# Temporal topological transformation in dynamic MEG-derived graph sequences

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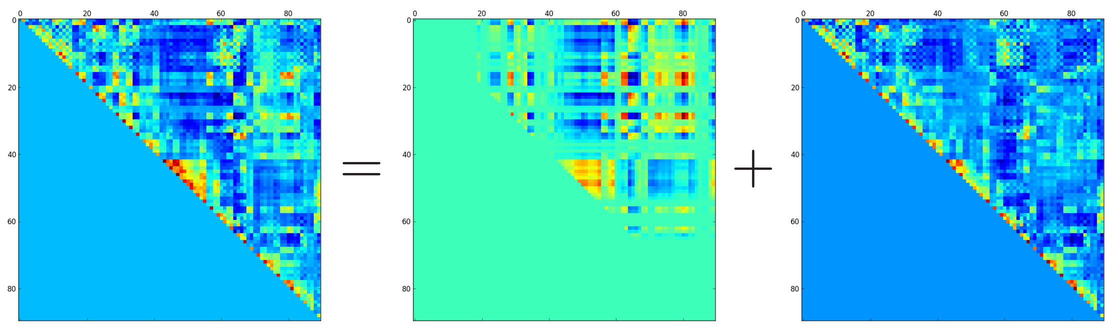
## Contribution

We present a framework for analyzing the topological evolution of graphs derived from MEG data with these new approaches:

1. Inferring graph sequences using sparse matrix separation and stabilizing heuristics.
2. Thresholding graph sequences using the theory of random matrices.
3. Abstract, motif-based, analysis.

## Sparse Separation

For a given matrix $M$, we decompose $M = L + S$ via the augmented Lagrangian alternating direction method, where $L$ is a matrix of low rank[a] and $S$ is a sparse matrix.




Physiologically, we justify this approach by hypothesizing that there are more MEG channels than there are truly independent signals of interest at a given point in time.

[a]Here, rank is automatically estimated by rank-revealing QR factorization

## Thanks

We thank the Natural Sciences and Engineering Research Council of Canada for funding.

## Future Directions

- Cross-validation on real and synthetic data, looking for consistent topology with varying pipelines.
- Optimization of edge stabilization heuristic function.
- Parameter optimization for window size/width and choice of graph metrics.
- Analysis of higher-order motifs and tabulation of common motif transformations.

## References

[1] Stam, C. J., Nolte, G., and Daffertshofer, A. Phase lag index: Assessment of functional connectivity from multi channel EEG and MEG with diminished bias from common sources. *Human Brain Mapping*, 28(11):1178–1193.

[2] Nicol, R. M., Chapman, S. C., Vértes, P. E., Nathan, P. J., Smith, M. L., Shtyrov, Y., and Bullmore, E. T. Fast reconfiguration of high-frequency brain networks in response to surprising changes in auditory input. *Journal of Neurophysiology*, 107(5):1421–1430.

## Step 1: Building Graph Sequences

We divide the set of all (preprocessed and bandpass-filtered) MEG gradiometer signals into (possibly overlapping) temporal windows and for each window we compute

1. A matrix of the *phase locking index*[1]: $\left|\frac{1}{N}\sum_{k=0}^{N-1} \mathrm{sign}(\phi_{x_i}(k) - \phi_{x_j}(k))\right|^a$ for all channel pairs $(i, j)$.
2. A *sparse separation* of this matrix into the sum of a low(er)-rank matrix and a sparse noise matrix.

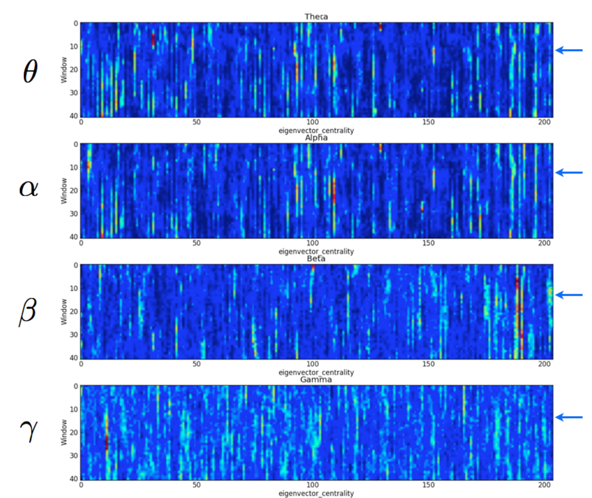
The noise matrices are discarded and the resulting sequence of low-rank matrices is then subjected to *heuristic edge stabilization*, in which matrix entries are "smoothed" across the temporal dimension. This might be a simple low-pass filter or an arbitrarily complex scoring function. After smoothing, each matrix is thresholded into a sequence of graph adjacency matrices using an approach based on random matrix theory[b]

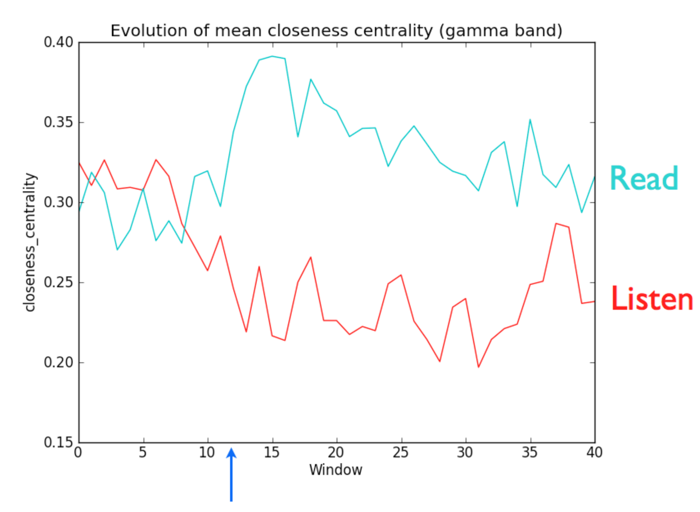
[a] $\phi_x(t) = \arctan \frac{\bar{x}(t)}{x(t)}$ is the instantaneous phase of timeseries $x(t)$ and $\bar{x}(t)$ denotes the Hilbert transform of $x(t)$

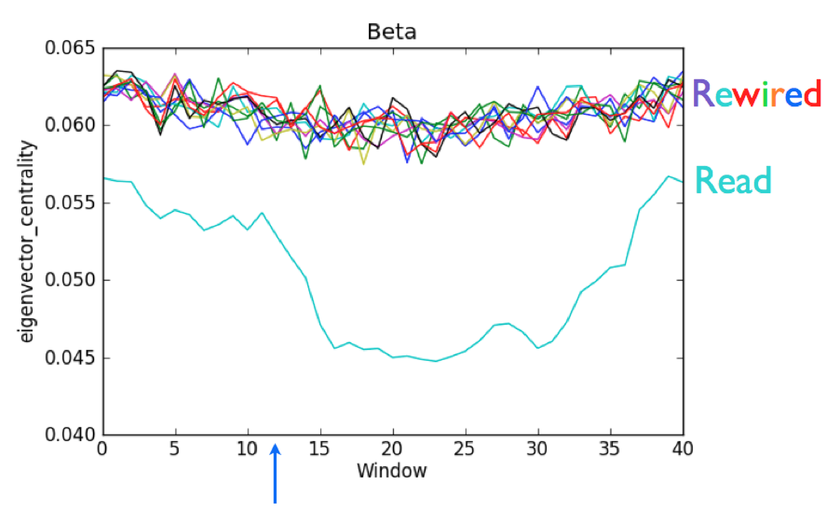
[b]We compute the set of eigenvalues for *all* matrices in a sequence and compensate for bias using standard spectral unfolding procedures. We next observe the *spacings* of the unfolded eigenvalues. Random matrix theory demonstrates that such spacings in a matrix dominated by noise will follow Gaussian Orthogonal Ensemble statistics; in a highly-modular matrix, they will follow Poisson statistics. The correct threshold is the one which makes the matrix "Poisson enough" for us (determined by Anderson-Darling goodness-of-fit test to an exponential distribution).

## Step 2: Analyzing Graph Sequences

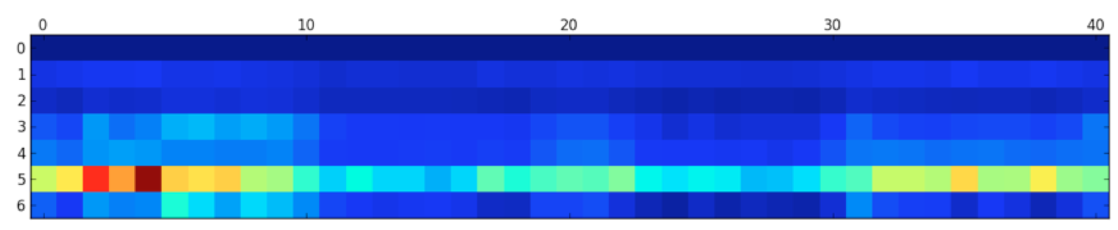
Given this sequence of graphs, we can now compute sequences of per-node(first figure), and whole-graph(second figure)[a], metrics to quantify the change in graph topology over time, under various experimental conditions. Statistical significance can be quantified by comparing to sequences of graphs subjected to degree-preserving edge permutation(third figure). Arrows denote task onset; task involved either reading a word or listening to a spoken word.



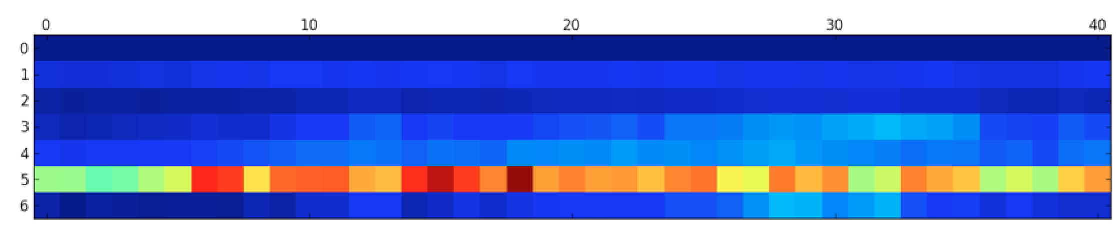



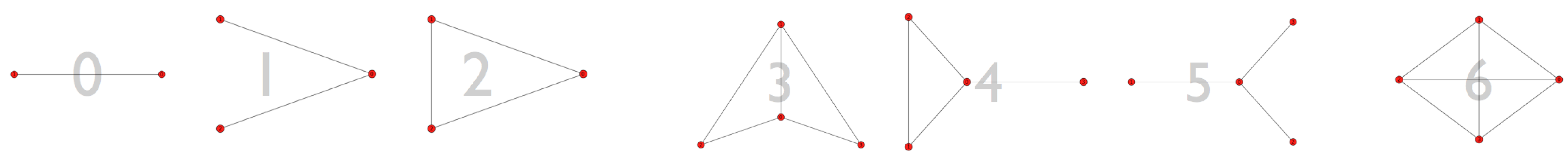

At a higher level of abstraction – removed completely from spatial embedding – we can quantify more general topological properties of the graphs, such as counts of subgraph motifs (figure below) and the number of nonisomorphic motifs of a given order.



Motif evolution during Listen task



Motif evolution during Read task




Motifs

[a]This is similar to the work of Nicol et. al.[2], though we compare timeseries, and build graphs, in a different manner

## Threats

- **Network-estimation approach is crude.** Existing, more elegant, approaches place constraints on the statistics of the data sources (e.g., GLASSO-like) and/or require convex likelihood functions (e.g., TESLA). Our approach operates at a higher level of abstraction and permits the use of arbitrary timeseries comparison metrics.
- **Too abstract.** Things which cannot be seen "in the small" are sometimes visible abstractly (e.g., changes in global topology). Concerns regarding whether one abstracts noise, rather than signal, can be addressed by searching for concordant results while varying every stage of the pipeline (e.g., different time series metrics).