ROI-based Task fC

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- Another way to minimise confounds is to compare fC across two or more tasks/conditions. Two main ways:

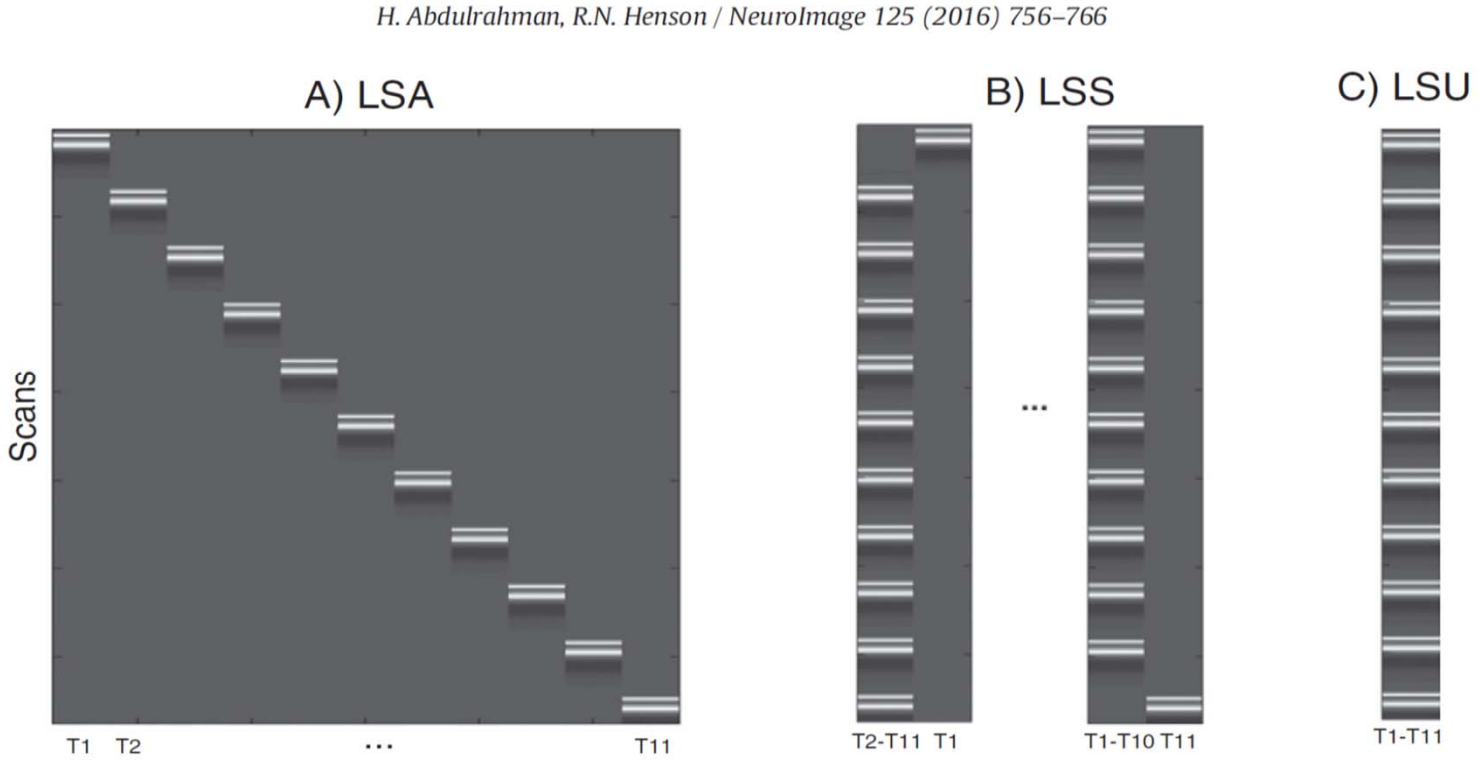
  I. Beta-Series Correlation/Regression (BSR): correlate Betas (trial-wise parameter estimates from single-trial model) across ROIs, and compare correlation coefficients/regression slopes across conditions

  II. Psycho-Physiological Interactions (PPIs): construct a model (GLM) of fMRI timeseries with regressors for 1) conditions ("psychological"), 2) timeseries from one ROI (seed) ("physiological") and 3) the interaction between 1+2 (the key PPI term), and test significance of interaction term

See Masharipov et al 2024 for comparison:
https://www.nature.com/articles/s42003-024-07088-3

1. BSR

- One problem with BSR is how to estimate single-trial responses for event-related designs with short SOAs:



- Bottom line: LSS better when scan noise higher than trial variability (normally the case); LSA better when trial variability higher than scan noise

http://dx.doi.org/10.1016/j.neuroimage.2015.11.009

2. PPIs

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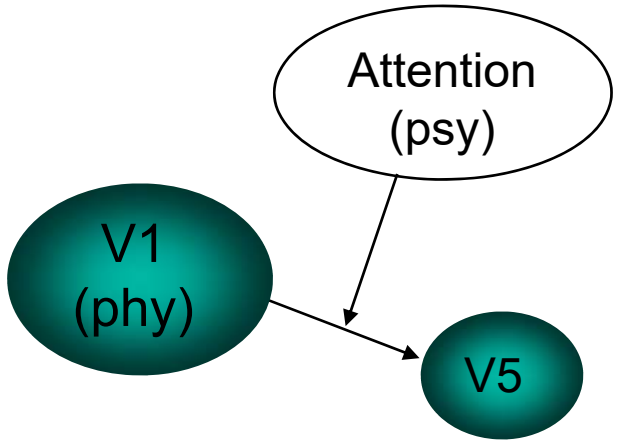
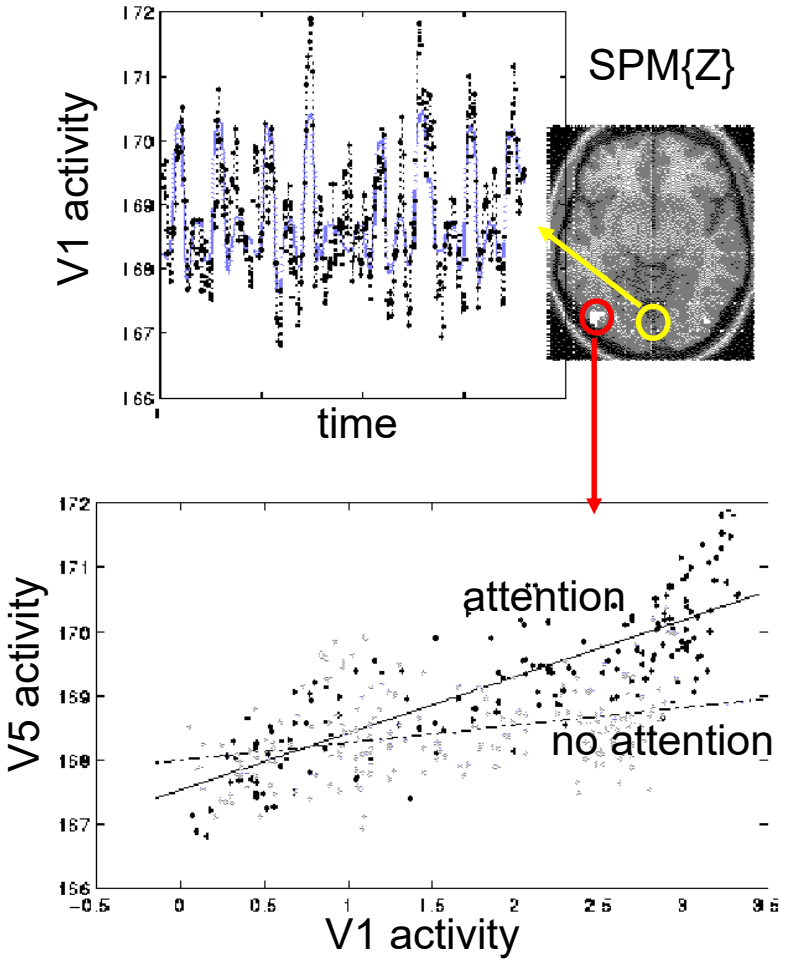
Parametric, factorial design, in which one factor is psychological (eg attention)

...and other is physiological *(viz. activity extracted from a brain region of interest)*





2. PPIs

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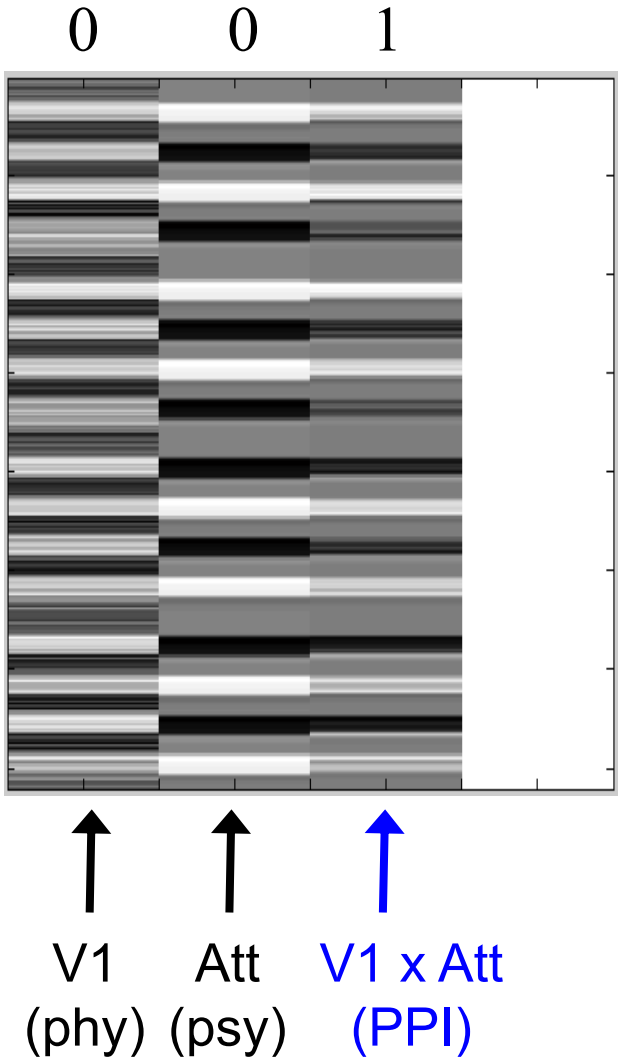

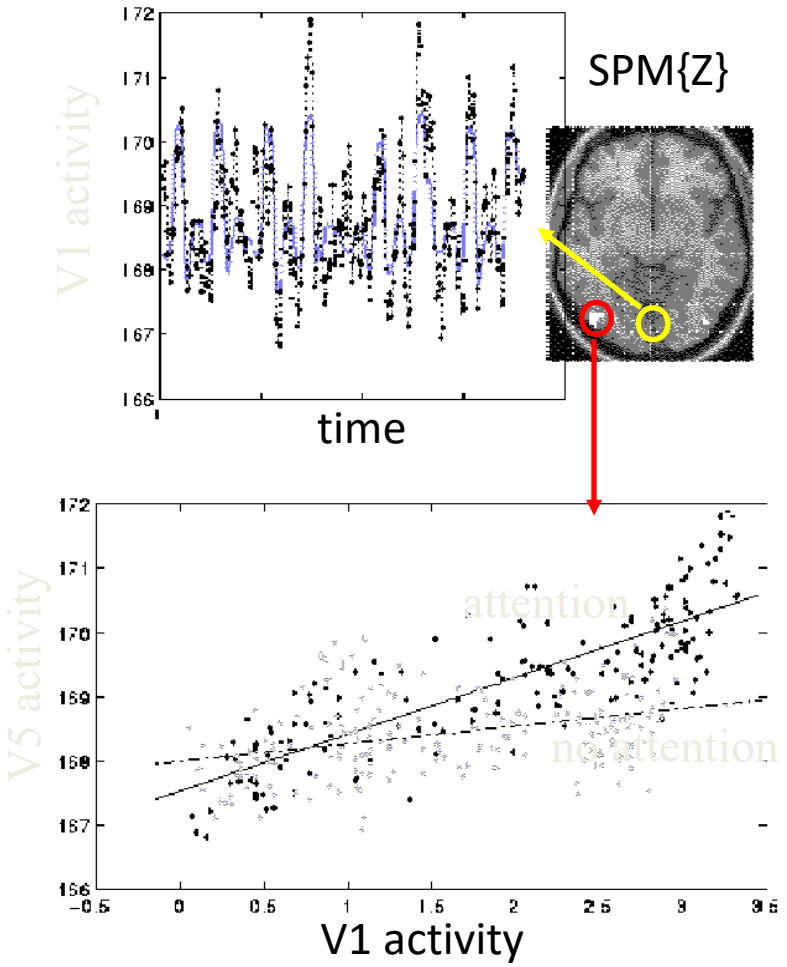

2. PPI problem with brief psychological factors...

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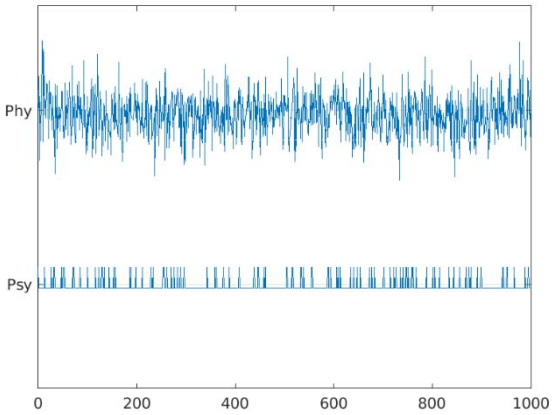
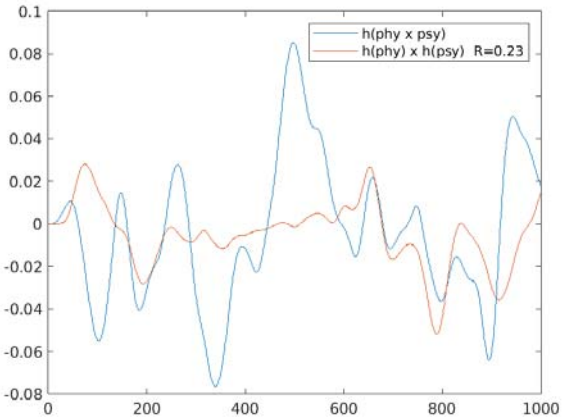
- PPI term is: $(Phy \cdot HRF) \times (Psy \cdot HRF)$
- True neural interaction is: $(Phy \times Psy) \cdot HRF$
- While:

$$(Phy \cdot HRF) \times (Psy \cdot HRF) \approx (Phy \times Psy) \cdot HRF$$

when Psy is low-frequency (e.g, blocked)...
...not case when high-frequency (e.g., event-related)



- So PPI only really suitable for slow (blocked) designs ("gPPI" option, but no true deconvolution – need forward model like in DCM...)
- (Similar problem with "Beta-series regression" – where short SOAs make separation of neural activity tricky...)



Effective-connectivity: Definitions of Causality?

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1. Direct experimental interventions (e.g, lesion, drugs)
2. Indirect experimental manipulations (e.g, PPI, DCM)
3. Network model inference (e.g, SEM, DCM)
4. Temporal precedence (e.g, Granger Causality, DCM)
5. …

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Functional vs Effective connectivity

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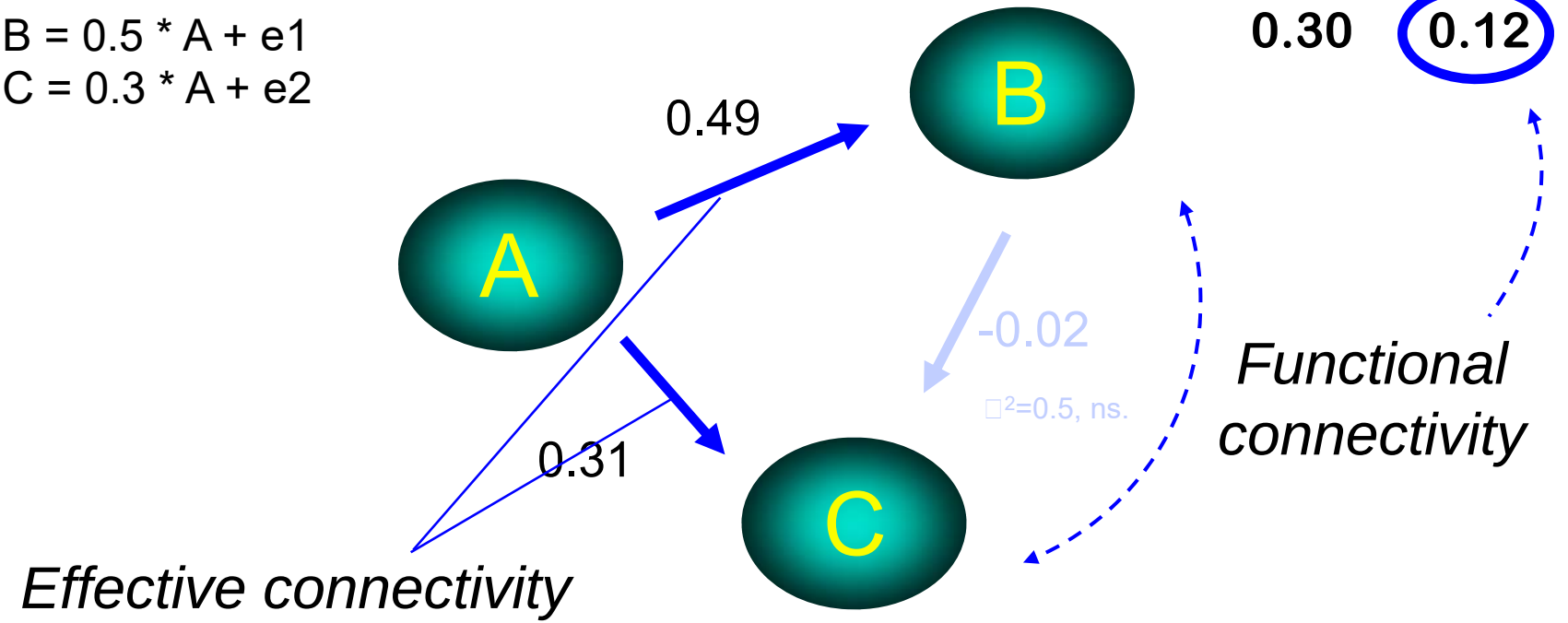
No connection between B and C, yet B and C correlated because of common input from A, eg:

A = V1 fMRI time-series
B = 0.5 * A + e1
C = 0.3 * A + e2

Correlations:

A	B	C
1		
0.49	1	
0.30	0.12	1



3. Explicit Network Models of Causality

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- (Bivariate) correlations do not use an explicit network (graph) model
- Can use ***partial*** correlation to adjust for all other connections within a graph (Smith et al, 2011; but often requires regularisation and can remove true connections)

- Multivariate methods like Structural Equation Modelling (SEM) can test different network models, by simply comparing *predicted* with *observed* covariance matrices, but...
  - has no dynamical model (stationary covariances)
  - has no neural–BOLD model
  - cannot test some graphs, eg loops (no temporal definition of direction)
  - restricted to classical inference comparing nested models

Effective-connectivity: Definitions of Causality?

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4. Temporal definition of Causality

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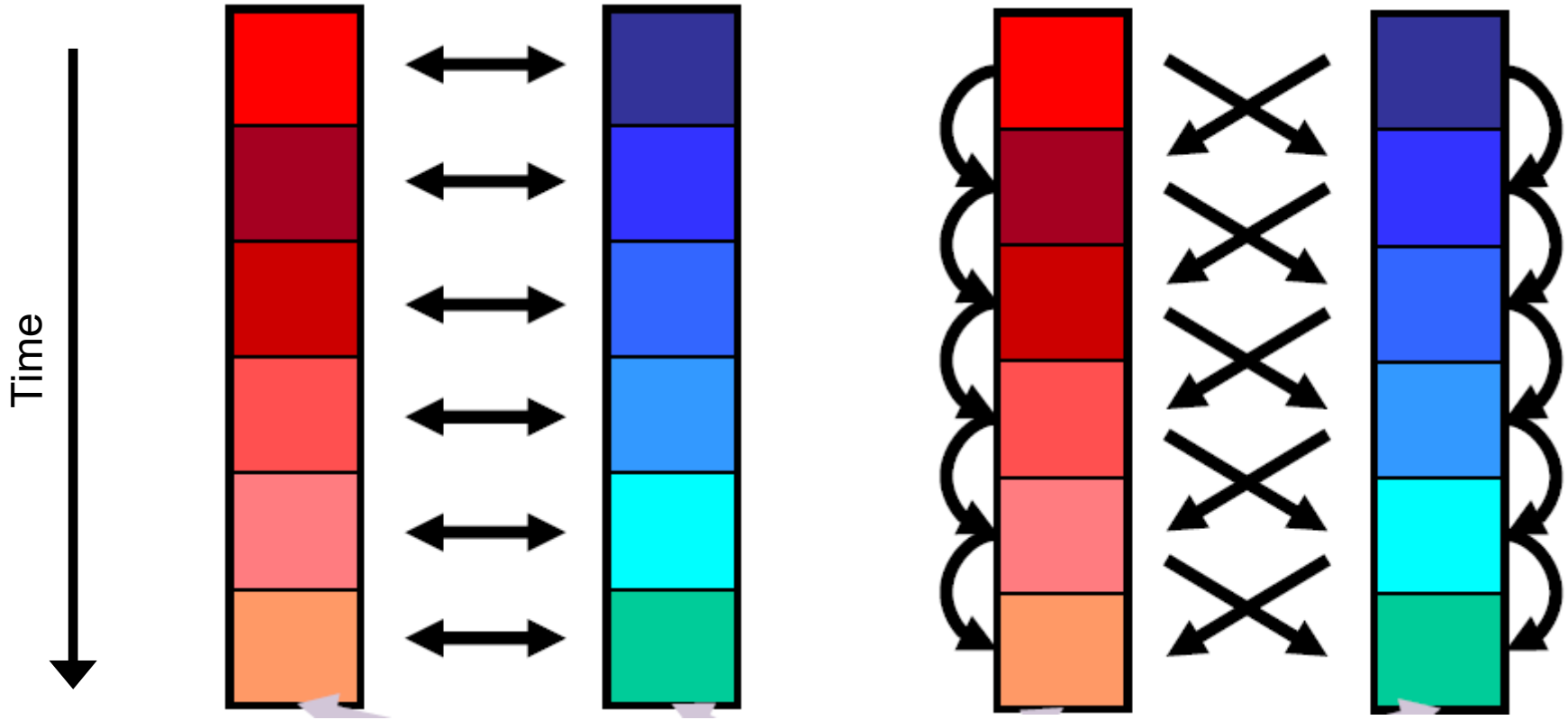
Stationary
(correlations, SEM)

Dynamic
(Granger, DCM)



("unfolding" in time is one way to infer direction of connectivity)

4. Note on temporal causality and fMRI

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- Problem with time-based measures of connectivity arises with fMRI: BOLD timeseries is not direct reflection of Neural timeseries
  - (e.g, peak BOLD response in motor cortex can precede that in visual cortex in a visually-cued motor task, owing to different neural-BOLD mappings)

- This compromises methods like Granger Causality and Multivariate Auto-Regressive models (MAR) that operate directly on fMRI data

  (Friston, 2010; Smith et al, 2011)

- (Note that this does not preclude these methods (eg MAR) for MEG/EEG timeseries, assuming these are more direct measures of neural activity)

=> Development of DCM

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1. *Dynamic:* based on first-order differential equations

   - at level of neural activity, with separate haemodynamic model for fMRI

2. *Causal:* based on explicit directed graph models

3. *Modelling:* designed to test experimental manipulations

   - "bilinear" approximation to interactive dynamics

4. (Estimated in a Bayesian context, allowing regularized estimation through priors, formal comparison of any number/type of models, etc...)

Rough comparison of popular methods?

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	Experimental modulation	Temporal/ Dynamical	Network model	Haemodynamic Model (for fMRI)
Correlation / ICA / PCA				
BSR / PPI	Y			
Granger		Y		
SEM			Y	
DCM	Y	Y	Y	Y

Other types of fC
(not covered here)

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- **Multi-dimensional** (pattern-based) fC (e.g., Basti et al., 2020, https://doi.org/10.1016/j.neuroimage.2020.117179)

- **Dynamic** fC (e.g moving windows or Hidden Markov Models, eg review: https://pmc.ncbi.nlm.nih.gov/articles/PMC3807588/)