THE RUSSIAN GOVERNMENT
FEDERAL STATE AUTONOMUS EDUCATIONAL INSTITUTION
FOR HIGHER PROFESSIONAL EDUCATION
NATIONAL RESEARCH UNIVERSITY
“HIGHER SCHOOL OF ECONOMICS”

Efficiency of transport networks: the case of International E-road network

Homework Project 2018/2019

The team:
Yulia Gurova
Igor Vasilev

MSc Program “Data Science”
1^{st} year
Faculty of Computer Science

Moscow 2019

Contents

Abstract

In this paper the European road network is studied with the tools of network analysis. The properties of transportation networks and their possible formalisation as model are explored. The E-road network has law clustering coefficient, large maximal and average shortest paths, smaller node degrees then usual 'small-world' networks. That puts them closer to regular, then to random networks on the range of 'small-world' networks.

1 Introduction

The international E-road network is a road system in Europe and eastern Asia. It is developed and supported by United Nations Economic Commission for Europe (UNECE). The roads are supposed to match some standards.

The road networks usually bear a set of properties, distinct from social networks. Startng from the paper of [2] the Power Law and Scale-free networks are intensively studied. Social networks usually have high clustering coefficient, law maximal shortest path, scale-free destribution of the nodes' degrees.

As for road networks, the maximal shortest path is usually large due to geographical factors: the nodes which are distinct at distance are usually connected through other nodes. The network has small assortativity coefficient. In social networks in is high as usually people, who have common friend, tend to be friends to each other. In road networks the effect is the opposite: if two large cities are connected through another city, they are less probably tend to build a direct connection.

2 Literature review

[1]

First, we discuss the social network analysis, then we switch public transport networks (PTN) analysed with the same tools, and then come to road networks.

The concept of small-world networks was developed in [2] and since then were studied in different aspects. The concept is called after the well-known sociological notion: social networks (as friendship network) are characterised in such a way. The main characteristics are high clustering coefficient and small average path which put them in between of regular lattices and random graphs.

It turned out that many kinds of networks follow the characteristics of small-world networks: social networks, neural networks of animals, transportation networks and so on.

There are several studies of particular kinds of parts of transportation networks. One of the first works [3] studied Boston subway network and was followed by other papers studying subways. In [3] the concepts of network efficiency, local and global efficiency were defined. The small-world networks are characterised with high local and global efficiency. Regular networks have high local efficiency and small global. Random networks have the opposite characteristics. That allowed to determine small-world network by one parameter instead of two formulated in [2] (clustering coefficient and average path).

Boston subway network is characterised by low local efficiency, but higher global efficiency then other small-world networks. As claimed in [3], because it is not closed network, but a part of the larger network (transportation network including buses, trams and so on), these indicators should be calculated for the full closed network to show clean result. And at local level other vehicles usually may have higher usage then metro.

The large analysis of 14 cities full transportation networks was presented in [1]. It is remarkable, that large cities are taken and the number of underground, buses, tram and other stops in the networks was from 1494 (Dusseldorf) to 44629 (LA). The transportation network was considered full as in included all means of public transport in the city.

In a later paper by the same authors [5] the *harness* is first introduced and the evolutionary model using geographical data is built. Harness $P(s,r)$ is calculated as the number of sequences of s consecutive stations that are serviced by r parallel routes. The authors introduce also self-avoiding walks (SAWs) for PTNs and use the same data for 14 large cities to illustrate their findings.

The road networks consist of cities as nodes and high-way roads between them as links, or of system of rural streets. So, these networks are less dense then the PTNs and usually cover large distances. They are characterised by less range of degrees as they are usually almost planar: [4], [6]. Due to the high costs of building the roads and long time of traveling between the cities, the evolutionary models of network development can be used for their description. There are used urban road networks in rural parts of Germany in [4] to illustrate the theoretical findings.

3 E-roads

For this study the data on International E-road network was used. It includes roads located in Europe and eastern part of Asia (Turkey, Kyrgyzstan,...). The cities are represented as nodes and the roads between them as edges. The system includes highways, that are developed and supported by United Nations Economic Commission for Europe (UNECE), so they should meet some quality requirements. So, mostly large cities and important highways are included in the dataset. There are 1174 cities and 1417 roads.

The information about distances was not included in the data originally. We used Google.Maps API to get the distances in meters and in traveling time.

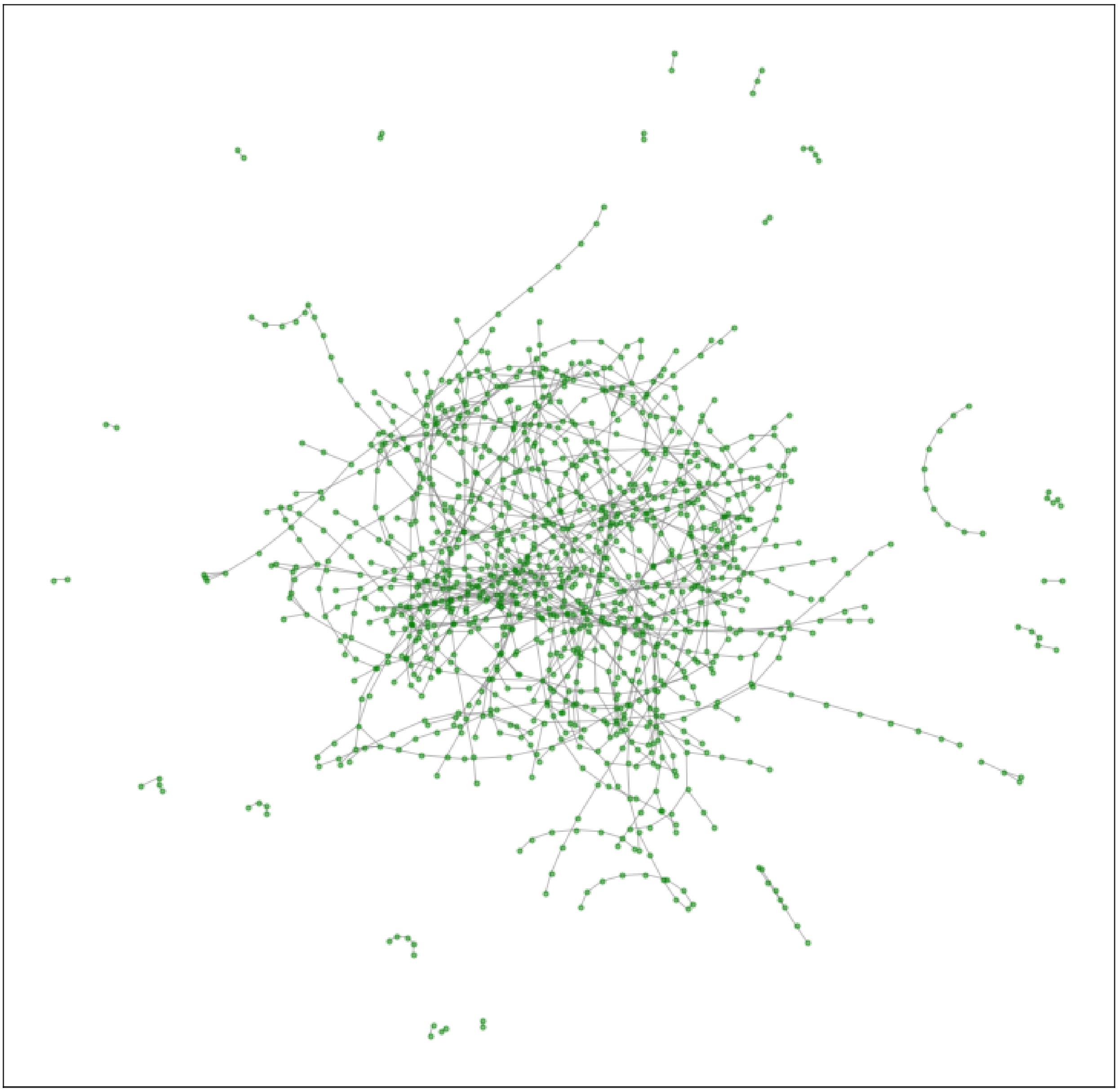


Figure 1: Network structure without lables

number of connected components	26
size of largest connected component	1039
number of nodes	1174
number of edges	1417
average degree	2.414
diameter	62
average shortest path length	18.395
clustering coefficient (transitivity)	0.0339

Table 1: E-road network characteristics

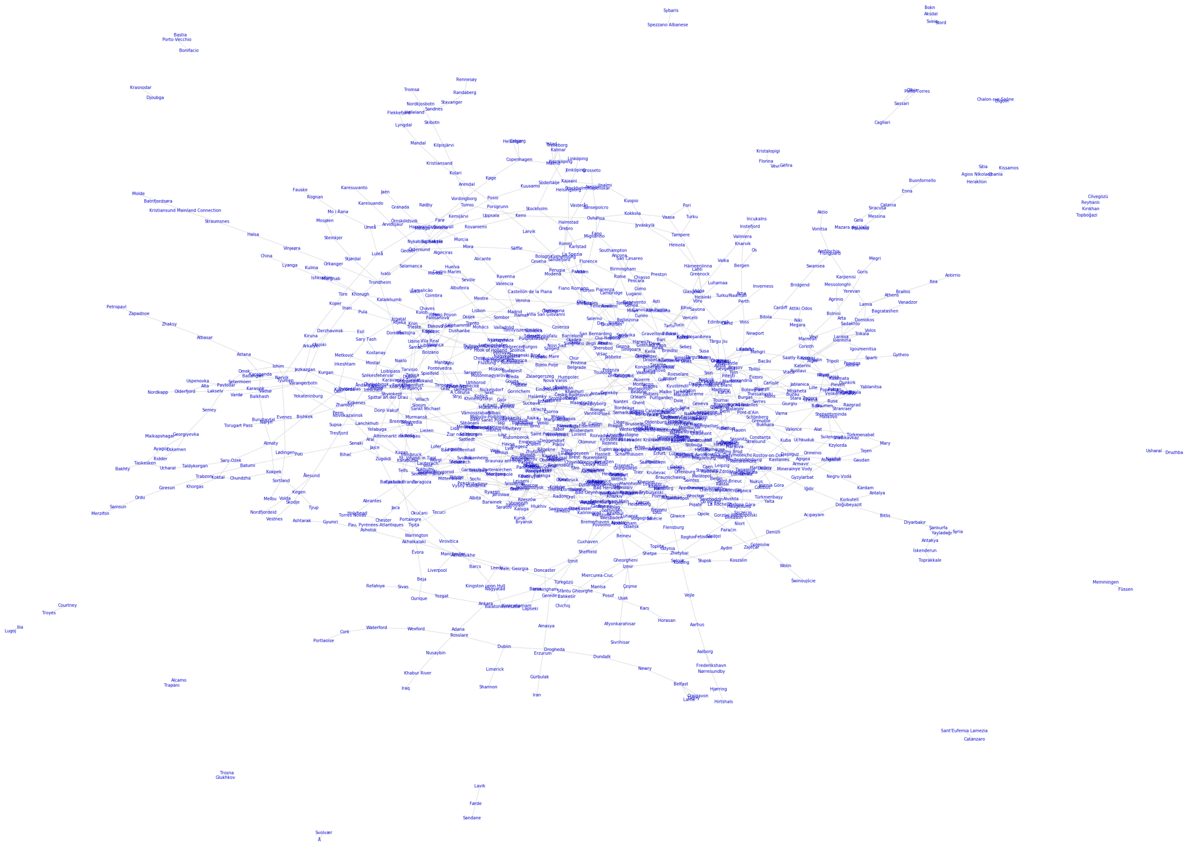


Figure 2: E-roads network with lables

Figure 1 illustrates the network structure without lables. It can be seen that the average degree is close to 2 in the network, the structure has long chains as large trees. Also, there are some small connected components but the main large compontnes. As can be seen from 2, these are some islands or other separated from the mainland territories (in Norway for example).

The information about the network is accumulated in the table 1. As was discussed in the previous section, the clustering coefficient is low, the average shortest path length and the deameter are comparatively high.

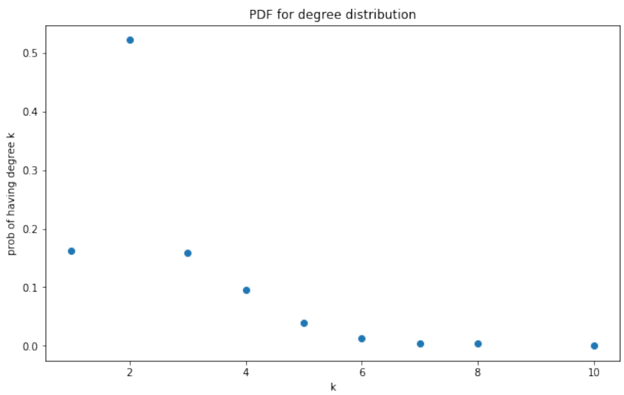
As was discussed in the literature review, the degree distribution is complicated to explore in such type of networks due to small variety of degrees. The highest degree for the E-roads network is 10, and it is impossible to say if 10 points satisfy power law or not. As the most part of the graph is connected, a litle amount of

degree centrality	closeness centrality	Betweenness centrality	eigenvector centrality	Page-Ran
Moscow 0.0085	Warsaw 0.0869	Brest 0.2148	Paris 0.3652	Moscow 0.0
Paris 0.0068	Brest 0.0868	Moscow 0.2125	Metz 0.3003	Berlin 0.00
Liège 0.0068	Minsk 0.0852	Saint Petersburg 0.1955	Reims 0.2808	Budapest 0
Berlin 0.0068	Lviv 0.0837	Le Mans 0.1751	Brussels 0.2363	Liège 0.002
Munich 0.0068	Lublin 0.0837	Rennes 0.1744	Liège 0.2060	Munich 0.0
Budapest 0.0068	Kaunas 0.0836	Minsk 0.1733	Le Mans 0.2042	Paris 0.001
Metz 0.0060	Rennes 0.0833	Warsaw 0.1601	Orléans 0.2017	Larissa 0.0
Prague 0.0060	Smolensk 0.0828	Smolensk 0.1565	Luxembourg 0.1906	Belfast 0.0
Vienna 0.0060	Piotrków Trybunalski 0.0827	Vyborg 0.1541	Charleville-Mézières 0.1874	Malmö 0.0
Bratislava 0.0060	Moscow 0.0825	Vaalimaa 0.1530	Lyon 0.1761	İzmir 0.001
Warsaw 0.0060	Kiev 0.0823	Kotka 0.1518	Rouen 0.1710	Bratislava
Lyon 0.0051	Gomel 0.0821	Helsinki 0.1509	Geneva 0.1603	London 0.0
Cologne 0.0051	Riga 0.0821	Paris 0.1443	Calais 0.1516	Innsbruck
Frankfurt am Main 0.0051	Rivne 0.0819	Jyväskylä 0.1394	Lausanne 0.1485	Vienna 0.0
Milan 0.0051	Radom 0.0819	Kemi 0.1346	Tours 0.1345	Prague 0.0

Table 2: The rankings of top-15 cities due to different centralities

nodes has degree 1. The most part of points has degree 2. The degree distribution is shown at figure 3.

The city with the highest degree is Moscow, the neighbours are Saint Petersburg, Kaluga, Orel, Yaroslavl, Voronezh, Tambov, Smolensk, Ryazan, Velikiye Luki, Vladimir.



The largest degrees:

Moscow 10	Warsaw 7
Paris 8	Metz 7
Liège 8	Prague 7
Berlin 8	Vienna 7
Munich 8	Bratislava 7
Budapest 8	Cologne 6

The betweennes, closiness, eigenvector and Page-Rank centralities were calculated for the network. The table 2 includes the top-15 cities for each centrality and the corresponding value.

The Appendix 4 includes graphs, which illustrate the connections in the subgraphs with the highest centralitis for each measure.

In [4] there was used a special measure of the physical distance between the cities which included the distance in meters and the travel time at the same time. But the network there was relatively small, and the relied on the model of a common driver's decision-making. We study a larger network, where most distances are not gone every day by anyone.

References

[1] von Ferber C. et al. Public transport networks: empirical analysis and modeling //The European Physical Journal B. – 2009. – T. 68. – №. 2. – C. 261-275.

[2] Watts D. J., Strogatz S. H. Collective dynamics of 'small-world'networks //nature. – 1998. – T. 393. – №. 6684. – C. 440.

[3] Latora V., Marchiori M. Efficient behavior of small-world networks //Physical review letters. – 2001. – T. 87. – №. 19. – C. 198701.

[4] Lämmer S., Gehlsen B., Helbing D. *Scaling laws in the spatial structure of urban road networks* //Physica A: Statistical Mechanics and its Applications. – 2006. – T. 363. – №. 1. – C. 89-95.

[5] C. von Ferber, T. Holovatch, Yu. Holovatch, V. Palchykov, Network harness: Metropolis public transport // Physica A: Statistical Mechanics and its Applications, Volume 380, 2007, P 585-591

[6] Barthélemy M., Flammini A. Modeling urban street patterns //Physical review letters. – 2008. – T. 100. – №. 13. – C. 138702.

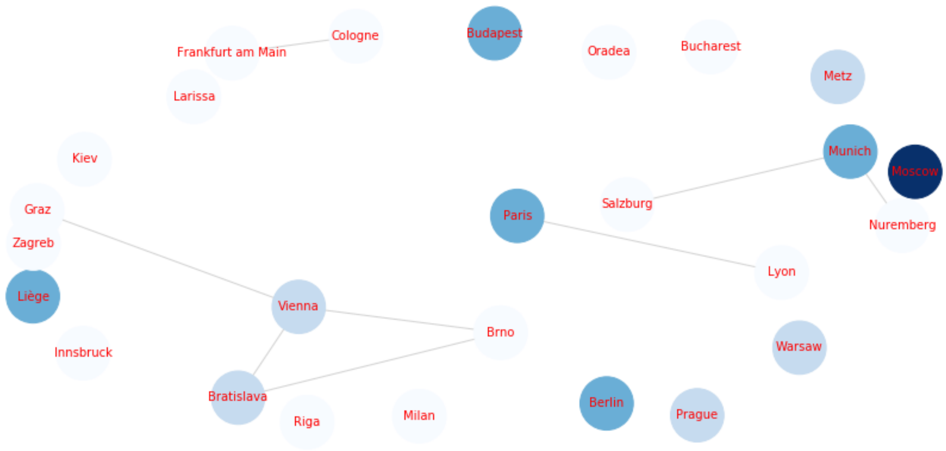


Figure 3: Subgraph with nodes with highest degree centrality

4 Appendix

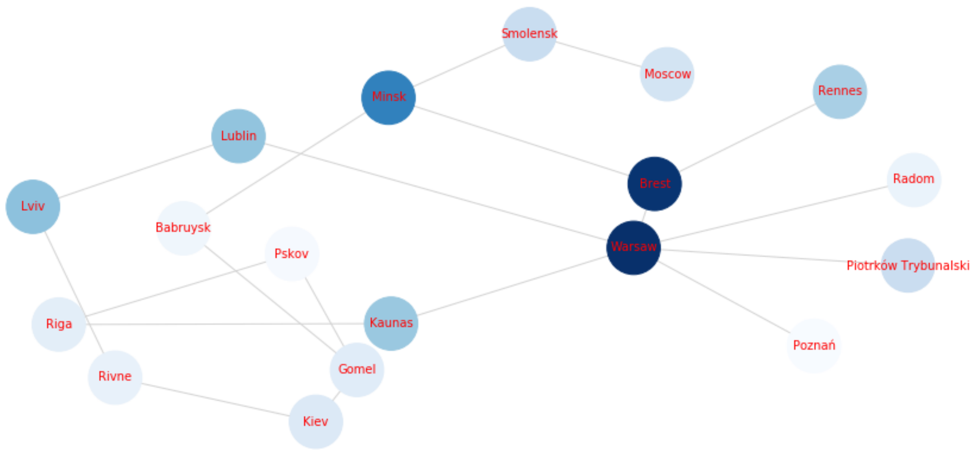


Figure 4: Subgraph with nodes with highest closeness centrality

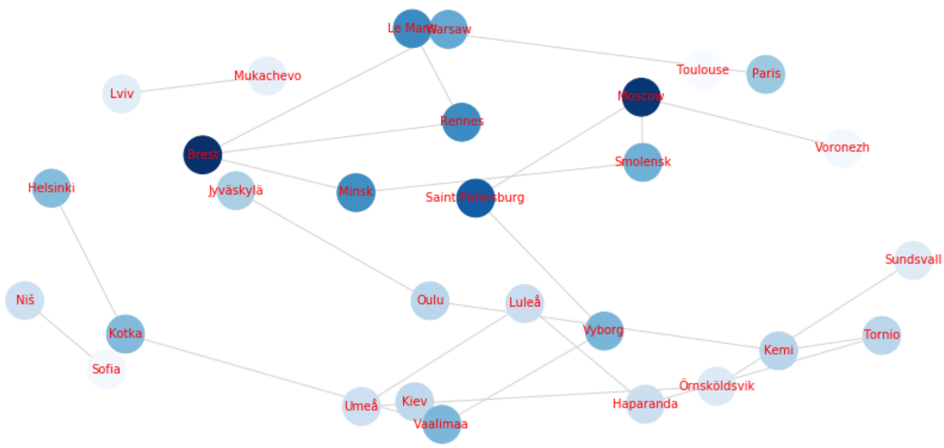


Figure 5: Subgraph with nodes with highest betweenness centrality

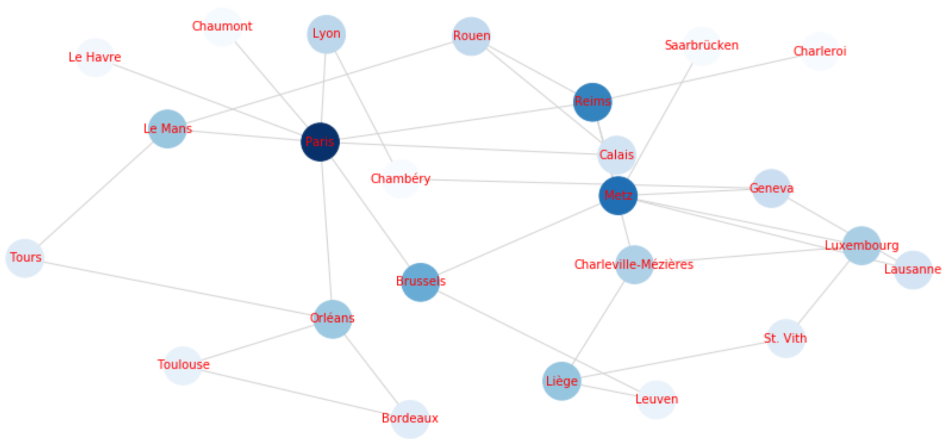


Figure 6: Subgraph with nodes with highest eigenvector centrality

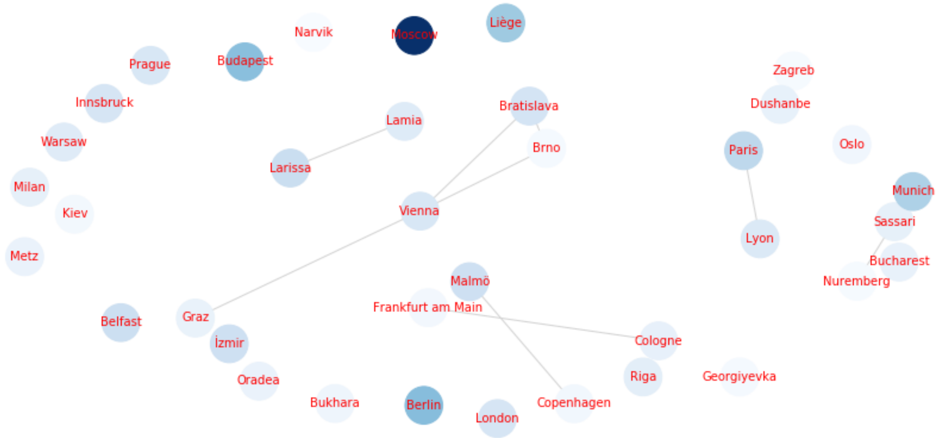


Figure 7: Subgraph with nodes with highest PageRank centrality