**Status Report**

**Background Information**

Functional connectivity in the brain reflects the synchronized activity between different brain regions, providing insights into neural networks and cognitive functions. Resting-state fMRI (rs-fMRI) has become a standard tool for assessing these intrinsic networks because it captures spontaneous fluctuations in the brain's blood oxygen level-dependent (BOLD) signals without external stimuli or tasks. This passive nature makes rs-fMRI a robust method for observing baseline neural activity and understanding how the brain organizes itself in a resting state.

The analysis of functional connectivity often involves modeling the brain as a graph or network. Key metrics derived from graph analysis, such as degree centrality, clustering coefficients, and characteristic path lengths, which are indicative of a system that balances efficient global integration with localized specialization.

For recent related works, integrating multiple modalities(e.g. combining fMRI and EEG data) is a promising approach that leverages each method. By merging these data, researchers hope to capture a more comprehensive picture of neural dynamics, advancing our understanding of both the temporal and spatial dimensions of brain activity.

**Research Question**

* What are the network characteristics of brain functional connectivity in resting state?
* How do these characteristics reveal patterns of functional connectivity and network organization in the brain?
* How do network metrics characterize the brain's functional connectivity?

**Objective**

In this project, we will experiment on a large simultaneous fMRI-EEG dataset obtained from human subjects during resting state and sleep. We will primarily focus on building and analyzing graph network(s) based on fMRI data, but we will also try to explore the possibility of fusing the EEG data to boost our analysis. We will identify and analyze the network properties of brain functional connectivity, aiming to reveal the structural and functional organization of the brain under baseline conditions.

**Materials**

* Dataset: Simultaneous fMRI and EEG scans of 33 healthy participants combining two 10-min resting-state sessions, and several 15-min sleep sessions.Blood oxygenation level-dependent (BOLD) fMRI data were collected at a 3T scanner with a resolution of 80 × 80 × 35 voxels and approximately 286 time points per scan. Dataset doi: https://doi.org/10.18112/openneuro.ds003768.v1.0.11

**Methods**

* **Data Processing:** We obtained our data from openneuro.org. The OpenNeuro website is a free and open platform for validating and sharing BIDS-compliant MRI, PET, MEG, EEG, and iEEG data. The BIDS format is a standard for the organization of neuroimaging data. Machine learning and neuroimaging libraries like pybids, nibabel, nilearn, nipype, networkx and gephi will be used for loading, preprocessing and processing of data into graphs and the calculation of graphs.
* **Network Creation**: The resting-state functional connectivity network is constructed by calculating Pearson correlations between predefined brain regions. Regions will be separated using brain atlases, which are reference maps that divide the brain into regions or areas, based on anatomical or functional criteria. Common atlases include Harvard-Oxford Atlas, AAL Atlas, Talairach Atlas and Allen Brain Atlas. We will be choosing one most suitable and common atlas for the experiment, and if time allows, explore other fitting atlases for our project.
  + Connections: Connections between nodes represent functional connectivity, quantified by correlation values.
  + Directed or Undirected Network: An undirected network is used, as functional connectivity is assumed to be bidirectional.
  + Network Type: The network is a one-mode network, where nodes represent brain regions, and edges represent connectivity between them.
* **Network Metrics**:
  + Degree: a high degree indicates that a brain region is highly connected to other regions, possibly acting as a hub for information flow within the brain.
  + Clustering Coefficient: represents the extent to which a node’s neighbors are also connected to each other, forming a “cluster.” A high clustering coefficient in brain networks suggests local integration and specialized processing within specific brain regions, often seen in functional modules.
  + Characteristic Path Length (average shortest path between nodes):This is the average shortest path between all pairs of nodes in the network. It reflects the efficiency of information transfer across the entire network. A shorter characteristic path length indicates that information can travel quickly across brain regions.
  + Small-World Properties: Small-world networks are characterized by a high clustering coefficient and a short characteristic path length. This combination enables both local specialization and efficient global integration, which is a prominent feature in brain networks and supports both segregated and integrated information processing.

**Results**

Since neuroimaging data is a bit complex and we changed subject halfway, we are still working on data processing.

**Problems and potential solutions**

Right now the primary challenge is to figure out what methods to choose for each step of processing neuroimaging data until we finally build the data into graph(s), since methods in this area vary and are dependent on individual cases. We will continue experimenting and searching.