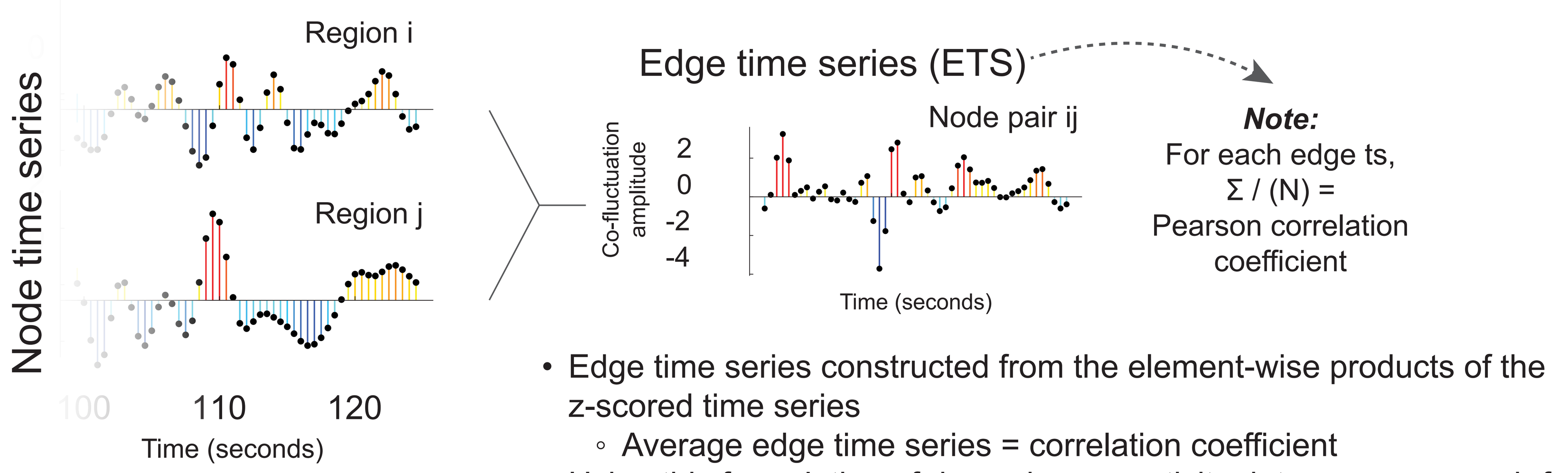
On the features of spiking connectivity

Joshua Faskowitz[1], Javier Gonzalez-Castillo[1],
Daniel A. Handwerker[1], Peter A. Bandettini[1,2]

[1] Section on Functional Imaging Methods,
[2] Functional Magnetic Resonance Imaging Core Facility,
National Institute of Mental Health, Bethesda, USA

Introduction

- The concept of functional connectivity is pervasive in modern fMRI research
  - Static functional correlation reveals *what* regions similarly fluctuate, i.e. highly correlated areas
  - Measuring dynamic similarities reveals *how* regions fluctuate over time, potentially falling in and out of synchrony on the scale of minutes, or even seconds
    - A long-standing finding in fMRI connectivity analysis is that punctuated moments in time contribute disproportionately to time-averaged similarity[1,2,7,9,12,14]
- **Edge time series**[3,14] render connectivity dynamics at the temporal resolution of the input time series
  - Using edge time series, we can extract features of connectivity dynamics, such as high-amplitude events and windows of variable fluctuation patterns. Such features have the potential to further our understanding of brain communication, as observed using fMRI.

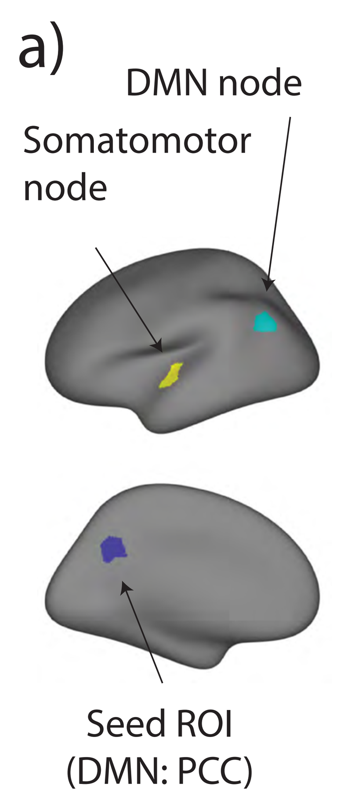


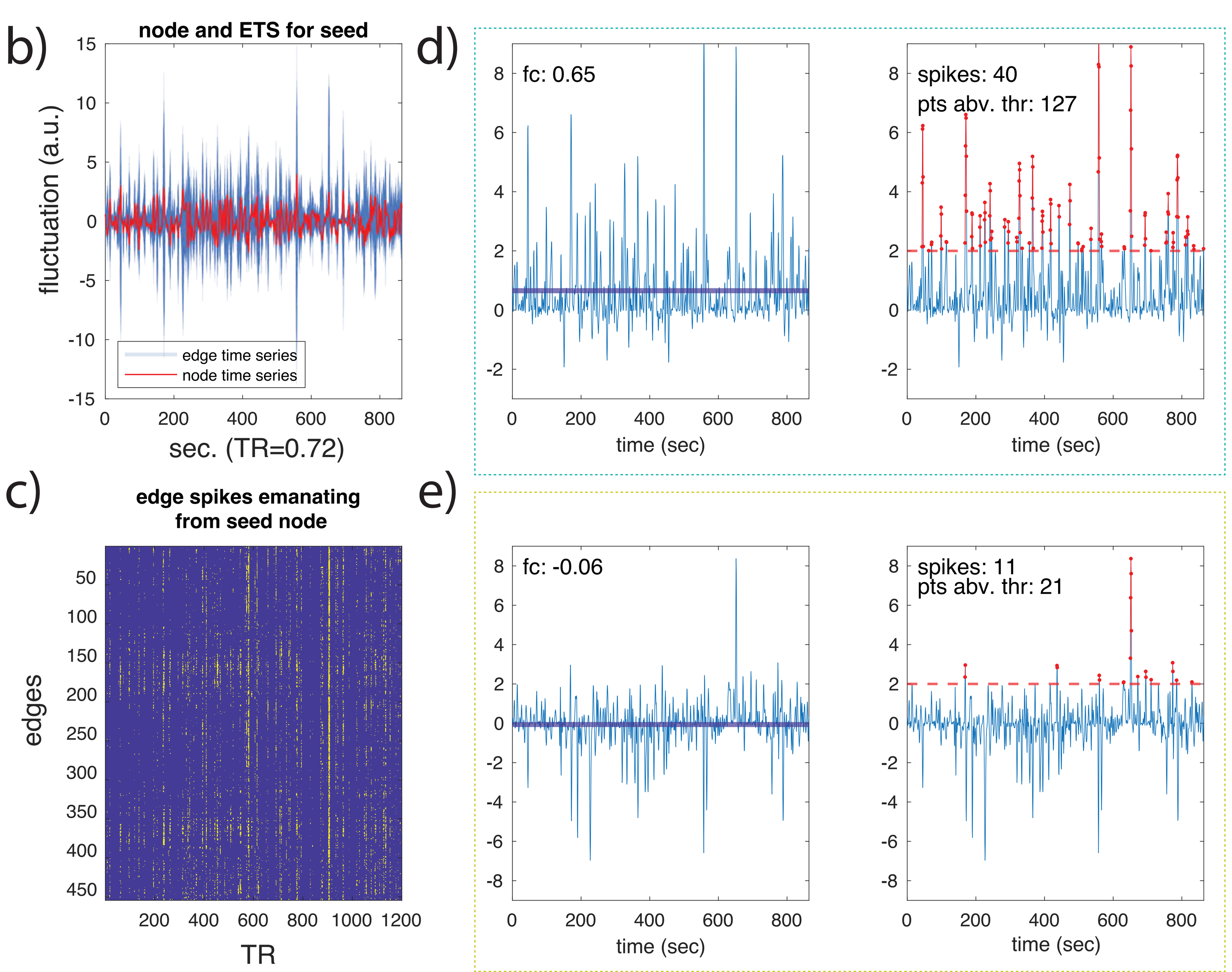
- Edge time series constructed from the element-wise products of the z-scored time series
  - Average edge time series = correlation coefficient
- Using this formulation of dynamic connectivity data, we can search for new features to differentiate different similarity patterns

Methods

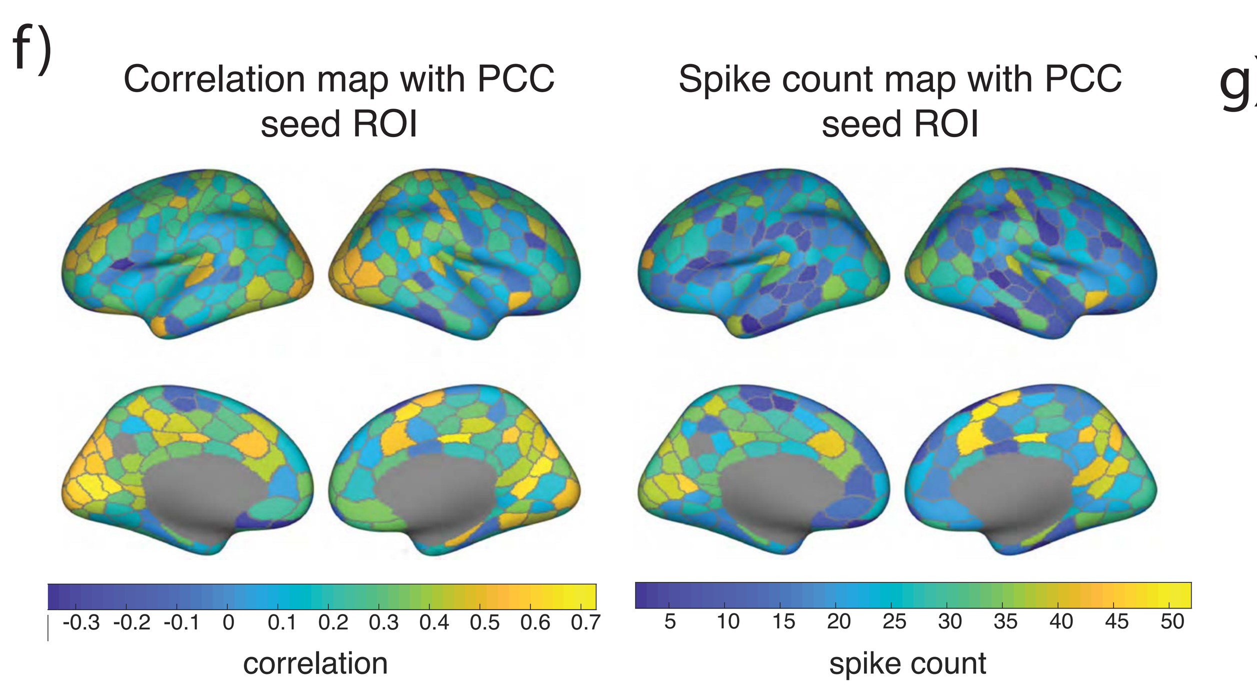
- **HCP**
  - Human Connectome Project resting-state data from 50 research subjects (0.72 TR, 1200 TRs, ~15 mins)
  - Minimally pre-processed: motion, distortion, high-pass filtering
  - Nuisance regressed using ICA FIX, plus average CSF and WM traces. Time series constructed by averaging vertex data within 400 node of Schaefer parcellation[10], at each time point, using Connectome Workbench
- **NIH Multi-task**
  - 7T data collected at NIH[4] from 20 research (1.5 TR, 1017 TRs, ~25 mins)
  - Preprocessed using AFNI including despiking, physiological noise correction (RETROICOR, respiration, and heart rate regressors), motion correction, motion regression, and ANATICOR
  - Subjects underwent 4 tasks (rest, memory, video, math) of 180 sec, with 12 sec instruction periods
  - Time series constructed using Yan homotopic parcellation[13], and filtered 0.006-0.18 Hz[6]
- **Edge time series**
  - Computed via the element-wise product of two z-scored time series; sum of which is correlation
  - High-amplitude events (i.e. spikes) defined as contiguous instances edge time series exceed threshold of 2

Results





- Connectivity information can be recapitulated using counts of high-amplitude edge time series spikes
- Results are robust to arbitrary changes in spike threshold



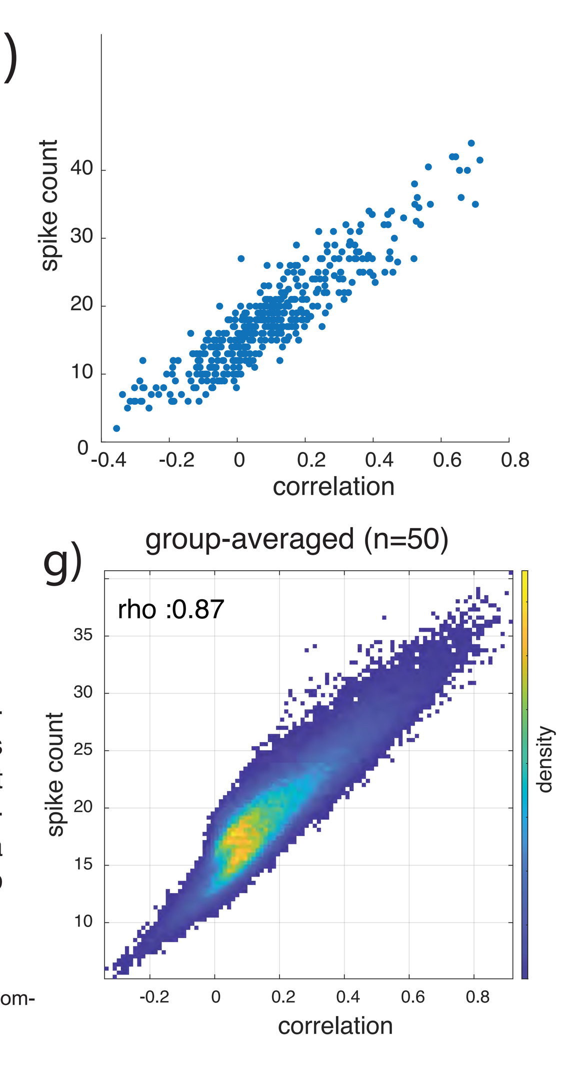
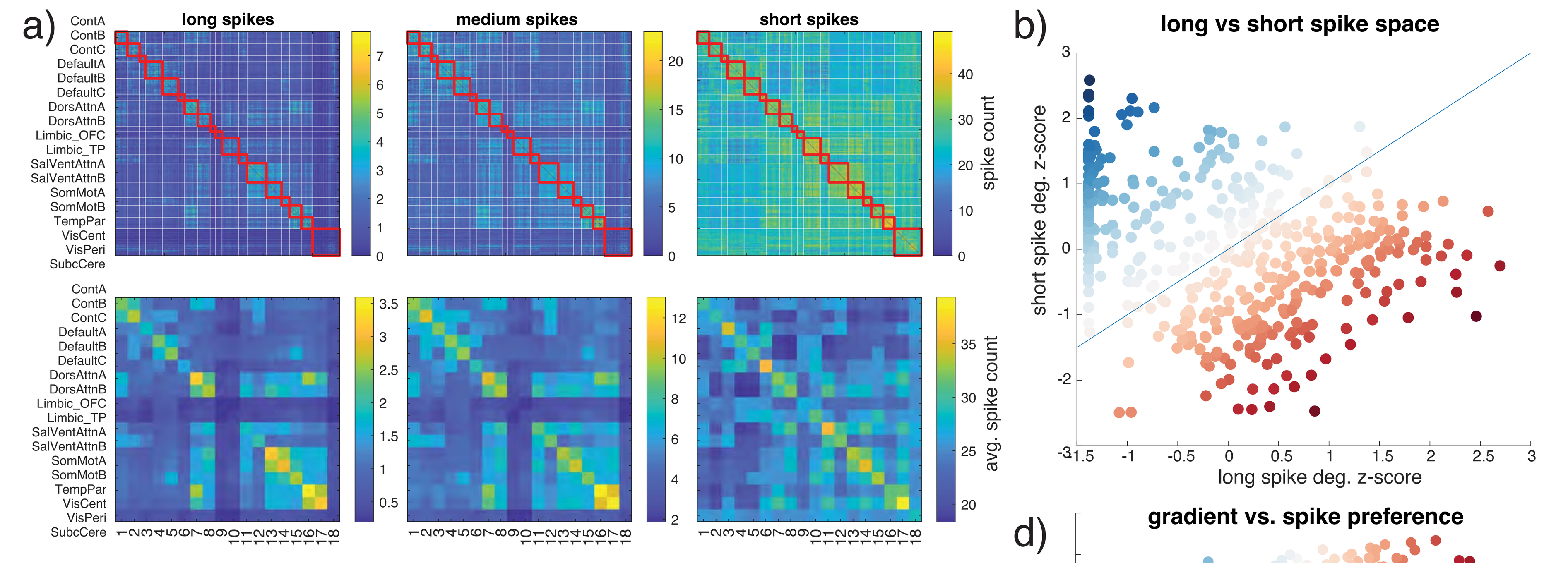


Figure 1. a) Visualization of seed node and target nodes in DMN and somatomotor systems. **b)** Visualization of seed node time series (red) and associated edge time series (blue). **c)** Raster of spikes from 454 emanating edges of seed node. **d)** "High"-connectivity edge time series, with spike count and number of supra-threshold points plotted to the right; corresponding visualization for a "low"-connectivity edge depicted in **e**. **f)** Cortical surface map of correlation and spike counts, which have a high spatial similarity, shown in scatter plot of **g**, top; the similarity between correlation holds for group avg. data, bottom, as expected based on canonical findings on point processes for fMRI[2,14]

This research was made possible thanks to the support of the NIMH Intramural Research Program ZIA-MH002783. This work utilized the computational resources of the NIH HPC Biowulf cluster (hpc.nih.gov).

Checkout profile github.com/faskowit/ for example code in MATLAB



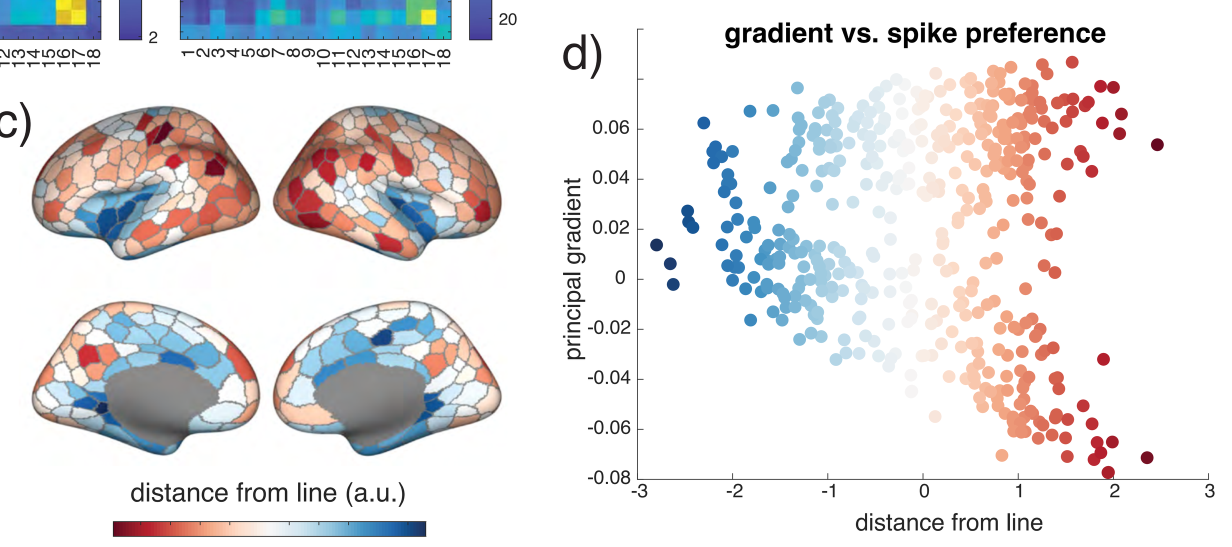


Figure 2. **a)** Group averaged edge spike count matrices (top), separated by spike duration into short (0.72-2.88 sec), medium (2.88-5.76 sec) and long (> 5.76 sec) supra threshold activity; information is groups by functional system. **b)** Short and long spike matrices were summed, z-scored, and plotted to illustrate the short vs. long spiking propensity for each node, which is also visualized on the surface in **c**; points are colored by the distance normal to the identity line. **d)** This distance is seemingly orthogonal to the 1st gradient of functional connectivity[8], defined as the principal axis of variation of the functional connectivity matrix.

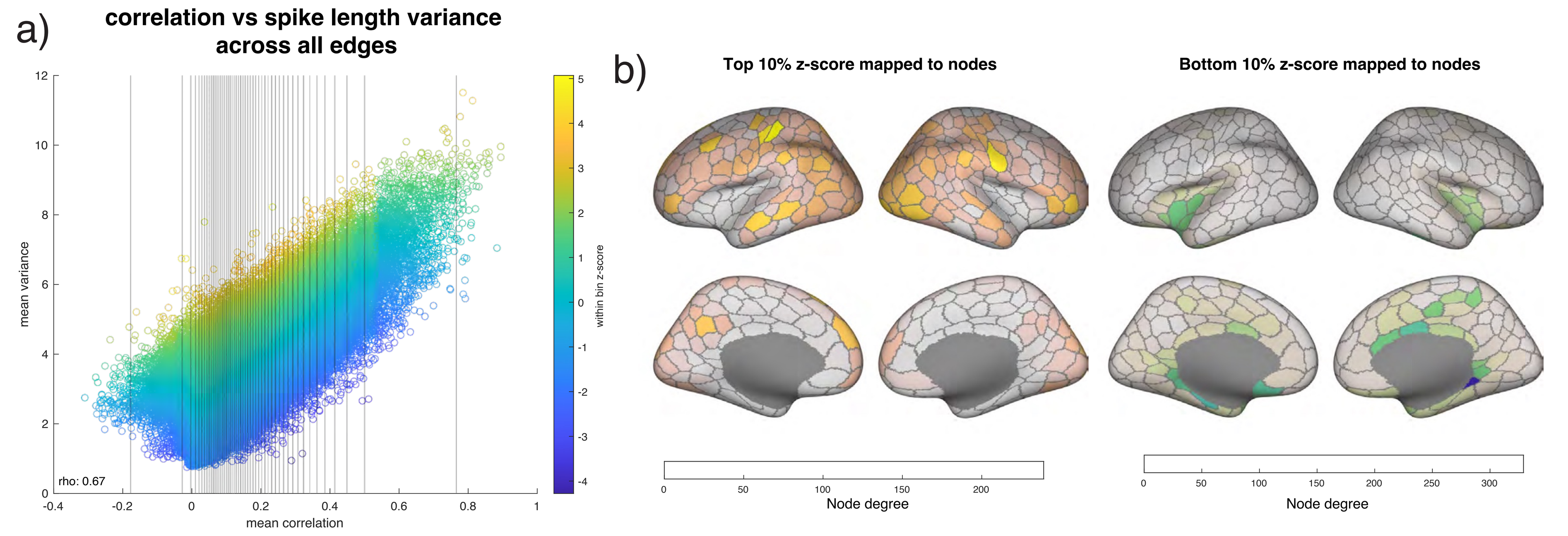
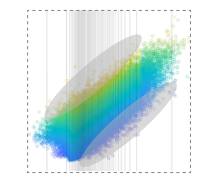


Figure 3. **a)** Across all edges of 400-node data, positive relationship between Pearson correlation of edge, and the spike length variability (the variance of spike lengths over the course of resting state session); for each 2% bin of correlation values, we identify edges that have relatively high or low variability (z-score color map) **b**) Top and bottom 10% z-scored valued edges, mapped to node surface; these maps show which nodes have edges (illustrated as gray ellipses to the right) with consistent length emanating edges (**b**, right) versus variable length (**b**, left)



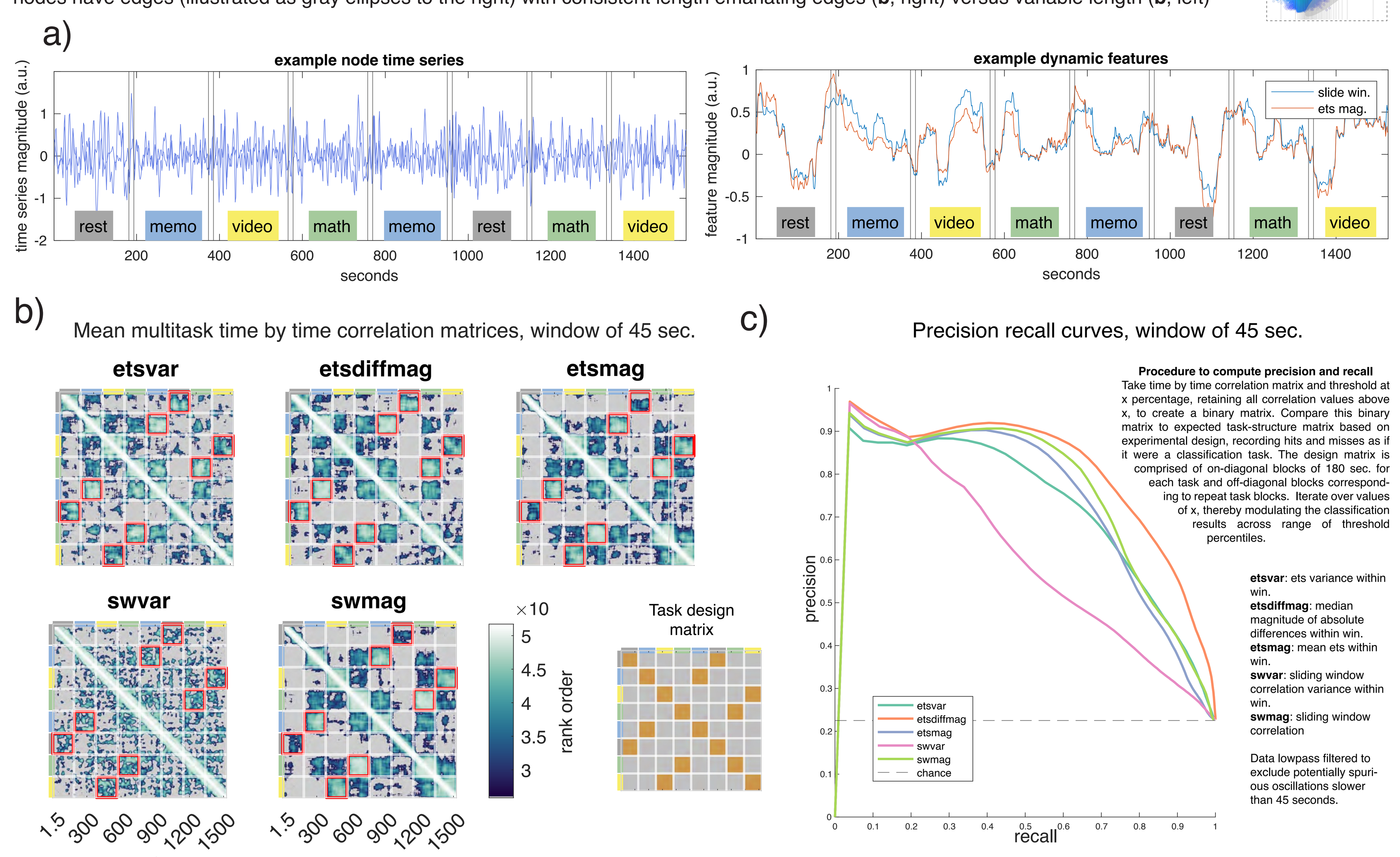


Figure 4. **a)** Using multi-task fMRI data, we can ask if there are dynamic connectivity-based features that correspond to different task demands or states; furthermore, could these features identify not only task blocks, but repeat presentation of tasks (off-diagonal red squares in panel **b** separated in time. Example time series shown on left, and their time-varying features on the right. **b**) Time-by-time correlation matrices constructed from different representations of connectivity dynamics; ideal data perfectly capturing task structure would fill on-diagonal blocks and off-diagonal blocks (see task design matrix, orange); data is median thresholded and colored by rank to facilitate comparison. **c**) Precision-recall curves generated by thresholding the dynamic connectivity matrices for each method, and treating the comparison of thresholded data to the design matrix as classification task

Discussion

- By virtue of unwrapping correlation into its moment-to-moment contributions, edge time series reveal the manners in which correlation values are realized. Although it is a mathematical necessity that the expected value (i.e., average) of edge time series equals correlation, here we demonstrate how there are variations in how correlations evolve over time.
  - In Figure 1, we illustrated a longstanding finding in the field[1,2,7,9,12,14], showing how connectivity can be estimated by simply counting punctuated high amplitude events (i.e., spikes) [11,14]
  - Connectivity spikes can be sorted by duration (Figure 2), which could reveal how different canonical systems correlate via patterns with different time scales; system to system correlation spike activity differs based on spike length sorting.
  - There is a strong relationship between correlation magnitude and spike length variability (Figure 3), but using z-score normalization we can ask, given a certain correlation magnitude, how variable is an edge; we can then evaluate which nodes have more heterogeneous versus uniform spike patterns emanating from them.
  - Since edge time series allows access to moment-by-moment connectivity information, we can extract connectivity features to differentiate different task states[4] (Figure 4); using edge time series to read variability information, such as the magnitude of moment-by-moment changes[5], has the potential to better correspond with task structure.
- An outstanding challenge is to ground spiking and edge time series temporal patterns with known functional neuroanatomy, and to use these patterns to establish how different cognitive systems might communicate during tasks and rest. In pursuit of this work, emphasis needs to be placed on separating real dynamic patterns from noise or statistically-based patterns.

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