Signed clustering in network neuroscience

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Networks in their simplest form are graphs, where nodes represent entities of interest and edges represent pairwise interactions of interest. They arise in a wide variety of systems, such as social, biological, ecological, financial, and technological systems. Depending on the application and question at hand, there are many real-world considerations one may want to include in a network representation, such as weights, direction, signs, and time-dependence. It is important to develop computational tools that can meaningfully incorporate these empirical features.

An application of network science that has gained momentum over the last years is “network neuroscience” [1]. A particularly fruitful technique from network science that has been used across a wide range of neuroscience applications is community detection [2]. Two common empirical features of neuroscience networks are signs (e.g., correlation networks computed from fMRI time series data) and time-dependence. While there are many community detection techniques for static networks with positive edge weights, far fewer exist for signed and time-dependent networks.

The goal of this master thesis will be to explore and implement a few approaches for signed community detection, and to apply them to neuroscience correlation networks. Questions to explore include whether signed techniques can better differentiate between brain-level cognitive functions than unsigned techniques. Possible methodological starting points are a generalisation of the popular modularity function [3], alongside an exploration of its limitations [4], as well as a more principled spectral approach to signed clustering [5]. Neuroscience data starting points could be publicly available time series data from repositories such as https://openneuro.org and pre-processed signed networks from https://github.com/multinetlab-amsterdam/network_TDA_tutorial. We will also have access to pre-processed signed networks and metadata from the Brain Mapping Unit of the University of Cambridge’s Department of Psychiatry.

Follow up research directions to this thesis may include developing techniques for the statistical inference of mesoscale structure and temporal dependencies in neuroscience networks, as well as Bayesian inference techniques for network construction from unreliable data [6].

References

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