

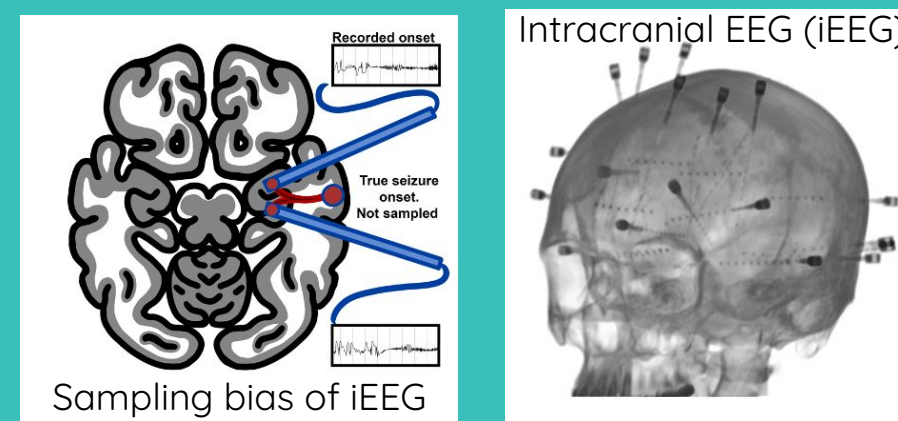
Machine learning of EEG to help diagnose epilepsy: Predicting functional connectivity from structural connectivity

Lena Armstrong SAS '23
Funded by PURM

Faculty Mentor: Dr. Kathryn Davis (Department of Neurology - HUP)
Graduate Student Mentor: Andy Revell

Introduction

A major problem in diagnosing and treating medically refractory epilepsy patients is that clinicians can miss where seizures are coming from with limited sampling of intracranial EEG (iEEG) electrodes. Thus surgeons treating these patients may not resect or ablate the correct regions. However, previous work has shown that there is a structure-functional relationship in the brain during seizures and shows promise for using whole-brain neuroimaging to overcome the sampling biases of iEEG.

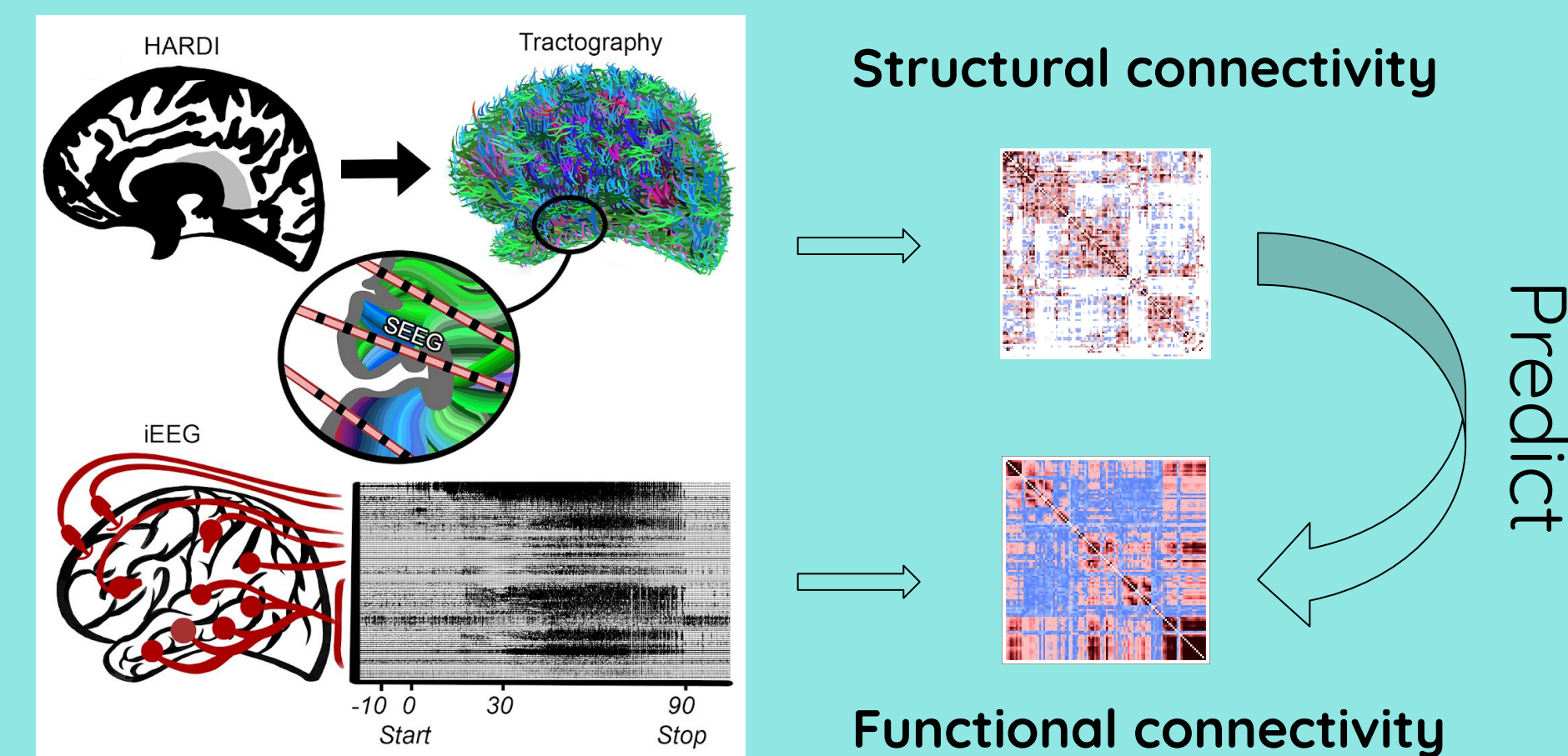


Significance

Predicting functional connectivity from whole brain neuroimaging could allow for predictions of seizure activity where there is no implanted electrode and help clinicians in their clinical decision making.

Objective

To predict functional connectivity from structural connectivity

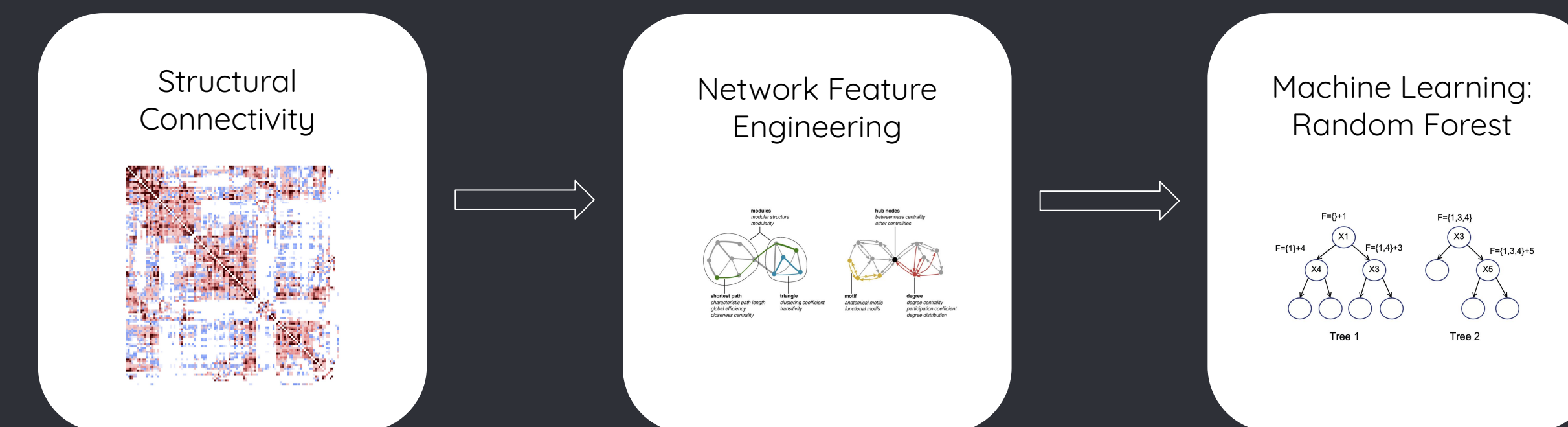


Definitions

Structural connectivity refers to the anatomical connections between different brain regions revealed by high angular diffusion imaging (HARDI).

Functional connectivity refers to the statistical dependence between the physiological recordings measured by iEEG.

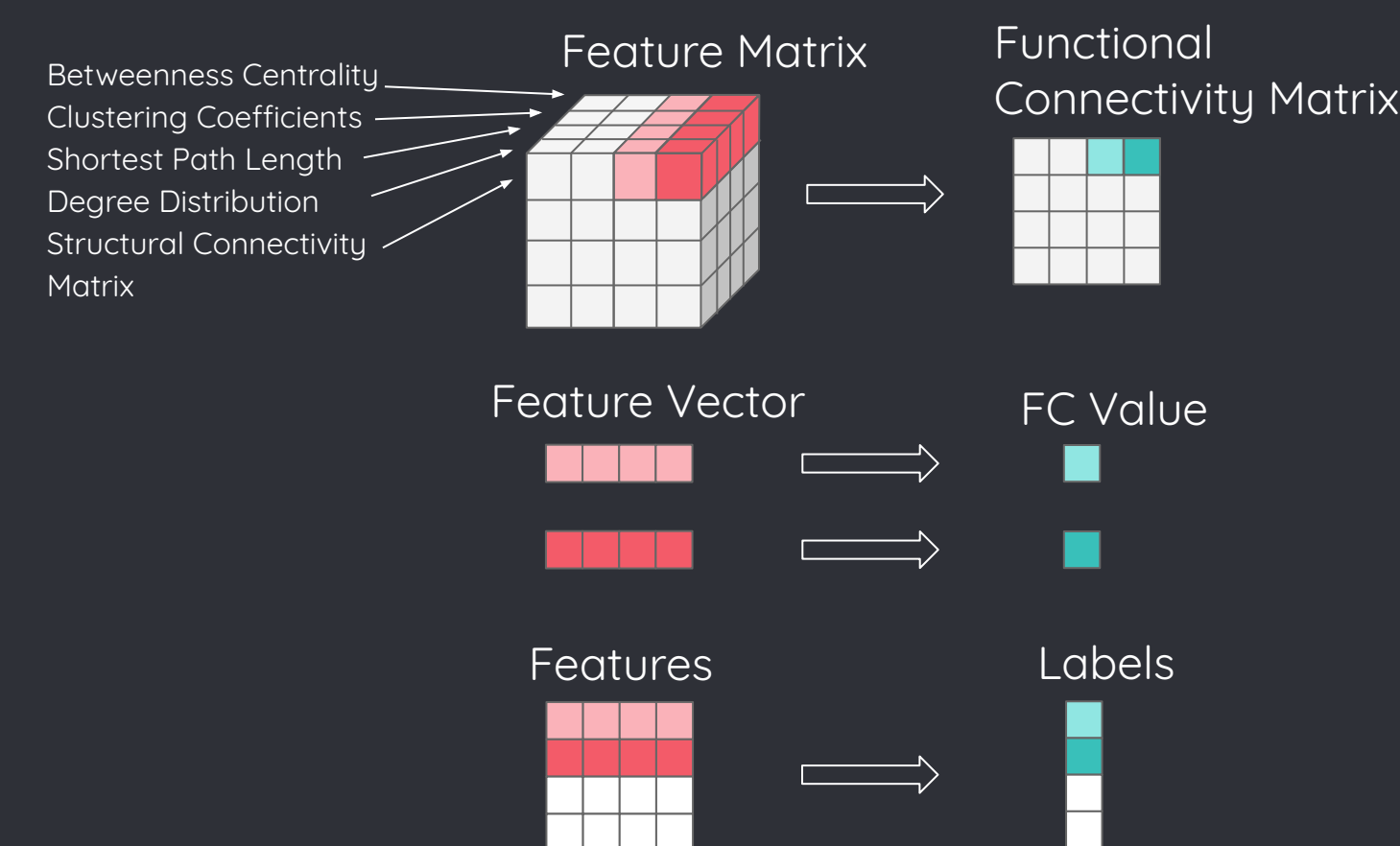
Methods



Network Features

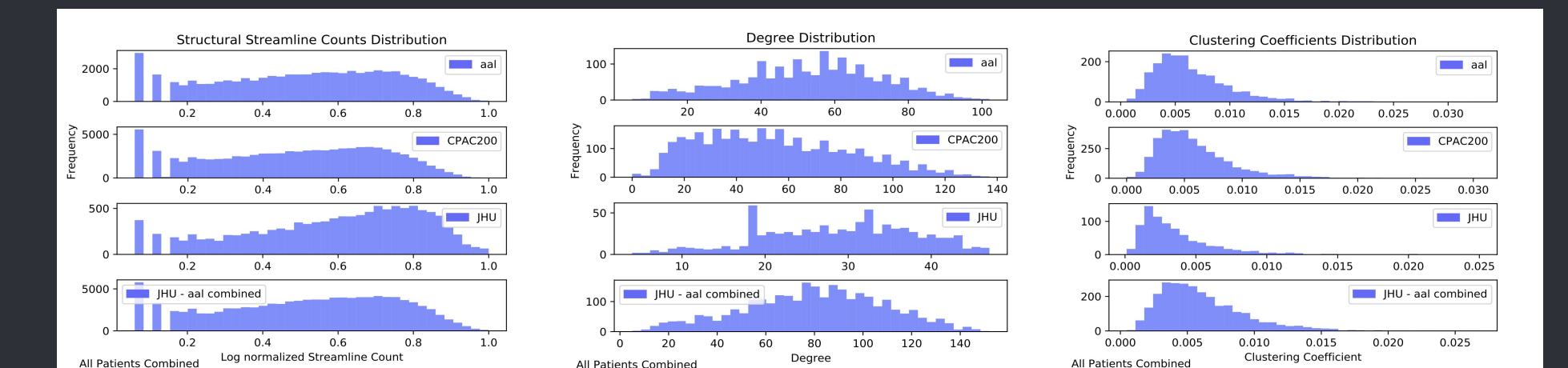
- Degree
- Node Strength
- Transitivity
- Density
- Assortativity
- Clustering coefficient
- Betweenness Centrality
- Eigenvector centrality
- Edge Betweenness Centrality
- Shortest Path Length
- Global efficiency
- Local efficiency
- Characteristic path length
- PageRank centrality
- Mean first passage time
- Search information
- Matching index
- Rich club coefficient

Feature Engineering

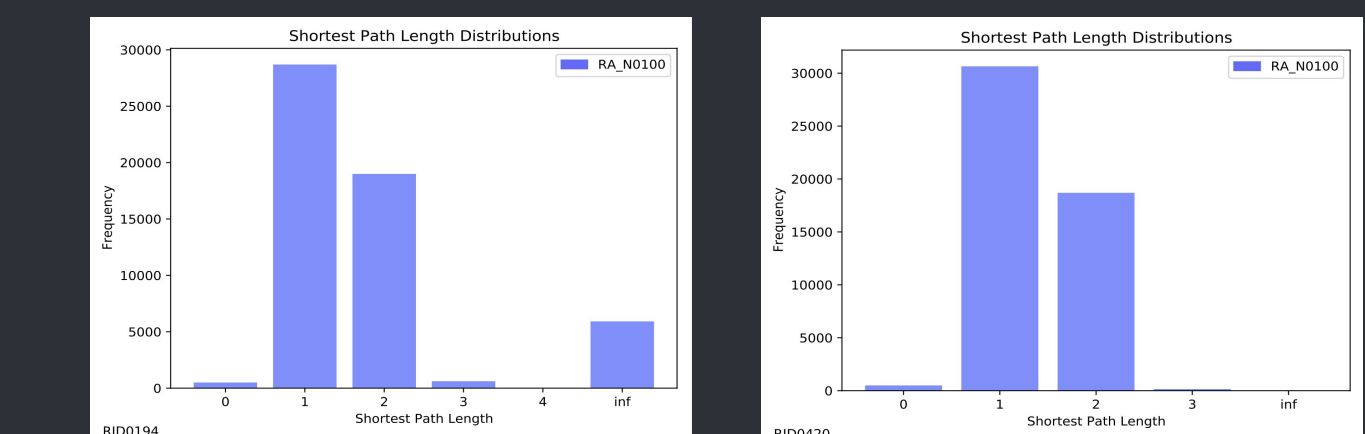


Preliminary Results

Distributions of Engineered Structural Network Features



Differences Between Patients



Discussion

Since there is no current framework for deep learning to predict one network from another, we used traditional machine learning approaches, like random forests. We focused on feature engineering, selecting the appropriate features and understanding their properties and distributions for the pipeline. The network features seem normally distributed in some atlases and skewed in others and there were differences between patients. Understanding distributions can help with feature selection and importance. Improving the model and predicting the functional connectivity from the structural connectivity could be relevant for patient surgical outcomes.

Future work includes incorporating all of the features calculated and regularization to prevent overfitting. Additionally, performing feature importance will help to determine which network features are most important and why they are important for predicting iEEG functional connectivity, which will help for model interpretability.

