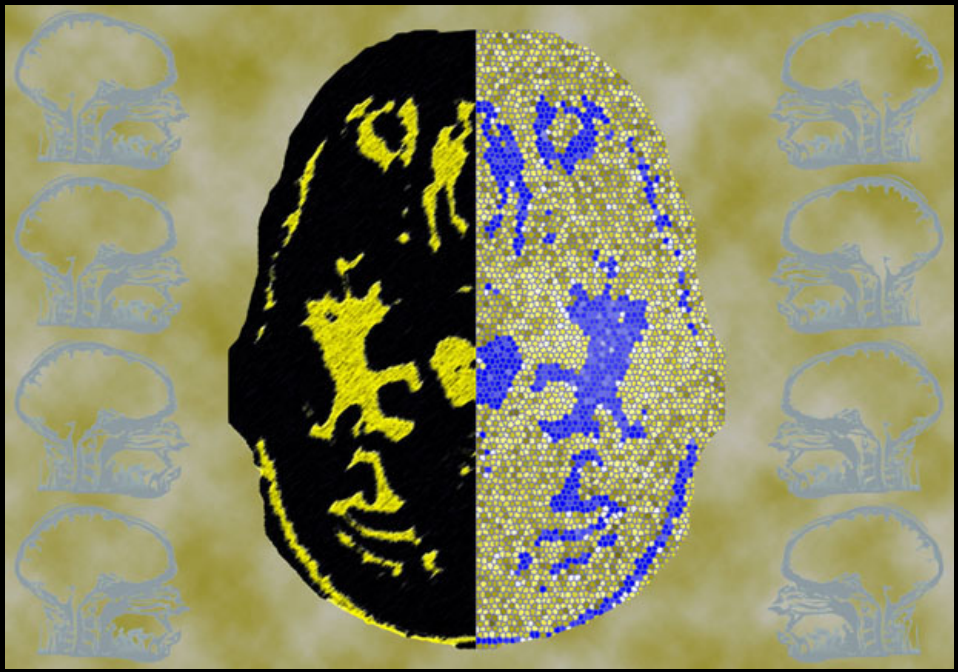
Characterizing task-related interactions between brain regions with fMRI

The Beta Series Correlation Approach

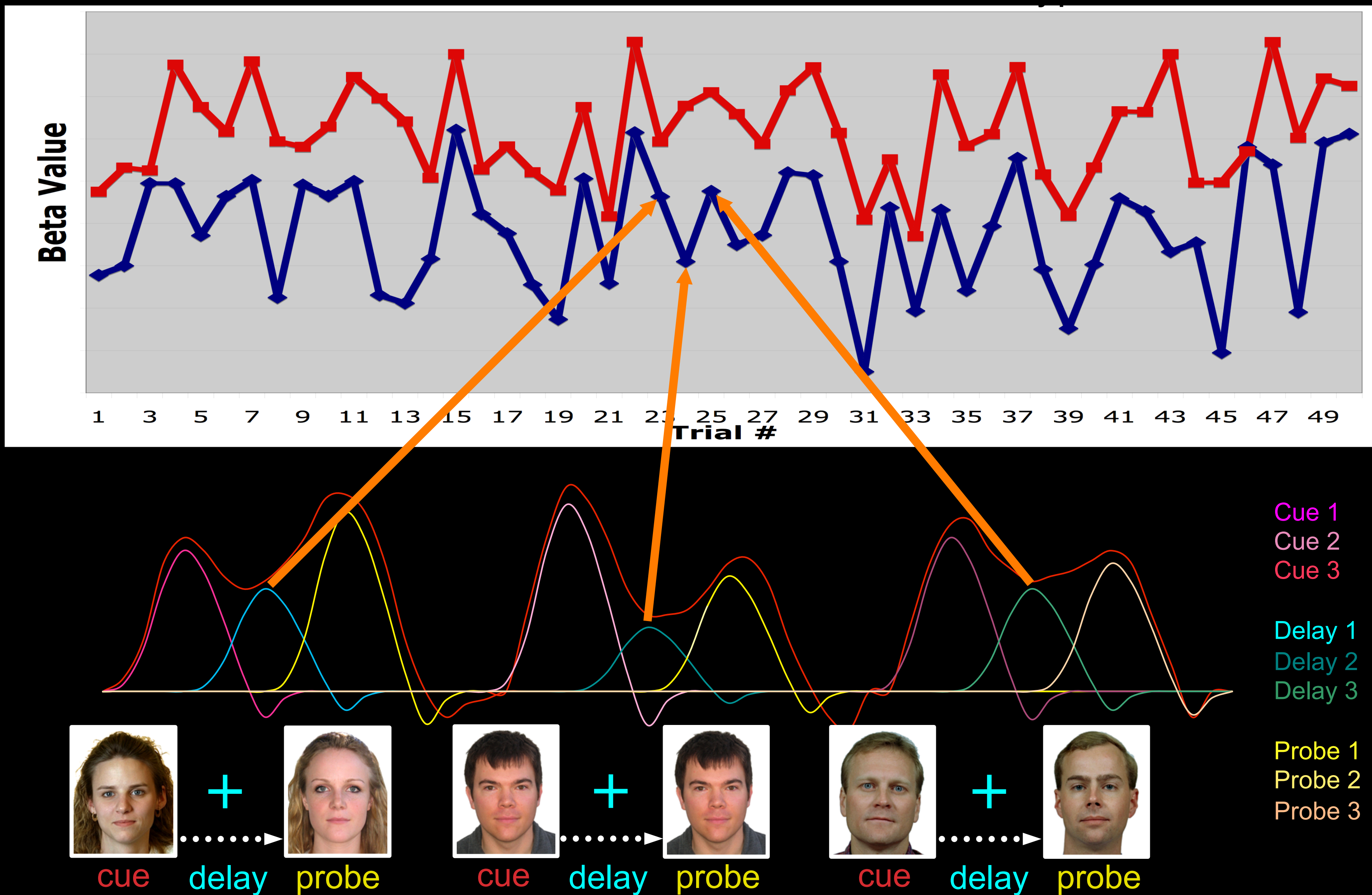


Jesse Rissman

NITP Summer Course 2016

UCLA

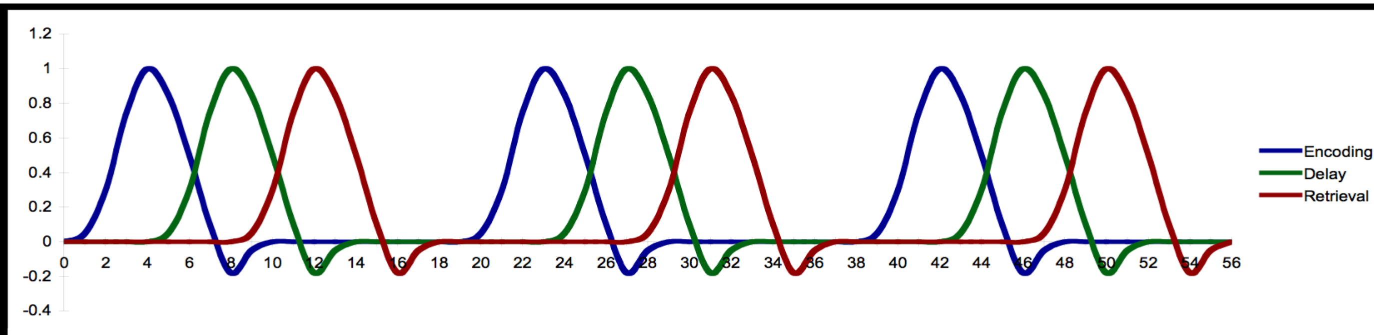
Measuring functional connectivity during distinct task stages:
Beta series correlation analysis



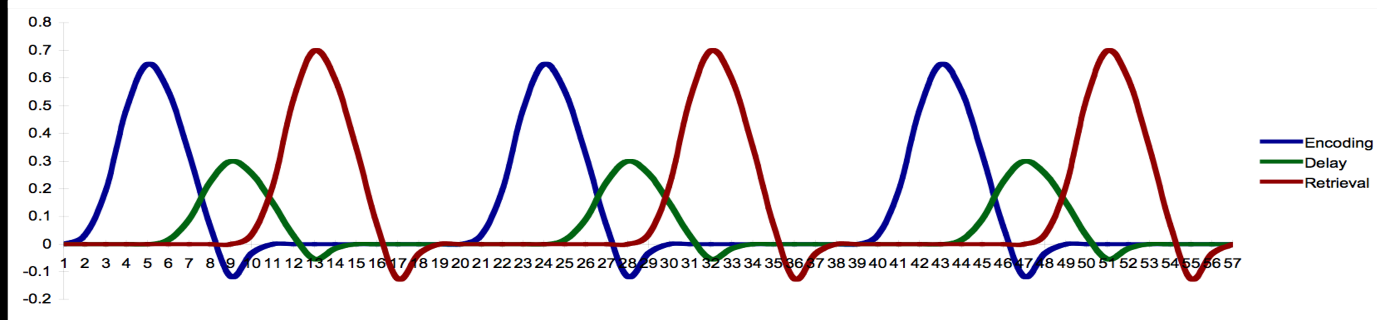
Rissman, Gazzaley, and D'Esposito (2004), *NeuroImage*

Standard GLM

Model regressors

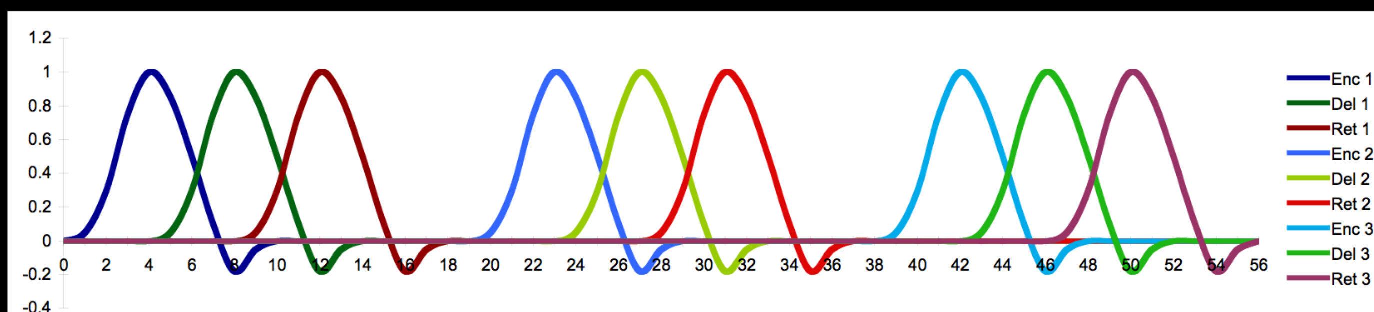


Fitted regressors

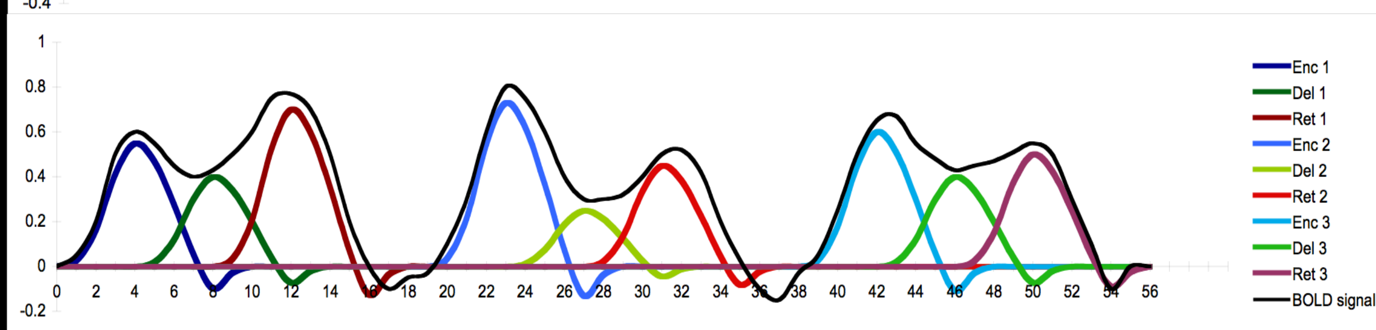


“Trialwise” GLM

Model regressors



Fitted regressors



Beta series correlations:

Initial effort to validate the approach

- Beta series correlation analysis method applied to simple bimanual motor task.

- In the **Right-then-Left** condition, subjects played a sequence of 4 keystrokes with their right hand and then played a different sequence with their left.

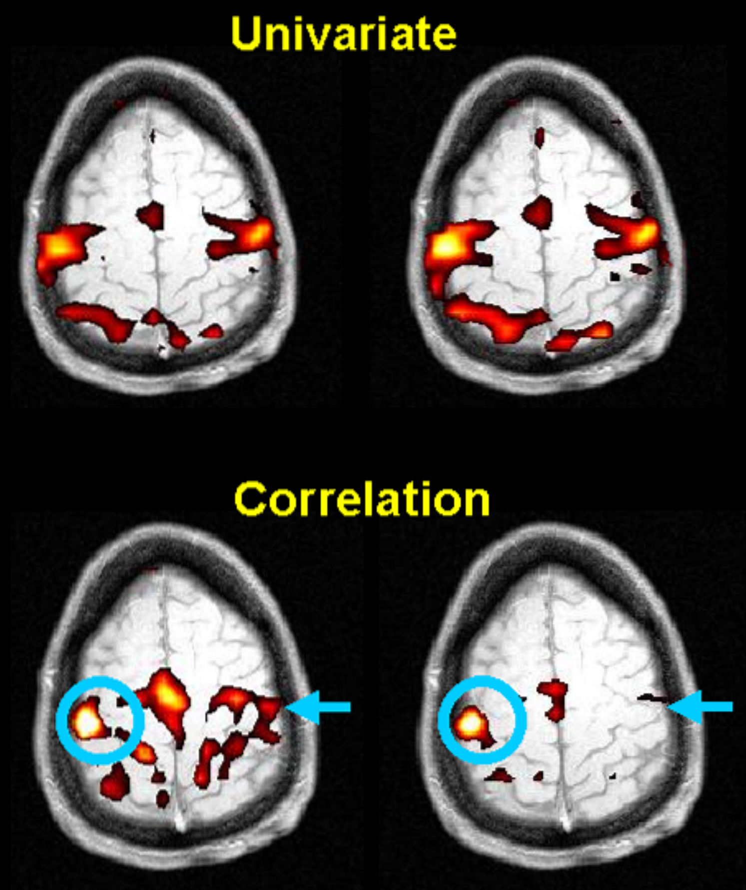
- In the **Interleaved** condition, subjects played 8 keystrokes alternating between hands – a task requiring increased bimanual coordination.

- <u>Hypothesis</u>: The Interleaved condition should induce more inter-hemispheric cross-talk between motor regions.

Beta series correlations:

A meaningful metric of inter-regional coupling?

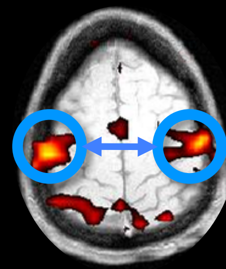
Bimanual coordination **One hand at a time**

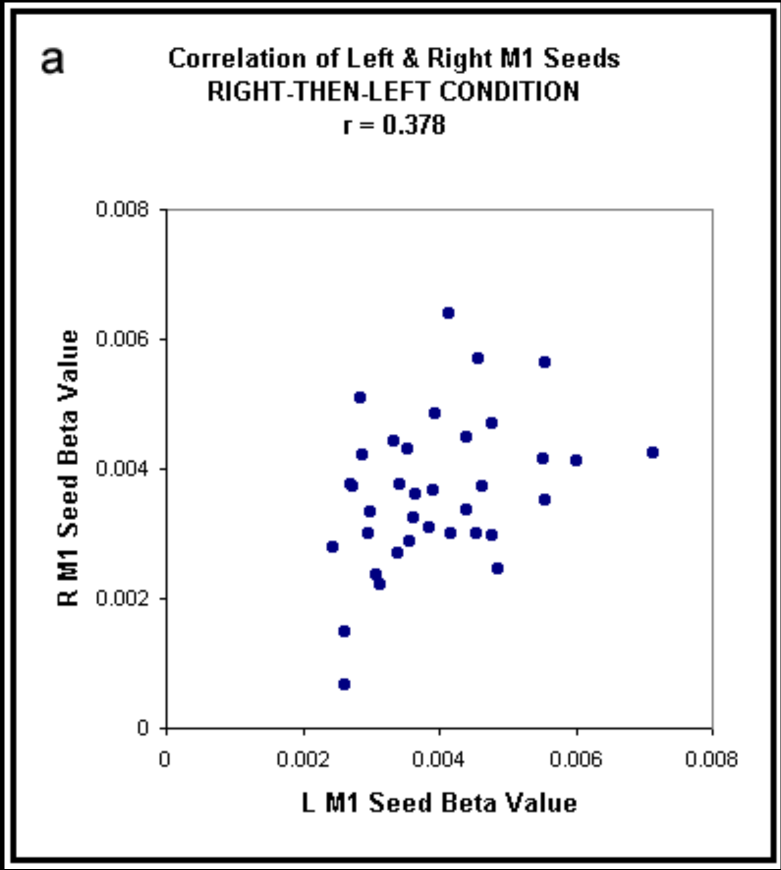


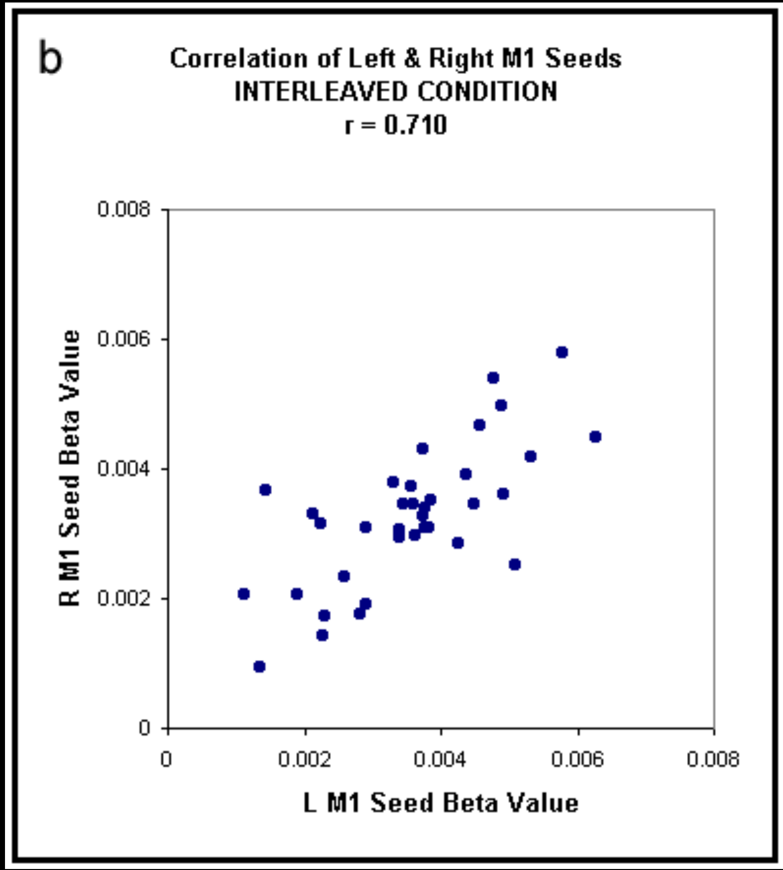
Rissman, Gazzaley, and D'Esposito (2004), *NeuroImage*

Beta series correlations:

A meaningful metric of inter-regional coupling?



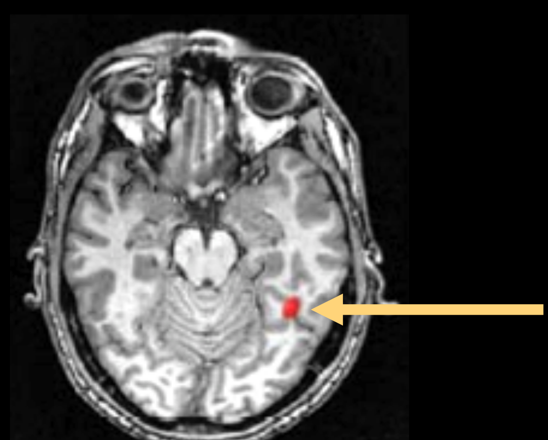




Rissman, Gazzaley, and D'Esposito (2004), *NeuroImage*

Beta series correlation analysis applied to a basic visual working memory task

- Hypothesis: Frontoparietal regions interact with neural ensembles in inferotemporal cortex to keep behaviorally-relevant visual representations active
- Analysis performed on fMRI data from 17 subjects
- Task: maintain a single face across a 7-8 sec delay period

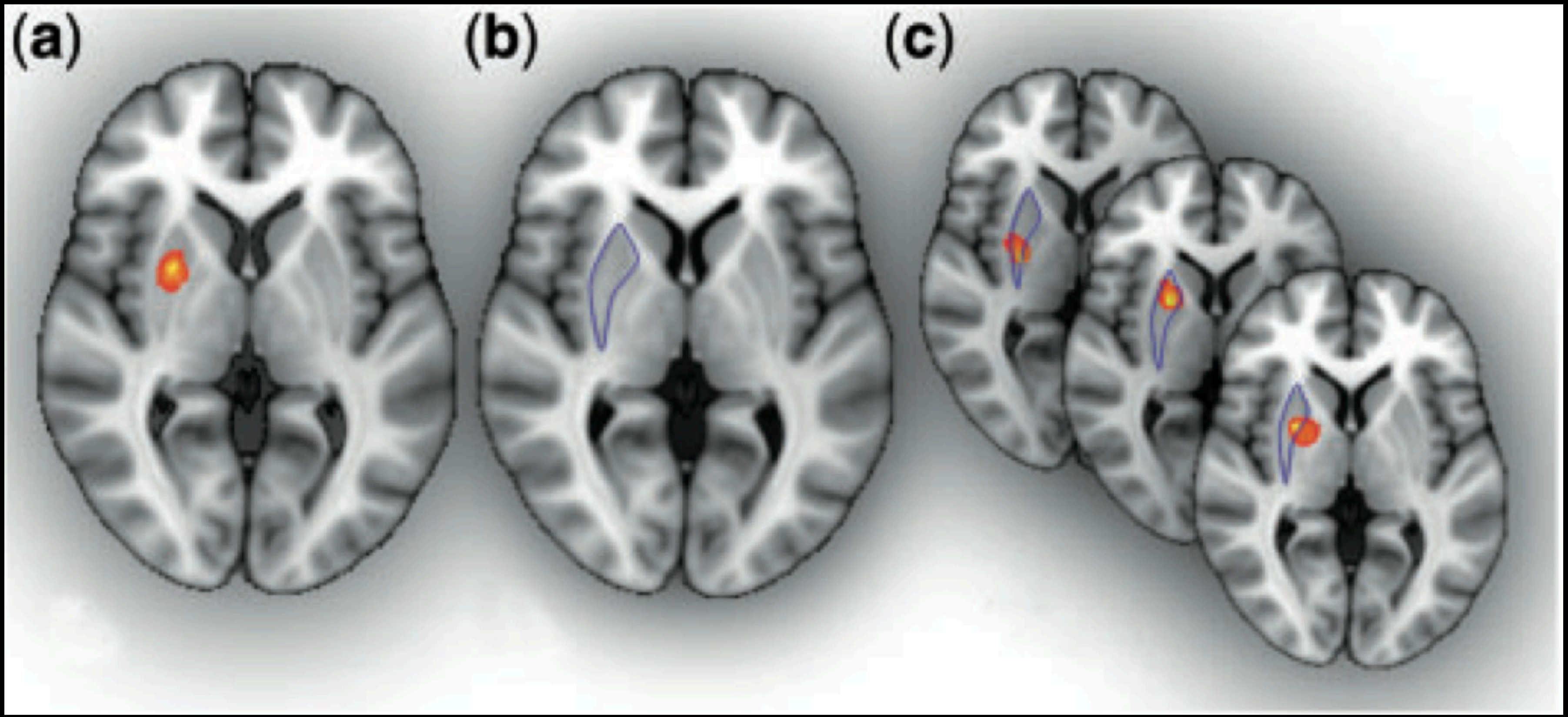


right fusiform face area (FFA) "seed"

Which brain regions are most strongly correlated with this seed region during face maintenance?

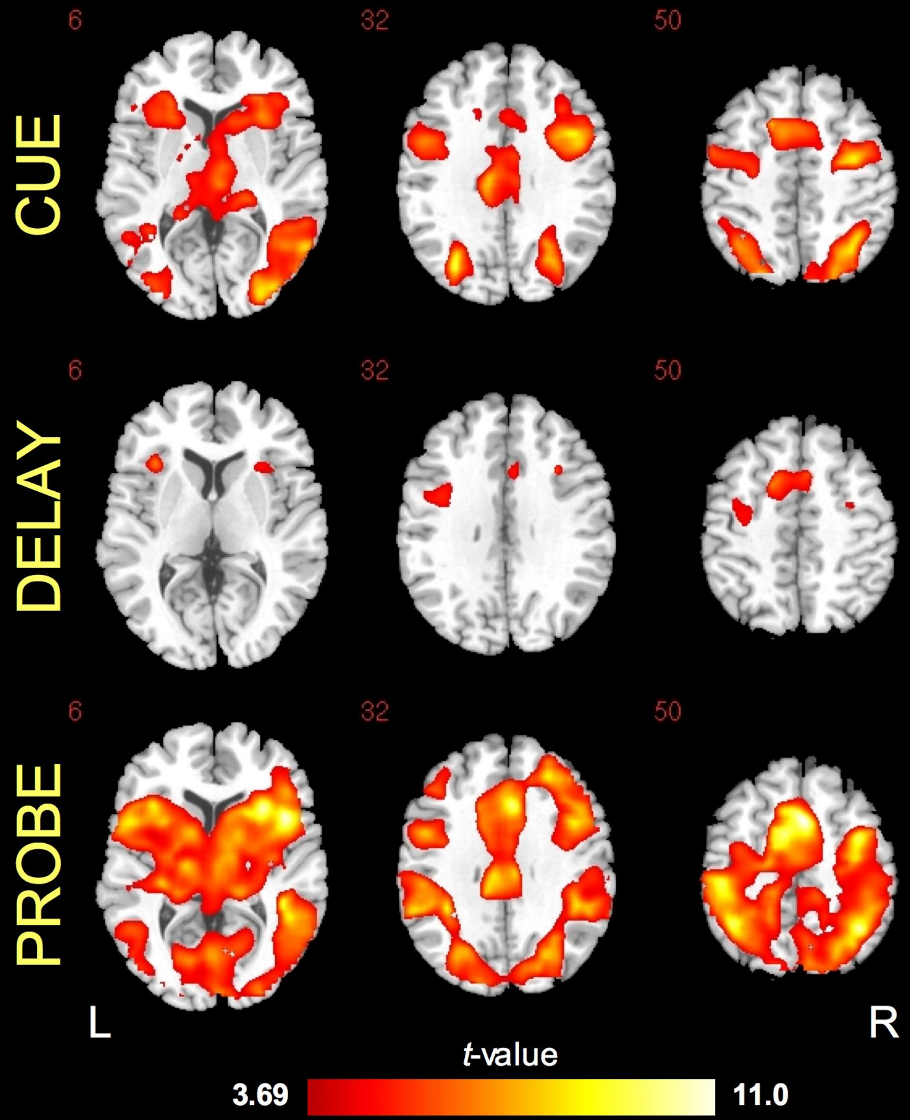
Side note: Defining a good seed ROI

Group-defined, anatomically-defined, or individually-defined?

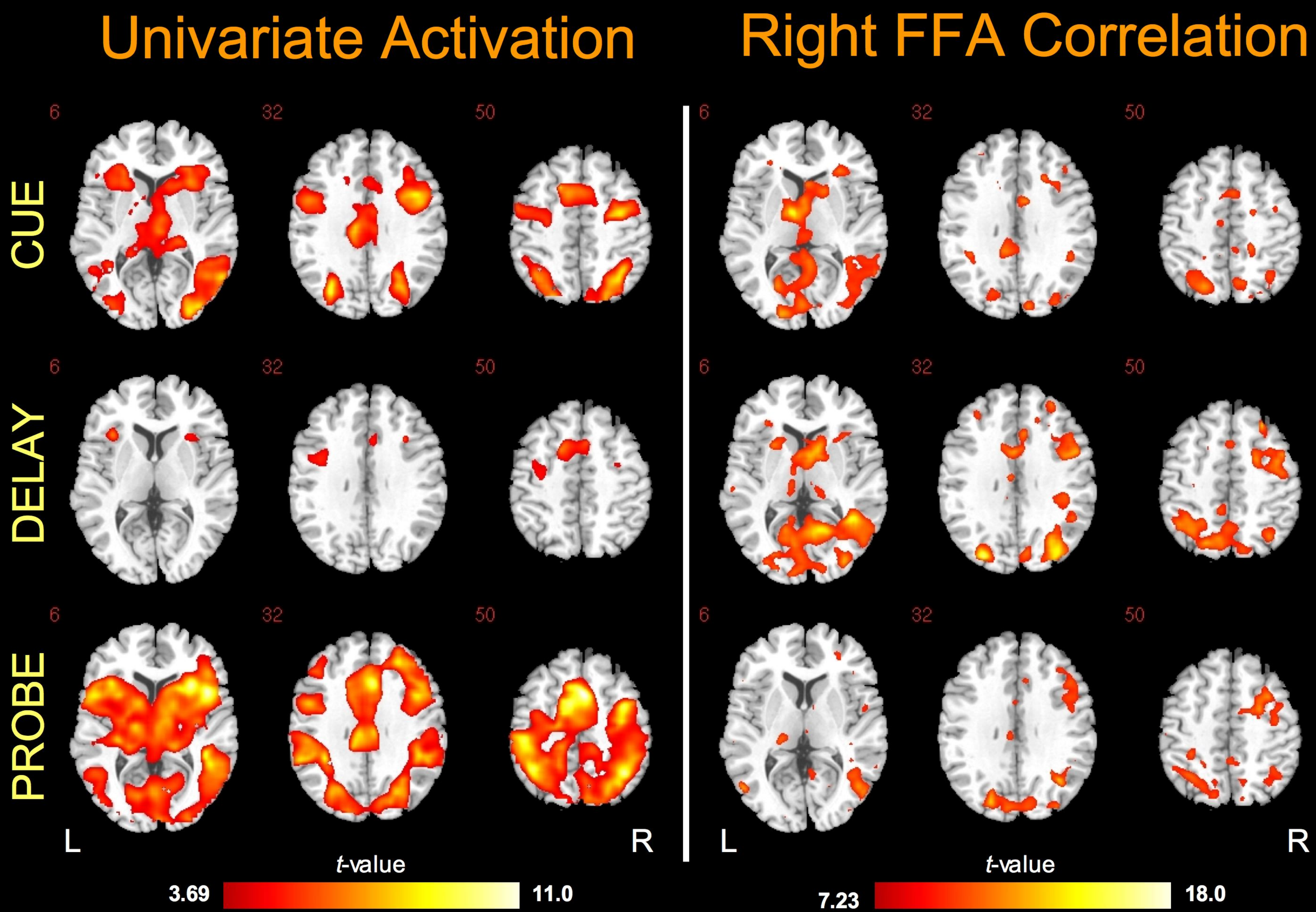


O'Reilly et al. (2012) *SCAN*

Univariate Activation

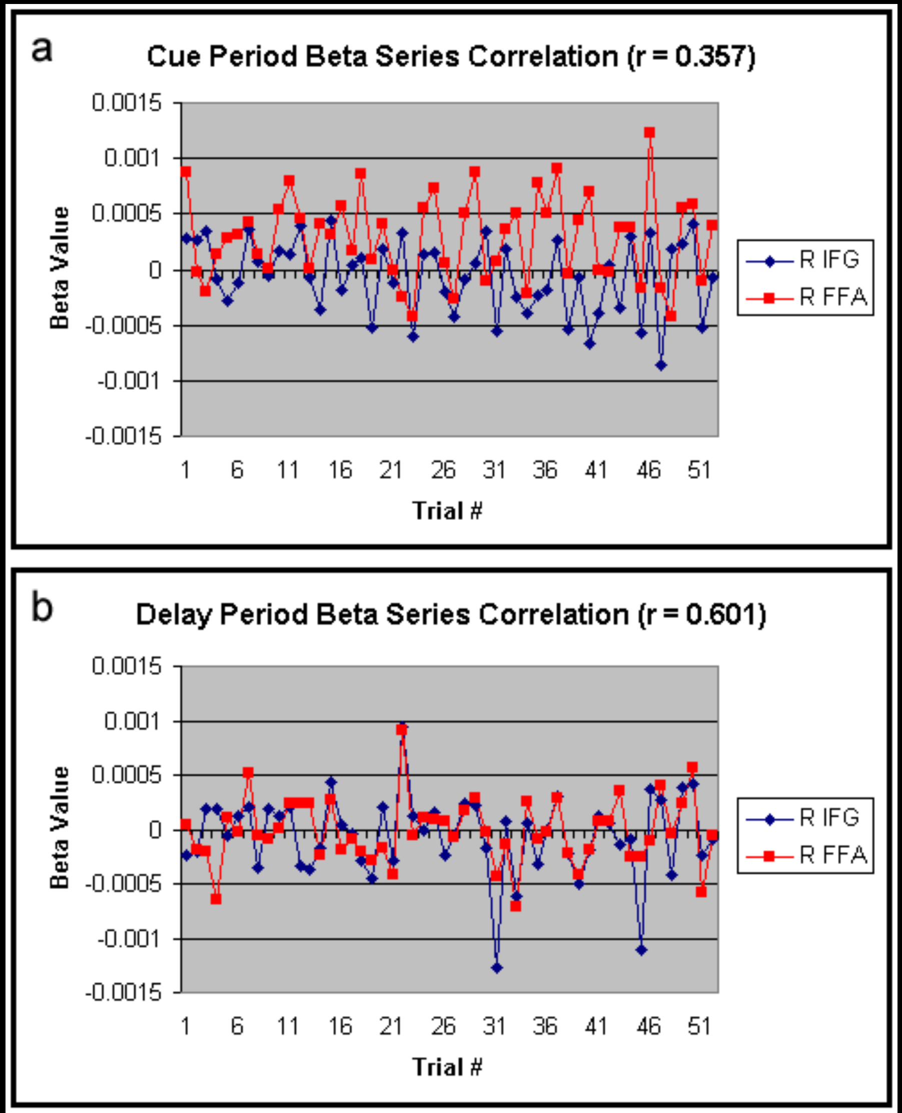


Gazzaley, Rissman, and D'Esposito (2004), *Cognitive, Affective, and Behavioral Neuroscience*



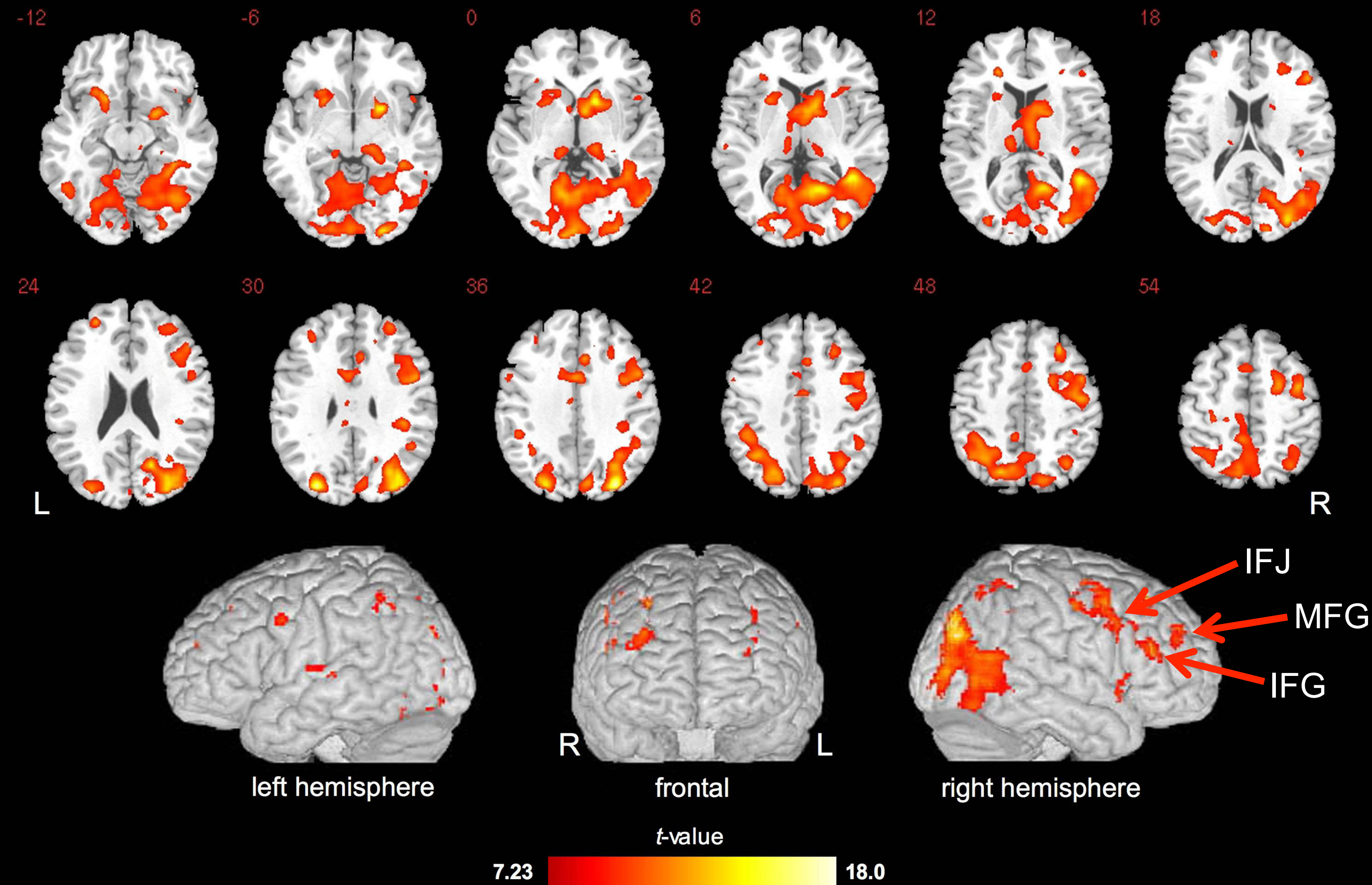
Gazzaley, Rissman, and D'Esposito (2004), *Cognitive, Affective, and Behavioral Neuroscience*

Higher mean activity does not necessarily imply higher connectivity



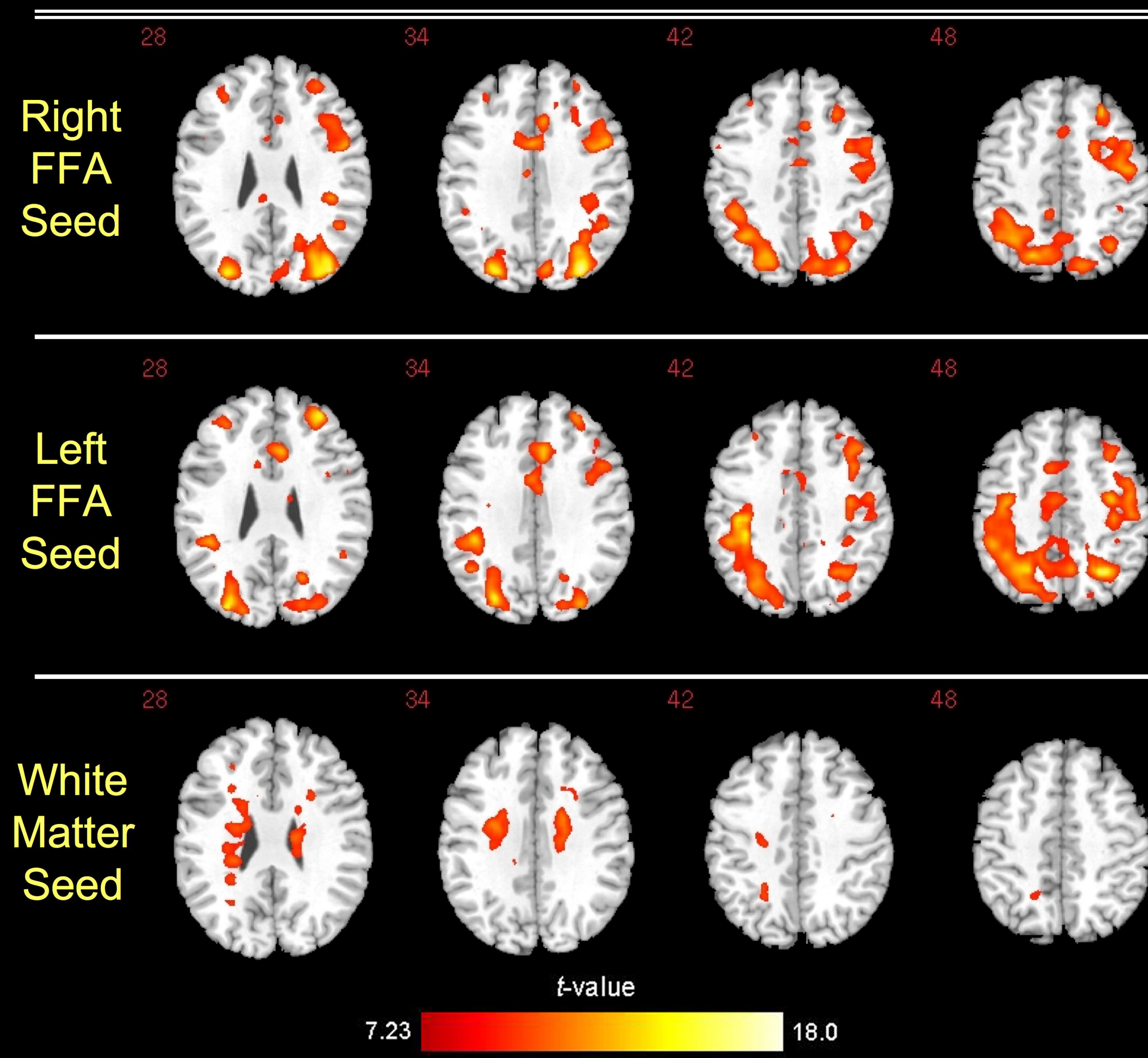
Rissman, Gazzaley, and D'Esposito (2004), *NeuroImage*

Visual WM maintenance network:
Delay period connectivity with FFA seed



Gazzaley, Rissman, and D'Esposito (2004), *Cognitive, Affective, and Behavioral Neuroscience*

Delay Network Maps

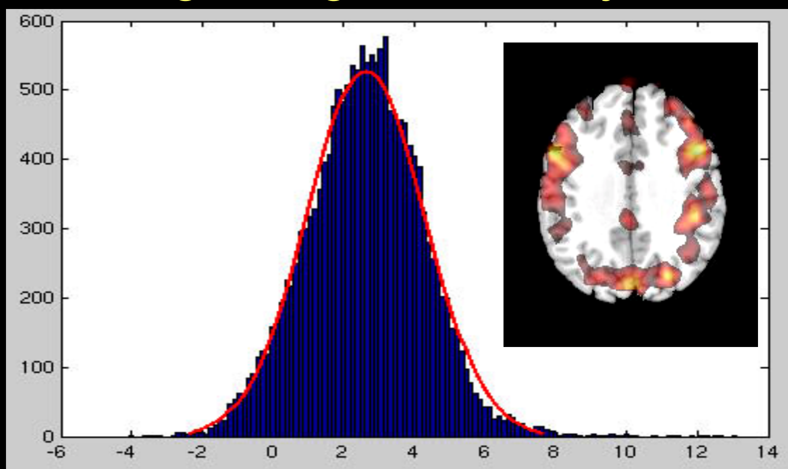


Gazzaley, Rissman, and D'Esposito (2004), *Cognitive, Affective, and Behavioral Neuroscience*

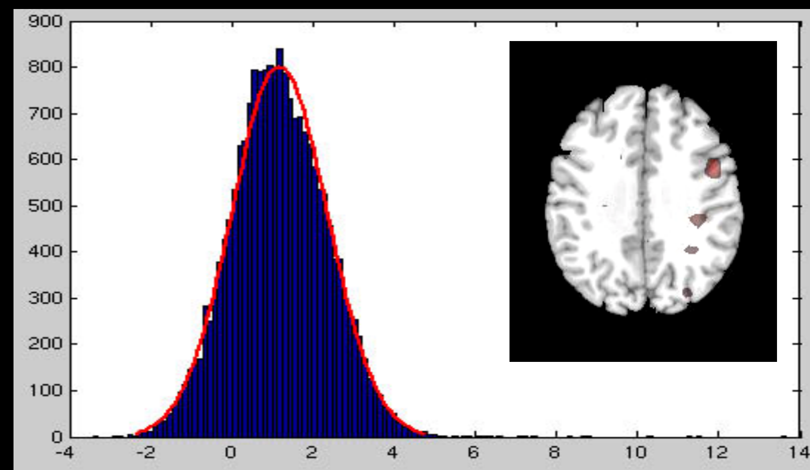
A few methodological considerations

- Across-subject differences in global correlation magnitudes

High Magnitude Subject

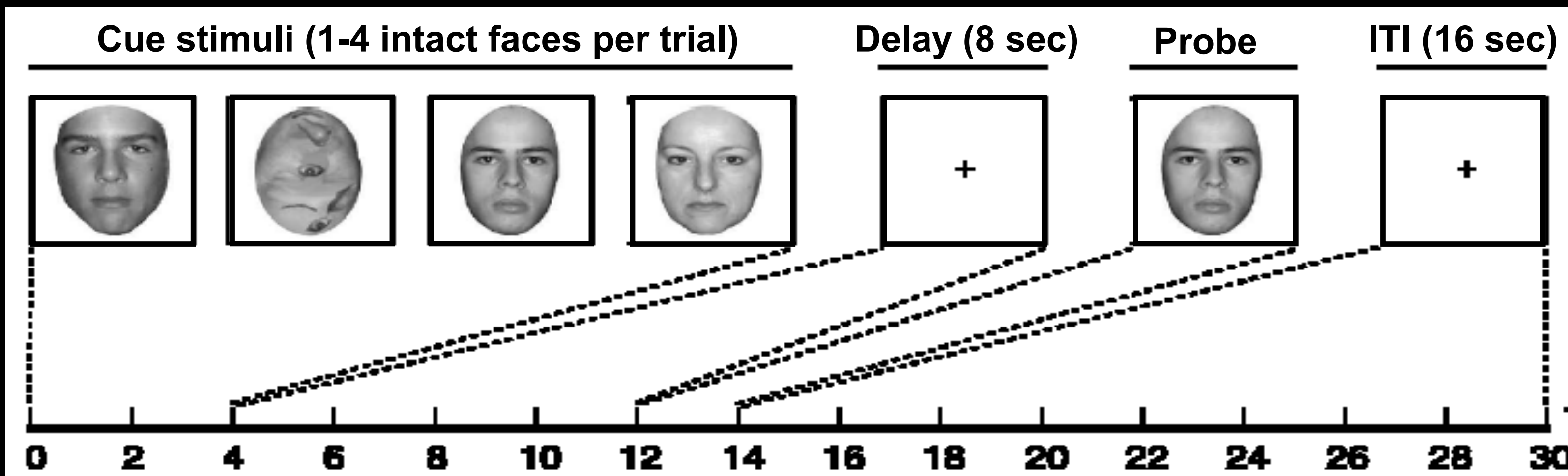


Low Magnitude Subject



- Potential solutions
  - -- Regress out global signal or signal from “noise” region (e.g., ventricle)
  - -- Contrast correlation maps with control condition
  - -- Ensure that outliers are not present in the seed’s beta series

The effects of increased mnemonic load on delay period connectivity



Druzgal & D'Esposito (2003), *JoCN*

Generate FFA seed correlation separately for each load condition

↓

Average delay period correlation maps across all four load conditions

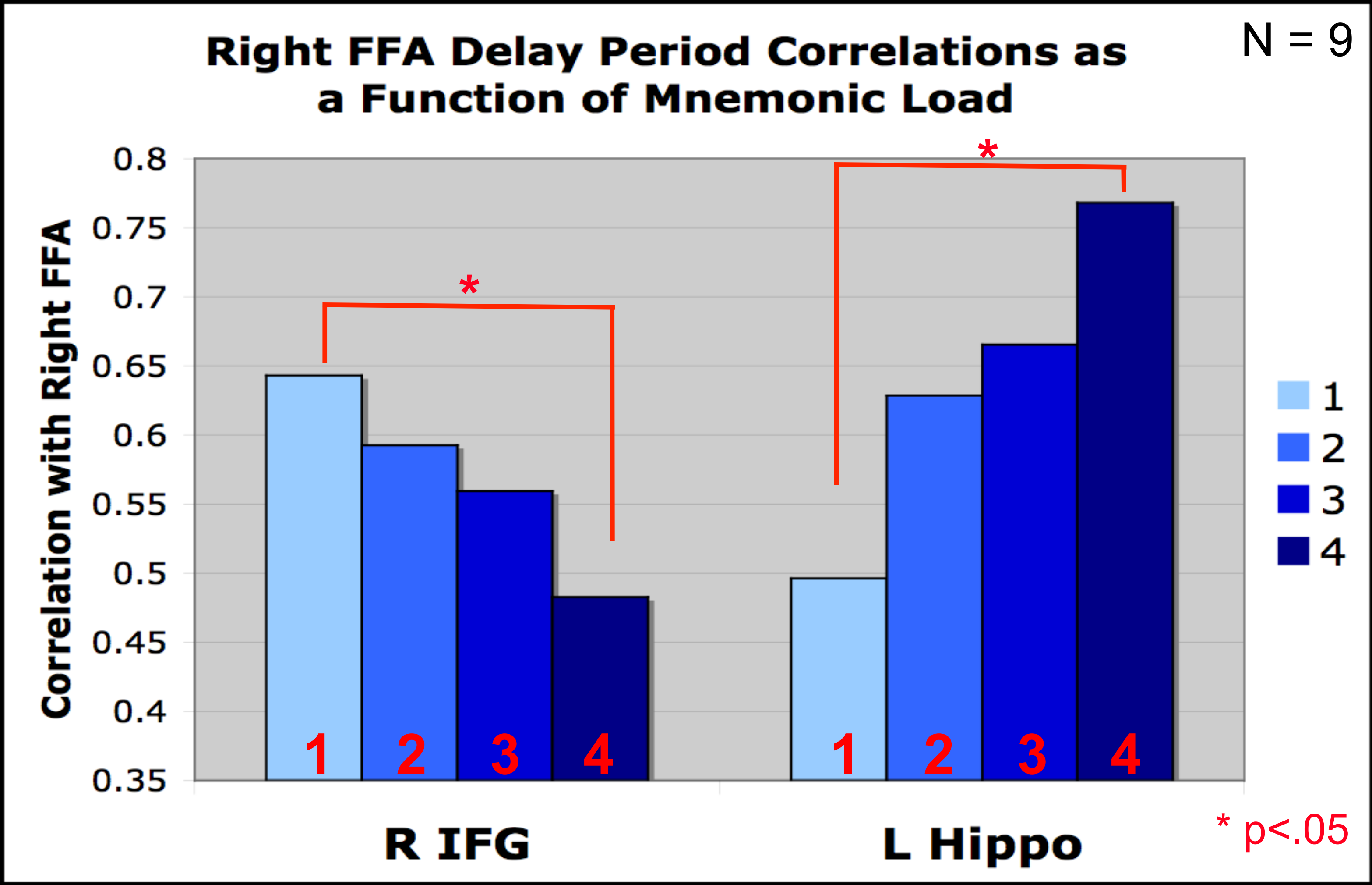
↓

Identify voxels in each subject's IFG, MFG, & HIPPO most correlated with seed

↓

Evaluate each region's correlation with FFA as a function of load

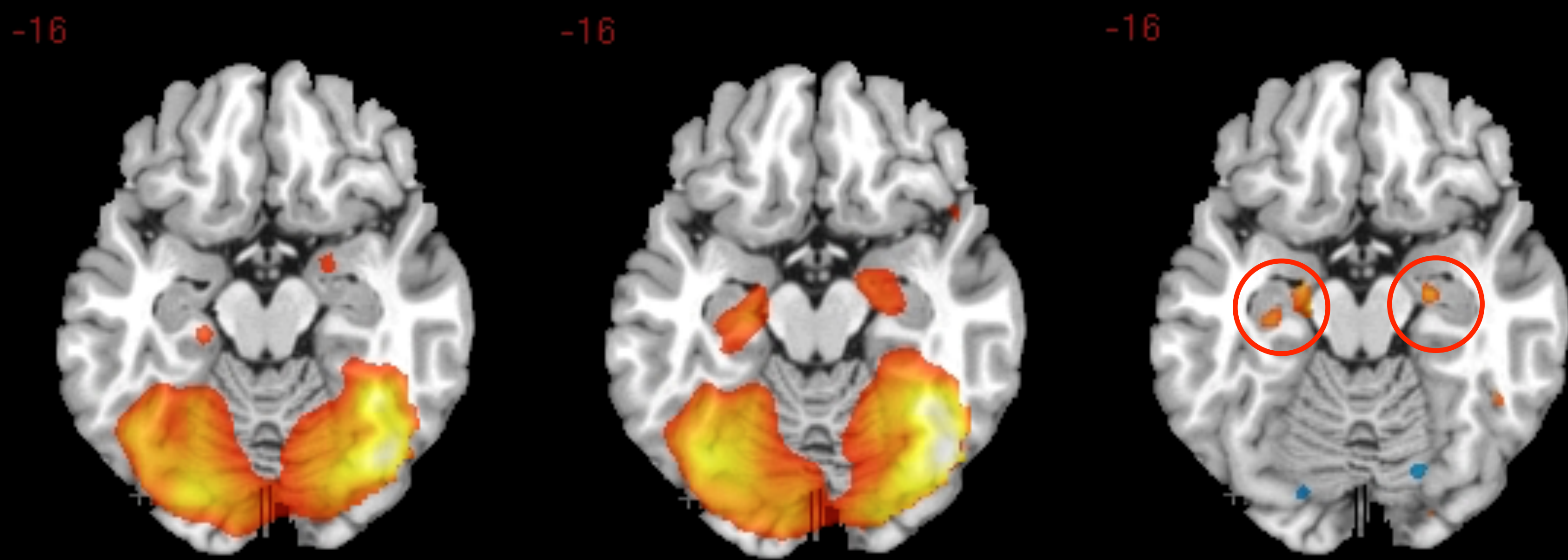
Regions exhibiting significant results



Rissman, Gazzaley, D'Esposito (2008), *Cerebral Cortex*

Group-averaged maps:

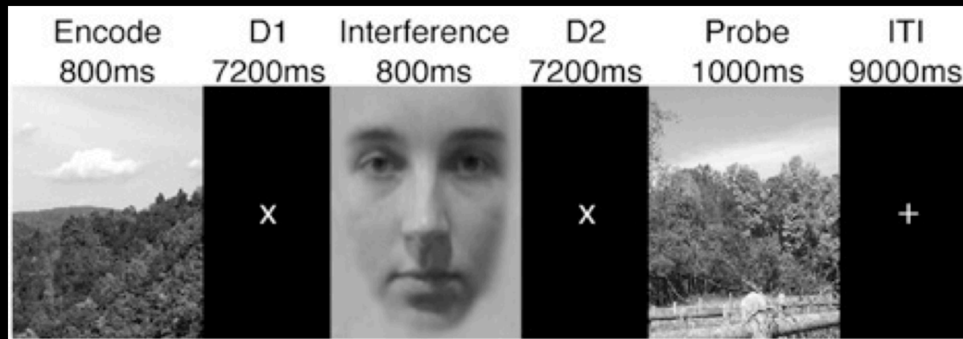
FFA ⇔ hippocampus connectivity effects



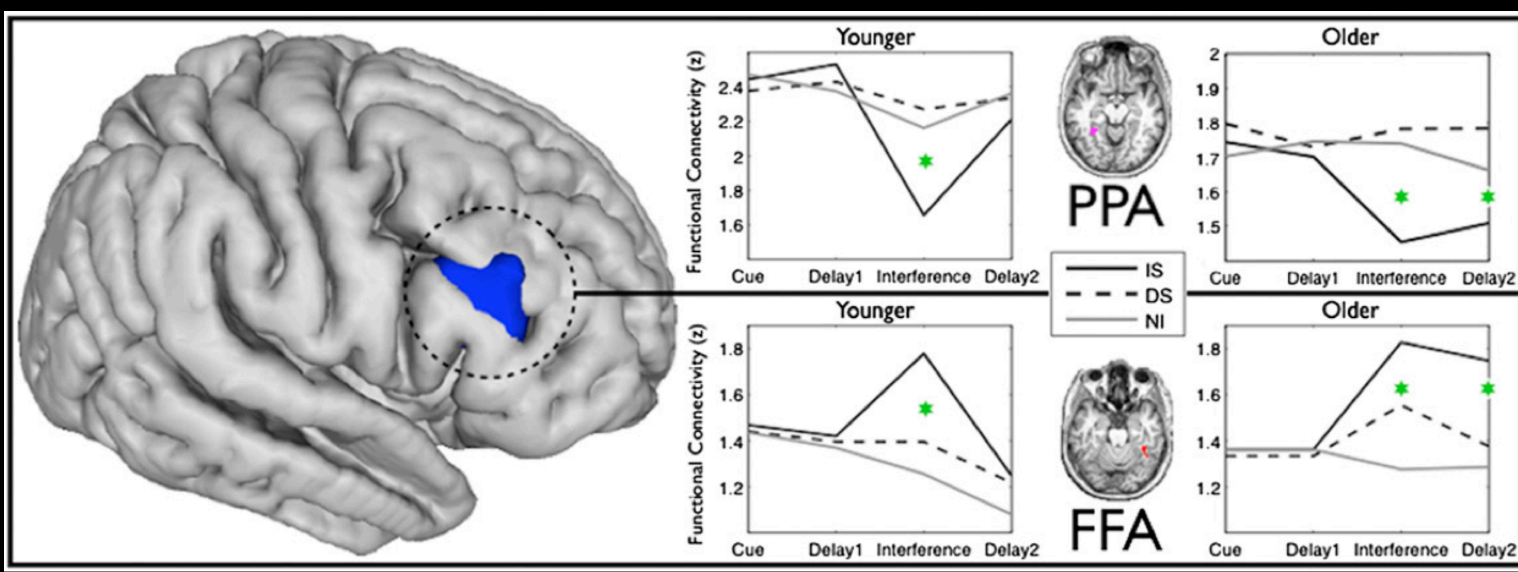
1 Face 4 Faces Linear Increase

Rissman, Gazzaley, D'Esposito (2008), *Cerebral Cortex*

Another example application:
Age-related changes in prefrontal coupling



<u>3 task conditions</u>:
- Interrupting stimulus (IS): *make judgment about face (male over 40?)*
- Distracting stimulus (DS): *ignore face; no decision required*
- No interference (NI): *no face stimulus presented*

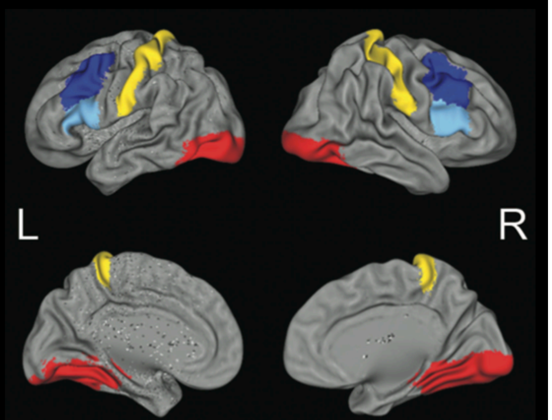


Older adults failed to reestablish connectivity following interruptions!

Clapp et al. (2011), *PNAS*

Another example application:

Sustaining a similar level of fronto-posterior connectivity from encoding to delay period leads to improved working memory performance



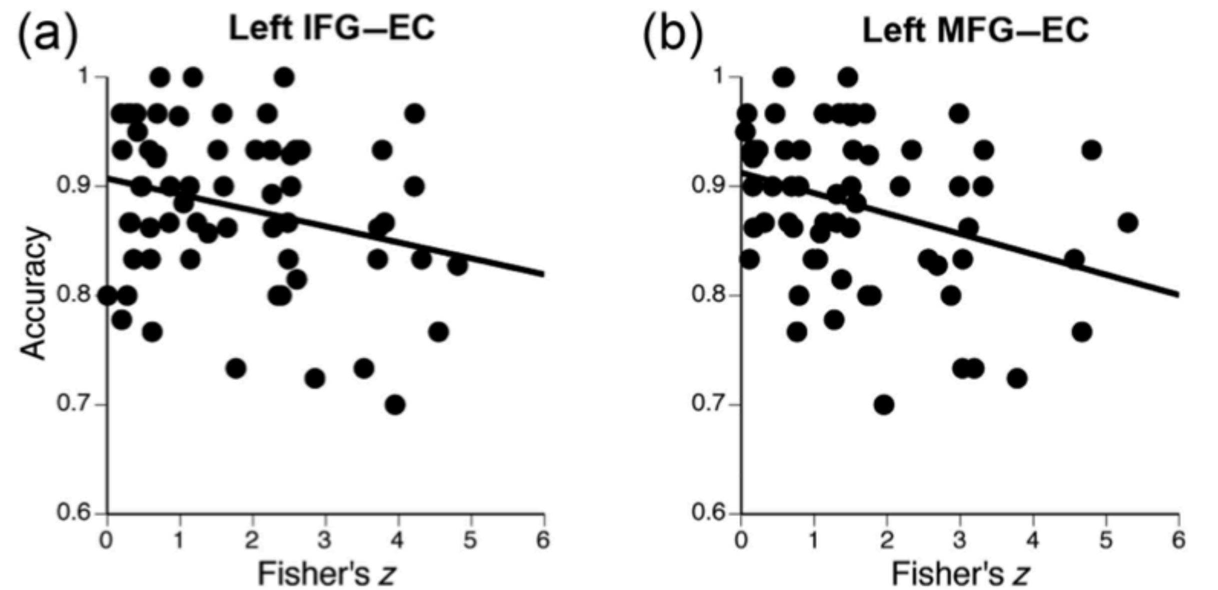


Figure 4. Connectivity Similarity relationships with behavior. Connectivity Similarity was comparably associated with accuracy for the (*a*) left IFG–EC and (*b*) left MFG–EC pairs. Note that the Connectivity Similarity metric is a difference score, thus smaller values are indicative of greater similarity.

Cohen et al. (2012), *Cerebral Cortex*

Pros & cons of beta series correlation method

- Pros:
  - Can examine how functional interactions between regions evolve over the course of a multi-stage trial
  - Relatively simple to implement (demo to follow)

- Cons:
  - Cannot determine whether inter-regional correlations reflect direct or indirect communication
  - Single trial activity estimates can be quite noisy
  - Serially-positioned HRF-convolved regressors may not provide ideal fit to data
  - Not ideal for rapid, jittered event-related designs
    - But might work with modified GLM model (Mumford et al., 2012)

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Deconvolving BOLD activation in event-related designs for multivoxel pattern classification analyses

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ABSTRACT

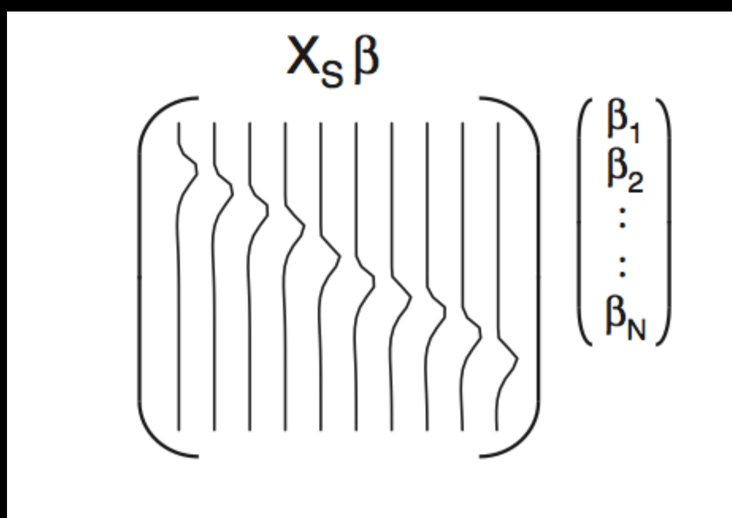
Use of multivoxel pattern analysis (MVPA) to predict the cognitive state of a subject during task performance has become a popular focus of fMRI studies. The input to these analyses consists of activation patterns corresponding to different tasks or stimulus types. These activation patterns are fairly straightforward to calculate for blocked trials or slow event-related designs, but for rapid event-related designs the evoked BOLD signal for adjacent trials will overlap in time, complicating the identification of signal unique to specific trials. Rapid event-related designs are often preferred because they allow for more stimuli to be presented and subjects tend to be more focused on the task, and thus it would be beneficial to be able to use these types of designs in MVPA analyses. The present work compares 8 different models for estimating trial-by-trial activation patterns for a range of rapid event-related designs varying by interstimulus interval and signal-to-noise ratio. The most effective approach obtains each trial's estimate through a general linear model including a regressor for that trial as well as another regressor for all other trials. Through the analysis of both simulated and real data we have found that this model shows some improvement over the standard approaches for obtaining activation patterns. The resulting trial-by-trial estimates are more representative of the true activation magnitudes, leading to a boost in classification accuracy in fast event-related designs with higher signal-to-noise. This provides the potential for fMRI studies that allow simultaneous optimization of both univariate and MVPA approaches.

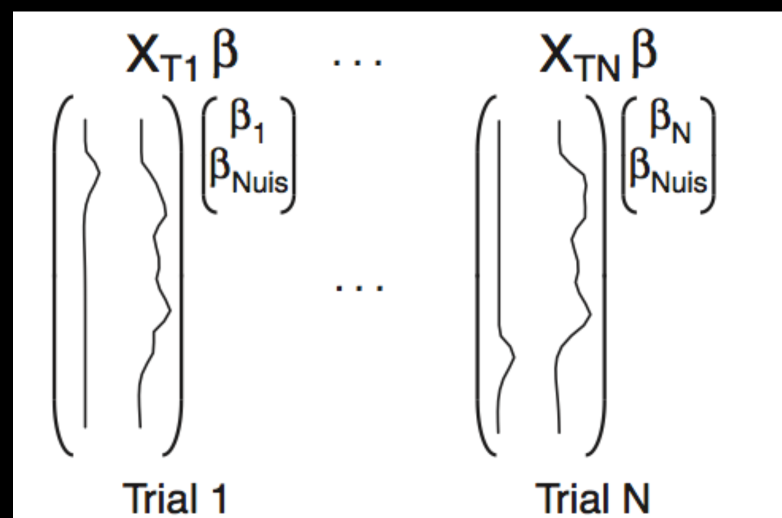
"Beta Series 2.0"

a.k.a. Least Squares Separate (LSS) model

<u>The Turner (2010) / Mumford et al., (2012) approach:</u>

- Estimate each trial's activity through a univariate GLM including one regressor for that trial as well as another regressor for all other trials.
    - Like beta series estimation approach, but involves running **many separate GLMs** (# of GLMs = # of trials)





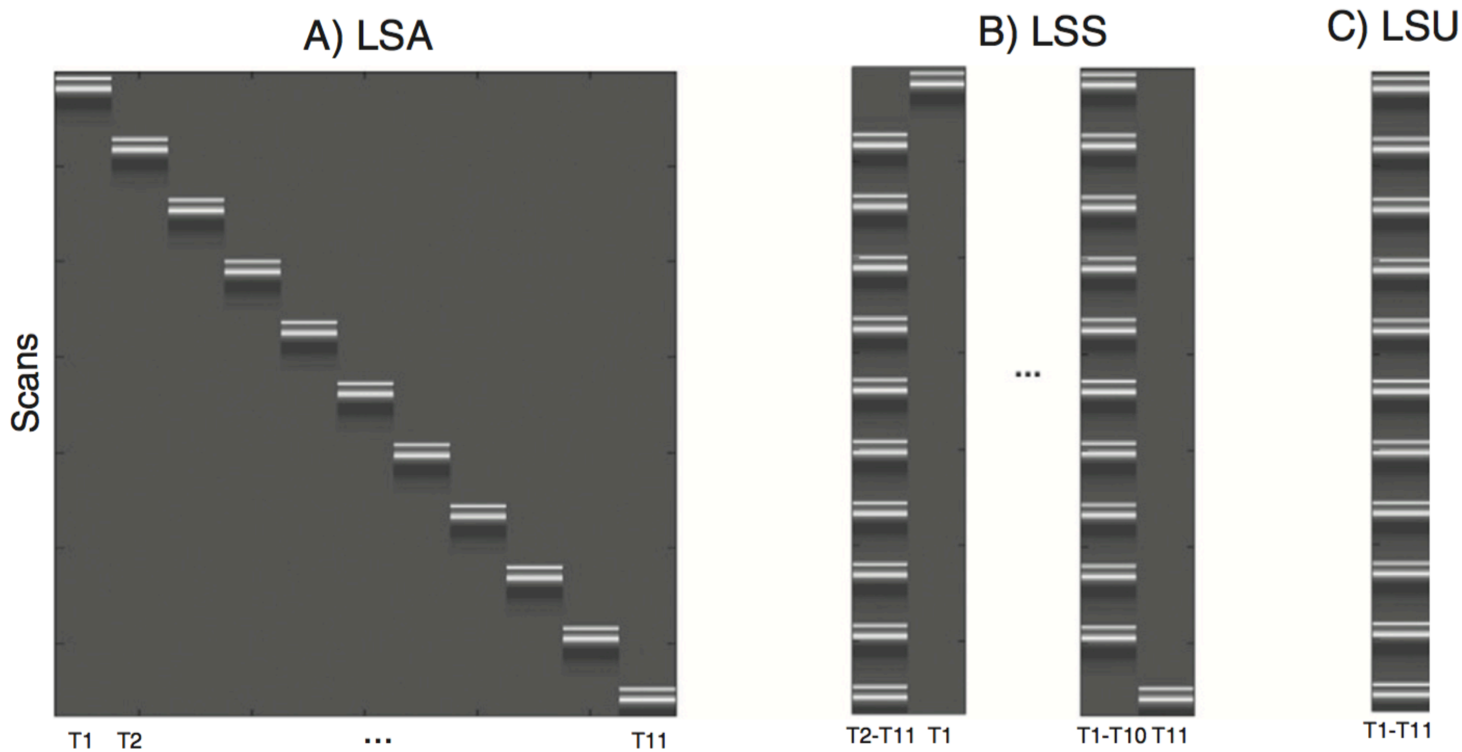


Fig. 1. Design matrices for (A) LSA (Least Squares-All), (B) LSS (Least Squares-Separate) and (C) LSU (Least Squares-Unitary). T(number) = Trial number.

"LSS effectively imposes a form of regularization of parameter estimates over time, resulting in smoother Beta series. This makes the estimates less prone to scan noise, which can help trial-based functional connectivity analyses too."