EN.580.694: Statistical Connectomics

Final Project Proposal

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Exploring features of the resected region that differentiate between successful and failed surgical outcomes for medically refractory epilepsy based on intracranial EEG (iEEG) data

OPPORTUNITY: 65 million people worldwide have epilepsy. About a third of these patients have medically refractory epilepsy (MRE), which is unresponsive to pharmacological intervention. Specifically, 10 million have focal MRE, meaning that the seizures originate from a specific focus within the brain. For these patients, the current standard of care is surgical resection of the part of the brain causing the seizures. This is an invasive, risky, and costly procedure that hinges on accurate localization of the seizure focus or epileptogenic zone (EZ).

CHALLENGE: Currently only 2% of possible candidates for surgical resection actually have the procedure done due to the high cost, risk, and failure rate. The current localization process is done by invasive monitoring for several days during which several seizures are induced, and then the clinician ***visually scans*** hundreds of channels of data to identify landmarks only visible to the well-trained eye that indicate the EZ. Because of the localization uncertainty associated with this procedure however, clinicians usually end up resecting a much larger region than they suspect, and even then the chance of success is 30-70% depending on the type of epilepsy and seizures. Improved localization is an obvious goal, but as a precursor to that, a tool that could take a guess for the EZ as the input and give some indication of the risk for failure would be very valuable to clinicians.

ACTION: The goal is to define exploratory features that may distinguish between a resected region that is likely to lead to a successful outcome vs a failed outcome, without trying to identify the "correct" epileptogenic zone. The underlying hypothesis is that the subnetwork defined by the epileptogenic zone is connected differently from other randomly selected subnetworks and therefore distinguishable from a subnetwork consisting of predominantly non-EZ nodes or random nodes. In order to do this, the resected regions of patients with successful outcomes will be used to define the epileptogenic zone subnetwork, and subnetworks generated from taking random subsets of nodes of similar size from the entire network of these patients will be used as simulated examples of incorrectly identified epileptogenic zones. Depending the data available, the resected regions of patients with failed outcomes may also be included as "wrong" identifications. The initial approaches studied in the networks will be looking at average centrality of the subnetwork and analyzing correlations between eigenvector centrality signatures during seizure.

RESOLUTION: Identifying some features that can be further explored to differentiate between the EZ as a subnetwork and other "incorrect" subnetworks is not only really valuable as a decision tool for

clinicians, but the nature of the features themselves can be indicative of the characteristic network structure and connectivity of the EZ, leading to insights about the cause and development of the disease.

FUTURE WORK: This tool can be integrated into any EZ localization tool, and the nature of the features themselves can help refine the localization algorithms as well. Future work would be to use this to improve blind EZ localization purely based on data with no clinician input.

Statistical Decision Theoretic

There are m connectivity matrices (one per subject), each with n_m nodes, and all of whom had successful outcomes. For each connectivity matrix, we can get one "correct" resected region of r nodes, and at most $(n_m choose\ r) - 1$ "wrong" resected regions. We can also get one "wrong" resected region for each patient with a failed outcome.

SAMPLE SPACE – Weighted connectivity matrices and respective vertex position labels

MODEL – SBM with two blocks: EZ/non-EZ

ACTION SPACE – $\{Success, Failure\}$ depending on some statistic (maybe p) computed for each block

DECISION RULE CLASS – $f: A_n \rightarrow \{Success, Failure\}$

LOSS FUNCTION – Number of incorrect classifications

RISK FUNCTION – Just by blindly guessing, there's a 50-50 chance at classifying correctly…

$E(L) = 0.50.$