EN.580.694: Statistical Connectomics
Final Project Report

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Using SBM to Discriminate between Resection Outcomes in Patients with Medically Refractory Epilepsy

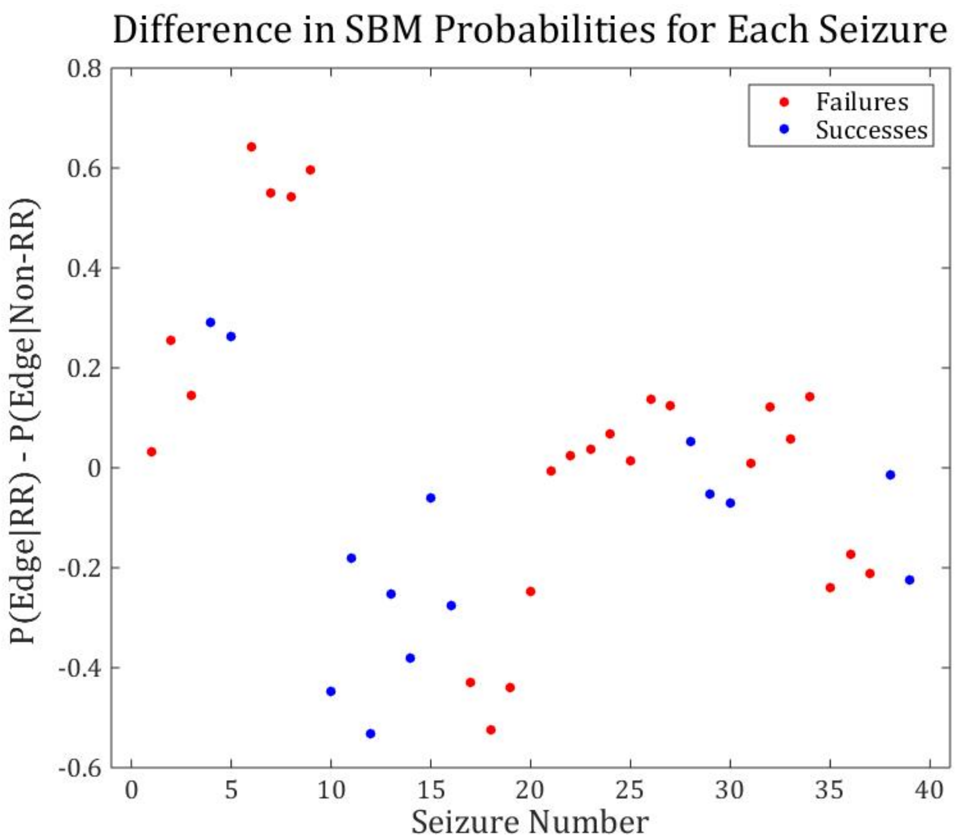

Figure 1: The difference in p(Edge) between the Resected Region and Non-Resected Region in the SBM for each seizure event in the data set, color indicating true outcome.

Table 1: The classification accuracy from the model versus random assignment of labels

	Classification Accuracy
SBM	0.7179
Random Assignment	0.5397

Opportunity Over 50 million people in the world suffer from epilepsy, a neurological disorder characterized by uncontrollable electrical activity in the brain called seizures[3]. Up to a third of them have medically refractory epilepsy, meaning that they do not respond to medication. In these cases, the only option for many of these patients is surgical resection, or removal of the part of the brain generating the seizures. This region is called the epileptogenic zone (EZ). One useful tool for clinicians would be a way to compute a probability of success or failure given a particular guess for the EZ. In other words, given a particular subset of nodes identified as a possible EZ, classify the predicted surgical outcome as success or failure. Being able to postpone an extremely expensive and risky surgery in cases when the outcome can already be predicted as a likely failure can save time, money, and avoid unnecessary risk.

Challenge Localization of the EZ is very difficult and currently done by clinicians visually scanning hundreds of channels of ECoG monitoring. Based on the presence or absence of specific waveform morphologies only visible to the trained eye, clinicians come up with their best guess of the EZ, and in most cases an even larger area is resected just to be safe. Despite this, the failure rate is up to 60-70 percent for certain types of epilepsy, largely due to mis-identification of the EZ and subsequent non-removal of the entire region [2].

Action My goal was to identify and test features that could possibly be used to predict resection outcome based on a given 'guess' for the EZ. The data I used came from 39 seizure events from 10 patients total, with a known surgical outcome for each patient. For each event, the eigenvector centralities (EVC) for each of the nodes in one second windows was calculated [1]. Then the absolute value of the pairwise correlation between each pair of EVC signatures from 60 seconds before onset to 60 seconds after offset was used to construct the network. I used an SBM to model the network, where the two blocks were the resected region and the remaining nodes. For each block, I estimated the edge probability by thresholding the network at 0.6 and calculating the edge density within the block. The parameter used to classify success or failure was the difference in edge probabilities between the two blocks. I computed the accuracy of classification using leave-one-out cross-validation, each time selecting the discrimination threshold that separated the training data best. As a comparison, I also computed the classification accuracy based on 10,000 trials where the same number of success labels were randomly assigned to the events.

Resolution Figure 1 shows the difference in block edge probabilities for each of the seizure events, where the events are also labeled by the true outcome. Table 1 shows the accuracy results of using the SBM with leave-one-out cross-validation vs. 10,000 randomly assigned trials. The random assignment had an accuracy of about 54 percent, while using the SBM yielded an accuracy of almost 72 percent. Specifically, Figure 1 shows that correctly identified EZ's seem to have a lower edge probability than the remaining nodes, while one sign for a potentially misidentified EZ is an edge probability that is higher than the remaining nodes. At first glance, this seems a bit counterintuitive, as it seems to indicate that the centrality signatures of the EZ are less correlated with each other than for the remaining nodes.

Future Work Future work could involve 1) training and testing on a larger data set, 2) exploring alternative measures of defining the network other than pairwise correlation, 3) testing the effect of varying the edge threshold for the network, and 4) exploring alternative base metrics for the network other than eigenvector centrality. Basically, varying every one of the parameters used in this classifier to optimize each individually may improve classification accuracy.

References

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