

Complex Networks: Graph Theoretical Analysis of Structural and Functional Systems

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Outline

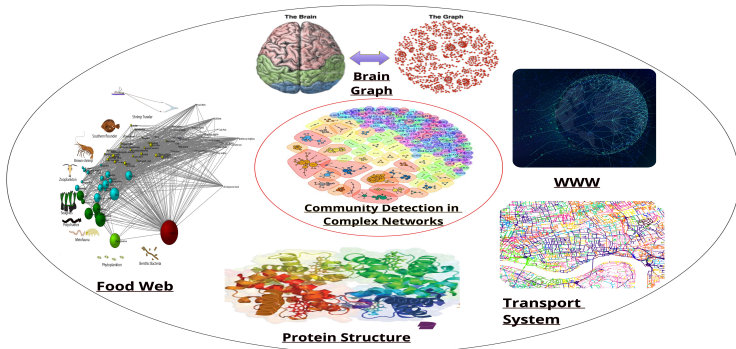
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Introduction

Connections between data are as important as the data itself

Introduction

- The amount of data traveling across the internet today is not only massive in terms of size but is complex as well.
- Big data of complex networks include very large scale networks with structured, unstructured, or semi-structured data and a set of the graph [6, 29]



Applications of Community Detection in Complex Network - Brain graph [9], protein structure [12, 14, 21] food web, transportation system [4], World Wide Web [3]

Use of data connections has created industry leaders



Google



monster
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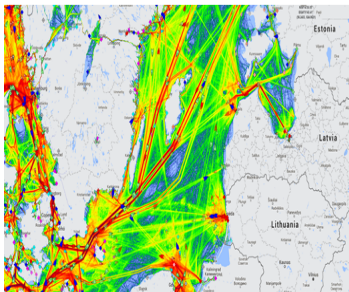
LinkedIn



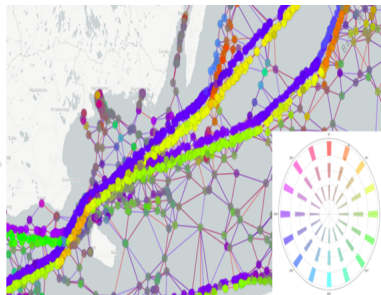
amazon



Use of data connections has created for Maritime



Maritime Traffic Data



Directed graph for the Baltic Sea generated on AIS data for an 8-week period

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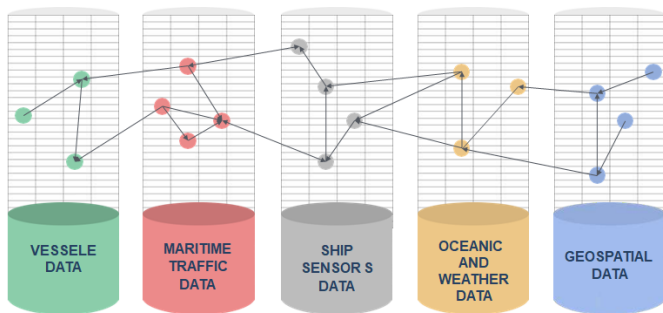
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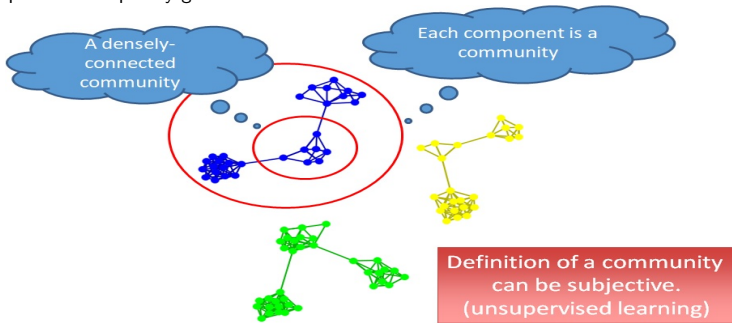
- Social Network Analysis has been used to show that enemy networks and relationships can be
 - accurately represented using weighted layers
 - with weighted relationships
 - in order to identify the key player(s) that must be influenced and/or removed so that
 - A particular effect on the enemy might be realized.



“The next wave of **competitive advantage** will be all about **using connections** to produce actionable insights.”

Community Detection

- Community is formed by individuals such as those within a group interact with each other more frequently than with those outside the group. Such as, group, cluster, cohesive sub-group, module in different contexts.
- Community detection is discovering groups in a network where individuals' group memberships are not explicitly given.

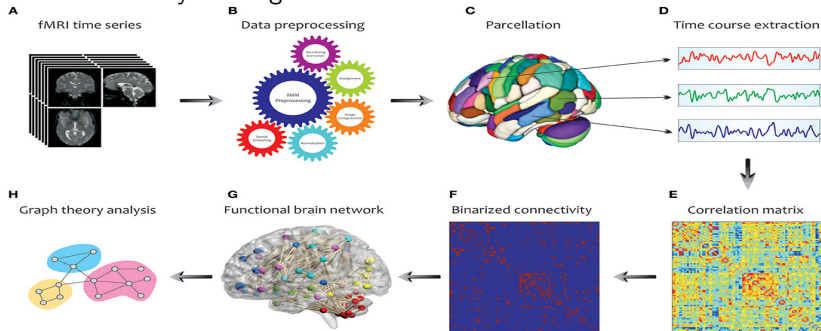


Graph Theoretical Analysis

- Most of the clustering methods on graphs predominantly emphasis on the topological structure without considering connectivity between vertices and not bearing in mind the vertex properties/attributes or similarity-based on indirectly connected vertices.
- Many scientific and commercial applications have complicated structures than sequential patterns and needs additional effort to analyze it.
- Community of brain graphs helps in the development of a new methodology to precisely parse and understand modularity in human brain function and structure [9].
- Communities of proteins networks identify functionally related to protein-protein interaction and also supports earlier stages of treatment of diseases and is related to drug discovery [11, 16, 18, 28].
- Modeling and generating a graph based on their structure, attributes, weight, and direction (whether directed or undirected) becomes an important task.
- Big Data Analytics refers to the process of collecting, organizing, and analyzing large data sets to discover different patterns and other useful information.

Graph Theoretical Analysis : for Brain Network

Schematic representation of brain network construction and graph theoretical analysis using fMRI data

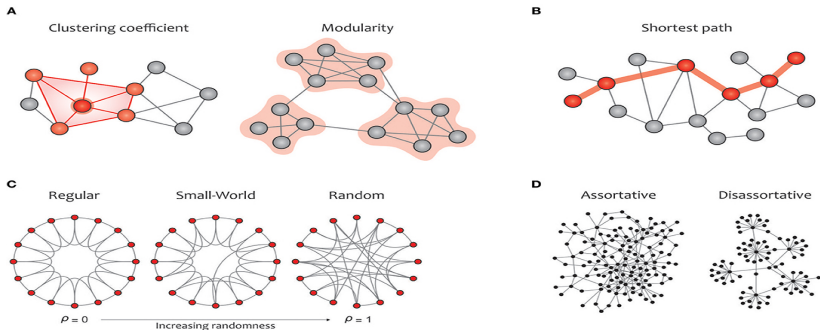


- After processing **(B)** the raw fMRI data **(A)** and division of the brain into different parcels **(C)**, several time courses are extracted from each region **(D)** so that they can create the correlation matrix **(E)**.
- To reduce the complexity and enhance the visual understanding, the binary correlation matrix **(F)**, and the corresponding functional brain network **(G)** are constructed, respectively.
- Eventually, by quantifying a set of topological measures, graph analysis is performed on the brain's connectivity network **(H)**.

Categorization of graph theory applied in neurological domain

- Graph Theory applications in neurological disorder
 - Epilepsy
 - Alzheimer disease
 - Multiple sclerosis
 - Autism spectrum disorder
 - Attention-deficit/hyperactivity disorder
 - other mental disorder
- Graph Theory applications in human cognition
 - Human intelligence and the brain topology
 - Topological changes across the lifespan
 - Working memory performance and network efficiency
 - Effect of cognitive loads on modularity

Computation of Graph Measures



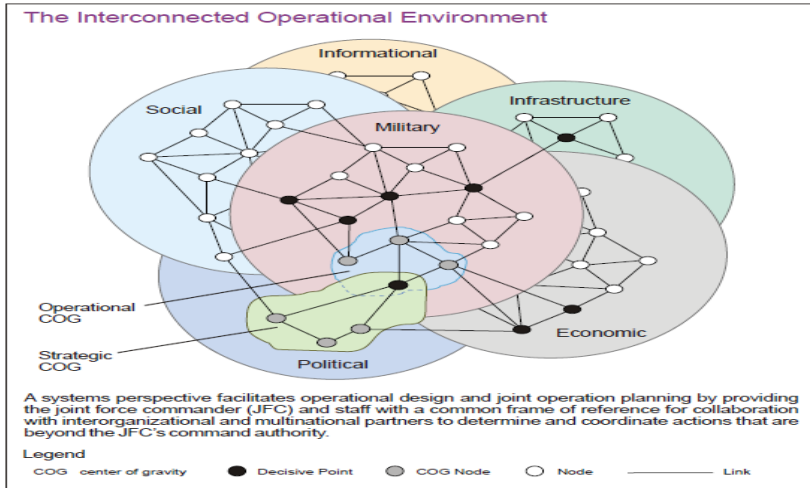
(A) Segregation measures include clustering coefficient, which quantify how much neighbors of a given node are interconnected and measures the local cliquishness ; modularity, which is related to clusters of nodes, called modules, that have dense interconnectivity within clusters but sparse connections between nodes in different clusters.

(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.

(D) The assortativity index measures the extent to which a network can resist failures in its main components (i.e., its vertices and edges).

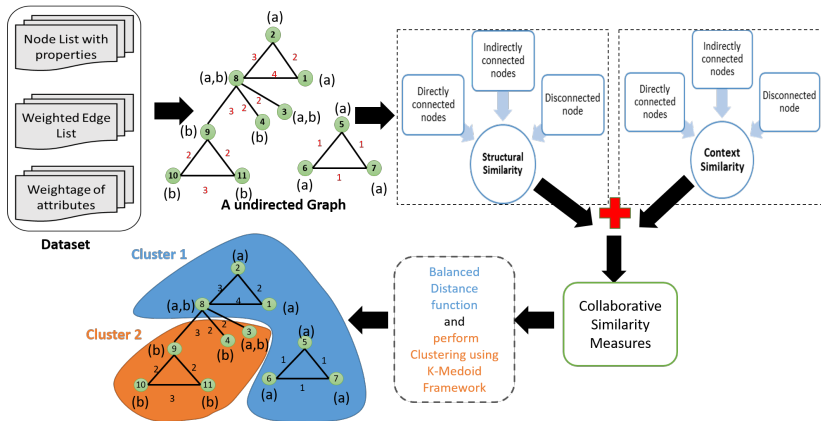
Graph Theoretical Analysis : for Military → The Interconnected Operational Environment



Categorization of Community Detection Criteria

Category	Methods
Node-Centric Community Detection	Complete Mutuality : cliques [26]
	Reachability of members :k-clique, k-clan, k-club [26]
	Nodal degrees :k-plex, k-core [26, 8]
Group-Centric Community Detection	Density-Based Groups [26, 27]
	Machine Learning Based Approaches [7]
Network-Centric Community Detection [26, 2, 13]	Clustering based on vertex similarity
	Latent space models (multi-dimensional scaling)
	Block model approximation
	Modularity maximization
	Spectral clustering
Hierarchy-Centric Community Detection [26, 5]	Divisive Hierarchical Clustering (top-down)
	Agglomerative Hierarchical clustering (bottom-up)

Case Study #1: A Collaborative Similarity Based Graph Clustering for Community Detection in Complex Networks



#2: Predicting overall Flight Delay caused by Origin Delay using Random Forest Algorithm and Path Finding



All the airports with their connections in the world

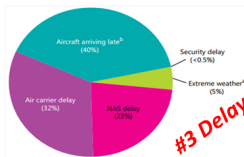
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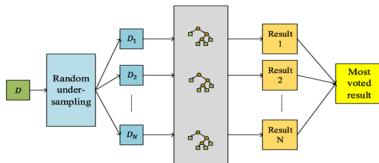
#1 Data Source



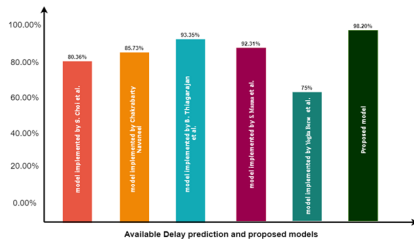
#2 Data Cleaning



#3 Delay Calculation



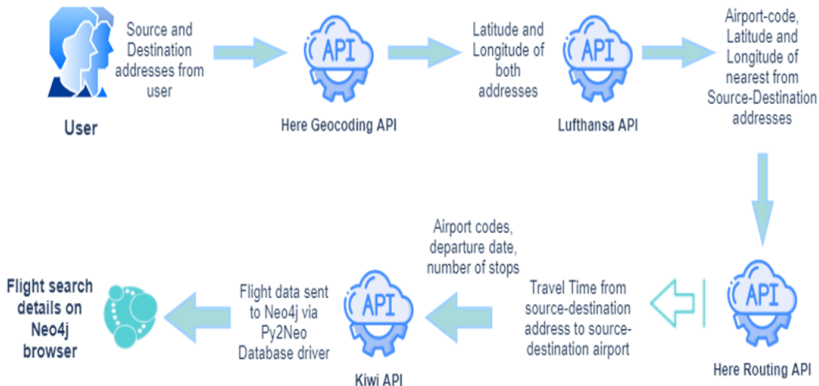
#4 Delay Prediction



#5 Result

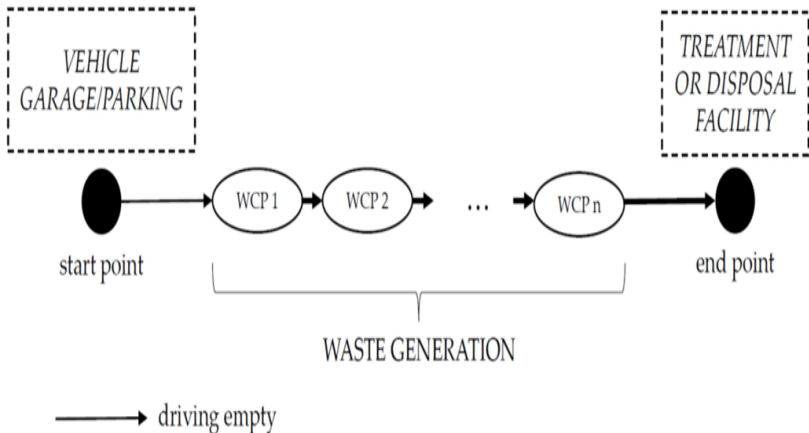
#2: Predicting overall Flight Delay caused by Origin Delay using Random Forest Algorithm and Path Finding

#Flight Search

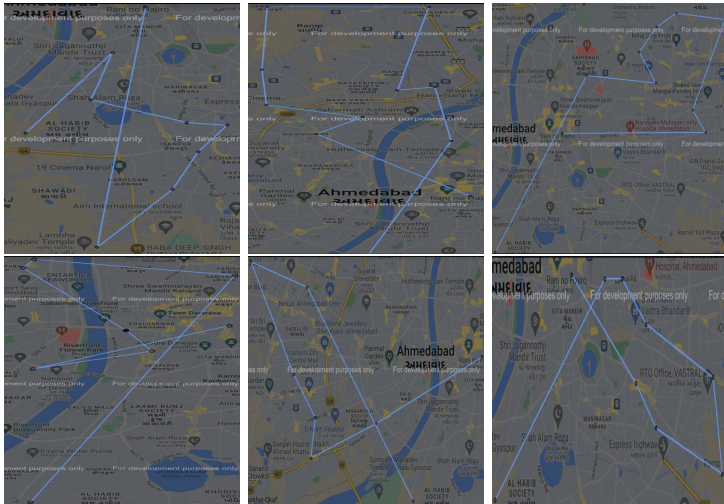


#3: AI-enabled optimize routing for solid waste collection in Ahmedabad city

Route finding for garbage collection is part of a waste management system that can be more cost-efficient with the help of technology.



#3: AI-enabled optimize routing for solid waste collection in Ahmedabad city



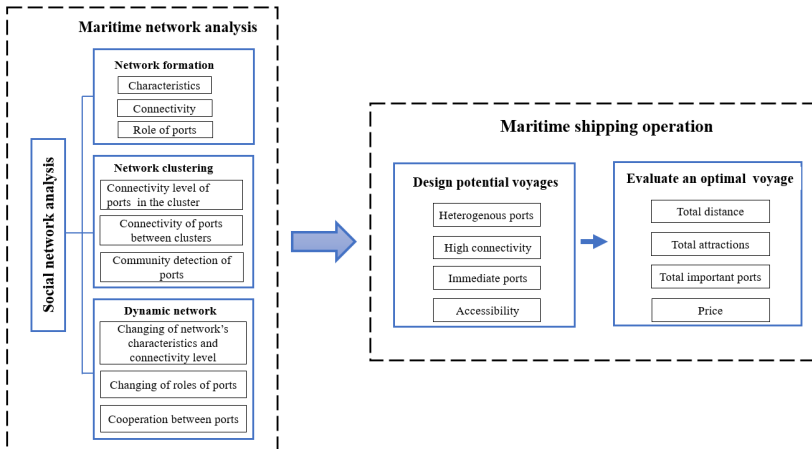
#3: AI-enabled optimize routing for solid waste collection in cities

- To find the optimized route for trucks to collect garbage from smart dustbins, reducing costs and making a more efficient and profitable system.
- Route finding is an NP- hard problem that can be solved by many algorithms, some are heuristics, meta heuristics, VRP, and genetic algorithms.
- Used clustering and genetic algorithm to find route optimization for the Ahmedabad city dataset

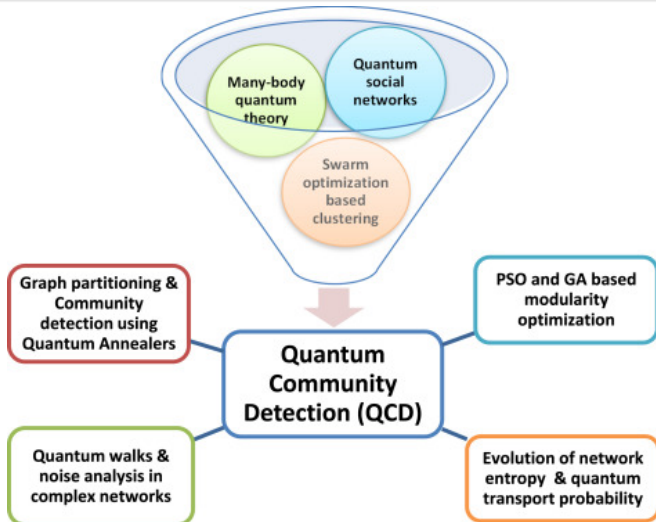
Research Opportunities

- The brain network topology is expected to be responsive to cognitive performance, behavioral variability, experimental task, and neurological disorders such as epilepsy, Alzheimer's disease, multiple sclerosis, autism, and attention-deficit/hyperactivity disorder.
- However, graph analysis in human neuroscience faces a number of issues that remain unaddressed, restricting its interpretation and application
- Some examples 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.
- Addressing any of these limitations in future studies will help advance our understanding of functional neural networks in the human brain.

Research opportunities in Maritime Network Analysis



Research opportunities in Quantum SNA paving way for QCD[1]



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Thank You
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