

Functional Connectivity in MEG

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Functional Connectivity Background



- Much interest in functional connectivity in fMRI
- And yet many neural interactions (e.g, coupled oscillations) occur at a timescale faster than visible by fMRI
- Beyond localization: the same set of brain regions could perform different functions depending on how they interact
- So, real promise of MEG/EEG is functional connectivity?

Talk Overview

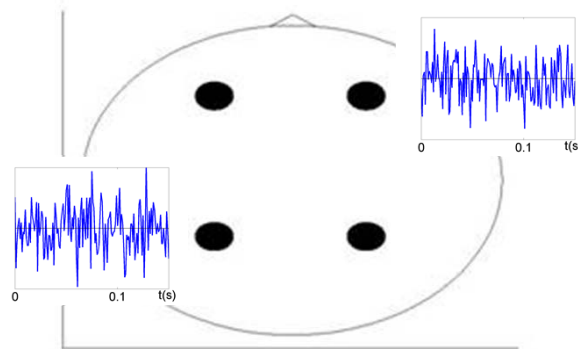


1. Problem of Field Spread (Volume Conduction)
2. Linear vs Nonlinear measures
3. Directed vs Undirected measures
4. Direct vs Indirect measures
5. Generative Models

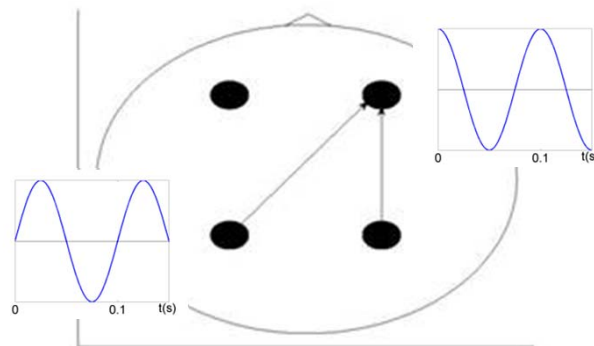
Field Spread Problem

Many (zero-lag) measures of functional connectivity between sensors can be spurious, i.e., reflect activity from single source

No true source connectivity



True source connectivity



Field Spread Problem

Source reconstruction reduces field spread problem...

...and allows easier comparison with fMRI connectivity

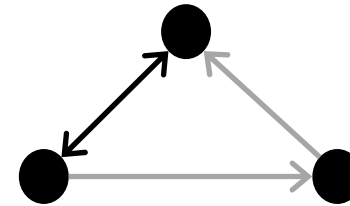
BUT spurious connections between sources can remain
("point-spread")

Hillebrand et al (2012) Neuroimage

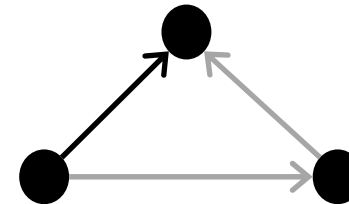
...and field-spread is instantaneous (zero-lag), so some
measures of connectivity between sensors are immune to
field spread (e.g, time- or phase-lagged measures)

Different Types of Connection

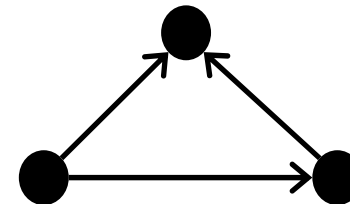
Undirected, Indirect (bivariate)



Directed, Indirect (bivariate)



Directed, Direct (multivariate)
("effective connectivity")



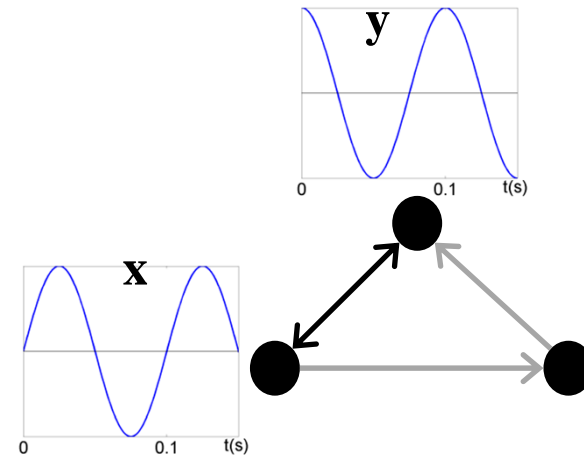
Cross-Correlation

Sensitive to Field-spread (when $l=0$), Undirected, Indirect, Linear

$$c_{xy}(l) = \left\langle (x_t - \bar{x})(y_{t+l} - \bar{y}) \right\rangle_t$$

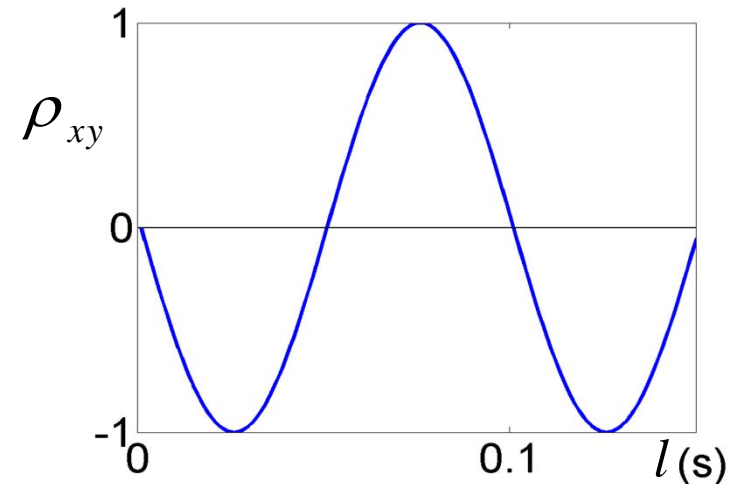
Cross-covariance

l = "lag"



$$\rho_{xy}(l) = \frac{c_{xy}(l)}{\sigma_x \sigma_y}$$

Cross-correlation



Coherency

(Fourier transform of cross-covariance)

Sensitive to Field-spread, Undirected, Indirect, Linear

$$c_{xy}(l) = \left\langle (x_t - \bar{x})(y_{t+l} - \bar{y}) \right\rangle_t$$

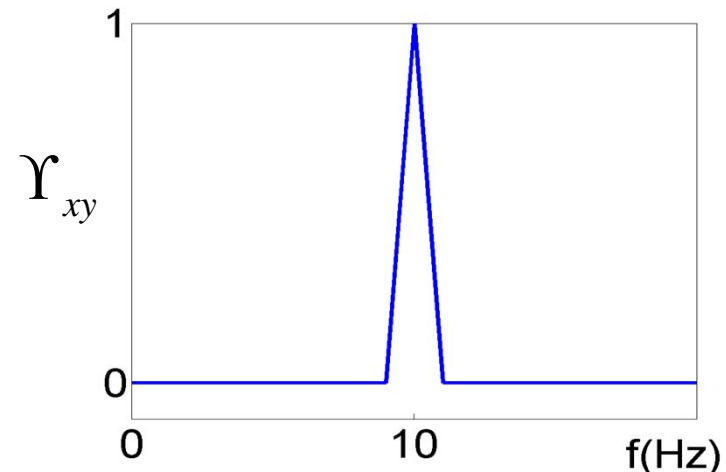
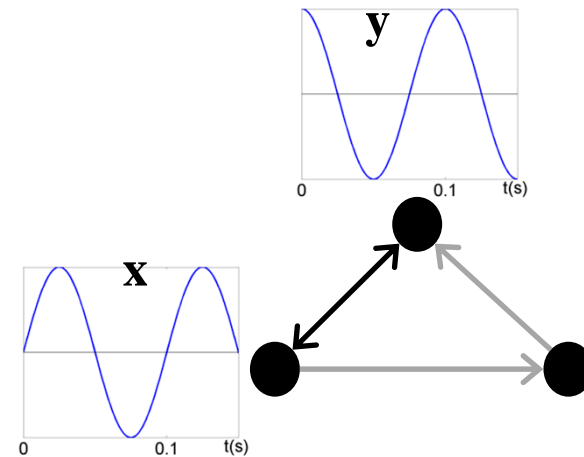
Cross-covariance

$$C_{xy}(f) = \sum_l c_{xy}(l) e^{-2\pi i.l.f}$$

Coherency

$$\Upsilon_{xy}(f) = \frac{|C_{xy}(f)|^2}{|C_{xx}(f)||C_{yy}(f)|}$$

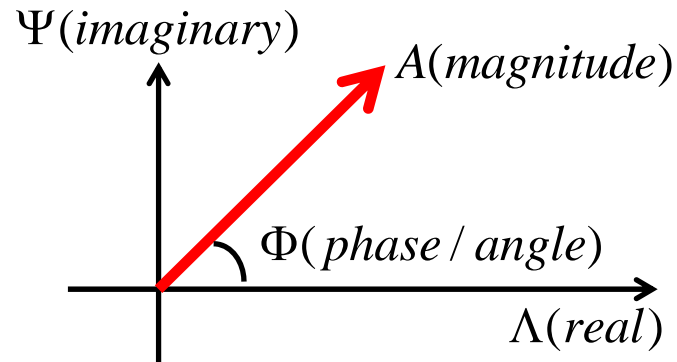
(Magnitude-squared) Coherence



Digression on Complex Numbers

An oscillation of frequency f can be represented in terms of amplitude and phase (polar coordinates), which can also be represented by a complex number

$$\begin{aligned} C(f) &= A(f)e^{i\Phi(f)} \\ &= \Lambda(f) + i\Psi(f) \end{aligned}$$



$$A(f) = |C(f)| = \sqrt{\Lambda^2(f) + \Psi^2(f)}$$

$$\Phi(f) = \arctan(\Psi(f) / \Lambda(f))$$

Coherence

Sensitive to Field-spread, Undirected, Indirect, Linear

$$c_{xy}(l) = \left\langle (x_t - \bar{x})(y_{t+l} - \bar{y}) \right\rangle_t$$

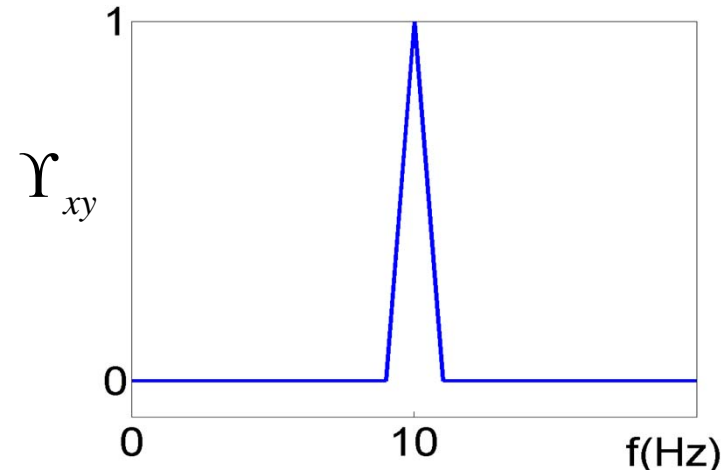
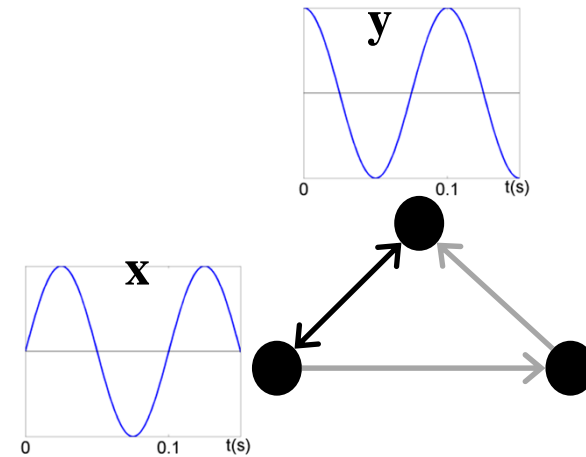
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Coherency

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(Magnitude-squared) Coherence



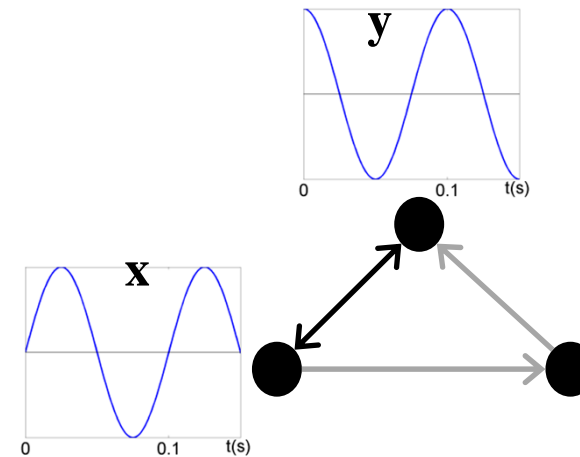
Imaginary Coherency

Immune to Field-spread, Undirected, Indirect, Linear

$$c_{xy}(l) = \left\langle (x_t - \bar{x})(y_{t+l} - \bar{y}) \right\rangle_t$$

$$C_{xy}(f) = \sum_l c_{xy}(l) e^{-2\pi i \cdot l \cdot f}$$

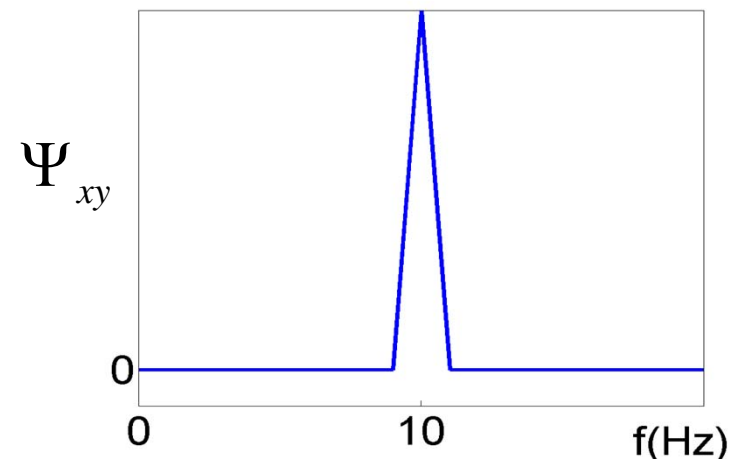
Coherency



$$\Psi_{xy}(f) = \text{imag}(C_{xy}(f))$$

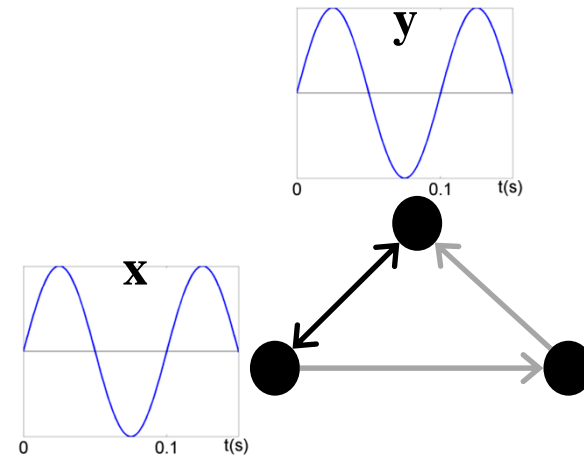
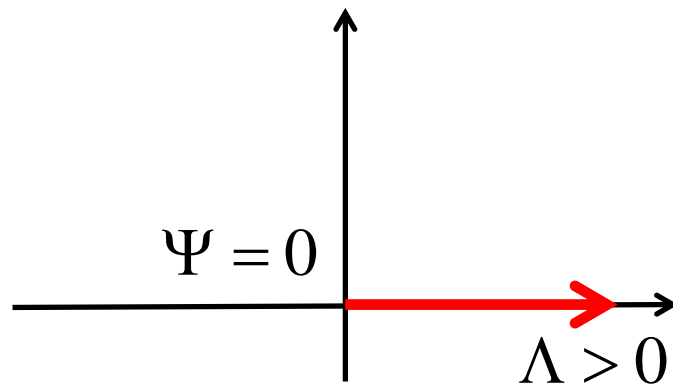
Imaginary Coherency

Nolte et al (2004) Clin Neurophys

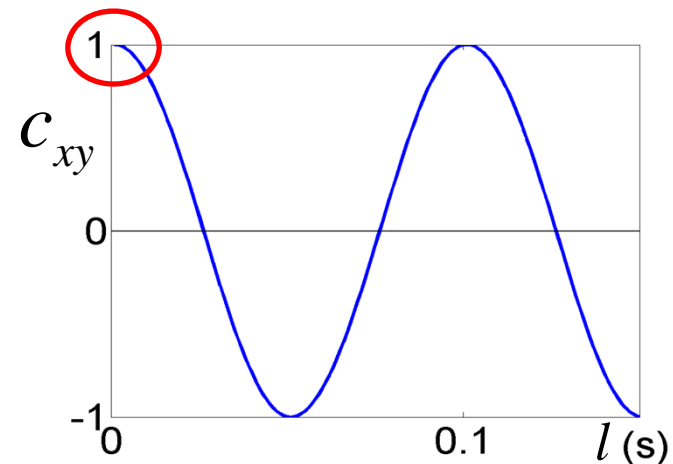


Imaginary Coherency

A zero imaginary component implies a phase of the coherency of either 0° or 180° , which could be caused by field-spread...

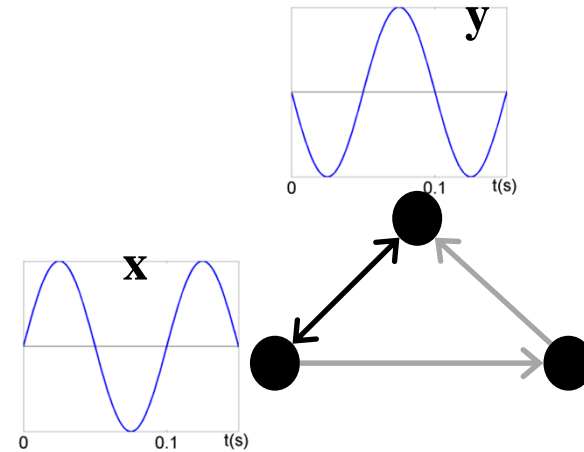
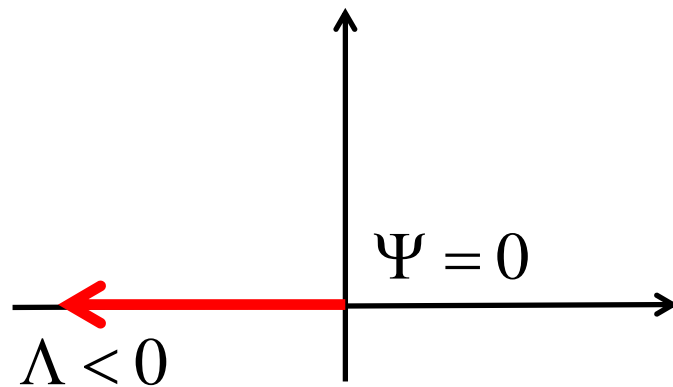


$$\Psi_{xy}(f) = \text{imag}(C_{xy}(f))$$

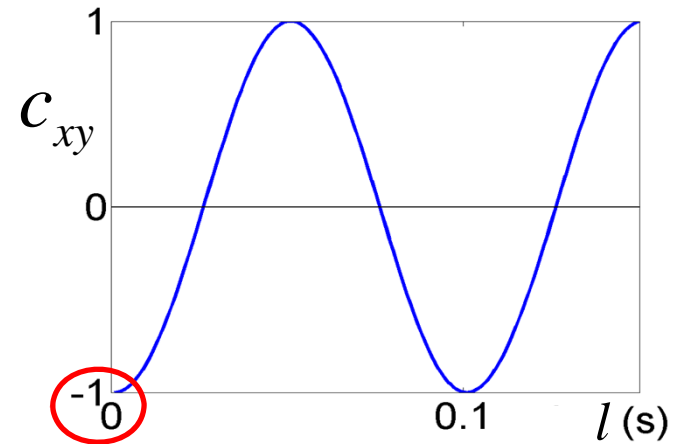


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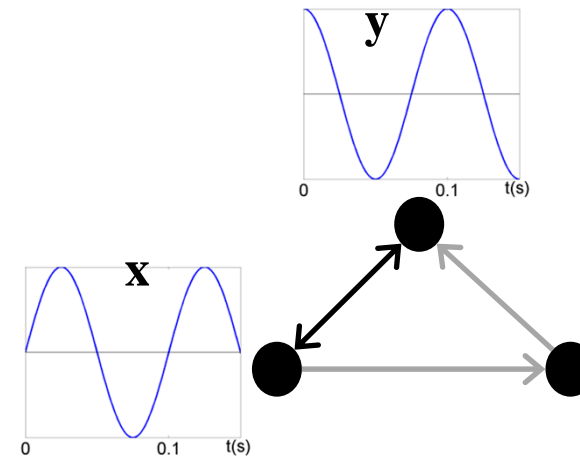
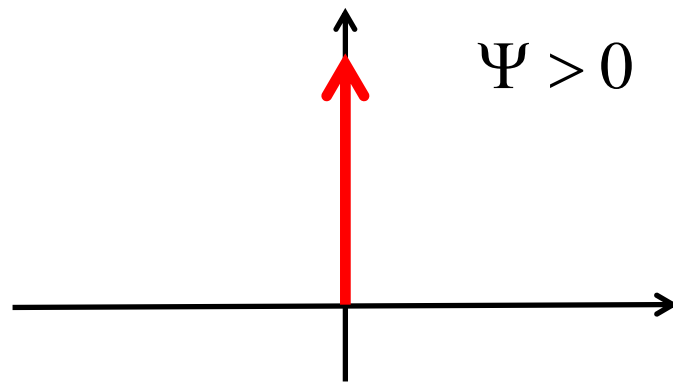


$$\Psi_{xy}(f) = \text{imag}(C_{xy}(f))$$

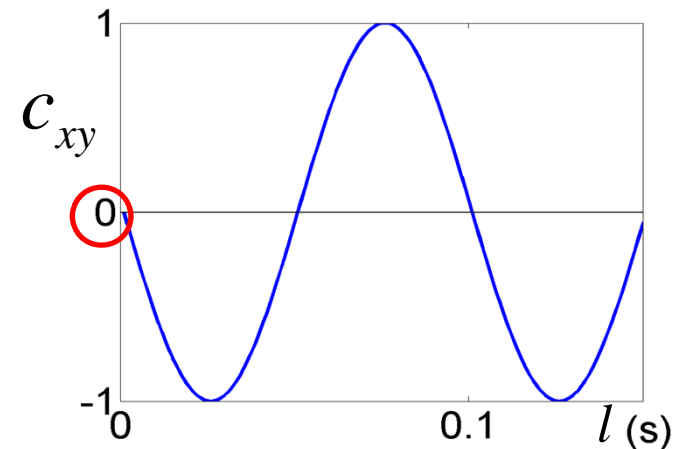


Imaginary Coherency

...whereas a NON-zero imaginary component implies a phase of the coherency other than 0° or 180°, which can NOT be caused by field-spread



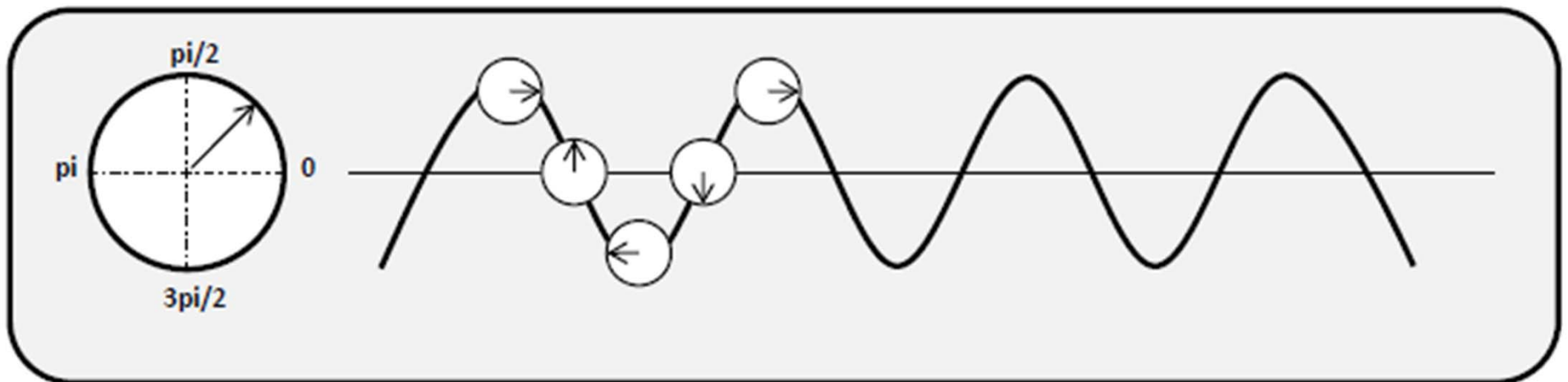
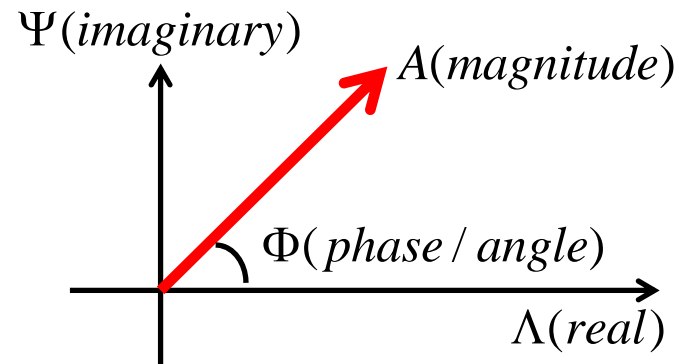
$$\Psi_{xy}(f) = \text{imag}(C_{xy}(f))$$



Digression on Analytic Signals

A signal can be represented analytically in terms of its amplitude and phase over time (within a narrow frequency band) (e.g, using Hilbert transform)

$$x(t, f) = A(t, f)e^{i\Phi(t, f)}$$



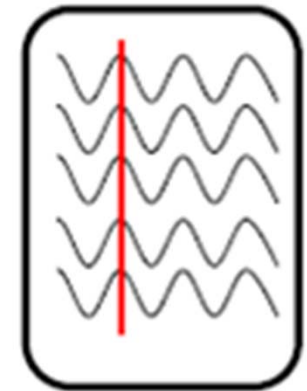
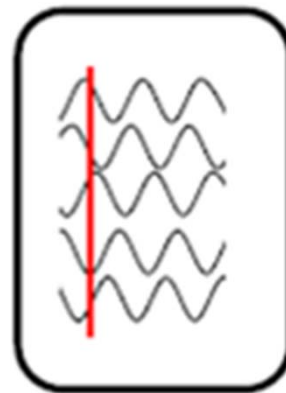
Phase-related Measures

Immune to Field-spread, Undirected, Indirect, Linear

$$x(t) = A_x(t)e^{i\Phi_x(t)}$$

$$y(t) = A_y(t)e^{i\Phi_y(t)}$$

$$\Delta\Phi(t) = \Phi_x(t) - \Phi_y(t)$$



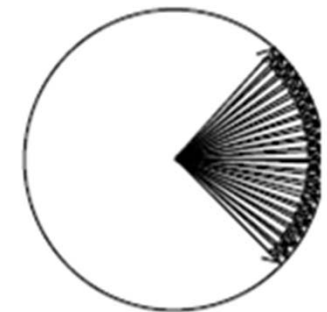
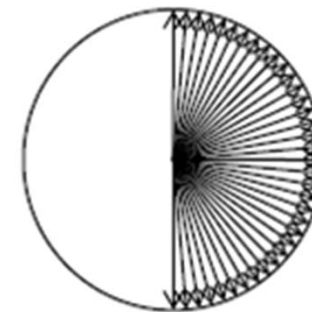
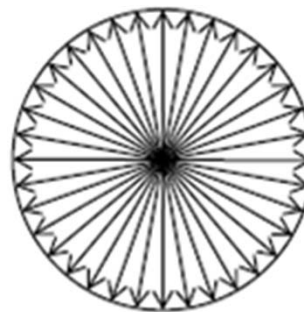
$$PLV = \left\langle e^{i\Delta\Phi(t)} \right\rangle_t$$

Phase-Locking Value

PLV=0

PLV=0.5

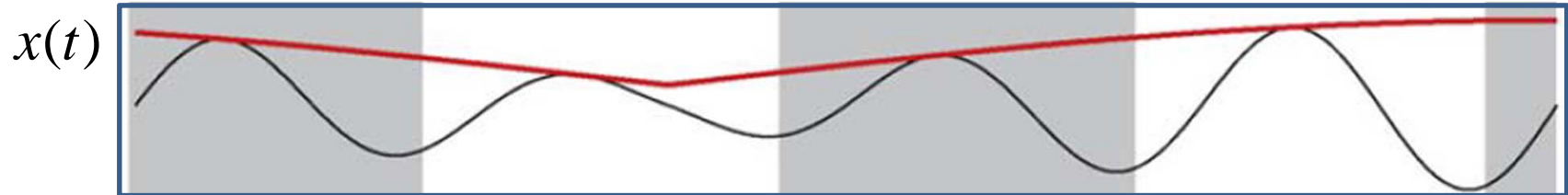
PLV=0.75



$$PLI = \left\langle \text{sign}(\Delta\Phi(t)) \right\rangle_t$$

Phase-Lag Index

More complex coupling



$y(t)$

Power-Power
 $A_x(t) : A_y(t)$

Phase-Phase
 $\Phi_x(t) : \Phi_y(t)$

Phase-Freq
 $\Phi_x(t) : F_y(t)$

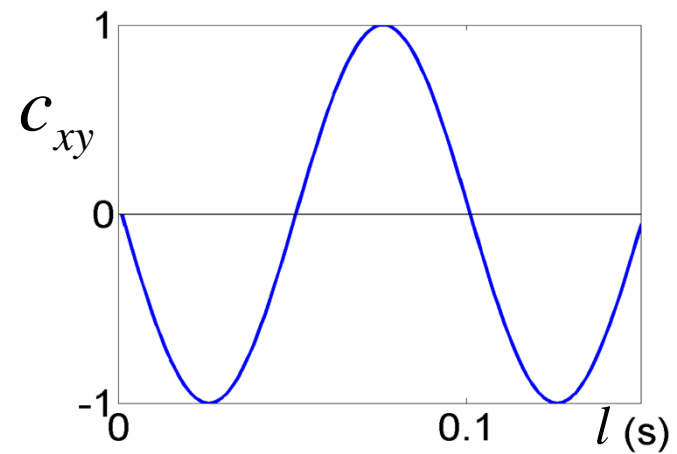
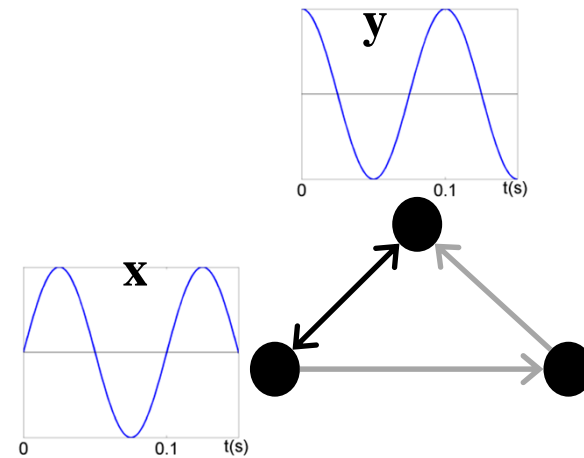
Phase-Power
 $\Phi_x(t) : A_y(t)$

Talk Overview



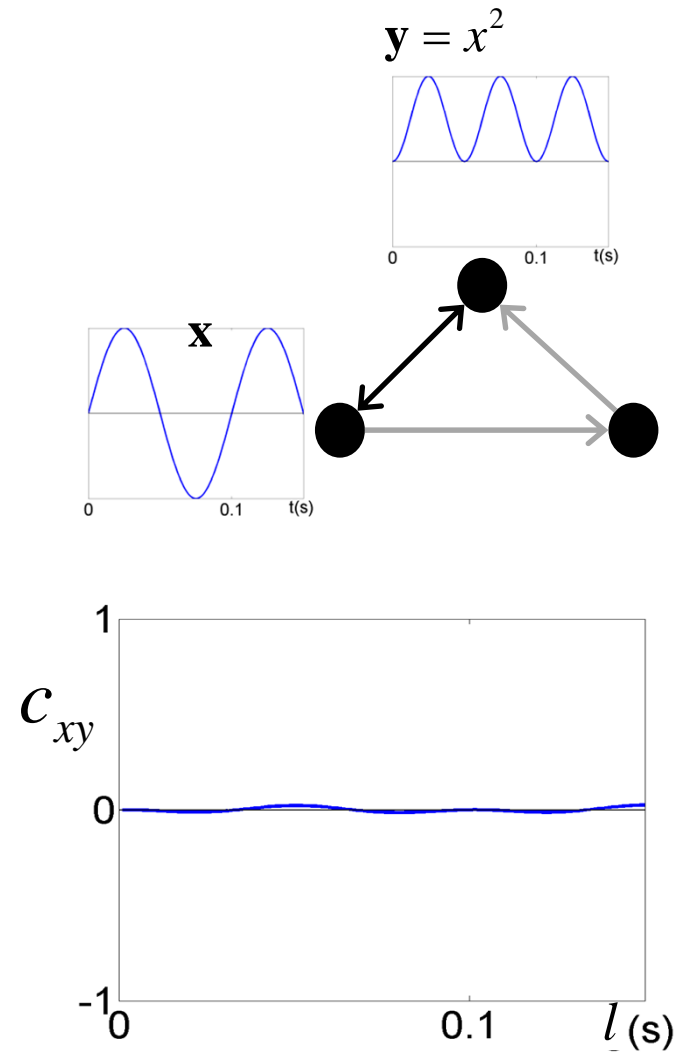
1. Problem of Field Spread (Volume Conduction)
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Nonlinear Measures



Nonlinear Measures

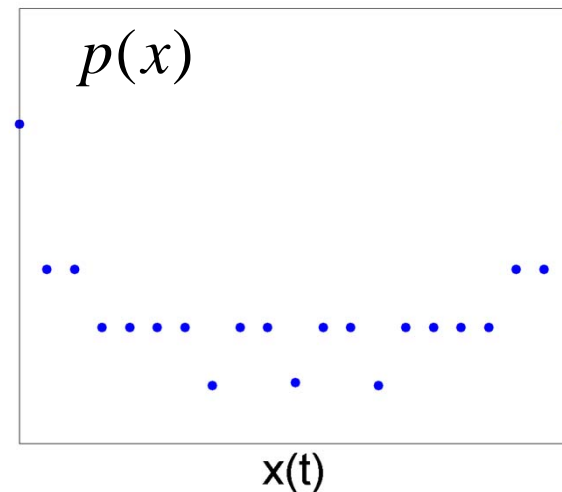
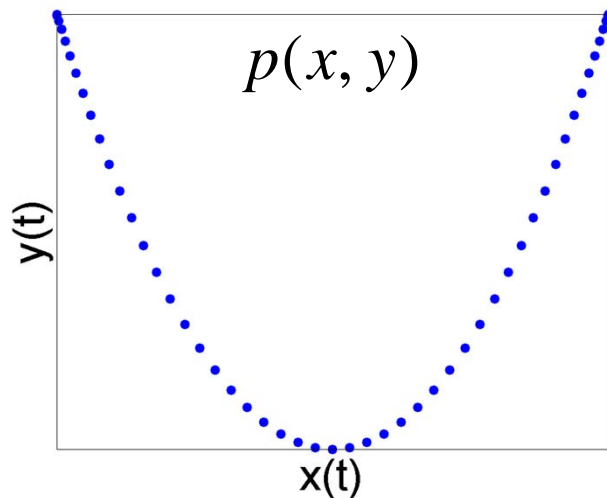
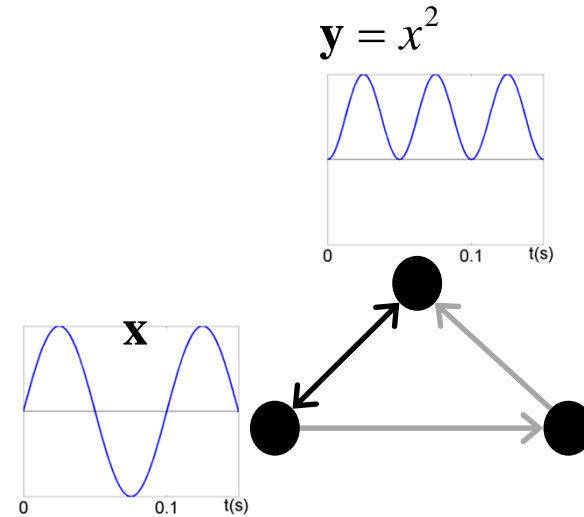
Cross-correlation/coherence insensitive to nonlinear dependencies



Mutual Information

Sensitive to Field-spread, Undirected, Indirect, **Nonlinear**

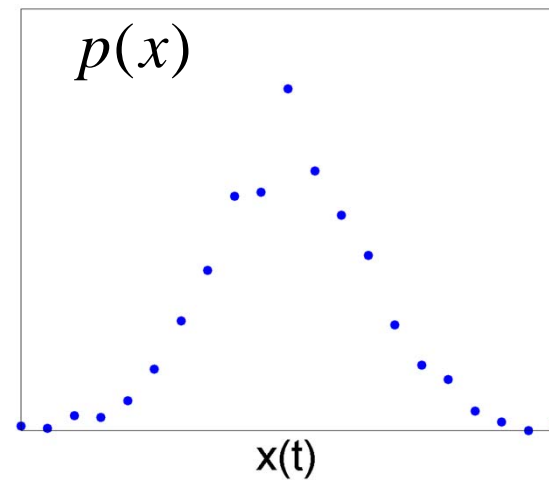
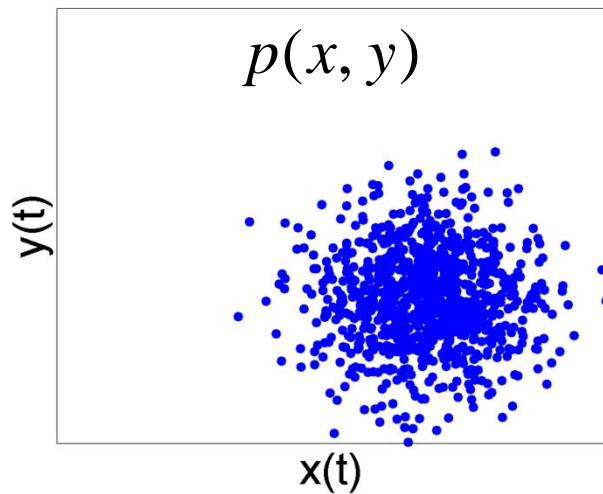
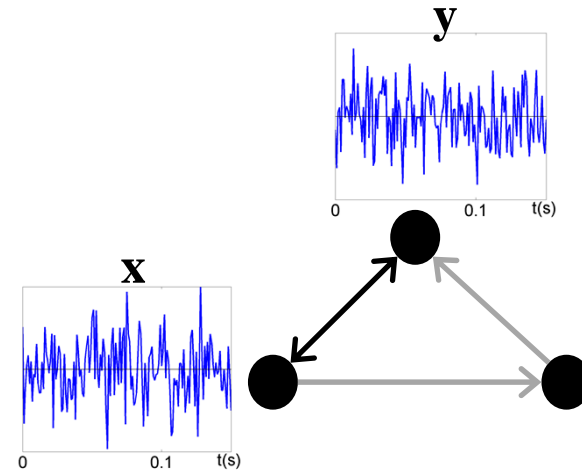
$$MI(x, y) = \sum_{x, y} p(x, y) \log \left(\frac{p(x, y)}{p(x)p(y)} \right)$$



Mutual Information

Sensitive to Field-spread, Undirected, Indirect, **Nonlinear**

$$MI(x, y) = \sum_{x,y} p(x, y) \log \left(\frac{p(x, y)}{p(x)p(y)} \right)$$



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2. Linear vs Nonlinear measures
- 3. Directed vs Undirected measures**
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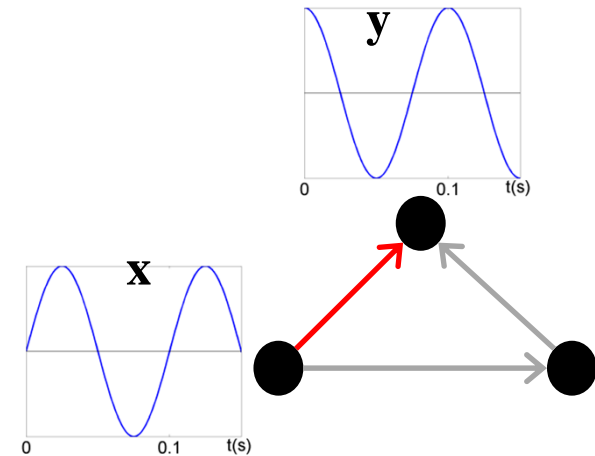
Directed Measures

(bivariate) Granger Causality

Immune to Field-spread, Directed, Indirect, Linear

Auto-regressive model to order p
(assuming mean-corrected, with residuals e)

$$y_y(t) = a_1 y(t-1) + \dots + a_p y(t-p) + e(t)$$
$$= \sum_{l=1}^p a_l y(t-l) + e(t)$$



Augmented model including past values of x (to order q)

$$y_{y \leftarrow x}(t) = \sum_{l=1}^p a_l y(t-l) + \sum_{l=1}^q b_l x(t-l) + e(t)$$

If classical F-test shows b parameters are non-zero, then x “Granger-causes” y
(special case of MVAR; see later)

Directed, Nonlinear Measures

MRC

Cognition and
Brain Sciences Unit

Transfer Entropy (lagged generalisation of mutual information)

Immune to Field-spread, Directed, Indirect, Nonlinear

$$TE_{y \rightarrow x}(l) = \sum_{x_{n+l}, x_n, y_n} p(x_{n+l}, x_n, y_n) \log \left(\frac{p(x_{n+l} | x_n, y_n)}{p(x_{n+l} | x_n)} \right)$$

$$TE_{x \rightarrow y}(l) = \sum_{y_{n+l}, y_n, x_n} p(y_{n+l}, x_n, y_n) \log \left(\frac{p(y_{n+l} | x_n, y_n)}{p(y_{n+l} | y_n)} \right)$$

Schreiber (2000) Phys Rev Letters

Generalised Synchronisation

Sensitive to Field-spread, Directed, Indirect, Nonlinear

$$x_t = [x_t, x_{t+l}, \dots, x_{t+(m-1)l}]$$

$$y_t = [y_t, y_{t+l}, \dots, y_{t+(m-1)l}]$$

$$S(x | y) = \frac{1}{N} \sum_{t=1}^N \frac{D_t(x)}{D_t(x | y)}$$

m is the embedding dimension and l lag

D is the Euclidean distance between x_t and embedded neighbours

Talk Overview



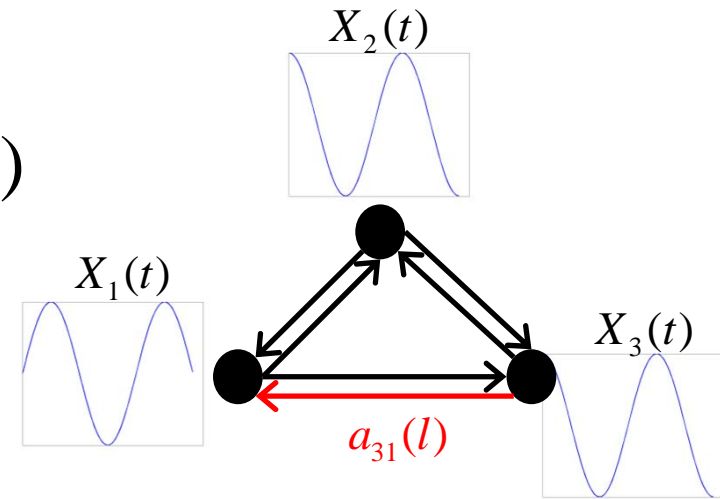
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Direct Measures

Multivariate Autoregressive Modelling (MVAR)

Immune to Field-spread, Directed, Direct, Linear

$$X_i(t) = \sum_{j=1}^N \sum_{l=1}^p a_{ij}(l) X_j(t-l) + u_i(t)$$



Various summary measures, eg,
Partial Directed Coherence (PDC):

$$PDC_{ij}(f) = \frac{A_{ij}(f)}{\sqrt{\sum_{k=1}^M |A_{kj}(f)|^2}}$$

$$A_{ij}(f) = F(a_{ij}(l))$$

Generalised form of Granger Causality

Though insensitive to true zero-lag dependencies (occur in reality?)

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Generative Models

Immune to Field-spread, Directed, Direct, Nonlinear, model-driven

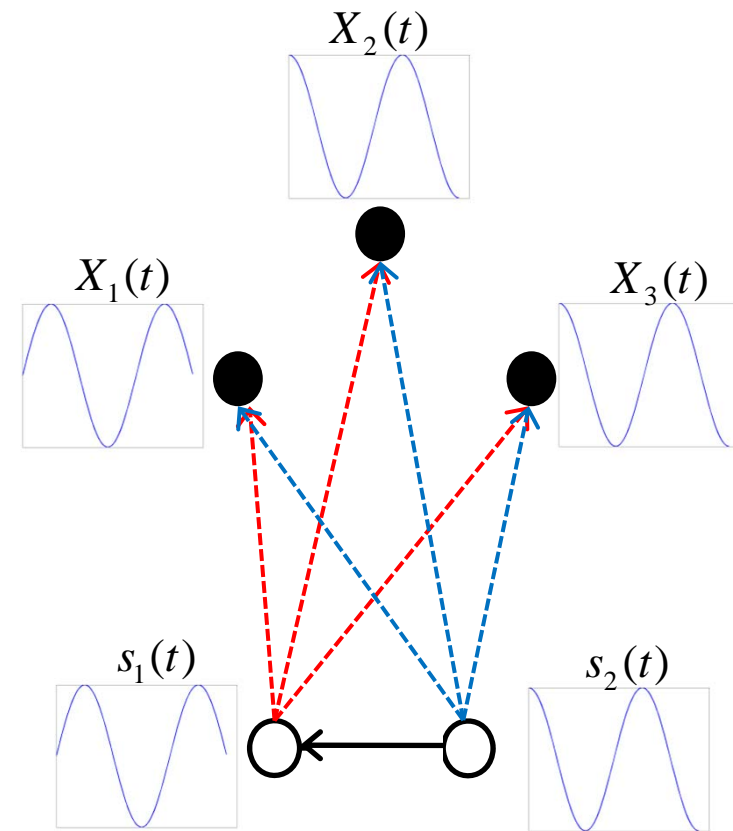
Connectivity modelled between
sources

Projected to sensors via headmodel

Typically a handful of sources, and
a range of networks fit to data

Bayesian methods for comparing
which network model is best

Dynamic Causal Modelling (DCM)
is one approach



Chen et al, 2009, Neuroimage

Measure	Immune to Field Spread	Directed	Nonlinear	Direct
Cross-Correlation	Y ($I > 0$)	N	N	N
Coherence	Y (imaginary)	N	N	N
PLV/PLI	Y	N	N	N
Granger (bivariate)	Y	Y	N	N
Mutual Information	N	N	Y	N
Transfer Entropy	Y	Y	Y	N
Generalised Synchrony	N	Y	Y	N
MVAR (eg, PDC)	Y	Y	Y	N
Generative (eg, DCM)	Y	Y	Y	Y

The End