BMED 7610: Quantitative Neuroscience
Final Project Report

Group 4

PROJECT TITLE:
Modeling Functional Connectivity Between Brain Regions During Movie
Watching with Intracranial EEG Recordings

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BACKGROUND AND MOTIVATION

Understanding how the human brain processes naturalistic, dynamic visual stimuli remains a fundamental challenge in neuroscience. Traditional neuroimaging studies have primarily relied on simple, static stimuli presented in highly controlled laboratory settings. However, real-world visual experiences, such as watching movies, involve complex temporal dynamics, continuous scene changes, and rich multimodal information that engage distributed brain networks in ways that artificial paradigms may not capture (Hasson et al., 2004; Sonkusare et al., 2019). Recent advances in intracranial electroencephalography (iEEG) have provided opportunities to study human brain activity during naturalistic tasks with exceptional spatial and temporal resolution (Parvizi & Kastner, 2018).

The dataset used in this project comes from Keles et al. (2024), who collected iEEG recordings from 16 epilepsy patients while they watched an 8-minute segment from Alfred Hitchcock's "Bang! You're Dead" movie and subsequently performed a recognition memory task. The recordings captured activity from brain regions central to memory, emotion, and cognitive control, including the amygdala, hippocampus, anterior cingulate cortex (ACC), ventromedial prefrontal cortex (vmPFC), and pre-supplementary motor area (preSMA). This dataset was retrieved from Dandi Archive, Dandiset 000623 at https://dandiarchive.org/dandiset/000623. It includes detailed manual annotations for scene cuts, distinguishing between continuous cuts (within the same scene) and scene changes (transitions to new locations or contexts), providing precise temporal markers for investigating how the brain processes different types of visual transitions. An overview of the task used is shown in Figure 1. To ensure the integrity of the recordings, the authors performed extensive quality assurance analyses. These checks included evaluating spike sorting performance for single-neuron data, assessing unit stability, and confirming consistent electrode localization. Additional validation steps included using ROC curves to characterize recognition memory performance during the task.

Functional connectivity offers a complementary, mechanistic view: we ask how information may be exchanged across the network when the visual narrative changes. We leverage both coherence, which measures the consistency of phase relationships between signals across frequencies, and Phase Slope Index (PSI), which estimates the directionality of information flow between brain regions by examining the frequency-dependent phase relationships (Nolte et al., 2008). These metrics provide insights into both the strength and directionality of neural communication during complex cognitive tasks.

In naturalistic viewing, continuous camera cuts and full scene changes place different demands on perception, attention, and memory. A continuous cut typically preserves the underlying scene and narrative context while altering viewpoint or composition. In contrast, a scene change introduces a new setting, characters, or narrative unit, likely requiring more extensive updating of predictions and memory representations. Regions such as the hippocampus, amygdala, anterior cingulate cortex, and prefrontal areas are all candidates for coordinating these updates. Our motivation is to characterize how connectivity between these regions reorganizes around two kinds of structural events in the movie

Given the baseline measures of cleanliness and effectiveness of the dataset, we thought about viable ways to learn things from the data in a Machine Learning manner. The purpose of this was to see if we could derive similar characteristics as our functional connectivity techniques. Given the ability to derive similar characteristics and the different methodology that potentially learns more patterns from the data, we may be able to propose new learnable notions with this method. Recent work in machine learning suggests that neural networks can uncover structure

in electrophysiological data that parallels, or adds to, what traditional functional connectivity measures reveal. Wu et al. (2024) showed that convolutional neural networks can learn informative patterns to predict observed character matrices from EEG data across multiple subjects. This indicates that CNNs can effectively learn appropriate states from given EEG data matrices. This raised the possibility that similar approaches could identify patterns in iEEG that relate to how the brain responds to scene transitions during movie watching. The EEGNet architecture introduced by Lawhern et al. (2018) is designed to model the spatial and temporal organization of EEG data and provides a suitable framework for exploring this question. If the representations learned by such a model resemble features found in coherence or PSI, this would suggest that neural networks can capture connectivity-relevant information and may offer new ways of characterizing how brain regions interact during naturalistic viewing.

At this point, it became clear that an EEGNet CNN was an appropriate choice for our learning of state. Our learned state would be discerning a continuous cut against a scene change given the stimulus movie watched during the intracranial recordings. Given different electrodes in the data corresponding to certain features, and each of these features being learned both separated and together in such a model, we thought that we could learn functional connectivity by drawing correlations between the spatial weights. These spatial weights correspond with the order of the data, thus, this seemed appropriate. However, we needed to make some educated assumptions and look for common data patterns, rather than necessarily do 1:1 comparisons. Our key assumption is our model should pick up some similar patterns. A few questions were important here and were some that we hoped to answer: Would the data be appropriate for this task? Do we have enough data across patients to come up with a model that reasonably learns to do this for new, unseen patient data? Is our CNN with an EEGNet architecture actually viable for our classification task? Would our spatial weights correlate well with stereotypical functional connectivity measures?

The motivation for this project comes from the need to understand how functional connections between brain regions change during dynamic, time-varying experiences. Movie watching provides a natural setting where the flow of information shifts rapidly, especially at scene cuts. These transitions are thought to influence attention, memory updating, and prediction. However, it is not yet clear how these moments shape the patterns of connectivity observed in iEEG. By leveraging this well validated dataset, the project aims to examine whether functional connectivity carries information about different types of scene transitions and whether these patterns can be used to predict or classify structural moments in the movie. This provides a way to link large-scale brain dynamics to the temporal organization of real-world experiences.
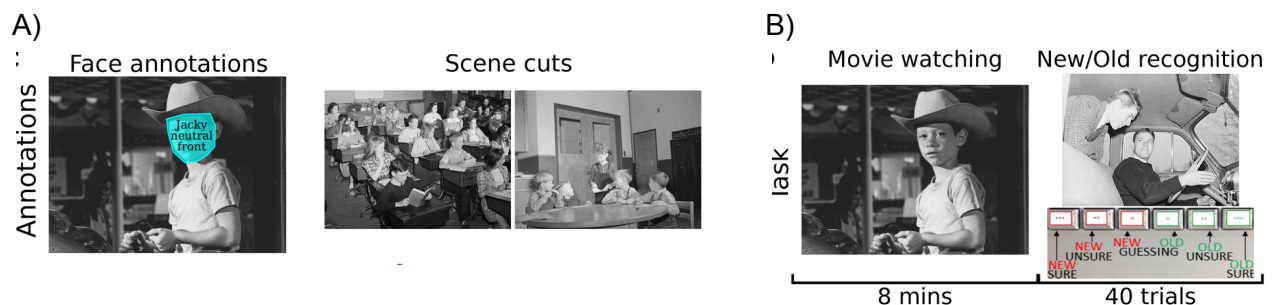

Figure 1: A) Task: Movie watching and recognition B) Manual annotations of movie stimulus.

AIMS

1. Determine whether large-scale network coupling differs systematically between continuous cuts and scene changes.

2. Identify which frequency bands (theta, alpha, beta) are most sensitive to these differences.
3. Provide a connectivity-based framework that can be directly compared to the spatial patterns learned by the EEGNet CNN, testing whether both approaches capture similar underlying communication motifs in the brain during dynamic visual experience that can be appropriately used on unseen data.
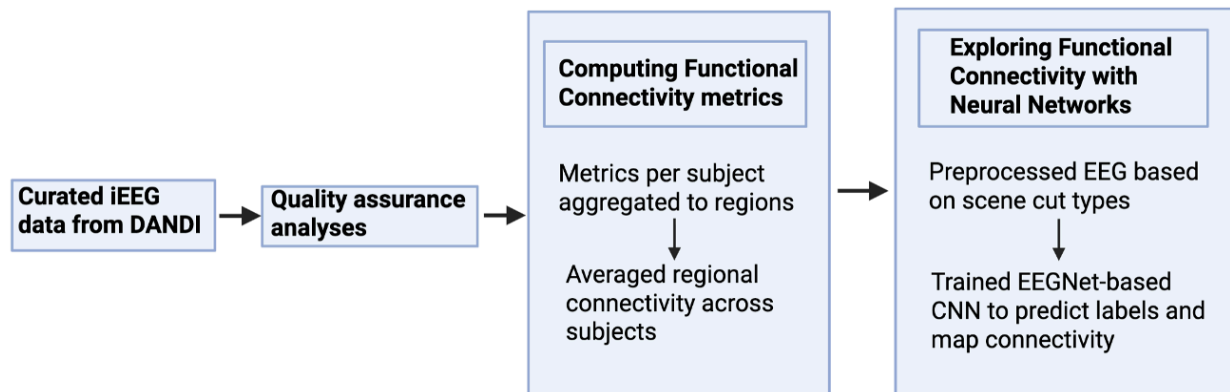
METHODOLOGY

Figure 2: Methodology

1. Quality Assurance Analyses

To ensure the iEEG data were suitable for connectivity analysis, we reproduced the quality assurance steps from the Keles et al. GitHub repository in the Python terminal. We performed the analyses on the following;

Single-Neuron Spike Sorting and Recording Quality Metrics: For single-neuron data, we inspected spike sorting and recording quality metrics such as isolation quality and firing statistics, using the summary distributions shown in the dataset and in slide 6.

Electrode Localization in 2D Sagittal Views: We then verified intracranial EEG electrode placement using the provided 2D sagittal localization maps, confirming that channels labeled as ACC, amygdala, hippocampus, preSMA, and vmPFC were positioned in the expected anatomical regions.

ROC Analysis of Recognition Behavior During iEEG Sessions: We reproduced the recognition memory quality check by generating ROC curves for each participant, ensuring that behavioral performance during iEEG sessions was reliable and above chance.

2. Functional Connectivity Analysis

We quantified functional connectivity time-locked to movie edits using coherence and Phase Slope Index (PSI). For each participant and recording session, we used the intracranial EEG during movie viewing and the accompanying metadata to define anatomically constrained connectivity matrices.

First, we constructed a global list of cortical and subcortical regions from the NWB electrodes table, using the recorded anatomical location to assign each contact to a region of interest (ROI)

and excluding noninformative labels. For each session, channels were grouped by ROI, and only regions with at least one valid contact in that session were retained. This yielded a subject- and session-specific ROI-channel map that we used to define connectivity pairs.

Scene cut annotations were loaded from the scene annotation table and recorded into two categories: continuous cuts within a scene ("cont") and scene changes between distinct scenes ("change"). For each cut, we obtained the corresponding EEG sample by converting the cut time into sample indices and applying a fixed offset to account for a known lag between the movie and the intracranial recordings. We then created event markers for each cut type and epoched the continuous data from t = [-1,1] around each event, without baseline correction. Separate epoch sets were constructed for continuity cuts and scene changes.

Connectivity analyses were performed in MNE-Python with the mne-connectivity extension (Gramfort et al., 2014). For each label (cont vs. change), session, and frequency band of interest (theta: 4–8 Hz, alpha: 8–12 Hz, beta: 12–30 Hz), we computed frequency-domain coherence using multitaper spectral estimation with averaging across frequencies within each band. Directed interactions were estimated with PSI using the same epochs, indices, and band limits. For each pair of ROIs, we included all available channel-channel pairs between those regions, computed coherence and PSI for those pairs, and then averaged across channels to obtain a single ROI × ROI value per band, cut type, and subject.

This procedure produced, for every participant, two connectivity matrices per band (one for continuity cuts and one for scene changes) for both coherence and PSI. We then aggregated across participants by taking the element-wise mean of the subject-level ROI × ROI matrices, separately for each cut type and frequency band. The resulting group-level matrices summarize how undirected (coherence) and directed (PSI) connectivity between key medial temporal and frontal regions differs around continuous cuts versus scene changes during naturalistic movie viewing.

3. Functional Connectivity Using Neural Networks: EEGNet Analysis

Since our EEG data was completely raw, we needed to do appropriate data pre-processing to pass it into our CNN. Along with this, we needed to ensure our label data was appropriate to work with in a Machine Learning classification sense. We also needed to make sure our CNN was appropriately designed to learn appropriate spatial and temporal relationships in our EEG Data. We started by developing our architecture based on the EEGNet paper, indicated in Figure 3.

We matched the architecture almost exactly in our implementation. We learned the frequency-selective temporal filters, meaning in the first layer, the learning of the temporal nature of the data is prioritized. The second layer focused on the spatial aspects of our electrode features, which is extremely important in our notion of functional connectivity. It is the learning in these weights that we correlated between to act as a proxy for comparison with our standard functional connectivity metrics.The third layer comes up with a summary of both the temporal aspects as well as the spatial aspects for each feature or in our case, electrode channel. Many research applications focus on CNNs for image classification, aiming to silo, squeeze and extend certain image regions. In the case of EEGNet, each layer has a specific purpose with the nature of EEG data in mind. In our case, layers 1 and 2 are the most important for the proper gathering of EEG information, though we only focus on layer 2 for this project.

In terms of implementation, we did this in Python with the Numpy and PyTorch packages from scratch. We aimed to follow the EEGNet architecture as closely as possible, having to make

certain assumptions given the lack of a code implementation provided in the paper. The learning of the CNN follows the standard deep learning paradigm: passing the raw data through an input layer, acting upon it by multiplication of set weights in the hidden layers, passing that through an activation function and reaching the output layer for a prediction. After comparing this with the ground truth labels through a loss calculation, the model backpropagates through the layers to learn the weights contributing to the most error. This is finally followed by updating the weights using our chosen optimizer.
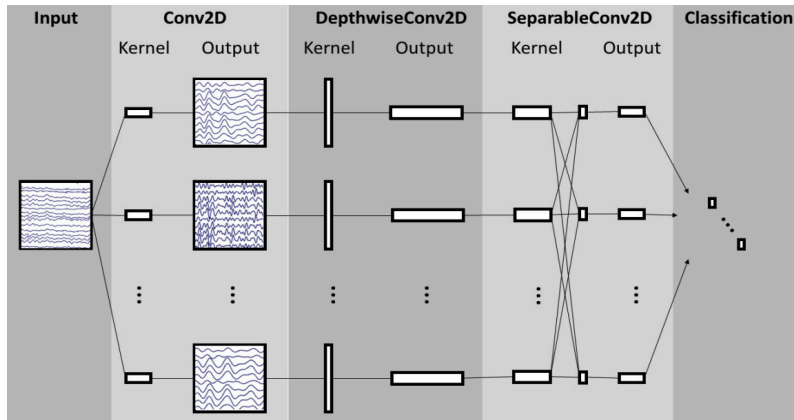

Figure 3: EEGNet Model Architecture

For our data preprocessing, the first challenge we faced was a major mismatch in terms of our continuous EEG data as compared to our discrete and specific label data. This meant that our label data only looked at the timesteps specifically corresponding to our cuts. To handle this, we gathered 500 ms of EEG data per data sample, which for each patient, was centered at the time the scene change or continuous cut happened. This was simply a reshaping of our timesteps data into windows of 500 ms, after which we only focused on samples corresponding to scene cuts or continuous changes. Since we had exactly 93 cuts, consisting of both continuous cuts and scene cuts for each subject's data, we ended up with 93 samples for 500 milliseconds by 96 electrodes per channel. This pre-processing was done for all 16 subjects in our experiment. The pre-processing pipeline is indicated in Figure 4.

```
Processing subject: 41
Patient 41 LFP Macro Data
data shape: (763964, 96)
sampling rate: 1000.0
timestamps range: 0.0 -> 763.963

Patient 41 Final X(EEG) Data shape: (93, 500, 96)
Patient 41 Final Y(Labels) Data shape: (93,)
```

Figure 4: EEGNet Preprocessing Pipeline

After doing this, our labels were simply 0 or 1 for either a continuous cut or a scene change. We adopted the Leave One Subject Out (LOSO) technique which involves testing on every subject's data but one. This paradigm is a standard train/test split technique used to generalize patterns across subjects. This is not distinct to EEG-based experiments, but is a common working theme in behavioral machine learning. This allows us to test our hypothesis of testing on previously unseen patient data and truly understand if there is appropriate learning of functional connectivity happening that is generalizable and learnable across new patient data. This paradigm resulted in our training set being all the patients data except for the one we were

testing. Along with having this done, we adopted this across patients using stratified k-fold cross validation. This meant that we would essentially have one training session per left-out test subject. Our major plot results(created with Matplotlib) indicate our test accuracy and test loss across all left-out test subjects, including the mean measure of all of them. We also calculated the confusion matrix for each test subject, to see the split of predictions for the two labels. We also calculated the correlations across the spatial weights corresponding to brain regions.

RESULTS

1. Quality Assurance Analyses

The reproduced spike sorting metrics (from Figure 5A) indicated well-isolated neuronal units with stable firing patterns, consistent with the quality reported in the original study. Sagittal electrode maps (from Figure 5B) confirmed accurate anatomical localization, with electrodes consistently clustered in the target regions across subjects. The ROC curves (from Figure 5C) showed recognition performance above chance, demonstrating that participants were attentive during the movie-watching sessions and that the behavioral and neural data aligned well. These checks confirmed that the iEEG signals were clean, accurately labeled, and behaviorally reliable, providing a solid foundation for downstream functional connectivity modeling.
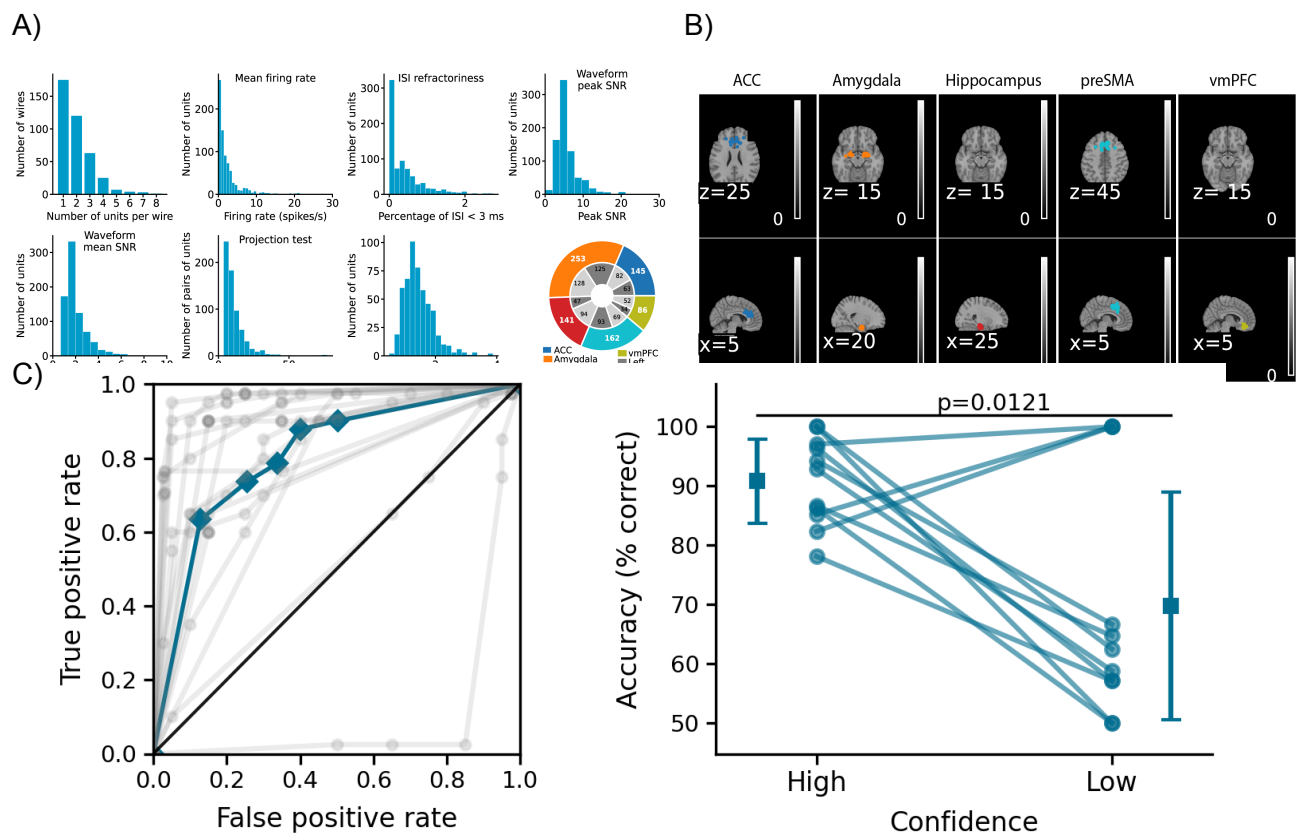

Figure 5: Quality Assurance Analysis A) single-neuron spike sorting and recording quality assessment metrics, B) recording locations in 2D on sagittal views and C) ROC curves for recognition behavior during iEEG sessions.

2. Functional Connectivity Analyses

Across conditions, we observed modest but structured differences in connectivity between specific medial temporal and frontal regions.

In the theta band, scene changes showed slightly higher coherence between hippocampus-vmPFC and hippocampus-ACC compared to continuity cuts. This pattern is consistent with a greater need for contextual updating and memory integration when the narrative switches to a new scene, whereas continuous cuts appear to rely on a more stable configuration of these connections.

In the alpha band, coherence was more diffuse, but we again noted a small increase in alpha coupling between prefrontal regions (vmPFC, ACC, preSMA) and temporal structures (hippocampus, amygdala) during scene changes. These effects are compatible with alpha-band interactions supporting attentional reorientation and gating when the visual and narrative context changes more substantially than during a simple camera cut.

In the beta band, overall connectivity was weaker and more heterogeneous. Some fronto-temporal pairs, such as ACC-hippocampus and preSMA-hippocampus, showed slightly elevated beta coherence around scene changes, whereas many other cross-regional pairs were similar across conditions. This may reflect a modest increase in top-down control or predictive updating, but the effect size is small and not uniform.

Directed connectivity estimates (PSI) were generally close to zero for most region pairs and bands. However, a PSI of 0.05 indicates a modest effect. We observed only weak trends, such as a slight positive PSI from hippocampus to vmPFC during scene changes in theta, suggesting a possible bias for hippocampal signals to precede prefrontal responses when context is updated. However, these effects were subtle and did not clearly distinguish scene changes from continuity cuts across the full matrix.
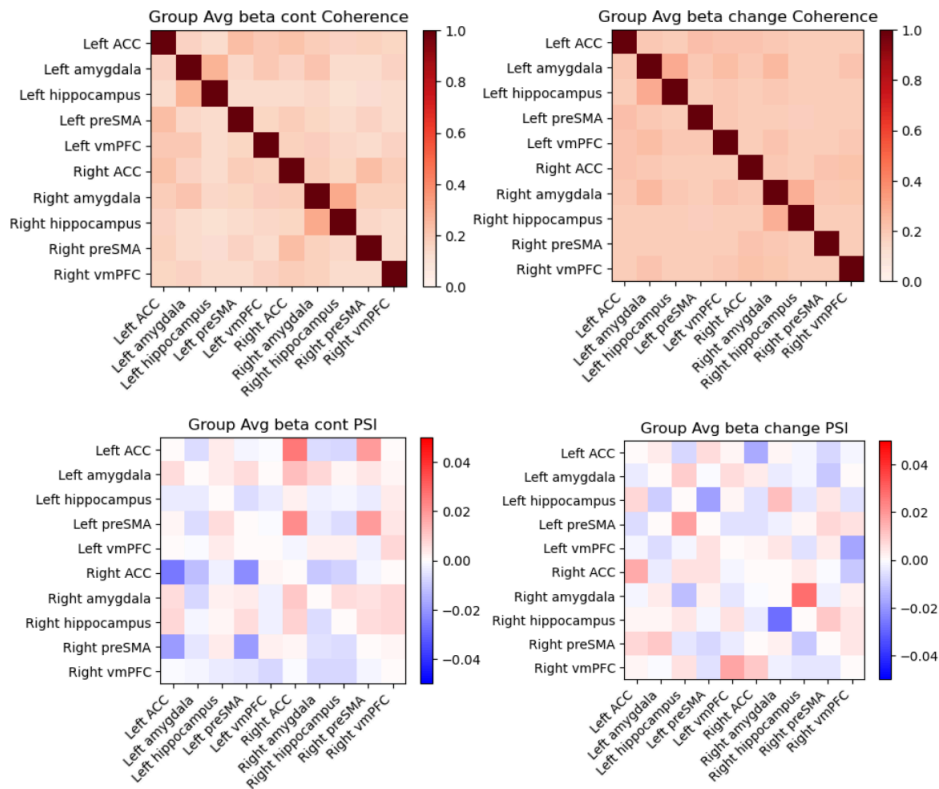
A)
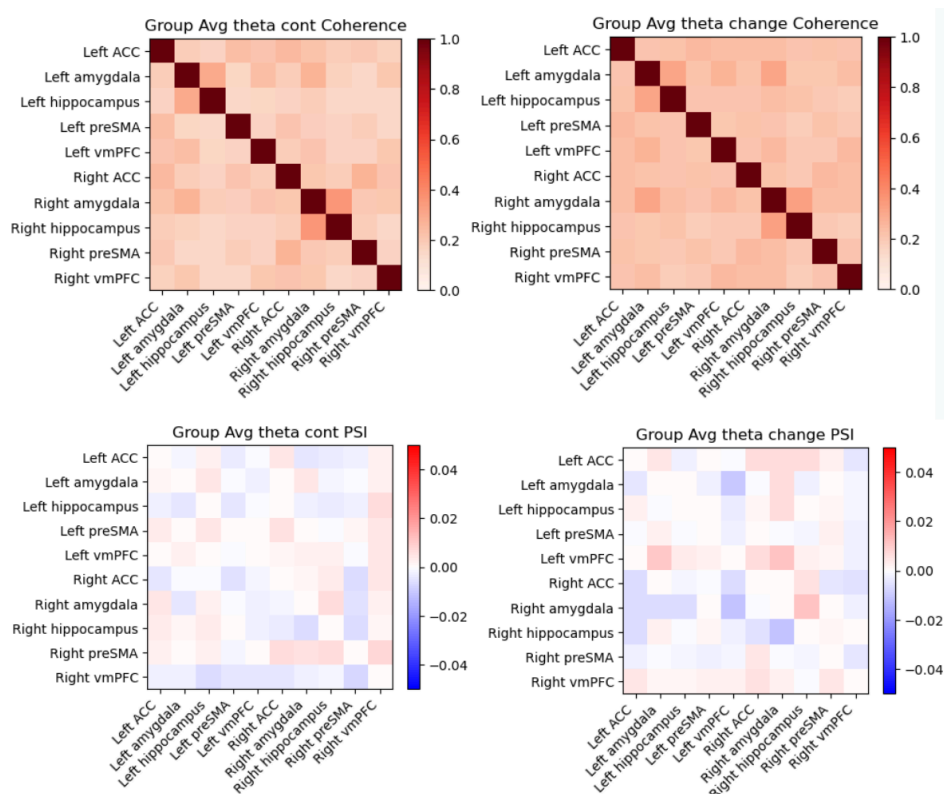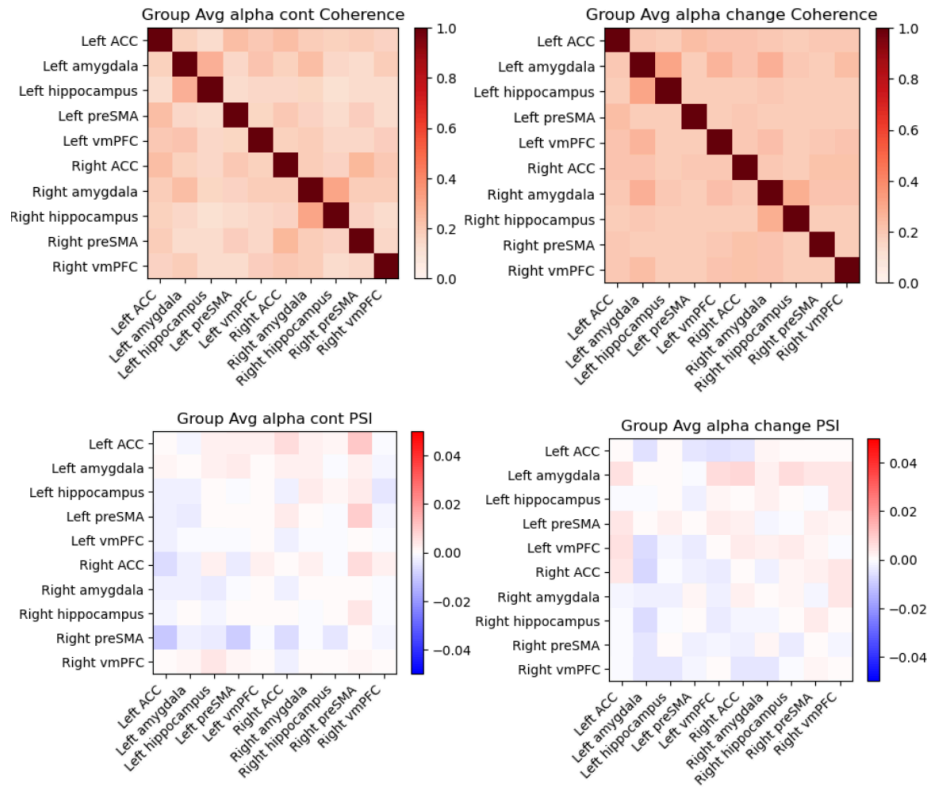
Figure 6: Continuous and Scene-Change Cut Coherence and PSI A)Theta Band Plots B)Alpha Band Plots C)Beta Band Plots

3. EEGNet Analyses

Our CNN results were very much across the board. We have indicated results from one subject below. Our stratified test accuracy and test loss graphs are indicated in Figure 7A and 7B. We saw erratic test subject accuracy and loss across different patients, with some test patients unseen data generalizing to the patterns learned in the other training subjects data. We saw a mean accuracy of 0.63 across different training and test pairings, noting that across the board we were learning something at least 13 points above chance. This was very relevant and indicated proper learning by the EEGNet model given the extremely noisy nature of the EEG data with little more preprocessing done on the data apart from windowing. We notice decreasing loss for more than half of our test patients, also indicating that there is also a decent amount of generalizability across patients. Our confusion matrix indicated the same numbers as our accuracy measure, which was expected. This plot is indicated in Figure 7C. For reference, in the matrix, label 0 is a continuous cut and label 1 is a scene change.
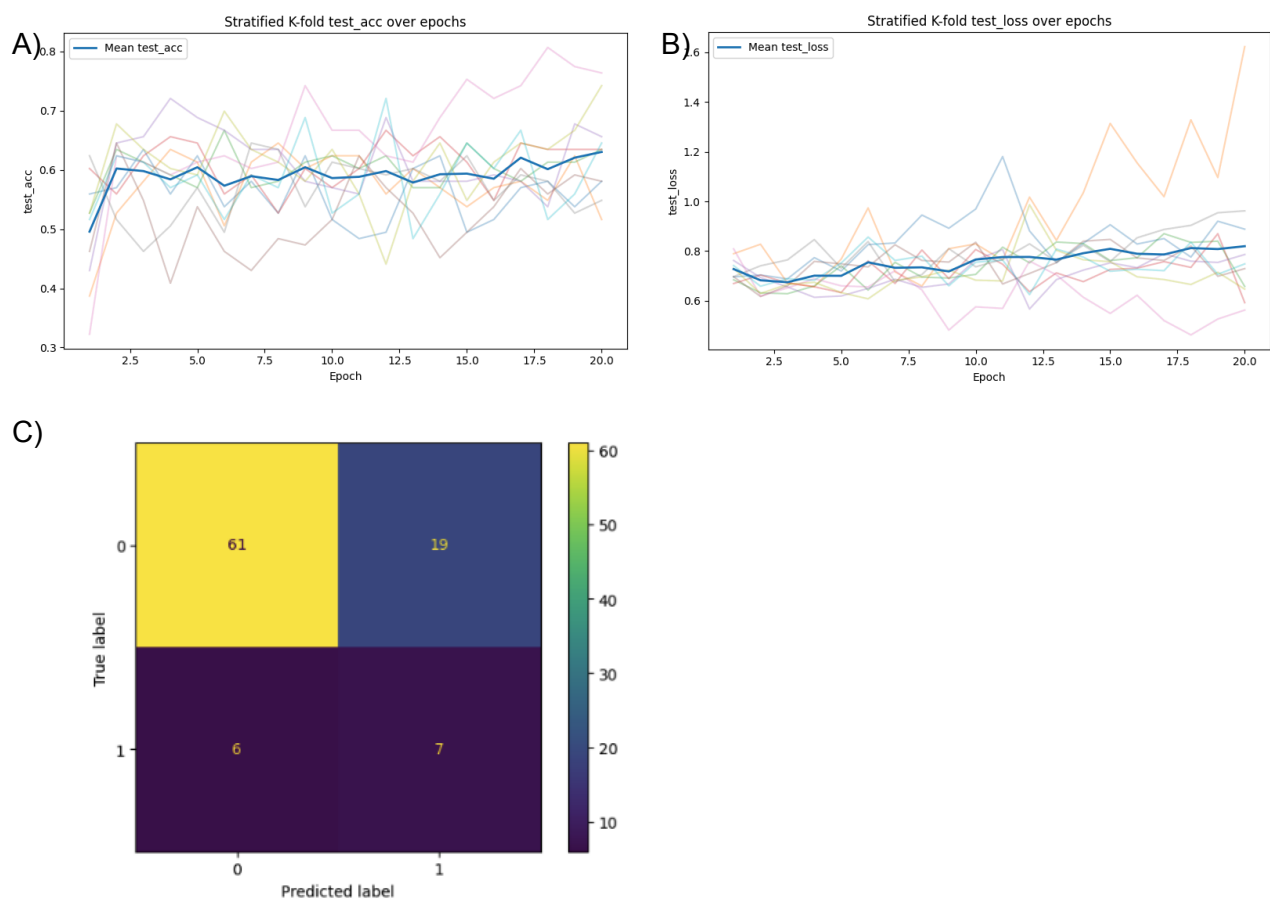

Figure 7: A)Test Accuracy across LOSO splits B)Test Loss across LOSO Splits C)Confusion Matrix for learned EEGNet Classifier

If we look at our plots of Pearson's correlation of coherence, phase slope index and the learned spatial weights, we notice some common patterns. These are the plots indicated in Figure 8A, 8B and 8C respectively. Between coherence and our learned spatial weights, we see similar exact relationships but this is hard to correctly pinpoint given the difference in shaping of the learned weights. The coherence plot is slightly bare and we notice much more with our PSI compared with the learned spatial weights. Given our background assumption of having to look

for patterns, we notice very similar patterns between the PSI/Coherence and learned weights, indicating proper overall structure has been learnt. This is given that some correlations may show up oppositely negative or positive to our PSI and Coherence plots, given the nature of deep learning.Specifically, similarly to functional connectivity, we notice the coupling between preSMA, ACC and vmPFC regions. We notice mild positive correlations between the preSMA and the hippocampus, similar to our functional connectivity measures, as well as positive correlations between the ACC and the hippocampus. We also notice some similar visual correlation patterns overall, specifically with our PSI plot. Given these common correlations in the learned weights of models with the functional connectivity measures, there is promising evidence that there may be more pieces of valuable information hidden in the other portions of the model that we did not study for this project.
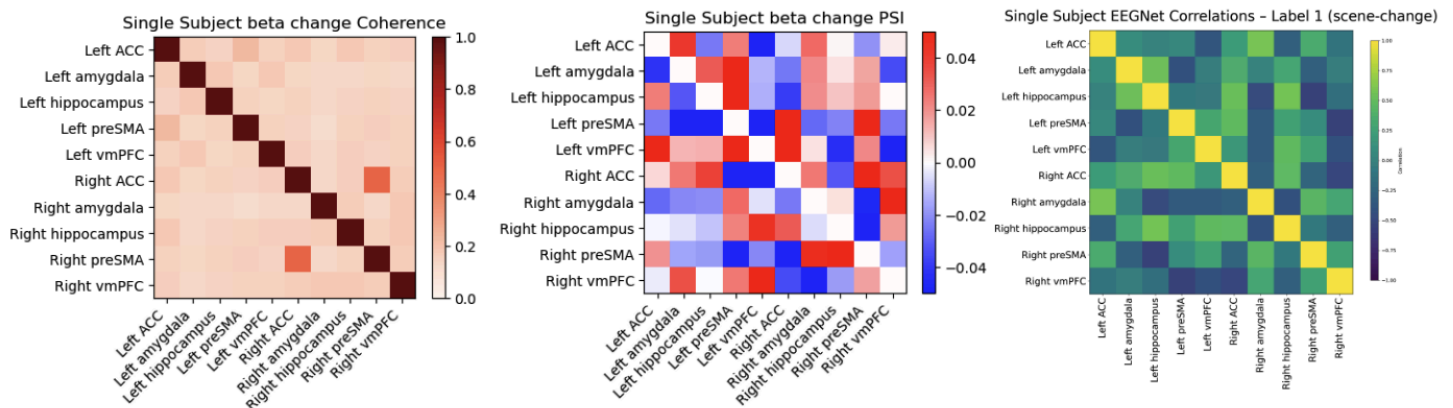

Figure 8: A) Subject 48 Beta Change Coherence B) Subject 48 Beta Change PSI C) Subject 48 EEGNet Spatial Layer Weight Correlations for Scene Change classification.

LIMITATIONS

Functional Connectivity Limitations

An important limitation of these analyses is that we did not explicitly mask out within-region connections (diagonal elements of the ROI × ROI matrices). Because within-ROI coherence tends to be high, these values can inflate the overall dynamic range of the matrices and visually dominate the plots, potentially obscuring more subtle differences in cross-regional connectivity. Future analyses should mask away diagonal edges at the channel level prior to aggregation so as to give an accurate representation of within region connectivity. Additionally, null distributions should be created via circular time shifting at the channel level. This circular time shifting would destroy any coupling between channels, allowing us to test the significance of the observed data. Finally, non-significant channels should be masked away prior to regional aggregation, resulting in a more robust, albeit timely, analysis.

EEGNet Limitations

Although our model is highly relevant and provides us with accurate representations above chance, the core limitation is that this model expects data to come in a very specific format and does not generalize to all types of visual or movie stimuli. However, with more data, further data preprocessing, and training examples of other sets of visual stimuli, we may be able to learn a more generalizable representation of functional connectivity in the brain when movie-watching. Given the scope of the project and the lack of appropriate computational power, this did not make sense to generalize beyond the dataset we have worked with. However, this does prove

that even with very limited data, the right model architecture, along with windowed raw eeg data, results in very telling results that are in line with proven ground truth neuroscience techniques.

CONCLUSION

Our project aimed to test whether the brain's functional connectivity changes in systematic ways during different types of movie scene transitions and whether a neural network could learn patterns that echo the corresponding brain region connectivity. After reproducing the original dataset's quality assurance steps, we confirmed that the neuronal recordings, electrode placements, and behavioral performance were reliable enough to support these goals.

Our functional connectivity analyses showed that theta and alpha band coherence increased modestly in hippocampal-prefrontal coupling during scene changes compared to continuous cuts, suggesting enhanced contextual updating when the narrative shifts. Beta band and directed connectivity showed weaker patterns. The EEGNet classifier achieved 63% accuracy (13 points above chance), demonstrating that minimally preprocessed iEEG signals contain learnable information distinguishing scene transitions. Importantly, the spatial weights learned by the model closely resembled patterns in our coherence and PSI analyses, particularly in coupling between preSMA, ACC, vmPFC, and hippocampus.

The findings support the project's motivation: scene transitions carry measurable signatures in large-scale neural communication, and both standard connectivity metrics and a compact CNN can detect these patterns. Our core aims of using a CNN for this classification task and learning notions unseen patient functional connectivity were relatively successful, enforcing the notion of further learning and improvements to this method meriting fruit. This combination of approaches offers a promising foundation for future work linking dynamic real-world events to moment-to-moment changes in brain network organization.

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