THE SPATIO-TEMPORAL ARCHITECTURE OF AUDITORY STATISTICAL LEARNING

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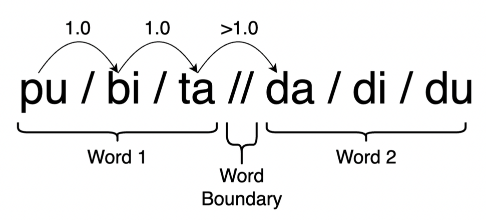
Research Q's

- How does auditory SL unfold over time in the brain?
- Are there "states" of learning, characterized by their neural profiles?
- Are "states" predictive of behavioral responses or other outcomes?

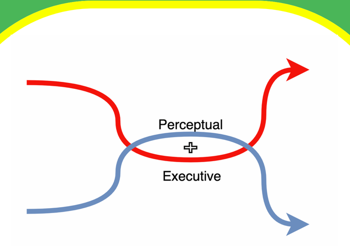
Background

$$P(Y|X) = \frac{P(X \cap Y)}{P(X)}$$

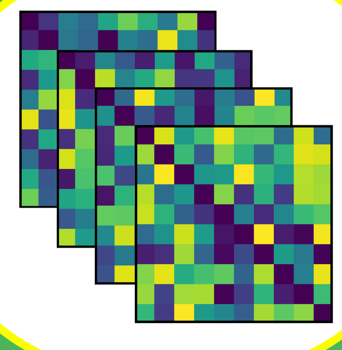


- Auditory statistical learning (SL) is the ability to identify, track and extract patterns of regularity from complex auditory input.
- This can be done by identifying transitional probabilities (TPs)[6].

- Perceptual regions (like the STG) are often implicated in auditory SL [4].
- Functional links across executive regions, like the DAN and DMN have also been observed [8].
- Distinct ICA networks exist during learning from speech[5].
- Learning does not occur immediately. One must detect that there is structure, encode the structure and utilize this to make predictions.



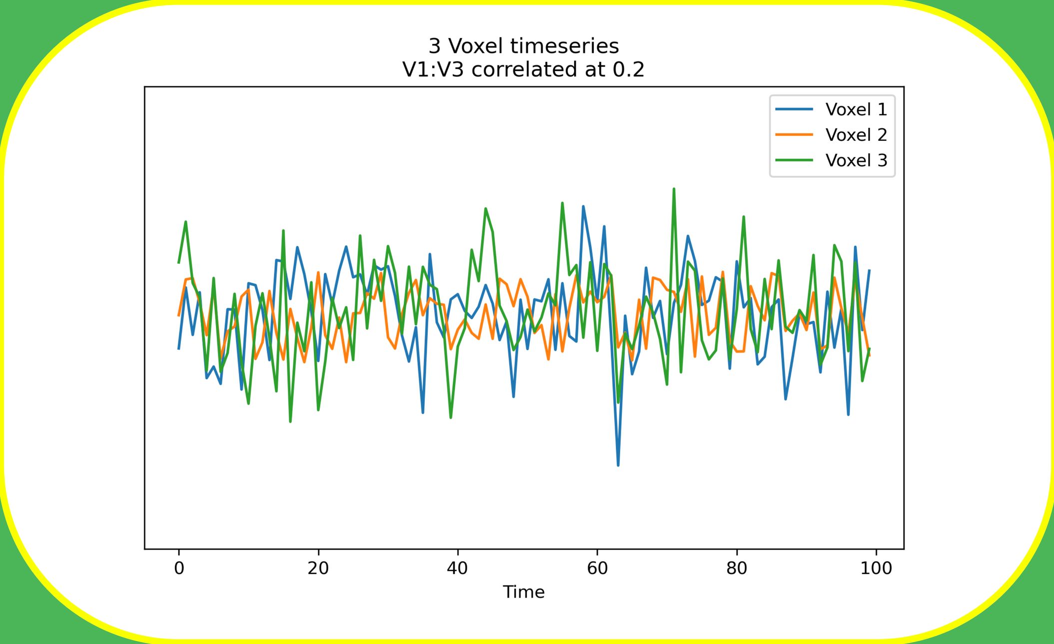
- A "dual-stream" model suggests that perceptual and executive regions and top-down and bottom up mechanisms work together to scaffold SL[2, 3].
- We propose a 3-process model of SL (3PSL) in which a detection process, encoding process and prediction process are all distinct subcomponents of SL that occur along different timescales and neural space.

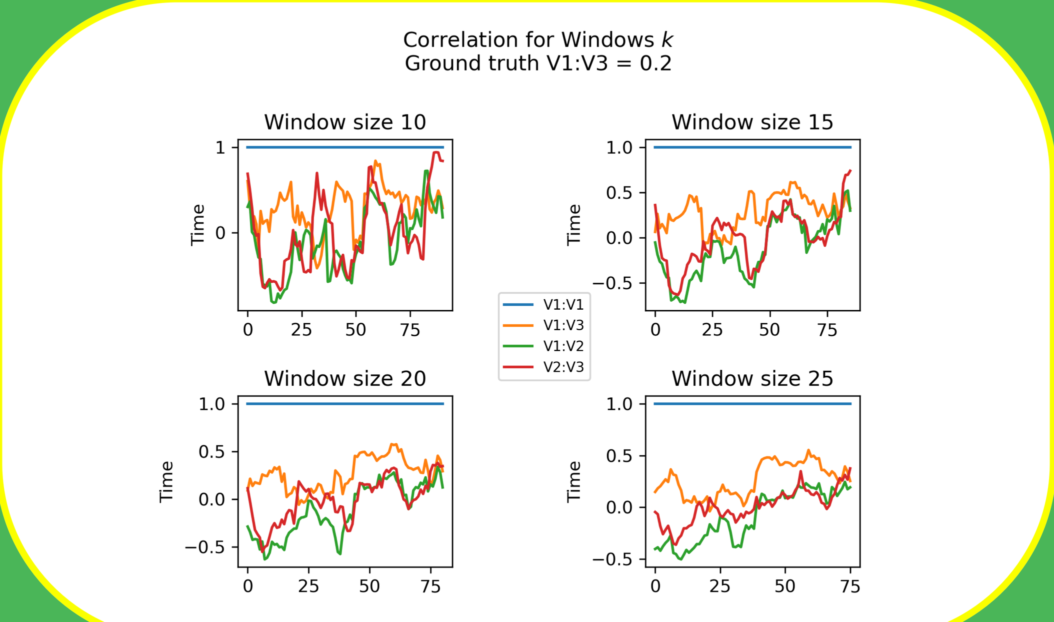


- We posit that each process will be characterized by its neural profile with distinct networks of activation across different timescales.

Proposed Methods

Dynamic Functional Connectivity[9]





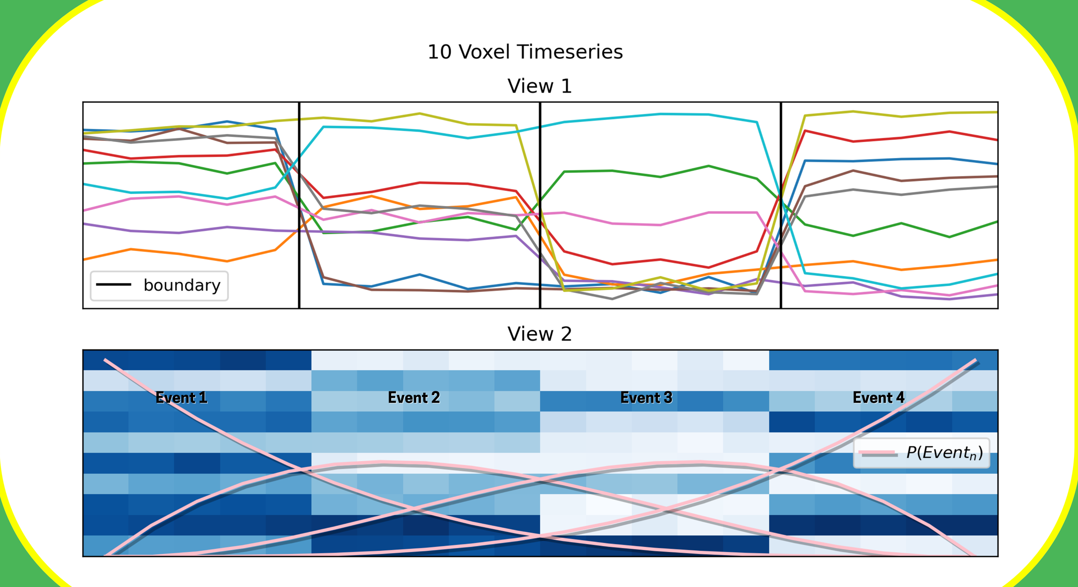
Simple simulated example:

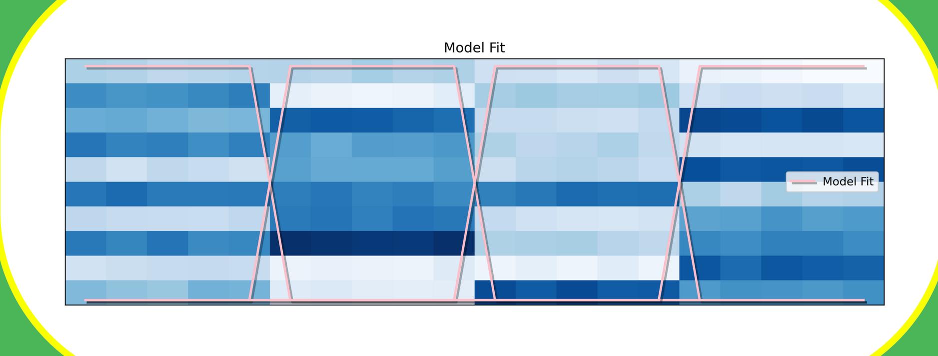
- Here, we have a timeseries of 3 voxels. Voxels 1 and 3 have a ground truth correlation of approximately 0.2.
- Static functional connectivity looks at this time-series as a single unit.
- Dynamic/sliding window looks at this across the temporal dimension.

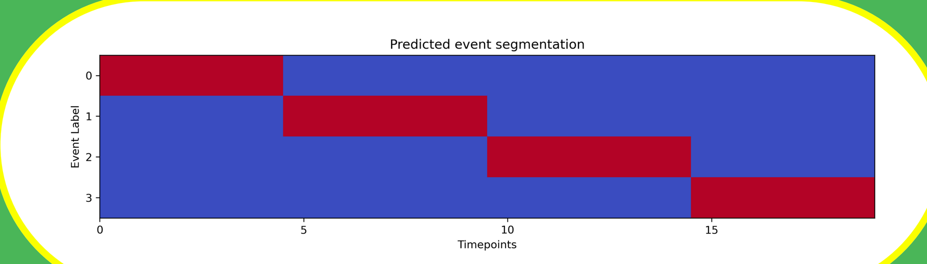
Choosing a window length:

- Goal: capture covariance over time.
- Things to note: windows should be small enough to detect change, but large enough to actually measure quantity of interest.
- Optimal window = 30-100s.

Hidden Markov Model[1]







Simple simulated example:

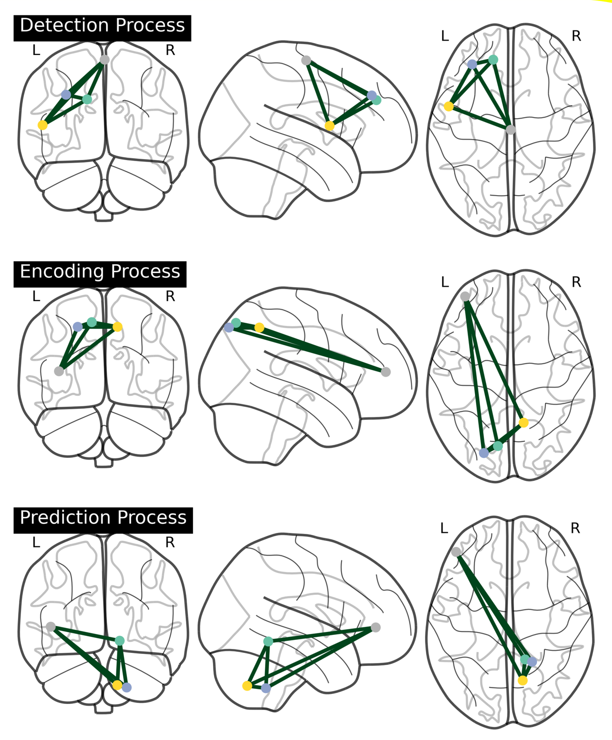
- 10 voxel timeseries where stable patterns of activity shift at predefined time points, t_n.
- The HMM works by estimating the patterns within each event and to what Event_n each time point, t_n ,belongs to.
- Here, we provide the model with ground truth of number of events (4), and can assess model fit.
- A nested cross-validation approach is used to make group level inferences

This Experiment

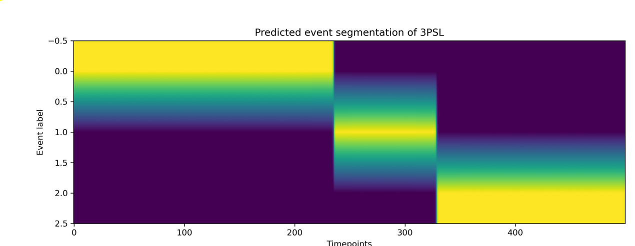
Experiment Design & Paradigm

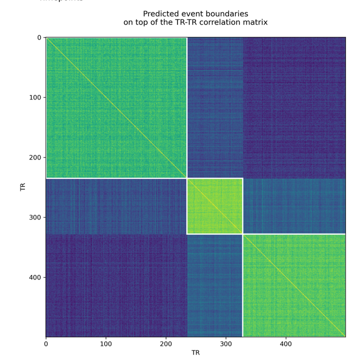
- 6 minute exposure of either structured or unstructured speech sequence in scanner[6].
- 3AFC in which a word from the exposure, a part word and foil are presented.
- Participants must choose the word from these three choices.

Expected Results



- FC in perceptual regions.
- FC in executive regions.
- FC in prediction regions.





- Expected 3 events states from time-series.

Future applications

- Expanding to children and infants.
- Manipulating 3PSL states with real-time fMRI.
- Are states predictive of cognitive deficits?

References

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Supplementals

The code used to generate figures can be found on my GitHub.

I am applying to PhD programs this cycle. Check out my website!

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