



OSL Workshop 2025: Dynamic Network Modelling

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Adapted slides from Chetan Gohil

Overview

- osl-dynamics toolbox
- Brain Networks and dynamics
- Data preparation: Amplitude envelope and Time delay embedding
- Data loading and preparation. [Practical: Notebook 1](#)
- Hidden Markov Model
 - HMM training. [Practical: Notebook 2-1](#)
 - Post-hoc spectral estimation. [Practical: Notebook 2-2](#)
 - Networks visualisation. [Practical: Notebook 2-3](#)
 - Dynamics visualisation. [Practical: Notebook 2-4](#)
 - Task evoked response analysis. [Practical: Notebook 2-5](#)
- Summary

Workshop materials

- <https://github.com/OHBA-analysis/osl-workshop-2025-dynamics>

osl-dynamics

osl-dynamics

Tools and Resources

Neuroscience

osl-dynamics, a toolbox for modeling fast dynamic brain activity

Chetan Gohil , Rukuang Huang, Evan Roberts, Mats WJ van Es, Andrew J Quinn, Diego Vidaurre, Mark W Woolrich

Oxford Centre for Human Brain Activity, Wellcome Centre for Integrative Neuroimaging, Department of Psychiatry, University of Oxford, United Kingdom; Centre for Human Brain Health, School of Psychology, University of Birmingham, United Kingdom; Center for Functionally Integrative Neuroscience, Department of Clinical Medicine, Aarhus University, Denmark

Jan 29, 2024 • <https://doi.org/10.7554/eLife.91949.3> 

osl-dynamics

- Python package for:
 - **Data manipulation:** Loading, preparing and creating datasets for model training.
 - **Static analysis:** Performing static analysis on the data.
 - **General Linear Model (GLM):** Basic GLM functionality and maximum statistic permutation testing.
 - **Dynamic Models:** Training and Evaluating dynamic models, including the **sliding window approach**, the **Hidden Markov Model (HMM)**, **Dynamic Network Modes (DyNeMo)**, and more.
 - **Post-hoc analysis:** Functionality for post-hoc analysis of the models.
 - **Visualisation:** Visualising the results of the models, including network visualisation and dynamic visualisation.
- There are also some additional functionalities, such as
 - **Simulation:** Simulating data for testing purposes.
 - **High-level pipeline API:** A pipeline for running analysis pipelines while being highly customisable.

osl-dynamics

- Public GitHub repository containing source code:

<https://github.com/OHBA-analysis/osl-dynamics>

- Official documentation: <https://osl-dynamics.readthedocs.io/en/latest/>.

Installation

- See: <https://osl-dynamics.readthedocs.io/en/latest/install.html>
- Also see the FAQ: <https://osl-dynamics.readthedocs.io/en/latest/faq.html>

Documentation

- API reference guide:
 - <https://osl-dynamics.readthedocs.io/en/latest/autoapi/index.html>
 - Provides a description (use, input and output) of the all functions/classes/methods in the osl-dynamics package.

Tutorials and Example Scripts

- Tutorials:

<https://osl-dynamics.readthedocs.io/en/latest/documentation.html>

- Contains jupyter notebooks (.ipynb) with explanations of common uses.
- Example scripts:

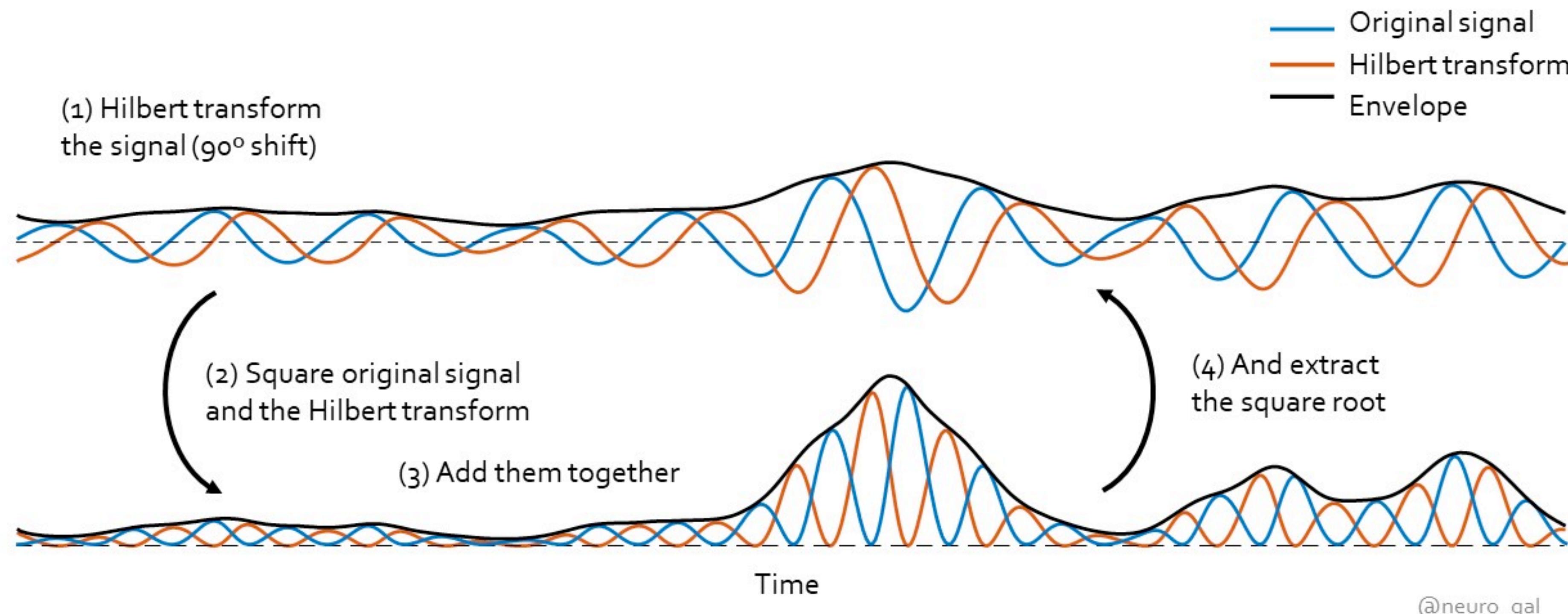
<https://github.com/OHBA-analysis/osl-dynamics/tree/main/examples>

- Contains normal python scripts (.py) without detailed explanations.
- Useful library of code snippets you can copy and paste from.

Data Processing

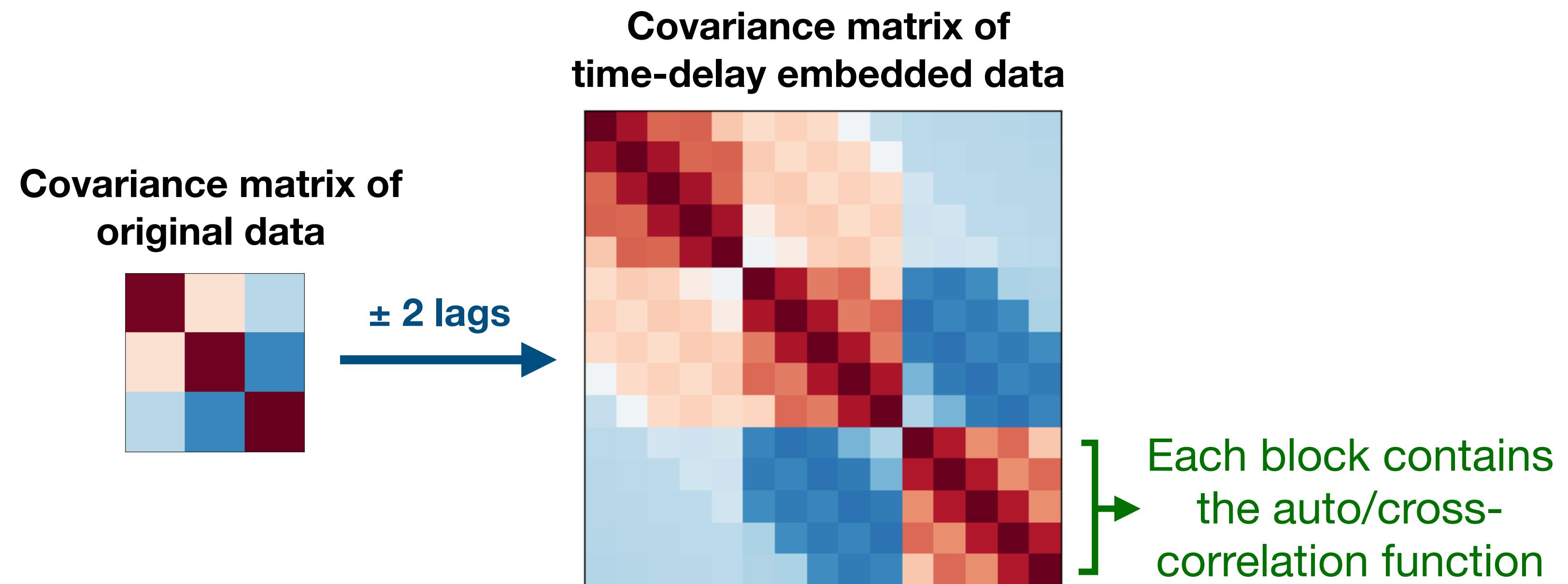
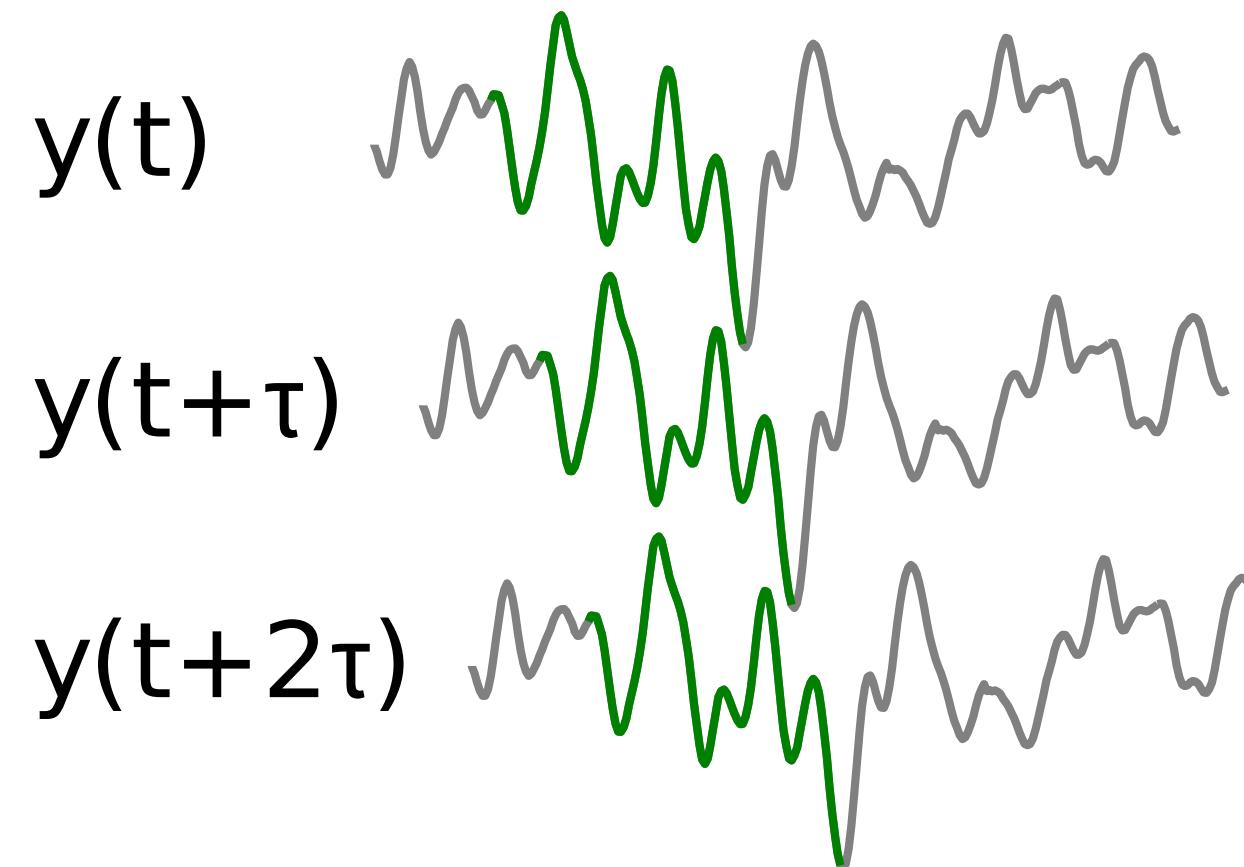
- ICA/PROFUMO/Parcellation
- Amplitude envelope (AE) - MEG/EEG
- Time-delayed embedding (TDE) -MEG/EEG

Amplitude Envelope



[Data.amplitude_envelope\(\)](#)

Time-Delay Embedding



[Data.tde pca\(n_embeddings=15, n_pca_components=80\)](#)

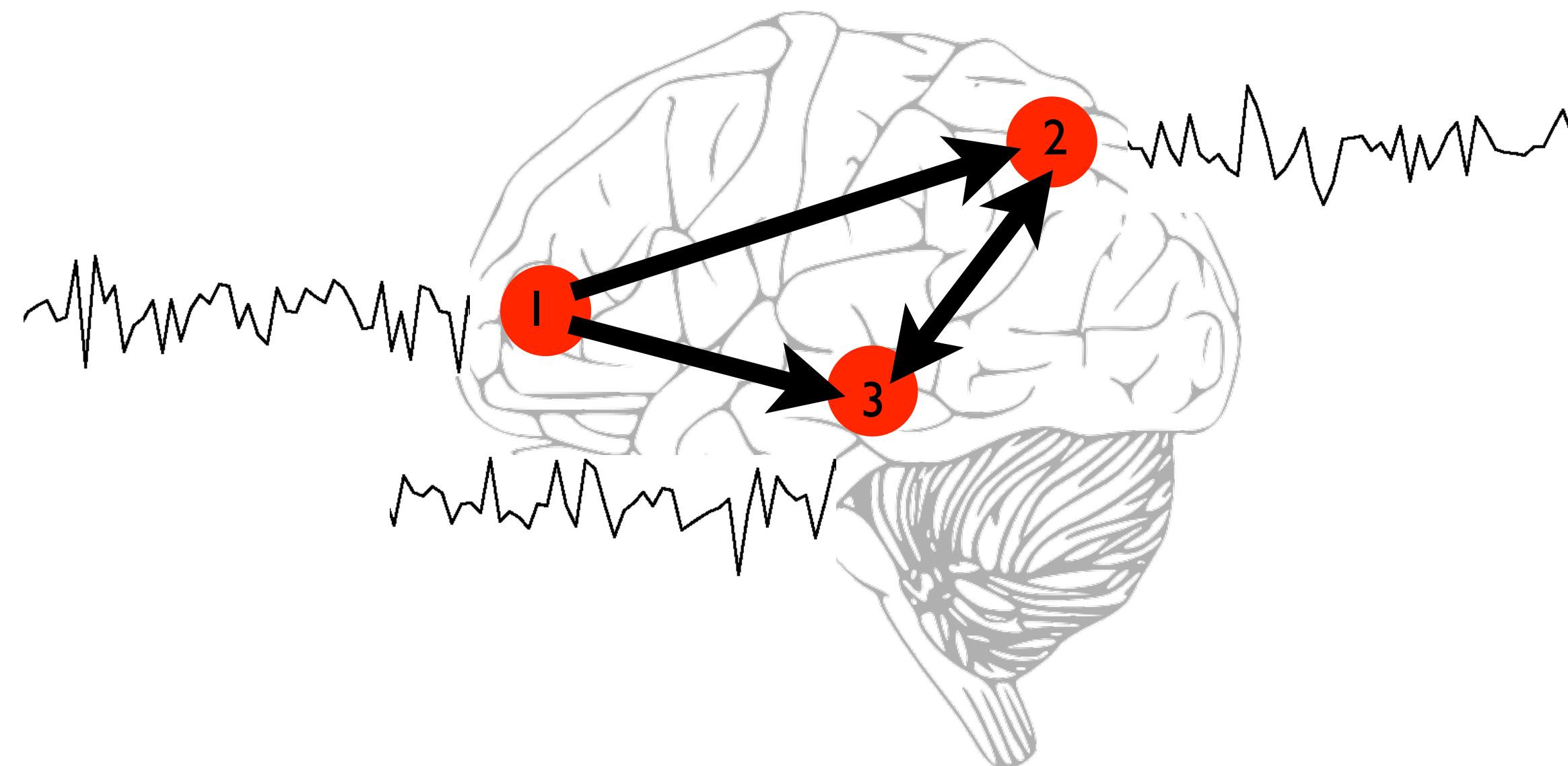
Exercise: Prepare TDE-PCA data

- Go through notebook 1.
- Remember to checkout notebook 0 first.

Brain Networks

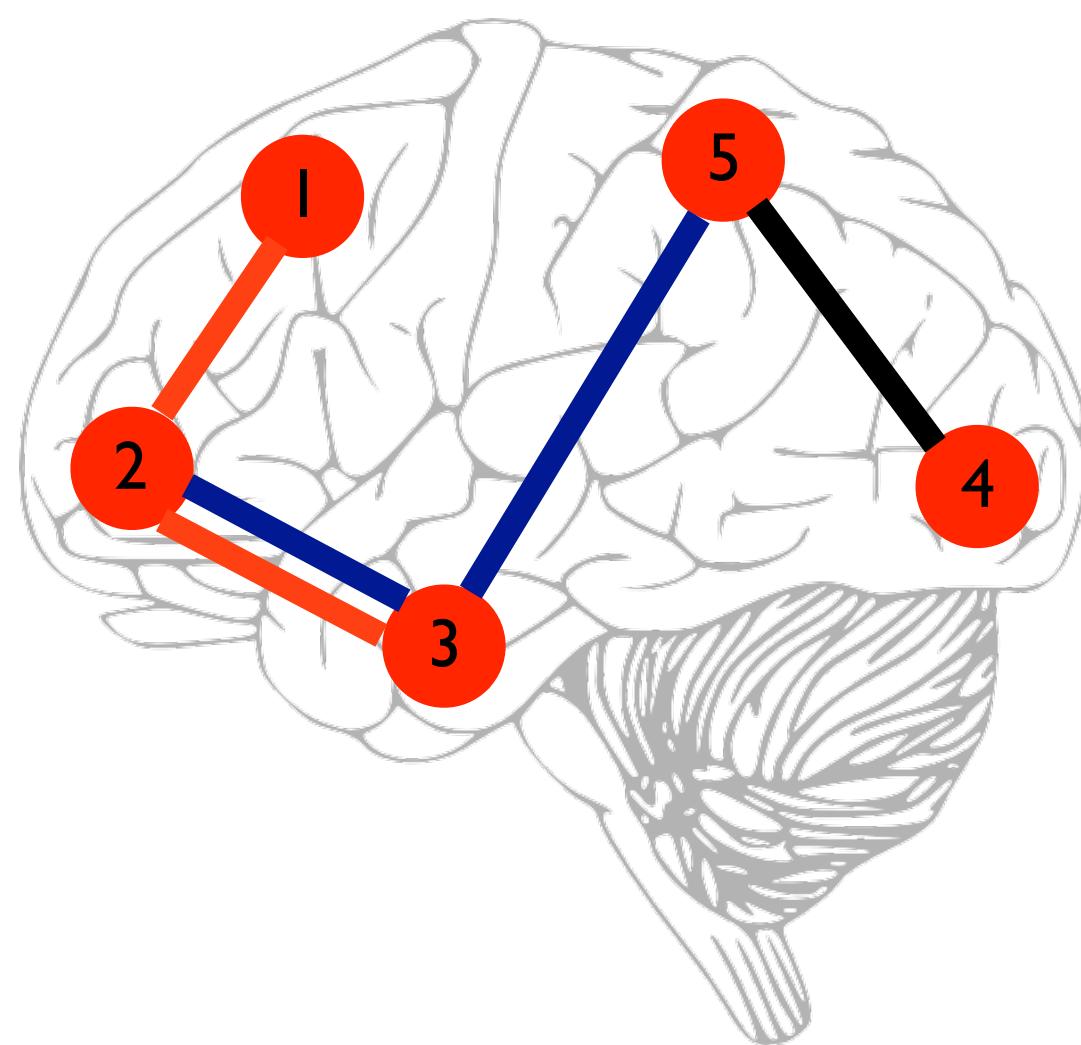
Brain Networks

- The brain performs cognition using distributed **networks**.
- Can describe **healthy** and **diseased** cognition.



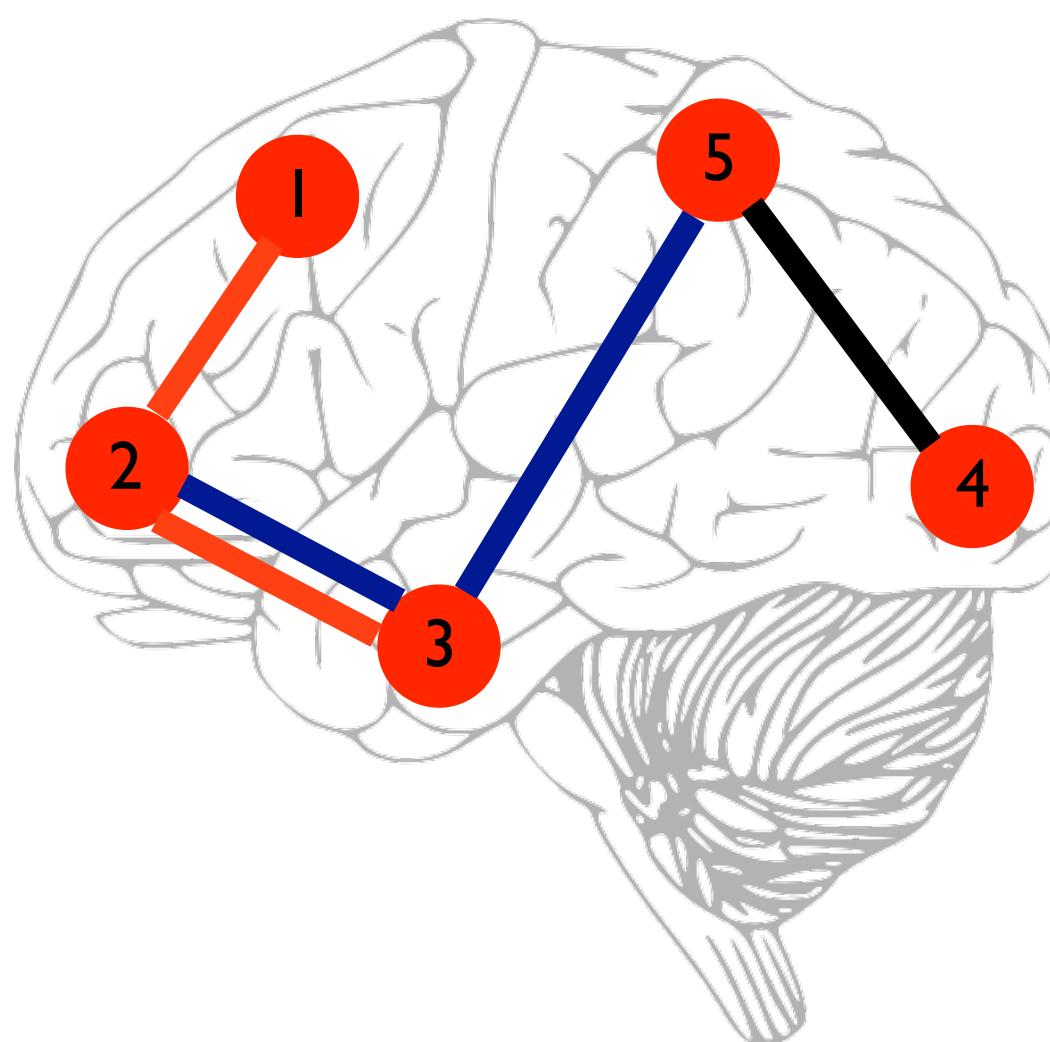
Brain Networks

Static Network

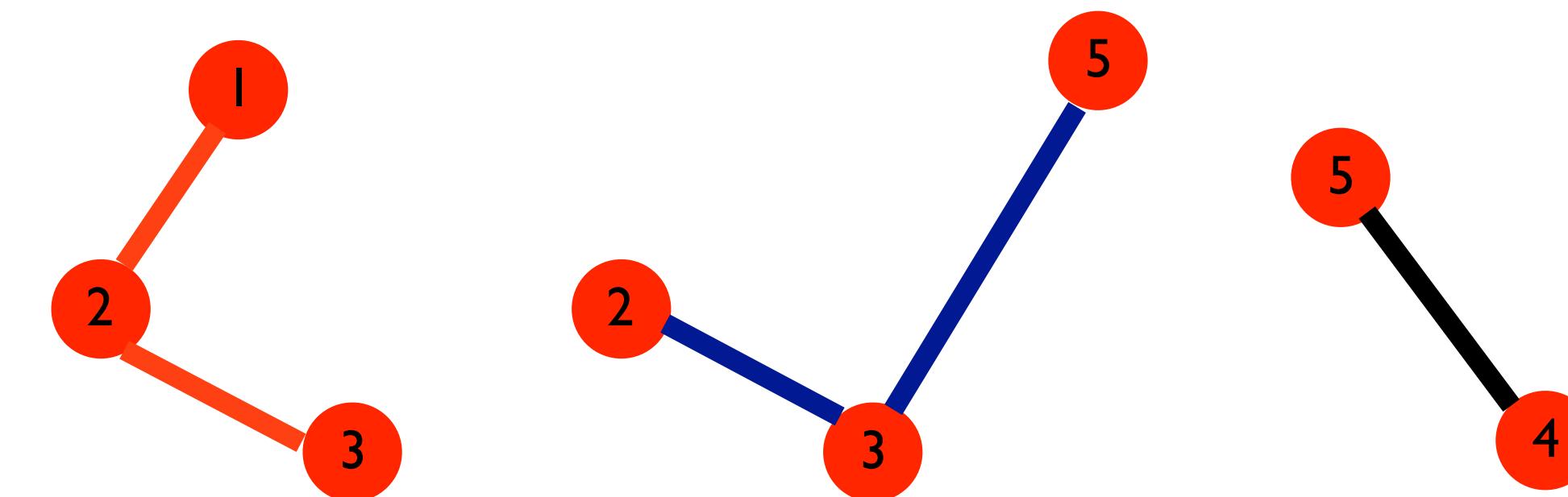


Brain Networks

Static Network

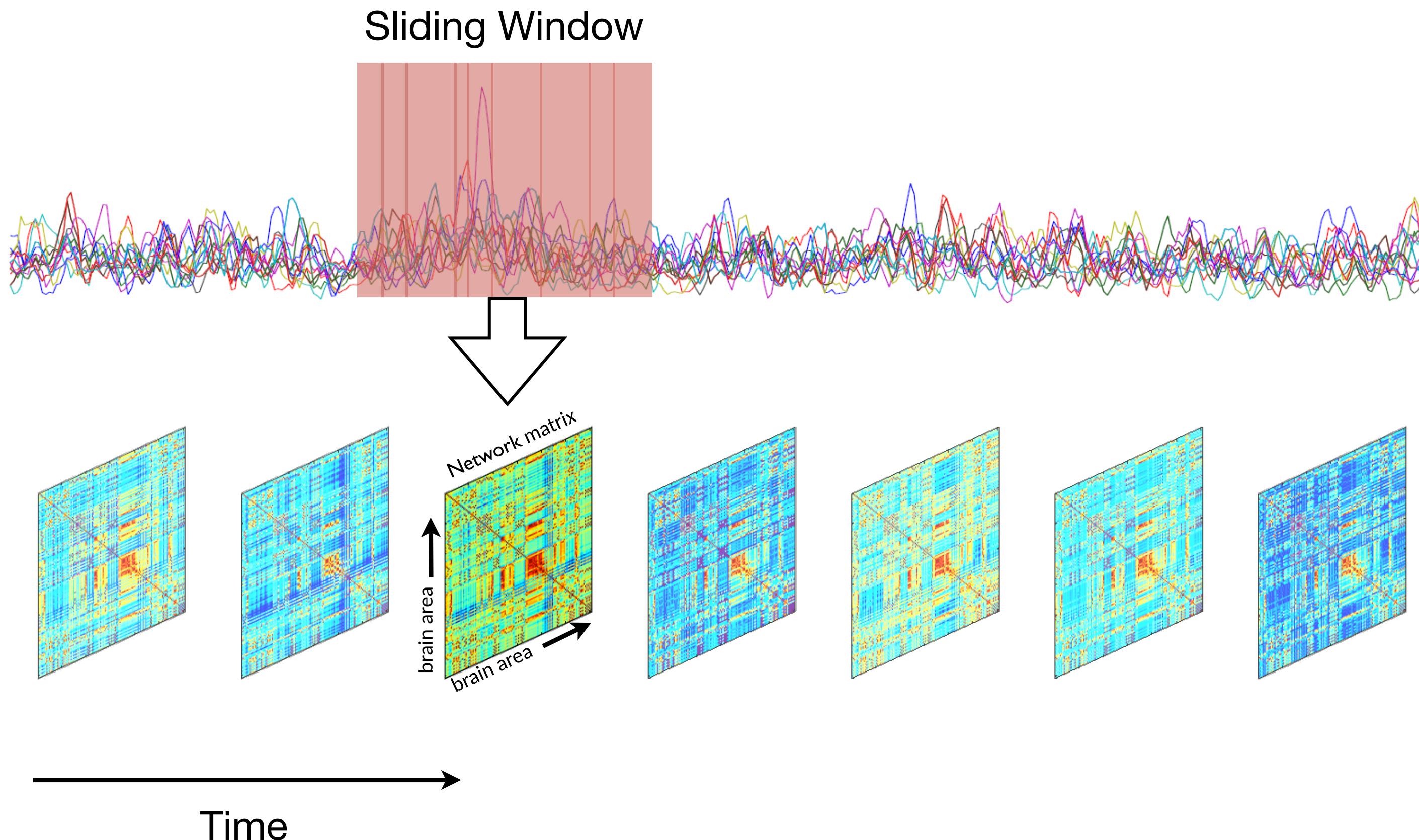


Transient Networks

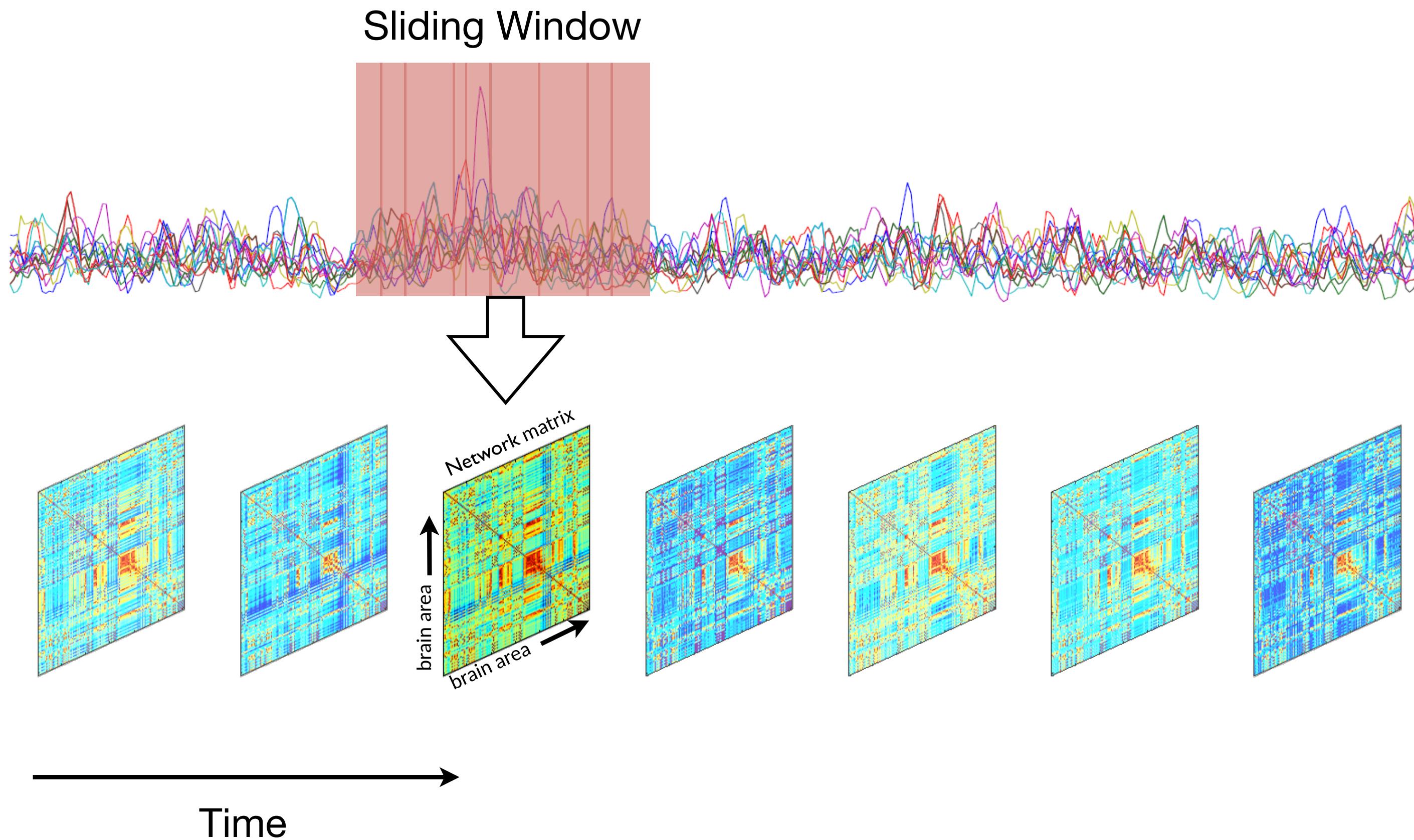


Modelling Dynamics

Modelling Dynamics



Modelling Dynamics

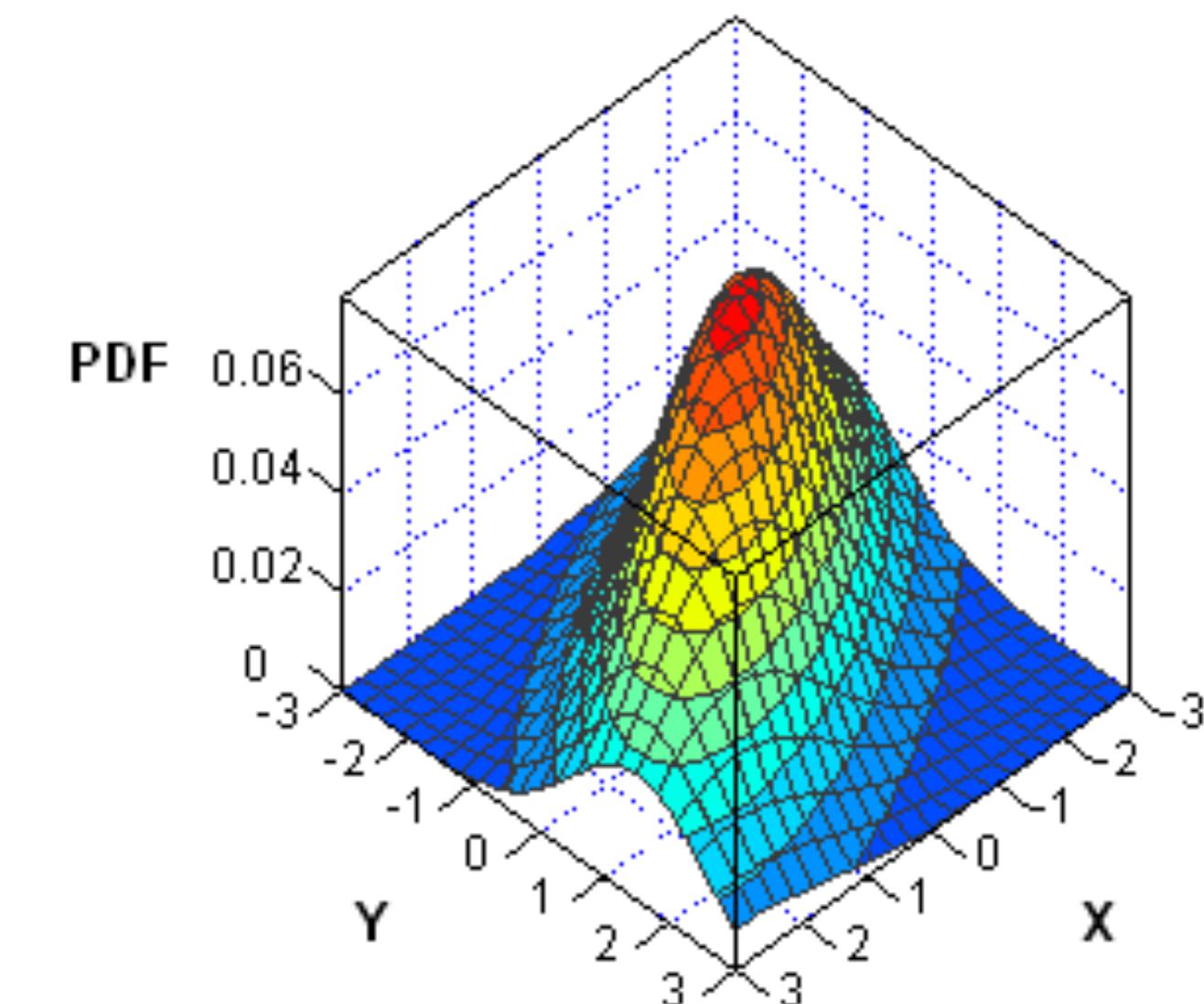
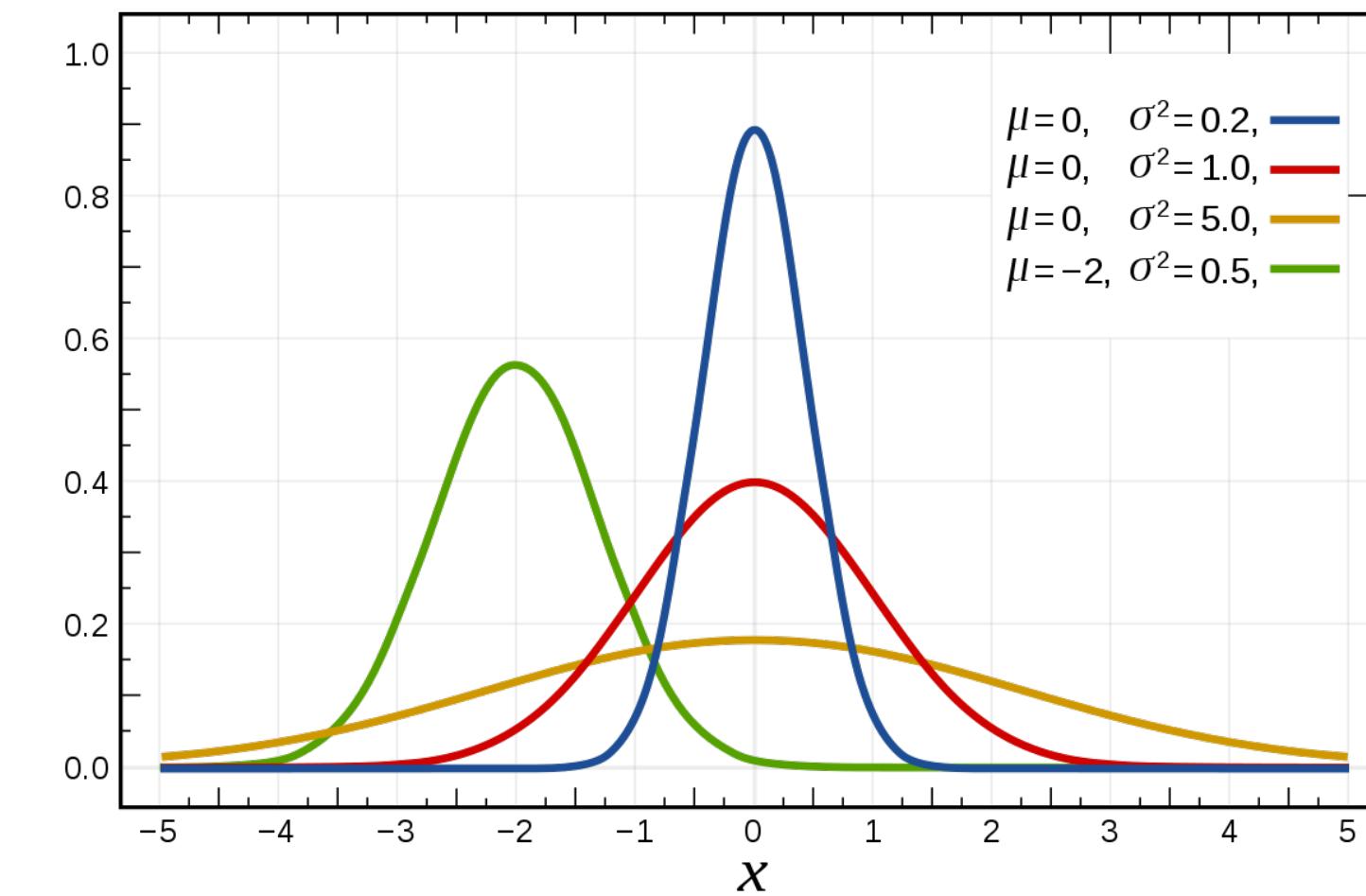


Pros: Easy to implement, fast to compute, can be used with any connectivity measure

Cons: Need to specify window length and step size, cannot capture fast dynamics (< 100ms)

Generative Modelling

- Specify a **mean m** and **covariance C** .
 - $x \sim \mathcal{N}(m, C)$.
- Can generate random values for x .
- Generating a time series:
 - $x(t) \sim \mathcal{N}(m_t, C_t)$



Hidden Markov Model (HMM)

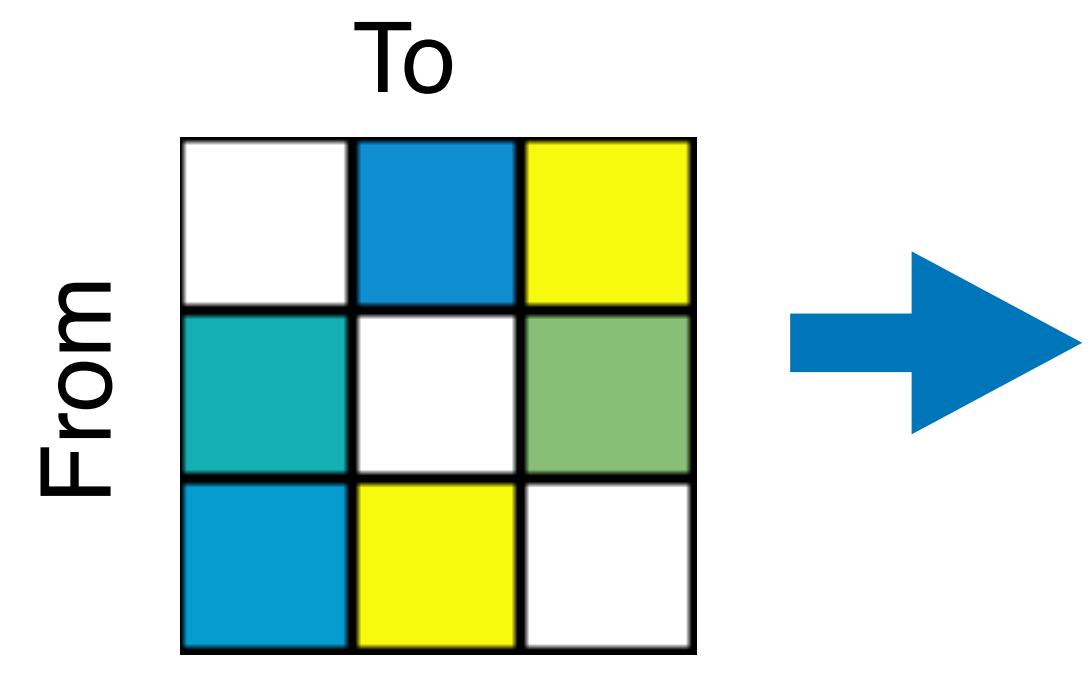
Hidden Markov Model (HMM)

**Transition
Probability Matrix**

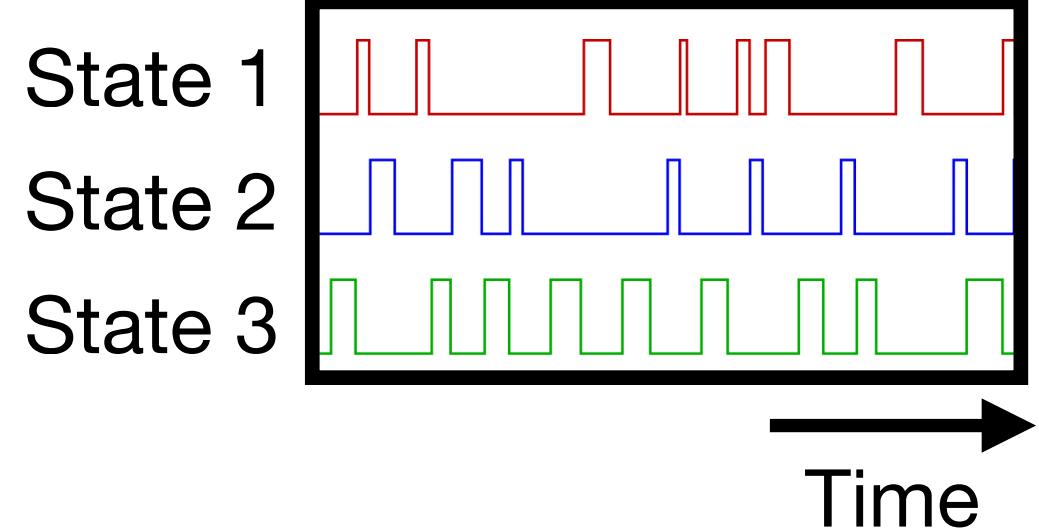
| To | | | |
|------|-------|--------|--------|
| From | 1 | 2 | |
| 1 | White | Blue | Yellow |
| 2 | Teal | White | Green |
| 3 | Blue | Yellow | White |

Hidden Markov Model (HMM)

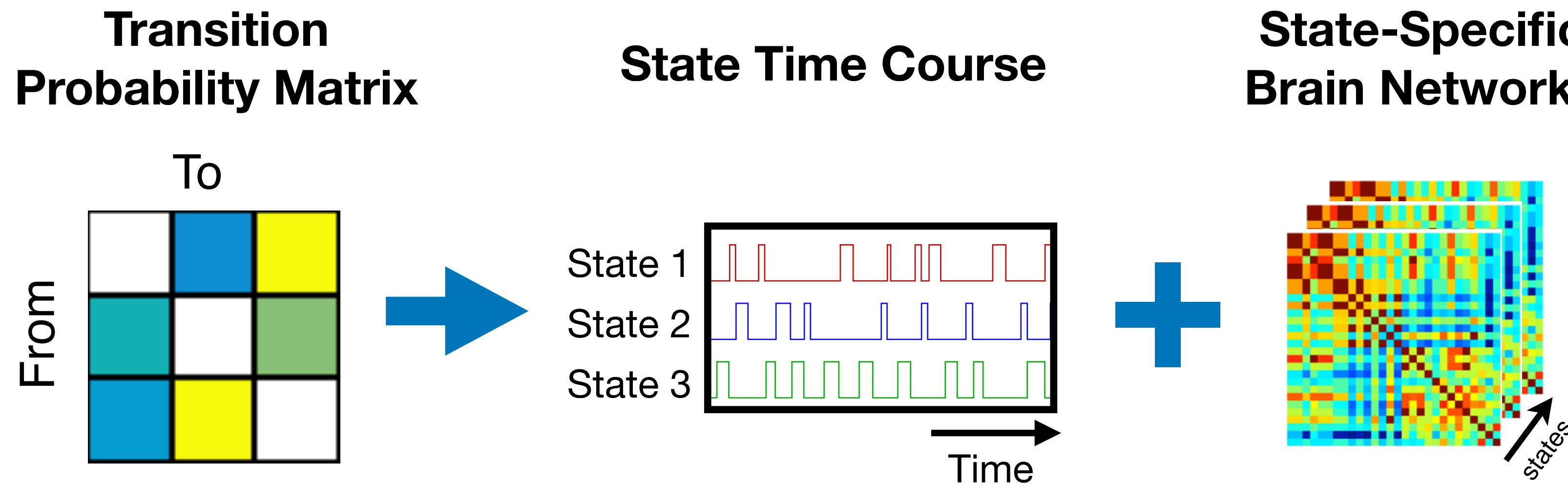
**Transition
Probability Matrix**



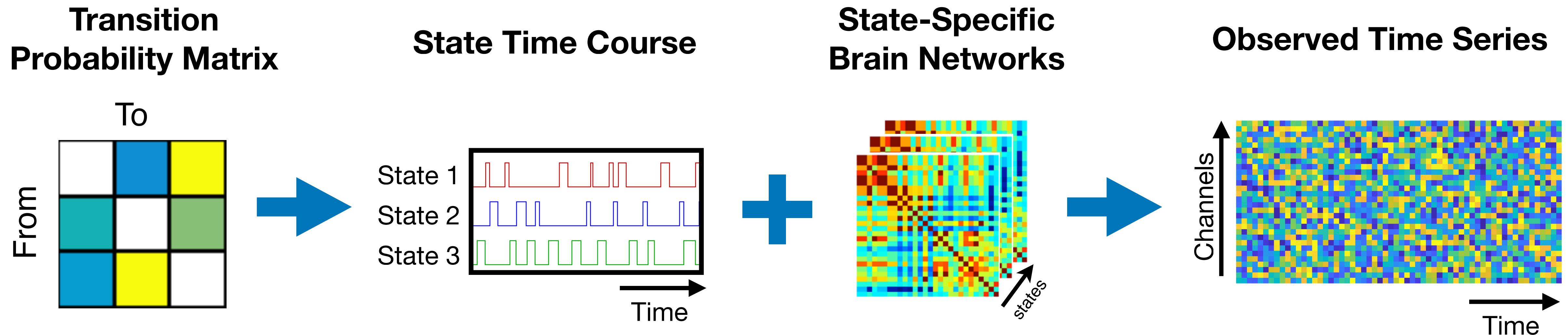
State Time Course



Hidden Markov Model (HMM)

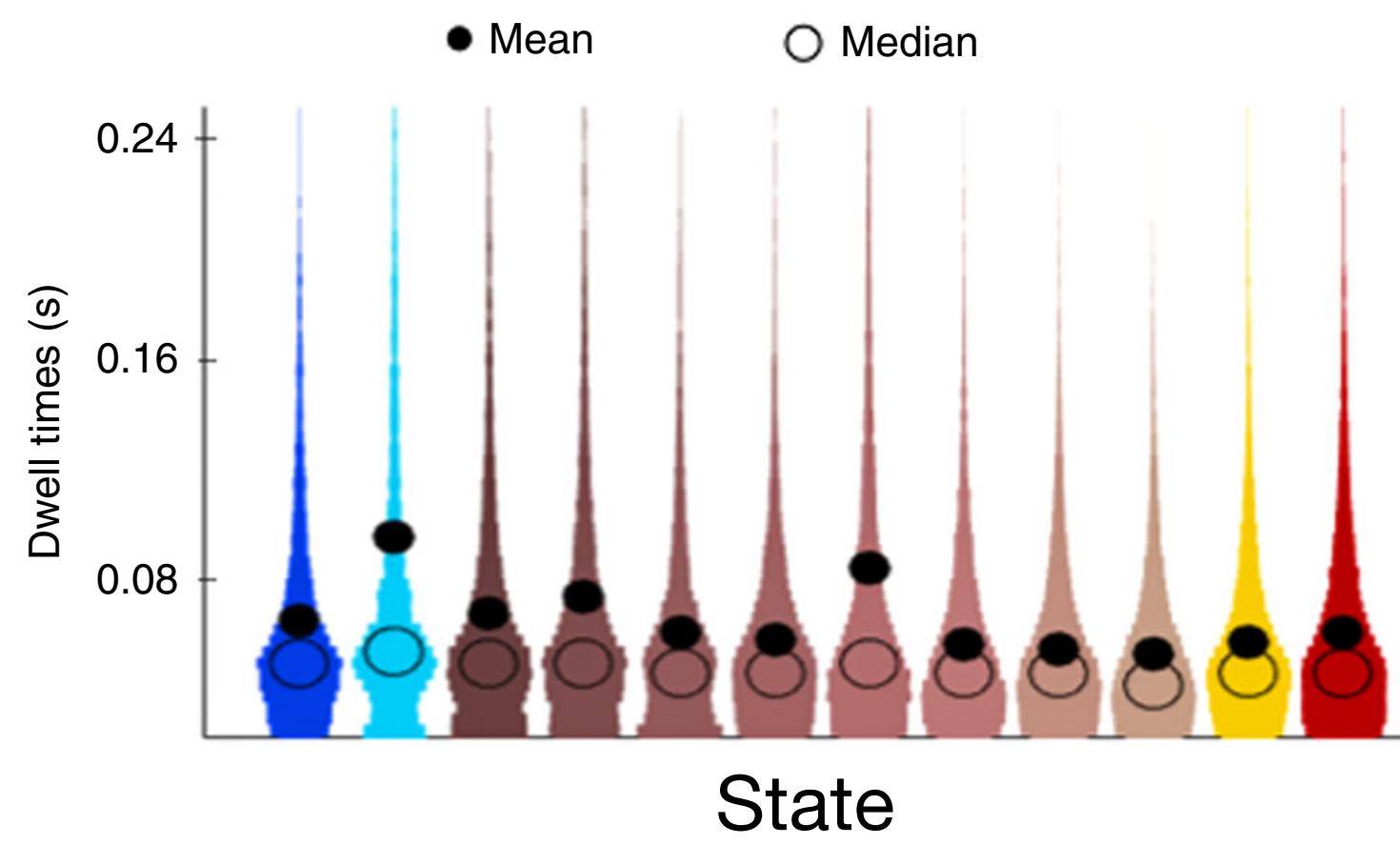


Hidden Markov Model (HMM)

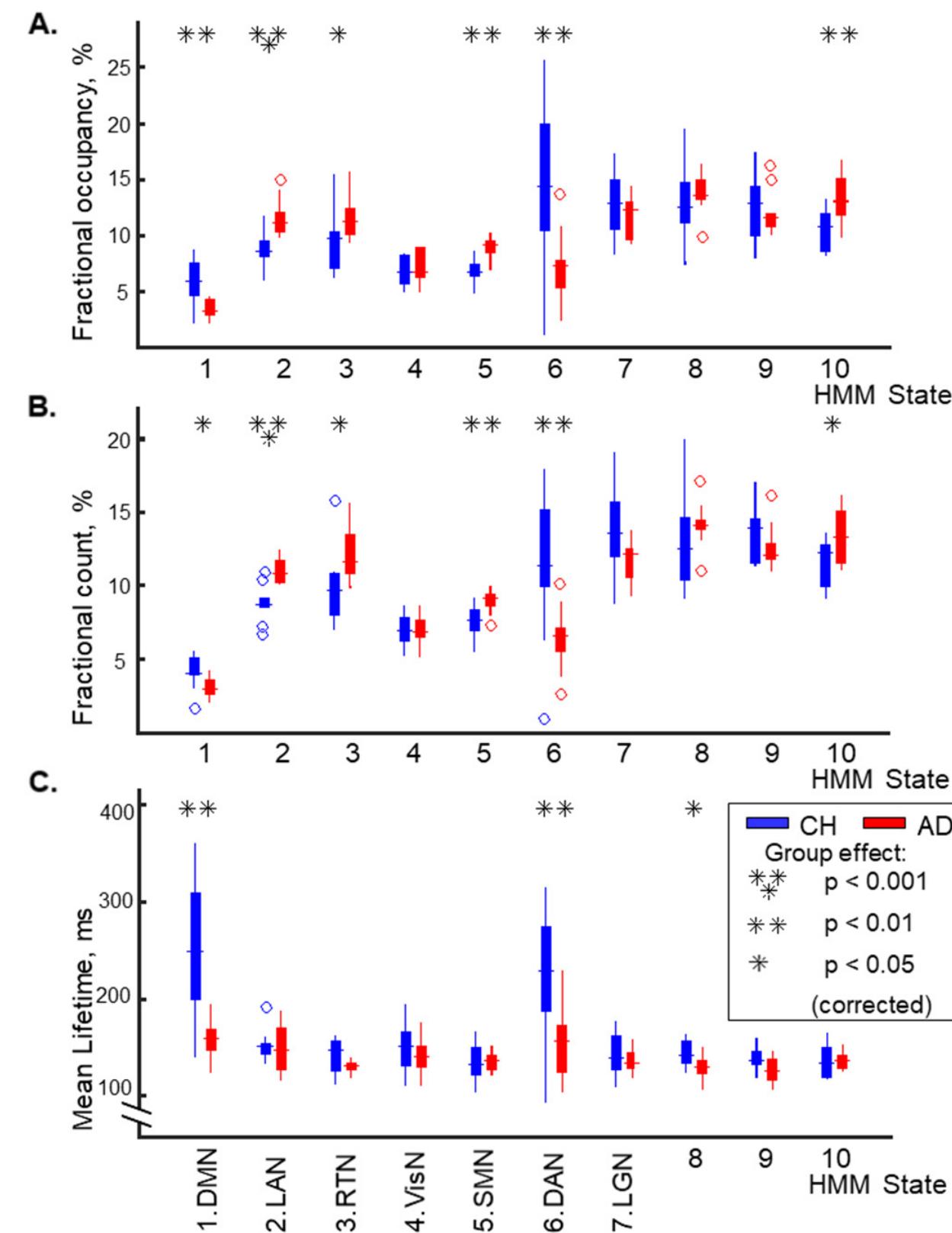


Hidden Markov Model (HMM)

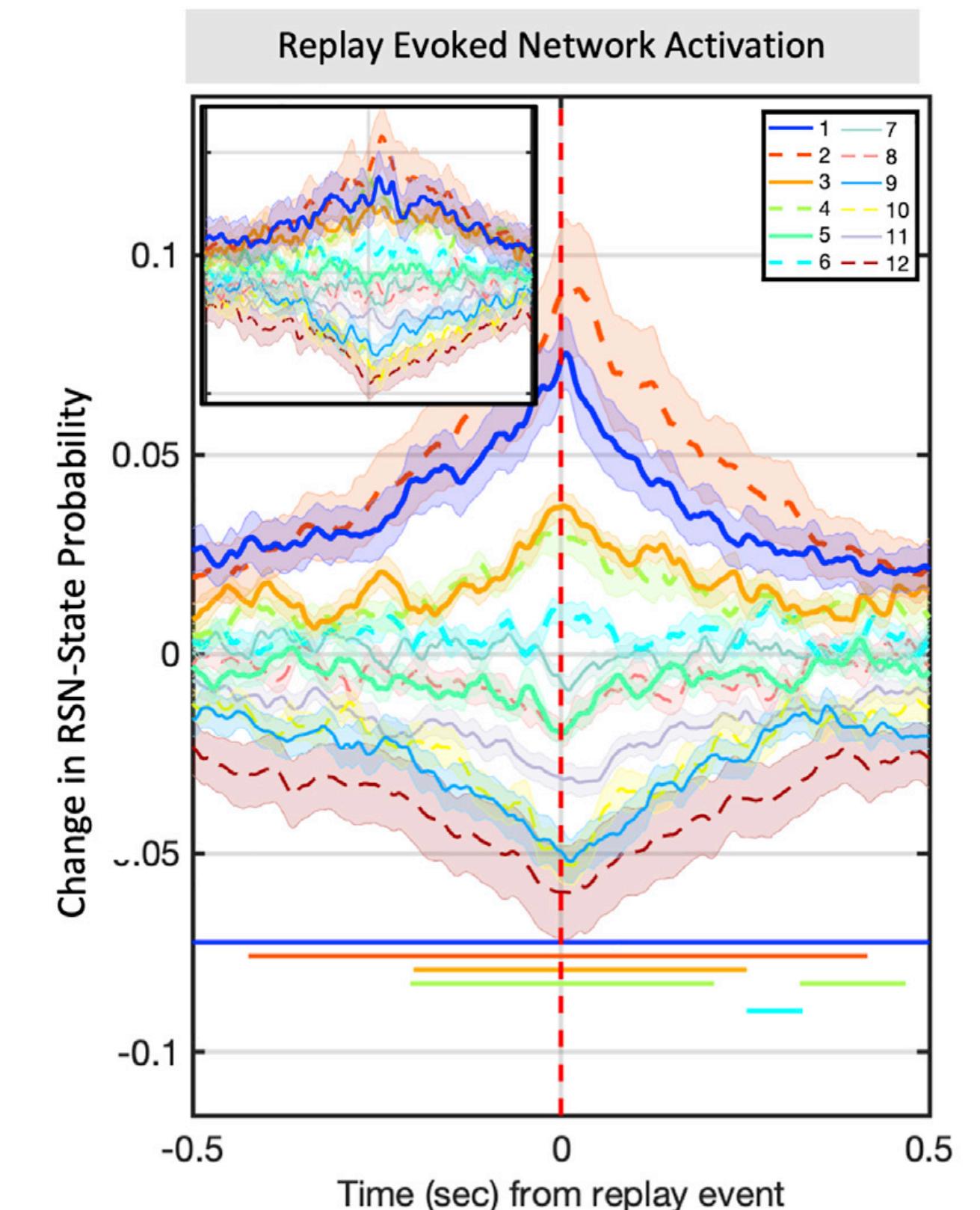
Fast dynamics (Vidaurre et al.,
Nature Comm. 2018)



Inferred states predict disease
(Sitnikova et al., NeuroImage 2018)



Replay relates to resting states
(Higgins et al., Neuron 2021)

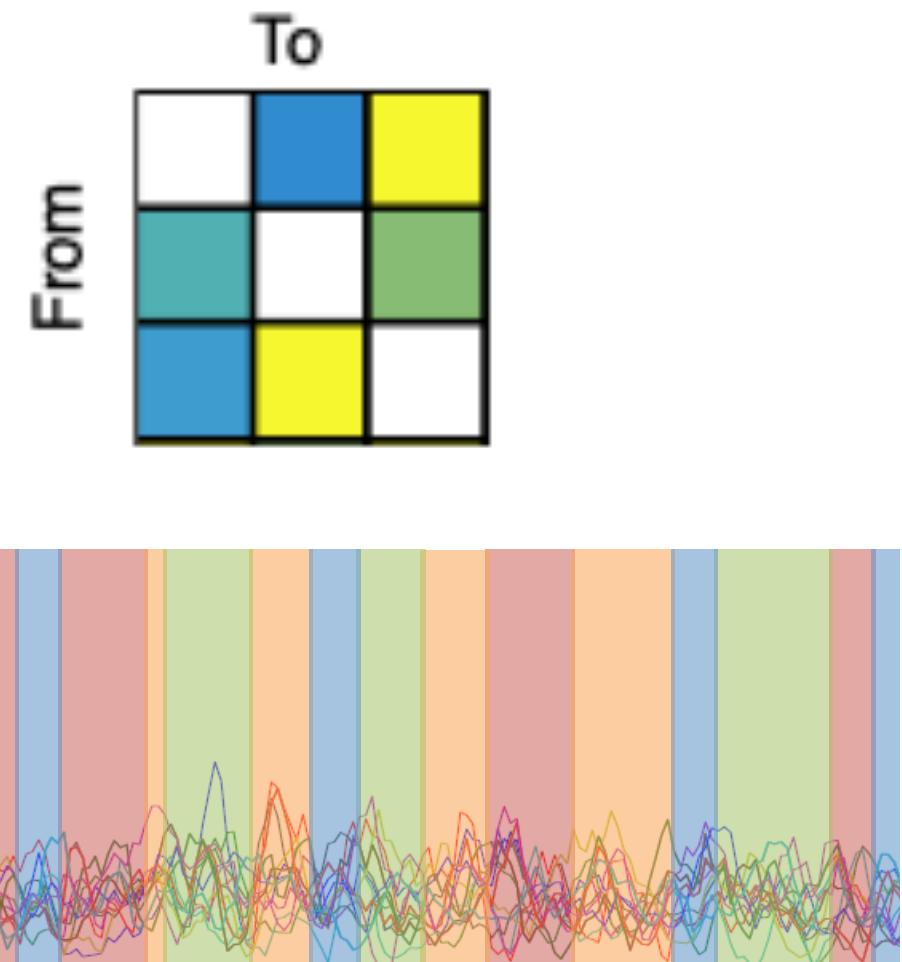


Hidden Markov Model (HMM)

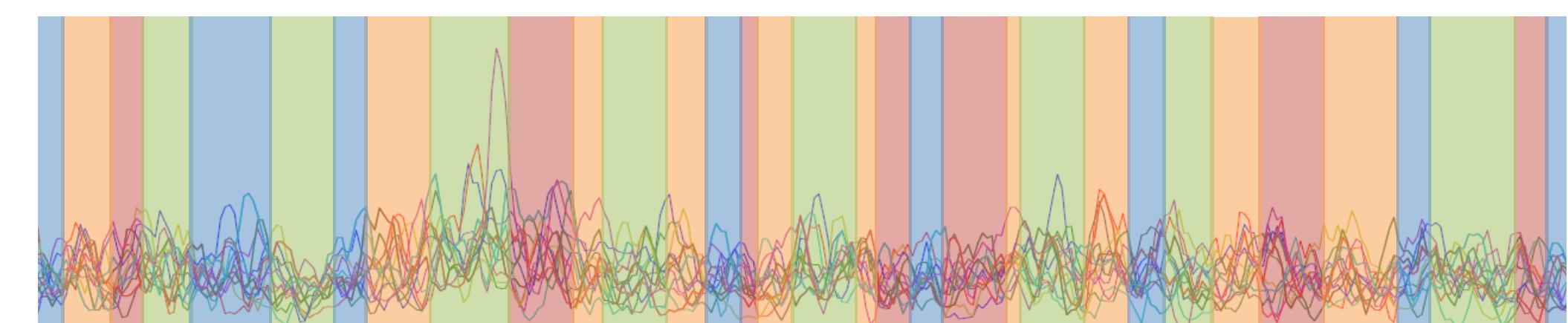
- Once you propose a generative model, you can perform **inference**:
 - Learn the parameters of your model from observed data.
 - Also referred to as **training** an HMM.

Parameters of an HMM

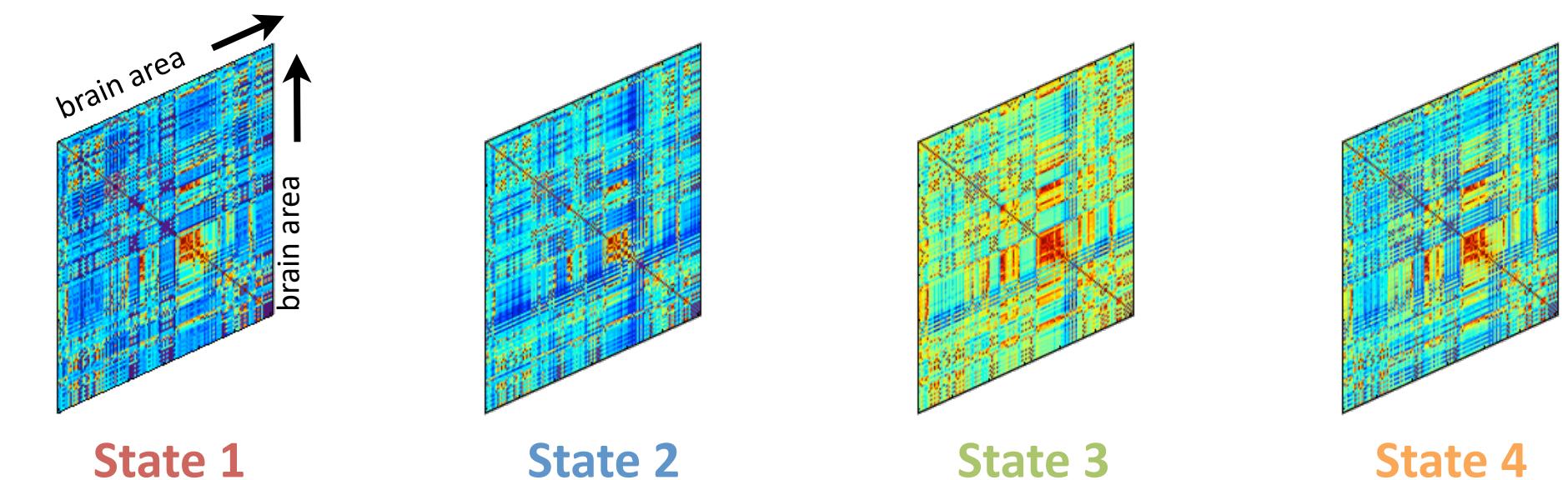
Transition probability matrix



Hidden states



State covariances (and means)



Hidden Markov Model (HMM)

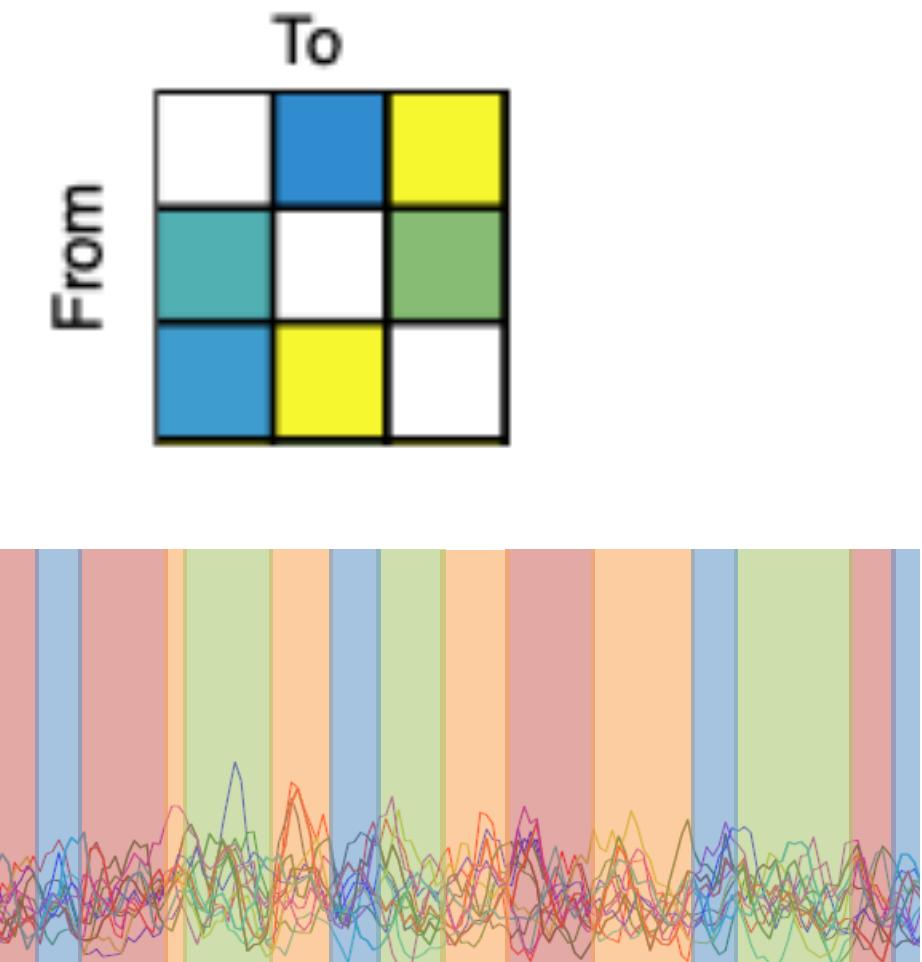
- Given the observed data we:

**Learn a probability for each state
(posterior):**
'alpha' in osl-dynamics



Parameters of an HMM

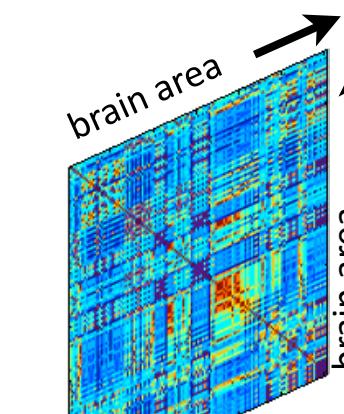
Transition probability matrix



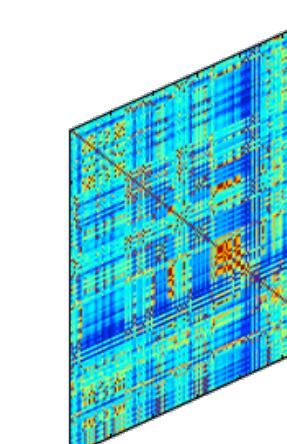
Hidden states

State covariances (and means)

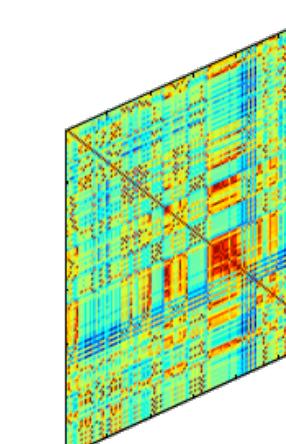
**Learn point estimates for the state
means/covariances:**
'means', 'covariances' in osl-dynamics



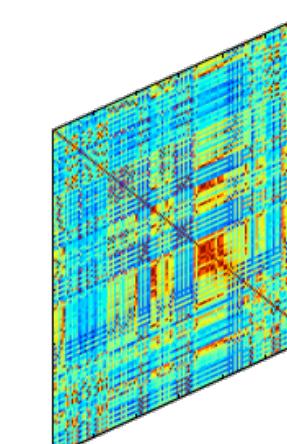
State 1



State 2



State 3



State 4

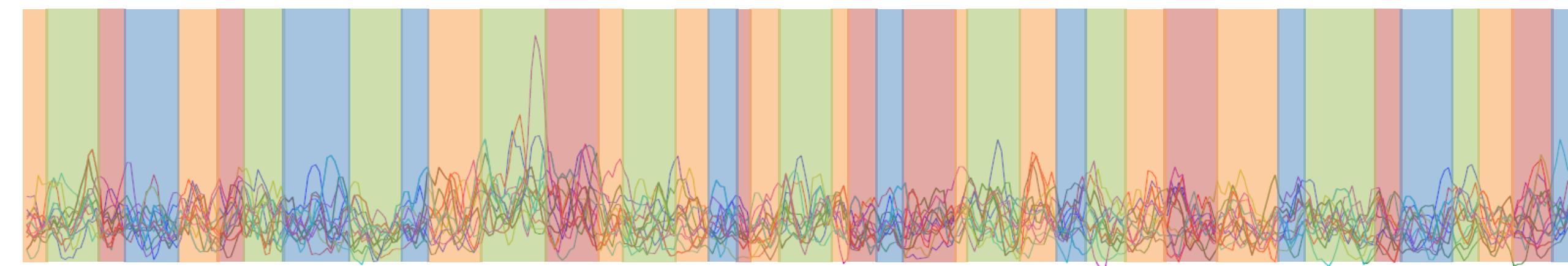
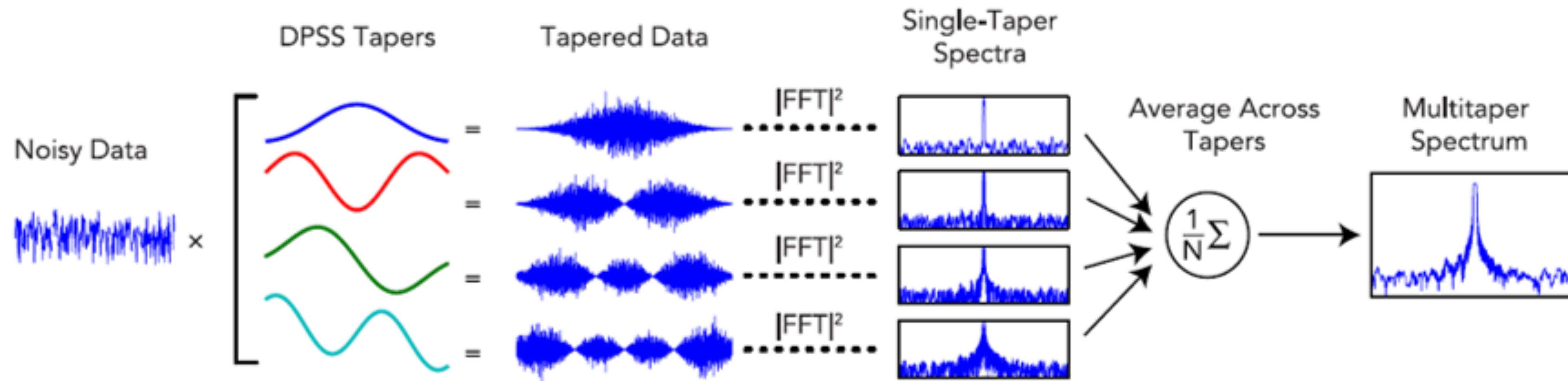
AE-HMM vs TDE-HMM

- HMM find segments of the time series where the mean and covariance is different.
- What are you interested in modelling the dynamics of?
 - Are you looking for high amplitude events?
 - Are you looking for bursts of oscillatory activity?

Exercise: HMM training

- Go through notebook 2-1.

Multitaper



Exercise: Post-hoc spectral estimation

- Go through notebook 2-2.

Exercise: Networks visualisation

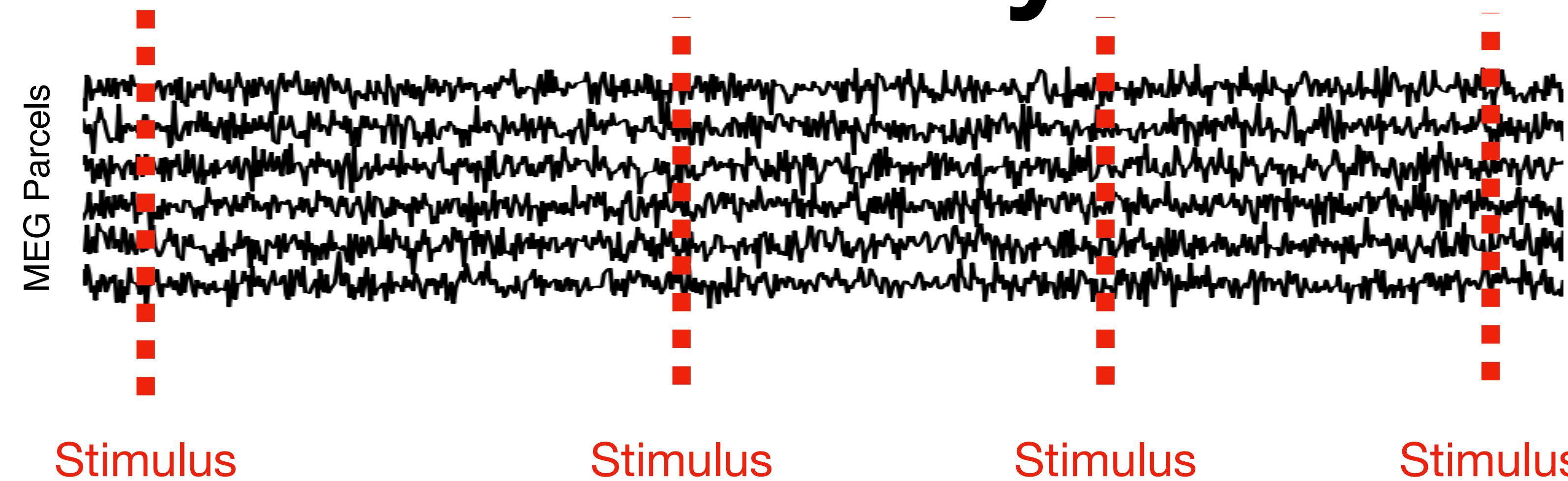
- Go through notebook 2-3

Exercise: Dynamics visualisation

- Go through notebook 2-4.

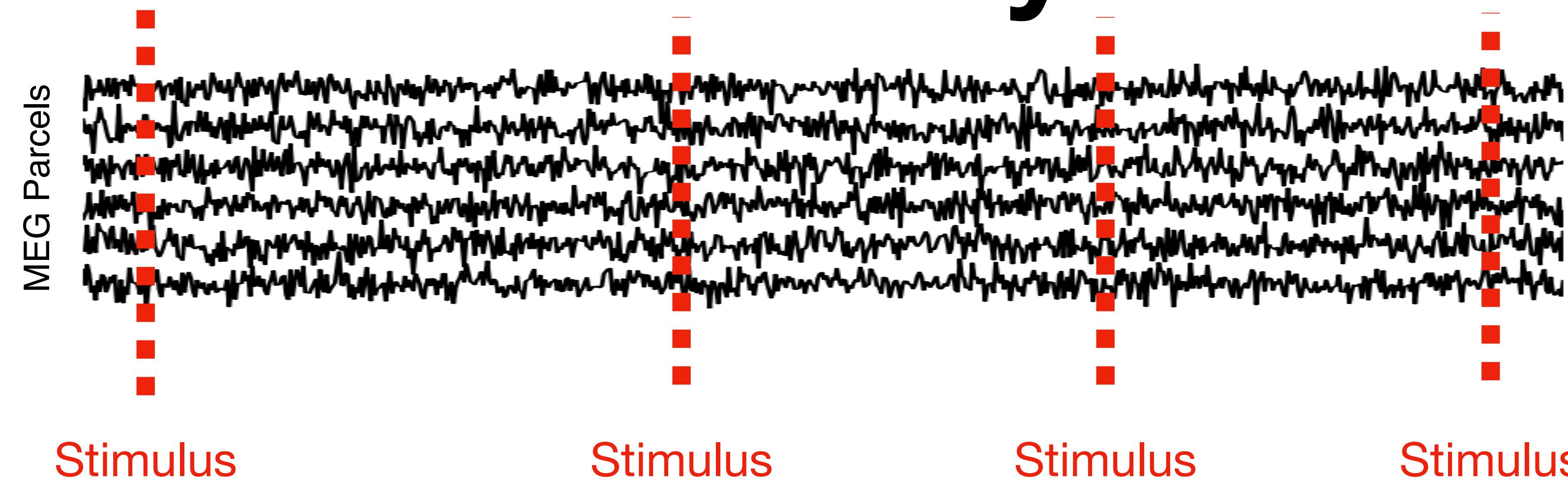
Task analysis

Task analysis



- Conventional approach: time-frequency analysis at the parcel/sensor level.
- Difficult to estimate the network response to the task.

Task analysis



- Conventional approach: time-frequency analysis at the parcel/sensor level.
- Difficult to estimate the network response to the task.
- Better approach: use the dynamic models.

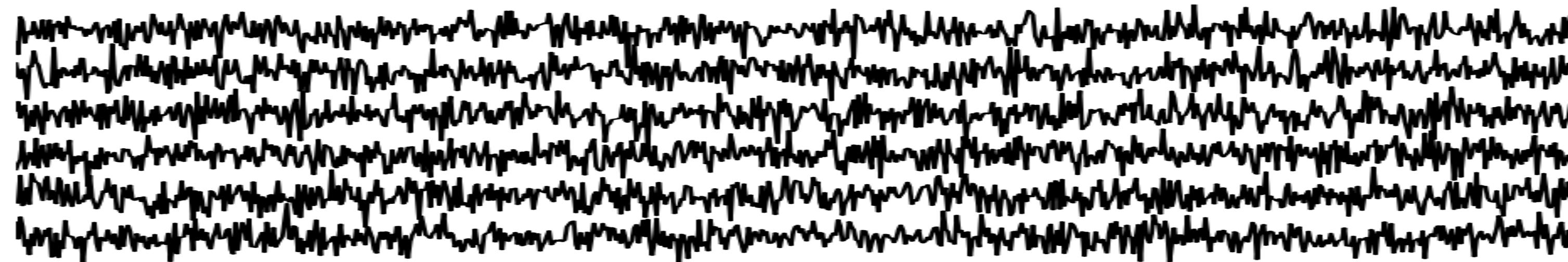
Task analysis

MEG Parcels

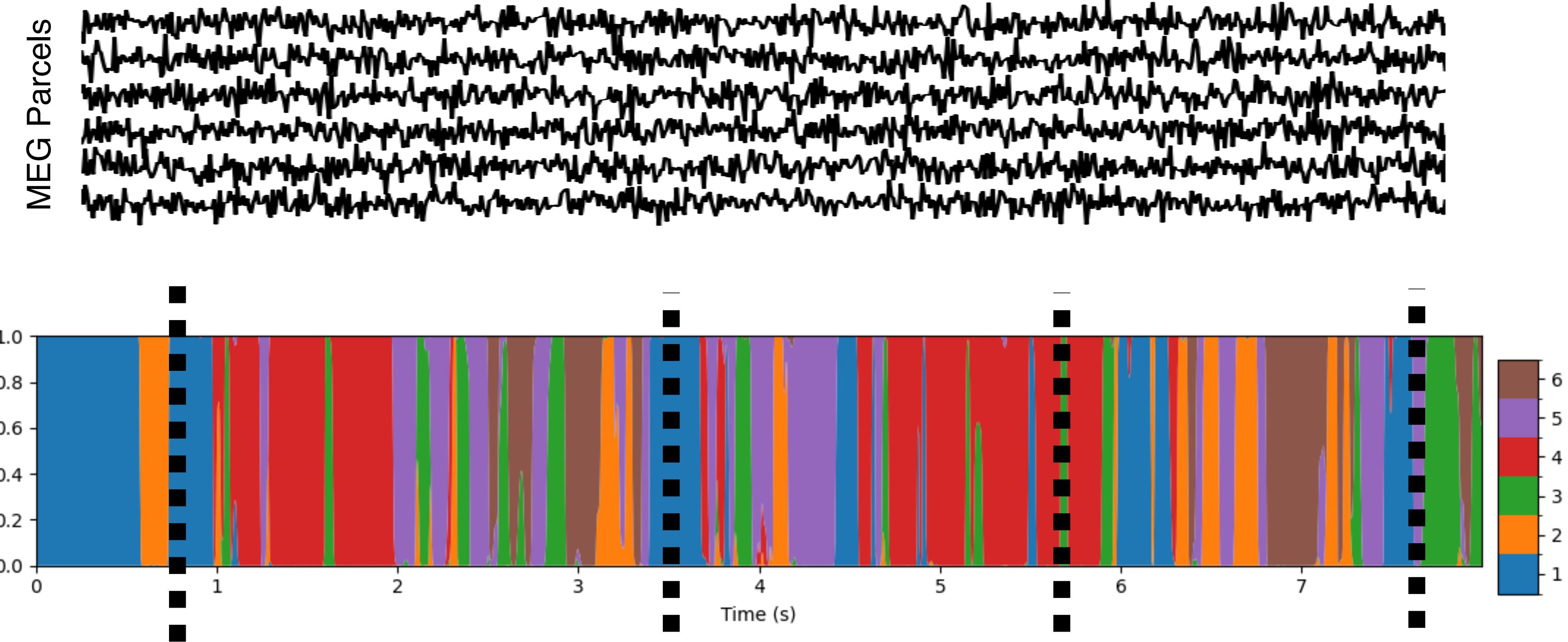


Task analysis

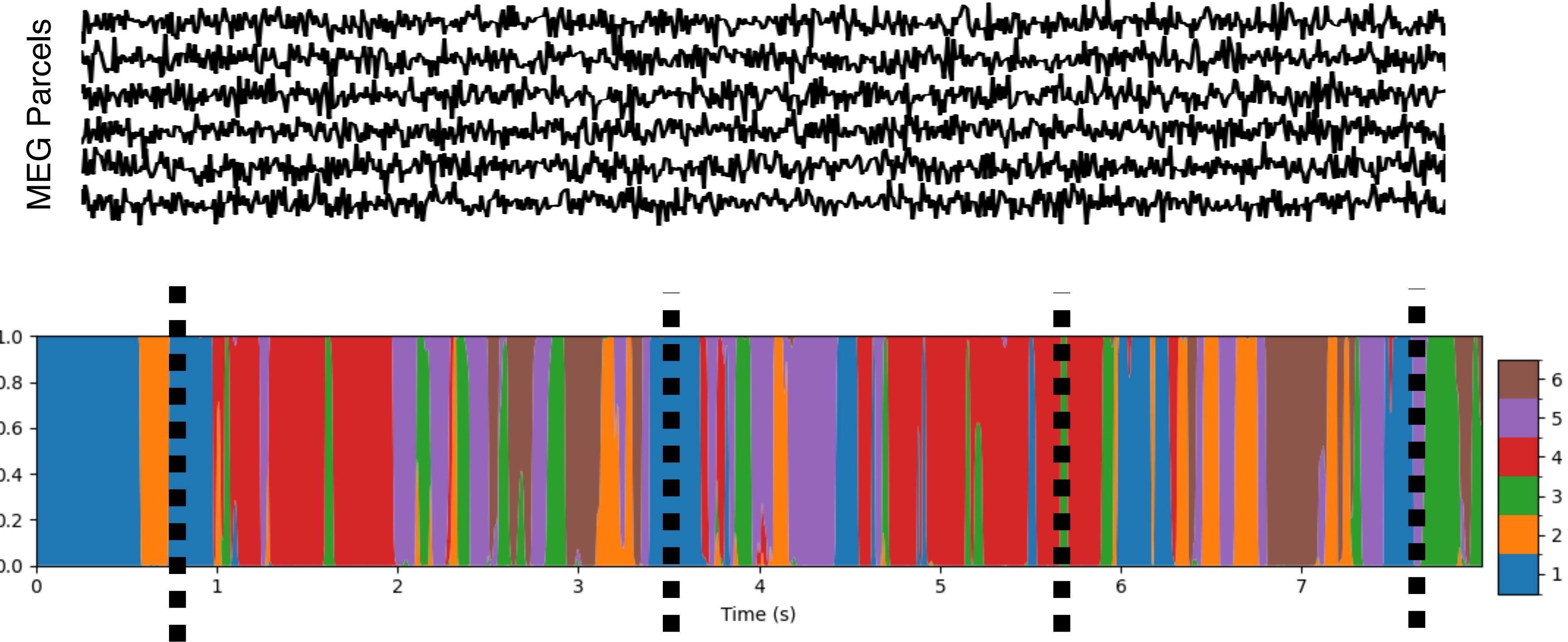
MEG Parcels



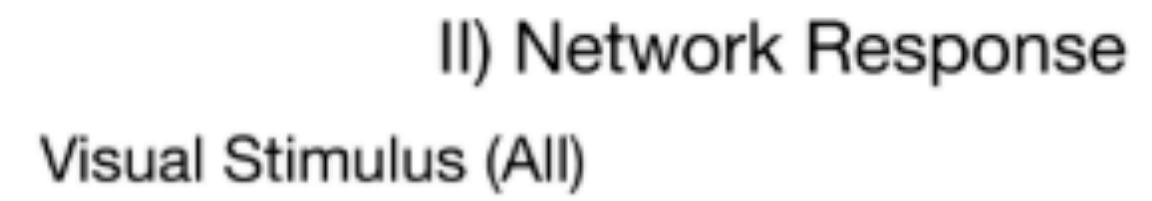
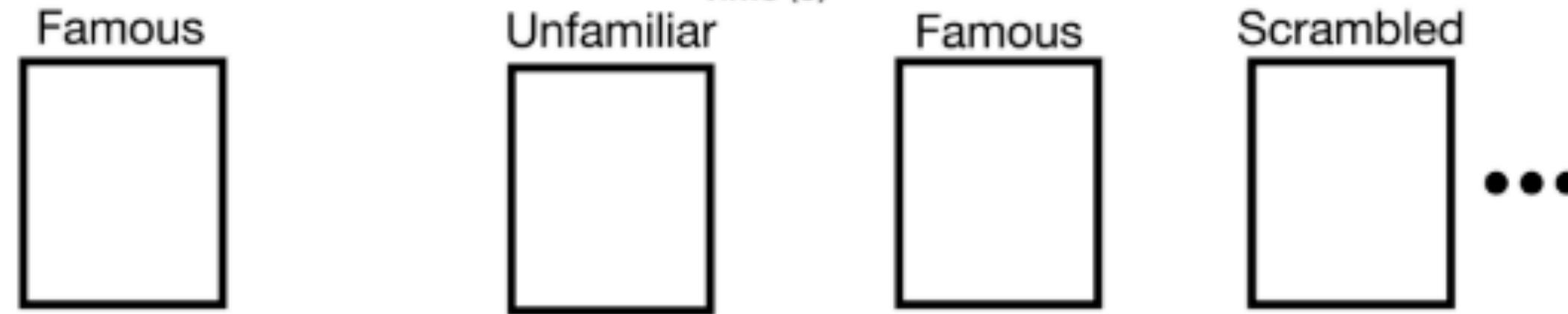
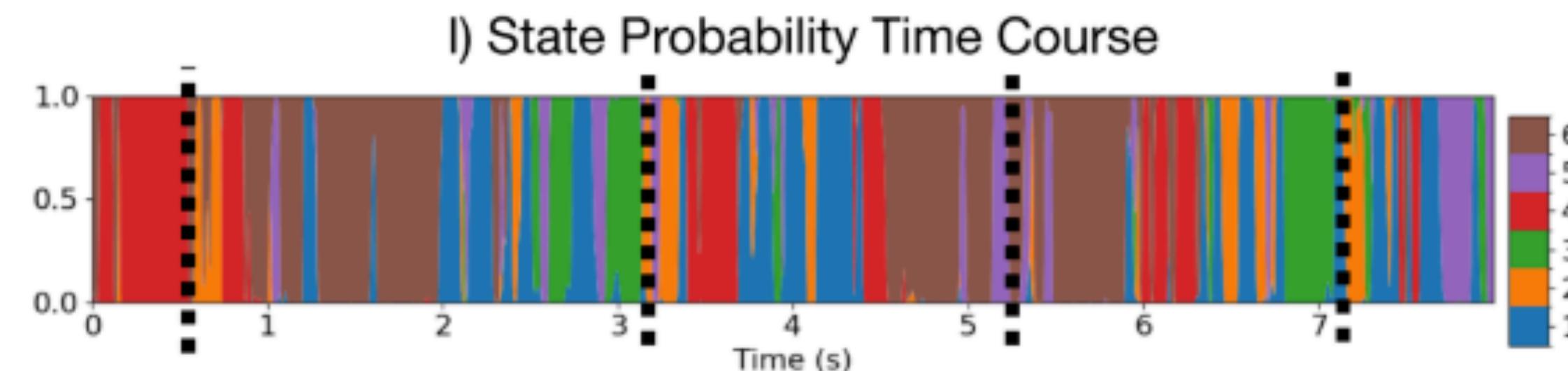
Task analysis



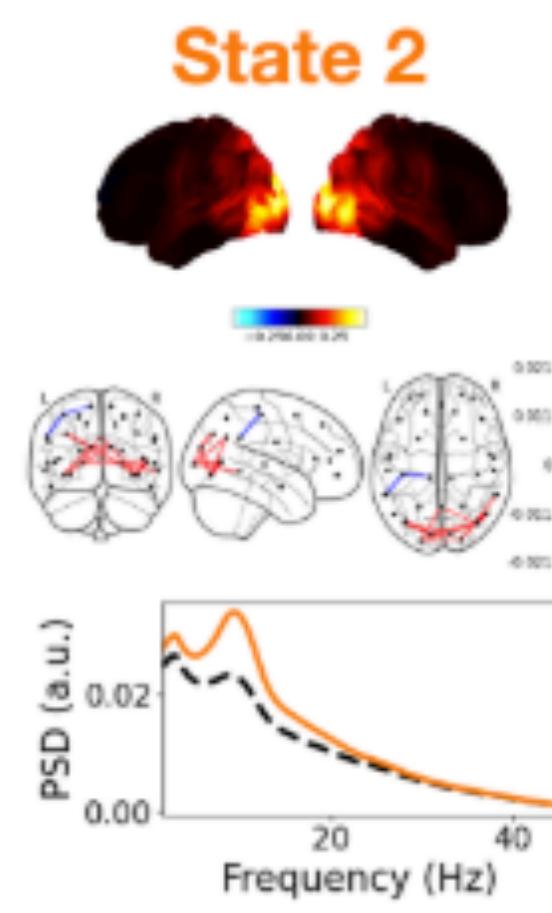
Task analysis



A) Parcel-Based HMM Networks



III) Significant Networks
(p -value < 0.05)

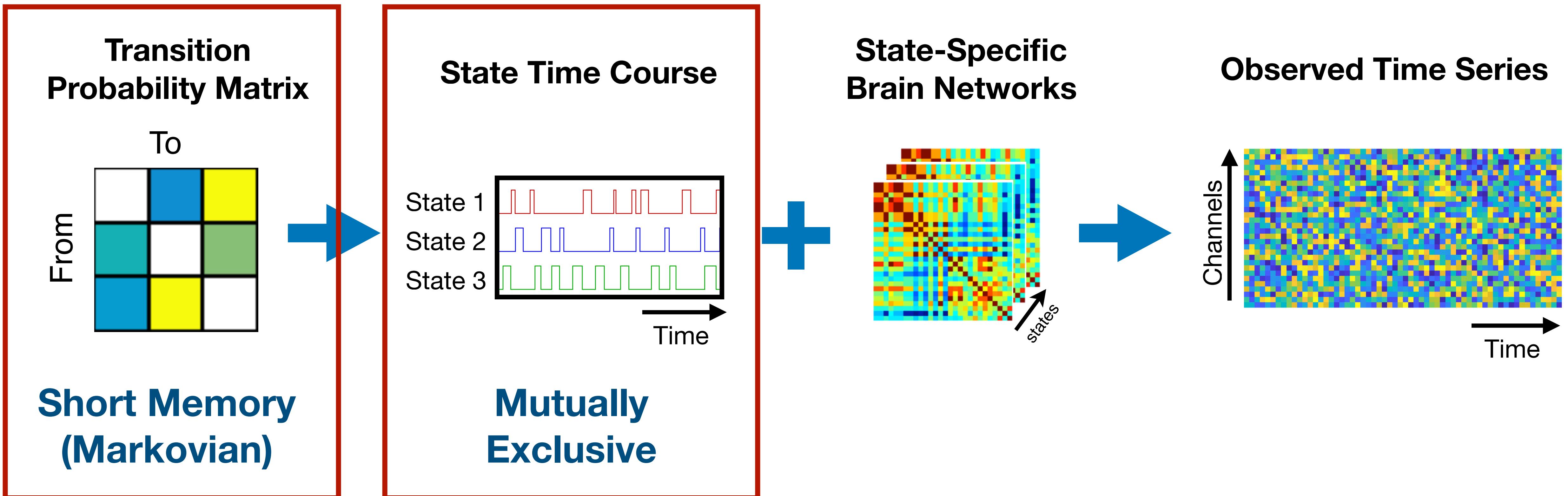


Exercise: HMM task analysis

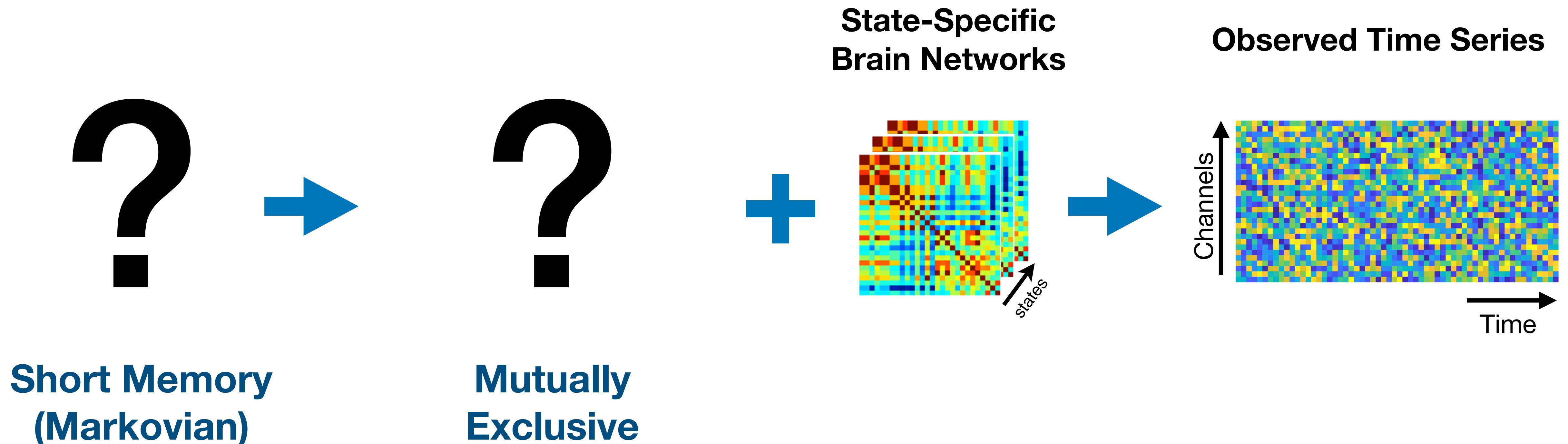
- Go through notebook 2-5

Dynamic Network Modes (DyNeMo)

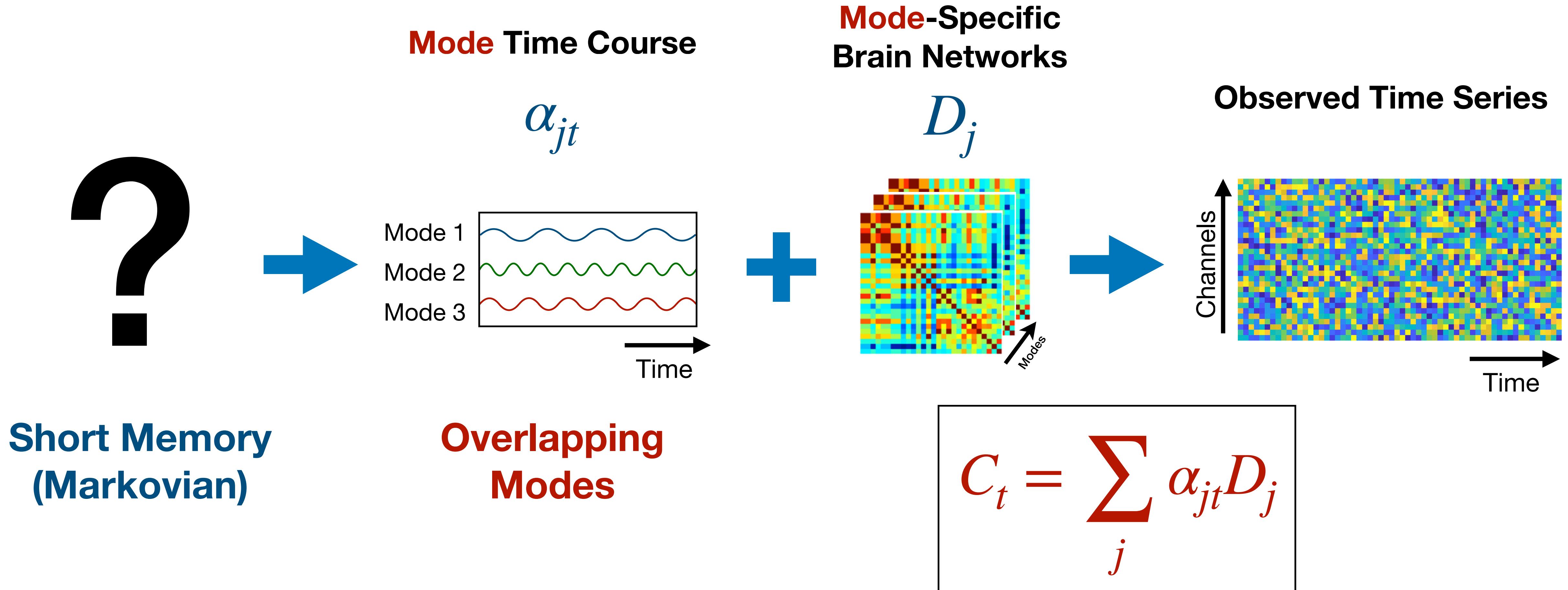
Hidden Markov Model (HMM)



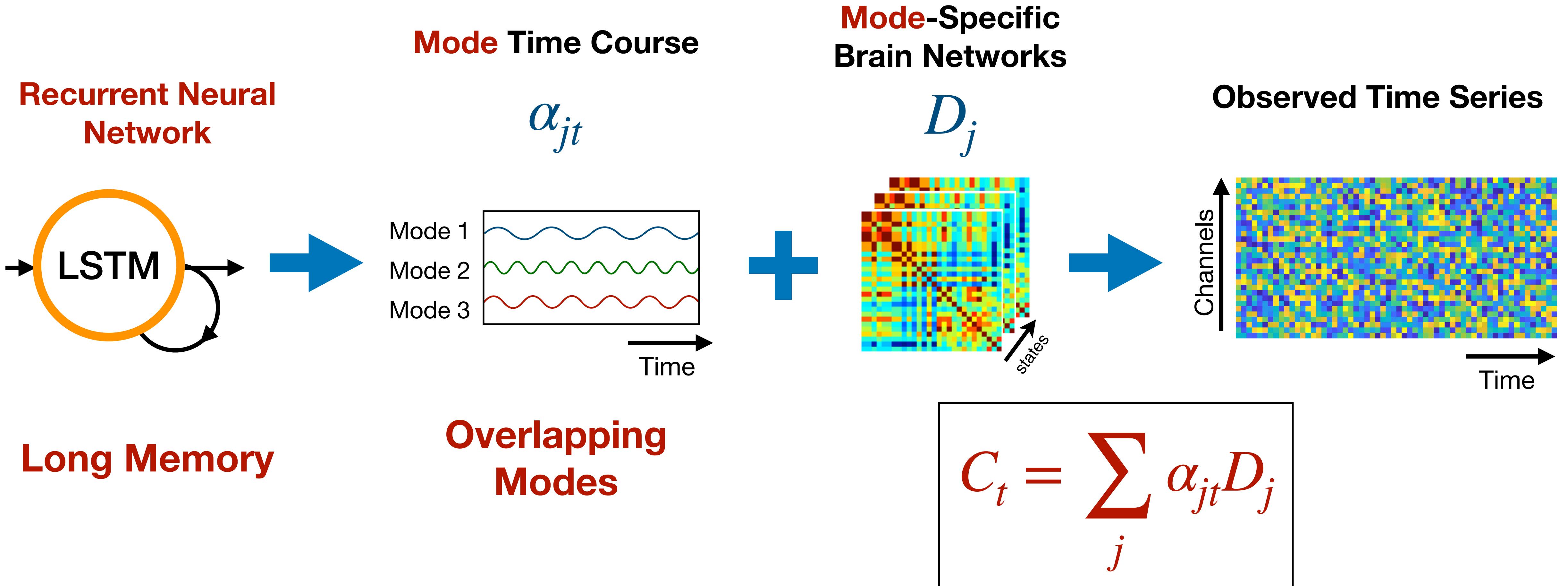
Dynamic Network Modes (DyNeMo)



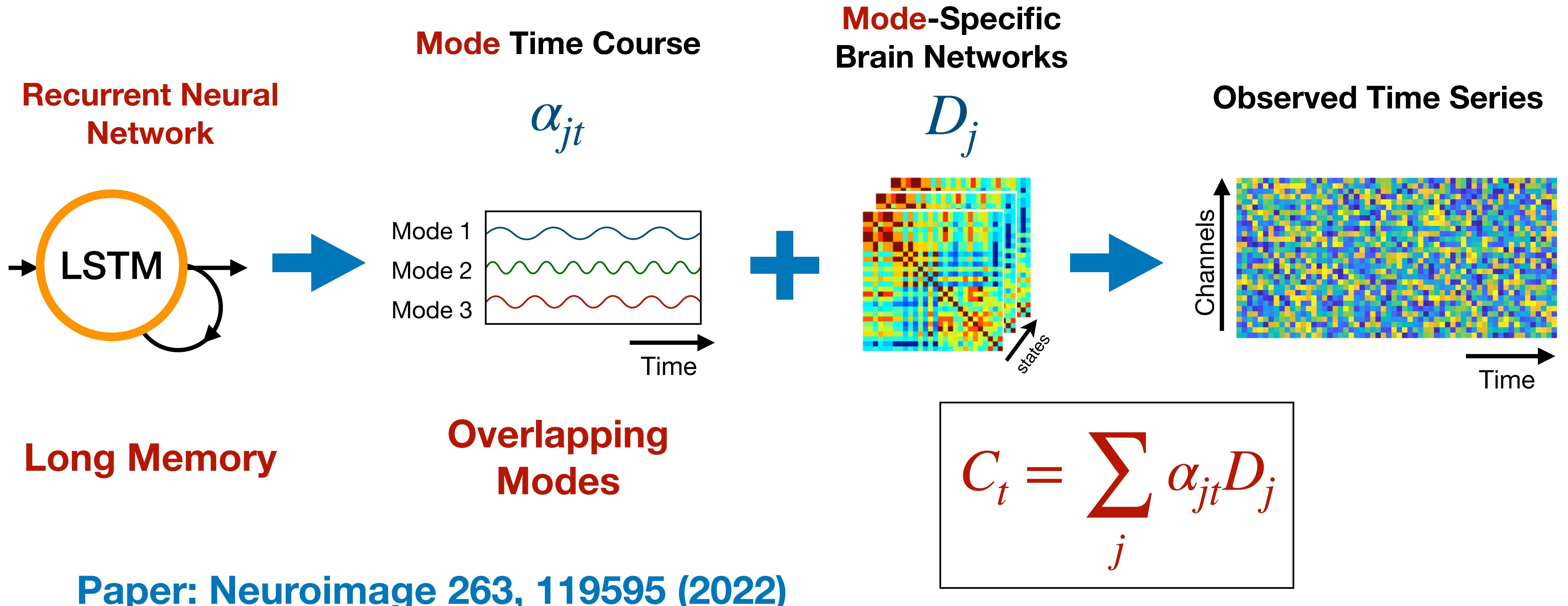
Dynamic Network Modes (DyNeMo)



Dynamic Network Modes (DyNeMo)



Dynamic Network Modes (DyNeMo)



Summary

- You can use the `osl-dynamics` package for network analysis.
- See the docs: [`https://osl-dynamics.readthedocs.io/en/latest/`](https://osl-dynamics.readthedocs.io/en/latest/).
- FAQ: [`https://osl-dynamics.readthedocs.io/en/latest/faq.html`](https://osl-dynamics.readthedocs.io/en/latest/faq.html)
- Raise an issue on the GitHub repo.
- rukuang.huang@psych.ox.ac.uk