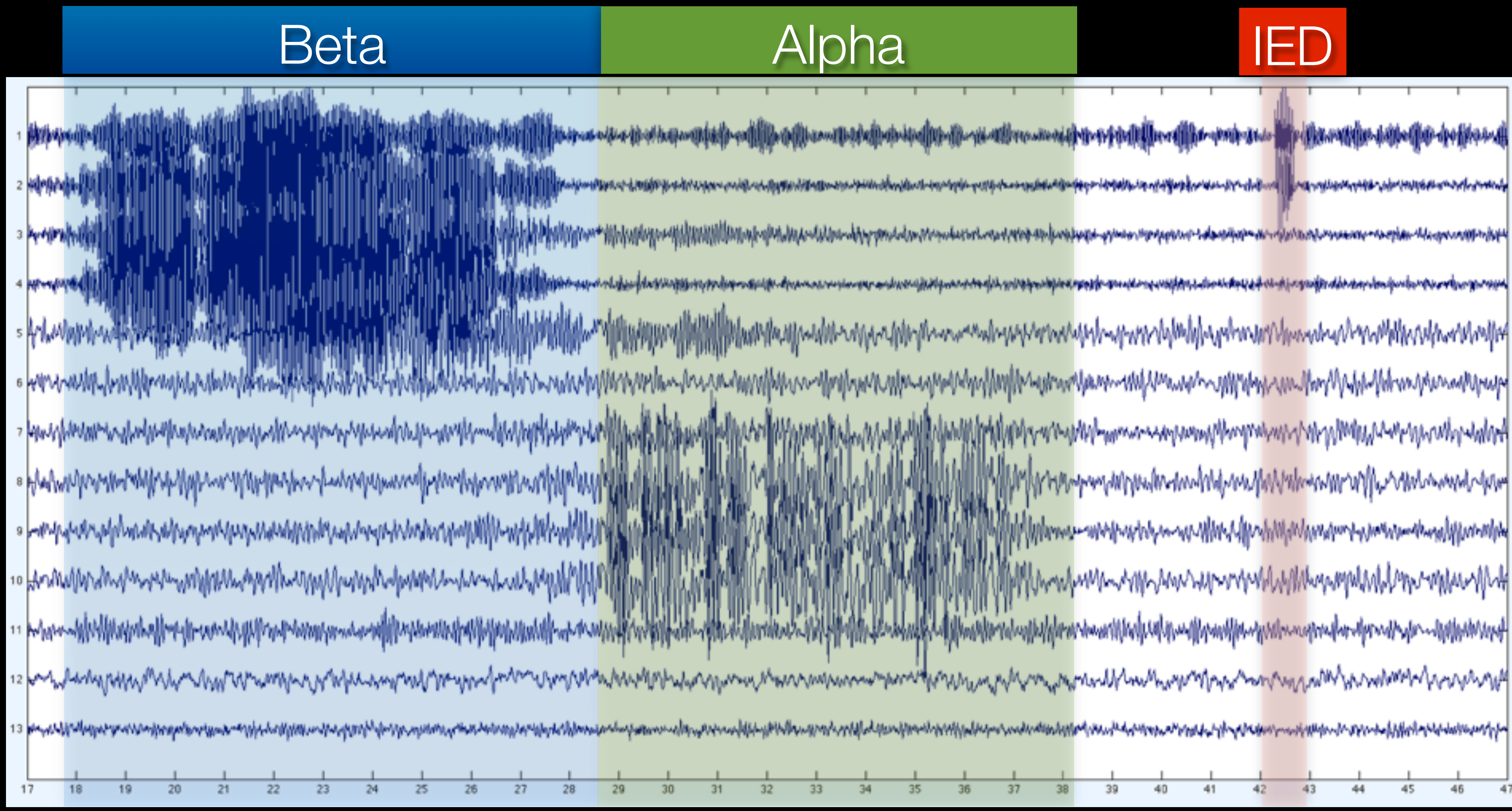


Amplitude Modulation (PAC)

Simulated Seizure

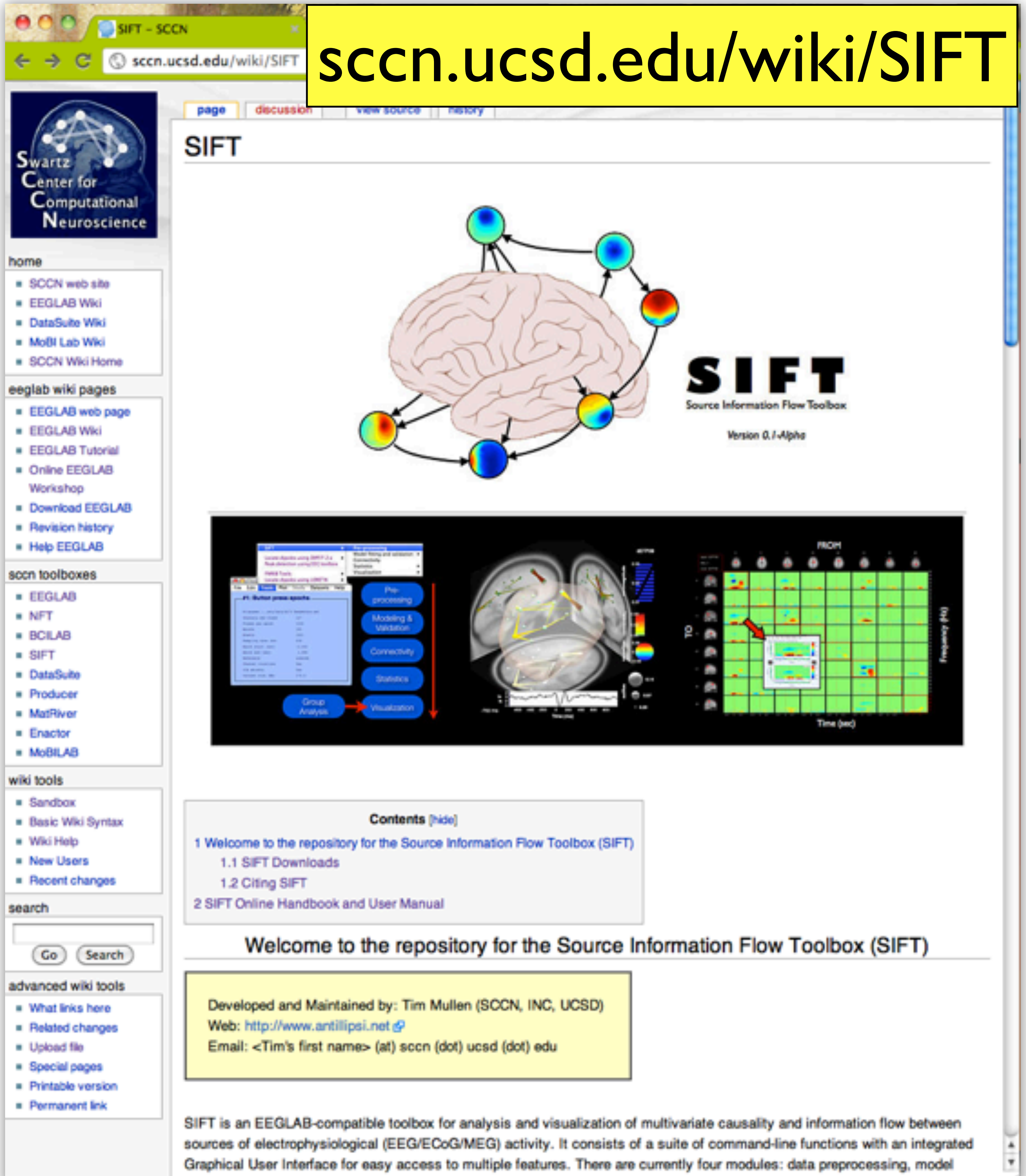


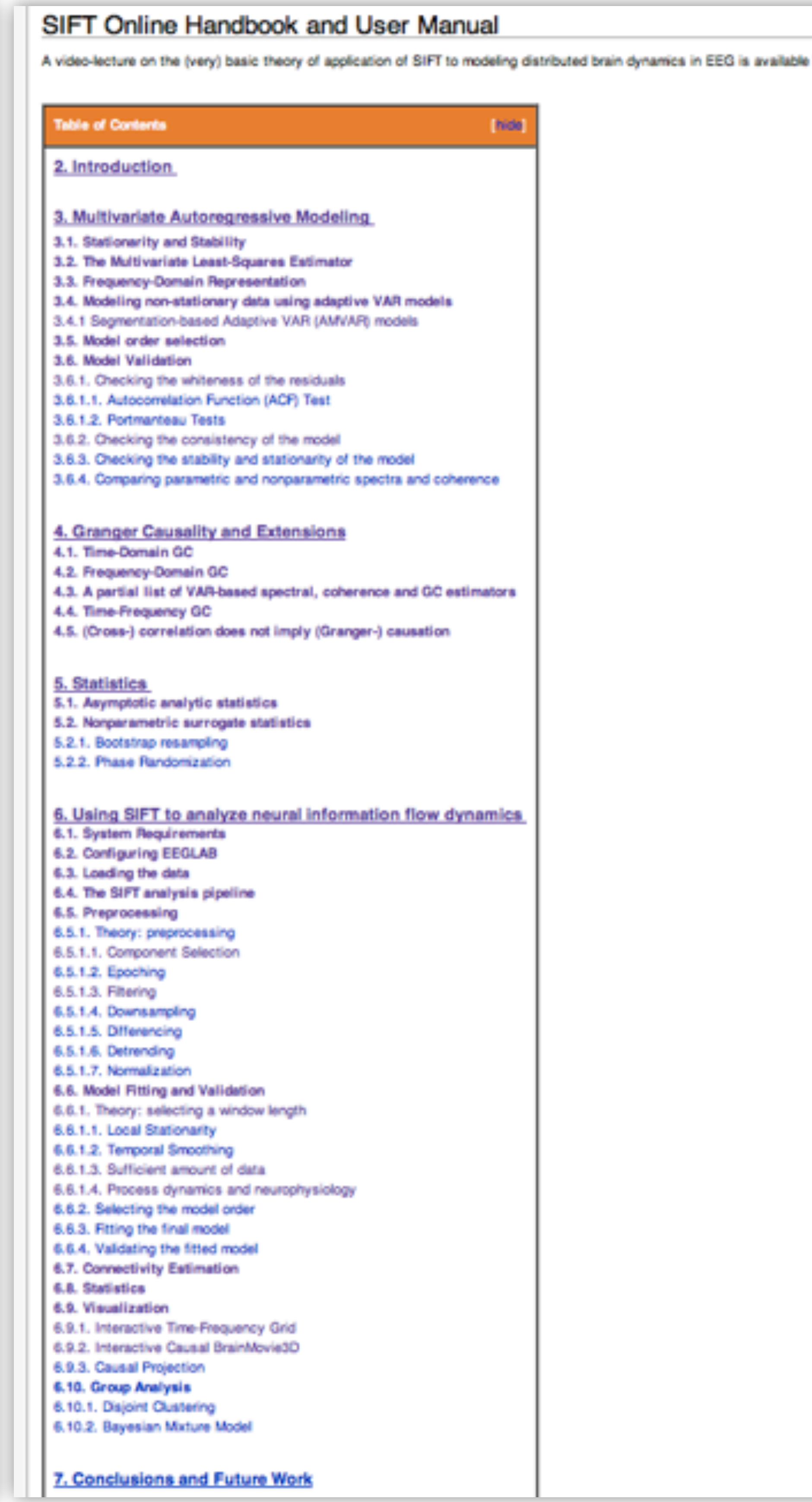
Simulated Seizure Sources



Where do I get SIFT?

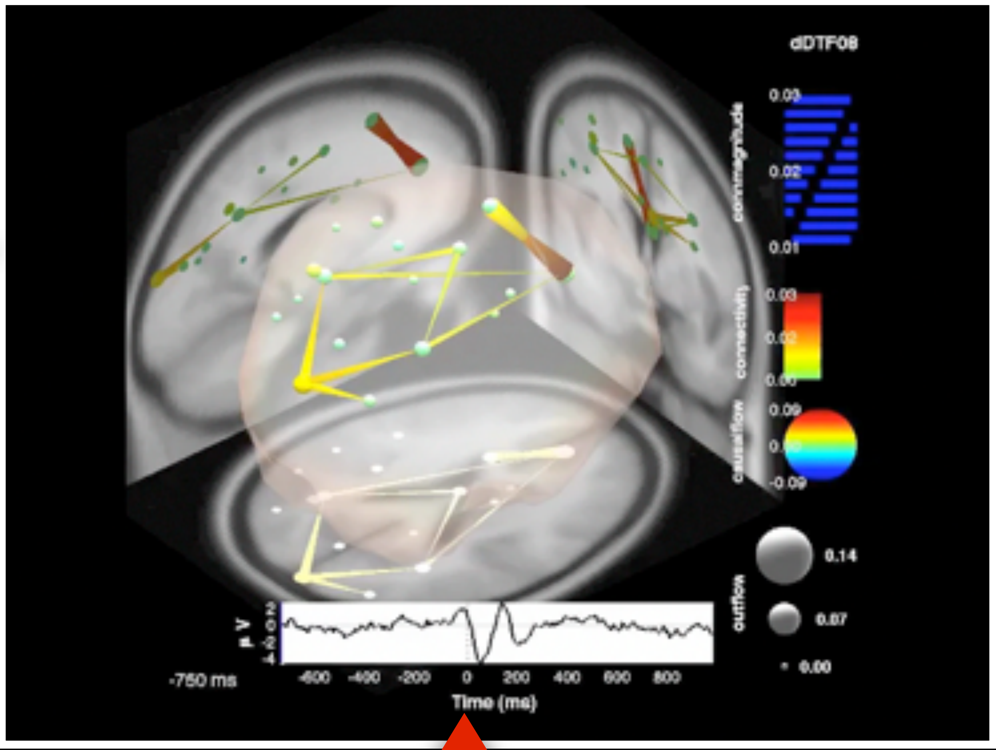
sccn.ucsd.edu/wiki/SIFT





Some Applications of SIFT

Identification of event-related shifts in effective connectivity which index and predict behavior



error event

Mullen et al, *HBM*, Barcelona, 2010

Single-trial spatiotemporal modeling of seizure propagation dynamics

Brain-Computer Interfaces:
Error correction/prediction
Neural Prostheses
...

Some Applications of SIFT

Identification of event-related shifts in effective connectivity which index and predict behavior

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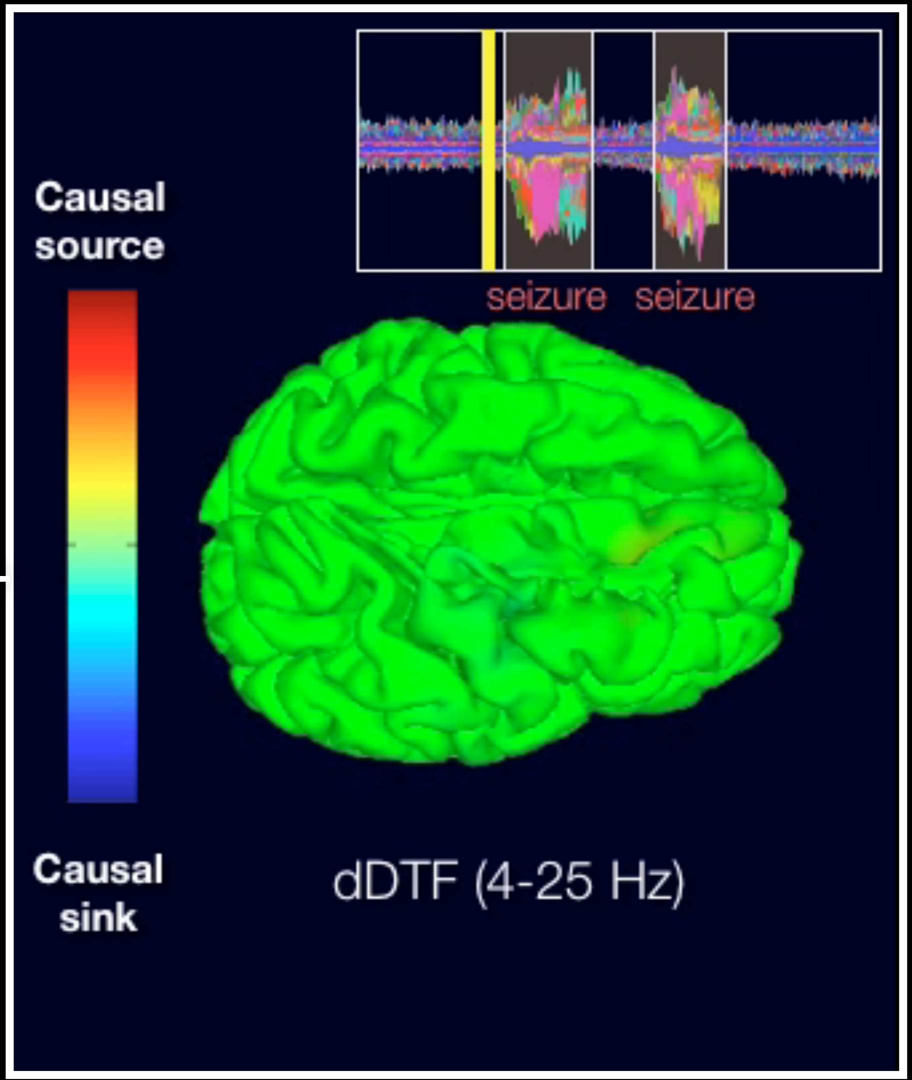
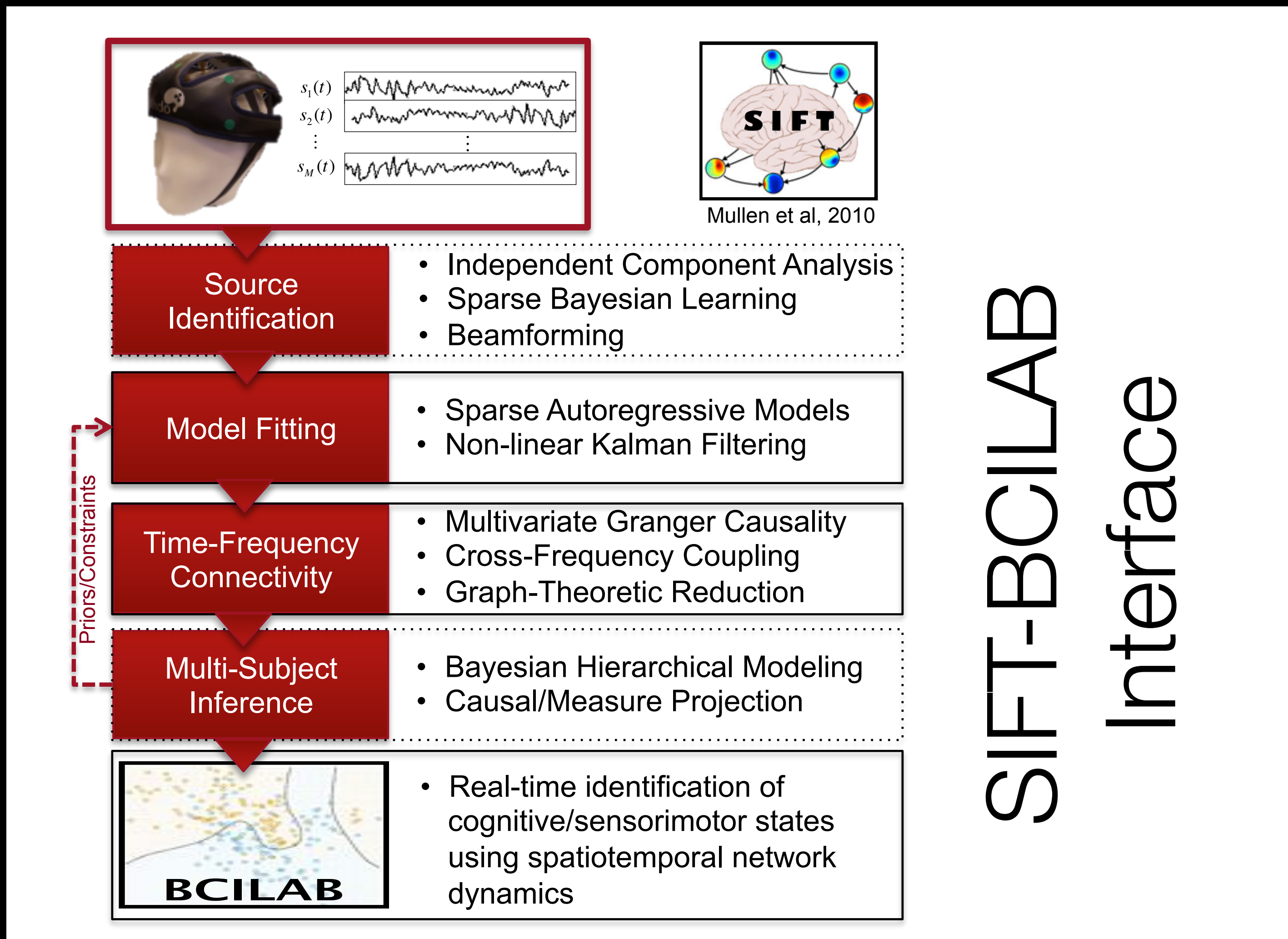


Mullen, et al *IEEE EMBC,* 2011

Some Applications of SIFT



Brain-Computer Interfaces:

Error correction/prediction

Neural Prostheses

...

The Road Ahead

- Public release of alpha-testing methods (SIFT 1.0-beta ... being released at sccn.ucsd.edu/wiki/SIFT in the next week)
- Ongoing development of sparse/regularized VAR and state-space models as well as nonlinear SSMs
- Improved Group Analysis and Statistics
- Integration with other toolboxes: Transfer Entropy (TRENTOOL), Dynamic Causal Modeling (SPM), Brain-Computer Interfaces (BCILAB)
- Incorporation of structural constraints on dynamic connectivity (e.g. from DTI, anatomical priors, etc)

Acknowledgements

Virginia de Sa
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Zeynep Akalin Acar
Jason Palmer
Zhilin Zhang
Scott Makeig

Wes Thompson