Neurographs: a thorough introduction to the state of the art

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Abstract

This paper presents a thorough introduction to the state of the art of Neurographs and Brain networks explaining the basic concepts and highlighting the most important features and techniques available today. I highlight the most used metrics and Global and Local properties of graphs. Then I explain two types of connectivity: effective and functional and list the most important techniques for each of them. Furthermore I point out a great new technique developed this year that may yield great results. I conclude wrapping up the exposed elements and talk about future challenges.

1 Introduction

The great advances in statistics,signal processing computation theory and physics allowed us to better our understanding of brain functioning. Of course the brain is a vast and complex system that depends on an astounding number of neurons linked together. These connections create a network which as today is still too complex to fully simulate, therefore many techniques were and are being developed to help us get as much information as possible. Of course the fundamental first step is to get an image of the brain we can manipulate and extract data from. There are different ways to obtain these images. The main ones are functional magnetic resonance imaging (fMRI), electroencephalography (EEG) and magnetoencephalography (MEG). Most of the papers I read and studied started from fMRI images, and there seems to be a preference towards this technique.

This leads up to a NxN matrix of multivariate relationships, from this we may derive a graph. This makes it easier to infer useful data and study the properties and metrics of the brain.[2][8]

Let's take a step back and explain exactly what a graph is.

A graph is a mathematical representation of a network. It is usually indicated with G = (V, E), where V is the set of vertices (also referred to as nodes) and E is the set of edges. Any edge consists of a pair of vertices, and can be distinguished according to four different categories: directed, undirected, binary, weighted edges. [1]

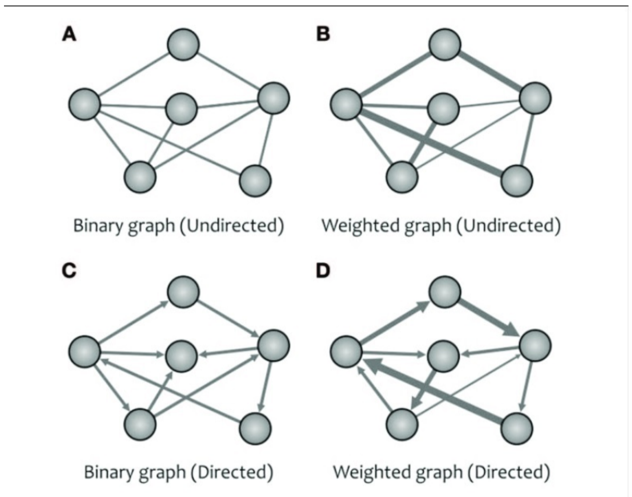


Figure 1: Types of Graph

An edge is directed when its starting vertex and its ending vertex are specified, otherwise it is said to be undirected. Whenever it is possible to associate a number to an edge then this number is called the weight of the edge, on the contrary if no weight is associated to an edge then the edge is binary. [1][13]
Why Graph Theory is so important in Neuroscience though ? The answer is that research in this field is centered around questions of how to relate brain functioning to parameters characterizing brain connectivity both in healthy people and in patient affected by neuropathology. Graph Theory is a perfect candidate in succeeding this challenge, in fact many studies point out that Neurological diseases may be a result of altered connectivity between brain regions.[1][2]
The human connectome for exemple tries to describe the complete set of all neural connections of the human brain. And it is astounding how different brains can share properties that allow us to identify similarities and infer valuable conclusions. A few of these properties can be connectivity, centrality, clustering, modularity and others.

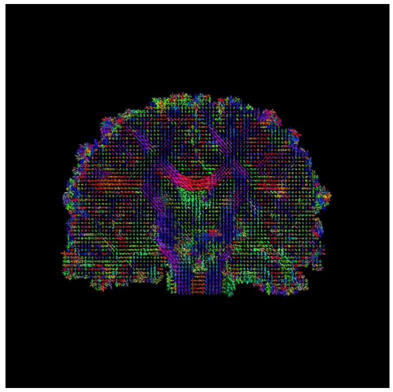


Figure 2: Human Connectome Project Image

2 Global Properties

I want to highlight now a few important Global Properties for graphs. Segregation refers to the degree to which network elements form specialized communities, provides insight into the efficiency of global information communication. Clustering coefficients and modularity are the most common metrics that quantify the properties of topological segregation in brain networks On the other side, functional integration is typically measured by the characteristic path length that quantifies the ability for global information integration. A small-world network refers to an ensemble of networks in which the mean geodesic (i.e., shortest-path) distance between nodes increases sufficiently slowly as a function of the number of nodes in the network. The term is often applied to a single network in such a family, and the term "small-world network" is also used frequently to refer specifically to a Watts–Strogatz toy network.In particular,the typical distance between two randomly chosen nodes grows proportionally to the logarithm of the number of nodes N in the network. Assortativity quantifies network resilience against random or deliberate damages in the main components, which is one of the most significant issues in network science[2][24]

3 Local Properties

Hubs are the nodes with a high centrality. Hub nodes of a network can be the connector or provincial, based on the high or low participation coefficient. Connector hubs tend to interconnect nodes between different modules, while the provincial hubs are responsible for linking nodes in the same module. Exemple of indexes to measure nodal centrality are betweenness, closeness, and eigenvector, participation coefficient,percolation, and PageRank.[2][22][23]

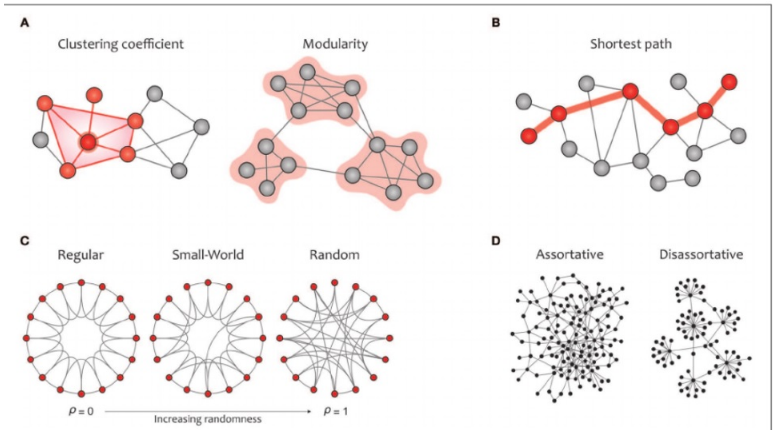


FIGURE 4 | Summary of global graph measures. **(A)** Segregation measures include clustering coefficient, which quantify how much neighbors of a given node are interconnected and measures the local cliquishness (i.e., the extent to which the neighbors of a node can build a complete graph); modularity, which is related to clusters of nodes, called modules, that have dense interconnectivity within clusters but sparse connections between nodes in different clusters. On the one hand, dense communications within a certain module increase the local clustering and, consequently, enhance the efficiency of information transmission in the given module. On the other hand, a few connections between different modules integrate the global information flow, which is associated with a reduction in the average path length in the graph **(B)** Integration measure include characteristic path length, which measures the potential for information transmission, determined as the average shortest path length across all pairs of nodes. **(C)** A regular network (left) displays a high clustering coefficient and a long average path length, while a random network (right) displays a low clustering coefficient and a short average path length. A small-world network (middle) illustrates an intermediate balance between regular and random networks (i.e., they consist of many short-range links alongside a few long-range links), reflecting a high clustering coefficient and a short path length. **(D)** The assortativity index measures the extent to which a network can resist failures in its main components (i.e., its vertices and edges). Notably, communication between hubs in assortative networks leads to covering each other's activities when a particular hub crashes, but the performance in disassortative networks will drop sharply due to the presence of vulnerable hubs.

Figure 3: Global Properties [2]

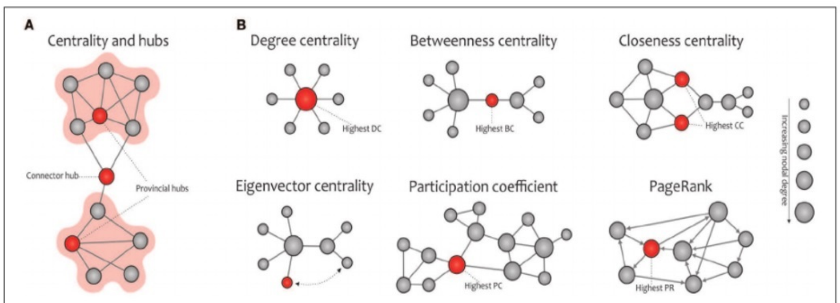


FIGURE 5 | Basic concept of network centralities. **(A)** Hubs (connector or provincial) refer to nodes with a high nodal centrality, which can be identified using different measures. **(B)** The degree centrality is defined as the number of node's neighbors. The betweenness centrality measures the node's role in acting as a bridge between separate clusters by computing the ratio of all shortest paths in the network that contain a given node. The closeness centrality quantifies how fast a given node in a connected graph can access all other nodes, hence the more central a node is, the closer it is to all other nodes. The eigenvector centrality is a self-referential measure of centrality that considers the quality of a link, so that being connected to a central node increases one's centrality in turn; the red colored node is more central than the gray colored node, although their degrees are equal. The participation coefficient of a node represents the distribution of its connections among separate modules. PageRank is a variant of eigenvector centrality, used by Google Search to determine a page's importance; the PageRank of an undirected graph is statistically similar to the degree centrality, but they are generally distinct. Note that the size of the nodes in all cases is proportional to the node degree, and the red nodes (except in the eigenvalue centrality) are the most central with respect to the corresponding definition of centrality, even though their degree are low.

Figure 4: Local Properties [2]

4 Connectivity

Functional connectivity Functional connectivity is defined as the temporal coincidence of spatially distant neurophysiological events. That is, two regions are considered to show functional connectivity if there is a statistical relationship between the measures of activity recorded for them. The notion behind this connectivity approach is that areas are presumed to be coupled or are components of the same network if their functional behavior is consistently correlated with each other. Hence, it is a statistical concept which relies on statistical measures, such as correlation, covariance, spectral coherence, or phase locking. In this regard it is worthy to recall that statistical dependencies are highly time dependent and fluctuate on multiple time scales ranging form milliseconds to seconds.[2][20]

Model Based:
Cross-correlation and coherence: which is the most classical way for testing functional connectivity and is defined by measuring the correlation between the BOLDS signals of any pair of brain regions.[2]
Statistical Parameter mapping: which is another approach used to detect region-specific effects such as brain activation patterns bu utilizing combinations of linear models.[2][16]

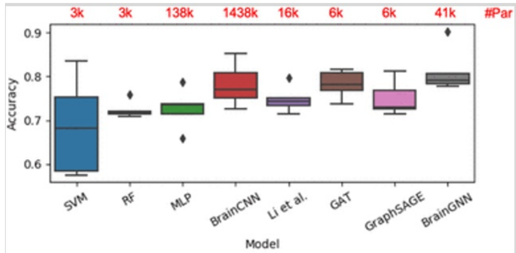
Model Free:
Decomposition based: which expresses the fMRI data with a linear combination of orthogonal contributors that greatly impact data variance. Each contributor contains a pattern of time variability multiplied by a pattern of spatial variability.[2]
Clustering: which is utilized to group voxels and regions of interest based on their similarities according to their BOLD time courses.[2][15]
Mutual Information: which quantifies the shared information between two random variables.[2][14]

Effective connectivity
It is a special kind of functional connectivity. In detail, effective connectivity describes the influence that one neuronal system or a brain region exerts upon another. This clearly results in reflecting causal interactions between activated brain areas. In this case direction plays an important role; in fact, direction gives information on which regions influence others. From an experimental point of view statistical causality can be inferred from network perturbations or time series analysis. It should be understood as the experiment and time-dependent, simplest possible circuit diagram that would replicate the observed timing relationships between the recorded neurons.[27] Both functional and effective connectivity refer to abstract concepts with no immediate connection to anatomical connectivity which physically mediates such correlations.[2][21]

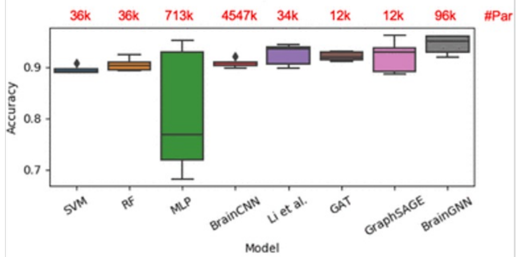
Model based
Granger casualty: which identifies the dependence between a brain area regions at different times. The main idea being that brain regions past configuration can modify the current state of other areas.[2][17]
Dynamic causal modeling:which is based on a general bi-linear state equation that quantifies how variations in neural activity in one node are affected by the activation in another node under predefined stimuli.[2][18]
Model-free
Baeysian network:which is a probabilistic model well suited for representing the conditional dependencies over a set of random variables through a directed acyclic graph.[2]
Transfer entropy: which is a non-parametric approach measuring the transfer of information between joint processes based on information theory.[2][19]

5 A promising new technique

BrainGNN is an interpretable graph neural network for fMRI analysis. BrainGNN takes graphs built from neuroimages as inputs, and then outputs prediction results together with interpretation results. It proposes an ROI-aware graph convolutional layer (Ra-GConv) with two insights. First, when computing the node embedding, they allowed Ra-GConv to learn different convolutional kernels conditioned on the ROI (geometric information of the brain), instead of using the same kernel W on all the nodes. Second, they included edge weights for message filtering, as the magnitude of edge weights presents the connection strength between two ROIs. This framework is generalizable to other neuroimaging modalities.[6] Two independent datasets were used: the Biopoint Autism Study Dataset (Biopoint) and the Human Connectome Project (HCP) 900 Subject Release. For the Biopoint dataset, the aim was to classify Autism Spectrum Disorder (ASD) and Healthy Control (HC). For the HCP dataset, the aim was to decode and map cognitive states of the human brain. Thus, they classified 7 task states - gambling, language, motor, relational, social, working memory (WM), emotion, then infer the decoded task-related salient ROIs from interpretation. BrainGNN not only performs better on prediction than alternative methods, but also detects salient brain regions associated with predictions and discovers brain community patterns. This model seems better than alternative graph learning and machine learning models for classification. In the image below it is shown the great accuracy and overall results of this model.(Par represents the number of paramters)[6]



(a) Biopoint



(b) HCP

6 Disorders and diseases

Disconnection in a brain made up of localized but linked specialized regions results in functional impairment, associating with atypical integration of distributed brain areas. Catani and Ffytche (2005) elaborated the rises and fall of disconnection syndromes and pointed out that many neurological disorders can be explained via these syndromes. Studies in the field of complex brain networks have demonstrated that analyzing the network properties and metrics derived from brain topology can help neurologists distinguish patient groups from control subjects in mental disorders.[2] Many studies that have used graph theory to investigate common neurological disorders and delving deeper into this kind of topics may help us prevent and treat diseases/disorders such as: Alzheimer's disease (AD), Multiple sclerosis (MS), Autism Spectrum Disorder (ASD), Attention-deficit/hyperactivity disorder (ADHD), Parkinson-s disease Insomnia Major depression OCD's

7 Conclusion

In this paper,I wanted to summarize the current state-of-the-art for Neurograph studies and brain networks,it is not meant to be an exhaustive explanation of every single technique but an overview that may spark the interest in the reader to delve deeper into this fascinating world and maybe contribute to it. There is many steps required to obtain information and as of right now each of them could benefit from further research and studies. Some of these issues are heterogeneity of the results, sensitivity to parcellation strategy and node specification, statistical variability of brain graphs due to noise, lack of attention to the structure-function relationship, neglecting the variations in network density and connection strength, and dynamics of the brain network, or that not much focus has been put into comparing different graphs[2][11] There are many challenges ahead of us but the benefits could be astonishing: from being able to prevent terrible and non-treatable diseases to understand better our brain and the incredible amount of processes and activities that are performed daily.

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