Triangulating Consciousness

PITFALLS AND FEEDBACK

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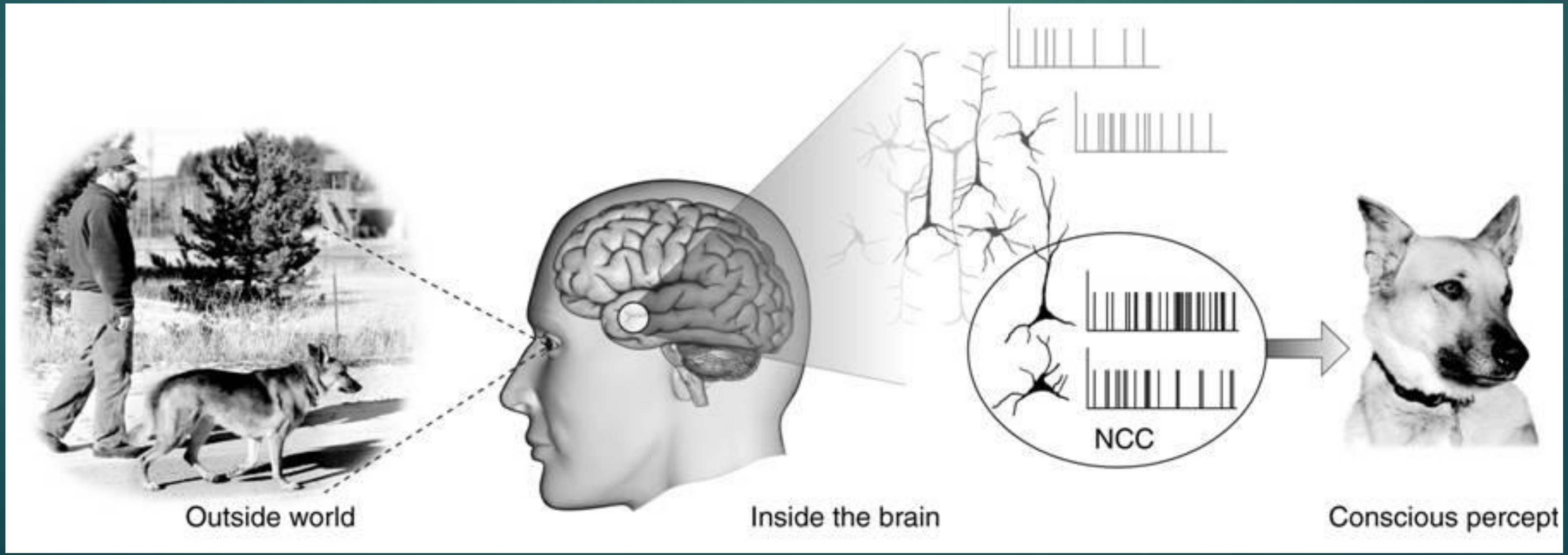
Introduction: The Neurocorrelates of Consciousness

- The set of minimal neuronal events jointly sufficient for a given conscious experience (Koch, 2003)
- Generally, NCCs are derived from experiments with 1 task, in which participants report immediately or delayed (Lepauvre & Melloni, 2021)
- However, task-related, report-related and post-perceptual neural signals may be confounds to true NCCs (Pitts et al. 2014, Schroeder et al., 2021).
- For example, recently Pitts et al. 2014 showed that the P3b, once thought to be a NCCs, was not present during a no-task inattentional blindness paradigm.

Introduction: The Neurocorrelates of Consciousness

- Not all stimuli are processed equally by the brain
- Some stimuli are experienced and could theoretically be responded to (seen), some are just never experienced (blinded).
- When the stimulus is task relevant, or when you respond to a stimulus, those stimuli are more than just conscious



Introduction: The Neurocorrelates of Consciousness

- In order to remove confounds from the analysis, we set to analyze three no-report tasks, with the same stimuli, but different mechanisms to induce visual (un)awareness.
- The project is data-driven, where we analyze the data in an unbiased manner, using machine learning to find the signals that are present in all three tasks
- We are also investigating 5 candidates for NCCs, including N140, P3b, Alpha suppression, late gamma bursts, and stability of activity patterns

Targeted Problems

1. How do you distinguish between a true NCC, and task- and report-related cognition?
2. How can I know which neural signal is a true NCC, and not a product of one particular task?
3. Can it be possible for a ML to learn from one task and generalize to another?
4. What can we learn from the ML about our NCCs?
5. Can we replicate these findings in different labs?

The Tasks

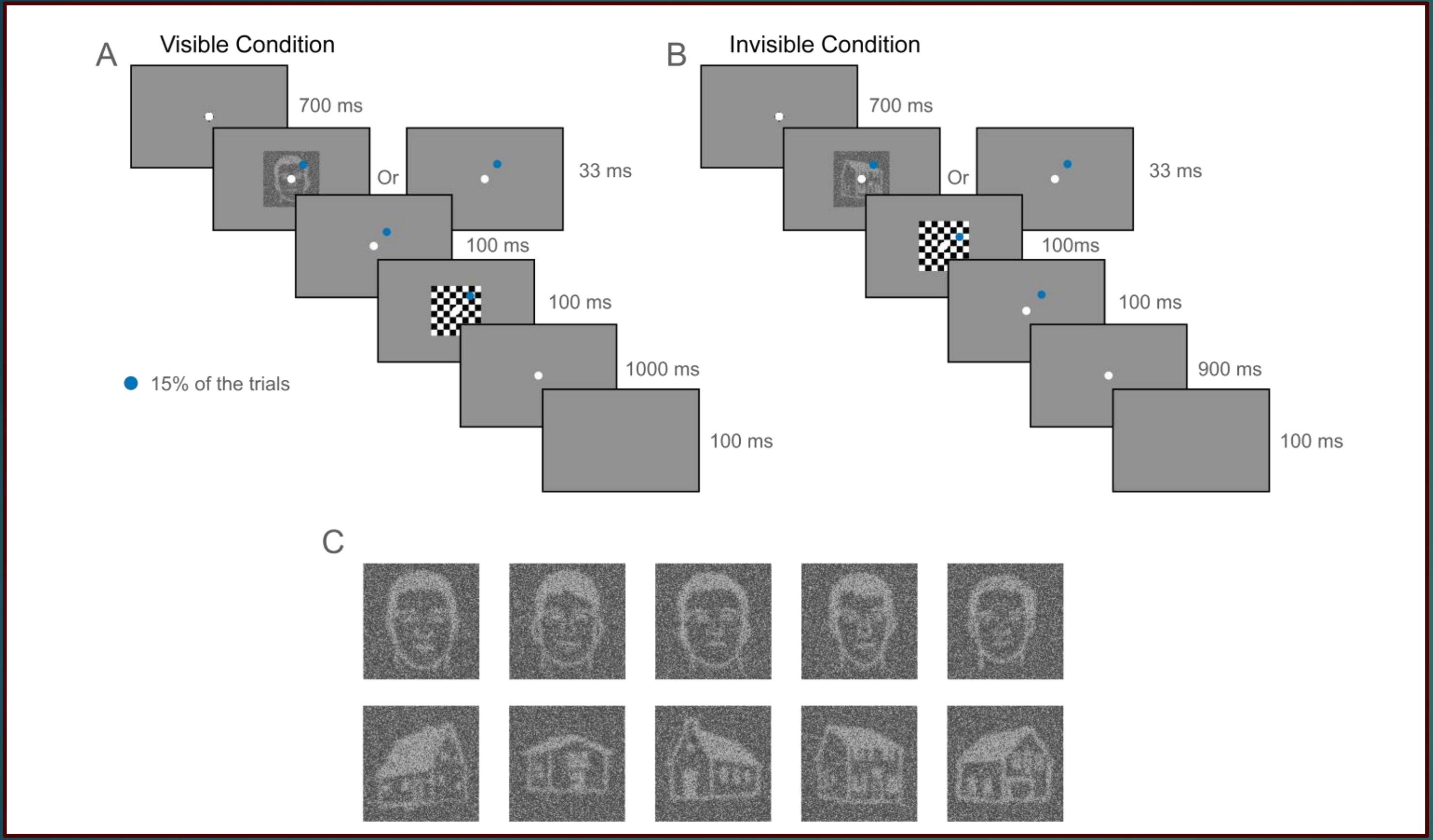
Backwards Masking

Inattentional Blindness

Dichoptic Color Fusion

- Very different approaches to manipulation of awareness
- Can be performed with same stimuli
- Can be performed without report

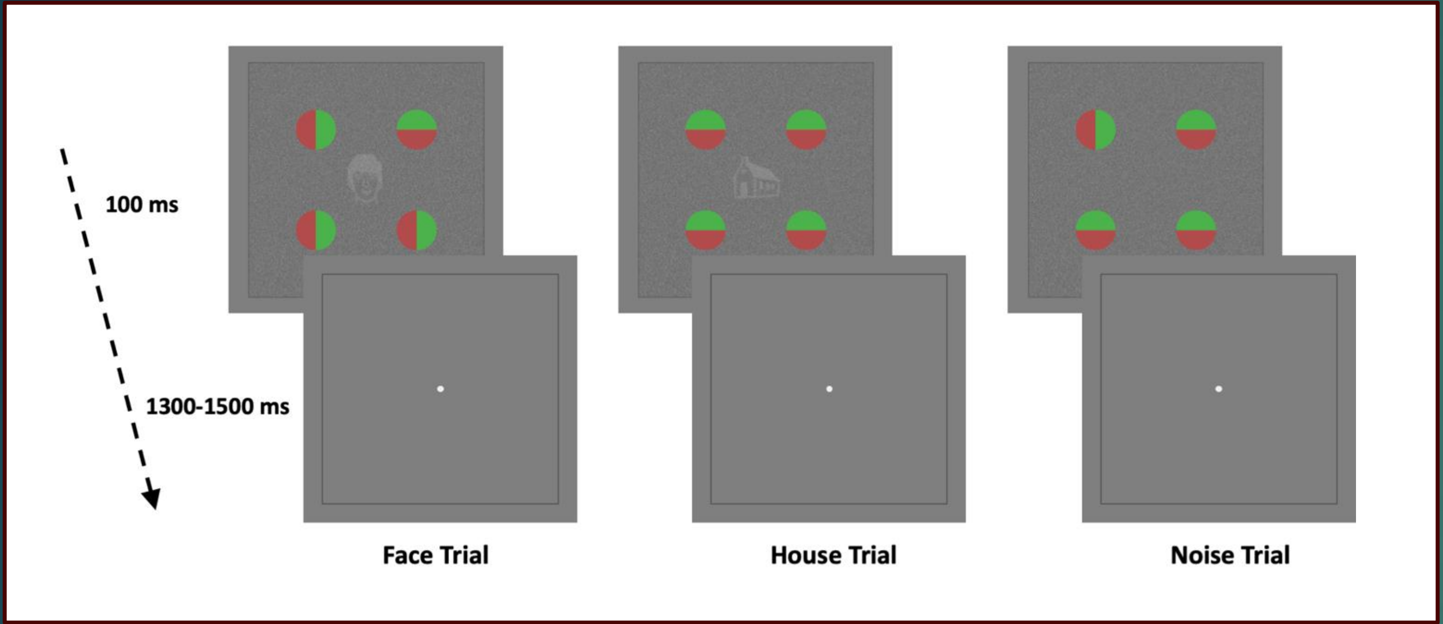
Backwards Masking



- Main task: in 15% of the trials, participants are instructed to click whether there is a blue circle in the screen.
- Conditions:
  - 25 ms SOA (invisible)
  - 100 ms SOA (visible)
- Phase 1: No-report
- Phase 2: Report

Examples of the stimuli and different trial types in the backward masking experiment. Face and house stimuli (or blanks) will be presented for 33ms, followed by a 100ms blank screen and then a 100ms mask (A: visible condition) or a 100ms mask and then a 100ms blank screen (B: invisible condition). On 15% of the trials, a small blue disk will be presented at a random location subtending the same area of the screen as the critical stimuli, and will serve as the task-relevant targets while the faces and houses will remain attended (spatially & temporally) but task-irrelevant. Examples of the face and house stimuli are shown in panel C.

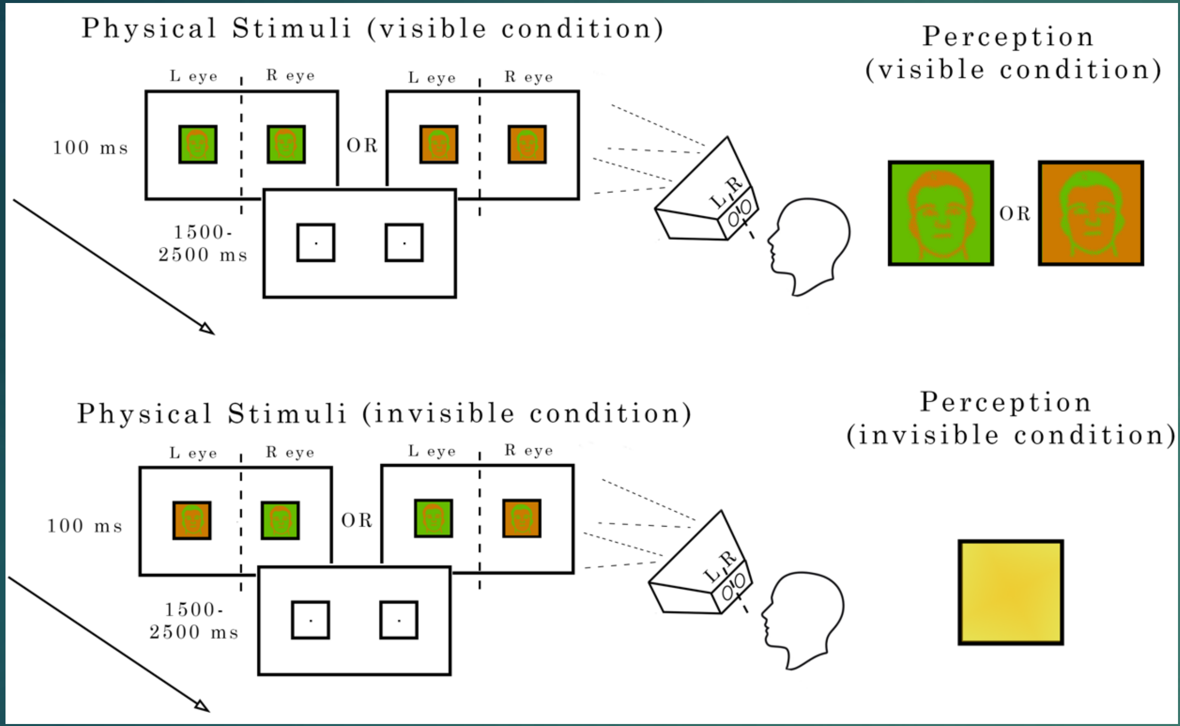
Inattentional Blindness



Face/Hose/Noise stimuli will be presented centrally at fixation for 100ms, together with four red/green circles presented in the periphery. In the example shown here, the top right circle is rotated in the face trial, and the bottom left circle is rotated in the noise trial, while the house trial shows an example of the circles oriented the same. In phase 1 and 2 subjects will perform a task on the color-bisected circles and in phase 3 they will discriminate faces/houses/noise. The physical stimuli will remain identical across all three phases.

- Main task: identify whether the circles are or are not facing the same direction
- In the center, a face , house, or nothing is shown
- Divided in 3 phases
  - Phase 1: “Blinded”
  - Phase 2: Not-blinded
  - Phase 3: Report

Dichoptic Color Fusion



Examples of stimuli and the different trial types in the dichoptic color fusion experiment. Face and house stimuli (or blank control stimuli) will be presented for 100ms in the same color configuration to both eyes (top panel: visible condition) or in opposite color configurations to the left and right eye (bottom panel: invisible condition). On 15% of the trials, a small blue disk (not shown here) will be presented at a random location on the same area of the screen as the critical stimuli, serving as the task-relevant target, while the faces and houses will remain task-irrelevant.

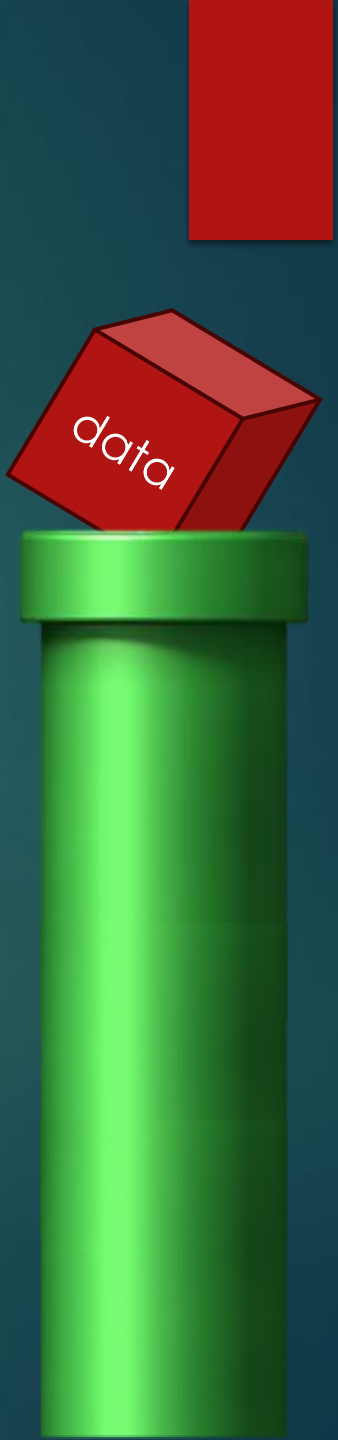
- Main task: in 15% of the trials, participants are instructed to click whether there is a blue circle in the screen.
- Conditions:
  - Congruent stimuli (visible)
  - Inverse stimuli (invisible)
- Phase 1: No-report
- Phase 2: Report

Proposed analysis

- **Time Decoding + Temporal Generalization**
- Time-frequency Analysis
- *Deep learning*
- *Compound Analysis of other potential NCCs*

The Pipeline

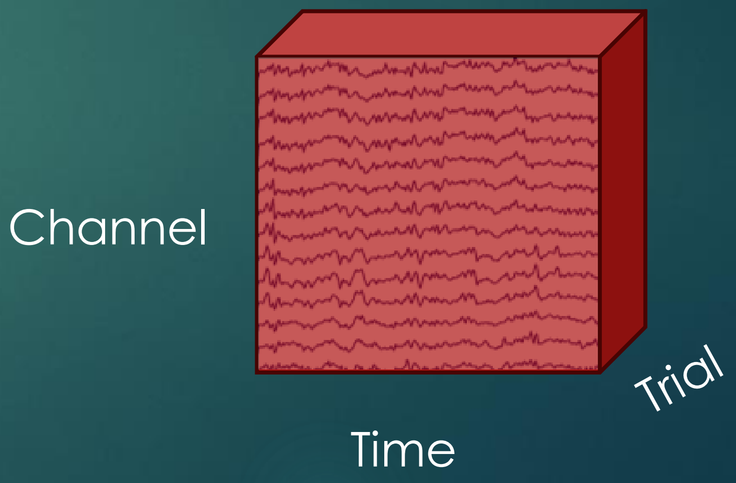
- **MATLAB:**
  - Preprocess the data following pre-determined protocol
  - Split the data train and test parts (for kfold cross-validation, 5 parts)
  - **Subtract the mask from Backwards Masking**
  - Extract/Export epochs
- **Python:**
  - Import and organize the data cube and ID arrays for experiment, phase, stimuli, test/train.
  - Created a structured way to train and test different sets of the data
  - Created the time-sliding window script that allows to run any ML or NN, an any given window sizes, step sizes, and any data manipulation necessary, training and testing at all windows
  - Save outputs and print results



Time-Decoding

- Because this is a data-driven experiment, a few files were separated to test and identify the best decoder and hyperparameters.
- I created a pipeline to allow me to "quickly" test various ML algorithms and hyperparameters, analyze and plot the results.

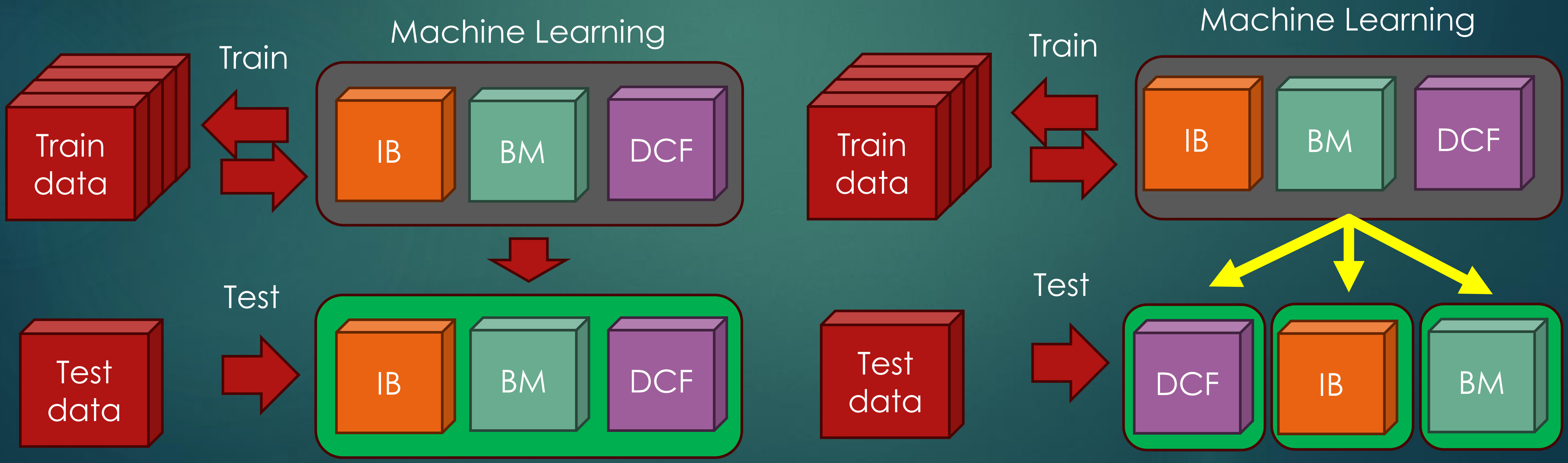
- Decoding: "Seen" vs "Unseen"
- Combined faces and houses for analysis
- Create 15-trial-average pseudo-trials
- Sliding window (10ms steps, 40ms window)
- Using ROC-AUC as a measure of accuracy
- 5-fold Cross-Validation
- Avg. Bootstrapped C.I. for significance



Methodology progression

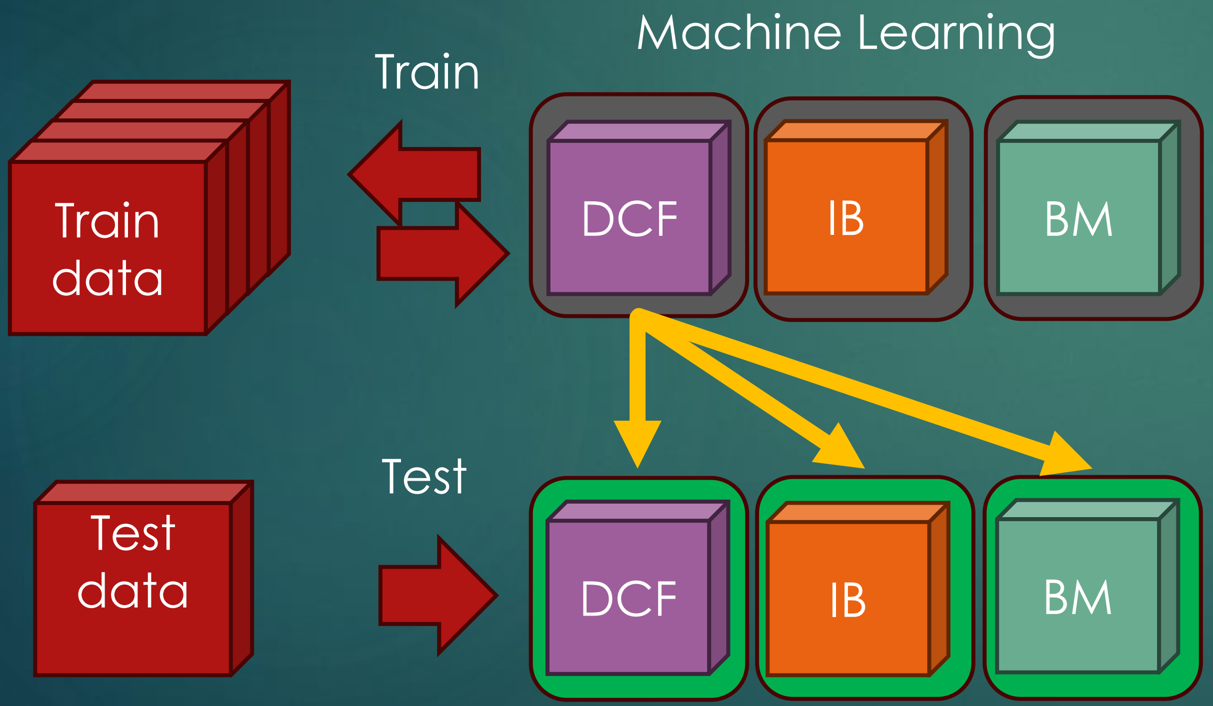
"Big soup" vs round-robin: train all test all, vs train 2 test 1.

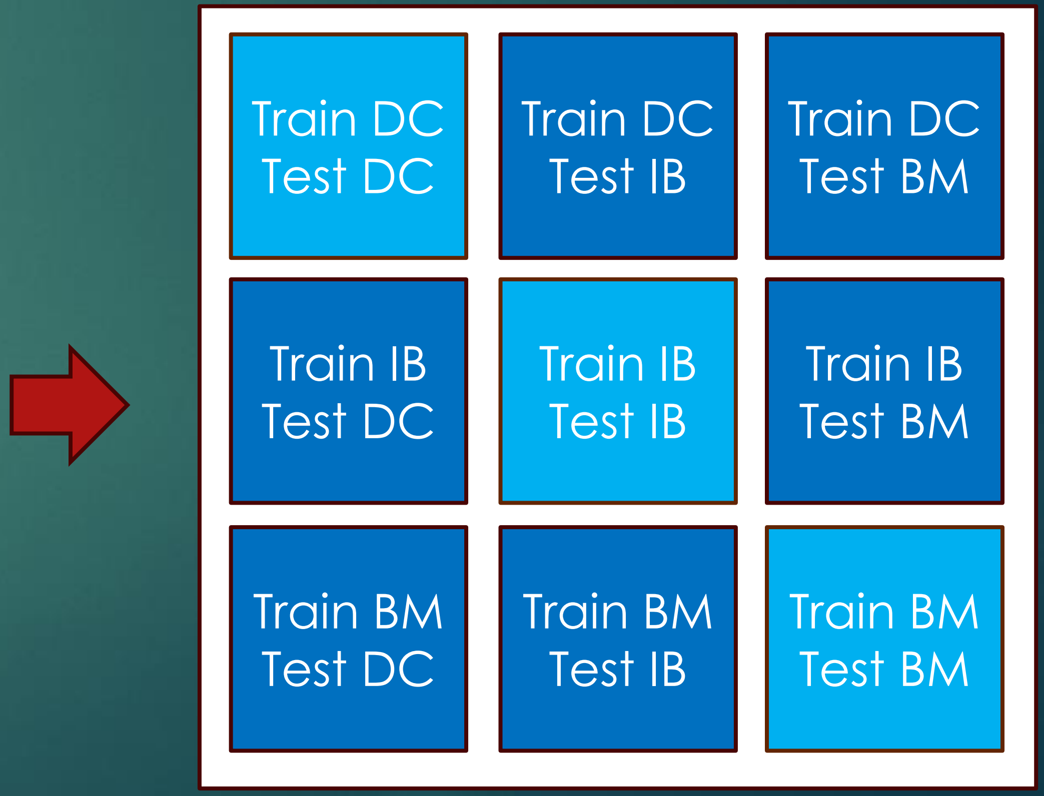
- Big Soup model
  - Issues: hard discerning ***source*** of the "decodability"
  - Solution: also test individual tasks after training all



Methodology progression

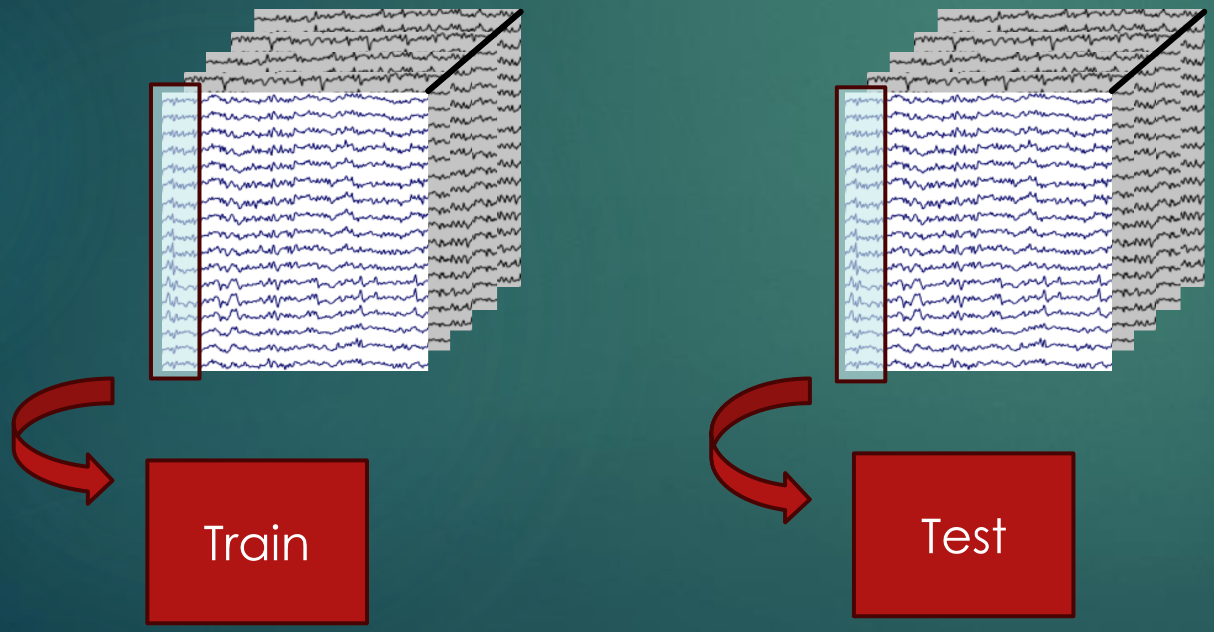
- We also decided to run a "Round Robin" model of testing
  - Source of decodability is known
  - Triangulation claims can be made



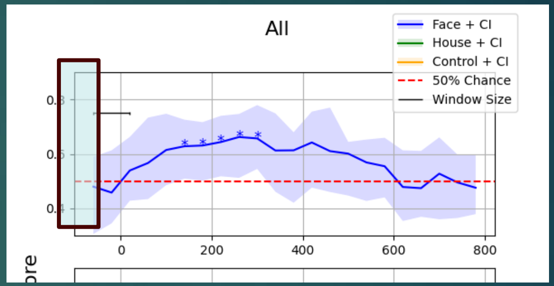


Methodology progression

- Sliding window for training and testing
- Temporal generalization
  - To test whether a signal is delayed in on paradigm

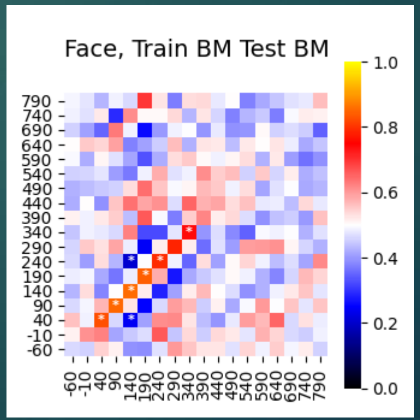


Train and Test at the same time points



Train and Test at the ALL time points

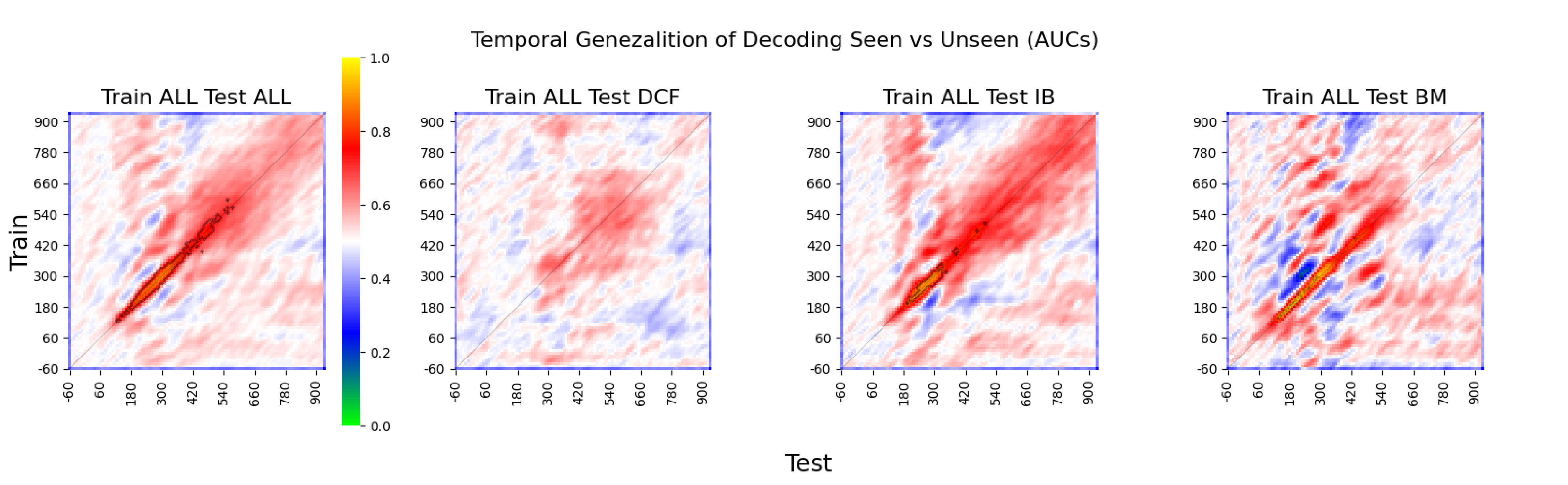
Train



Test

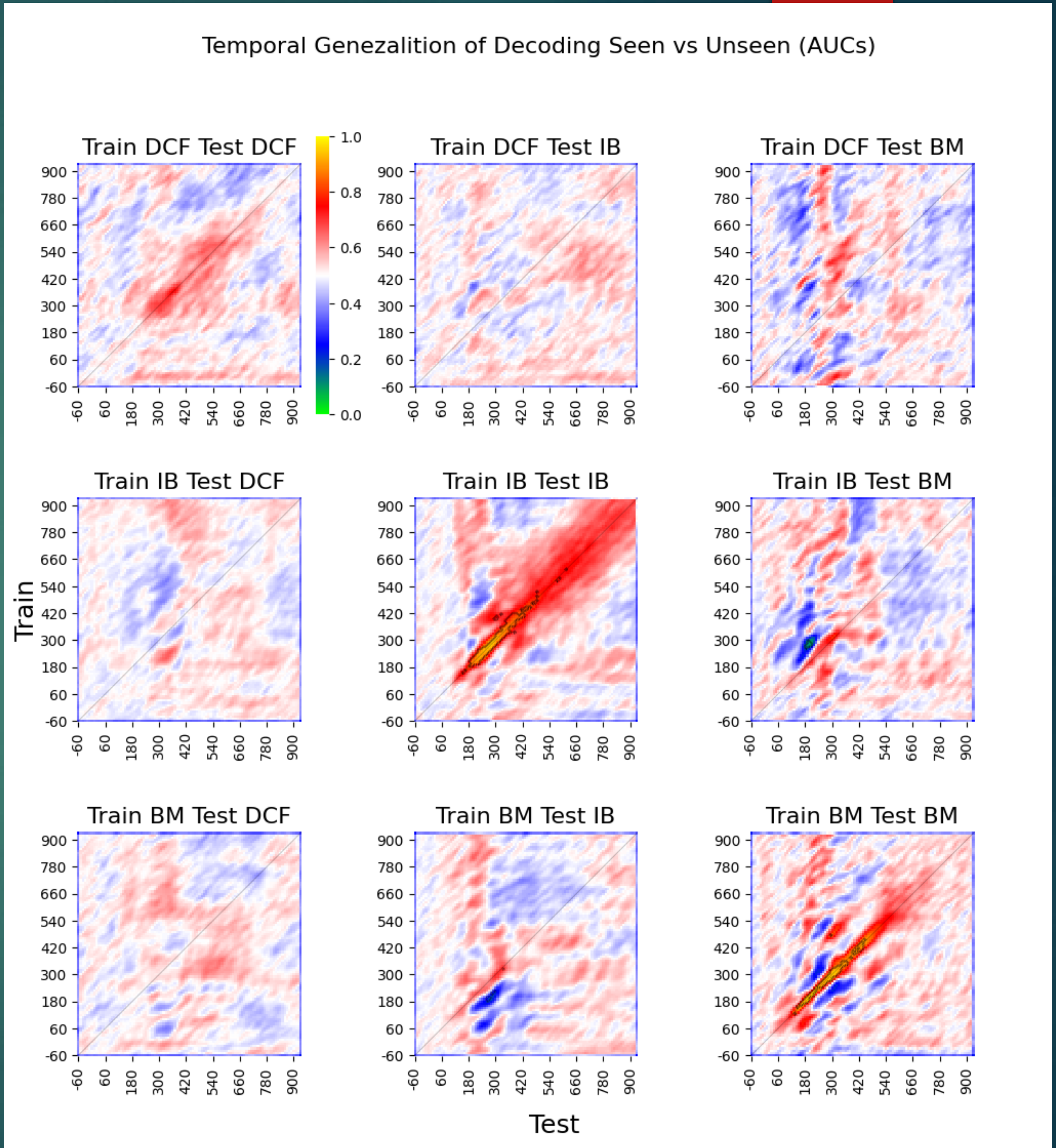
Current pilot results

- Big Soup + individual tests (4 participants)
  - Trending significance in DCF, while reaching significance in IB and BM
    low C.I. > 50% and high C.I. < 50%



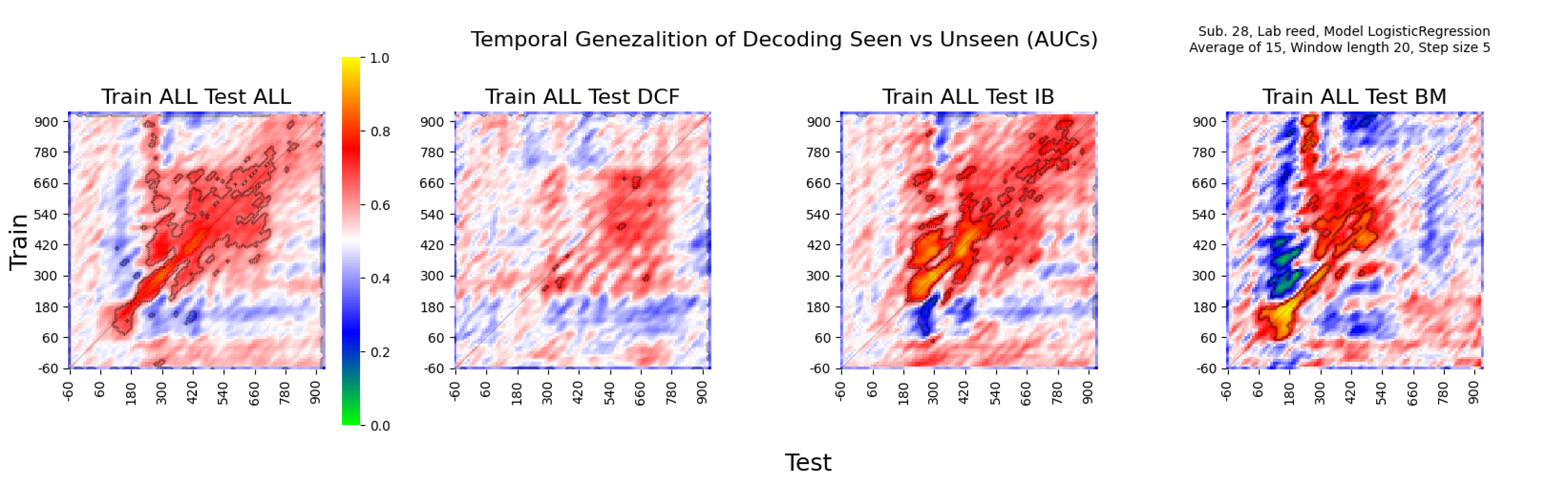
Current pilot results

- Round Robin
  - Significant Generalization Between IB and BM (low C.I. > 50%)
  - Weak but significant generalization between BM and DCF
  - This weak DCF generalization is due to a weak visual stimulus



Current pilot results

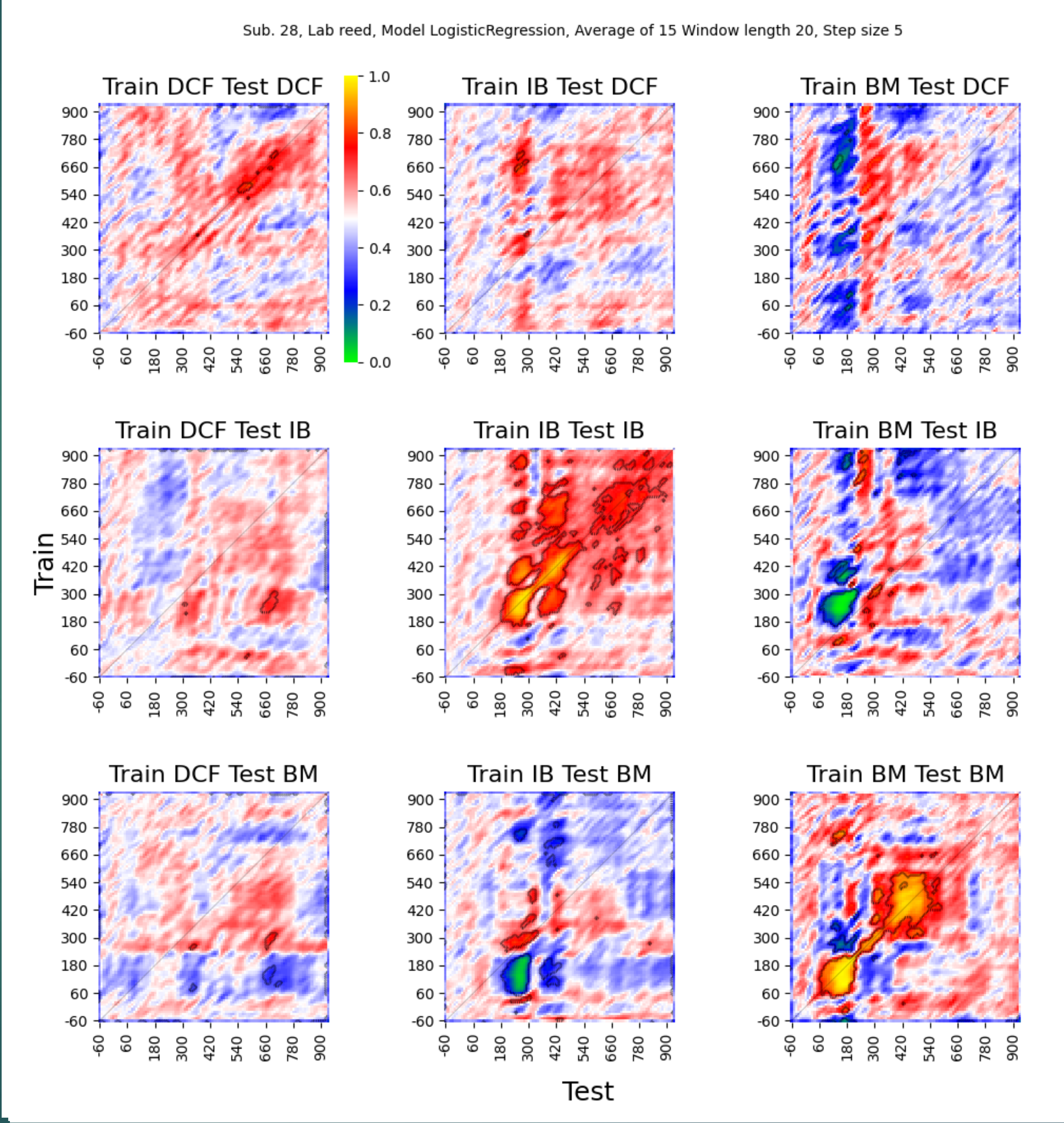
- Individual participants did display significant generalization between paradigms



Current pilot results

- Individual participants did display significant generalization between paradigms

- Participant 38 had the strongest color contrast (8) as well as the strongest behavioral response in block 2 of DCF, and the strongest within-decodability in DCF



Discussion

- Found strong signs of triangulation, with significant generalization between IB and BM
- Issue with a conservative choice for DCF’s color contrast levels
- In participants with decodable DCF, we observe significant generalization among all three tasks for most models
- On those participants, we do observe a generalizability with the Big Soup model, not only significantly decoding a test-set without labels, but each paradigm independently.

Next steps

- Plotting the head-model weights for the significant regions
- Complete Time-frequency analysis
- Open the full dataset and run the analysis on all the participants
- Compound analysis of the ERPs

Suggestions, Comments, Questions?

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- Sub 38
- Seen - Unseen