

Measuring Connectivity with RS-FMRI

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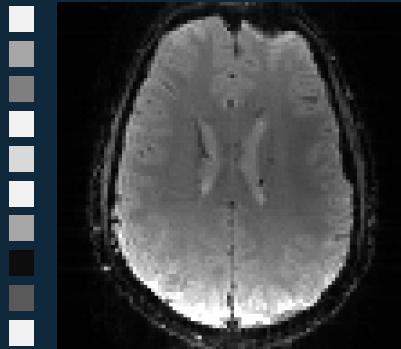
University of Oxford



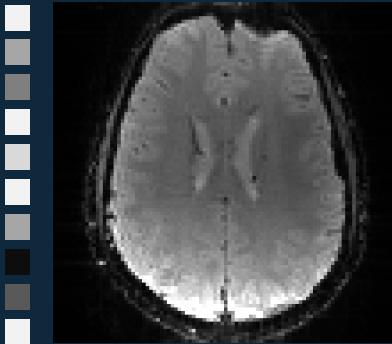
UNIVERSITY OF
OXFORD

LINEAR MODELS IN FMRI

Data as a Space-Time Matrix



Time point 1

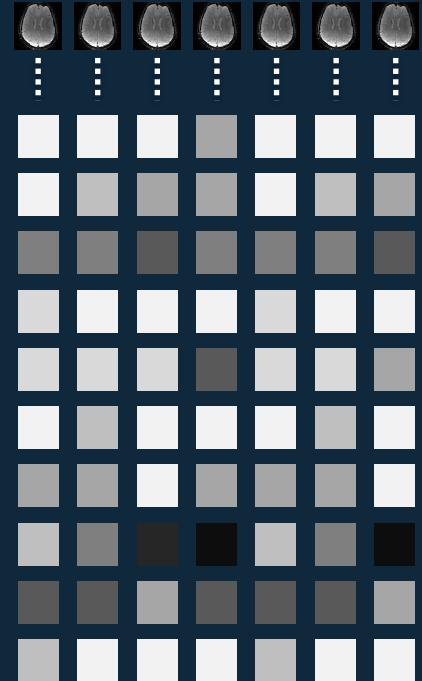


Time point 2

...



Space



Signal characteristics, are important, not structure

Spatial Dimensions: $64 \times 64 \times 48 \sim 10^5$

Temporal Dimensions: $\sim 10^2$

Time

Linear Models

$$Y = \beta \cdot X$$

Diagram illustrating the decomposition of a data matrix Y into spatial maps and time-courses:

The diagram shows a large matrix Y on the left, labeled "Data". Above it, a smaller matrix is shown with "space" on the vertical axis and "time" on the horizontal axis. This matrix is decomposed into three components:

- A vertical matrix of "Spatial Maps" (red, green, blue blocks).
- A horizontal matrix of "Time-Courses" (red, green, blue blocks).
- A product symbol (\times) between the two matrices.

A brace groups the "Spatial Maps" and "Time-Courses" matrices, labeled "Paired spatial and temporal ‘components’". Below the matrices, a brain scan image and a wavy line represent the spatial and temporal components respectively.

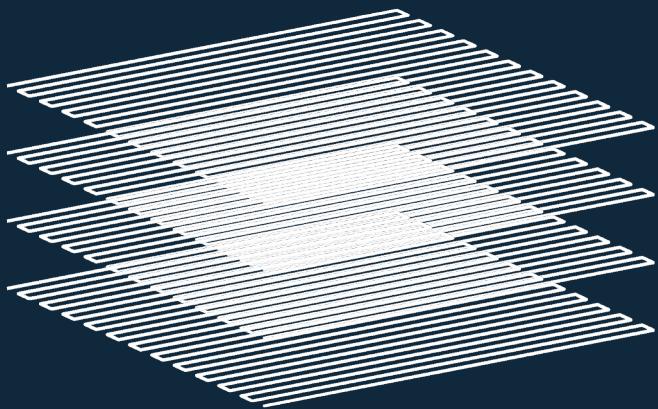
Below the matrices, the equation $Y = \beta \cdot X$ is written, where β is labeled "Spatial Maps" and X is labeled "Time-Courses". A brace groups the β and X terms, labeled "Consistent mathematical framework".

ACQUISITION & PRE-PROCESSING

Typical Acquisition Parameters

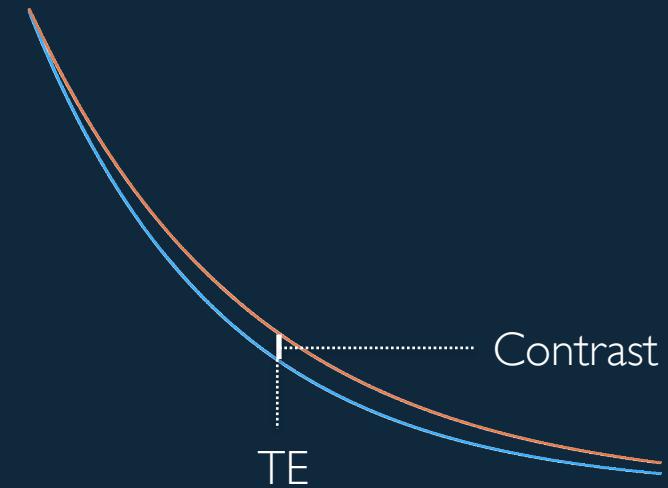
	Typically:
Acquisition Type	Single-shot, gradient-echo

Multi-slice EPI



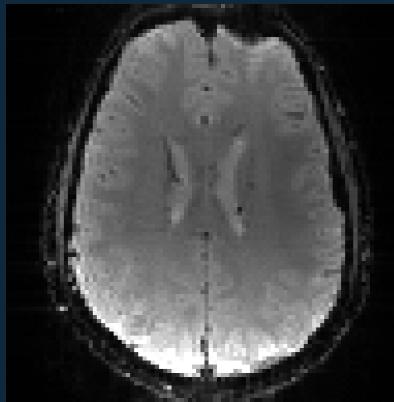
Typical Acquisition Parameters

	Typically:
Acquisition Type	Single-shot, gradient-echo
Contrast	T2* - BOLD

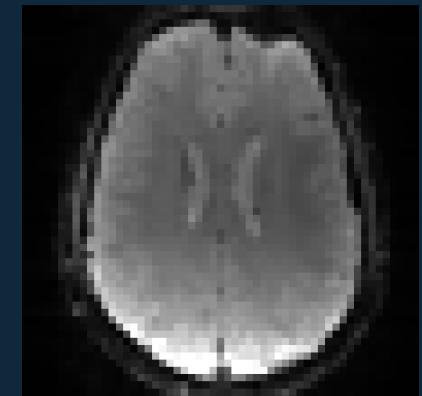


Typical Acquisition Parameters

	Typically:
Acquisition Type	Single-shot, gradient-echo
Contrast	T2* - BOLD
Spatial Resolution	2.0 ~ 3.5 mm



2.0 mm



3.5 mm

Typical Acquisition Parameters

	Typically:	
Acquisition Type	Single-shot, gradient-echo	
Contrast	T2* - BOLD	
Spatial Resolution	2.0 ~ 3.5 mm	
Temporal Resolution	1 ~ 3 seconds	0.16 – 0.5 Hz sampling
Duration	5 ~ 15 minutes	100 ~ 1000 time points

Typical Acquisition Parameters

	Typically:
Acquisition Type	Single-shot, gradient-echo
Contrast	T2* - BOLD
Spatial Resolution	2.0 ~ 3.5 mm
Temporal Resolution	1 ~ 3 seconds
Duration	5 ~ 15 minutes
Condition	Eyes open – “think of nothing”



Data Pre-Processing

Geometry	Filtering
Brain Extraction	Spatial Smoothing
Motion Correction	Temporal Filtering
Distortion Correction	Nuisance Regression
Registration	Global Signal Regression*

*Murphy & Fox, "Towards a consensus regarding global signal regression for resting state functional connectivity MRI", NeuroImage 2016

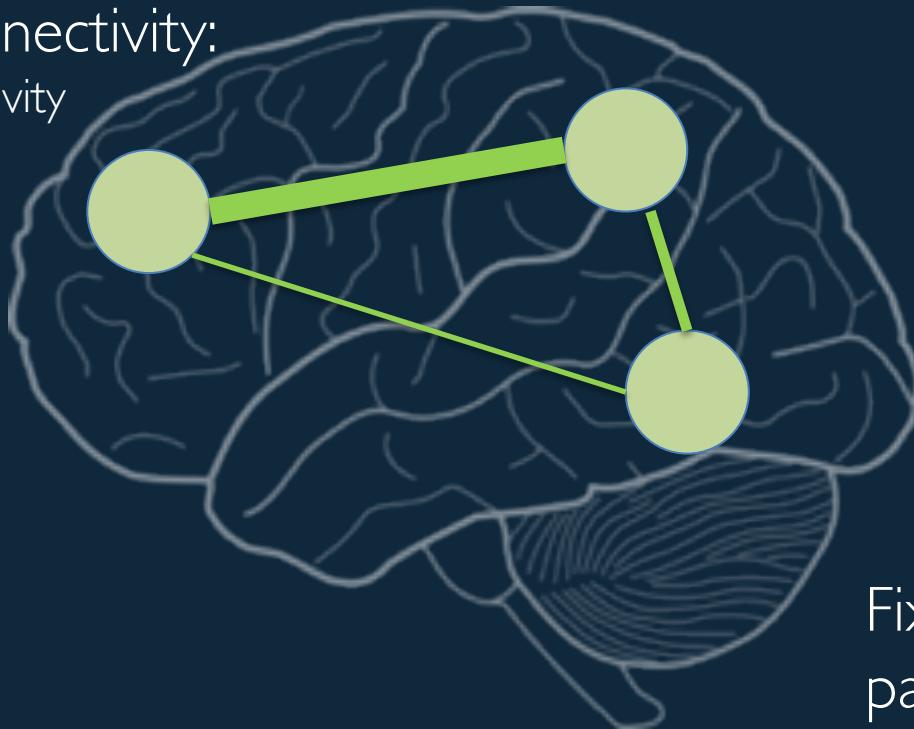
STATIC FUNCTIONAL CONNECTIVITY

Static Functional Connectivity

Functional Connectivity:

Strength of connectivity

Un-directed



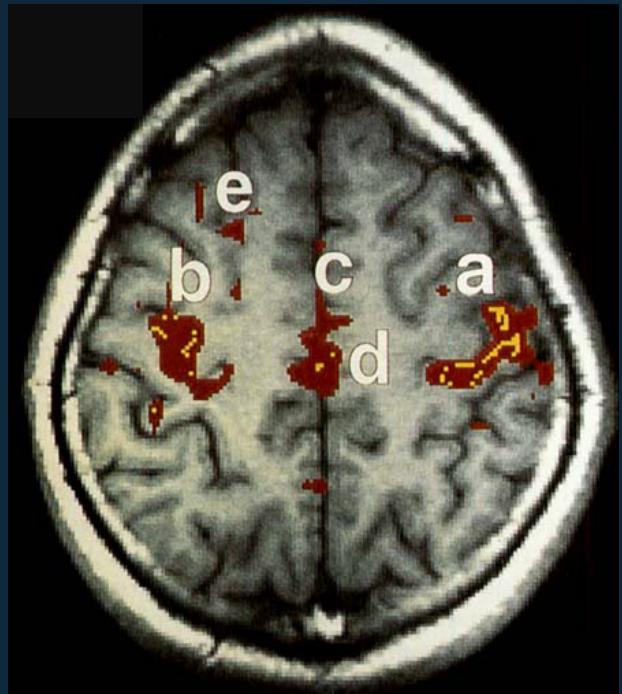
Fixed connectivity
pattern over time

I. SEED CONNECTIVITY

Seed-Based Correlation

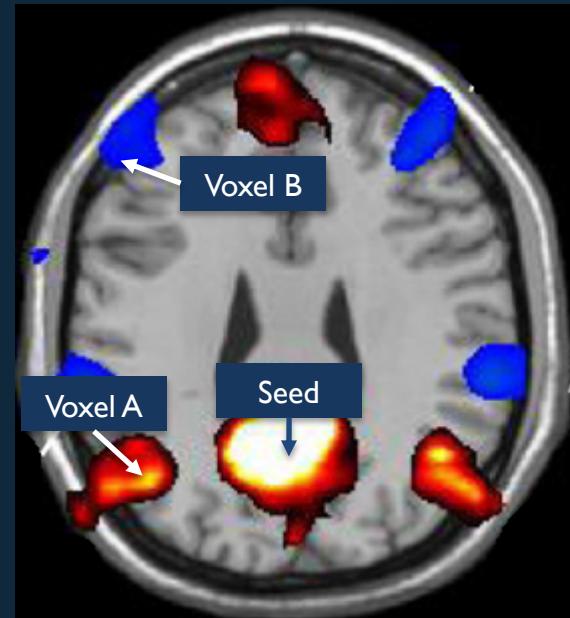
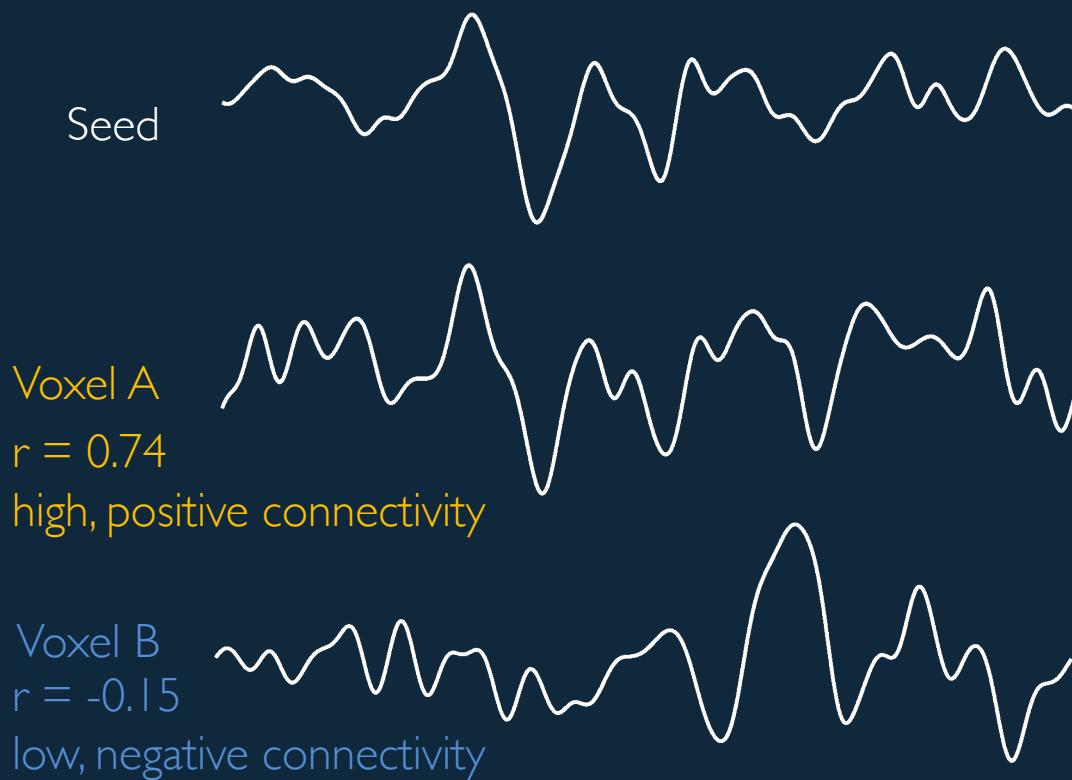


Connectivity as a pattern matching problem



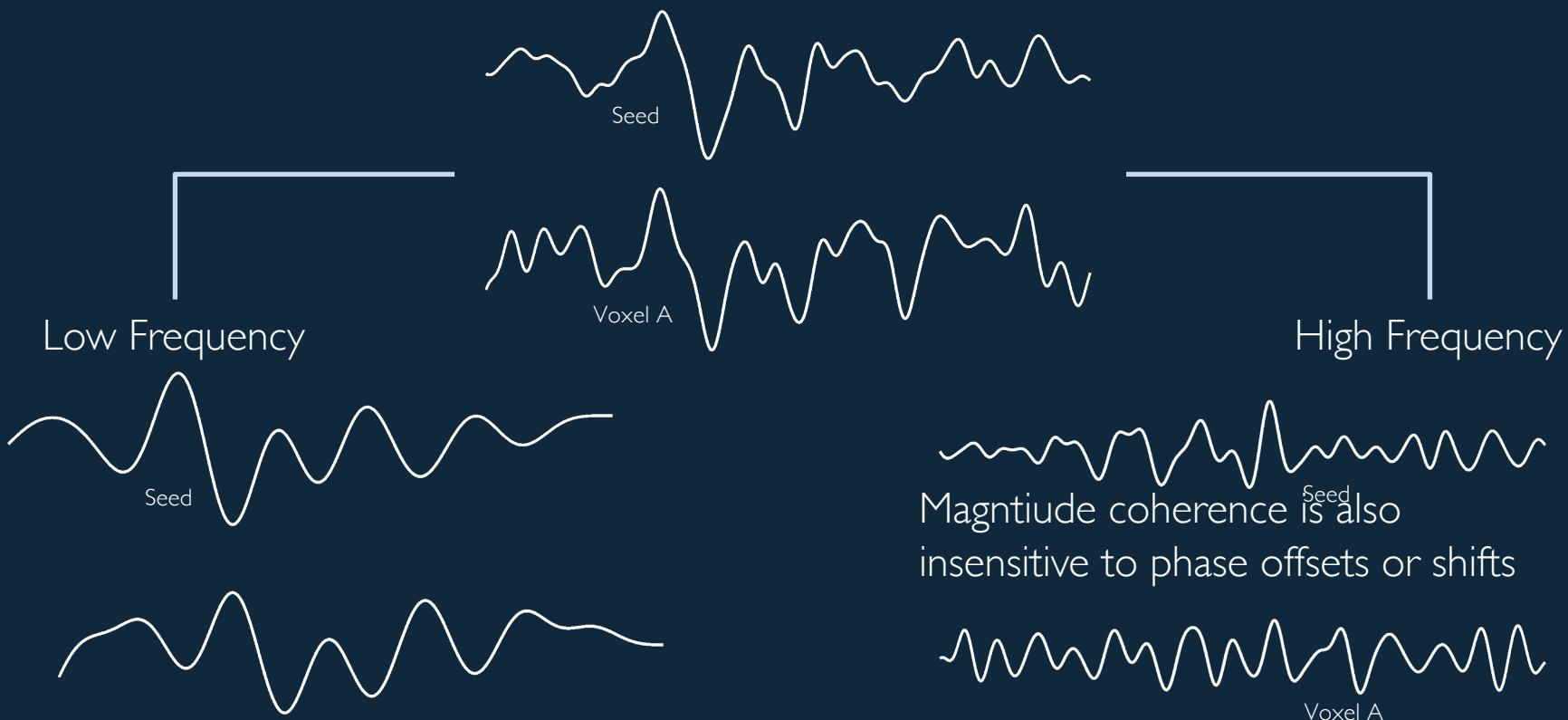
Biswal et al., MRM 1995

Connectivity Metric: Temporal Correlation

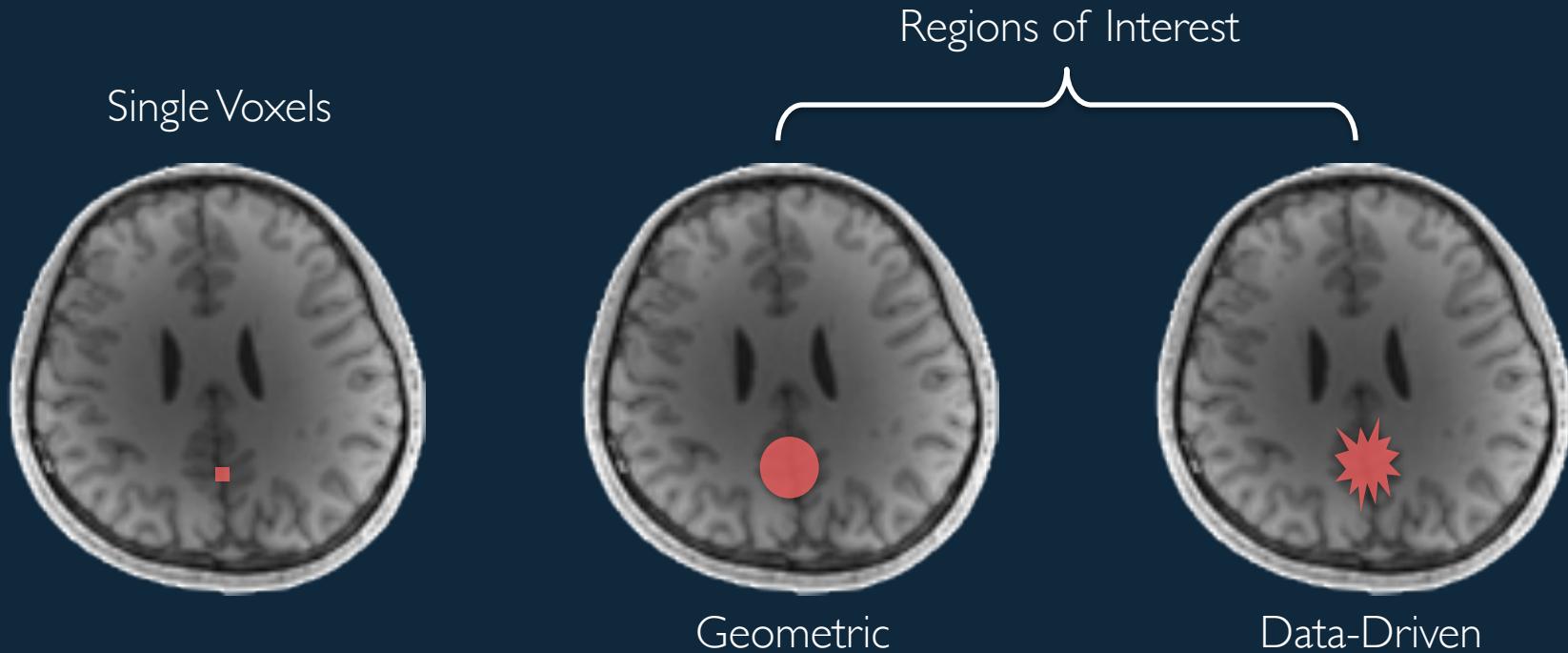


Chang et al., *NeuroImage* 2010

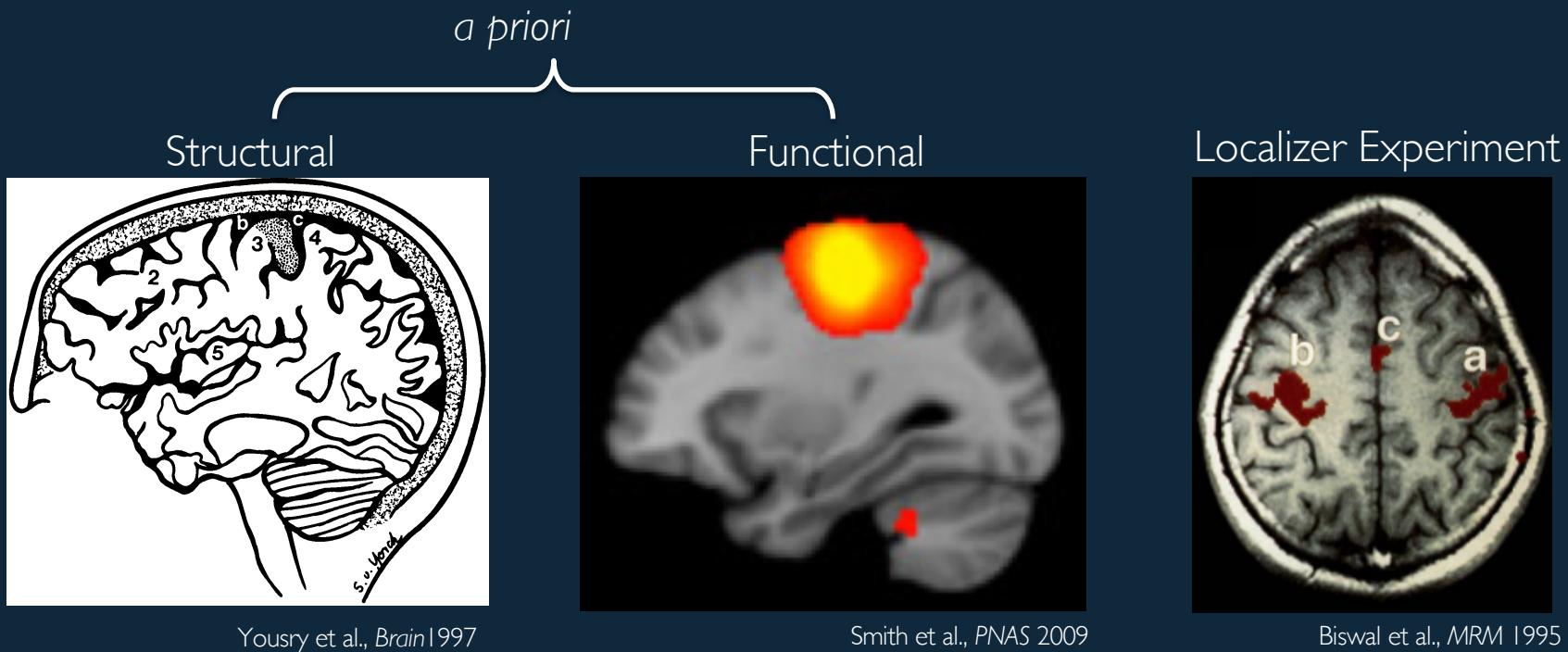
Connectivity Metric: Coherence



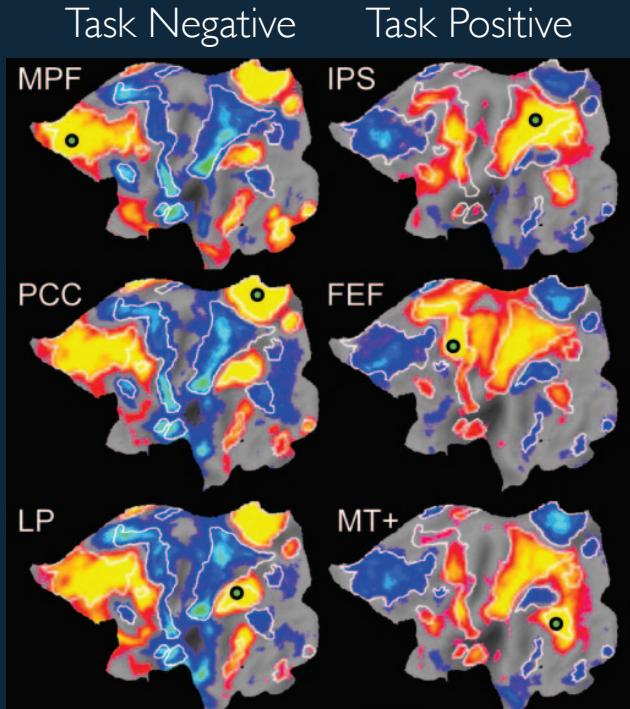
Defining Seeds – ROI size



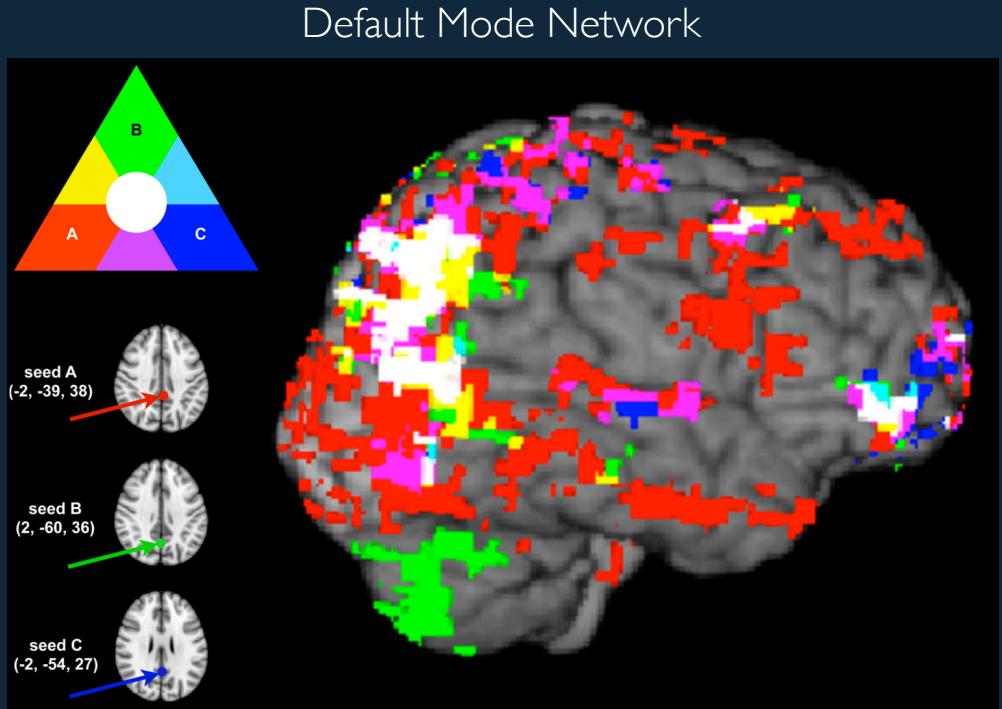
Defining Seeds - Sources



Different Seeds, Different Connectivity

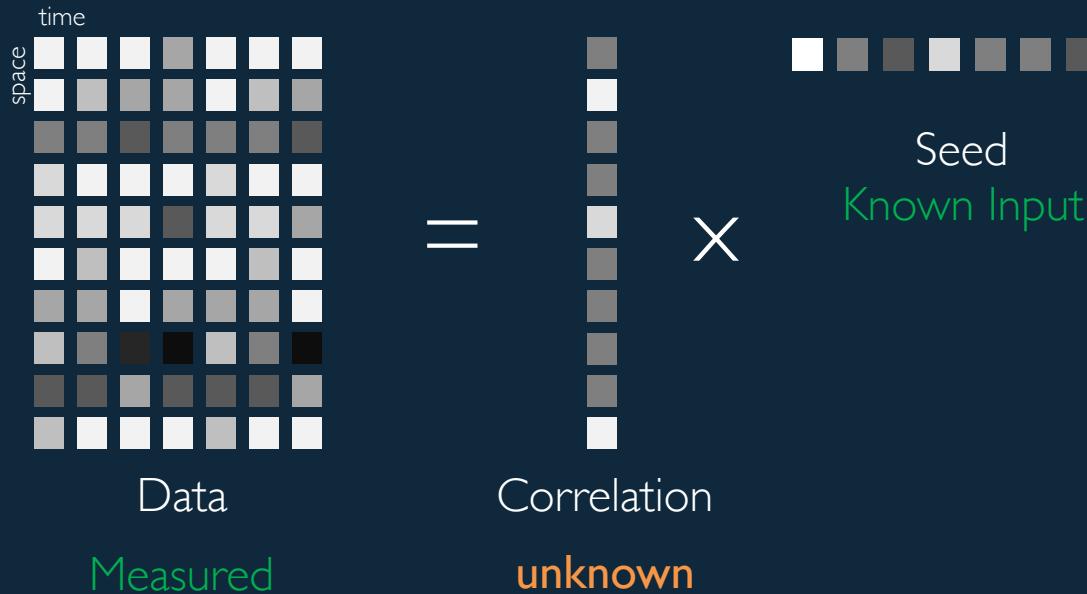


Fox et al., PNAS 2005



Cole et al., Front Sys Neurosci 2010

Seed-Based Correlation: Linear Model

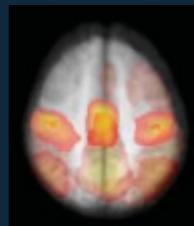
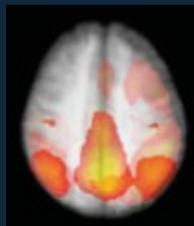
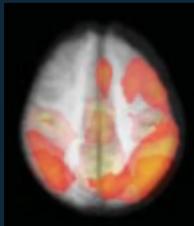


Seed-correlation is a linear model

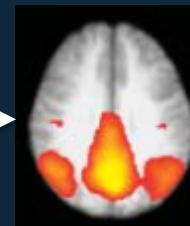
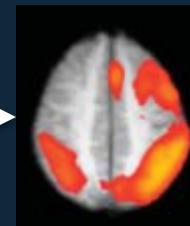
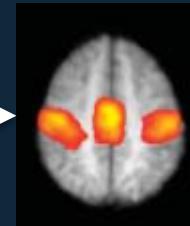
2. SPATIAL ICA

Spatial Independent Component Analysis

Observed Mixtures



Networks (sources)

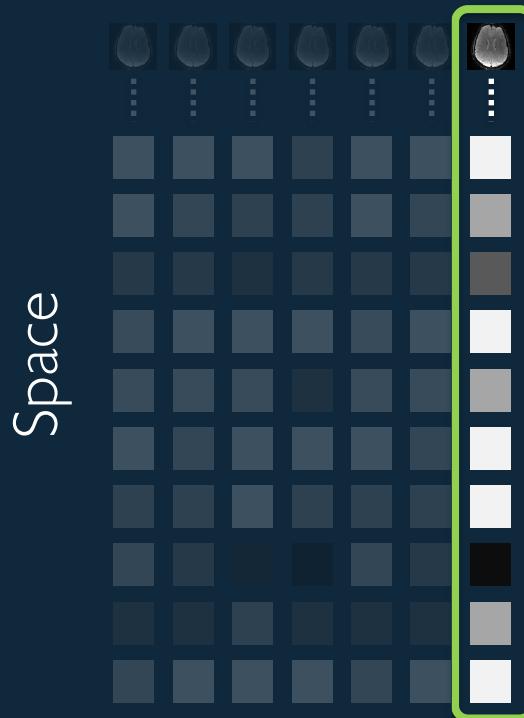


Mixtures alone:
insufficient

Extra constraint:
indepdendence

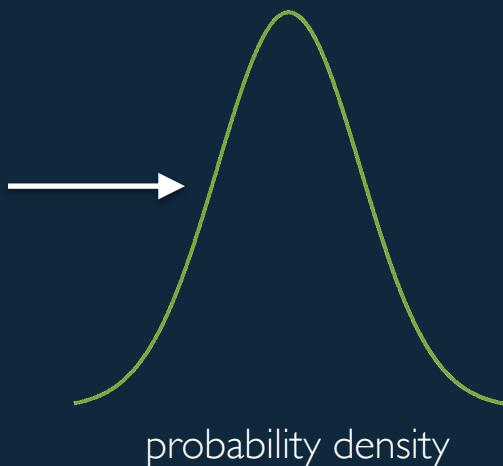
Spatial ICA Statistical Model

Spatial networks are *independent*



Assessed with probability distributions

histogram of voxel coefficients



Non-Gaussianity – Central Limit Theorem

FastICA – Non-Gaussianity

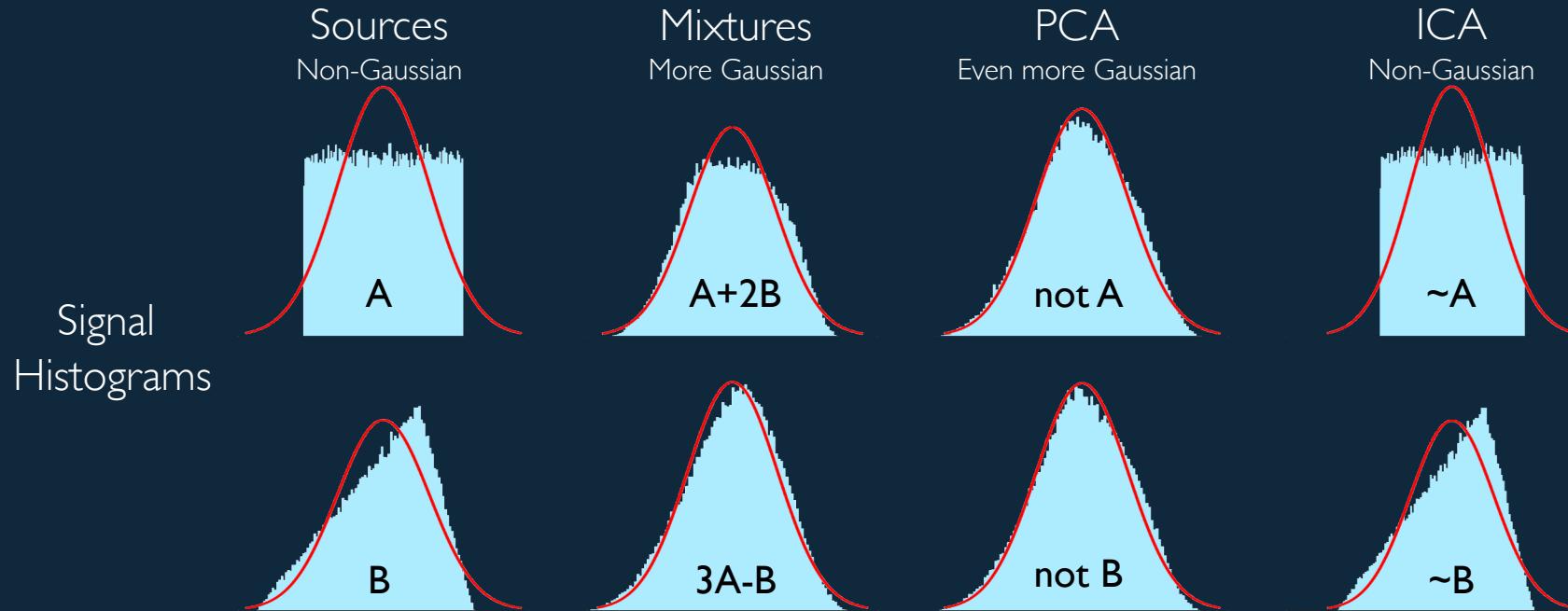
Hyvärinen et al., *IEEE-TNN* 1999

Probabilistic ICA

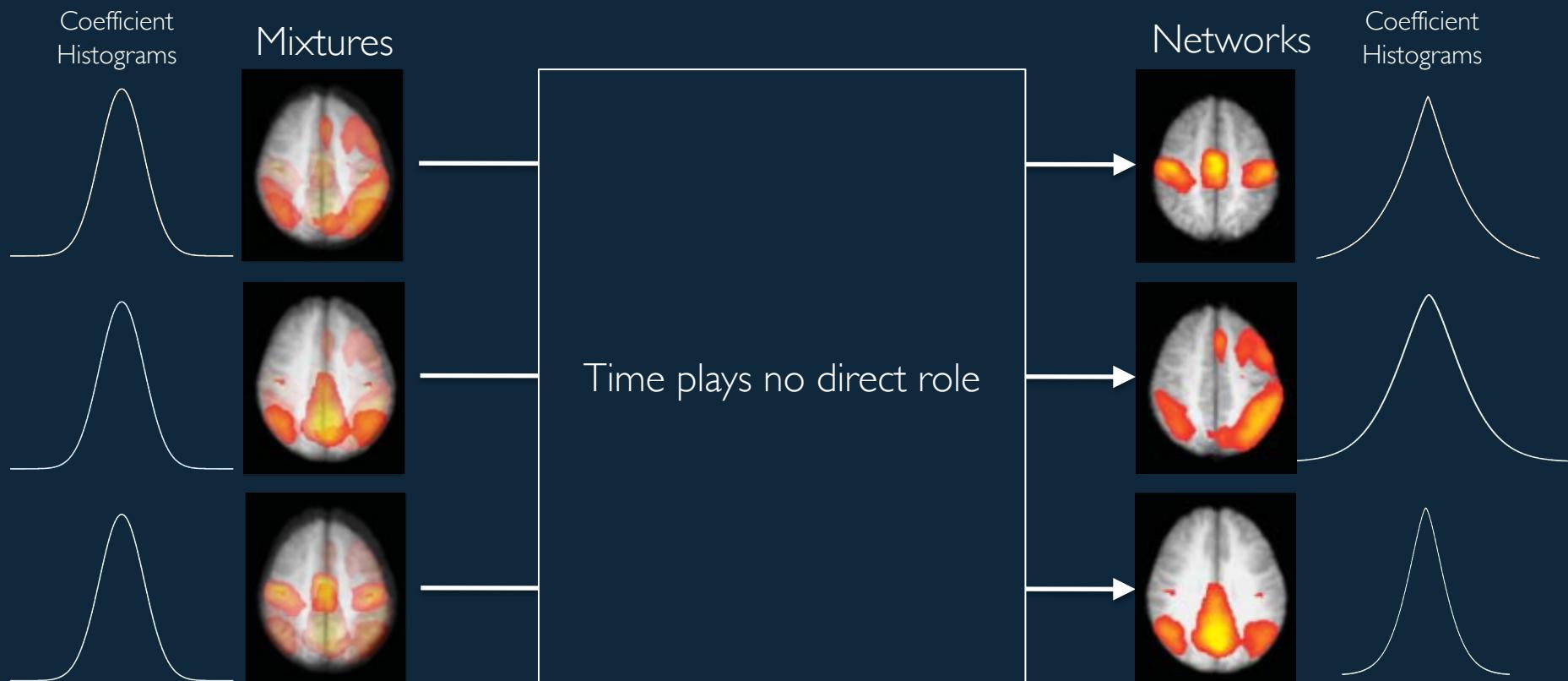
Beckmann et al., *IEEE-TMI* 2004

InfoMax – Mutual Information

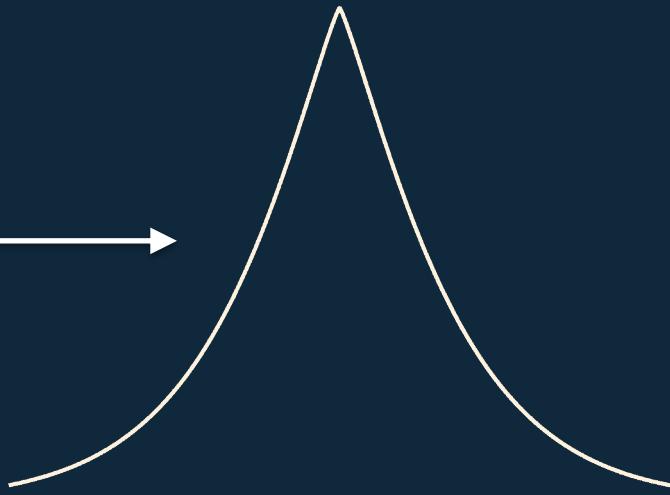
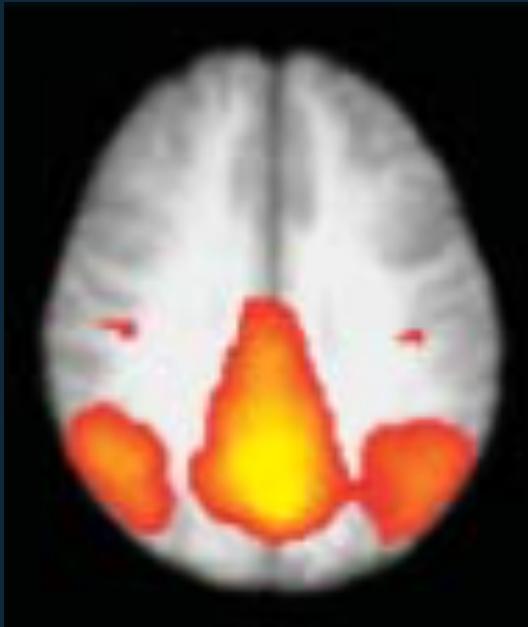
Bell et al., *Neural Comp* 1995



Spatial Independent Component Analysis



Spatial ICA “Connectivity”



These voxels are implicitly “connected” because the spatial coefficients produce a maximally non-Gaussian histogram

Connectivity Comparison

Spatial Information

Spatial ICA

Spatial coefficient distributions

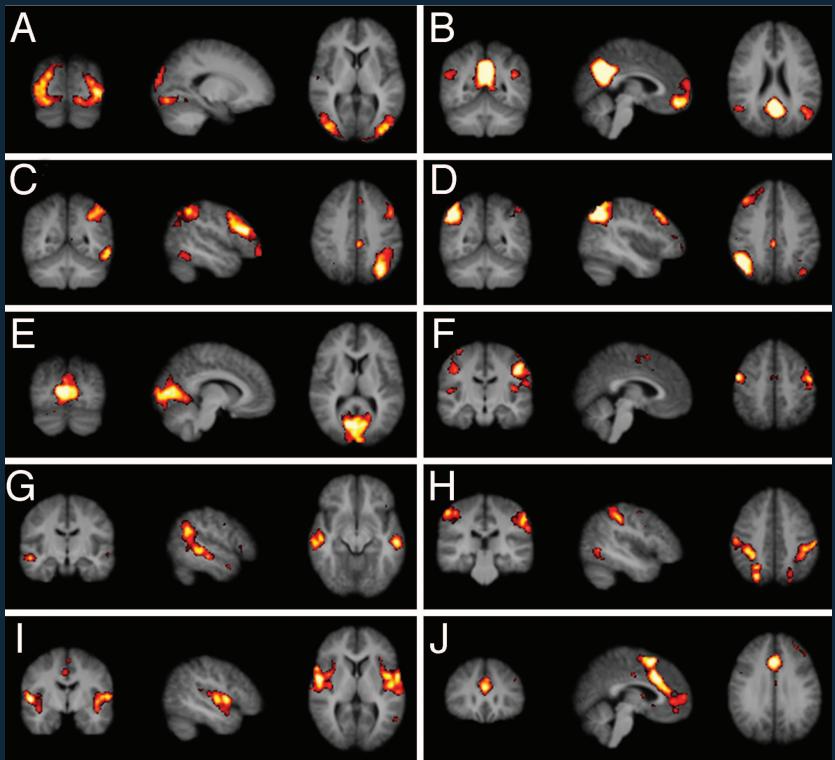
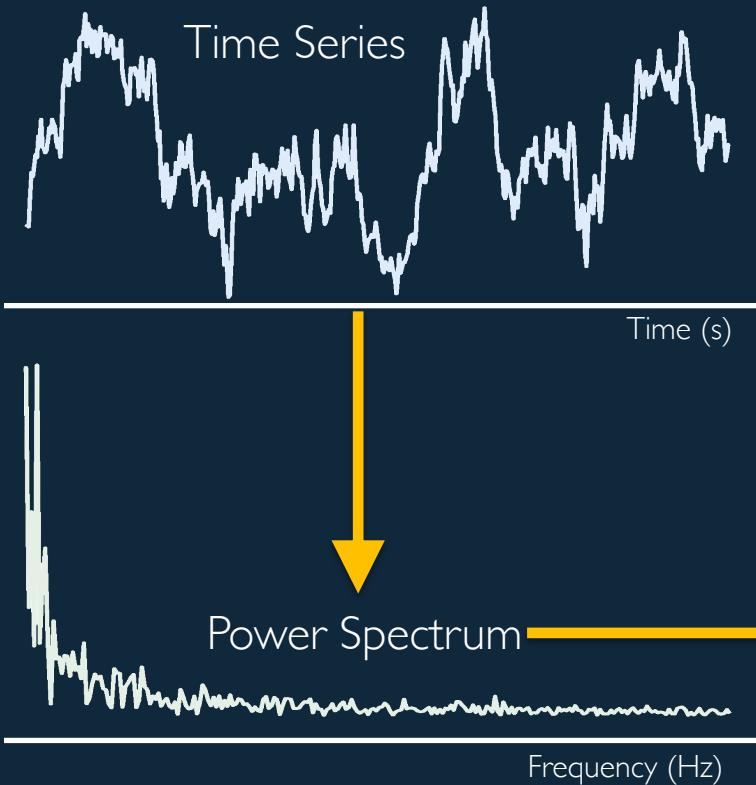
Seed Correlation

Seed size, location

Temporal correlations

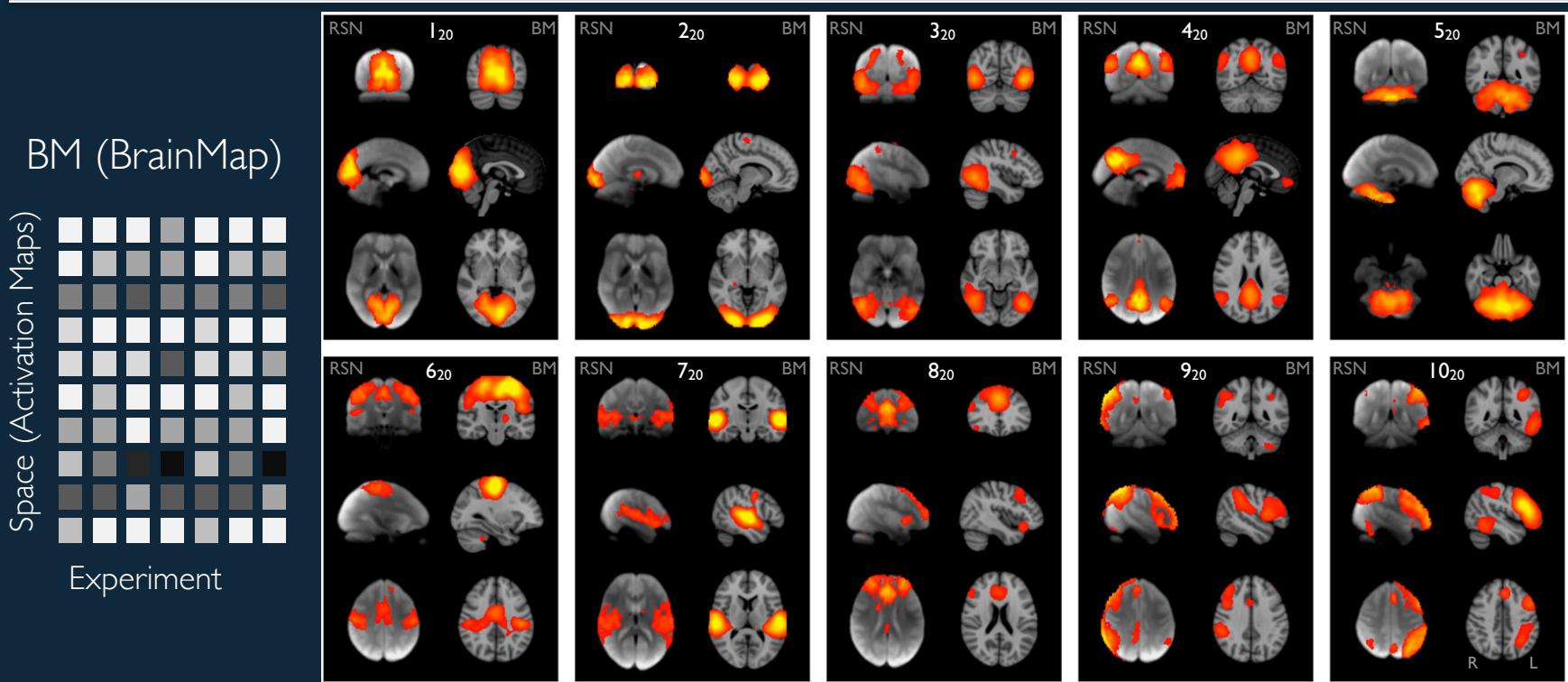
Temporal Information

Space x Frequency

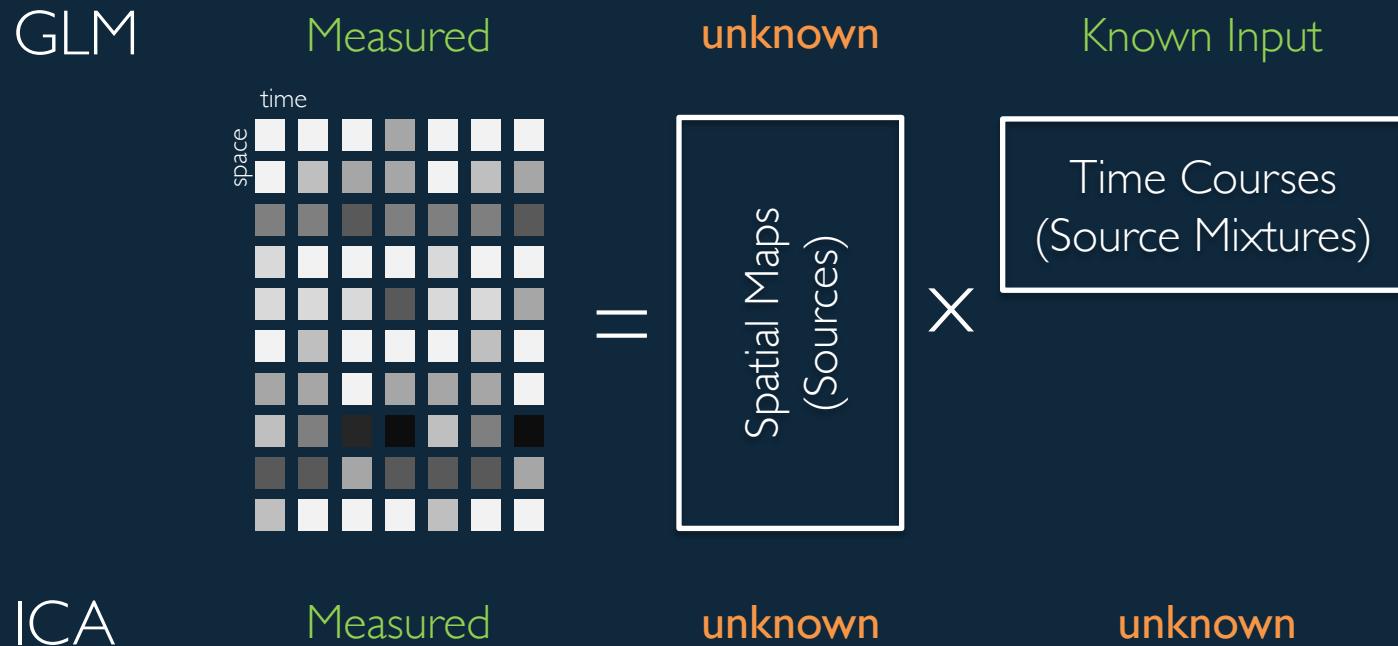


Damoiseaux et al., PNAS 2006

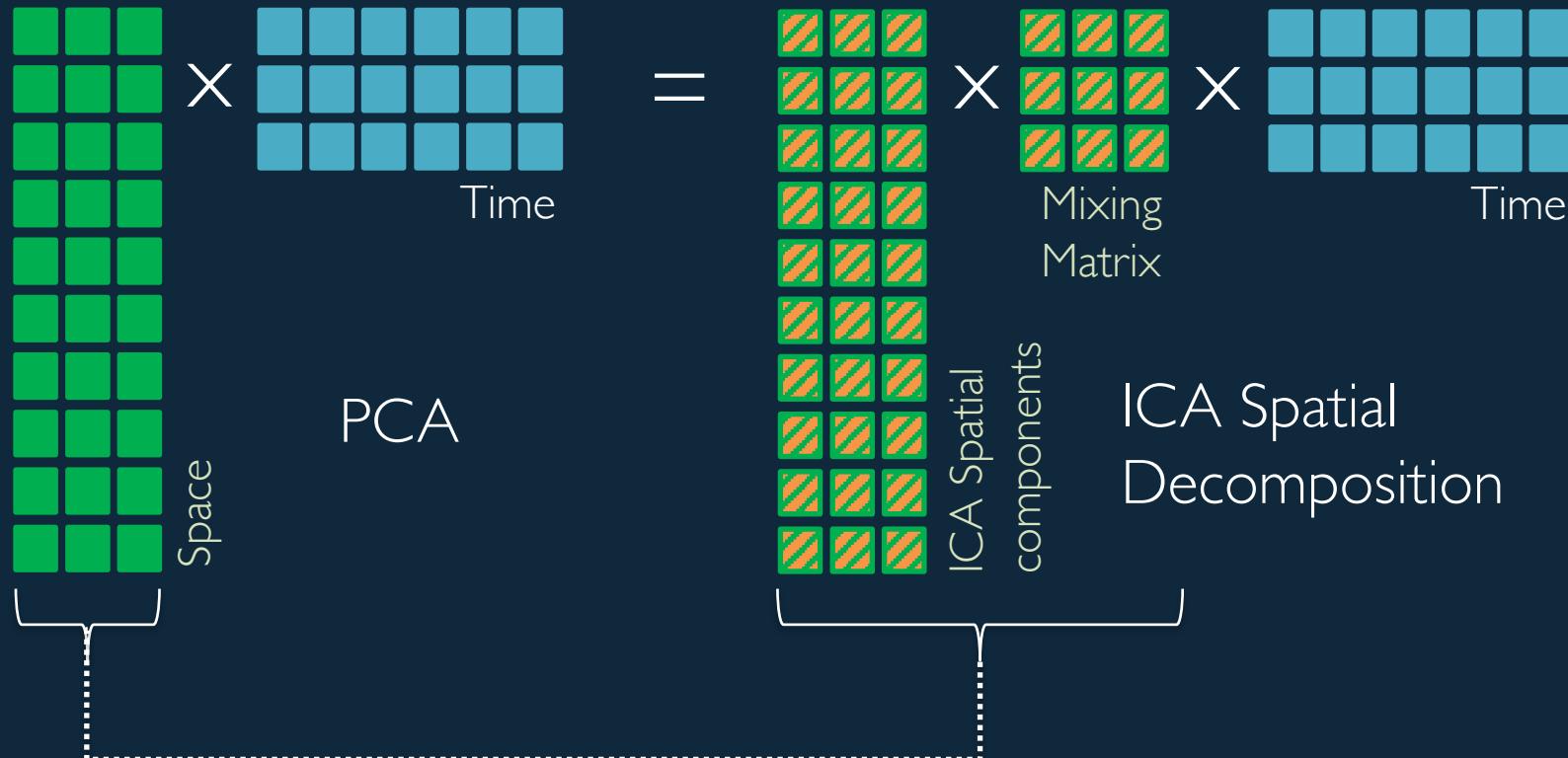
Space x Experiment



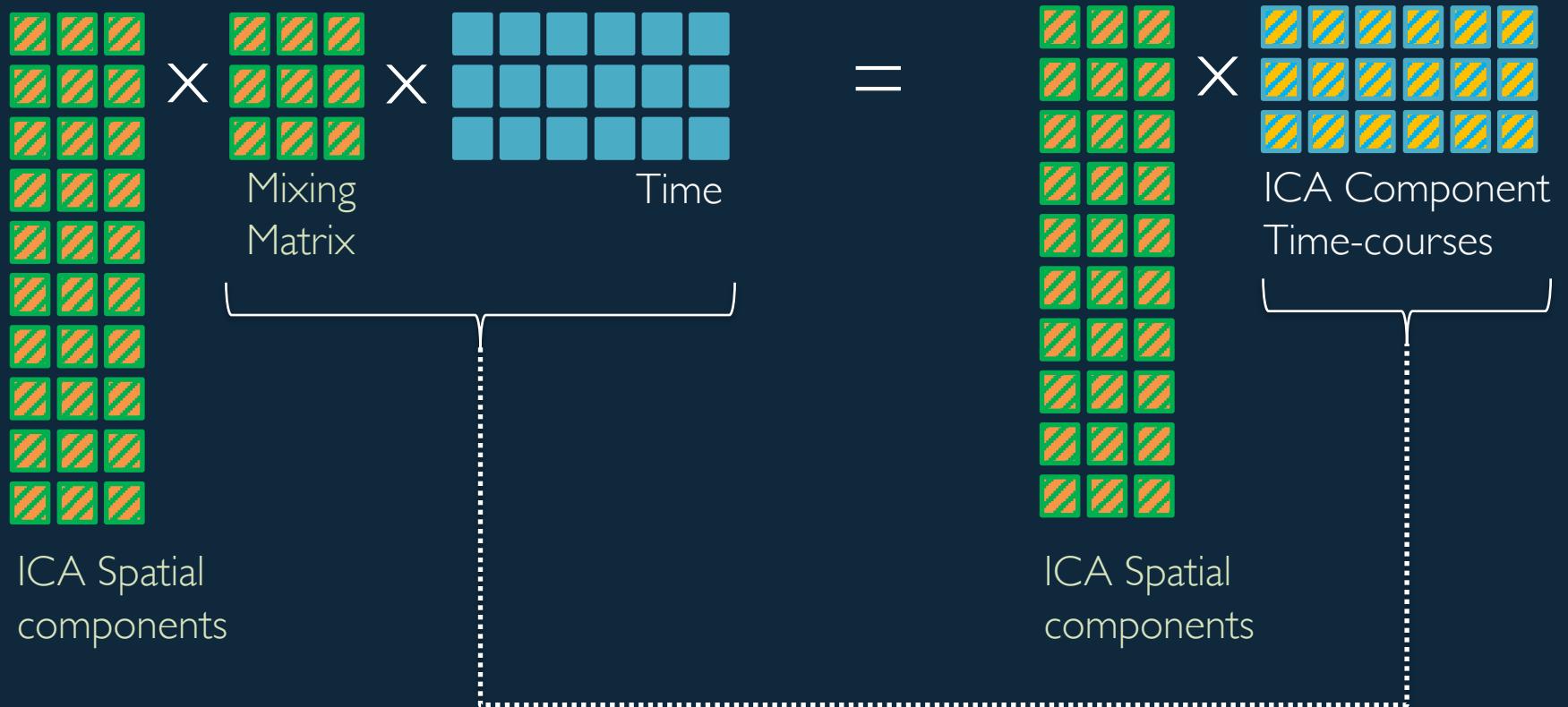
ICA Linear Model



PCA Pre-processing

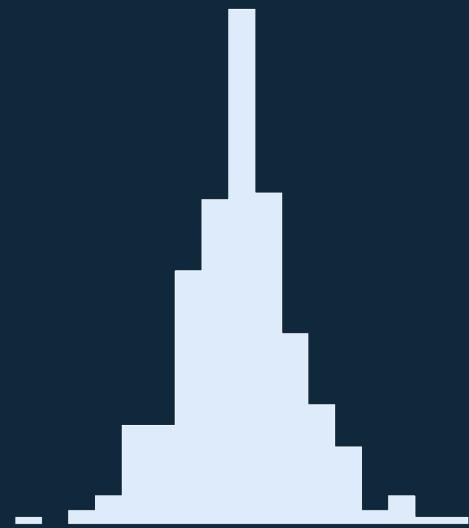


ICA Time-Courses



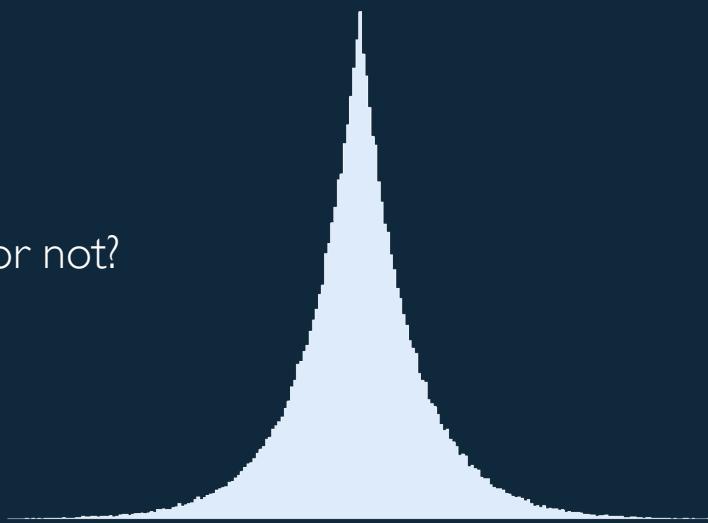
ICA Spatial and Temporal dimensions

Temporal Dimensions: $\sim 10^2$



300 time-points

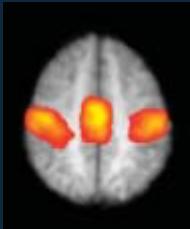
Spatial Dimensions: $64 \times 64 \times 48 \sim 10^5$



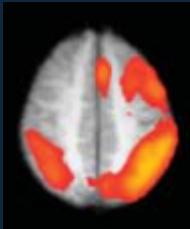
Gaussian or not?

200,000 voxels

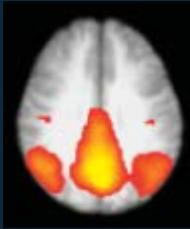
ICA – Inputs and Dimensionality



Multiple networks simultaneously from a single decomposition

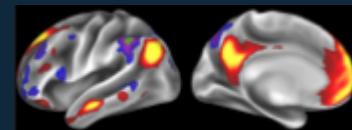


Very little user input (model free)

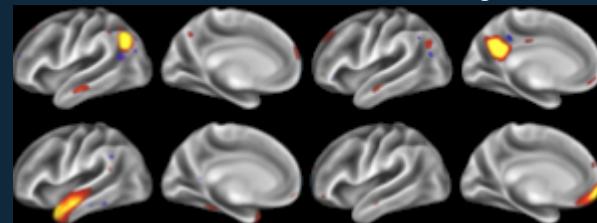


ICA takes a dimensionality (number of networks) input parameter

- *a priori*
- maximising model evidence
- model complexity metrics: AIC/BIC/MDL



Low Dimensionality

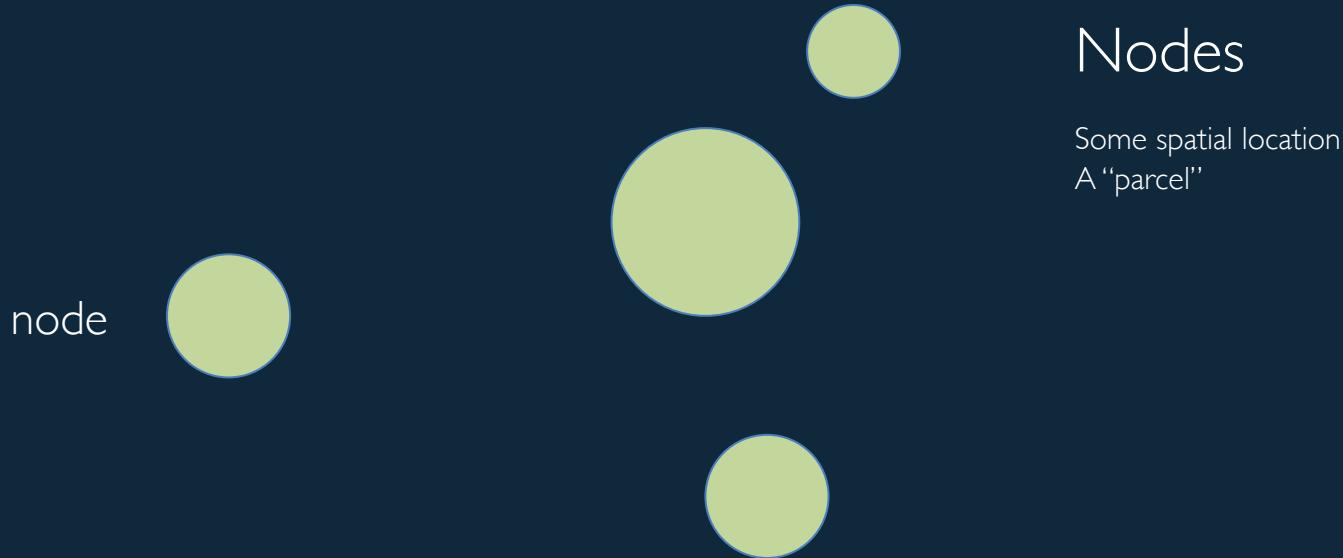


High Dimensionality

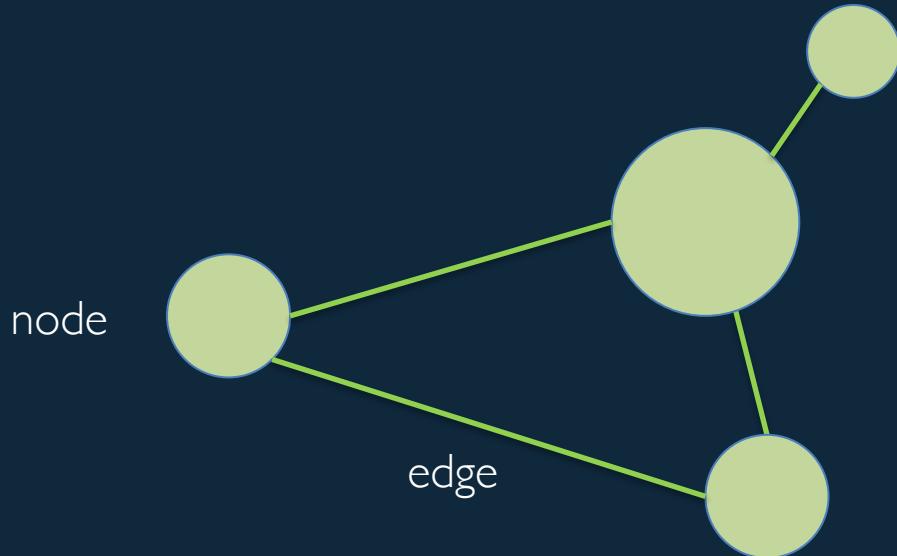
Smith et al., Trends Cog Sci 2013

3. GRAPH METHODS

What are Graphs?



What are Graphs?



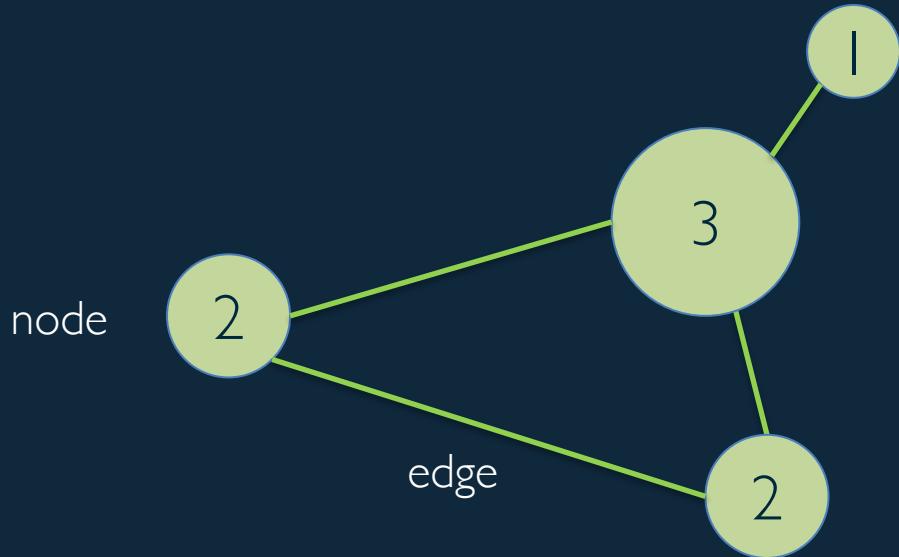
Nodes

Some spatial location
A “parcel”

Edges

Relationship between nodes
Defined by some connectivity metric
Function connectivity → undirected edges

What are Graphs?



Nodes

Some spatial location
A “parcel”

Edges

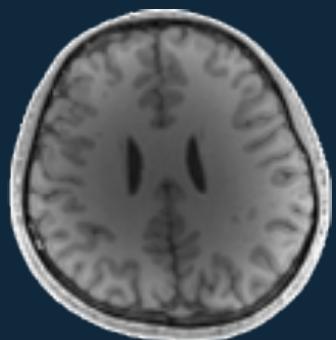
Relationship between nodes
Defined by some connectivity metric
Function connectivity → undirected edges

Degree

Number of connections a node has

Defining Nodes: Parcellation

Voxels

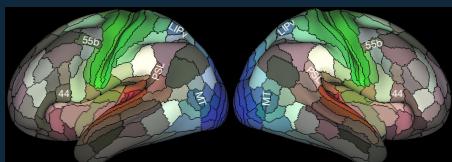


Atlas



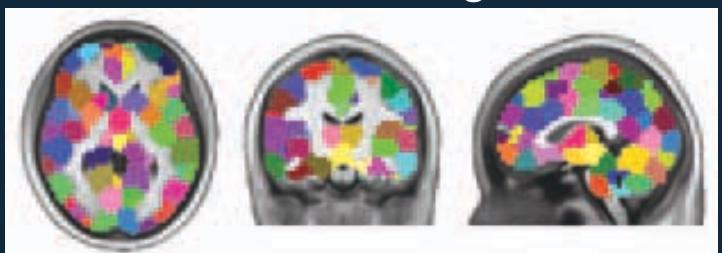
Bohland et al., PLoS One 2009

Multi-Modal



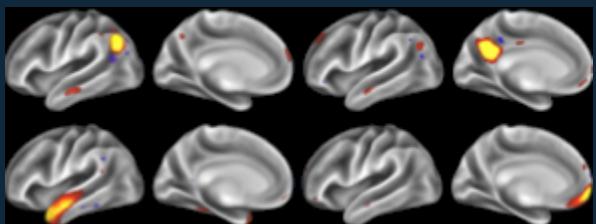
Glasser et al., Nature 2016

Clustering



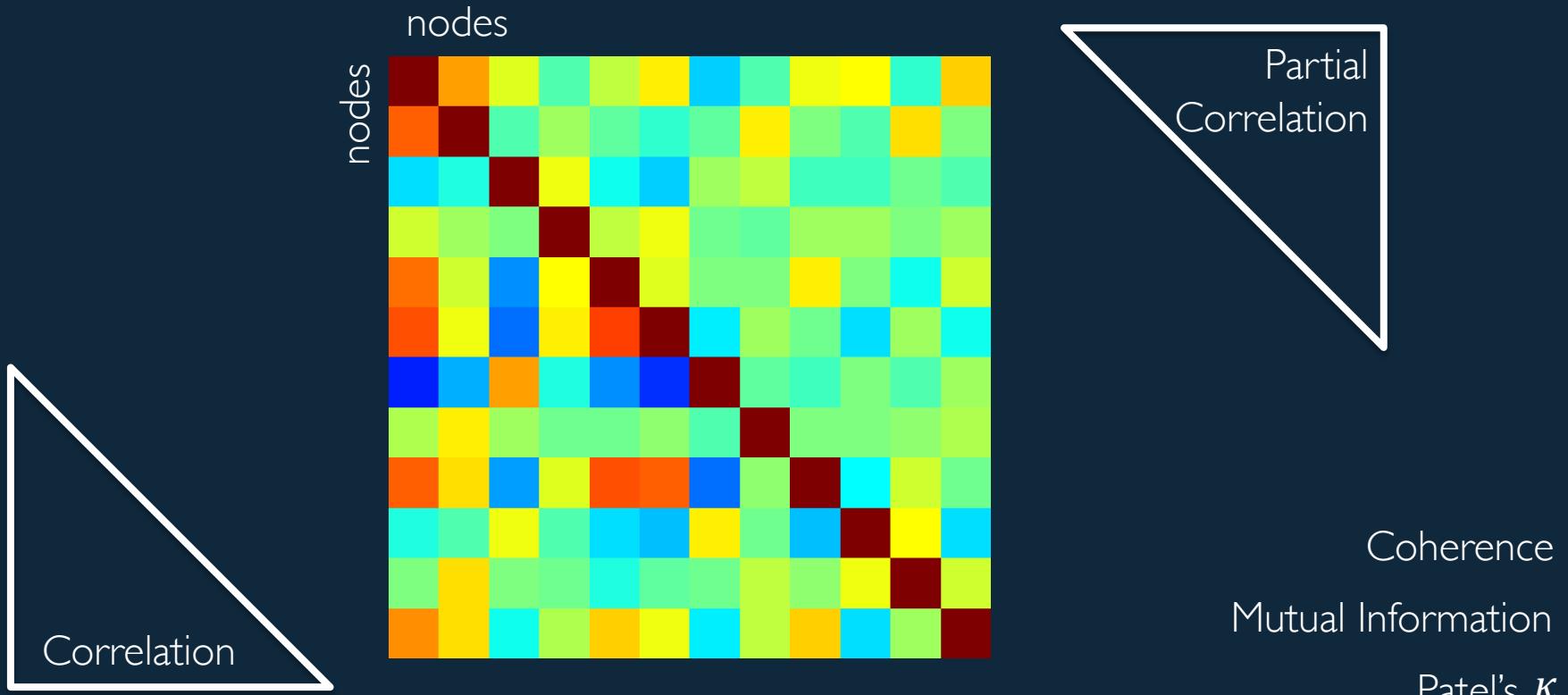
Craddock et al., Human Brain Mapping 2012

ICA

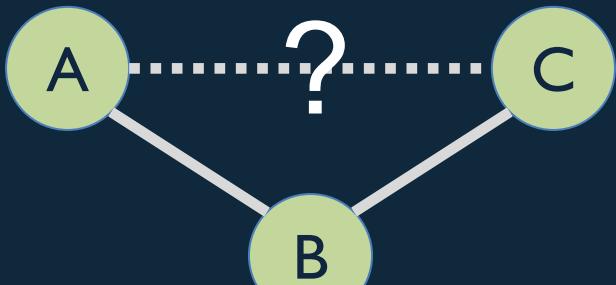


Smith et al., Trends in Cognitive Neuroscience 2013

Defining Edge Strengths

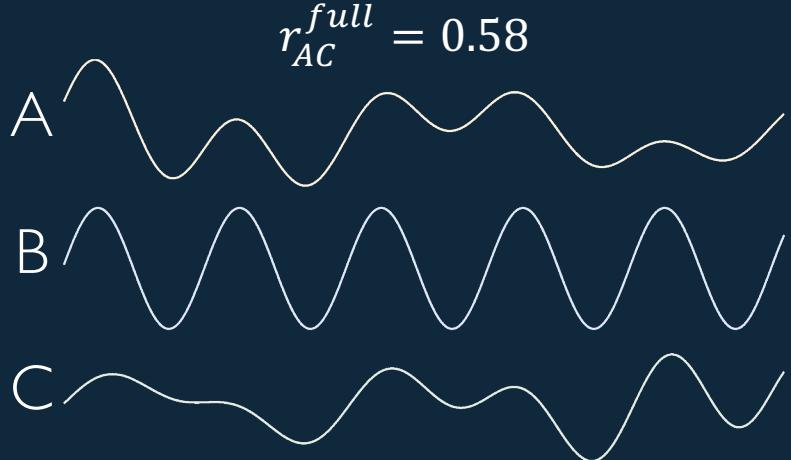


Partial Correlation



Full Correlation

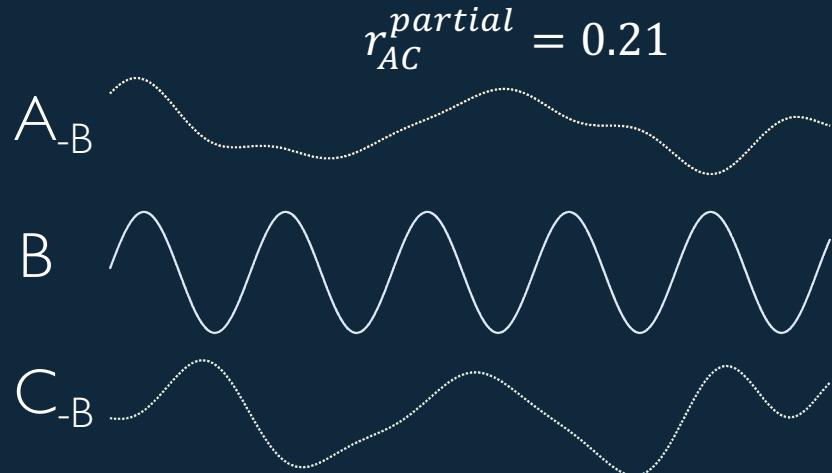
$A \rightarrow C$ strong connectivity



$$r_{AC}^{full} = 0.58$$

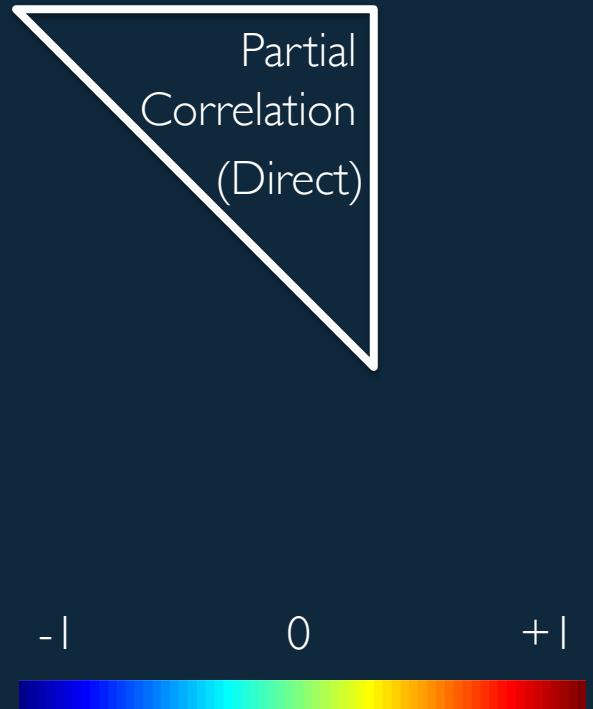
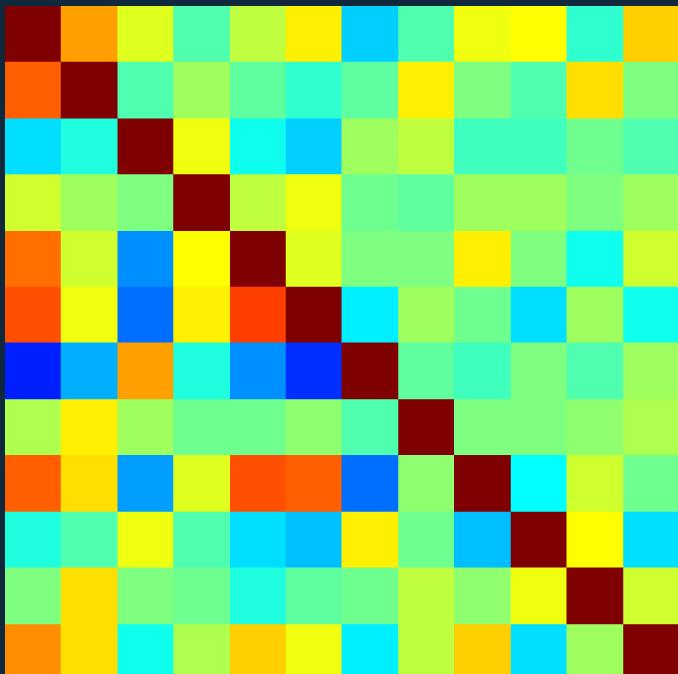
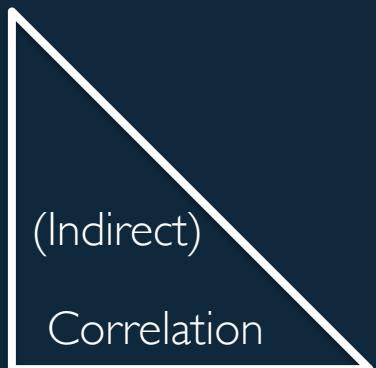
Partial Correlation

$A \rightarrow C$ weak connectivity

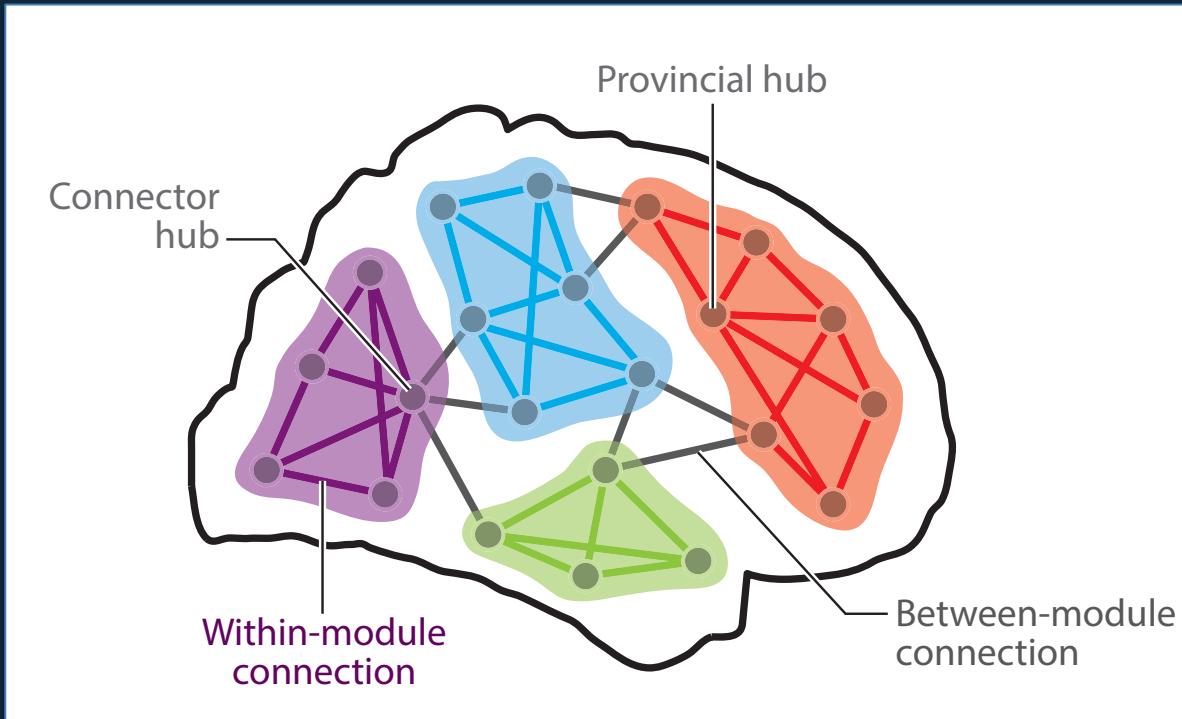


$$r_{AC}^{partial} = 0.21$$

Partial Correlation Network Matrix

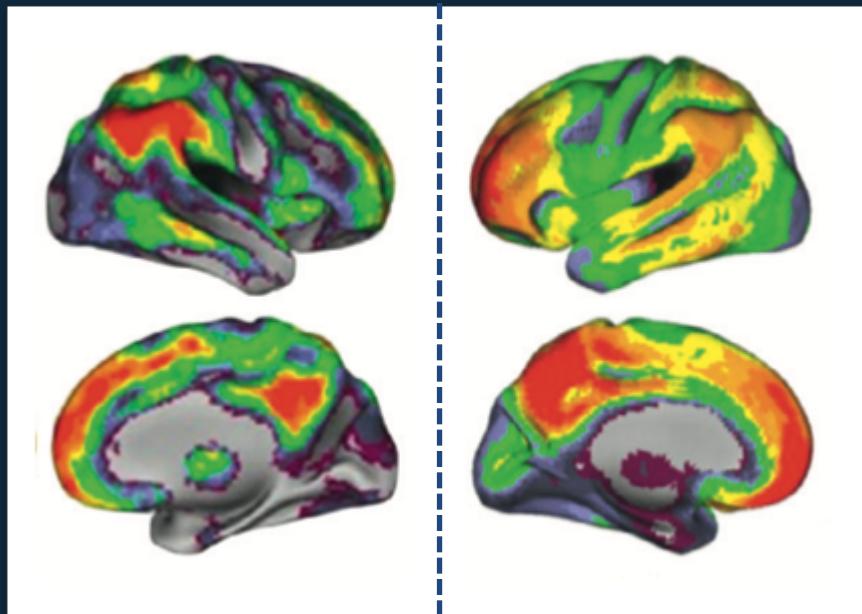


Network Features - Hubs



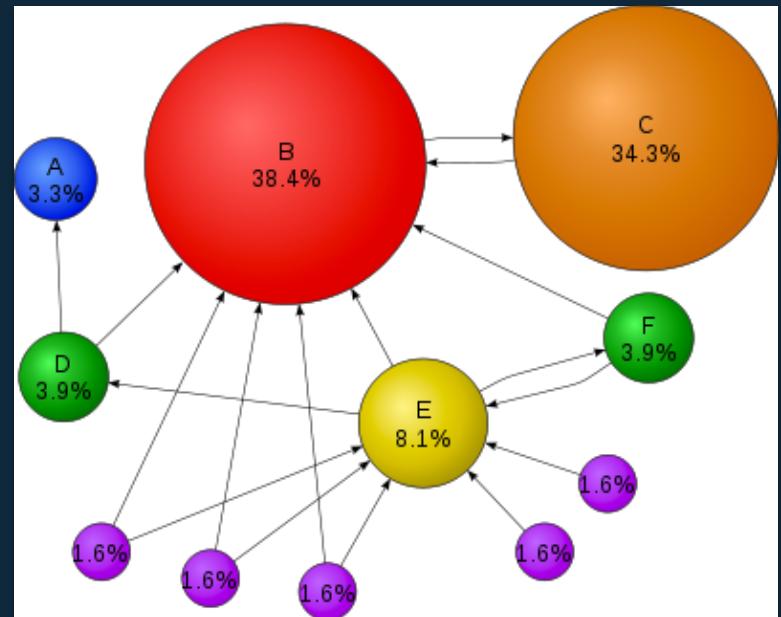
Network Features – Hubs and Centrality

Functional
Connectivity Hubs



Alzheimer's
A β Deposition

Google PageRank Centrality



van den Heuvel, *Trends in Cog Sci* 2013

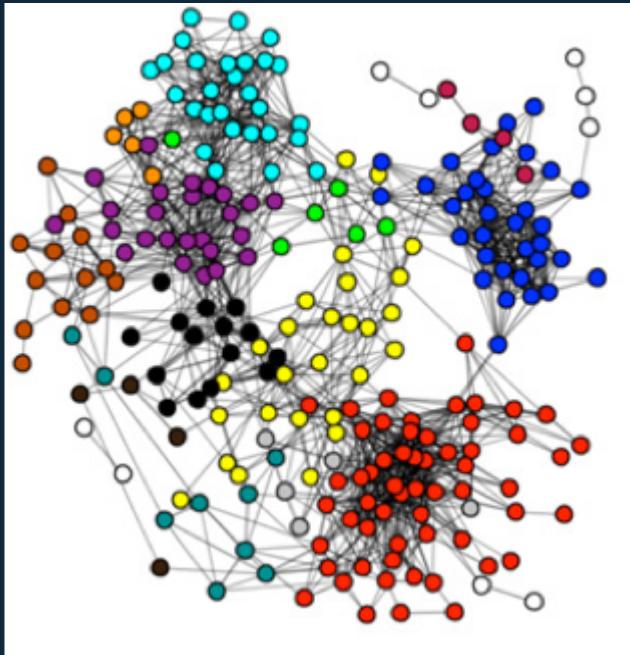
courtesy of Wikipedia

Network Features - Communities

Community/Subgraph/Module Detection
network efficiency

InfoMap

Rosvall et al., PNAS 2008



Power et al., Neuron 2011

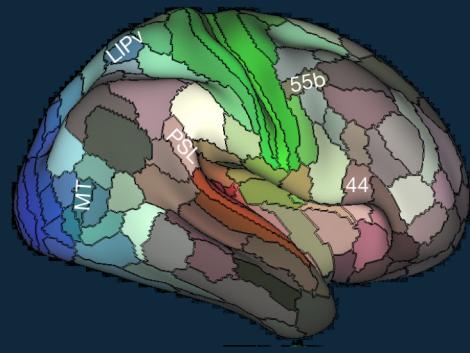
clustering coefficients

small worldness

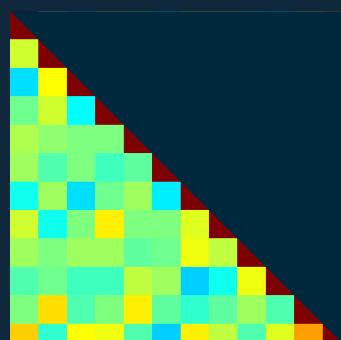
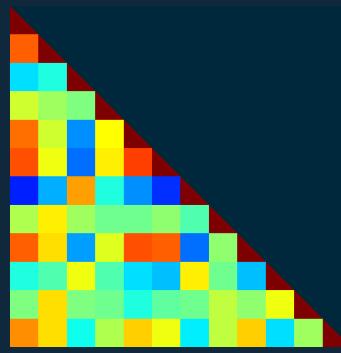


Graph Analysis – Many Choices

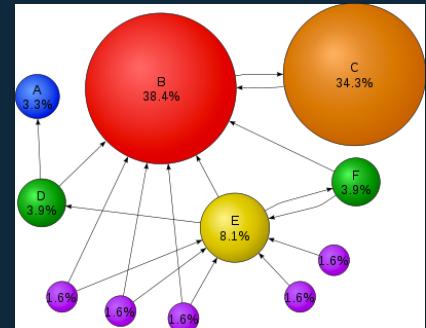
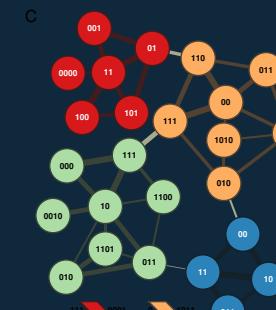
Node Definition / Parcellation



Edge Metric



Feature Extraction



Connectivity Comparison

Spatial Information

Spatial ICA

Spatial coefficient distributions

Graph Methods

Parcellations

Edge metrics

Seed Correlation

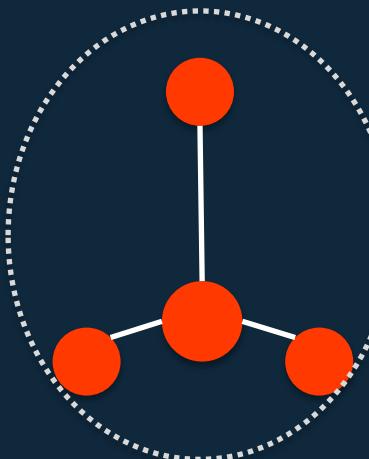
Seed size, location

Temporal correlations

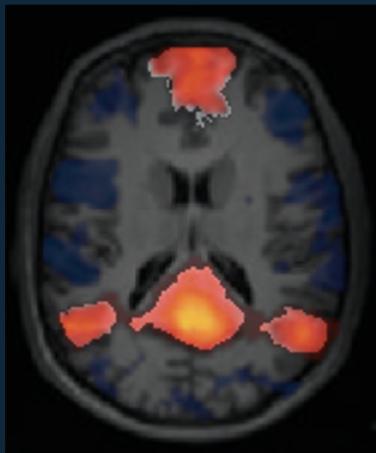
Temporal Information

Connectivity Comparison

Default Mode Network

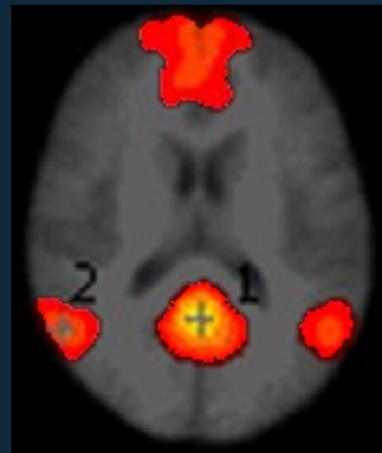


Seed Correlation
(PCC)



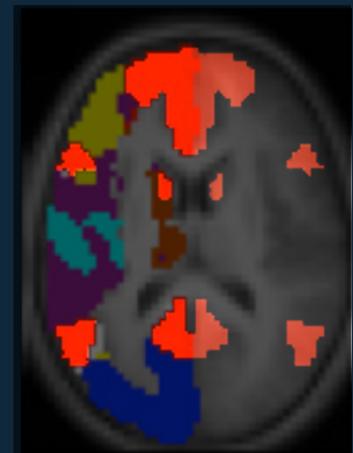
Uddin et al., HBM 2009

Spatial ICA



De Luca et al., NeuroImage 2006

Subgraph Detection
(red)

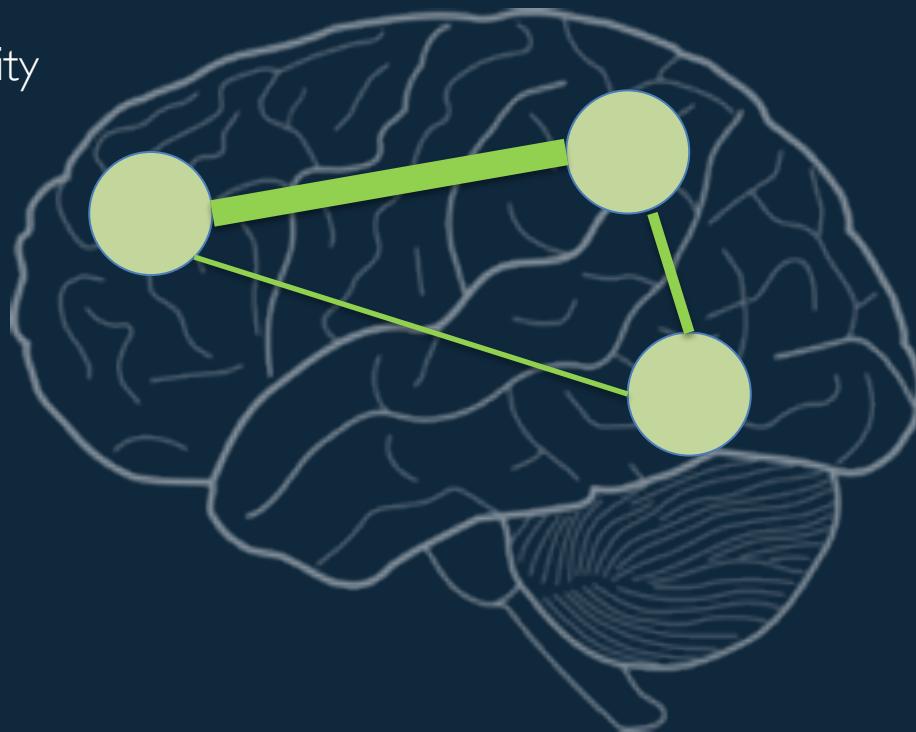


Power et al., Neuron 2011

DYNAMIC FUNCTIONAL CONNECTIVITY

Dynamic Connectivity

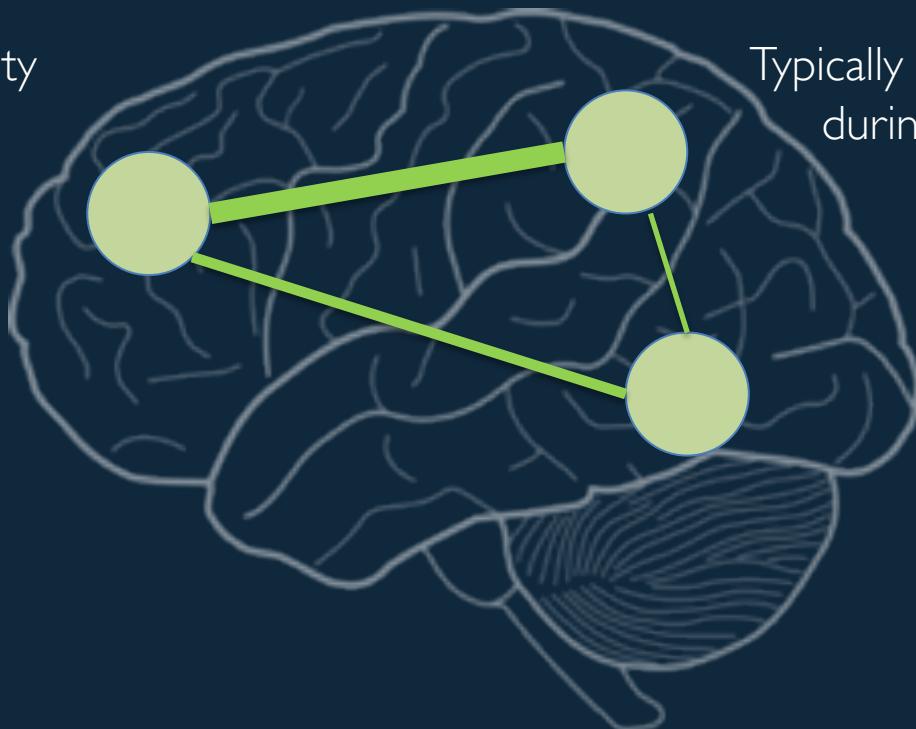
Changing connectivity
profiles over time



Dynamic Connectivity

Changing connectivity
profiles over time

Typically refers to changes
during a scan or experiment

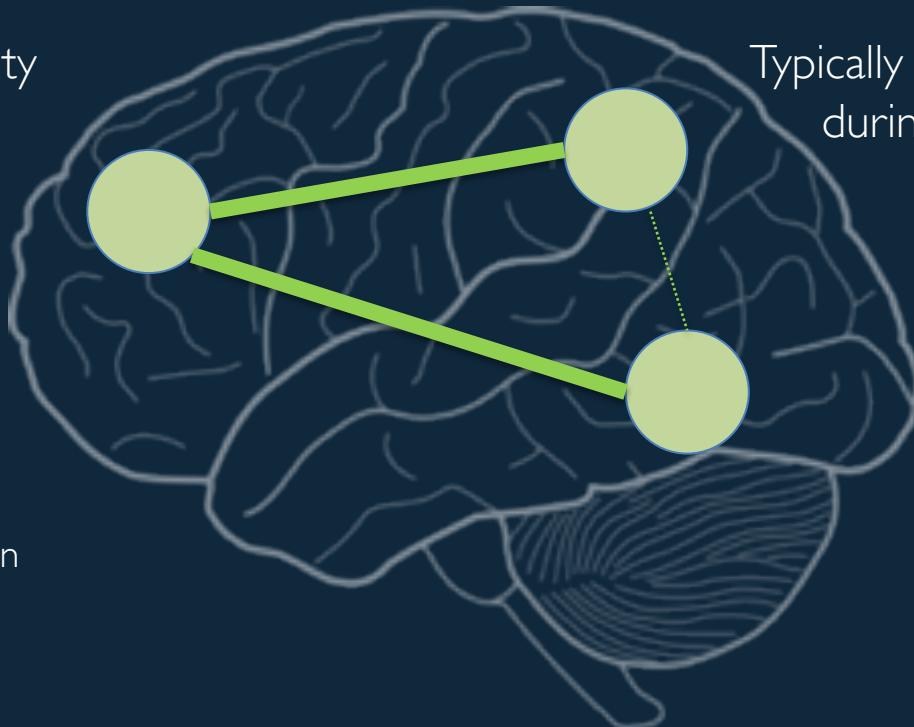


Dynamic Connectivity

Changing connectivity profiles over time

Typically refers to changes during a scan or experiment

- Changes in :
- internal “state”
 - top-down modulation
 - attention
 - learning
 - etc



Dynamic Connectivity

Changing connectivity profiles over time

Typically refers to changes during a scan or experiment

- Changes in :
- internal “state”
 - top-down modulation
 - attention
 - learning
 - etc



Sliding Window Correlation

Chang et al., *NeuroImage* 2010

Temporal Independent Component Analysis

Time-courses are *independent*

Functional Integration:

Spatial ICA –
spatially non-overlapping

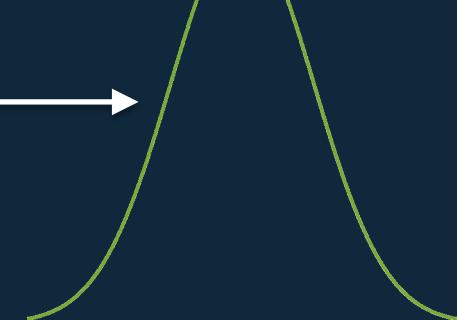
Temporal ICA –
spatially overlapping

Accounts for temporal
non-stationarity in correlation models



Time

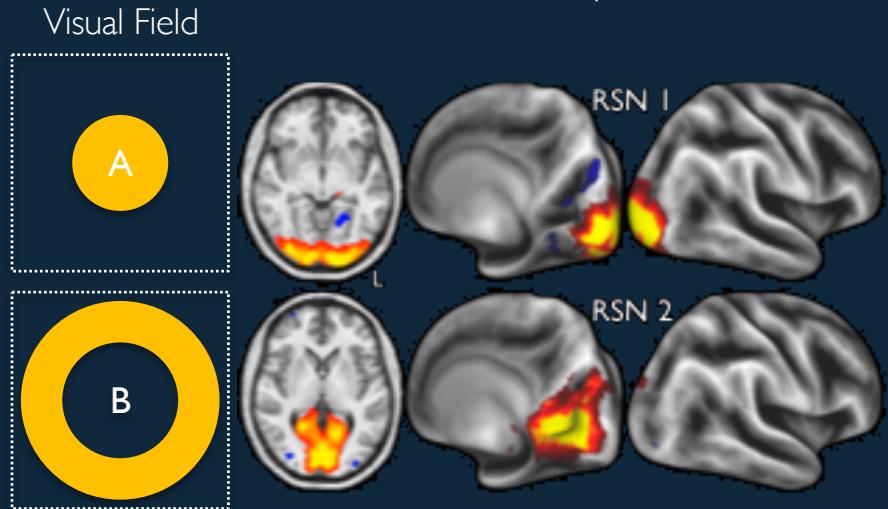
histogram of time-points



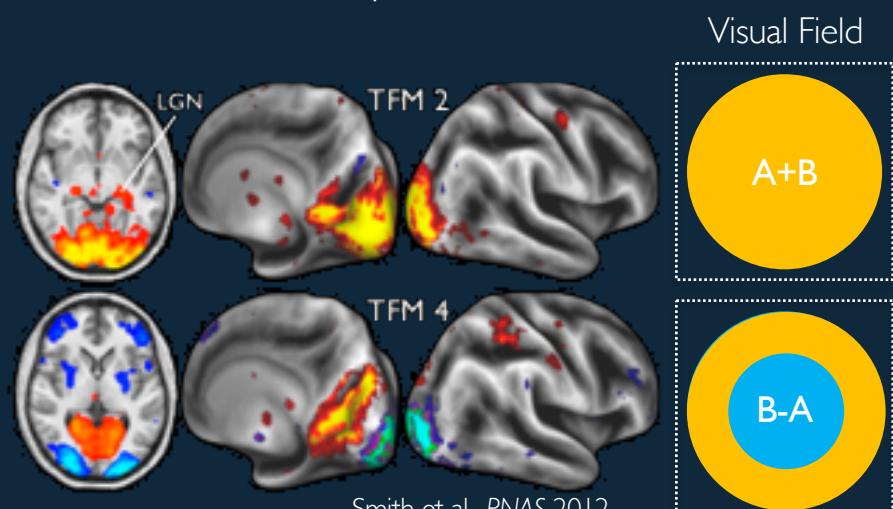
probability density

Spatial vs Temporal Decompositions

RSN: Spatial ICA



TFM: Temporal ICA



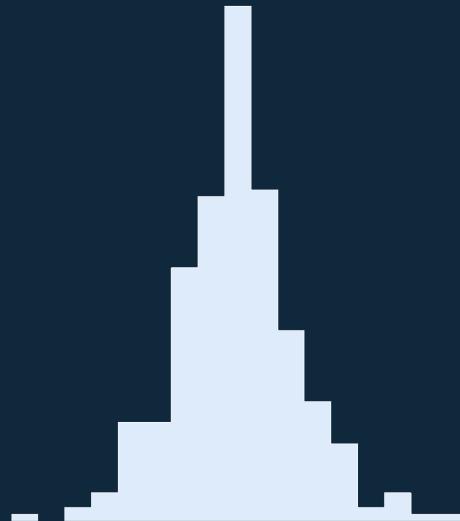
Smith et al., PNAS 2012

Spatially non-overlapping

Spatially overlapping

Temporal Dimensionality

Temporal Dimensions: $\sim 10^2$

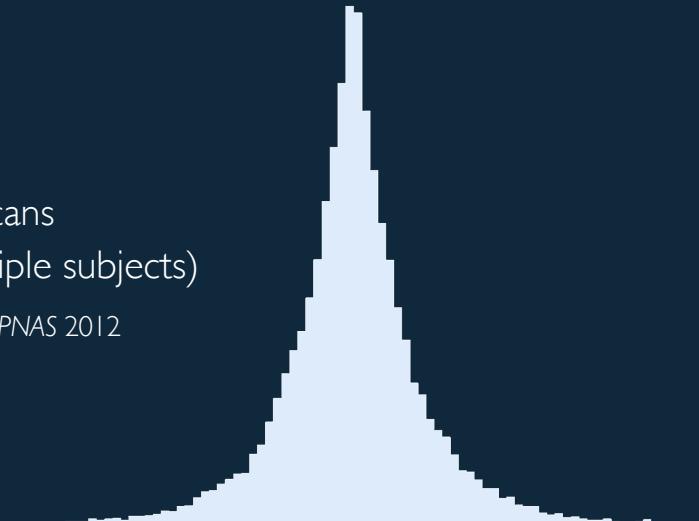


300 time-points

Temporal Dimensions $\sim 10^4$

36 x 10 minute scans
(SMS-EPI, multiple subjects)

Smith et al., PNAS 2012



24,000 time-points

SUMMARY

Summary

- Not an exhaustive list of connectivity methods!
- Many different methods and metrics for quantifying connectivity
 - Using information across space, time, or some combination
- Connectivity in RS-FMRI shows remarkably robust structures
- But outputs reflect constraints, assumptions and models used