Analysis of the Structure of the Road Networks: A Network Science Perspective

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Abstract

Studies on road networks have received extraordinary and overwhelming attention during the last few years as it is closely related to human life and city evolution. Current studies cover many aspects of a road network, for example, road feature extraction from video/image data, road map generalization, traffic simulation, optimization of optimal route finding problems, and traffic states prediction. However, little affords are given on the analysis of road networks as a graph. This study presents comparative studies on analyzing the Porto road network in terms of degree distributions, clustering coefficients, centrality measures, connected components, k-nearest neighbors, and shortest paths between three regions of Porto: Matosinhos, Paranhos, and Real. We also examined the community structures, page rank, and small-world analysis of the three regions to provide further insights into the network. The results demonstrate the information exchange efficiency of Matosinhos of 0.8, which is 10 and 12.8% higher than that of Real and Paranhos networks, respectively. Other findings are (1) road networks are highly reachable and densely connected (2) road networks are small-world with an average length of the shortest paths (between any two roads) of 12.8 (in case of the REAL road network), (3) the most important nodes of the network are 'Avenida da Boavista, 4100-119 Porto (latitude: 41.157944, longitude: -8.629105)' and 'Autoestrada do Norte, Porto (latitude: 41.1687869, longitude: -8.6400656)' based on analysis of centrality measures.

Introduction

Since Watts and Strogatz, 1998 [28], and Barabasi and Albert, 1999 [3], figured out the collective dynamics of small-world networks and scale-free networks, the complex network has grown in popularity as a new multidisciplinary research direction in network science. The analysis of road networks as a complicated graph arises from this foundation. Roads are typically spatial networks with nodes and edges embedded in space due to their geographical features. The road network model is constructed in such a way that the nodes represent intersections and the edges represent the road sections that connect the two intersections directly. Gao et al. 2013 [16] discovered strong signatures in these networks, which are typically real physical entities that connect points in geographic space. Montis et al. 2007 [13] employed a weighted network model to investigate the structure of the road network that represents interurban commuting traffic in the Sardinia region. They quantitatively analyzed the topological and weighted properties of the resulting network, as well as the interplay between topological and dynamical aspects. They were also discussed in respect to socio-demographic characteristics such as population and monthly income.

Masucci et al. 2014 [23], in their works, studied the growth of London's street network in its dual representation and showed that logistic laws could analytically describe the growth of the network. The network's topological properties are governed by robust log-normal distributions characterising the network's connectivity and small-world properties that are consistent over time. Zheng et al. 2012 [30] analysed the topological properties of the Beijing public transport network and found that the node strength, ordinal number and cumulative strength distribution of the nodes all follow the power-law distribution showing the network characteristics of the scale-free and small world. In this study, we analysed the road network of Porto in terms of the degree distribution, including the power-law fitting, various centrality measures, i.e., degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality, community detection, and page rank. We obtained some beneficial insights into the network, which are presented in the following sections.

This article is organised as follows: first, we made some brief descriptions of the related topology/algorithm used in the studies; then, the description of real-world data and results are presented; and, finally, discussion and conclusion are stated.

Key Concepts

Centrality Measures

In a network, the importance of any node can be measured by its centrality. Throughout the literature in network science, there are various categories of centrality measures. The four most widely applied centrality measures are degree centrality, closeness centrality, betweenness centrality, and eigen vector centrality (Borgatti, 2005 [10]; Newman, 2018 [24]; Otte and Rousseau, 2002 [25]).

Degree centrality Degree centrality is the most intuitive and computationally efficient measure to describe the importance of a given node. It is defined as the total number of edges that the node connects (Borgatti, 2005 [10]). This measure has been frequently used in mapping out biological, social, and information networks. For example, Otte and Rousseau, 2002 [25] use degree centrality to measure the collaboration network of scholars in information sciences; Bodendorf and Kaiser, 2009 [8] use the same measure to detect opinion leaders in online communities. This concept is also applied in urban transportation research to evaluate the road network (Crucitti et al. 2006 [12]) and model patterns of traffic flows (Jayasinghe et al. 2015 [20]).

Closeness centrality To better describe closeness centrality, the concept of faness is useful. For a given node, the farness is the sum of the length of the shortest paths from this node to all others in the network (Borgatti, 2005 [10]). Closeness centrality is in fact defined as the reciprocal of the farness. A larger value of closeness centrality represents that node is more central and closer to other nodes in a network.It has been widely applied in social and biological networks (Chea and Livesay, 2007 [11], Newman and Mark, 2018 [24]). In urban planning, Porta et al. 2009 [26] examine the correlation between closeness centrality and various economic activities in the city of Barcelona and suggest that central urban arterials should be conceived as the cores of neighborhoods. Another strand of research combines closeness centrality with other measures to describe urban road network and capture different aspects of urban forms (Crucitti et al. 2006 [12]).

Betweenness centrality Betweenness centrality is defined as the fraction of shortest paths passing through a given node (Barthelemy, 2004 [4]). It describes the extent to which a node is located 'between' other pairs of nodes in the network. A node has a high value of betweenness centrality when it reaches other nodes through the shortest paths or lies on many shortest paths. This concept has been applied in various applications from different domains. Researchers use betweenness centrality to understand land use intensity in different cities of the US and Europe (Porta et al. 2009 [26]). Furthermore, Barthelemy et al. 2013 [5] use it to understand the driving forces of the evolution of urban fabric in Paris. For transportation-related studies, however, Gao et al. 2013 [16] have revealed that betweenness centrality is not a good predictor of urban traffic flows. Nevertheless, we include all the three centralities (i.e., degree centrality, closeness centrality, and betweenness centrality) as the key measures of road network structure in our empirical analysis.

Eigenvector centrality Eigenvector centrality measures a node's importance while giving consideration to the importance of its neighbors. For example, a node with 300 relatively unpopular friends on Facebook would have lower eigenvector centrality than someone with 300 very popular friends (like Barack Obama). It is sometimes used to measure a node's influence in the network. It is determined by performing a matrix calculation to determine what is called the principal eigenvector using the adjacency matrix (Golbeck, 2013 [18]). The main principle is that links from important nodes (as measured by degree centrality) are worth more than links from unimportant nodes. All nodes start off equal, but as the computation progresses, nodes with more edges start gaining importance. Their importance propagates out to the nodes to which they are connected. After recomputing many times, the values stabilize, resulting in the final values for eigenvector centrality (Hansen, 2010 [19]). In summary, the four types of centrality mentioned above describe the network characteristic of a given node as follows:

- Degree centrality: the larger the value, the more edges the node connects.
- Closeness centrality: the larger the value, the more central and closer to other nodes in a network a given node is.
- Betweenness centrality: the larger the value, the more shortest paths amongst different pairs of nodes have to pass through the node.
- Eigenvector centrality: A high eigen vector score means that a node is connected to many nodes who themselves have high scores.

Average nearest neighbor degree

Whether a given node prefers to connect to others who also have a large number of connections, we can also compute an index called the average nearest neighbor degree (Xia et al. 2015 [29]), which is conventionally abbreviated to knn. This is given by the following formula:

$$Kmn_i = \frac{1}{K(i)} \sum_{j \epsilon N(i)} K(j) \tag{1}$$

which says that to compute the knn of node i we take sum of the degrees of each of their neighbors j and then divide it by the degree of node i. The knn can also be written in terms of the graph's adjacency matrix. If K_i is the sum of the i^{th} row in the graph adjacency matrix ($\sum_j a_{ij}$), then the calculation of each node's average nearest neighbor degree simplifies to:

$$Kmn_i = \frac{1}{K(i)} \sum_{i} a_{ij} K(j) \tag{2}$$

Community

A community is defined as a subset of nodes within the graph such that connections between the nodes are denser than connections with the rest of the network i.e., the groups of nodes, which are highly connected to each other than to the rest of the nodes in the network (Yang et al. 2010 [32]). Community detection is the key characteristic, which could be used to extract useful information from networks. Some key aspects of community detection can be stated as:

- It allows classification of the functions of nodes in accordance with their structural positions in their communities.
- It reveals the hierarchical organization that exists in many real-world networks.
- It improves the performance and efficiency of processing, analyzing, and storing networked data (Reddy et al. 2002 [27]).

The greatest challenge in community detection is that no universal definition of community structure exists (Fortunato and Hric 2016 [15]). Therefore, community detection in large-scale networks is computationally intractable.

Modularity Modularity is a system property which measures the degree to which densely connected compartments within a system can be decoupled into separate communities or clusters which interact more among themselves rather than other communities. Modularity is often considered as a property that enhances the stability and robustness of trophic networks by limiting the diffusion of perturbations through the web and is often found in empirical data (Massol et al. 2017 [1]).

The Girvan-Newman algorithm The Girvan–Newman algorithm detects communities by progressively removing edges from the original network. The connected components of the remaining network are the communities. Instead of trying to construct a measure that tells us which edges are the most central to communities, the Girvan–Newman algorithm focuses on edges that are most likely "between" communities (Girvan and Newman, 2002 [17]).

The Louvain method The Louvain method is an algorithm to detect communities in large networks. It maximizes a modularity score for each community, where the modularity quantifies the quality of an assignment of nodes to communities. This means evaluating how much more densely connected the nodes within a community are, compared to how connected they would be in a random network. The Louvain algorithm is a hierarchical clustering algorithm, that recursively merges communities into a single node and executes the modularity clustering on the condensed graphs (Lu et al. 2015 [22]). The Louvain method is a simple, efficient and easy-to-implement method for identifying communities in large networks. The method has been used with success for networks of many different type and for sizes up to 100 million nodes and billions of links. The analysis of a typical network of 2 million nodes takes 2 minutes on a standard PC. The method unveils hierarchies of communities and allows to zoom within communities to discover sub-communities, sub-sub-communities, etc. It is today one of the most widely used method for detecting communities in large networks (Blondel et al. 2008 [7]).

The MaxClique algorithm Cliques are subgraphs in which every node is connected to every other node in the clique. As nodes can not be more tightly connected than this, it is not surprising that there are many approaches to community detection in networks based on the detection of cliques in a graph and the analysis of how these overlap. As a node can be a member of more than one clique, a node can be a member of more than one community in these methods giving an "overlapping community structure". One approach is to find the "maximal cliques". That is to find the cliques which are not the subgraph of any other clique. The classic algorithm to find these is the Bron–Kerbosch (Konc and Janezic, 2007 [21]) algorithm. The overlap of these can be used to define communities in several ways. The simplest is to consider only maximal cliques bigger than a minimum size (number of nodes). The union of these cliques then defines a subgraph whose components (disconnected parts) then define communities (Everett and Borgatti, 1998 [14]).

The PageRank algorithm

The PageRank algorithm measures the importance of each node within the graph, based on the number incoming relationships and the importance of the corresponding source nodes i.e., by counting the number and quality of links to a page to determine a rough estimate of how important the website is. The underlying assumption is that more important websites are likely to receive more links from other websites (bidoni et al. 2014 [6]; Yan and Ding, 2011 [31]).

Data

Real-world data of the Porto road network was extracted using Python OSMnx module (Boeing, 2017[9]). The network has a total of 17851 and 40091 number of nodes and edges, respectively. For making comprehensive comparisons, we selected three regions of the entire network: Matosinhos (11961 nodes and 28459 edges), Paranhos (1926 nodes and 4508 edges), and Real (273 nodes and 645 edges).

Results

In this section, the results and findings are described. The analysis was conducted utilizing Python NetworkX package. First, the results of the degree distribution analysis of the network are presented. Then, Centrality measures and community detection findings are described, and finally, page rank and average path distance based results are presented.

Degree Distribution

The degree of a node in a network is the number of connections it has to other nodes, and the degree distribution is the probability distribution of these degrees over the whole network. The network in which each of n nodes is independently connected with probability p has a binomial distribution of degrees k:

$$P(k) = n - 1kp^k(1-p)^{n-1-k} \tag{3}$$

Figure 2 depicts the degree distribution of the Porto road network as a histogram as well as in normal and log scales. The maximum and minimum degree of the network was found to be 9 and 1, respectively, with a mean value of 2.83. However, for Matosinhos, the mean value was 4.76 with a maximum and minimum value of 12 and 1, respectively. On the other hand, for Paranhos and Real, the min-max values were 10, 1, and 8, 2 with a mean of 4.68 and 4.73, respectively. Figure 1 illustrates the comparison between the first thirty values of the degree of Porto, Matosinhos, Paranhos, and REAL road networks. The power law fitting of the network was also analyzed. Figure 3 illustrates the power law fit of the degree distribution comparing with Log-normal and Stretched-exponential distribution. The calculated best minimal value for power law fit was -55.32 which further indicated the rarity of full power low fit of real world network.

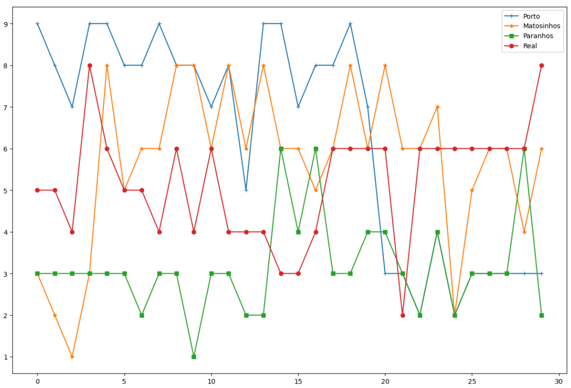

Figure 1: Comparative analysis of the four studied road networks.

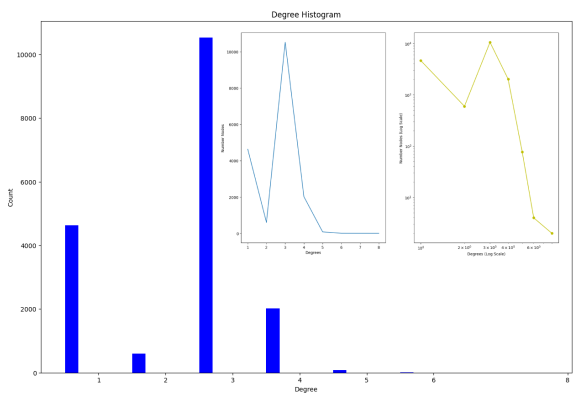

Figure 2: Degree distribution of Porto road network as a histogram and also with both normal, and log scale.

Average Neighbor Degree To get a sense of whether a given node prefers to connect to others who also have a large number of connections, we computed the average nearest neighbor degree. The results showed the value of the average nearest neighbor degree of the road network of REAL to be 2.6 and 7.5%, higher than that of Matosinhos and Paranhos as is shown in figures 4 and 5.

Centrality Measures

The maximum and minimum value of degree centrality of Real road network was 0.0294 and 0.0074, respectively with an average value of 0.017, which is 97.7 and 86.5% higher, relatively to the networks of Matosinhos and Paranhos, respectively. In case of closeness centrality, the Paranhos road network showed an average value of 0.0344, with a maximum and minimum of 0.051 and 0.0. The average value of closeness centrality of Paranhos is 42.4% higher and 128.78% lower than that of Matosinhos and REAL. The average Eigen vector centrality of the REAL road network was found to be 0.0256 which is 96.9 and 88.04% higher than that of Matosinhos and Paranhos, respectively, as is illustrated on figure 7. Table 1 presents the summary of Eigen

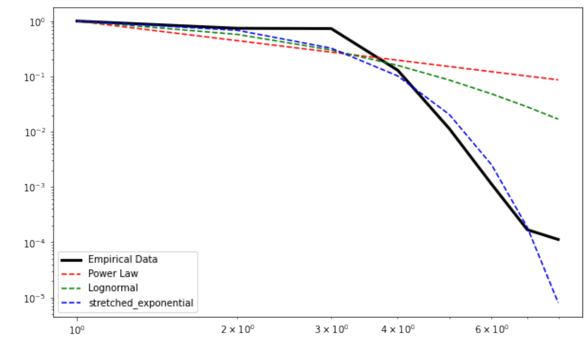

Figure 3: Degree distribution of Porto road network as a power law fit by comparing with Log-normal and Stretched-exponential distribution.

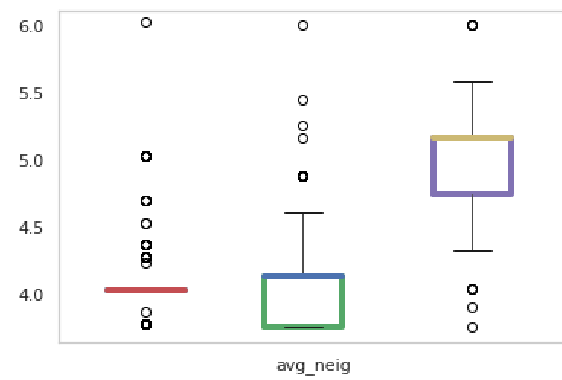

Figure 4: Box plot of the average neighbor degrees of the road network of Matosinhos, Paranhos, and REAL

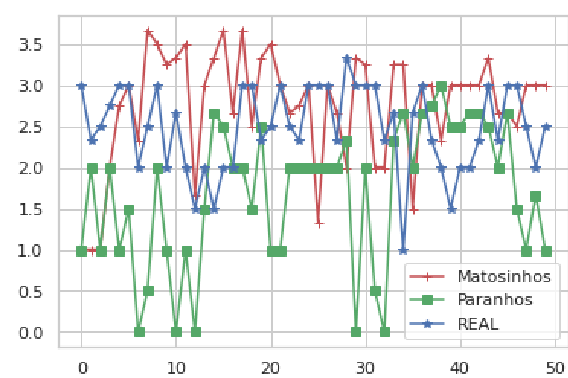

Figure 5: Comparative analysis of the average neighbor degrees of the road network of Matosinhos, Paranhos, and REAL

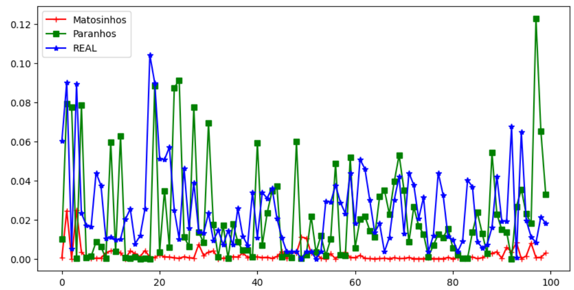

Figure 6: Comparison of the betweenness centralities of Matosinhos, Paranhos , and Real

Eigen Vector Centrality	Max	Min	Average
Matosinhos	0.27	$5.7e^{-272}$	0.000789
Paranhos	0.263	$5.4e^{-97}$	0.00306
Real	0.272	$9.4e^{-06}$	0.0256

Table 1: Eigen Vector Centrality of the network

vector centrality of the three regions. In case of betweenness centrality, the REAL road network possessed a value of 0.02065, which is 91.3 and 70.9% greater than the road networks of Matosinhos and Paranhos, respectively. Table 2 presents more insights of the betweenness centrality of the road networks. A comparison of the four types of centrality measures of the road network of REAL is illustrated in figure 8.

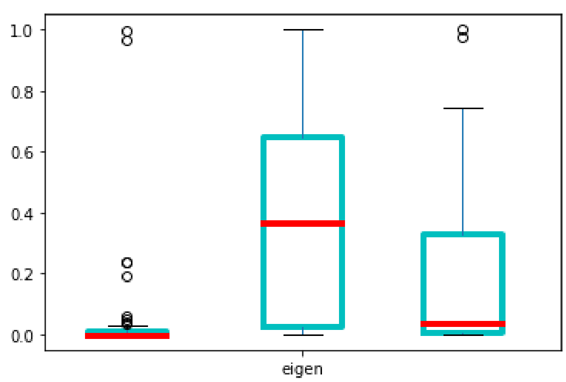

Figure 7: Box plot of the Eigen vector centrality of the studied three regions

Betweenness Centrality	Max	Min	Average
Matosinhos	0.198	0.0	0.00179
Paranhos	0.123	0.0	0.0060
Real	0.130	$1.34e^{-05}$	0.02065

Table 2: Betweenness Centrality of the network

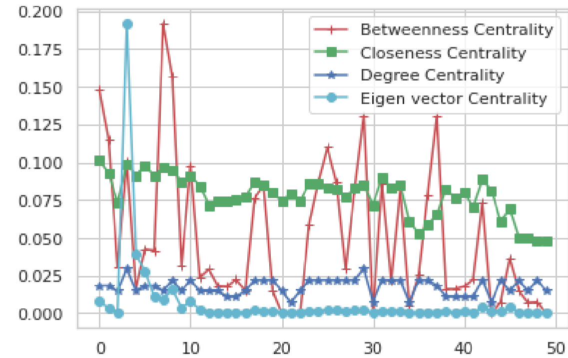

Figure 8: Four centrality measures are compared based on REAL road network (for each case, the first 50 readings were considered)

Connected Components

In graph theory, a component of an undirected graph is an induced subgraph in which any two vertices are connected by paths and which is connected to no additional vertices in the rest of the graph. Connected components form a partition of the set of graph vertices, meaning that connected components are non-empty, they are pairwise disjoints, and the union of connected components forms the set of all vertices. The Porto road network is a connected graph, and the number of the connected component is 1, which indicates the reachability of the network. This implies that one can reach all other nodes by traversing edges from any node of the network.

Community Analysis

The modularity value of the network was calculated as 0.9469 utilizing the Louvian algorithm which indicates that it has dense connections between the nodes within modules but sparse connections between nodes in different modules. The number of communities of the Paranhos road network found by the Girvan–Newman algorithm was 3 as well as using the MaxClique algorithm for the value of $k = 3$. Figure 9 represents the visualization of the found communities using the Louvian algorithm. The spring layout was drawn using the Fruchterman-Reingold force directed algorithm (Derek et al. 2020 [2]).

subsectionPageRank PageRank computes a ranking of the nodes in the graph based on the structure of the incoming links. The maximum and minimum value of the page rank of Matosinhos road network was calculated as 0.0002 and $1.68e^{-05}$ respectively with an average of $8.36e^{-05}$. Compared with Paranhos and REAL road network it was 18472.7 and 18473.2% lower than Paranhos and REAL network respectively. Table 3 and figure 10 represent more insights of the network. From the analysis it is observed that the nodes of REAL road network posses higher rank thank the other regions.

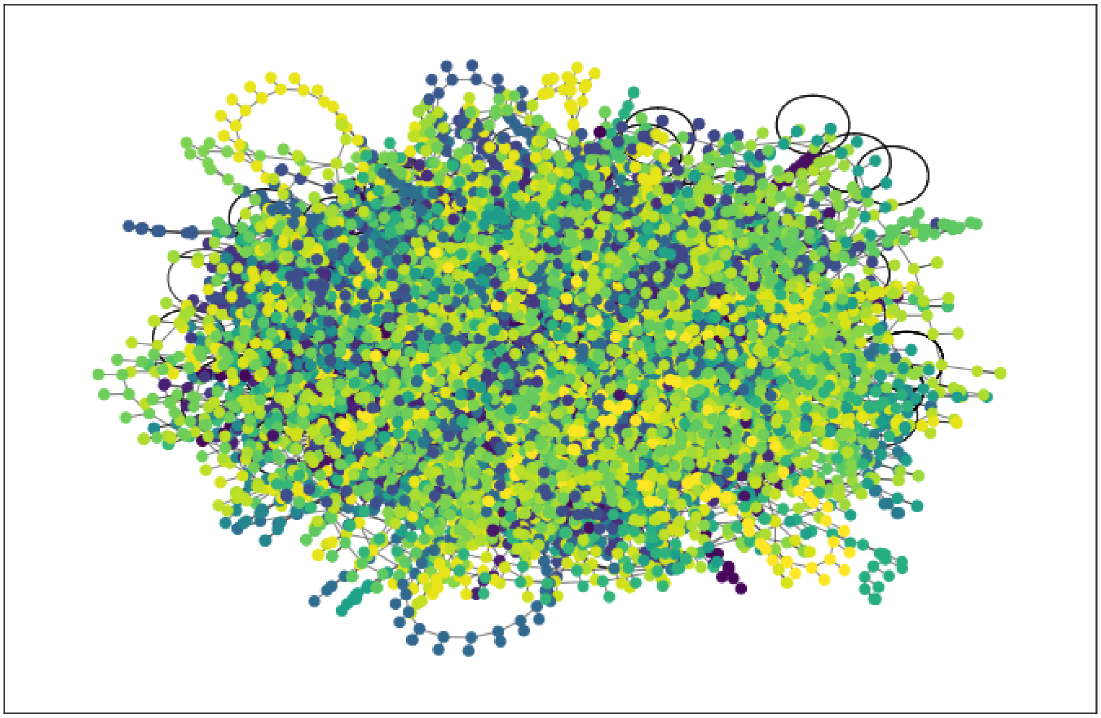

Figure 9: Visualization of founded communities of the studied network (the node size is 40 and the value of alpha is 0.5)

Page Rank	Max	Min	Average
Matosinhos	0.0002	$1.68e^{-05}$	$8.36e^{-05}$
Paranhos	0.0013	0.000106	0.000519
Real	0.0061	0.00182	0.00366

Table 3: PageRank value of the network.

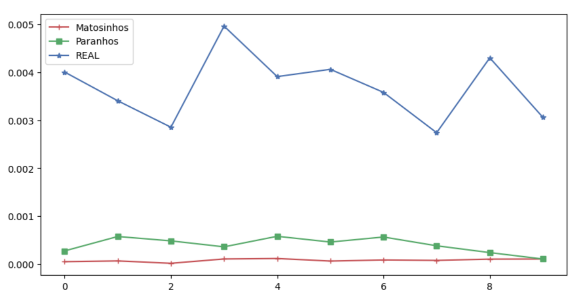

Figure 10: Comparative analysis of the page rank of the networks (the figure was drawn by considering the first 10 values of page rank of each network)

Average path distance

The average path distance between the nodes of the network was also measured. Average shortest path of the Matosinhos, Paranhos, and REAL road networks were found to be 50.09, 26.74, and 13.07, respectively. Figure 11 illustrates the analysis of path distances of the road network of REAL with the help of a histogram.

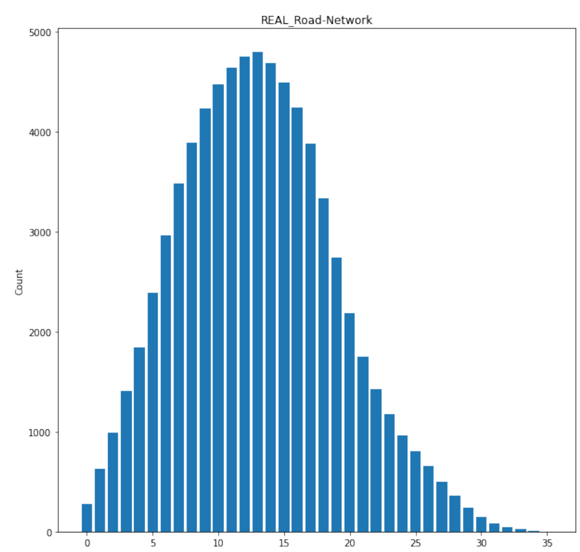

Figure 11: All shortest path distances of the REAL studied road network illustrated using histogram

Network	Best	2nd Best	3rd Best
Porto	1725588144	1725588066	8390291008
Matosinhos	3521762508	3677979834	263576269
Paranhos	128597080	432578781	112613584
Real	2584249513	8272473900	2584536902

Table 4: Top three most important node labels of the network measured using the betweenness centrality.

Discussion

A comprehensive analysis of the road network of Porto was analyzed in terms of the degree distribution, including the power-law fitting, various centrality measures, i.e., degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality, community detection, and page rank. The degree distribution showed that most nodes possess a relatively small degree, but a few nodes have a considerable degree connected to many other nodes. We measured the best minimal value of power-law fit from the power-law fitting to be 55.32, and the network does not fully follow the power-law distribution. The nodes of the REAL road network seemed to have the strongest tendencies to connect to others who are also popular, while the nodes of the Matosinhos road network displayed the weakest such tendencies as indicated by the box plot diagram of figure 4. From the centrality measures, the most critical nodes were shortlisted, as is shown on the table 4. The most critical nodes of the network based on betweenness centrality measures were labelled as 'Avenida da Boavista, 4100-119 Porto (latitude: 41.157944, longitude: -8.629105)' and 'Autoestrada do Norte, Porto (latitude: 41.1687869, longitude: -8.6400656)', respectively.

We found only one connected component of the network, which means the network is highly reachable, i.e., from any node of the network, one can reach all other nodes by traversing edges. The modularity values were found as 0.9469, which is relatively high and indicates dense connections between the network nodes. The page rank analysis found that the REAL road network nodes have higher values than the Matosinhos and Paranhos network. Moreover, lastly, the average path distance was found to have low values indicating the small world characteristic of the road network..

Conclusions

From a network science perspective, the analysis of road networks is fundamental to invent valuable insights into the network. We selected the beautiful and historic city of Porto, Portugal, and its three sub-parts: Matosinhos, Paranhos, and REAL, to conduct our studies. The Python OSMnx module was utilized to capture the network data, and the NetworkX package of Python was used to analyze the results. We found some beneficial insights into the network:

- Most nodes have a relatively small degree while a few have a very large degree.
- The network does not fully follow the power-law distribution.
- The bigger the network, the lower the tendency to connect to other popular nodes.
- The higher the value of modularity, the higher the reachability of the network.
- The smaller the average path distance, the higher the representability of small-world phenomena.

This information can be beneficial in modelling the real-world road network. Although our analysis was only based on the Porto road network, we can conclude that any road network can be analyzed following our methodology.

Future Works

In the future, we plan to concentrate on finding subgraph patterns of the road network. More analysis will be performed on small-world phenomena, for example, studying small-world coefficients (sigma, omega). The congestion spreading analysis will also be conducted.

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Visualization

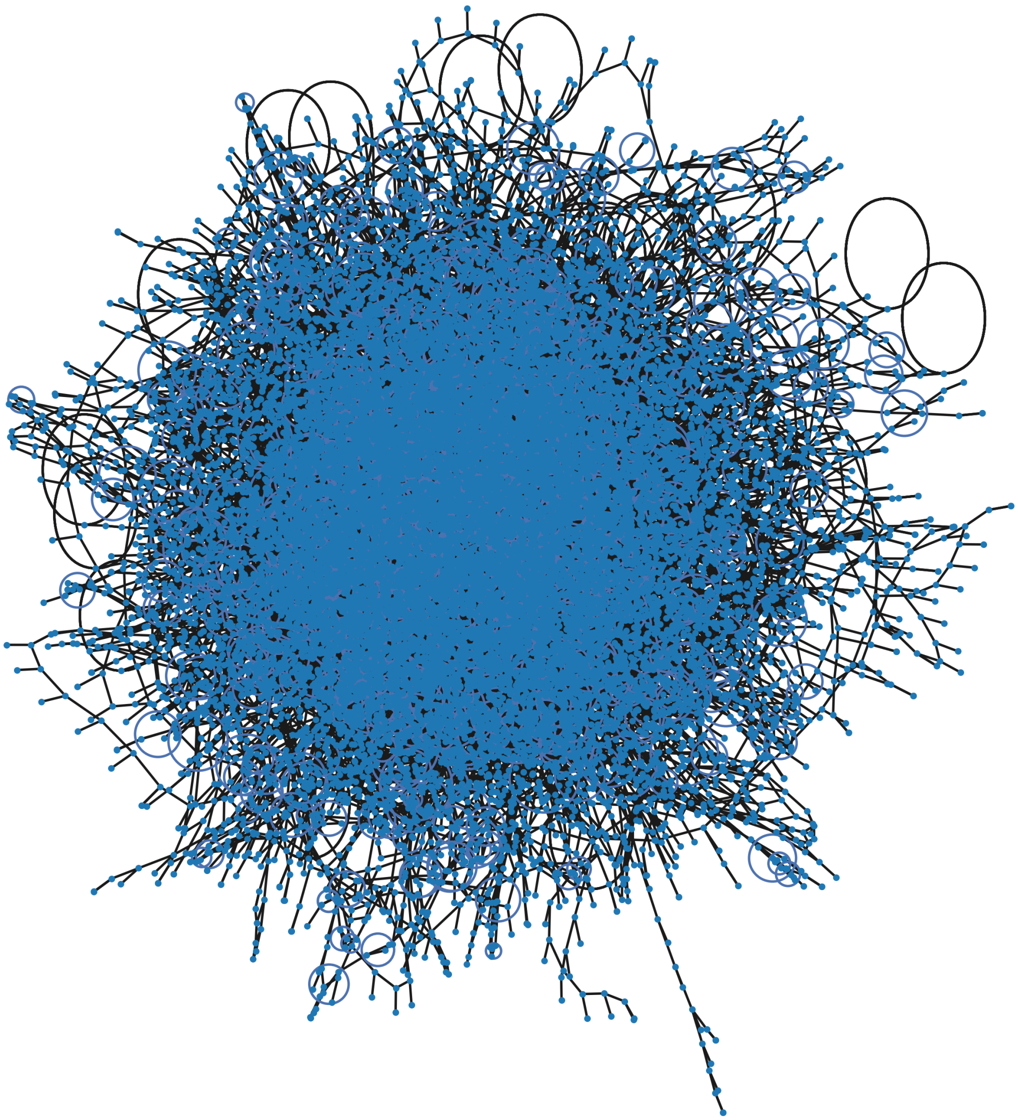

Figure 12: Visualization of the found communities using maximal clique algorithm

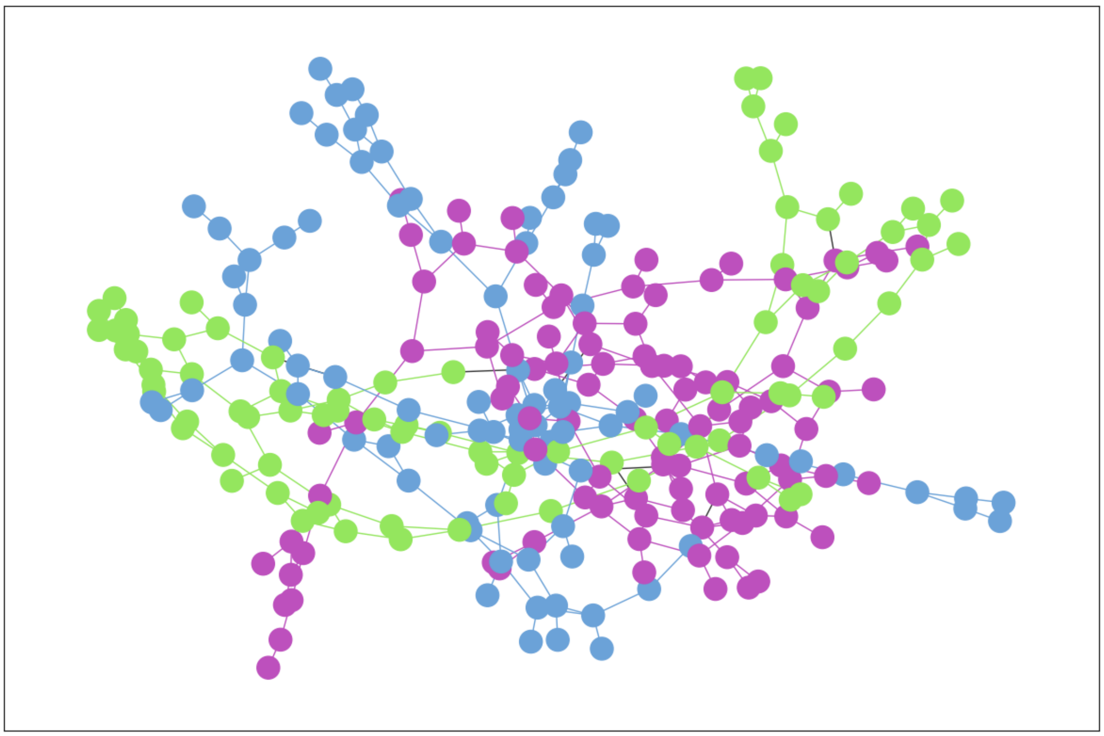

Figure 13: Visualization of the found communities using he Girvan–Newman algorithm on REAL road network (as one can see, 3 communities were found indicated by three different colors)

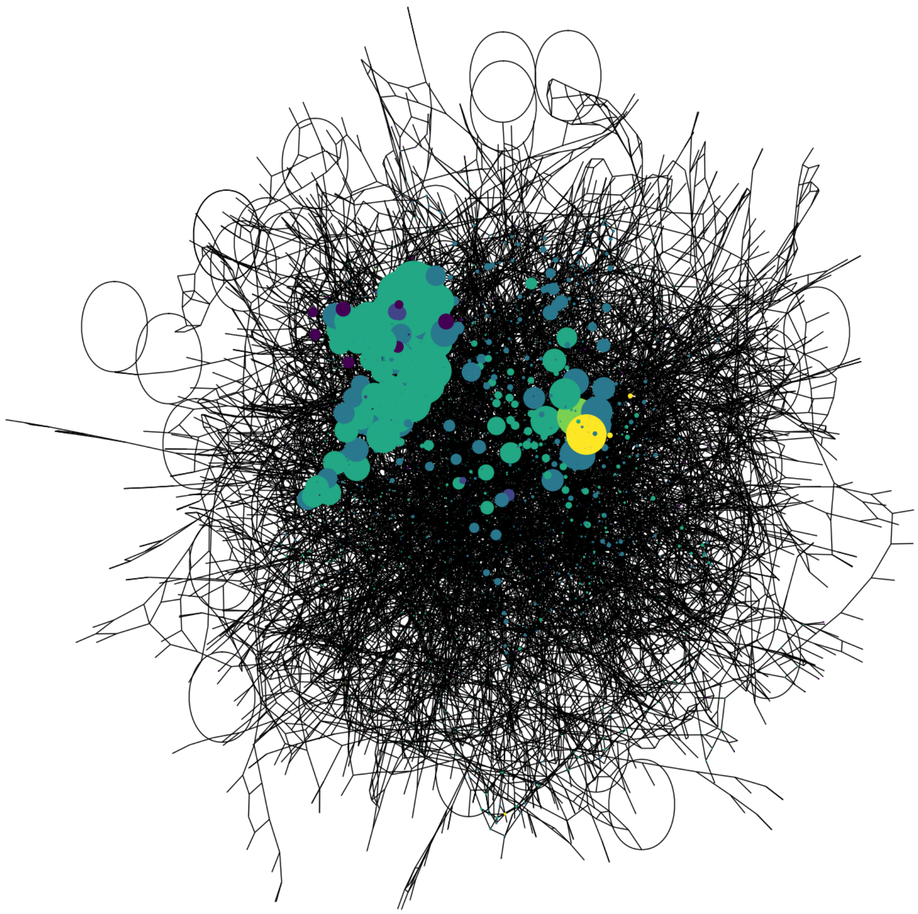

Figure 14: Visualization of the network with respect to eigen vector centrality