Multimodal Static and Dynamic Connectomes

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Oxford centre for Human Brain Activity

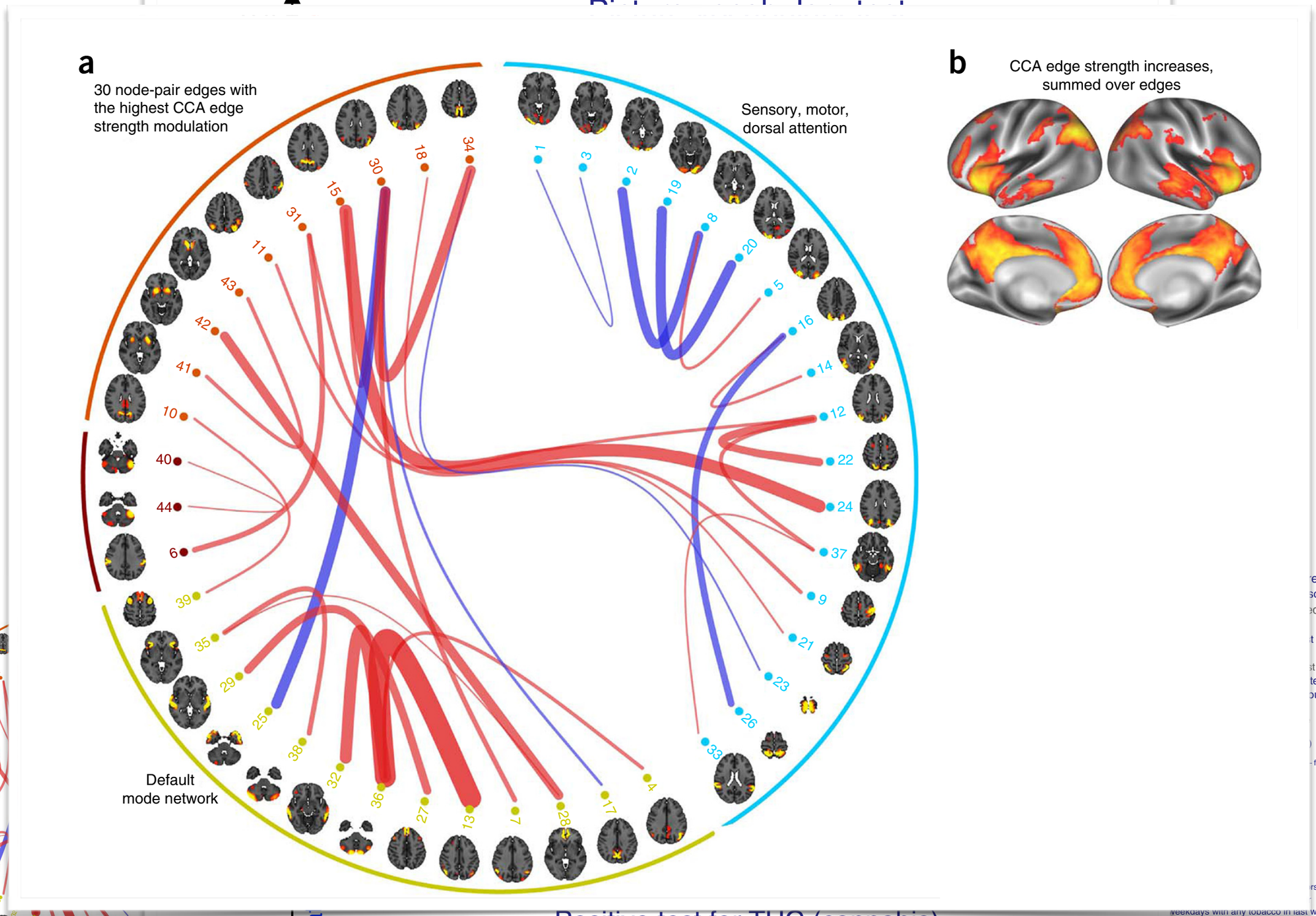
Centre for FMRI of the Brain

Overview

- Static Connectomes
  - Individual parcel variability
  - Electrophysiological connectomes
- Dynamic Brain Networks
  - Going beyond sliding window with Hidden Markov Models

Human Connectome Project resting state fMRI data (~1000 subjects)

SM Smith et al (2015) Nature Neuroscience



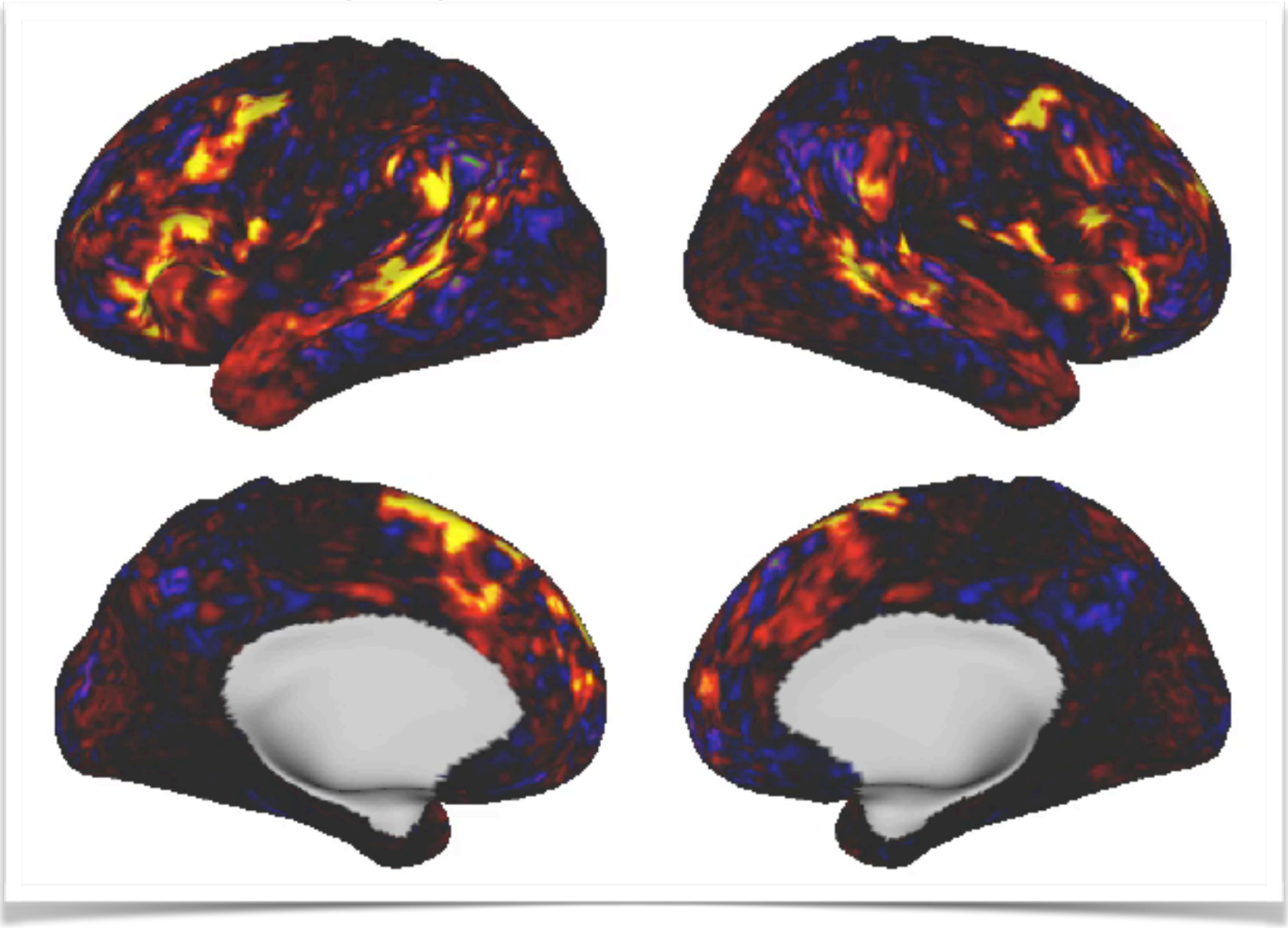
Positive test for THC (cannabis)

–0.36 Nega

Fluid intelligence (number of skipped responses)

But what about individual variability?

Language network subject maps



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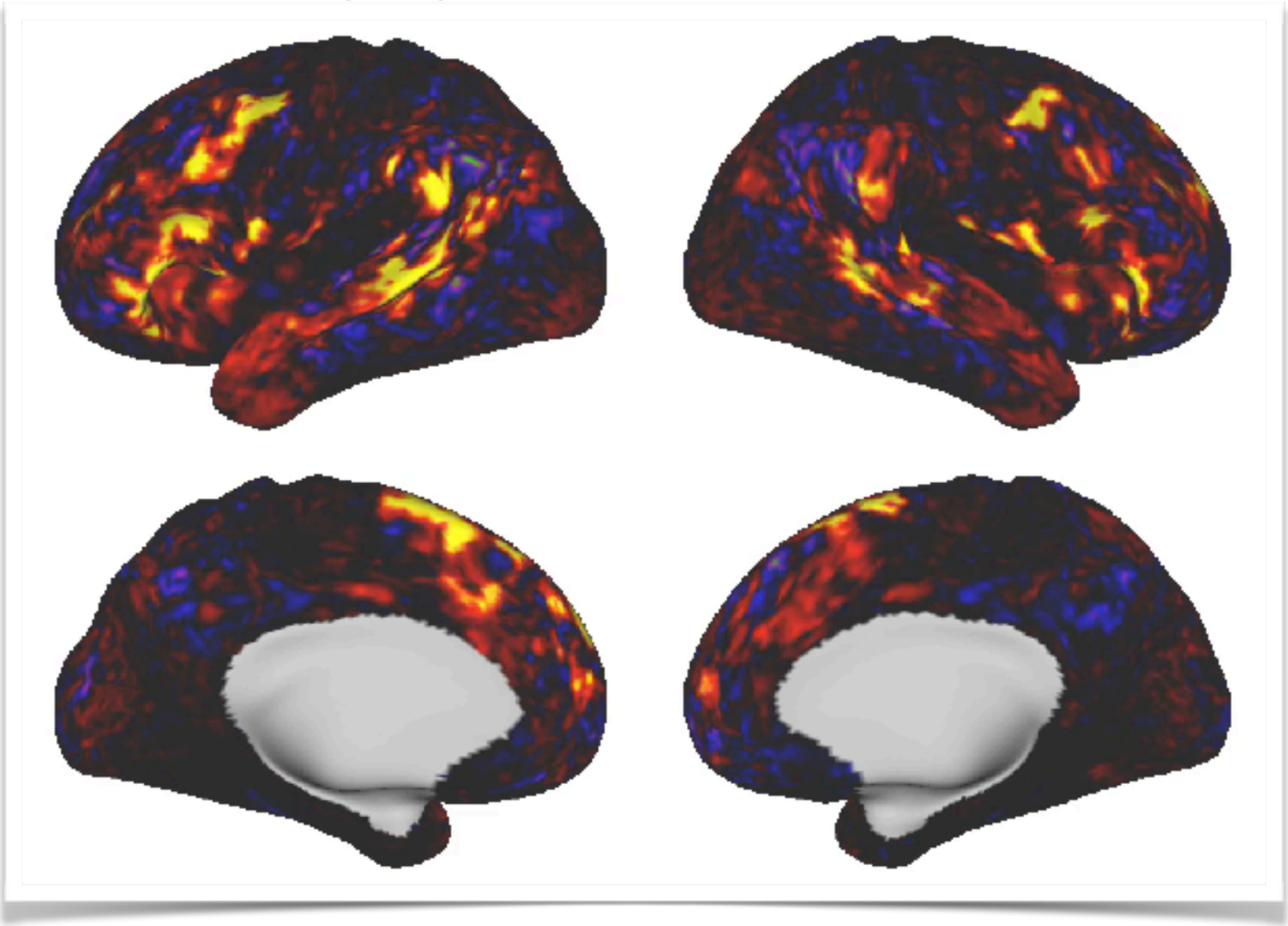


- Individual variability in spatial maps/parcellations can translate into apparent changes in functional connectivity

But what about individual variability?

- Two step procedure:

1. Predefine or estimate group atlas

2. Estimate how individuals vary from the group atlas

But what about individual variability?

- Two step procedure:

  1. Predefine or estimate group atlas

  2. Estimate how individuals vary from the group atlas

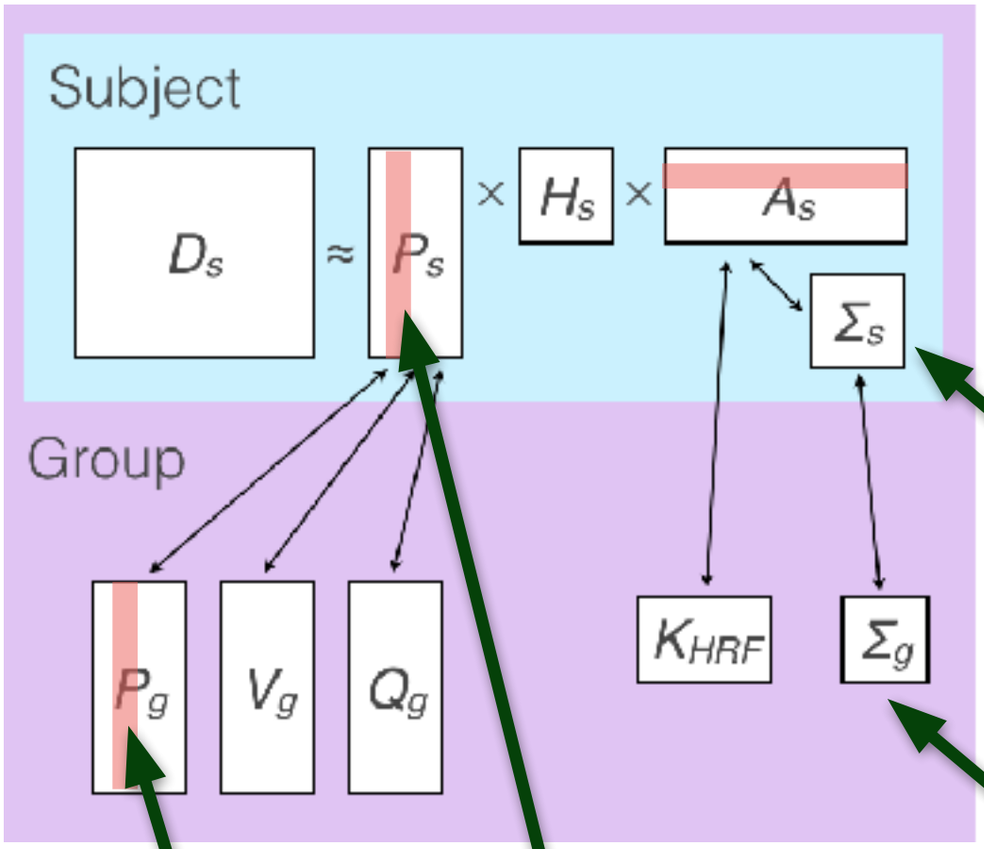
- All-in-one:

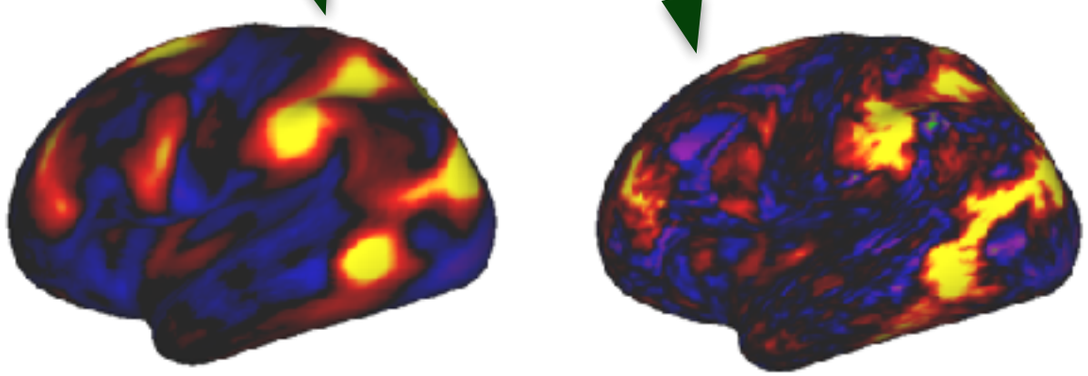
  Estimate a group atlas

  Estimate how individuals vary from the group atlas

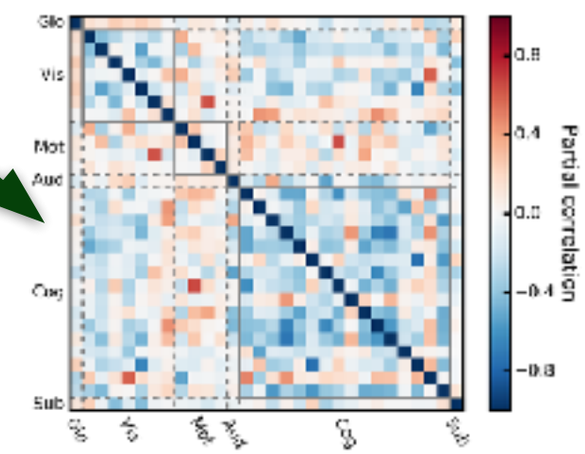
ProFuMo

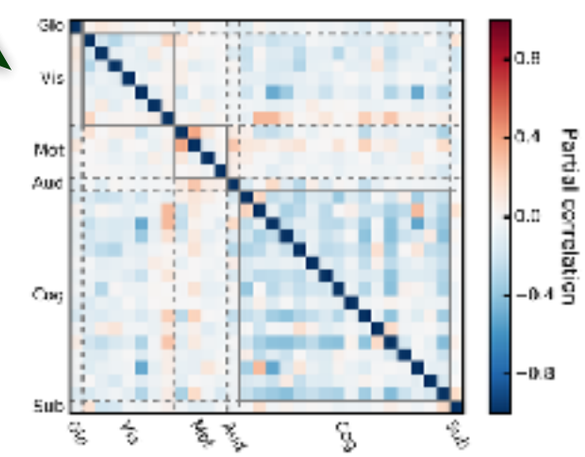
Harrison et al. Large-scale Probabilistic Functional Modes from resting state fMRI., Neuroimage 2015





Spatial subject variability



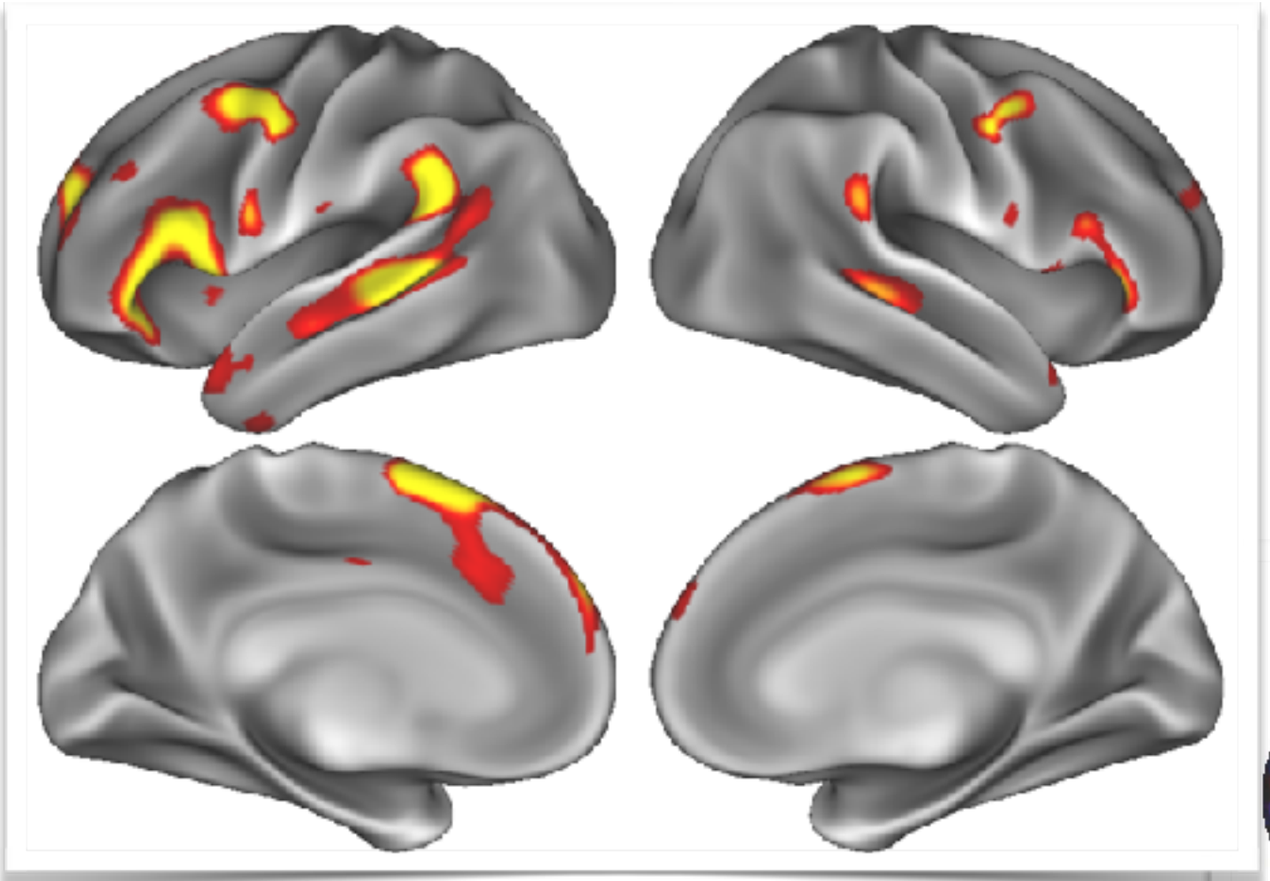


Temporal subject variability

ProFuMo

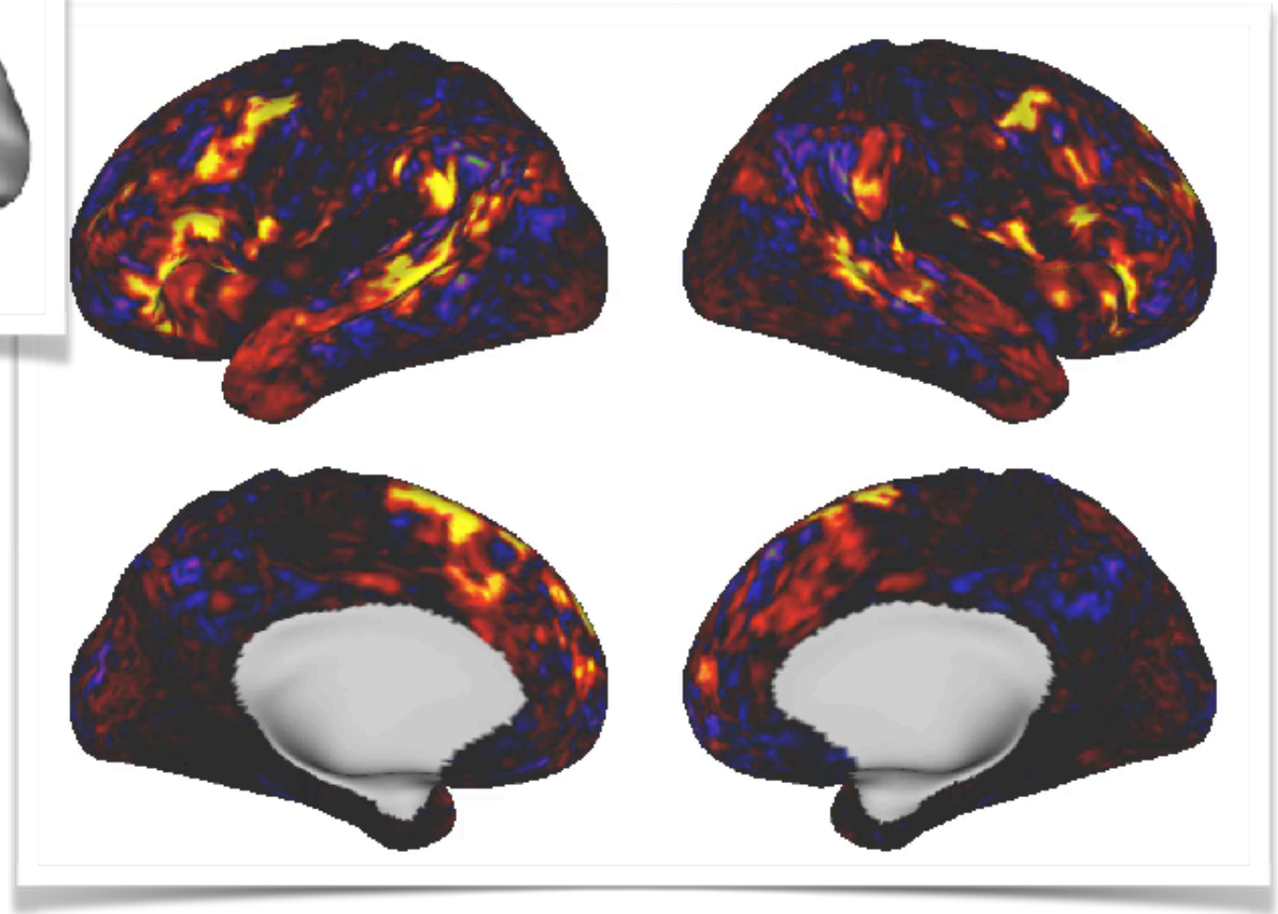
Harrison et al. Large-scale Probabilistic Functional Modes from resting state fMRI., Neuroimage 2015

Language network group map



HCP resting state fMRI data

Language network subject maps

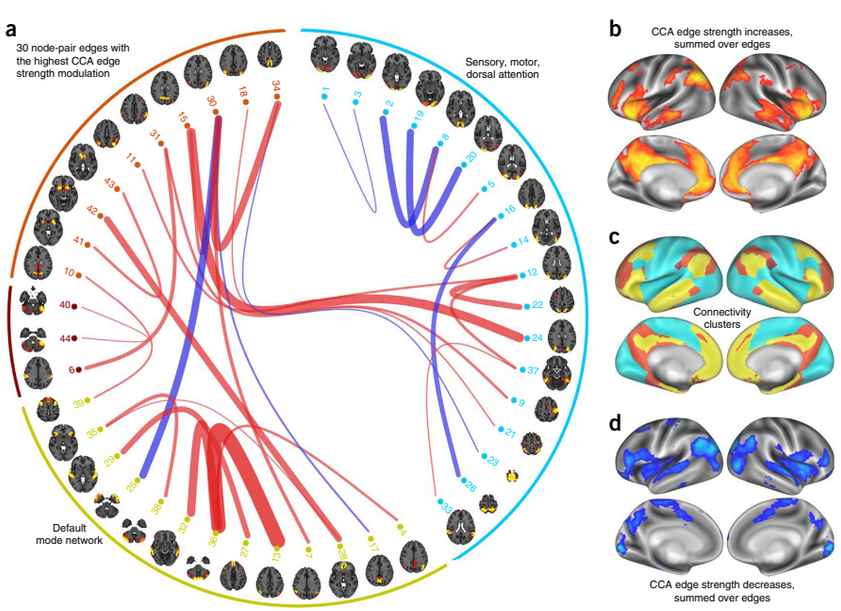


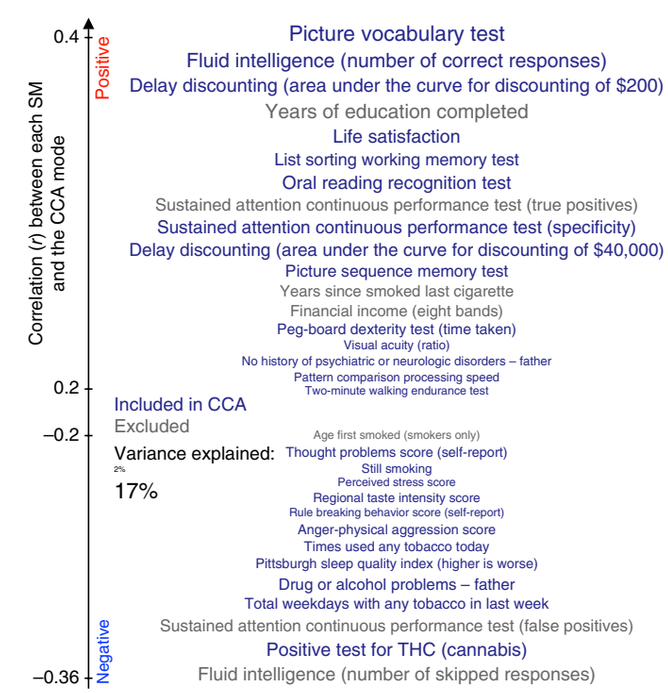
Human Connectome Project resting state fMRI data (~1000 subjects)

SM Smith et al (2015) Nature Neuroscience

Functional connectome

Behavioural data





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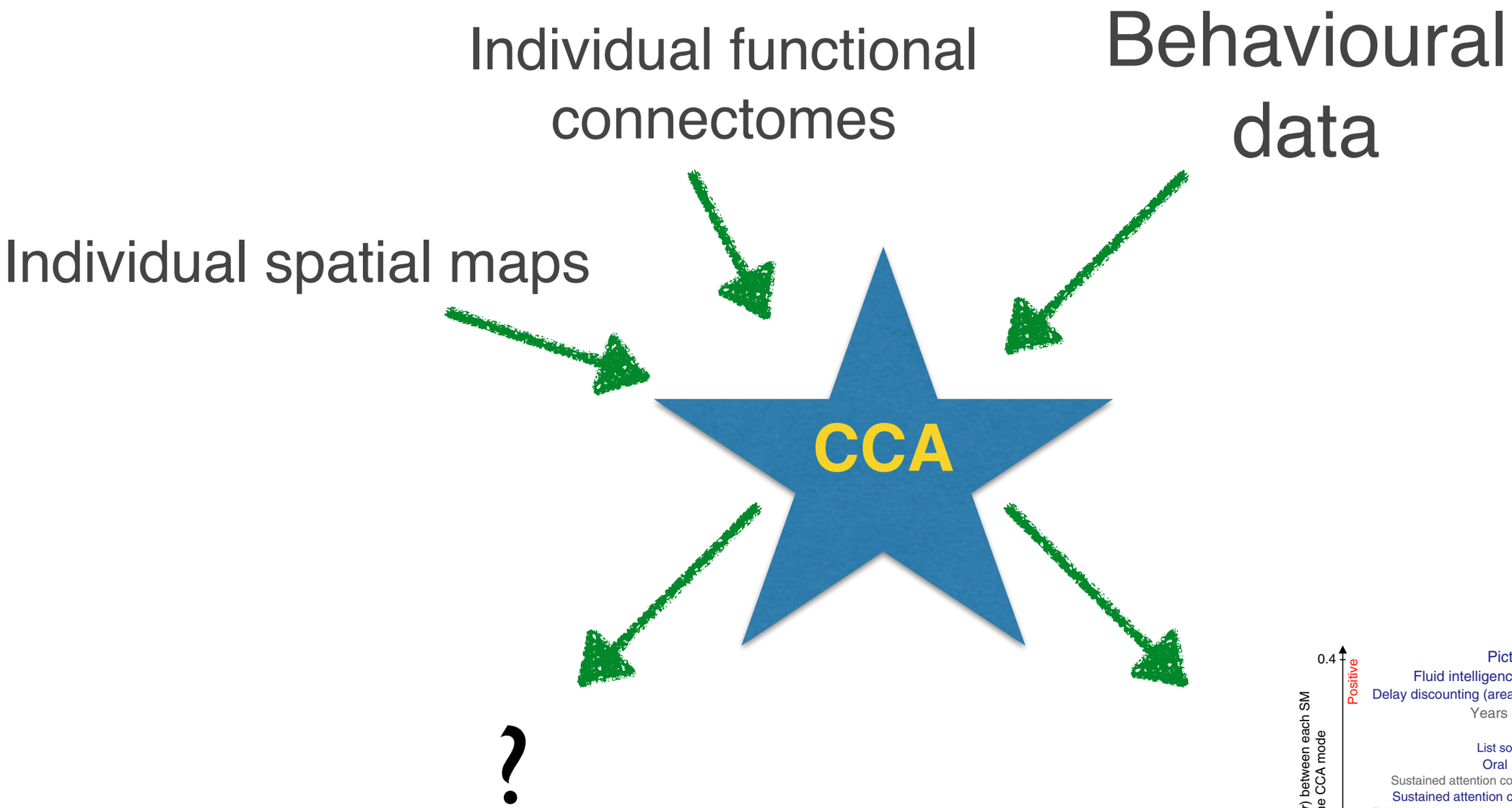
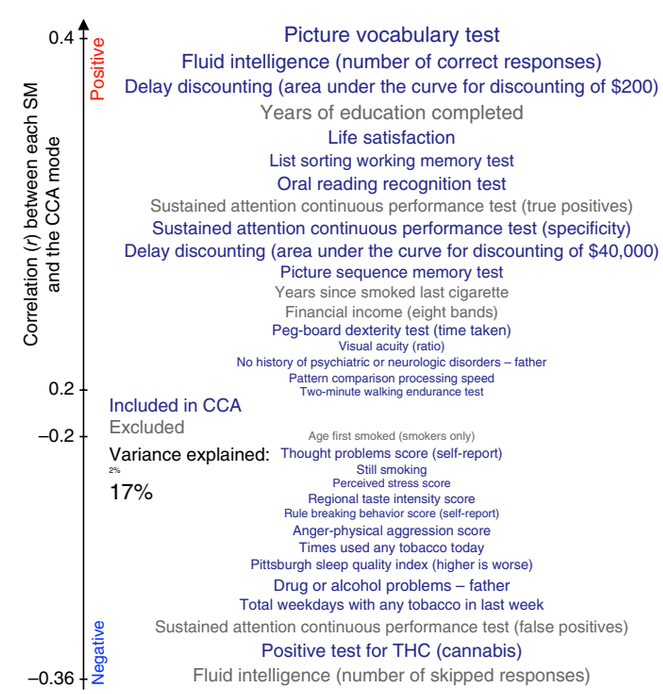




Individual variability in spatial maps dominates!

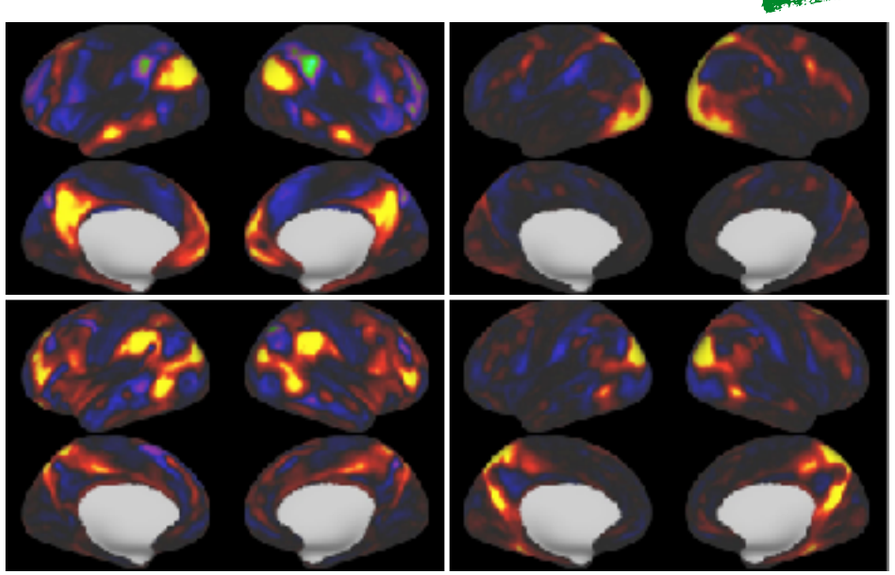
Harrison et al. Abstract #1890

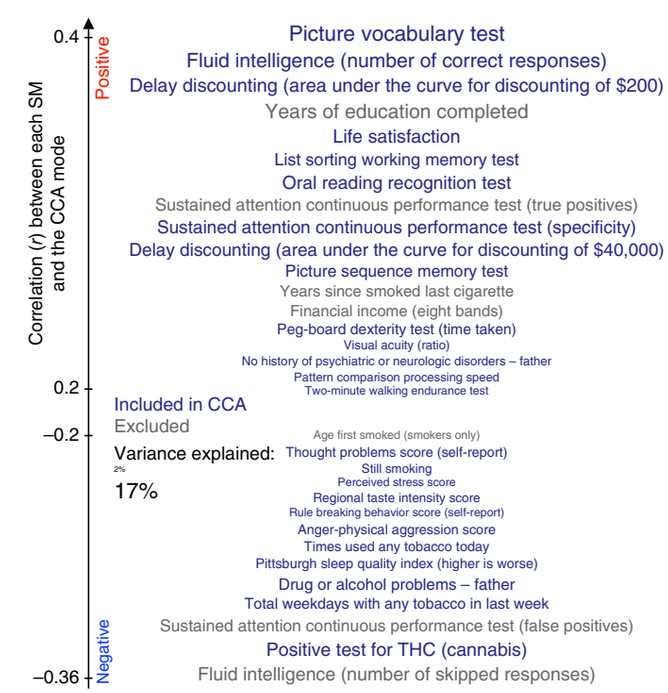
Bijsterbosch et al. Abstract #4020

Individual functional connectomes

Behavioural data

Individual spatial maps



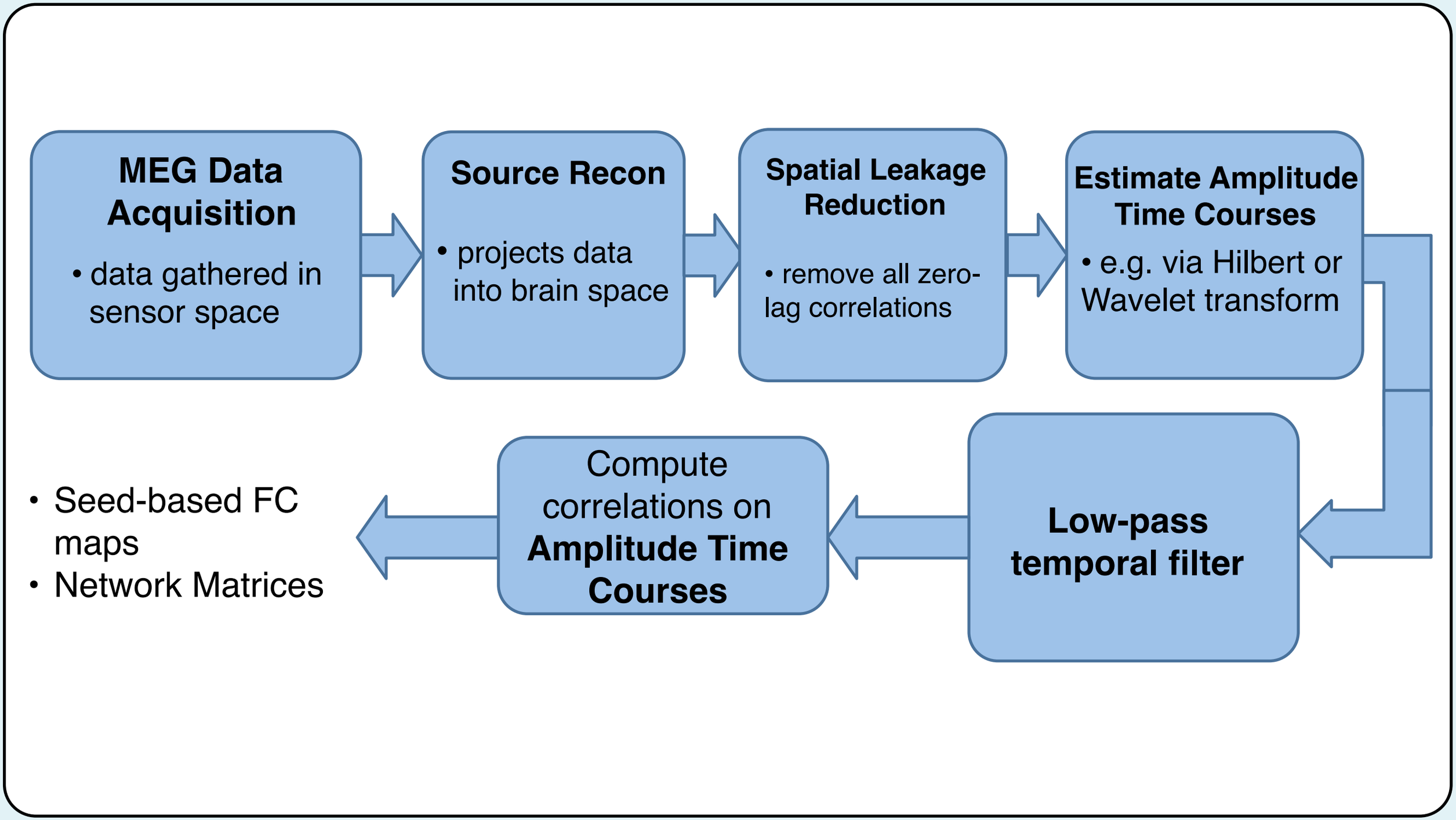


Large-scale Networks in M/EEG?

- What is happening at **faster** time-scales?
- What are the specific neuronal **interactions**?

- Can we use MEG to answer these questions?
  - excellent temporal res (millisecs)
  - good spatial res
  - non-invasive

MEG: Amplitude Coupling

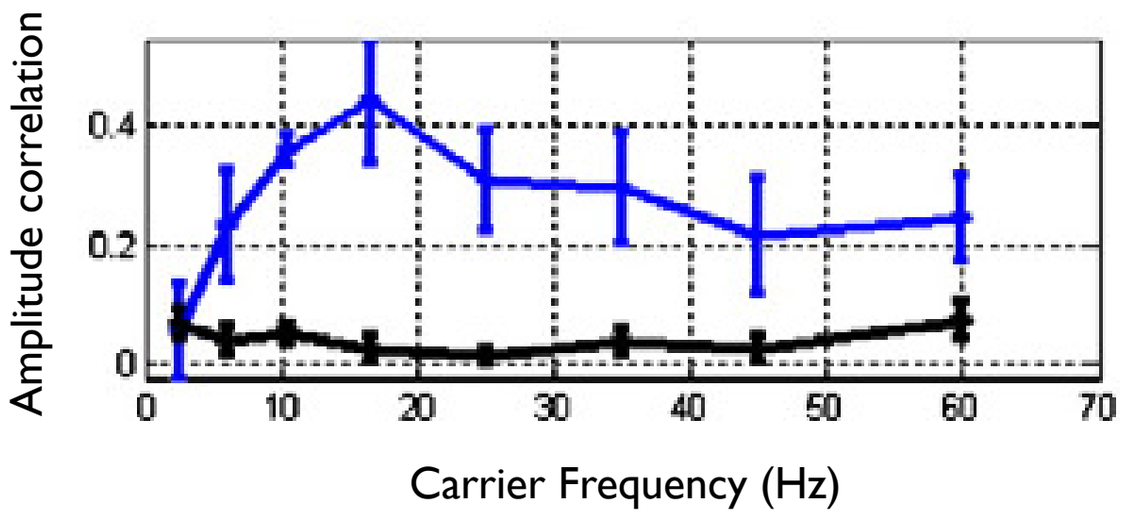


Hipp et al.; Nat Neuro (2012)

Brookes et al.; Neuroimage (2013)

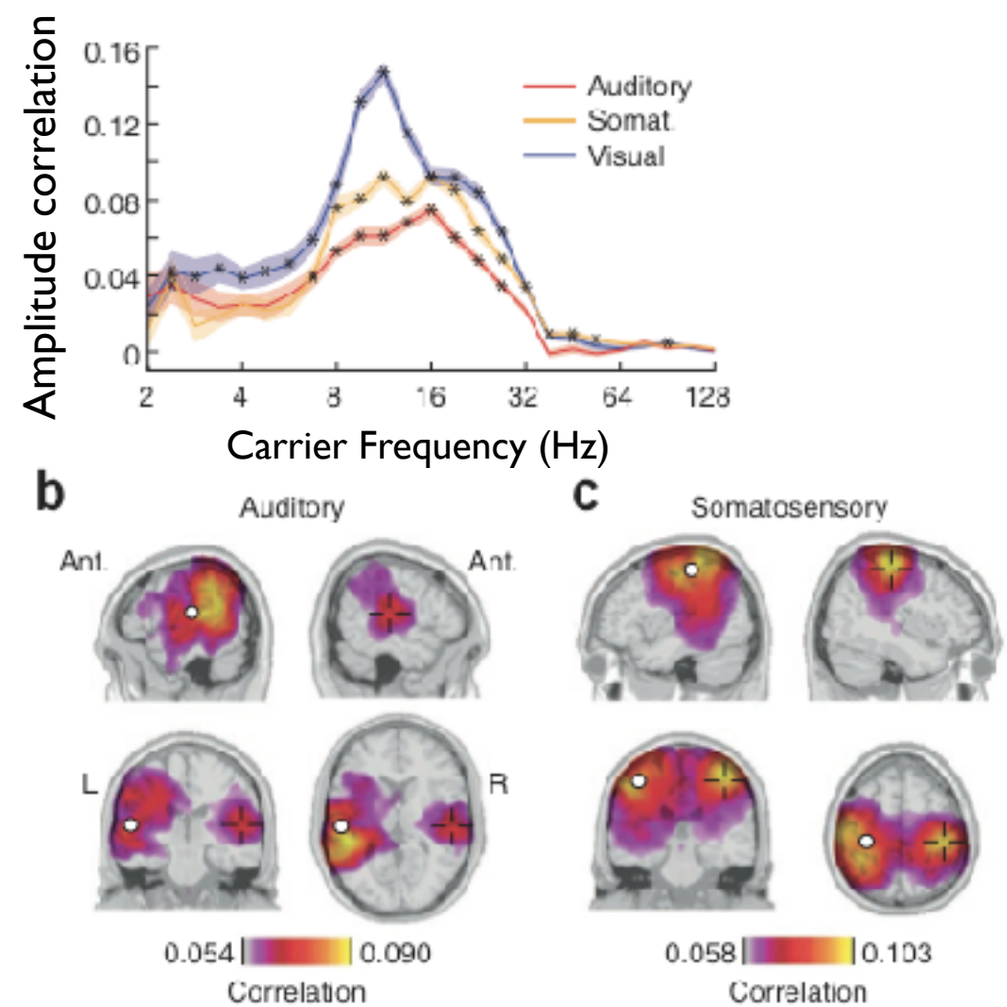
MEG: Amplitude Coupling

- Resting state data



Significant beta band ***amplitude correlation*** between the left and right motor cortices

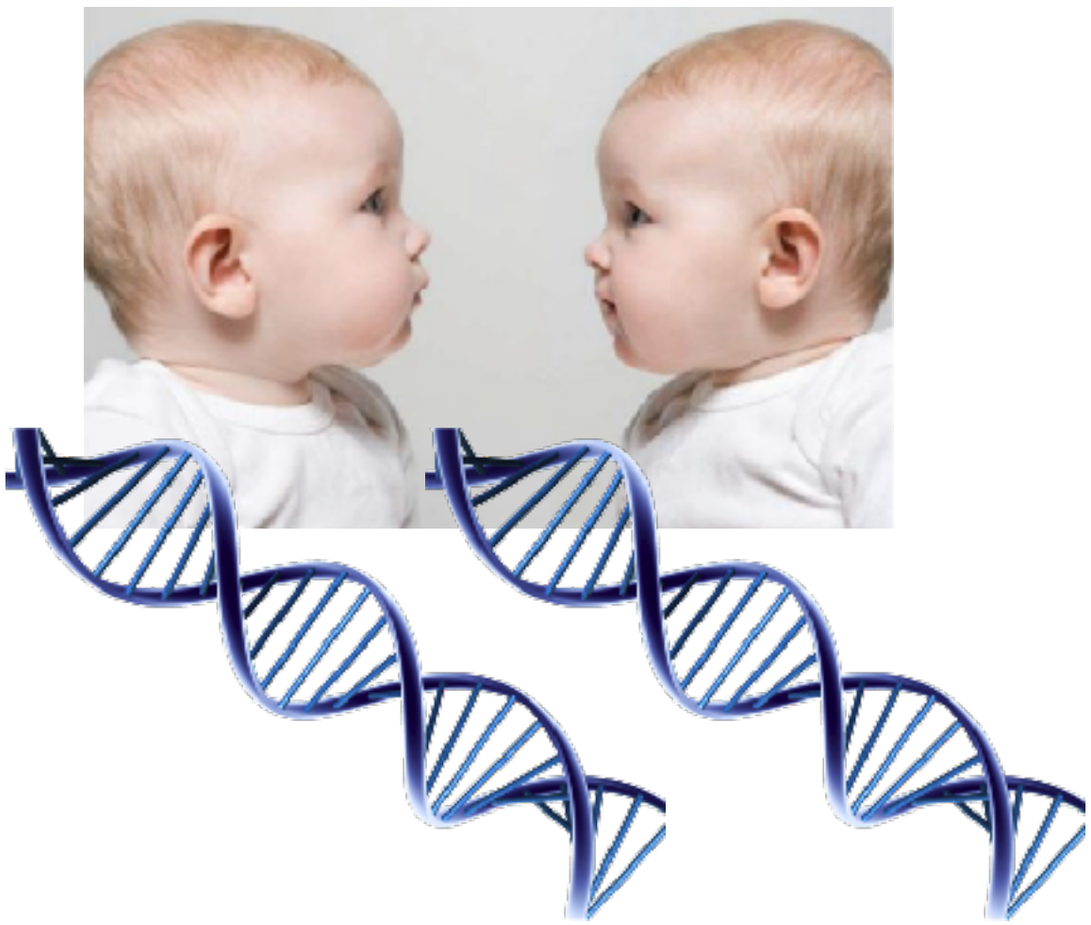
Brookes et al., Neuroimage, (2011)



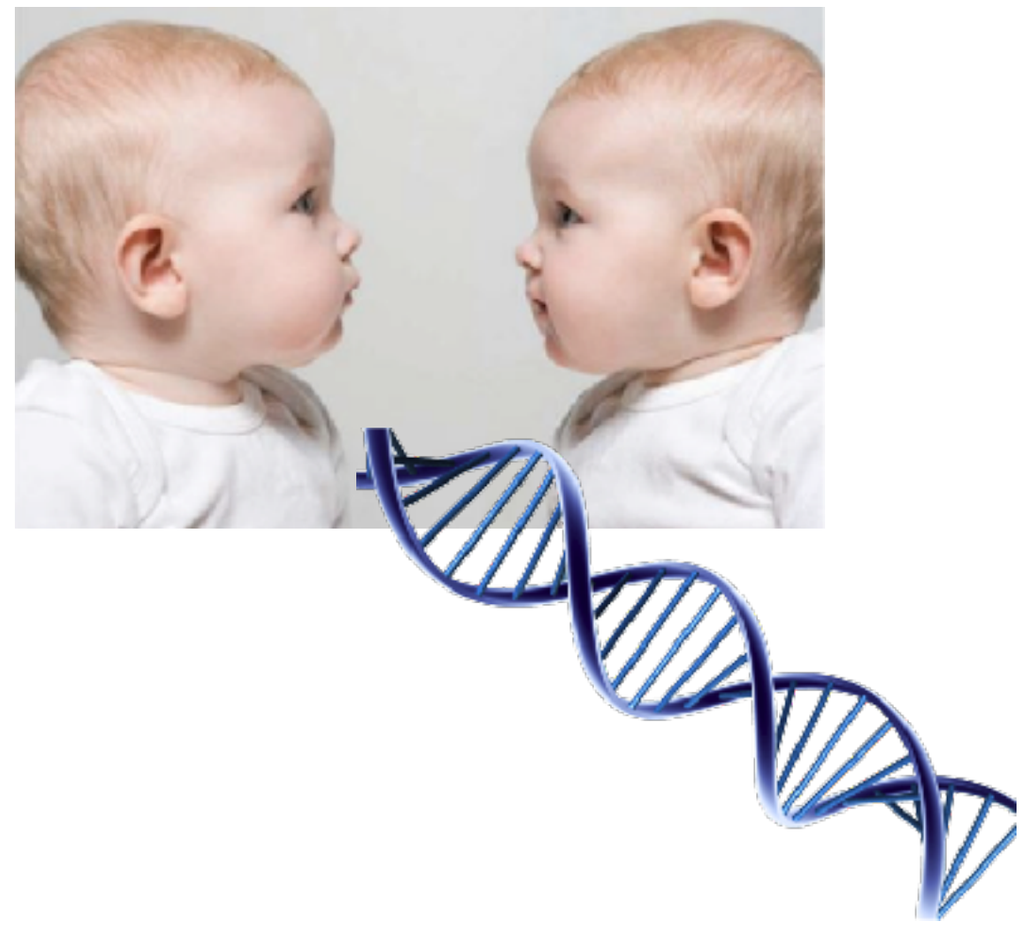
Hipp et al. 2012 (Nat Neuro)

Example Application: Heritability of connectomes

Human Connectome Project twin rest data



MZ



DZ

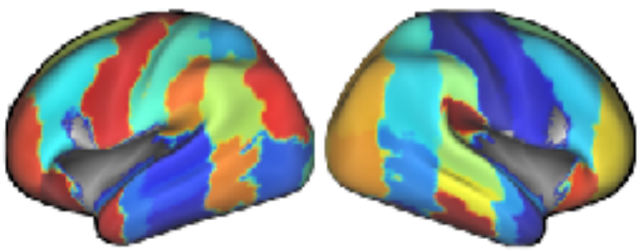
Colclough, Smith … Woolrich; Under Revision

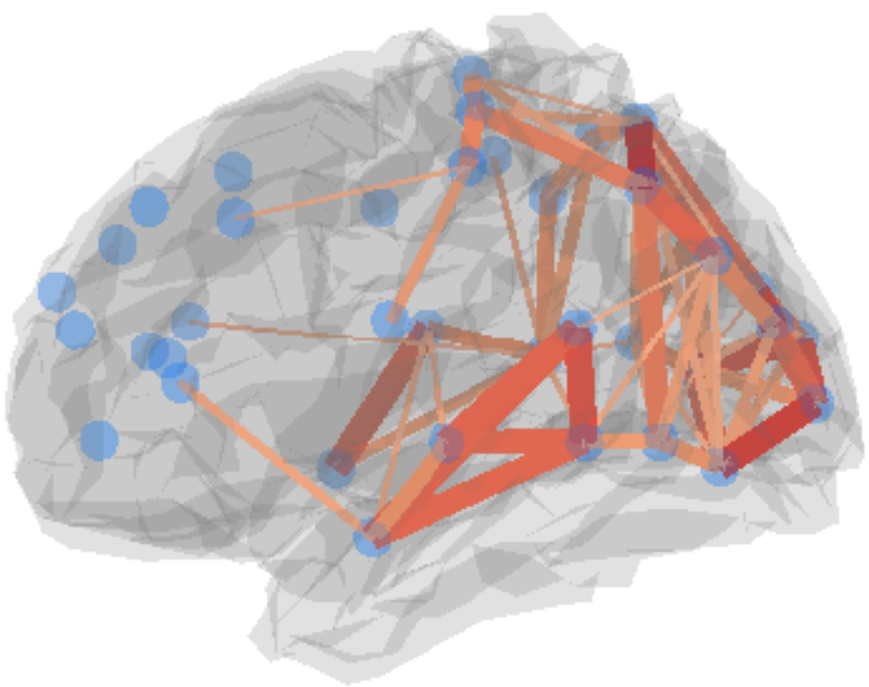
Example Application: Heritability of connectomes

Human Connectome Project twin rest data

MEG - alpha band amplitude correlations (~100 subjects)

38 cortical regions





Colclough, Smith … Woolrich; Under Revision

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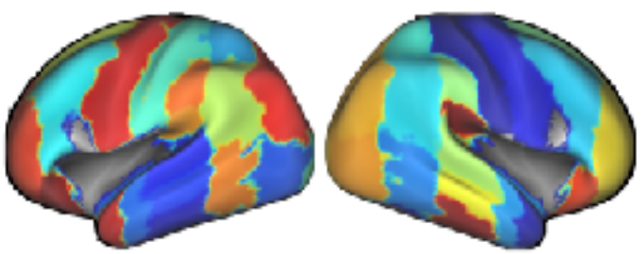
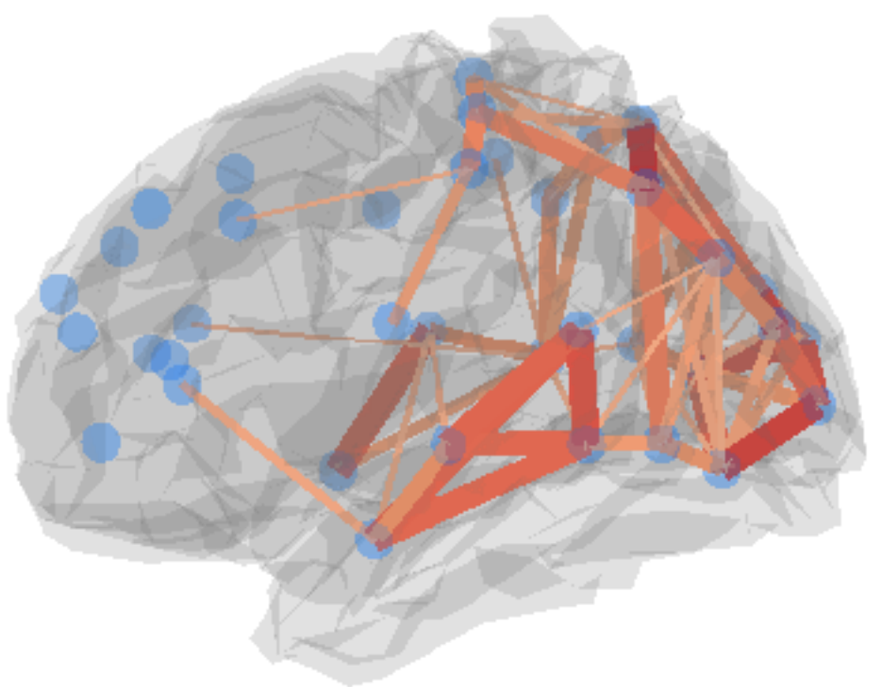
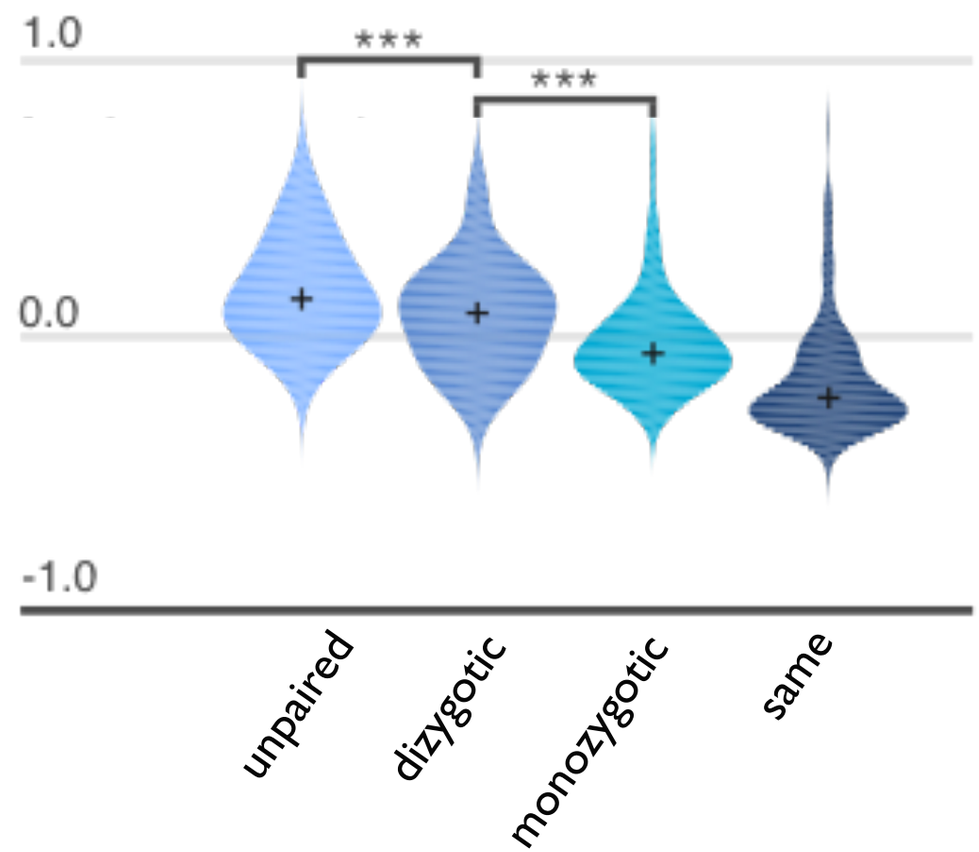




log(difference in network matrices)



- Mean edge heritability: 33% (p = 0.01)

Colclough, Smith … Woolrich; Under Revision

Example Application: Heritability of connectomes

Human Connectome Project twin rest data

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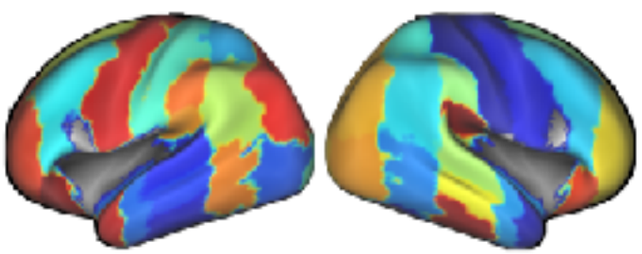

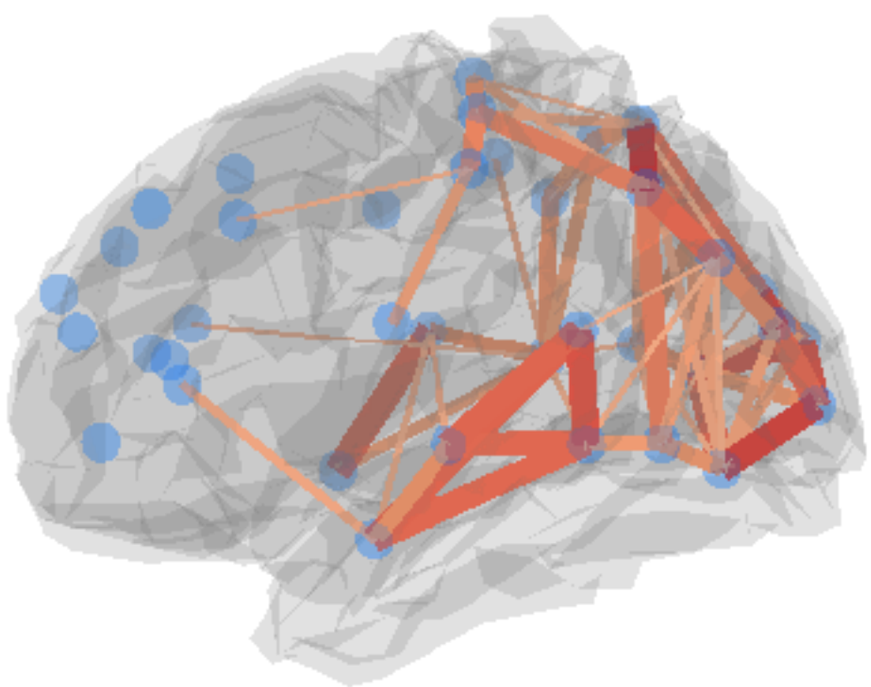

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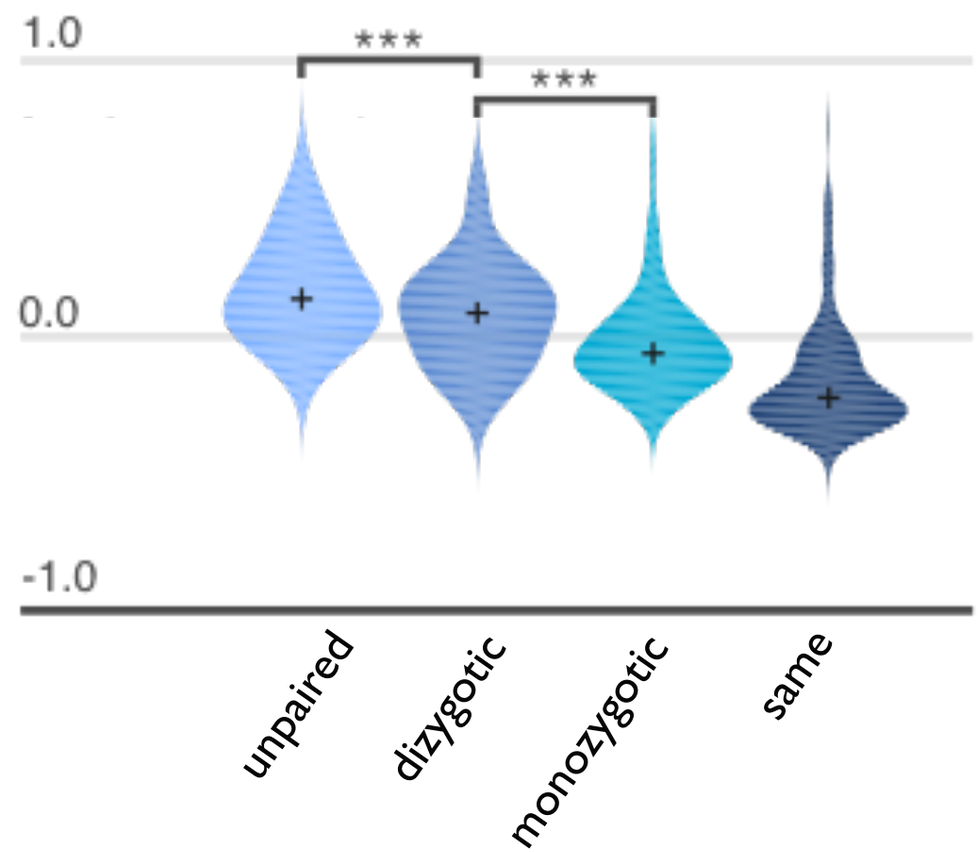


- Mean edge heritability: 33% (p = 0.01)
- Shared genetics outweigh shared environment (p = 0.02)

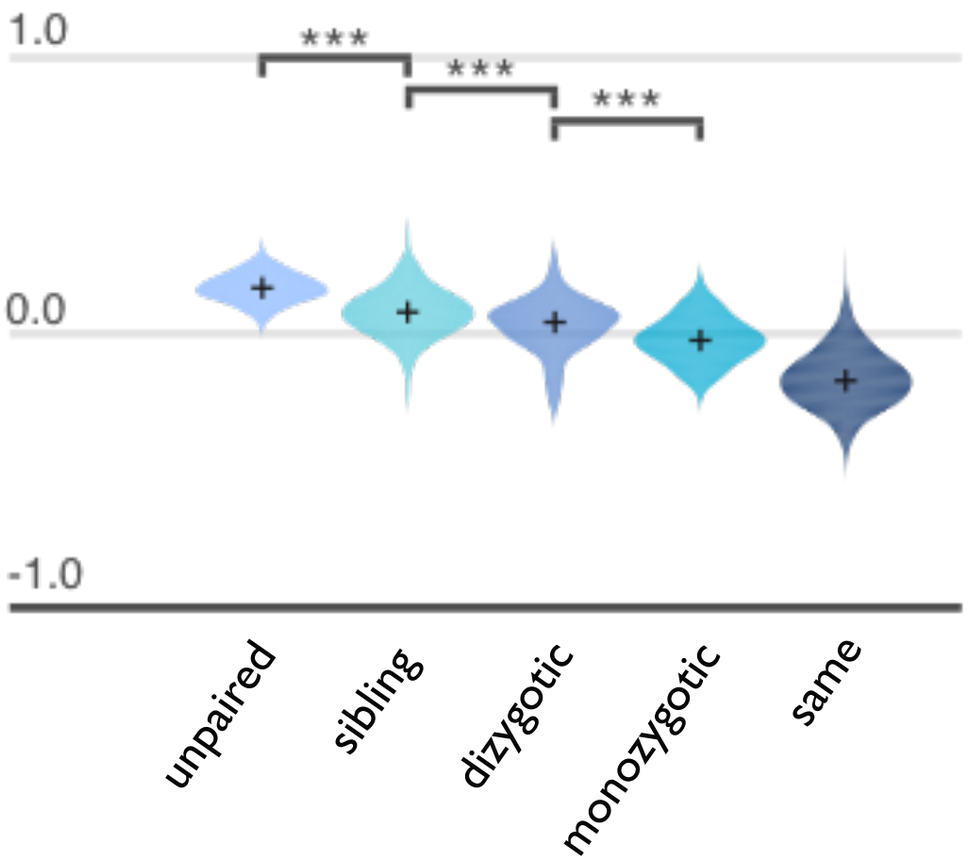
Colclough, Smith … Woolrich; Under Revision

Example Application: Heritability of connectomes

Human Connectome Project twin rest data

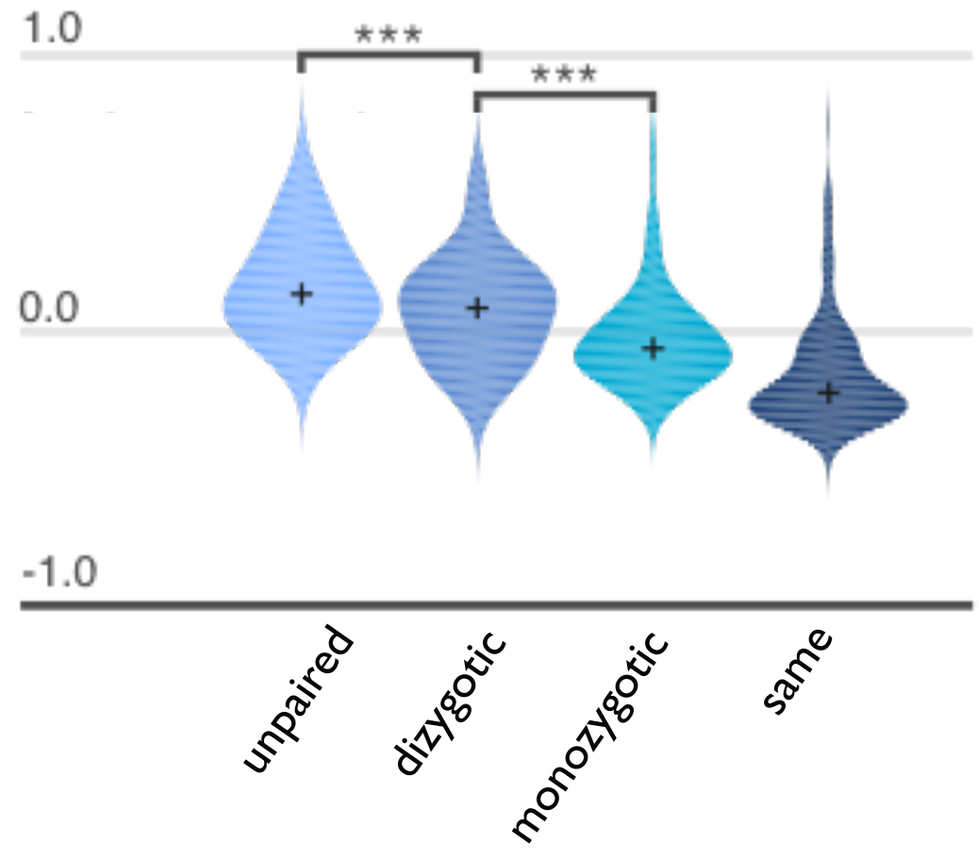
fMRI (~1000 subjects)

log(difference in network matrices)



MEG - alpha band (~100 subjects)

log(difference in network matrices)



- Mean edge heritability: 33% (p = 0.01)
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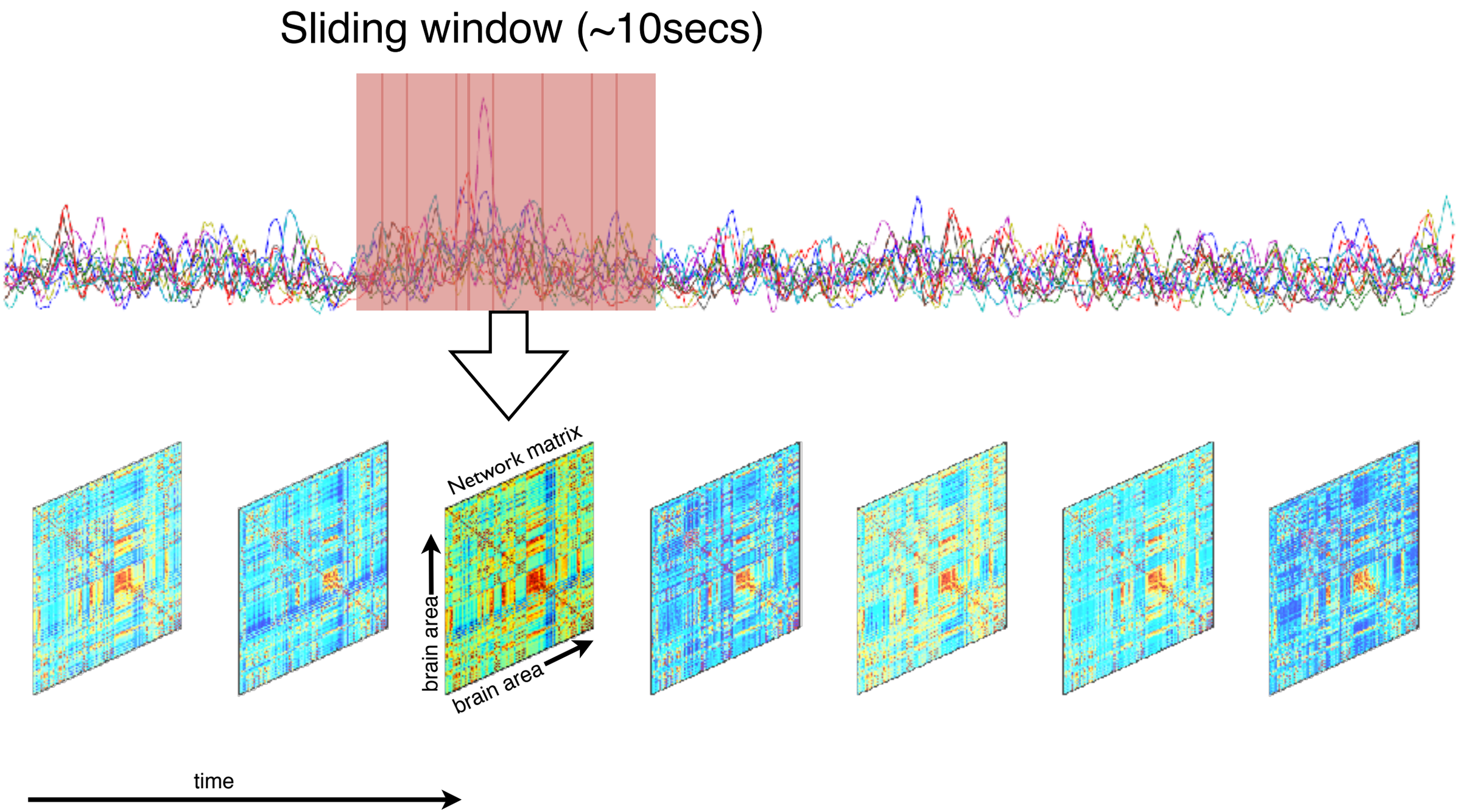
Colclough, Smith … Woolrich; Under Revision

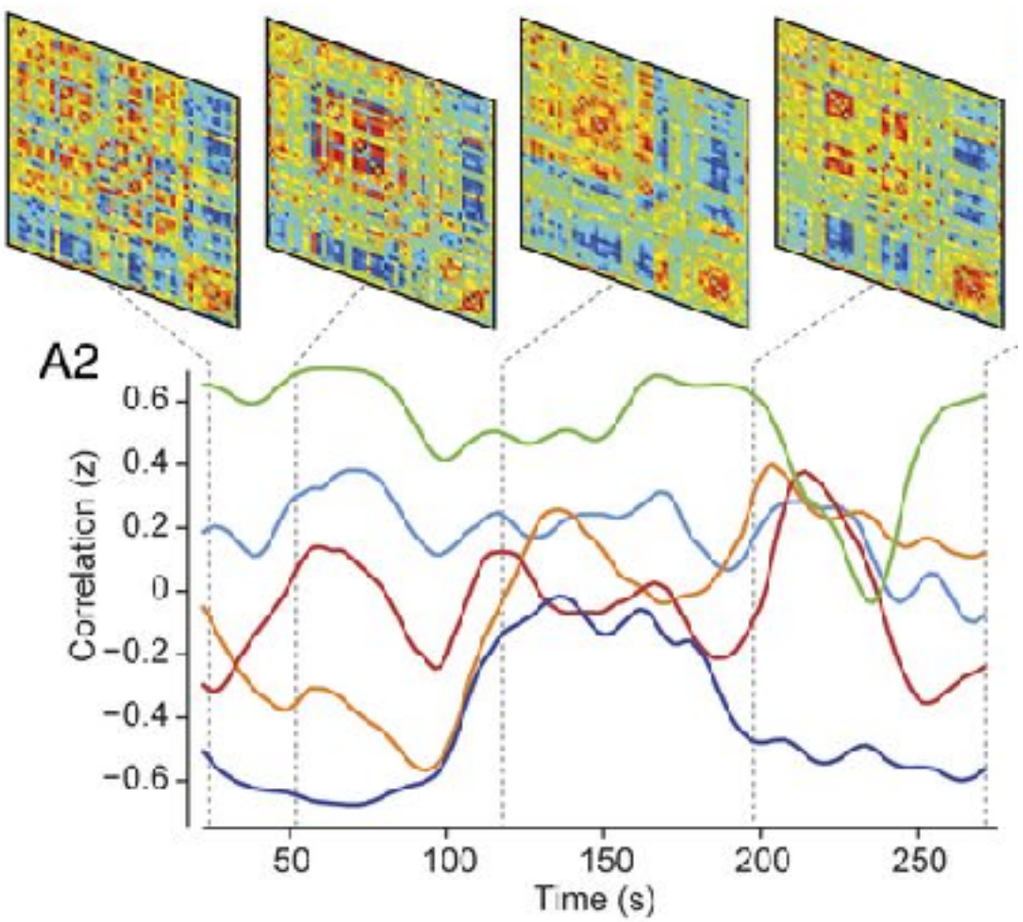
Dynamic Connectomes

Compute ***sliding window*** correlation network matrices



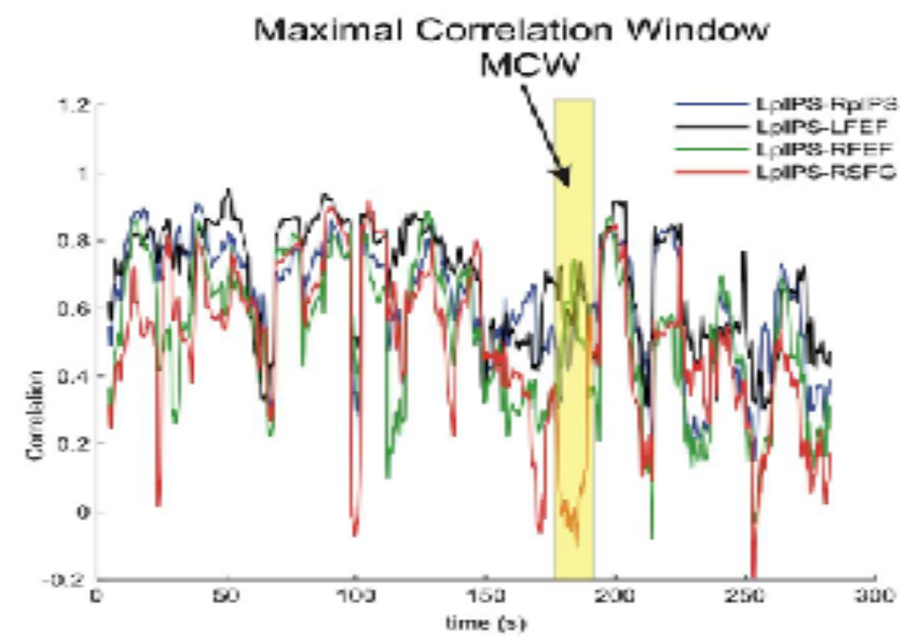
Non-stationary functional connectivity

Sliding window FC in fMRI:



Allen et al. (Cerebral Cortex 2012)

Sliding window FC in MEG:



de Pasquale et al. (PNAS 2010)

Issues with sliding windows

How to choose the width of the window?

- too short - unreliable estimation
- too long - misses quick changes

NeuroImage 127 (2016) 242–256

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

Can sliding-window correlations reveal dynamic functional connectivity in resting-state fMRI?

R. Hindriks [a,*], M.H. Adhikari [a], Y. Murayama [d], M. Ganzetti [b,c], D. Mantini [b,e], N.K. Logothetis [d], G. Deco [a,e]

ORIGINAL ARTICLE

On the Stability of BOLD fMRI Correlations

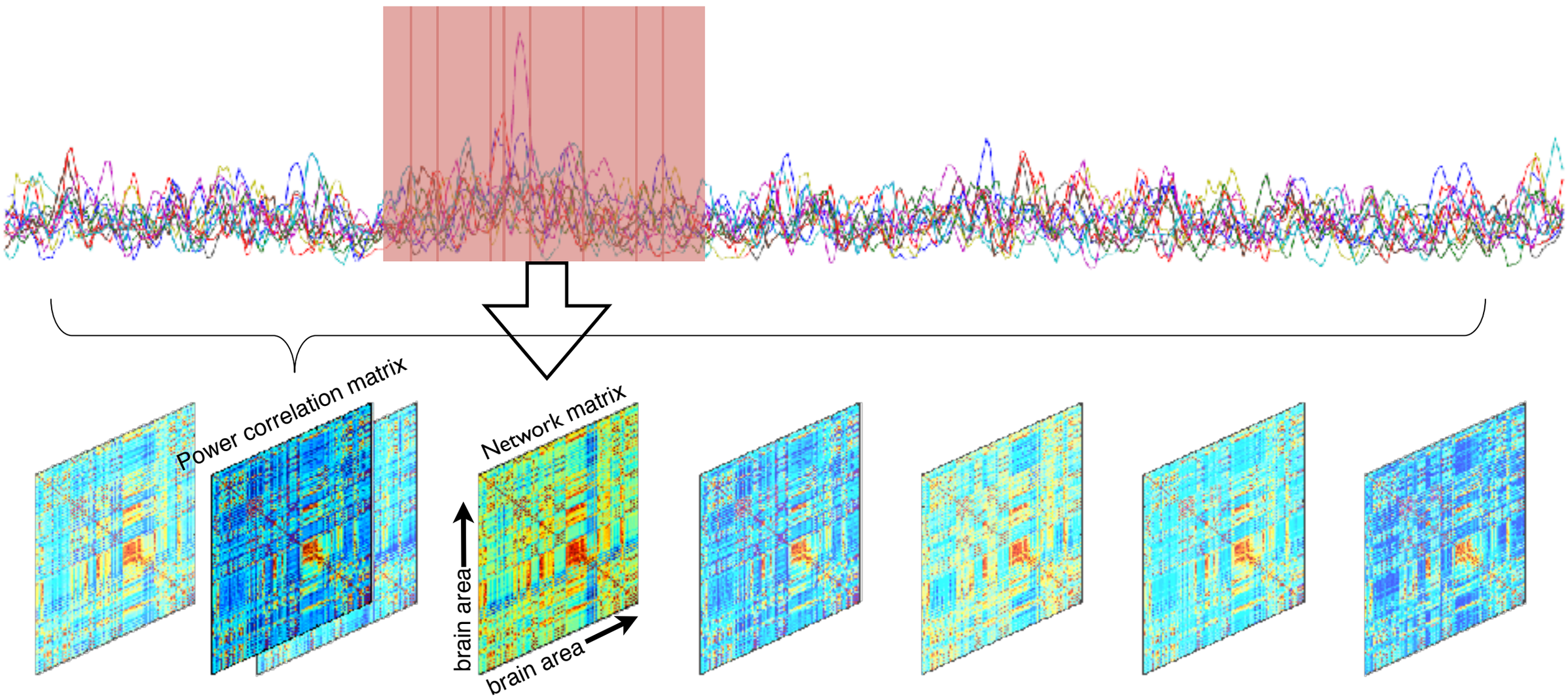
Timothy O. Laumann[1], Abraham Z. Snyder[1,2], Anish Mitra[2], Evan M. Gordon[3,4], Caterina Gratton[1], Babatunde Adeyemo[1], Adrian W. Gilmore[5], Steven M. Nelson[3,4], Jeff J. Berg[5], Deanna J. Greene[2,6], John E. McCarthy[7], Enzo Tagliazucchi[8,9], Helmut Laufs[9,10], Bradley L. Schlaggar[1,2,6,11,12], Nico U. F. Dosenbach[1], and Steven E. Petersen[1,2,5,12]

Cerebral CORTEX

Dynamic Connectomes

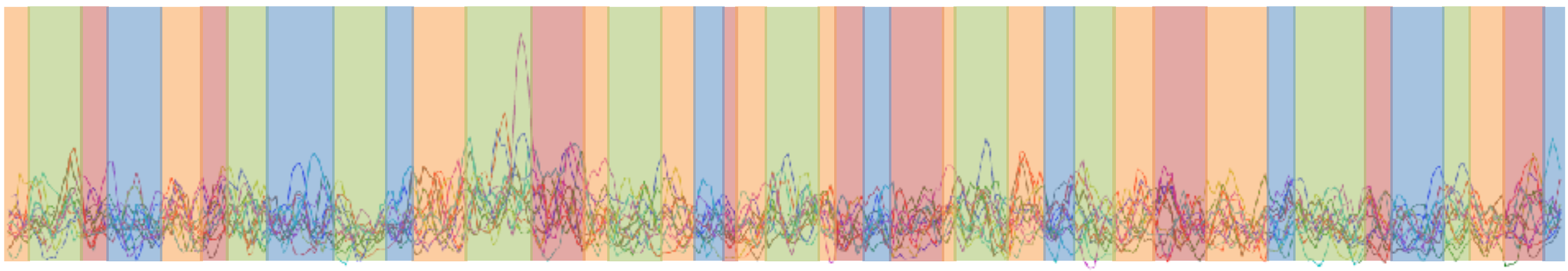
Time-varying FC as short-lived brain states:

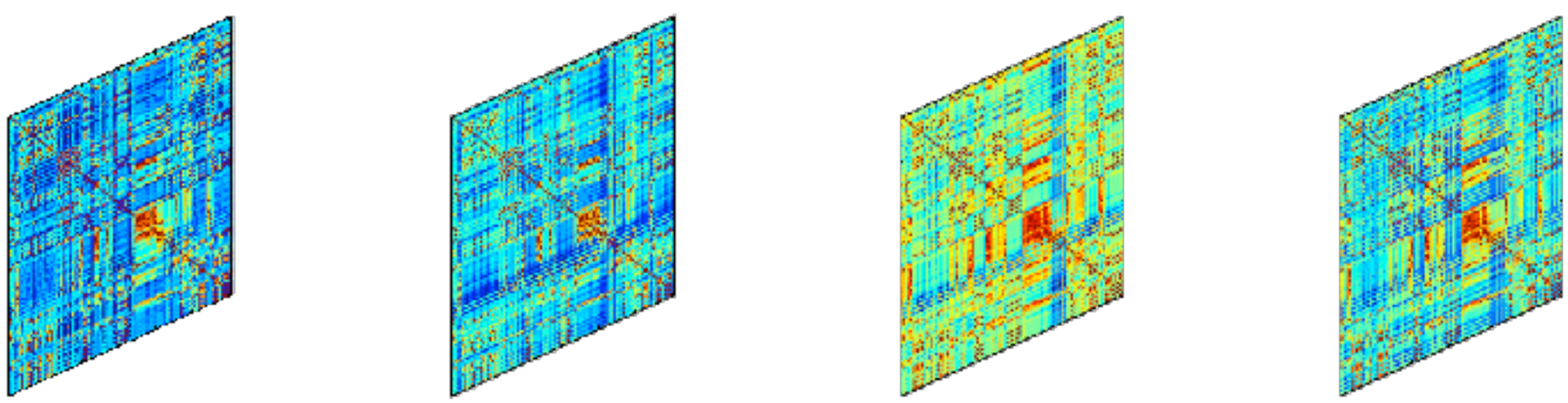
Sliding window (~2-10secs in MEG, ~30-60secs in fMRI)



Dynamic Connectomes

Time-varying connectomes as short-lived brain states:

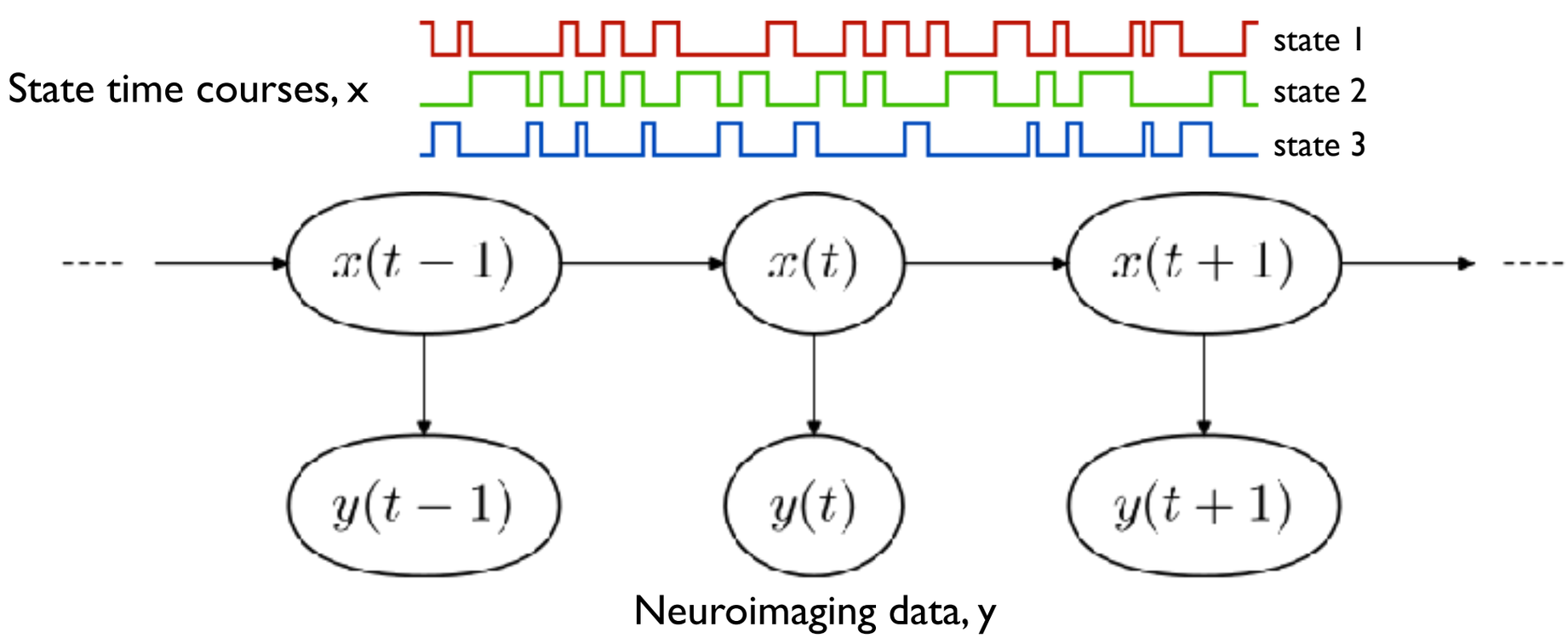




State 1 State 2 State 3 State 4

Hidden Markov Model (HMM)

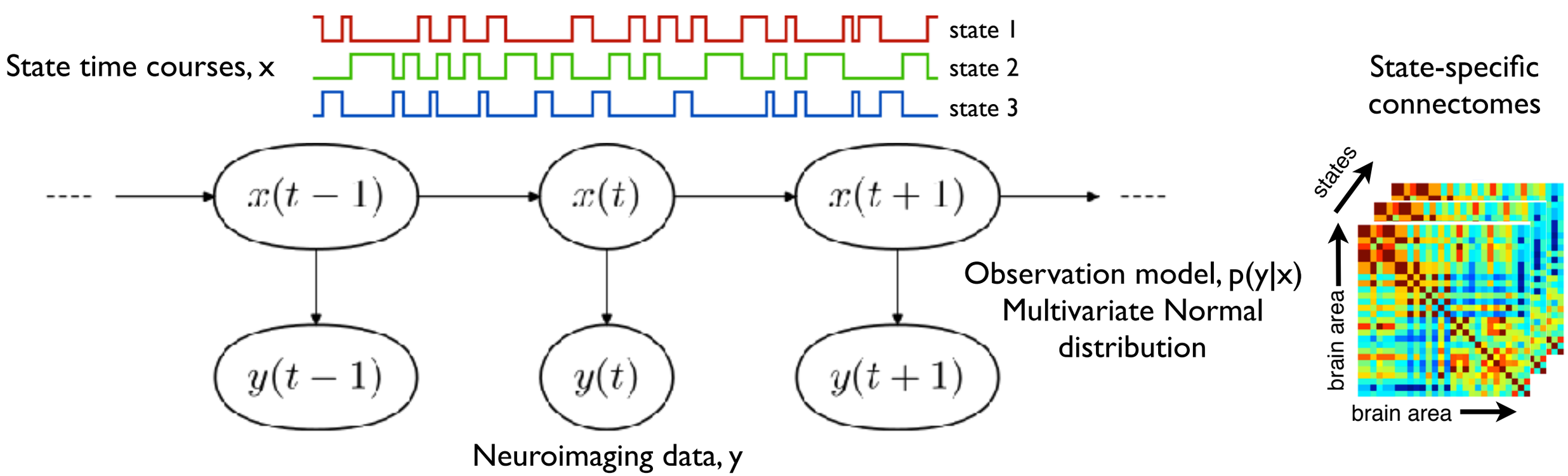
- Generative model, consisting of:
  - state time courses, x - indicating which state the system is in at each time point



Baker,…,Woolrich; eLife (2014)

Hidden Markov Model (HMM)

- Generative model, consisting of:
  - state time courses, x - indicating which state the system is in at each time point
  - observation model - which predicts the data, y, for a given state



Baker,…,Woolrich; eLife (2014)

Hidden Markov Model

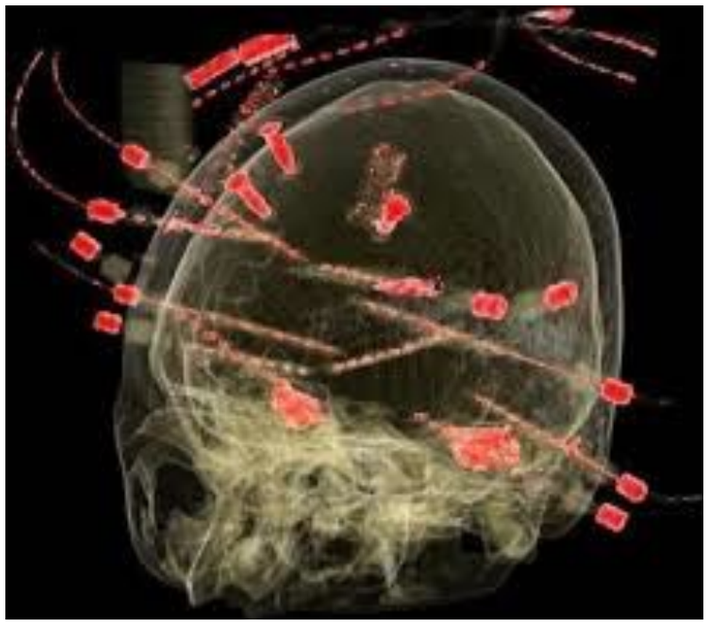
https://github.com/OHBA-analysis/HMM-MAR

EEG

fMRI

MEG

HMM



Intracranial recordings

Hidden Markov Model

https://github.com/OHBA-analysis/HMM-MAR

EEG

fMRI

MEG

HMM

Intracranial recordings

HMM on resting fMRI data

- Can we use the HMM to infer ***dynamic networks in resting fMRI*** data?
- What is the nature of the dynamics?

Vidaurre et al., Poster #3955: talk on Wed 10:43am
Vidaurre et al., Under Revision

HMM on resting fMRI data

- Can we use the HMM to infer ***dynamic networks in resting fMRI*** data?
- What is the nature of the dynamics?
    - Resting state (eyes open) ***Human Connectome Project*** fMRI data
    - ~1000 subjects (1hr each) - HMM on BIG data (stochastic learning)

      Vidaurre et al., Under Revision, Neuroimage SI "Dynamic Brain Networks"
    - 12 HMM states

Vidaurre et al., Poster #3955: talk on Wed 10:43am
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HMM on resting fMRI data

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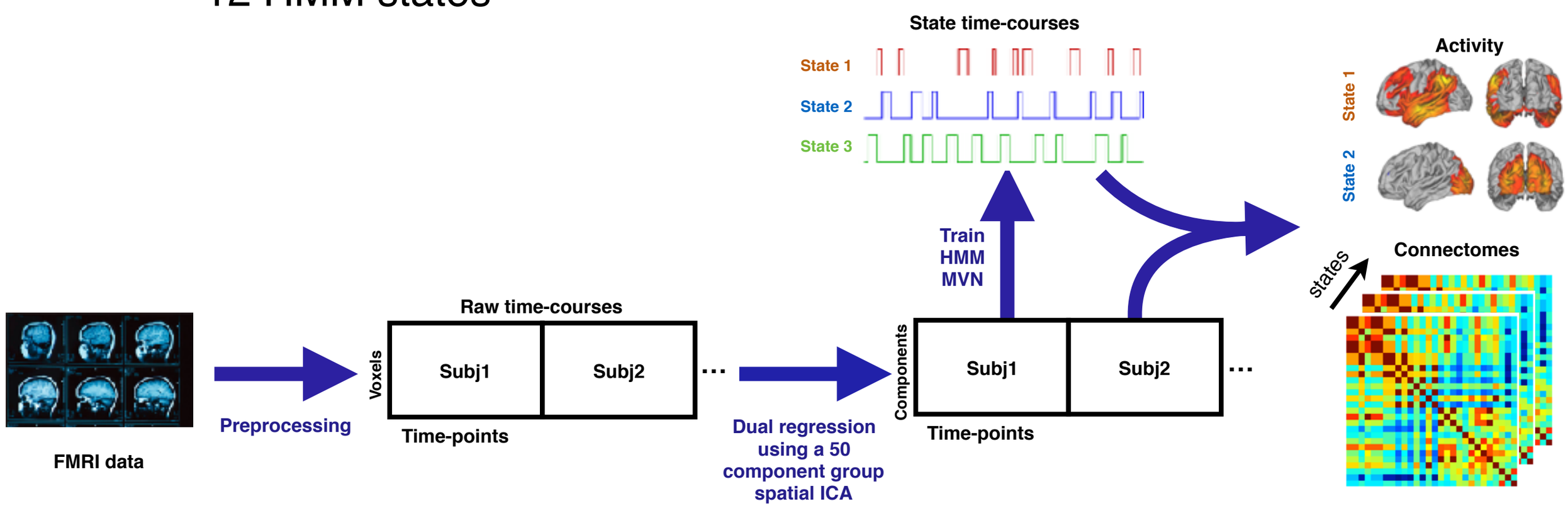


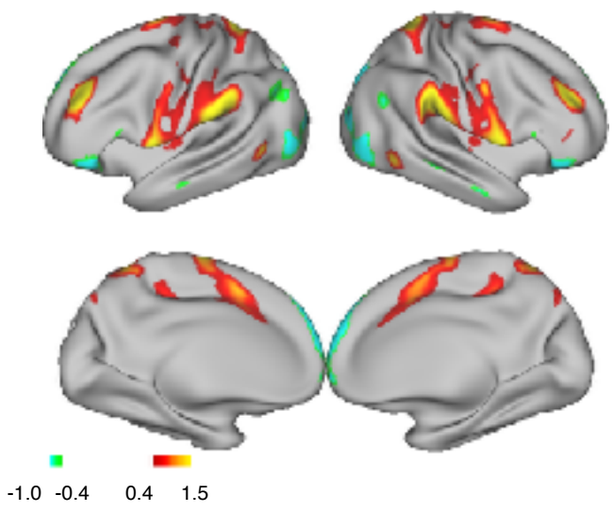
Vidaurre et al., Poster #3955: talk on Wed 10:43am

Vidaurre et al., Under Revision

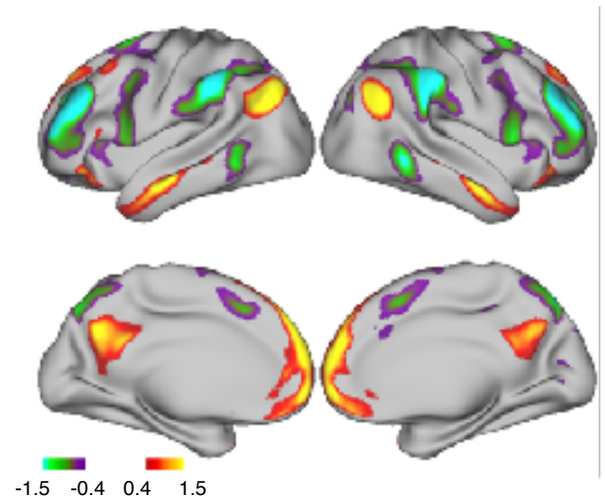
FMRI HMM state spatial maps

Vidaurre et al., Poster #3955: talk on Wed 10:43am

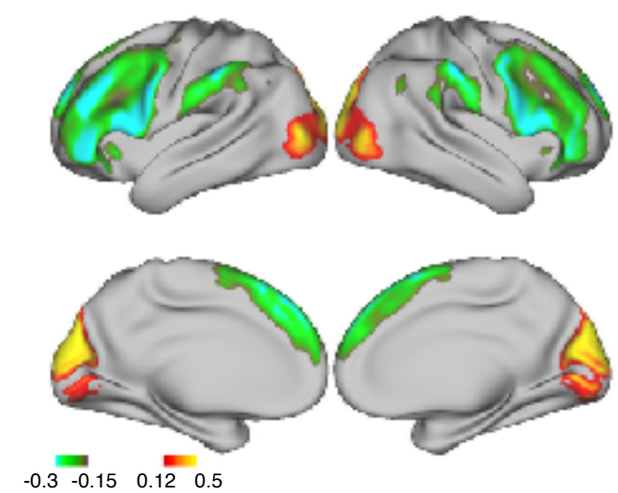
Vidaurre et al., Under Revision



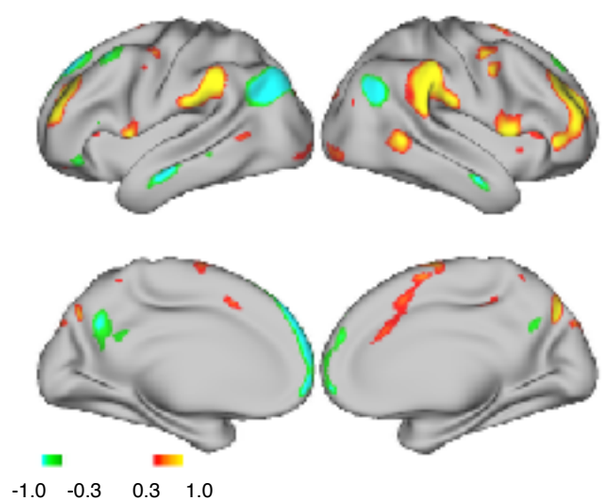
Salience (s10)



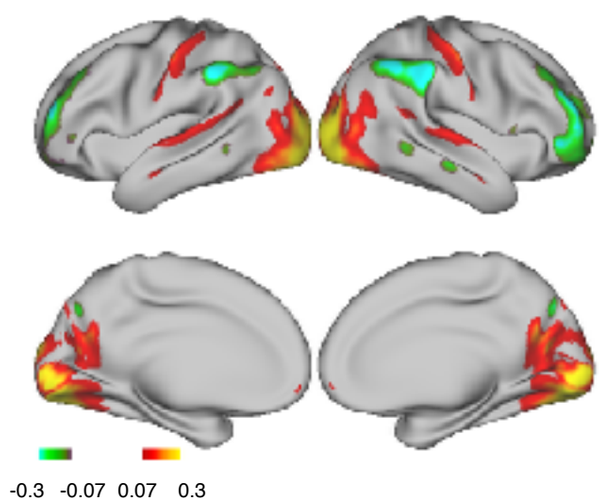
DMN (s1)



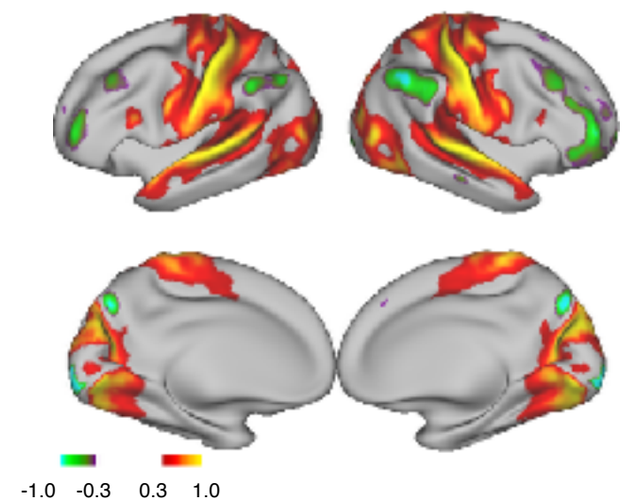
Higher order visual (s7)



Language (s6)



Lower order Visual (s2)

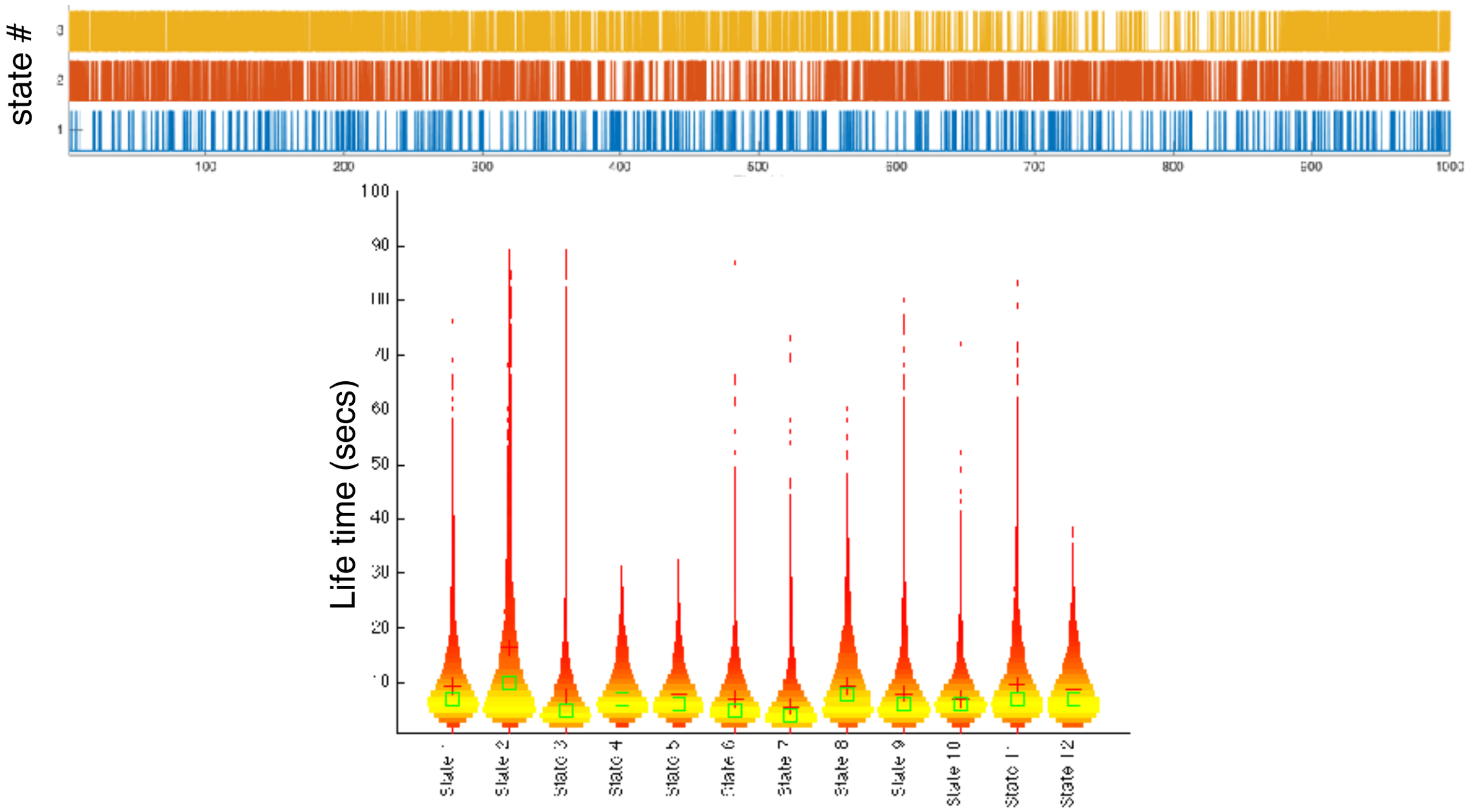


Sensorimotor (s12)

FMRI HMM state dynamics

Vidaurre et al., Poster #3955: talk on Wed 10:43am

Vidaurre et al., Under Revision



FMRI HMM state dynamics

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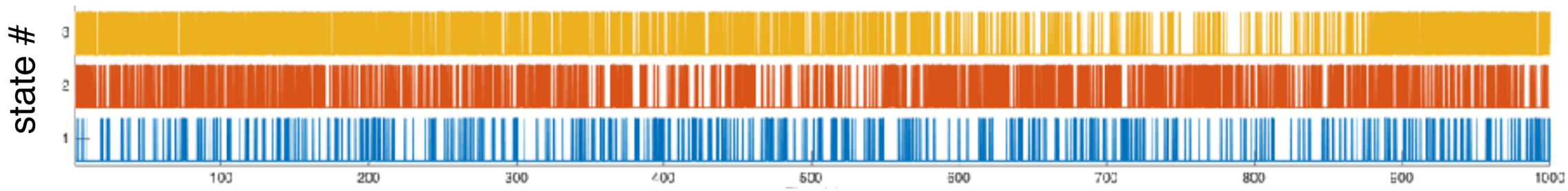

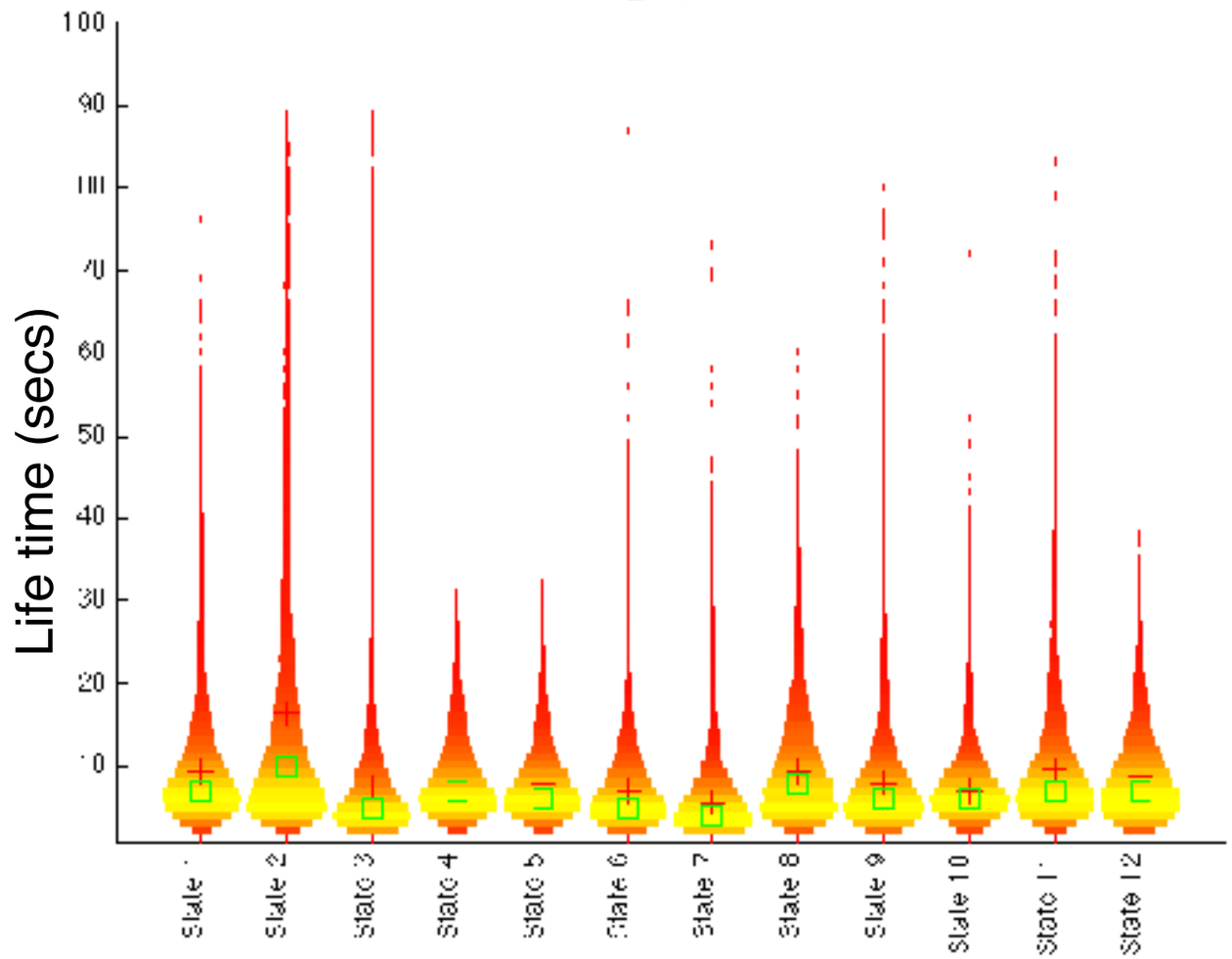

Is there hierarchical temporal structure in the state time courses?

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Is there hierarchical temporal structure?

- in the rate of occurrence brain states?

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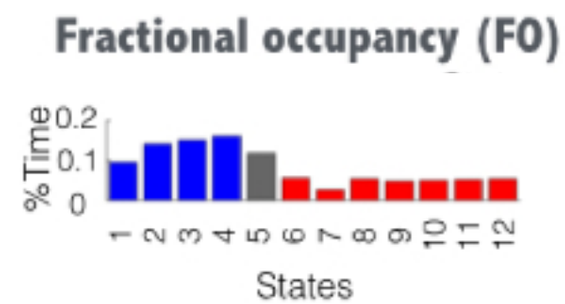

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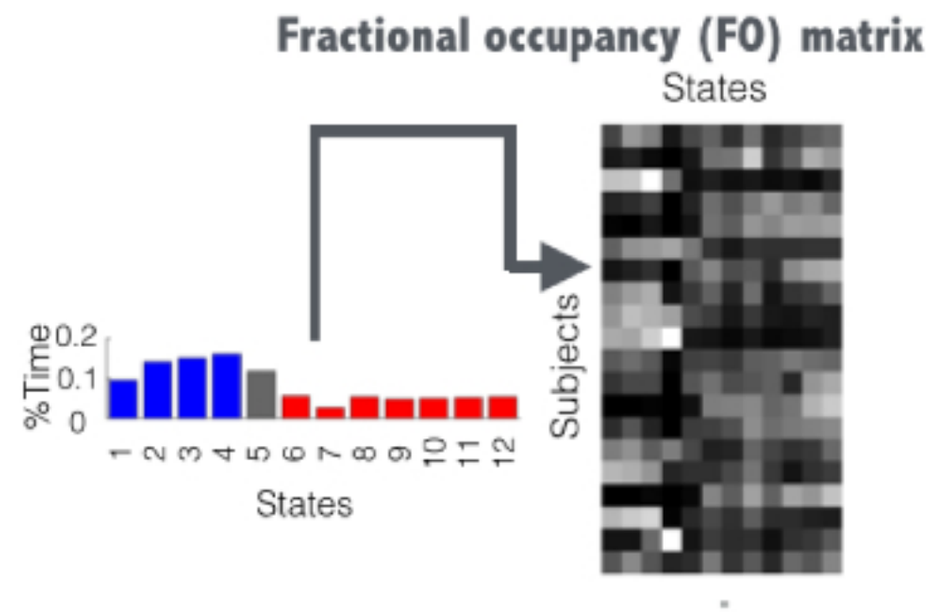

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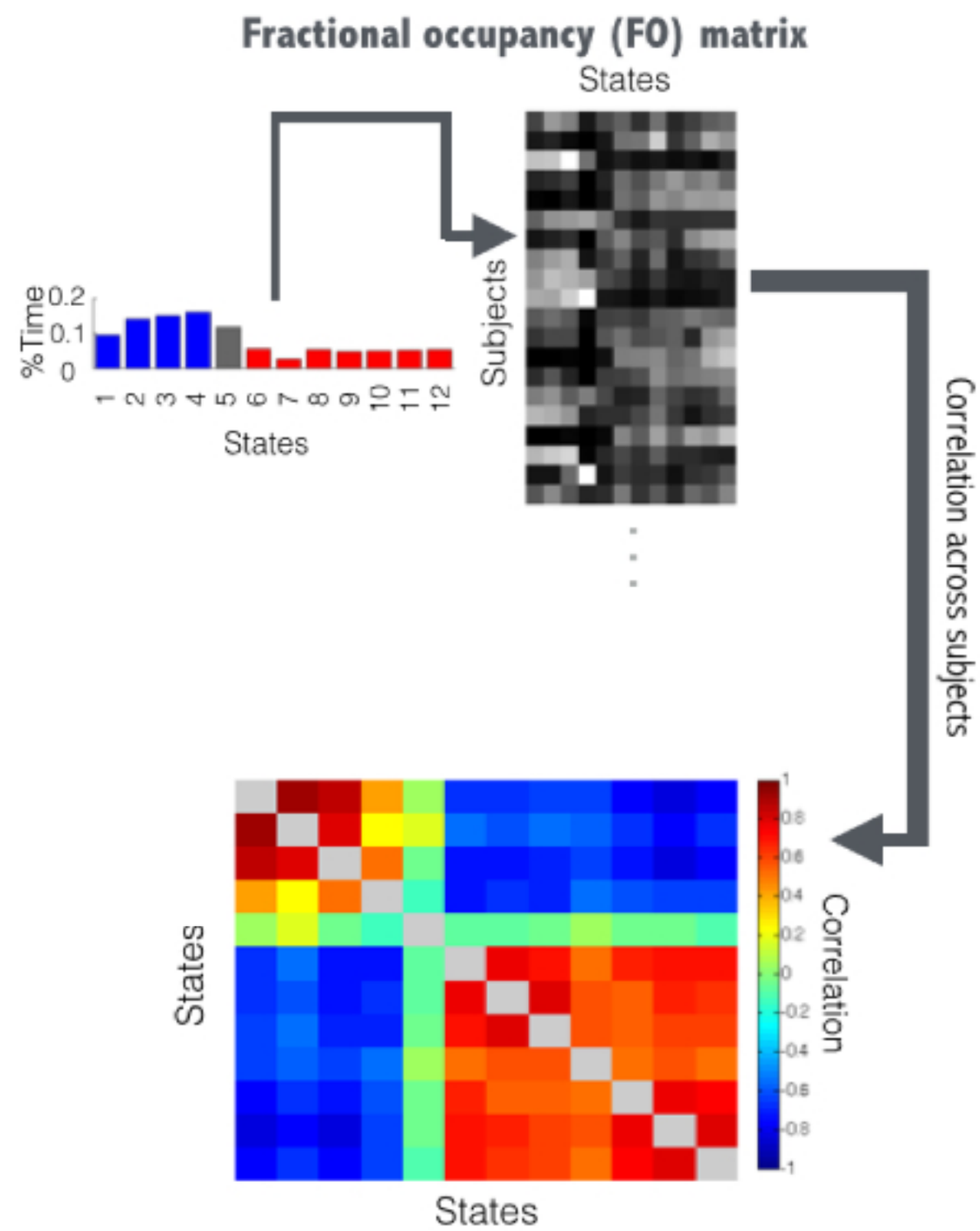

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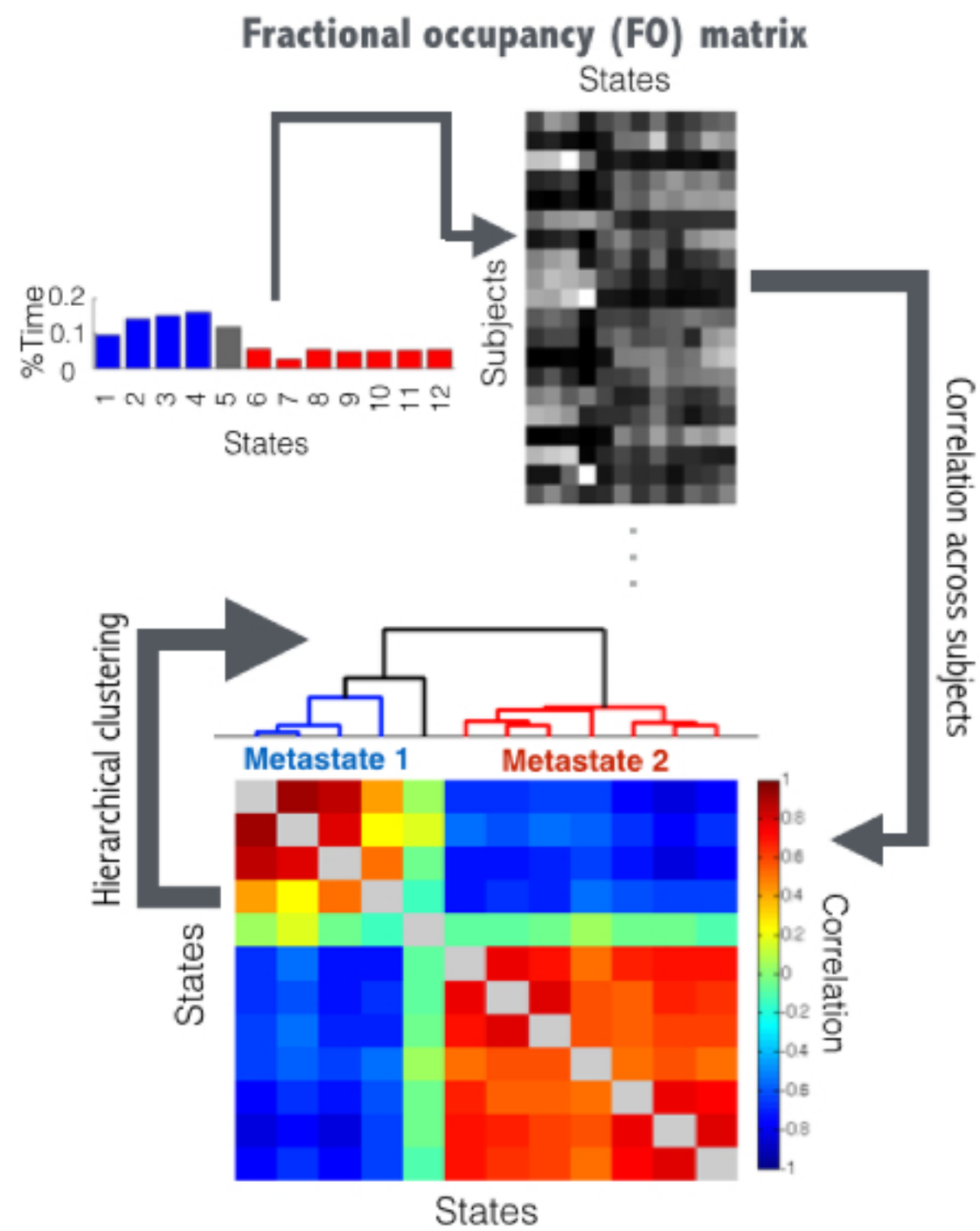

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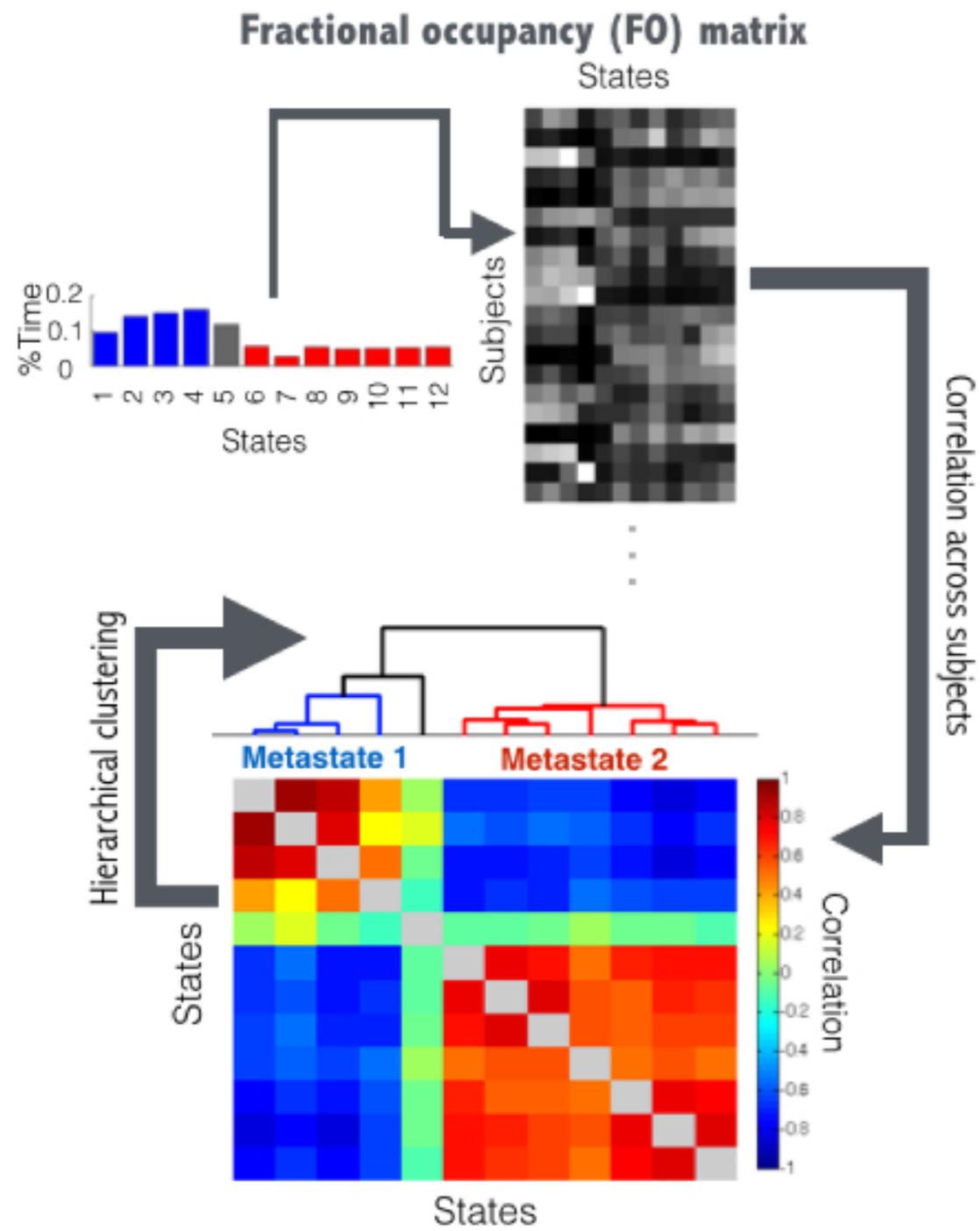
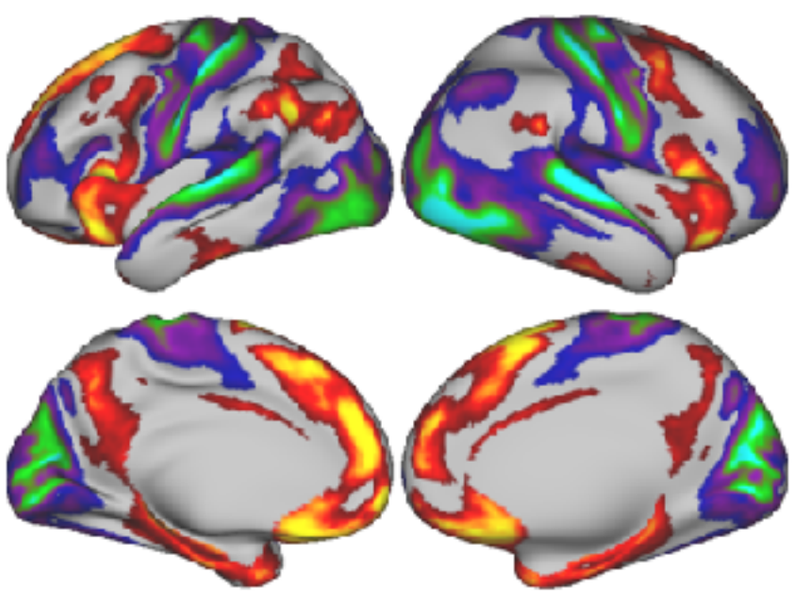


Degree maps



Metastate 2 Metastate 1

Cognitive Sensory/motor

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Is there hierarchical temporal structure?

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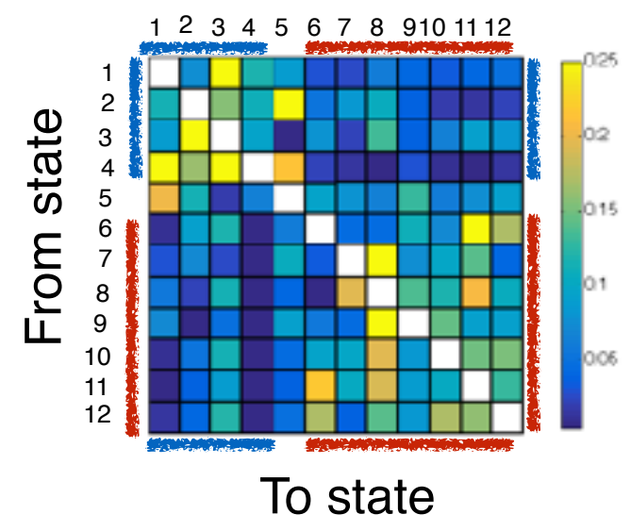
Transition probabilities between the states



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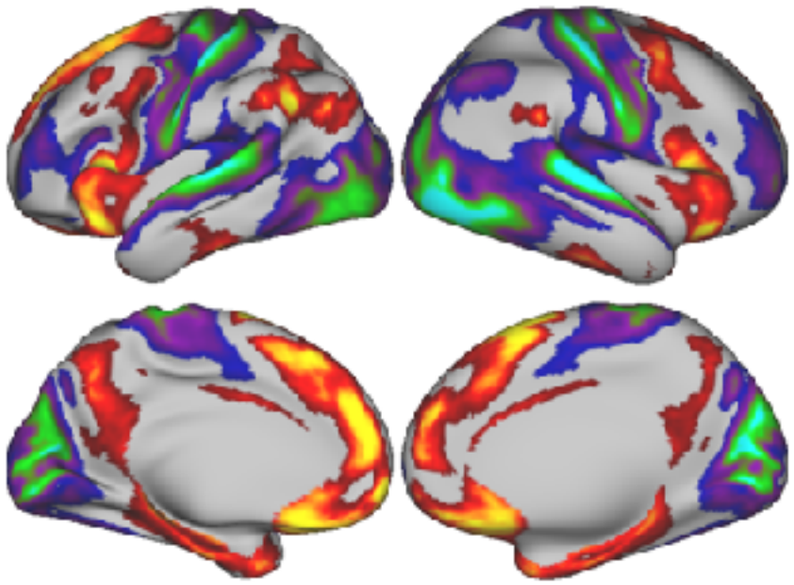

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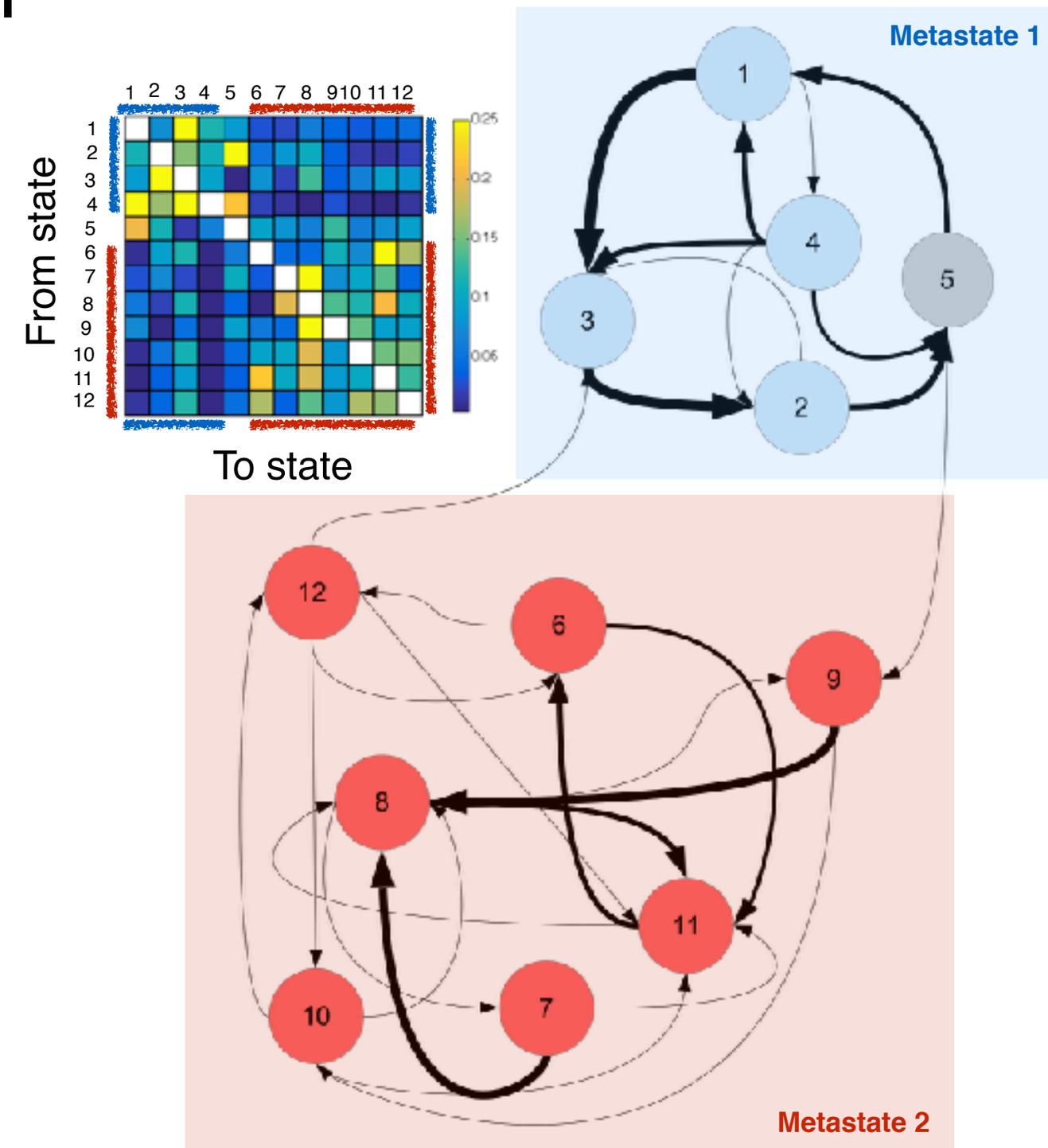

Hidden Markov Model

https://github.com/OHBA-analysis/HMM-MAR

EEG

fMRI

MEG

HMM

Intracranial recordings

Hidden Markov Model (HMM)

- Can we use the HMM to infer ***dynamic networks in resting MEG*** data?
- How fast are the dynamics?

  - Resting state (eyes open) CTF MEG data
  - 9 subjects (10 minutes each)
  - 8 HMM states

Baker,…, Woolrich; eLife (2014)

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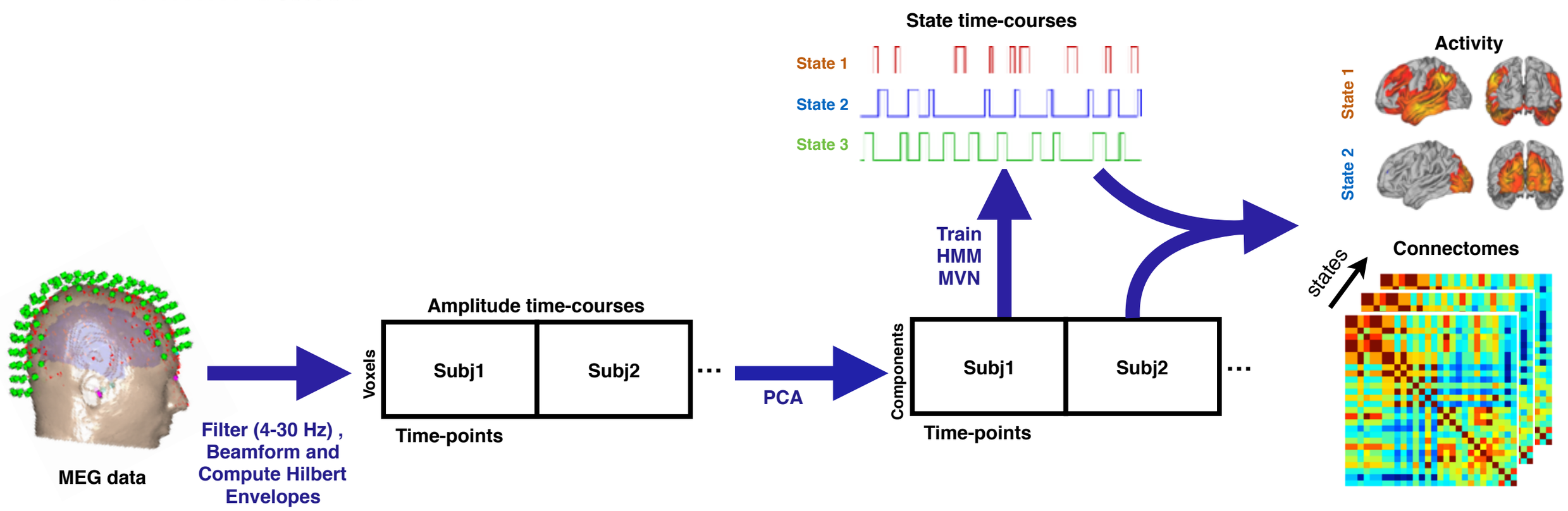
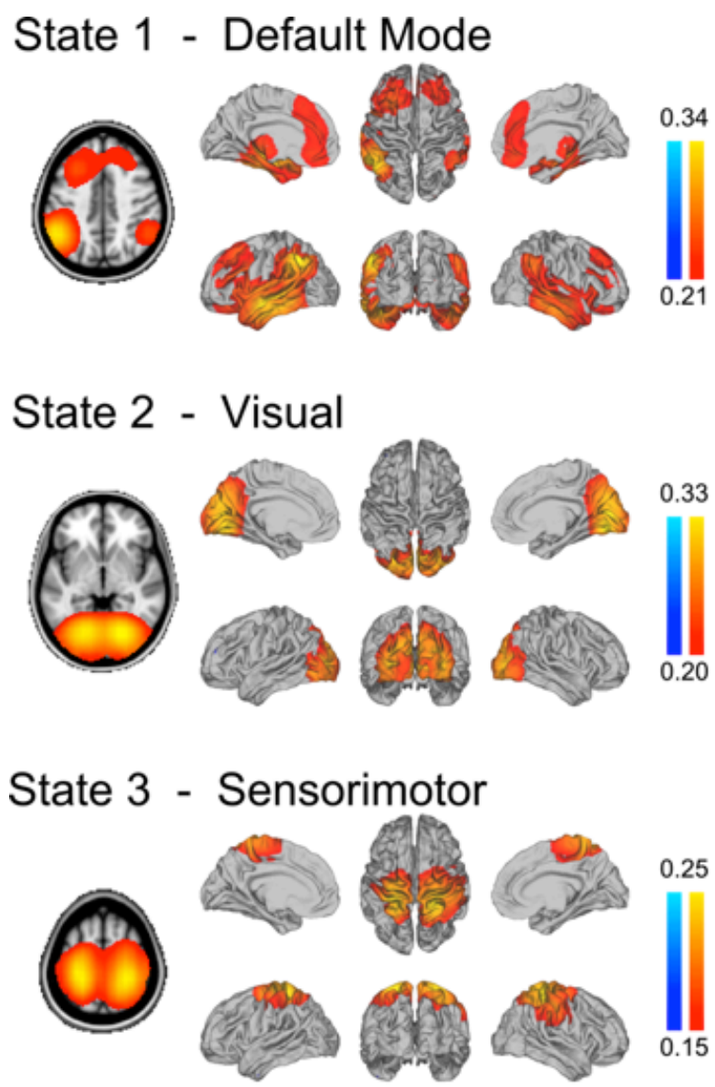
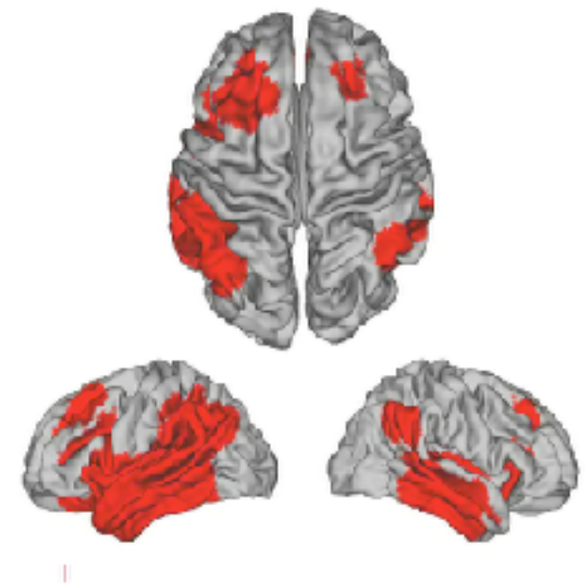


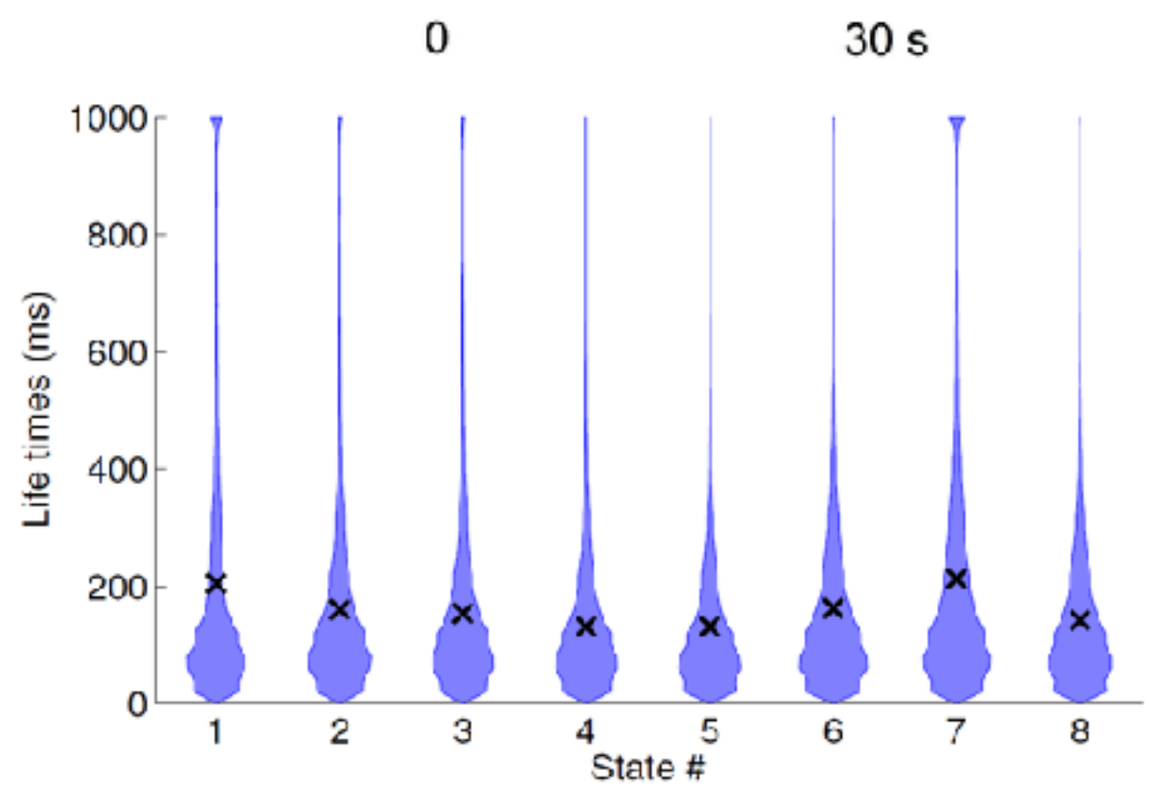
Baker,…, Woolrich; eLife (2014)

Brain Network Dynamics

HMM reveals MEG resting state networks that switch on fast sub-second timescales (~100 ms)







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MEG: TIme Delay Embedded HMM (TIDEH)

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  - Are there transient states of distinct **phase coupling**?

"Communication through neuronal coherence", Fries et al., TICS, 2005

Vidaurre et al., BioRxiv, 2017

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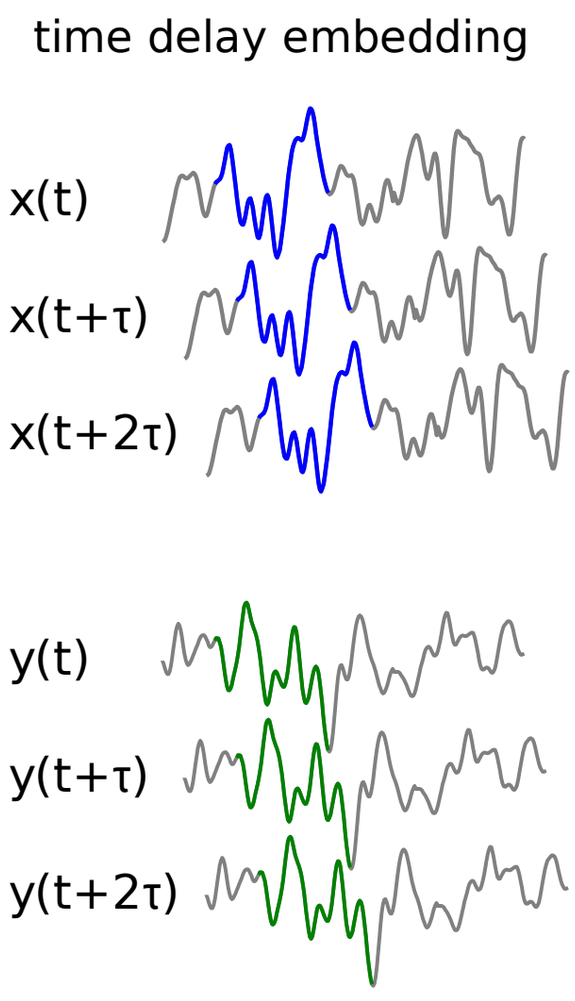

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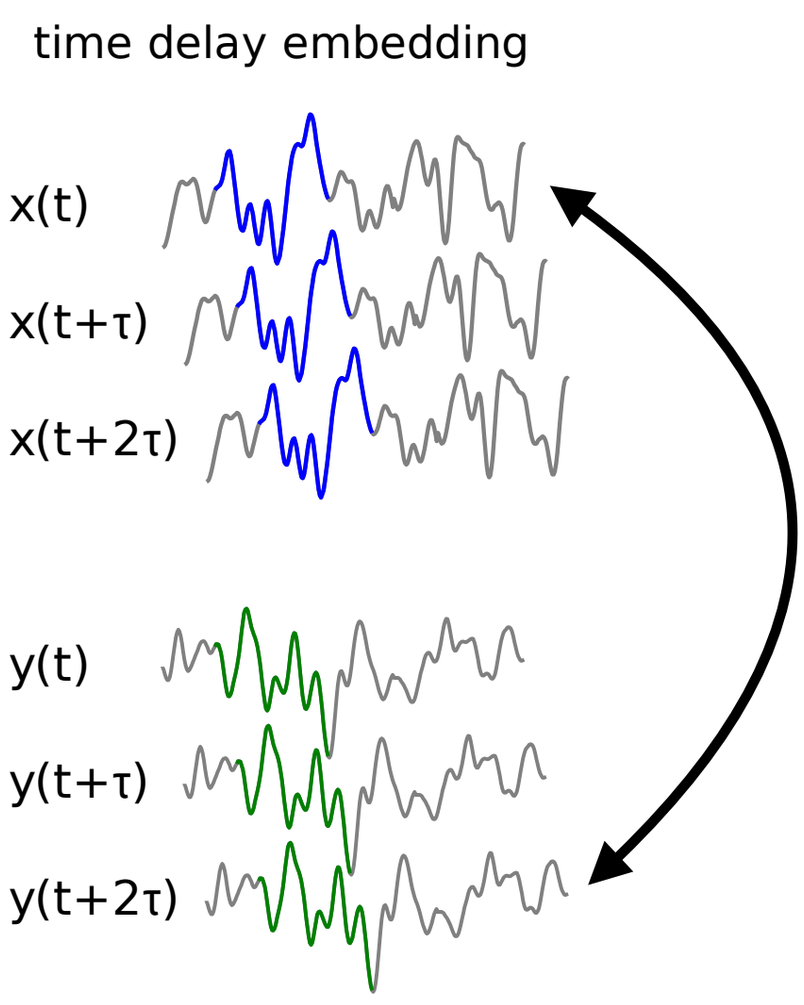

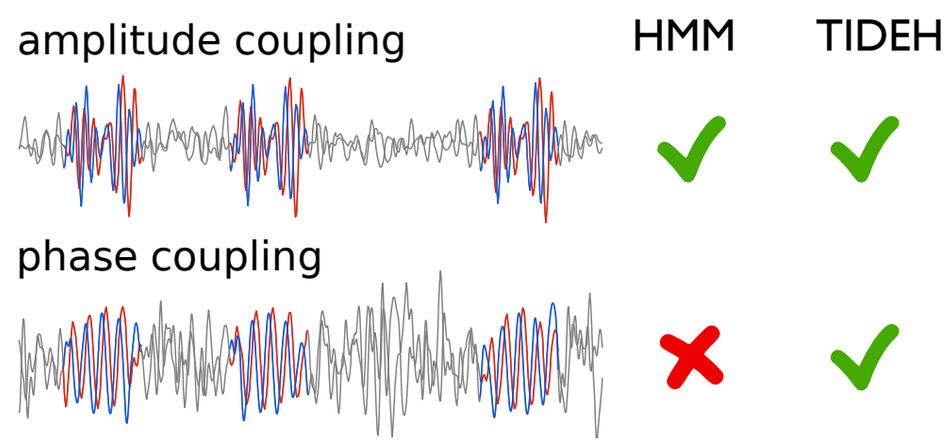

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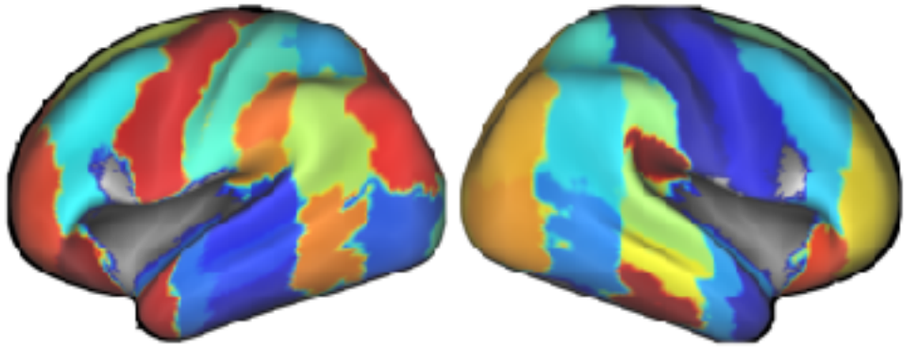
MEG: TIme Delay Embedded HMM (TIDEH)

- Are there fast transient brain states of distinct ***phase locking*** in the resting state?

- Time embedded HMM on:
  - Resting state (eyes open) CTF MEG
  - 51 subjects (6 mins each)
  - 38 node parcellation
  - 1-45Hz raw time courses
  - 8 HMM states



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Rel. Amplitude
(1-30Hz)

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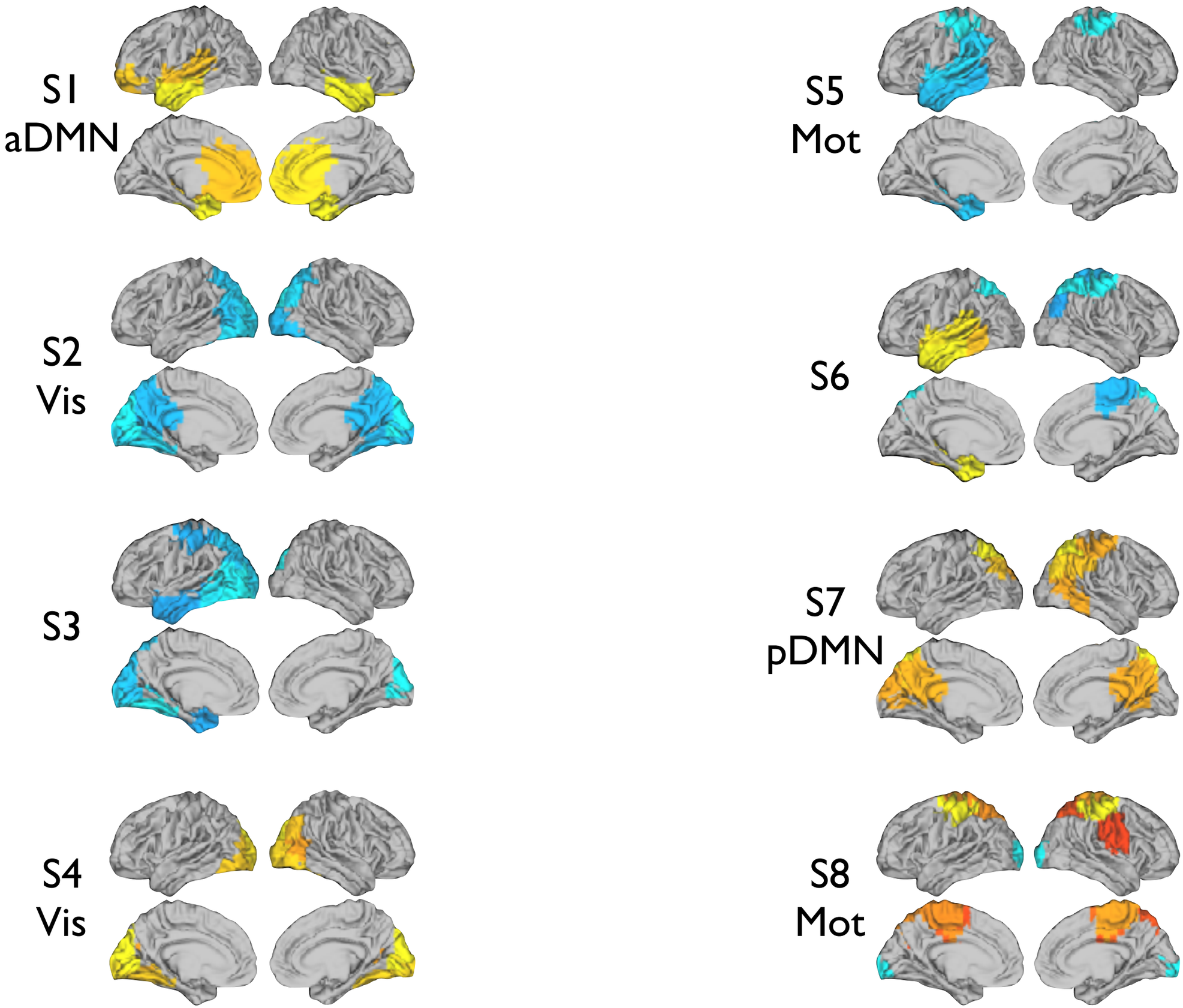
Vidaurre et al., BioRxiv, 2017
Poster #1892



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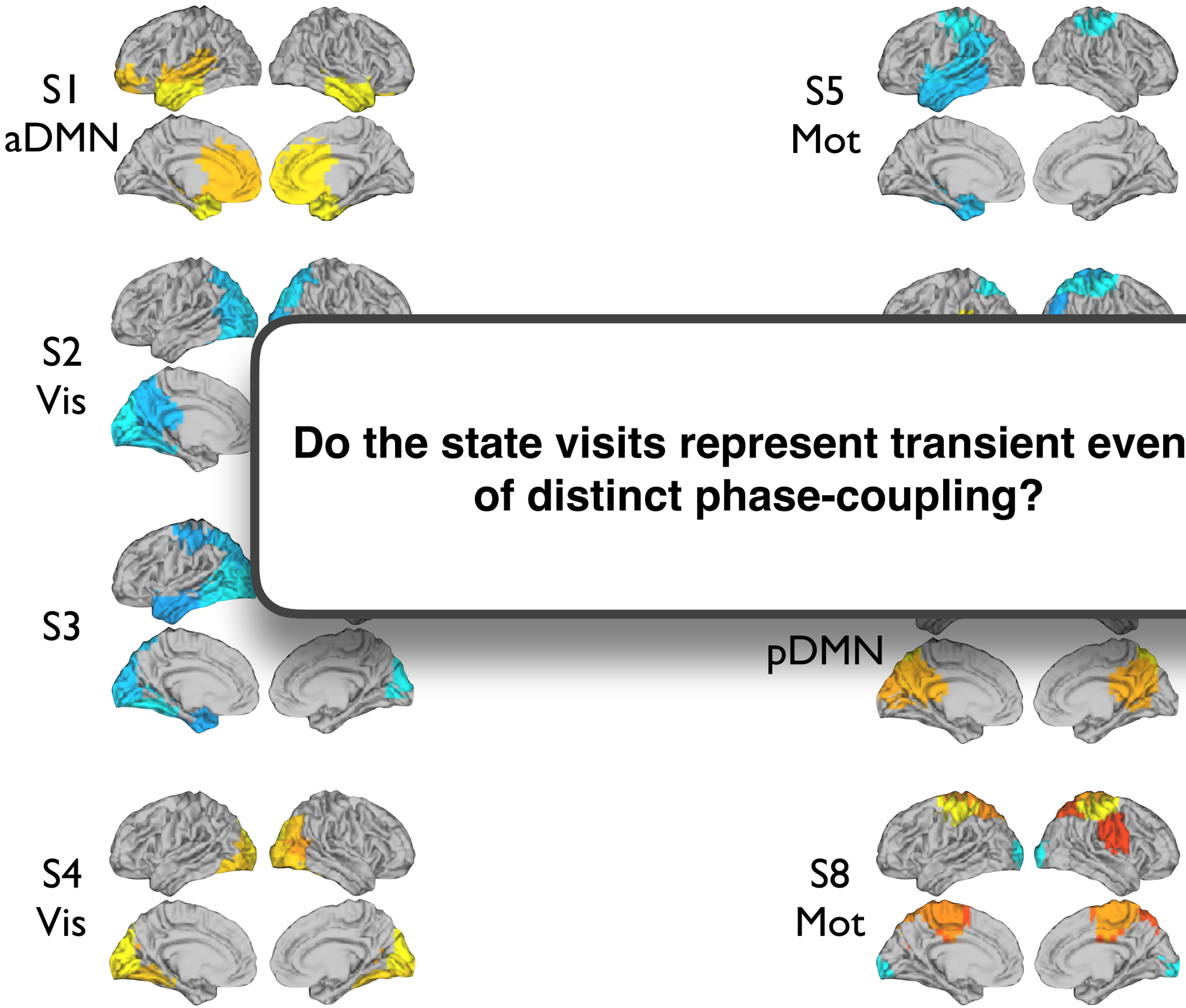
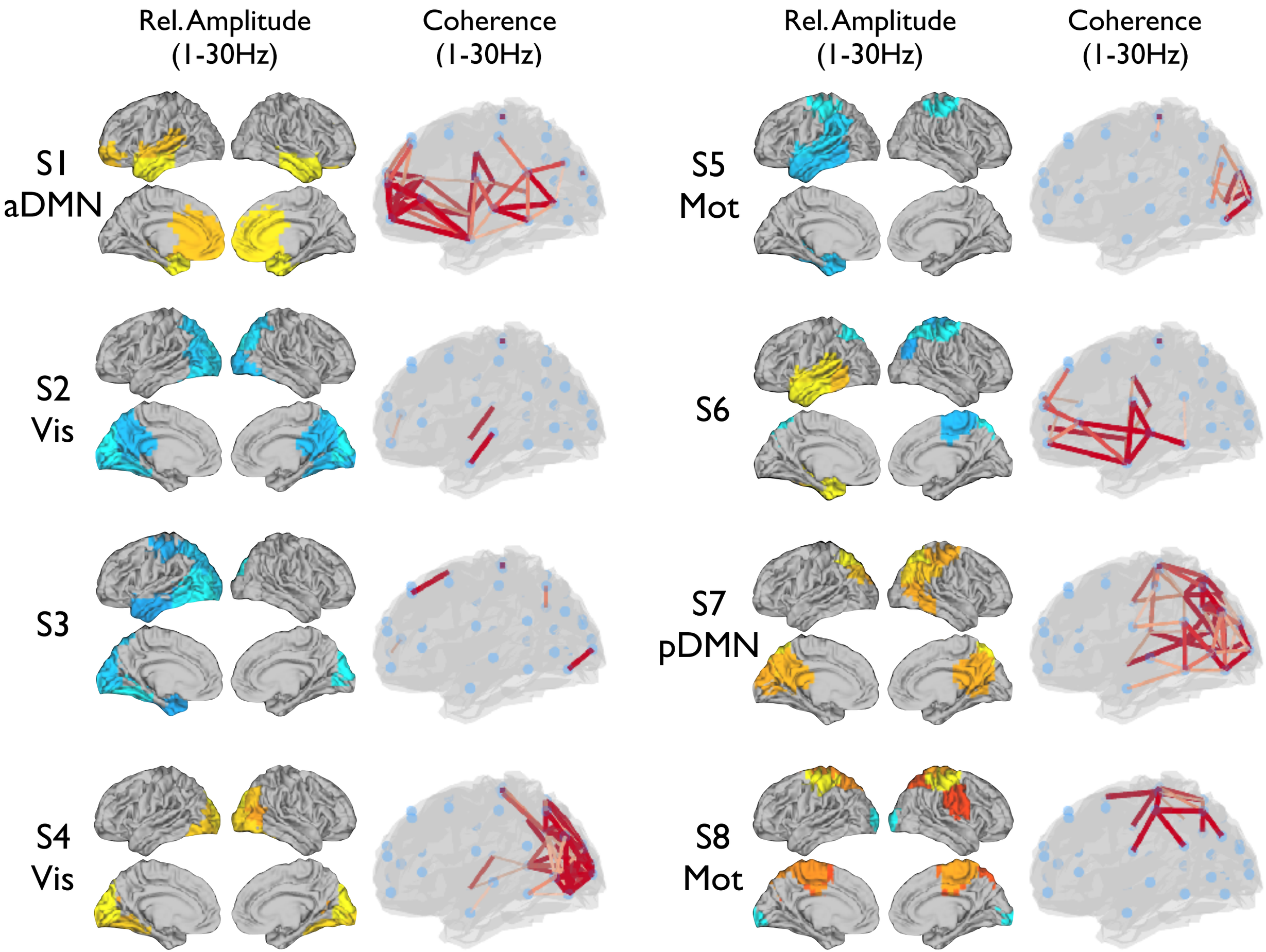


Do the state visits represent transient events of distinct phase-coupling?


Rel. Amplitude (1-30Hz)
Coherence (1-30Hz)
Rel. Amplitude (1-30Hz)
Coherence (1-30Hz)
S1 aDMN
S2 Vis
S3
S4 Vis
S5 Mot
S6
S7 pDMN
S8 Mot

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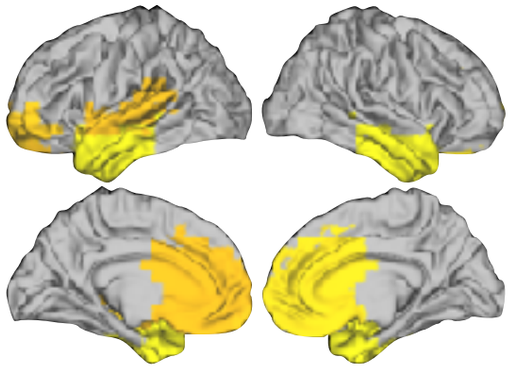
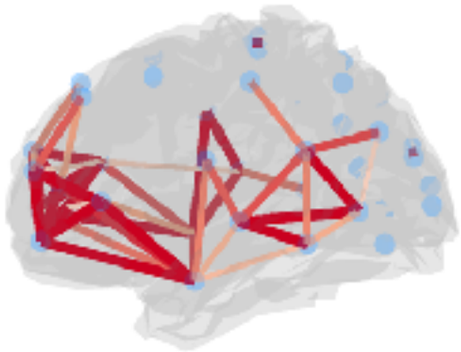
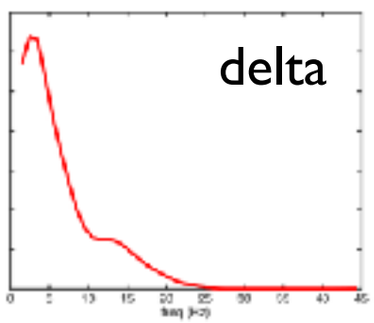
S1 - anterior DMN

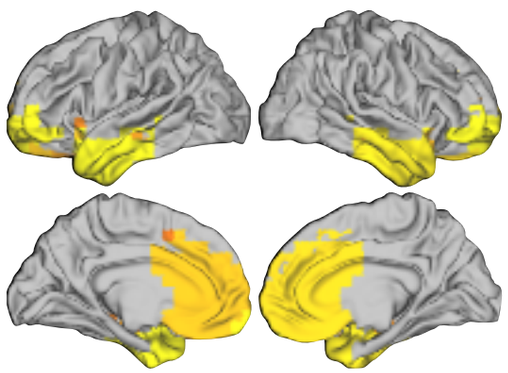
Amplitude | Coherence

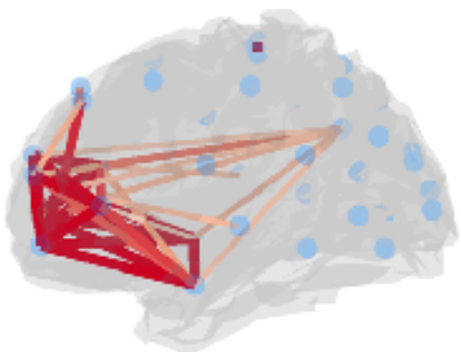
wideband
1-30Hz

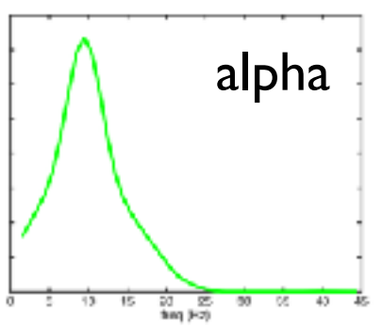


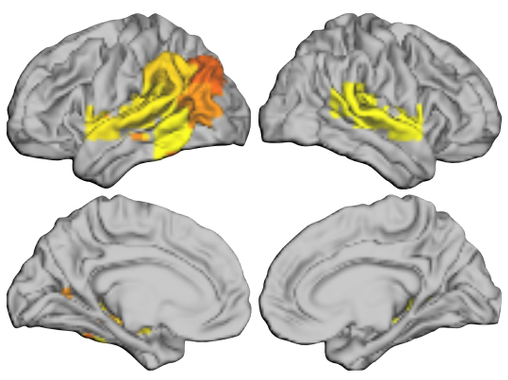


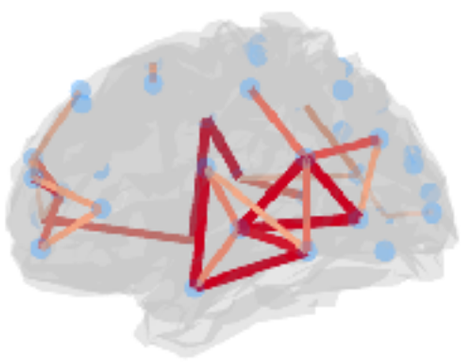


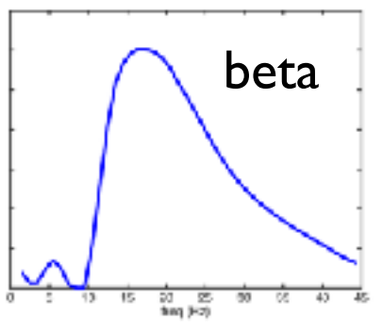


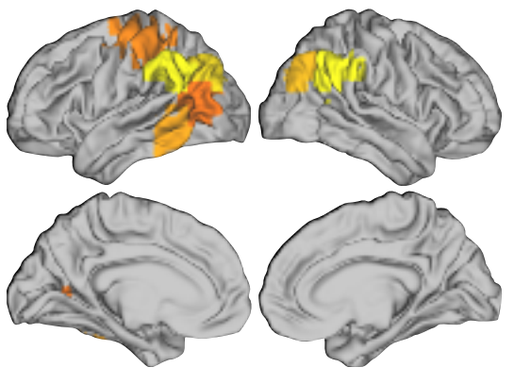


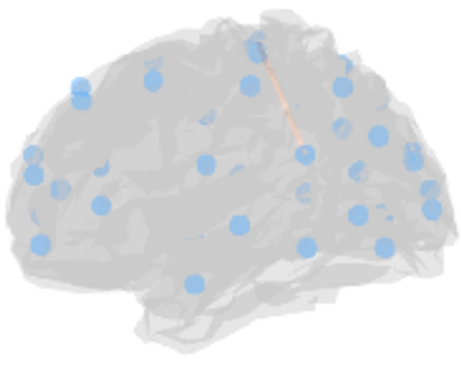












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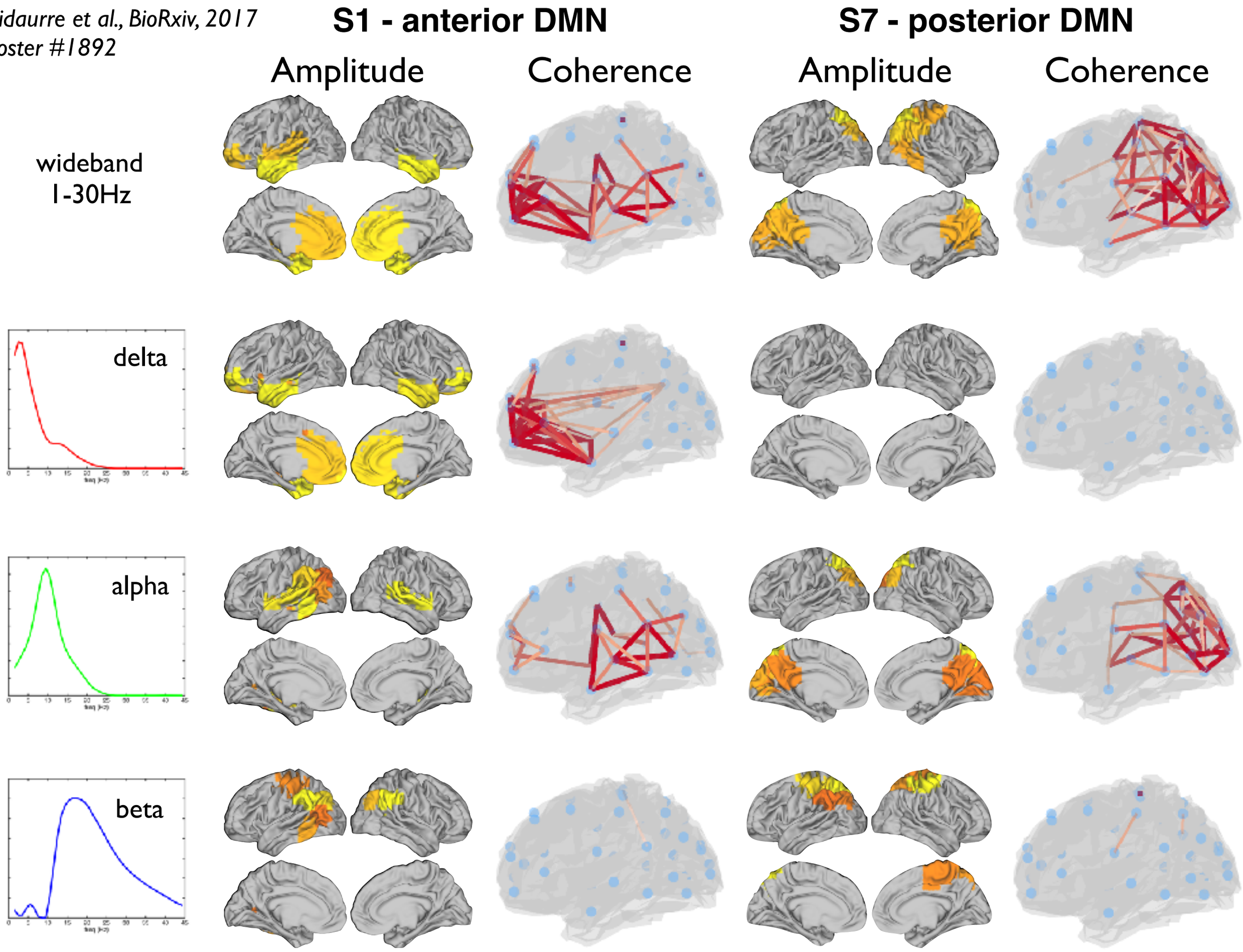

Summary

- **Static connectomes** can be computed using fMRI raw correlations and MEG amplitude correlations
    - Beware spatial misalignments over subjects!
- **Dynamic connectomes** can be computed across modalities using Hidden Markov Modelling (HMM), e.g.:
    - Hierarchical temporal organisation of networks in resting **fMRI**
    - Dynamics of large-scale phase coupling in resting-state **MEG**

Acknowledgements

wellcome trust

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MRC MEG UK Partnership

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  - George O'Neill
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