RECENT DEVELOPMENTS IN NETWORK ANALYSIS AND THEIR APPLICATIONS

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1. INTRODUCTION

When analyzing complex networks, statistical techniques such as resampling [15], bootstrapping [40], randomization [46] have been proven useful. For instance, typical network structures represent technical networks, biological networks, and social networks. Technical networks appear for example in communication technology, transportation, and energy. In computational biology, several biological networks such as gene networks have been investigated. Emmert-Streib et al. [16, 8] found that biological networks are often non-deterministic, that means they cannot be inferred deterministically. Therefore statistical methods to analyze such networks have been crucial, see [16, 8].

In complex network analysis, there are several problems to deal with. For example, it has been challenging to collect network data properly such that statistical methods become applicable. Another problem that has been often demanding relates to visualize and analyze networks meaningfully [17]. To analyze networks, structural graph measures have been often used, see, e.g., see [16, 8]. Examples are the clustering coefficient, cohesion measures, connectivity measures and other topological indices to map graphs to real numbers [10]. The latter method relates to determine the complexity of networks. By employing statistical methods, important applications in network theory such as subgraph sampling and link mining. Link mining techniques have been also applied in Web Structure Mining [7] and related disciplines. Another striking problem in statistical network analysis is network inference [3].

In the age of big data, analyzing massive data sets become more and more important. In case of structural data (networks), tackling the complexity of the data sets has been often challenging. Either the networks are very large or one needs to deal with a huge number of graphs, see [9]. In both cases, applying statistical methods has been fruitful. The main contribution of the paper is to survey recent work on statistical network analysis. The survey aims to highlight the interdisciplinary character of the field and, hence, the paper can be useful for those who want to tackle problems in statistical network analysis and related disciplines.

2. STATISTICAL NETWORK ANALYSIS

In the following we start surveying recent contributions. We begin with a paper due to Eldardiry and Neville [15] dealing with network sampling. Eldardiry and Neville [15] proposed a novel subgraph resampling approach which cannot only generate pseudo samples with sufficient global variance. The method also maintains local relational dependencies and link structures. The algorithm is based on a two-phase relational subgraph resampling technique. The first phase selects subgraphs of same size from the original relational data, and the second phase links up the selected subgraphs. Finally the authors applied two different relational settings to evaluate the resampling method.

In [11], Dehmer and Basak explored several statistical methods to analyze complex networks. Also, the book deals with explaining machine learning methods for networks such as graph classification. Importantly [11] shows that graph theory, machine learning and statistical techniques have been applied in an interdisciplinary manner.

It is known that bootstrapping is a well-known data-driven approach used to create random pseudo samples with just one empirical observation. In this context Tremblay et al. [40] presented an approach for statistical resampling based on bootstrapping of nodes under constraints. The whole network was used to do the analysis and the aim of their study was to design a statistical test and find acceptance intervals for various null hypotheses concerning relevant observable features of groups of nodes in a given network. They demonstrated the performance of the network by using real data sets.

Detecting communities in graphs has been useful to identify functional sub units of a system and to reveal the similarities among vertices. In [20], Fortunato explored the problem of community detection by defining the problem and discussing issue regarding the significance of the method. This method is mainly based on bayesian inference where the best fit is obtained through the maximization of likelihood (generative models). The observations are used by using Bayesian inference to estimate the probability to verify whether the given hypothesis is true or false.

Djidjev et al. [13] analyzed traffic patterns by using statistical network analysis. Djidjev represented large computer traffic networks as time-labeled graphs and made use of temporal characteristics to partition the graph in subgraphs where they called them telescoping subgraphs. The statistical analysis aimed to explore characteristics of the subgraphs statistically. As statistical techniques, Djidjev et al. [13] applied methods from supervised learning.

Lancichinetti et al. [28] introduced a new measure called C-score aiming at quantifying the statistical significance of communities in networks. The C-score is the probability of occurrence of a community that has the same number of nodes with the same degree sequence and the same internal connections under two hypothesis: The first is that the nodes are randomly connected in the network, and the second is that the group is chosen. In order to predict the statistics associated with individual clusters, statistical measures have been used. The proposed measure of C-score has been successfully tested on several networks such as the random graphs, artificial networks and real networks.

Guillaume [21] studied p2p query graph by using statistical graph analysis. To to so, Guillaume used complex network analysis methods to analyze large traces of queries and exchanges processed in such p2p query systems. The authors defined a labeled weighted bipartite graph called the query graph representing the query information. In this query graph, the time-evolution of degrees has been mainly studied. As demonstrated in [21], degree distributions of query graph follow power laws.

A similar analysis using randomization techniques have been performed in [46]. In this paper, two edge-based randomization techniques have been introduced. More precisely, Ying and Wu [46] developed spectrum preserving randomization methods. The proposed method has been proven useful when preserve graph properties meaningfully. In [46], Ying and Wu mainly focused on two important eigenvalues of graph spectrum, namely the largest eigenvalue of the adjacency matrix and the second largest eigenvalue of the Laplacian matrix respectively.

In [29], community structures have been explored too. Here, the problem has been explored based on the local optimization of a fitness function that expresses the statistical significance of clusters. Also Lancichinetti et al. [29] the Order Statistics Local Optimization method (OSLOM) to detect clusters in large complex networks. In order to give evidence, mathematical properties of OSLOM have been explored and the methods have been demonstrated by employing real world data sets, see [29].

Albert and Barabási [2] performed significant work in statistical network analysis dealing with exploring dynamics of complex networks. In [2], important network models are discussed which include random graphs, small-world networks, scale-free networks and evolving networks. Those have been analyzed statistically, see [2].

Simpson et al. [37] explored functional brain networks statistically. First they performed a survey on the statistical methods to analyze these networks and for exploring functional magnetic resonance imaging (fMRI) network data. Moreover, they also discussed techniques for modeling and inferring brain networks.

In order to model social networks by using statistical models, exponential random graph models (ERGMs) have been used. Snijders et al. [38] explored convergence problems of estimation algorithms and inference problems using these ERGMs. To tackle this problem they used new specifications of ERGMs allowing to represent structural properties such as transitivity and heterogeneity of complex social networks. As result, they have demonstrated that their new model outperform classical techniques.

3. NETWORK ANALYSIS IN NEURO SCIENCES

As we know, neuroscience is mainly used to study the nervous system. The research scope of neuroscience is very extensive, such as molecular, cellular, evolutionary, computational, functional, and medical aspects of the nervous system. In this section, we conduct some investigations relating to neuroscience principal from the perspective of network analysis.

Unlike the conventional networks usually with predefined nodes and edges, the nodes and edges of brain network are mainly derived from neuroimaging data. So, the structure of brain network, with many noises and uncertainties, is nondeterministic. Therefore, novel methods dealing with these challenges are required for the analysis of brain network. In [27], Kong and Yu introduced data mining methods to analyse the brain network. The authors primarily focused on analysing neuroimaging data using imaging-based approaches such as tensor-based modeling and supervised tensor learning, extracting the brain network from neuroimaging data, and mining subgraph patterns.

It is known that functional magnetic resonance imaging (fMRI) is broadly used to study human brain in both normal and pathological conditions. The bayesian networks (BN) can be used to model complex dataset with uncertainties and needing expert prior knowledge. Moreover, it is found that many neurological and mental illnesses such as Alzheimer and Parkinson diseases are associated with functional connectivity. In [22], Ide, Zhang and Li not only reviewed in detail the recent literatures concerning the fMRI connectivity analysis using BN, meanwhile they also presented a BN group modeling of fMRI dataset. By applying BN modeling to fMRI dataset obtained from a stop-signal task, some novel results regarding the response inhibition network were also presented in [22].

In recent years, resting-state functional magnetic resonance imaging (R-fMRI) used to measure spontaneous neural activities in the human brain has obtained great attention. In [42], Wang, Zuo, et al. reviewed literatures on graph-based brain network analysis of R-fMRI signals. Through summarizing these literatures, the nontrivial topological properties of functional networks of human brain were demonstrated. Furthermore, it is found that the intrinsic activity of human brain actually could be represented as a small-world, highly efficient network. At the same time, the authors also discovered in their review that the graph-based network analysis was able to reveal system-level changes associated with diverse processes in the resting brain.

When analyzing neuroscience data, some insights with regard to the network of physiological pathways could be obtained by identifying task-related causal relationships among different areas of brain. Ramb, Eichler, et al. [36] firstly introduced the concept of Granger causality and the vector autoregressive (VAR) modelling. Furthermore, the authors also demonstrated the effect of latent confounders in linear systems, and studied the paths of influence among three components in both linear and nonlinear systems. The effects of latent confounders were also studied in nonlinear systems. In addition, the combination of bivariate and multivariate analysis was taken into account in [36].

Recently, it was reported that rare missense mutation on triggering receptor expressed on myeloid cells 2 (TREM2) gene would significantly increase the risk of late onset Alzheimers disease (LOAD). In order to better understand TREM2 biology in human brain, Forabosco et.al [19] put microarray-based expression datasets to use for network analysis. Through the weighted gene co-expression network analysis (WGCNA), the authors discovered a highly preserved TREM2-containing module in human brain, meanwhile substantiated that the TREM2 was actually a hub gene in five brain regions containing the hippocampus. Moreover, other important results were also acquired by conducting the enrichment analysis and inspection of genes with the highest connectivity to TREM2 in [19].

To understand development of preterm infants is exceedingly important because they are at higher risk of brain pathology than those born at term. The technology of diffusion tensor imaging (DTI) can help observe the brain development of preterm infants at a very early age. Recently, many researchers found that the brain network would display small-world properties by conducting analysis of structural connectome of the brain scans adopting the method of network analysis. For the sake of further understanding how the structural connectome develops, Brown et al. [4] carried out examination on 47 normal preterm neonates. By analyzing the connectomes and probing the differences between weighting edges, the authors found that the brain networks in preterm infants exhibited high efficiency and clustering measures, actually very like those born at term. Meanwhile, it was also revealed that the development of many individual region-pair connections was very relevant to age. By adopting the established brain network measures in the context of [4], the phenomenon was observed that the connectome of preterm infant maintained highly efficient, but would become more clustered across the given range of age.

In [45], Wu, Zhang, et al. explored the effects of music on brain functional networks using the method of network analysis. The authors took advantage of electroencephalography dataset to construct weighted connectivity graphs, meanwhile utilized the clustering coefficient and the characteristic path length to quantify the topological properties of weighted graphs. Further, in order to make the most of information in the weight and to avoid arbitrary selection of threshold for values of phase lag index, the network analysis was performed by using the weighted network measures.

4. SPATIO-TEMPORAL NETWORK ANALYSIS

In the context of [25], Kang et al. conducted researches on the spatiotemporal dynamics of transcriptome of human brain. The authors represented the co-regulated genes as the co-regulated transcriptional networks. Since the given multi-dimensional transcriptome dataset might imply some additional important biological information, in order to extract which, the weighted gene co-expression network analysis was implemented for identifying modules of co-regulated genes. The results indicated that these different modules were related to distinct spatio-temporal expression patterns and biological processes. In addition, gene ontology enrichment analysis was also performed in [25].

Conventional approaches for analyzing brain function network mainly concentrated upon the spatial dimension of the brain function network data while disregarded the temporal dimension. In the context of [23], Janoos et al. proposed a fully spatio-temporal multivariate analysis approach. Based on a state-space model, the presented fully multivariate spatio-temporal model could delineate both the spatial activity distribution over the functional networks of brain and its temporal structure. In [23], the authors provided a quantitative validation of the efficient estimation algorithm, and derived a kind of novel low-dimensional feature-space. Further, the ability of the proposed neurophysiologically model was validated by adopting a real functional magnetic resonance imaging (fMRI) study for mental arithmetic.

The brain can be regarded as a spatio-temporal information processing machine. In order to understand processes of brain and recognize the signal pattern of brain better, Kasabov [26] presented a new evolving spiking model called NeuCube that was 3D evolving Neurogenetic Brain Cube of spiking neurons. The architecture of the proposed NeuCube consisted of input encoding module, NeuCube module, output function module and gene regulatory networks module. In [26], the author modeled Spatio- and spectro-temporal data (SSTD) and recognized the pattern using the brain-inspired spiking neural networks. Moreover, the gene regulatory networks was adopted for controlling parameters of neurons from the NeuCube in [26].

For analyzing brain dynamics, based on the relative convergence of electroencephalograms (EEGs) of brain loci, Ahmadlou, Adeli, et al. [1] presented a new nonlinear technique named by spatiotemporal analysis of relative convergence (STARC) of EEGs. The proposed STARC methodology can be used to bring the gender differences in the pathophysiology and brain dynamics of patients with major depressive disorder (MDD) to light. The enhanced probabilistic neural network (EPNN) was applied for discriminating the EEGs of the male and female patients with MDD, the same time the statistical analysis and classification was also conducted in [1]. In addition, as a validation to the proposed approach, EEG datasets of 22 adult patients with MDD and 20 healthy adults were investigated.

In the context of [39], Tapson, et al. introduced a new neural synthesis algorithm, and described the linear solutions to higher dimensional interlayer (LSHDI) networks. In order to generate neurons used to recognize and process the spatio-temporal spike pattern, the LSHDI principle was applied. The authors also described in detail the LSHDI for spike encoded neural representations, that is, the SKIM method that provided a simple process for synthesizing the spiking neural networks which were susceptible to spikes in spatio-temporal patterns. Further, the SKIM method was made comparisons with other existing methods.

West, Bailey, et al. [43] introduced a novel data analytic method called Spatial Principal Components Massive Univeriate Analysis (SPC-MUA) and a kind of distributed source analysis approach i.e. a standardized Low Resolution Brain Electromagnetic Tomography or a standardized low resolution tomography (sLORETA). Importantly, in order to research the spatio-temporal features and neural generator of event-related brain potentials (ERPs) derived from a virtual Blackjack game during feedback processing, the SPC-MUA was carried out in combination with sLORETA. The mean voltage analysis was also performed to validate the convergence or divergence of the ERP data. Finally, some caveats of current study were described in [43].

In [47], Zhang, Guindani et al. described a novel wavelet-based Bayesian nonparametric methodology used for modeling brain connectivity adopting the functional magnetic resonance imaging (fMRI) data. First, the authors used a hemodynamic response function (HRF) to model the data. In addition, the mixture priors with a spike for examining the regions of brain were adopted. Moreover, the complicated spatial correlation structure of brain was illustrated by using a Markov random field (MRF) prior. In the context of [47], a Dirichlet process (DP) prior was applied for clustering of the voxels, and the Markov Chain Monte Carlo (MCMC) sampling techniques were used for inference in combination with Metropolis-Hastings schemes. In the end, the performances of the proposed wavelet-based Bayesian nonparametric regression model were probed on both simulated data and real fMRI data.

It is known that the functional connectivity can be construed as the temporal correlation among electrophysiological signals. Based on the K-means clustering of connectivity networks, Mheich, Hassan, et al. [31] presented a novel algorithm used to conduct spatio-temporal analysis of brain functional connectivity over very short durations of time. The connectivity networks could be acquired through the method of Phase Locking Value (PLV) applied on high-resolution electroencephalogram (hr-EEG) signals. In [31], the authors described in detail the segmentation algorithm including its flowchart and details of its main steps. Finally, the performances of the proposed algorithm were evaluated on the hr-EEG signals during a picture naming task.

5. ANALYSIS OF TRANSPORTATION NETWORKS

Transportation network can be represented as $G = (V, E)$, where V denotes vertices, E denotes edges. If G consists of public railway systems or bus systems, V means all stations, E means all available lines between stations. However, if the air transport systems or highway systems of a country are expressed as G, V signifies all cities of the country, E signifies all airlines or highways between cities. In this section, we mainly discuss the railway systems and bus systems from the point of view of network.

As an example, we consider the case that the public railway systems are modelled as an undirected graph or network $G(V, E)$ with n vertices and m edges, where vertex set $V = \{v_1, v_2, ..., v_n\}$ denotes stations, edge set $E = \{e_1, e_2, ..., e_m\}$ denotes lines between stations. The symmetric adjacent matrix A of G is given by $a_{ij} = a_{ji} = 1$ if and only if two nodes or stations v_i and v_j are connected by a line, namely there is at least one train used for directly linking stations v_i and v_j, $a_{ij} = 0$ otherwise. Basically, the transportation networks are regarded as abstract concept of the authentic railway systems, just like social network versus social relationship net among human beings. Specially, there is an advantage on expressing the railway systems as the transportation network, that is, we can obtain some general or specific properties and characteristics of the network by analyzing it using the existing complex network analysis methods. Actually, in the project RiKoV [44], researchers had begun to explore the public railway systems ever since 2010, they also represented the public railway systems as transportation networks. The project RiKoV is sponsored by the German Federal Ministry of Education and Research. It mainly deals with the problem on mitigating the risks and the costs of terrorist threats to rail-bound public transportation. Moreover, its another important goal is to develop a holistic risk management and strategic planning approach for better protecting public railway systems against terrorist attacks[34].

In recent years, many terrorists took the transportation systems as their attacking targets, such as the terrorist activities against railway systems in Madrid (March 11, 2004), London (July 7, 2005), and Mumbai (July 11, 2006), which resulted in not only a large number of casualties, but also considerable economic losses, and sometimes even unpredictable political consequences. So it is very imperative to take some security measures for lessening the impact of ongoing terrorist activities or preventing such terrorist attacks from happening by analyzing the transportation networks deeply. Thus, the project RiKoV supporting researches on protecting public railway systems against terrorist attacks is very necessary. Furthermore, the analysis of transportation networks including risk analysis and structural analysis, on one hand, could help mitigate the risk of terrorist attacks. On the other hand, the cost caused by terrorist activities could be decreased on certain extent.

When a network is nondeterministic or we know nothing about its structures, through the structural analysis of network using some structural measures such as degree distribution measure, clustering coefficient measure, and centrality measures, we can derive some useful structural properties of the network, and further infer what kinds of characters and functions the network has. For example, we could identify critical nodes through the structural analysis of networks, if transportation networks, the crucial stations with certain properties being more likely to become the attacked targets could be detected, so the responding security measures can be deployed ahead to protect these vital stations against being attacked by terrorists. In this section, we mainly summarize contributions focusing on the structural analysis of transportation networks. Starting with a paper authored by Meyer-Nieberg, Dehmer, et al. [30], in which, for the sake of evaluating the vulnerabilities of public transportation systems, the authors proposed a three-model-based approach which combined multi-agent systems, dynamical system, and graph models. Where, the multi-agent systems were mainly used to analyze the system behaviors of the most detailed level. By using difference or differential equations, the dynamical systems were used to describe the development of system behaviour over time. Moreover, based on the dynamical system model, the graph models could be constructed. Afterwards, the complexity of the network-based systems was analyzed by using some quantitative network measures such as distance-based graph measures, eigenvalue-based graph measures, and entropic graph measures.

In [18], Emmert-Streib not only introduced some well-known network classes such as simple networks, random networks, small-world networks, scale-free networks, and trees; but also presented some useful methods for structural analysis of networks such as degree distribution measures, clustering coefficient measures, path-based measures, centrality measures, and a method for identifying the community structure of networks.

Ducruet and Lugo [14] discussed the structures of transportation networks from the perspective of both network level and node level measures. To understand transportation networks better, the usefulness of these measures was also discussed. Regarding the problem of how transportation networks had been defined and analyzed, the authors made some reviews from four aspects concerning spatial structure, geometry, morphology, and topology of transportation networks. Furthermore, the dynamics in transportation networks was explored by adopting the Agent-based Models (ABMs). In order to apply the ABM on transportation networks for dynamic analysis, two distinct approaches including the generative and degenerative processes were presented.

Derrible [12] examined the network centrality of subway networks. The assessment of centrality was conducted by adopting betweenness centrality. To make research on the emergence of global trends with network size in the evolution of centrality, the betweenness centrality was applied to 28 metro systems with different sizes around the world. It was found that the betweenness become more uniformly distribution with size. Moreover, it was showed that the share of betweenness decreased in a power law with size, however, the share of nodes with the most central properties decreased much slower than those with the least central properties. In the end, the betweenness was demonstrated to be useful to locate stations for helping relieve pressure from overcrowded stations by analyzing the betweenness of individual stations in several systems.

It has been found that a macroscopic fundamental diagram (MFD) could be presented in the urban transportation networks when meeting certain conditions. In order to analyze whether the MFD exist in heterogeneously congested transportation networks or not, Ji and Geroliminis [24] mainly conducted research on the clustering problem of transportation networks. As one category of clustering algorithms, partitional method was used in [24]. To minimize the variance of link densities as well as to preserve the spatial compactness of clusters, a new partitioning mechanism was proposed. The presented method consisted of the normalized cut algorithm, the merging algorithm, and the boundary adjustment algorithm. In addition, density variance and shape smoothness metrics were also introduced to examine the proposed partitioning mechanism.

The urban bus and subway networks of Madrid were studied by Mouronte and Benito [33]. Many characteristics of these two networks such as stops, routes, and densities of these two networks were analyzed. The authors represented these two networks as a graph. Moreover, some structural parameters including average distances between nodes, betweenness, robustness, sensitivity and communities of the graph were evaluated not only in the entire city but also in its different districts. Furthermore, the singularity of one transport line in a district was also explored in [33]. And many useful results were achieved through the aforementioned analysis.

Based on the shortest path betweenness centrality measures of complex networks, Puzis, Altshuler, et al. [35] proposed a new betweenness-driven traffic assignment model for deploying the traffic monitoring units optimally in transportation networks. For the sake of coping with the problem of traffic assignment given an arbitrary travelling cost definition, the problem of how to augment the betweenness was discussed. In order to evaluate the proposed model used for generating efficient deployment schemes, a high-resolution Israeli transportation dataset was used for examining. Meanwhile, the correlation was analyzed between betweeness centrality and traffic flow. Finally, it was illustrated that the group variant of the augmented betweenness centrality used to optimize the locations of traffic monitoring units could decrease the cost and enhance the effectiveness of traffic monitoring.

In order to improve the design of the transportation networks and to conceive the plans dealing with the problems on failures of transportation networks, the centrality measures identifying crucial nodes in a transportation network were explored by Cheng, Lee, and et al. [6]. In this paper, a new centrality measure named DelayFlow was proposed. Unlike common centrality measures, the new presented centrality measure was not only taking topological structure of network into account, but also considering two transportation factors namely travel time delay and commuter flow volume. In the end, the proposed measure was compared with some common centrality measures such as degree centrality, closeness centrality and betweenness centrality by using the Singapores Mass Rapid Transit network.

Discovering the Hub road sections is not only in favor of protecting urban infrastructure from being attacked, it is also useful to solve the design problem of traffic network. Based on Girvan and Newman (GN) algorithm, Chen and Hu [5] proposed a new algorithm called GN-T algorithm used to detect community structure and uncover Hub road section in urban traffic network. Also in [5], an improved modularity determining the proper numbers of community structure was presented. Through studying the traffic network of Wuchang, it was validated that the characteristics of community structure existed in the urban traffic network, meanwhile the Hub road sections deduced by using the proposed algorithm was also demonstrated to accord with actual situation.

When analyzing the interregional transportation network in Greece, Tsiotas and Polyzos [41] proposed a novel centrality measure called mobility centrality. It was assessed that the presented measure could be applied efficiently during the operational network analysis. Additionally, the Pearsons Linear Bivariate Coefficient of Correlation and the Linear Regression Backward Elimination method were used to test the ability of the proposed measure. Moreover, the presented centrality measure was compared with other four traditional existing centrality measures including betweenness, closeness, straightness and degree centrality measures. Finally, it was showed that the status of the Greek interregional commuting system could be described properly by the presented measure through the empirical analysis.

As one of the most important modes of transportation across the world, railways play a crucial role in establishing efficiently complex transportation networks. The structural properties of Pakistan railway network (PRN) were studied by Mohmand and Wang [32]. Specially, the PRN was represented as an unweighted graph. Through the network analysis, it was found that the PRN clearly manifested the small world properties. Moreover, the betweenness and closeness centrality measures were also applied to detect the critical stations with high traffic and potential congestion.

6. SUMMARY AND CONCLUSION

In this paper we performed a brief survey of the recent literature on statistical analysis of networks. For instance, we reviewed contributions dealing with statistical properties of complex networks like the degree distribution, the clustering coefficient, and other statistical analysis techniques such as resampling, bootstrapping, randomization and so forth. We see that those statistical techniques are suitable to investigate so-called non-deterministic networks. That means, we refer to networks that cannot be inferred deterministically as in graph theory. Therefore we believe that these approaches complement classical ones meaningfully and, hence, we continue doing research in this field.

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