Members: Clayton Schneider

I. Electroencephalography (EEG) measures voltage dipole time-series at multiple locations on the scalp, conveying information about general cortical brain activity. What it lacks in spatial resolution, it makes up for by its ease-of-use. Compared to other measures of brain activity like fMRI, it is extremely cheap to gather data from large swaths of patient populations, and anyone can be trained to use a simple headset like the WAVi Medical system in mere minutes. There's a lot of different ways to draw edges between the different nodes (electrodes), but in this project I will begin by implementing a coherence algorithm.
   - Discrete time fourier transformations (DTFTs) convert the data into the frequency domain. E.g, a 5 minute time-series may be converted into a distribution of spectral powers at frequencies ranging from 0 to 125 Hz. In EEG, different ranges of these spectra are known to vary between patient populations. E.g, in opioid-medicated patients, the "alpha peak" falling somewhere between the 6 and 10 Hz range is usually slower than that of a control population.
   - Coherence is then derived for each frequency band of interest, via cross-spectral density, and estimates the extent to which one signal may be predicted from another. In a nutshell, it tells us when two electrode locations influence and/or correlate with each other. This also varies between patient populations - the neurotypical coherence between frontal-left and frontal-right electrodes may not exist as strongly in, say, an ADHD patient.
II. Using this method of drawing edges between electrodes in the course of an eyes-closed resting-state EEG scan may allow us to gather insight into potential biomarkers of various disease states. If so, I'd like to know to what extent this can be a valuable measure for small EEG networks, with about 19 channels.
III. I expect that for some of our patient populations, there will be significant differences in diseased populations compared to general reference population data, but that in many (or most) cases, this alone will not be a sufficient metric to use for diagnostic purposes. Preliminary studies have shown that it is extremely difficult to differentiate between populations such as chronic pain patients vs. opioid addicts, but this is an extremely pertinent diagnostic tool that many clinicians around the globe are searching for.

Through my work with WAVi Medical, I have access to a large amount of data collected from several different disease-state populations, including anesthetized patients, fibromyalgia, chronic fatigue syndrome, mTBI, opioid rehabilitation, chronic pain, acute pain, and reference populations. For each patient, I will calculate the coherence for a 5-minute P300 scan, and simulate the resulting networks using ER and Chung-Lu random graph models, comparing the summary statistics of each with that of the true

network. I expect that one major difference between clinical populations will be the sorted degree distribution of coherence network maps.

As an extension of this project, the maximum k-core algorithm may be implemented in order to localize the most important nodes to measure for a given disease state. This has very useful applications within other machine learning models, as it allows us to expand the number of data by shrinking the amount of “artifacted” timepoints.