JOHNS HOPKINS BLOOMBERG SCHOOL of PUBLIC HEALTH

University of Colorado **Boulder**

CANlab

SMART JHSPH Biostatistics

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@fMRIstats

Dynamic Connectivity

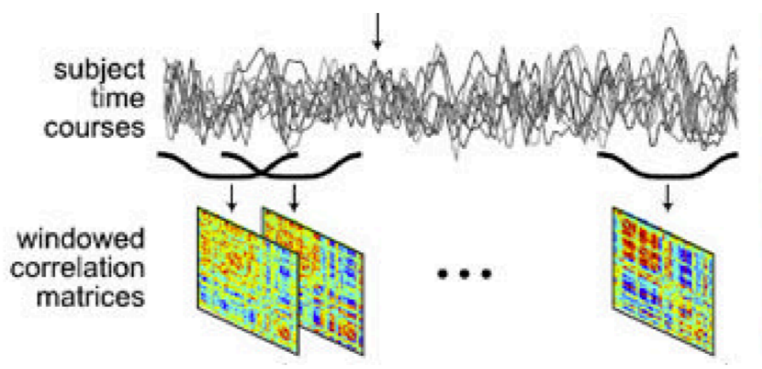
Dynamic Connectivity

- To date, most resting state fMRI studies have assumed that the functional connectivity between distinct brain regions is constant across time.

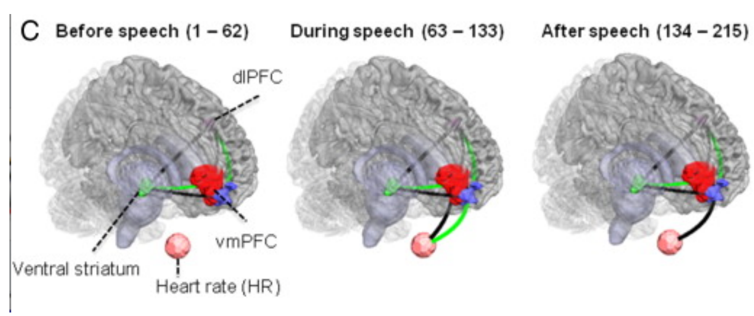
- Recently, there has been interest in quantifying possible dynamic changes in connectivity.
  - Changes in connectivity thought to provide insight into the fundamental properties of brain networks.

Dynamic Connectivity

- The so-called sliding-window approach is the most common analysis strategy, though independent component analysis, time-frequency coherence analysis, and change-point detection methods have also been used.



Hutchison et al. 2013



Cribben et al. 2012

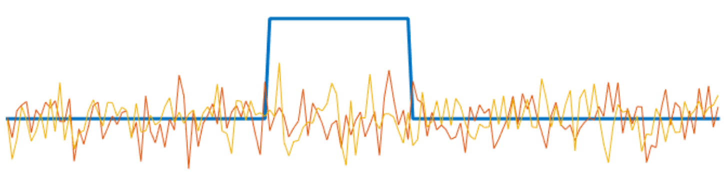
Dynamic Connectivity

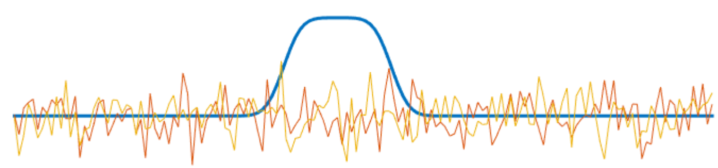
- Interpreting fluctuations in connectivity is difficult due to low signal-to-noise ratio, physiological artifacts and variation in signal mean and variance over time.
  - It is unclear whether observed fluctuations in connectivity should be attributed to neuronal activity or random noise.
  - There remains uncertainty regarding the appropriate analysis strategy to use and how to interpret results.

Sliding Windows

- In the sliding window approach, a time window of fixed length is selected, and data points within that window are used to compute the correlation.

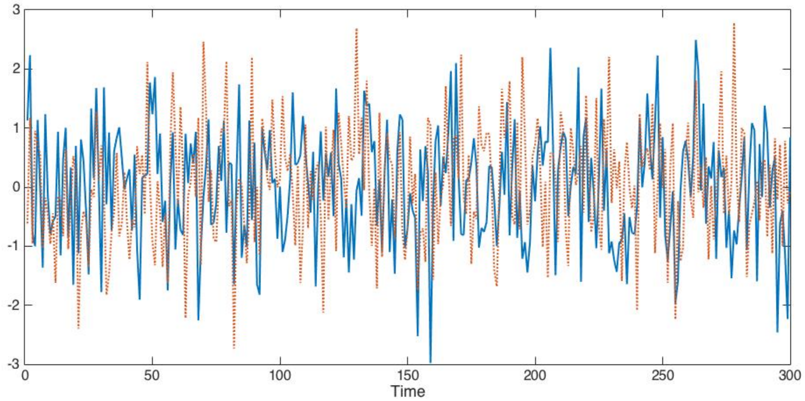
- In contrast, in the tapered sliding-window approach, the window is first convolved with a Gaussian kernel, allowing points to gradually enter and exit from the window as it moves across time.



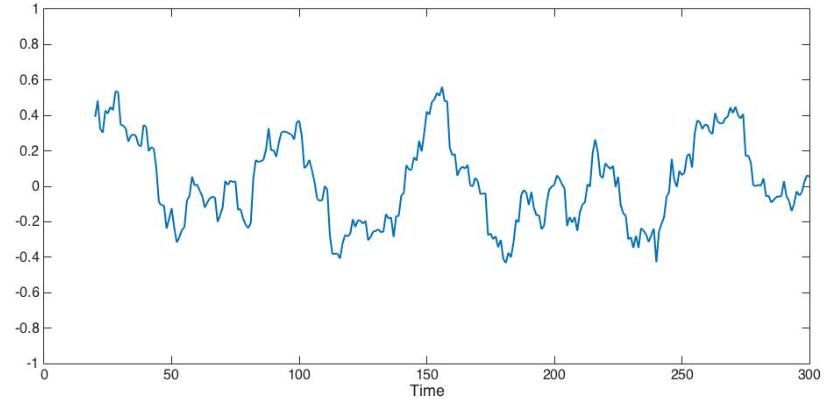


Dynamic Connectivity

Data



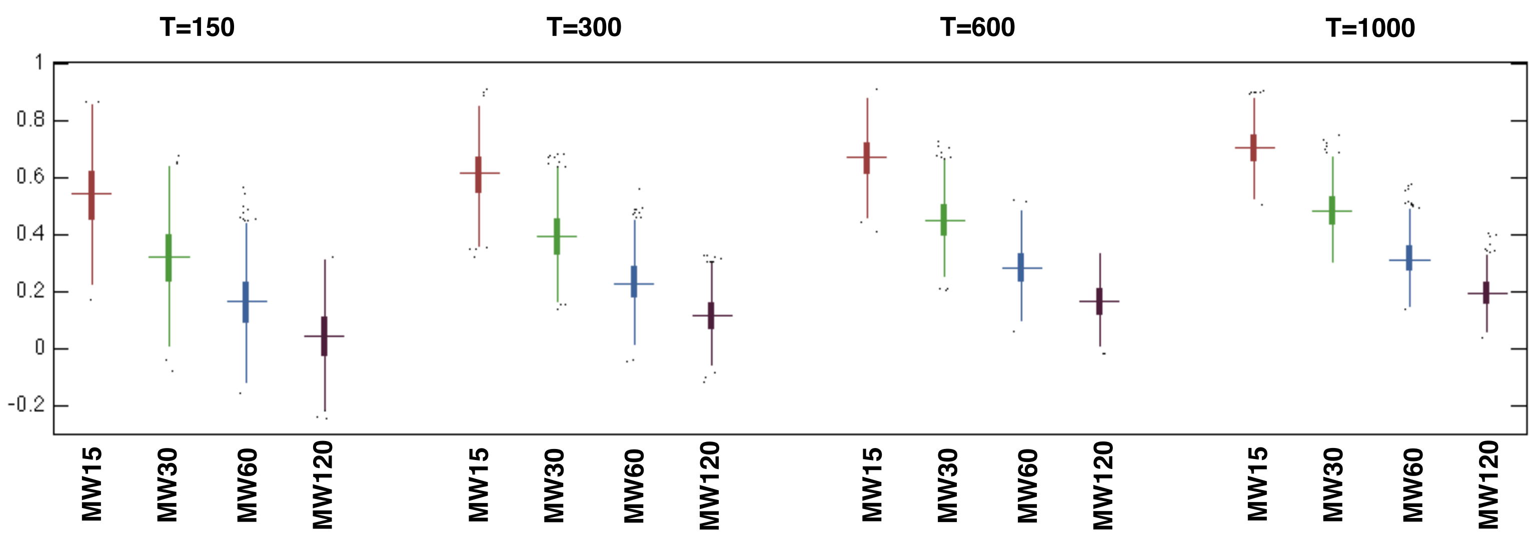
Sliding window w = 20



Lindquist et al. 2014

Example

- The estimated max correlation using null data of length T, analyzed using sliding windows of lengths w = 15, 30, 60 and 120.



Time-varying Correlations

- In the finance literature both time-varying variances and correlations between time series have been extensively studied.
  - Sliding window methods have been widely used.
  - Generally accepted that time series models preferable.
    - Generalized AutoRegressive Conditional Heteroscedastic (GARCH) processes

- A univariate GARCH(1,1) process:

$$y_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha y_{t-1}^2 + \beta \sigma_{t-1}^2$$

DCC

- Dynamic Conditional Correlations (DCC) is a multivariate GARCH model.

  - Fit GARCH model to each time series
  - Compute standardized residuals

$$\sigma_{i,t}^2 = \omega_i + \alpha_i y_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2$$

$$\mathbf{D}_t = diag\{\sigma_{1,t}, \sigma_{2,t}\}$$

$$\varepsilon_t = \mathbf{D}_t^{-1} \mathbf{y}_t$$

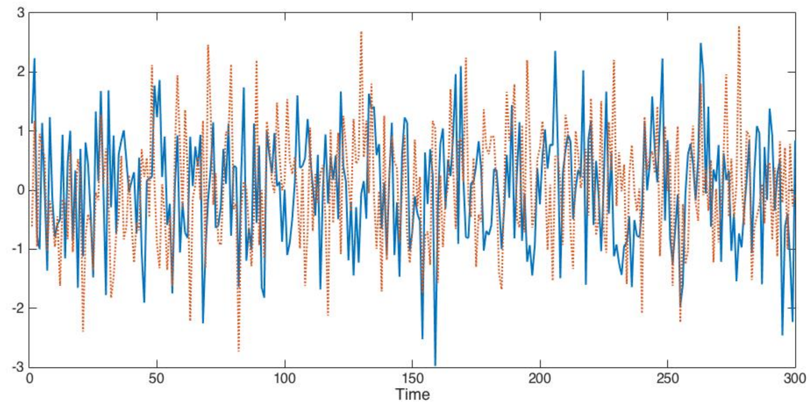
  - Use EWMA-type method to compute time-varying correlation matrix

$$\mathbf{Q}_t = (1-\lambda)\varepsilon_{t-1}\varepsilon_{t-1}' + \lambda \mathbf{Q}_{t-1}$$

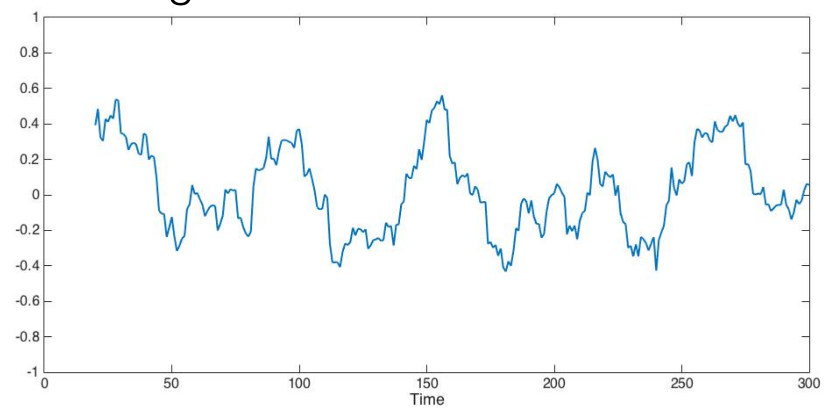
$$\mathbf{R}_t = diag\{\mathbf{Q}_t\}^{-1/2} \mathbf{Q}_t diag\{\mathbf{Q}_t\}^{-1/2}$$

Dynamic Connectivity

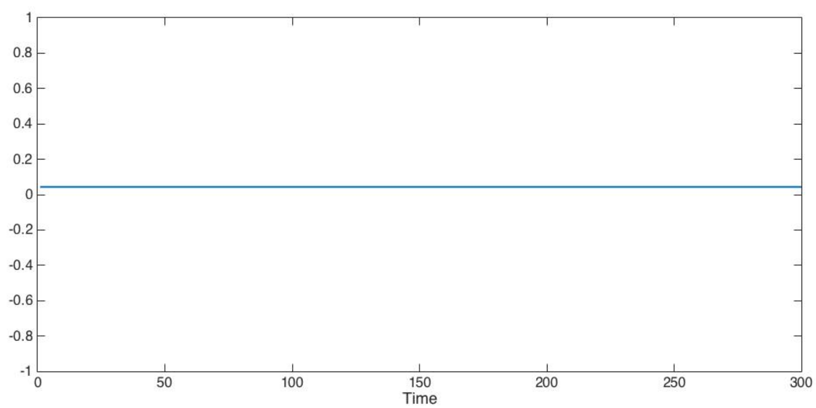
Data



Sliding window w = 20



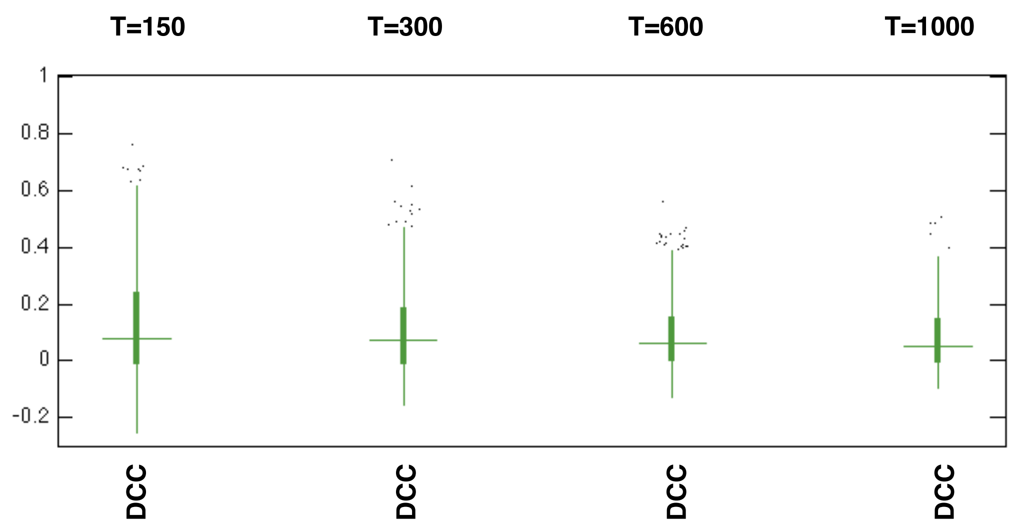
DCC



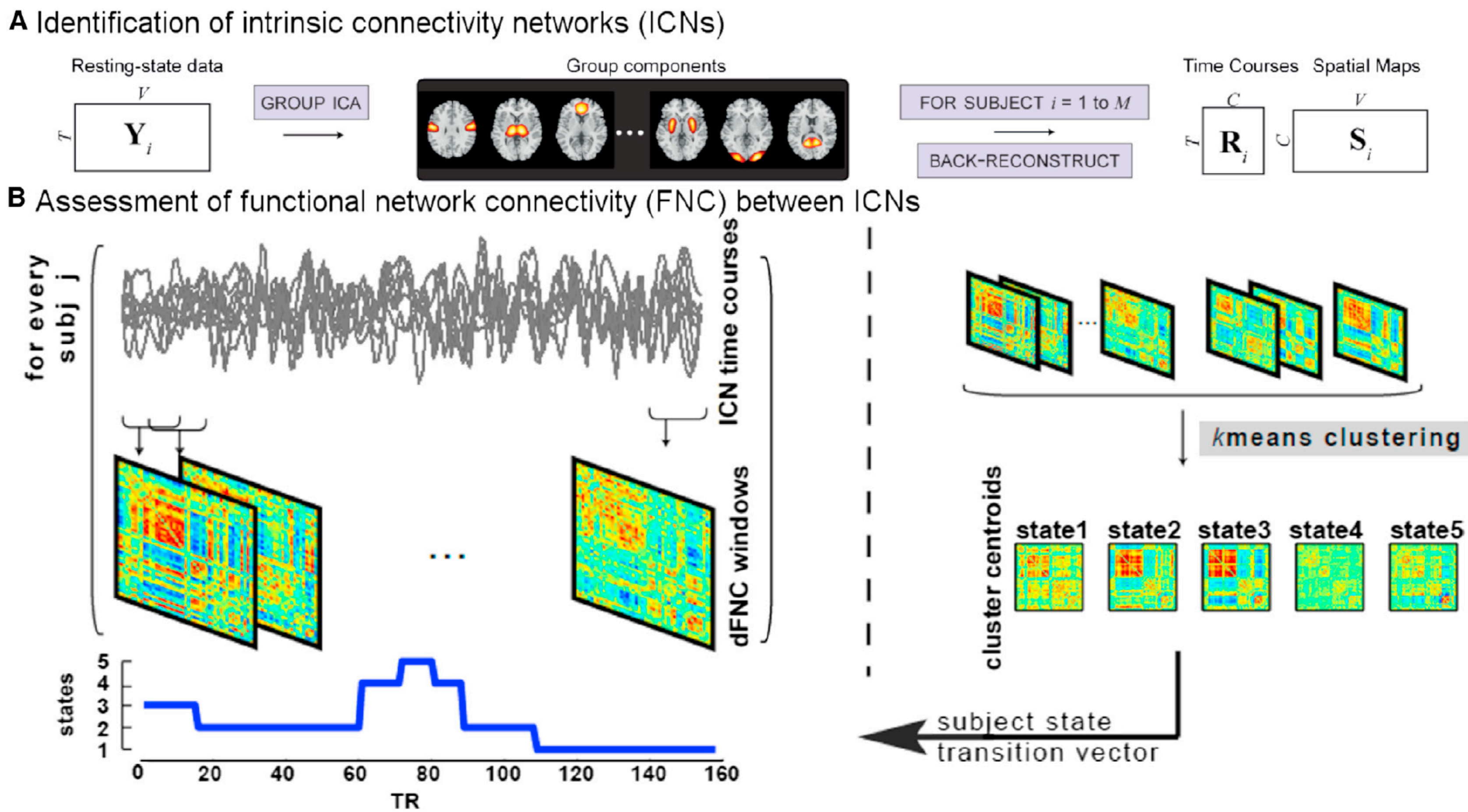
Lindquist et al. 2014

Example

- The estimated max correlation using null data of length T analyzed using DCC.



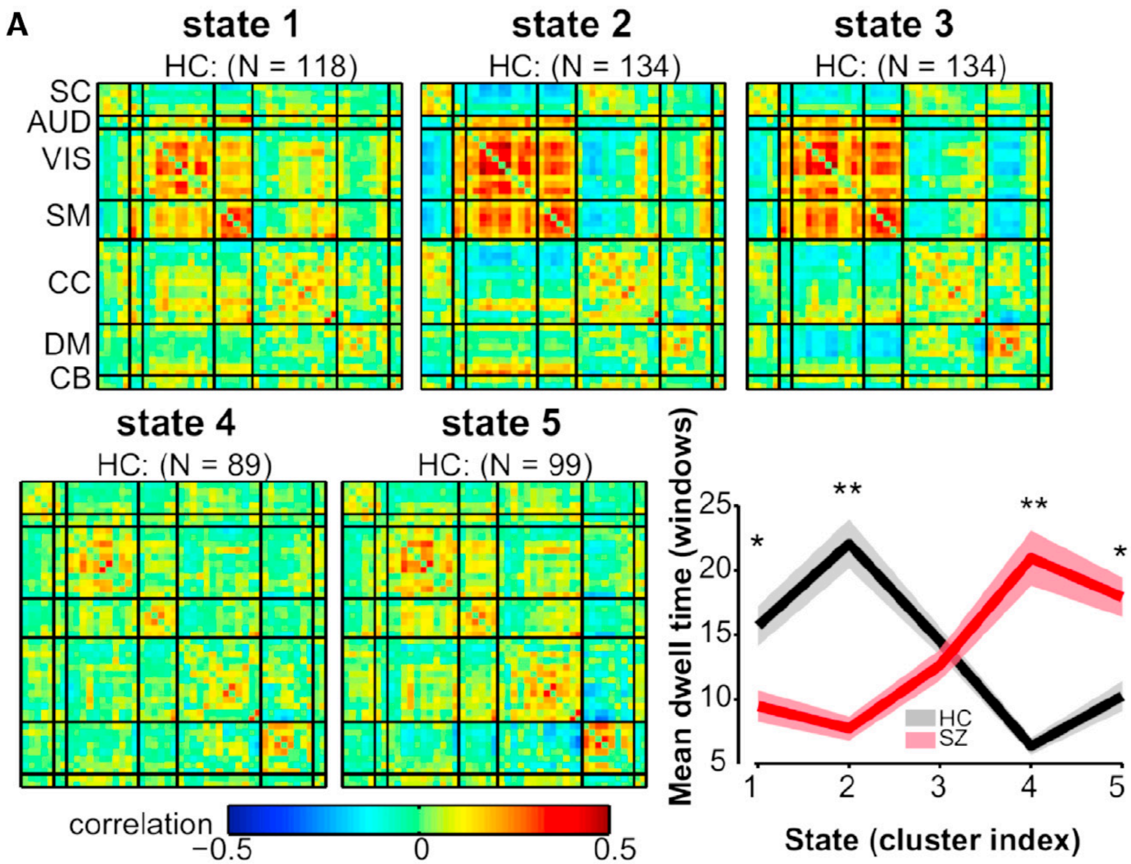
Dynamic Functional Networks



Calhoun et al 2014

Dynamic Functional Networks

Five transient state connectivity patterns estimated from schizophrenia data



Damaraju et al., 2014

End of Module