Exploring the flow of development funds

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Abstract: Exploring the data in terms of network science perspective can lead to some interesting insights. Using the Official Development Assistance (ODA) data collected by Organisation for Economic Co-operation and Development (OECD), the work focused on creating a network graph from the data and applying different network science techniques to draw certain conclusions along with opening up new paths for further work.

Index Terms: Development aid, network analysis.

1. Introduction

Organisation for Economic Co-operation and Development (OECD), an organisation with 38 member countries was established in 1961 for the progress in terms of international aid. One of the implementations of this organisation is Official Development Assistance (ODA) which essentially means the donors recognised by the OECD donate funds to the developing countries and even organisations in an international scale.

Understanding this data is very crucial since the impact of foreign aid on economic development of the countries is very huge[1]. Looking at this data in network science perspective is also not new, [2] talks extensively about network analysis to understand the importance of a country not just based on the amount received as aid but also on the position of that node and its donor in the network will significantly explain about the impact of the aid beyond the volume of aid. [3] shows how recursive financial aiding can hold more than just monetary value and is an intricately part in the political globalisation of major donor countries.

The intention of the proposed work is conduct network analysis on the data from Query Wizard for International Development Statistics (QWIDS)[4], specifically perform community detection to understand the characteristics of the countries that would differentiate them from the countries in a different community, vary the analysis over the years and look for any potential insights. The different approach this work tries to take is to relate the results from the community detection to real world analogies.

2. Methods

The source data used for the work is from QWIDS, and the filters applied on are as follows: Donor(s): select only countries, Recipient(s): select only countries, Flow(s): ODA, Flow Type(s): Disbursements, Sector(s): All Sectors, Total, Time Period: 5 Selected (2017 - 2021)

The network graph construction is done converting the data into edgelist, the resultant graph is a weighted directed graph with the nodes representing the countries and the edges representing the amount of the aid.

2.1. Gephi

Gephi is a visualisation tool for network graphs and is extensively used in the scope of this particular work. Using gephi, the data is represented as networks and the respective visualistion

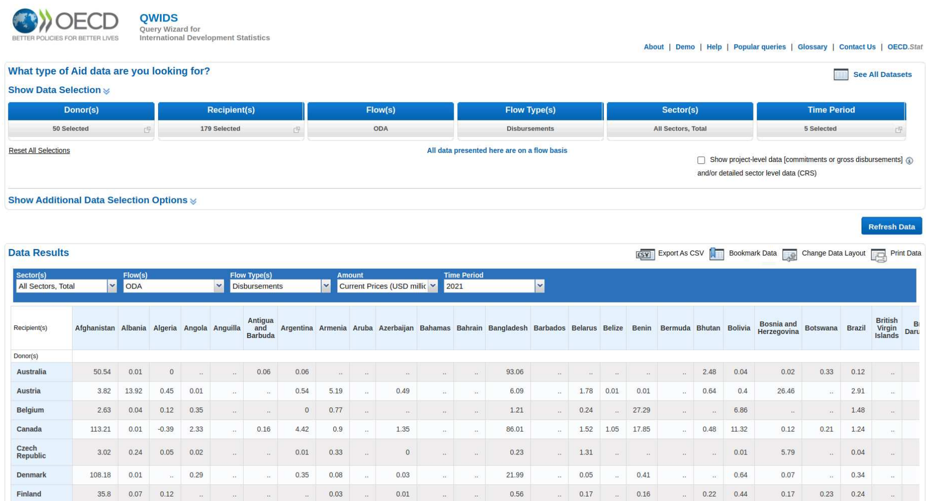

Fig. 1. Filters used in QWIDS

operations are performed[5].

For community detection, after importing the data, run the modularity option in the graph properties panel, after which in the node setting upon choosing color based on modularity class the resultant graph is the one with communities. For a better layout select any of the layout that works best and make the visualisations interpretable. In this work, ForceAtlas with Attraction Distribution and Adjust by Size settings on was used.

Degree centrality and pagerank options are enabled in the node rank under size attribute upon running the respective options in the graph properties panel.

2.2. NetworkX

NetworkX is the python package for analysing networks and performing various operations. After creating a `DiGraph` from the edgelist, in order to create communities networkx inbuilt function `community.louvain_communities` is used. The country sets of these communities are used for further visualisations.

3. Results

3.1. Community Detection

Using the Gephi's modularity class partition, 6 communities were obtained (Fig. 2.). Although there not a concrete interpretation of what they could represent, it is interesting to that certain communities are highly geographic. The community that is represented in orange, the nodes in that community are mostly the Oceania. Similarly the green community contained a lot of countries from arab regions, these observations can be attributed to the fact that certain high donating countries are mostly focusing on donations in their neighbourhoods or share a geographical commonness.

From the networkx's community detection, which is visualised in a world map reflects 4 communities (Fig. 3.). From this community detection, one inference that can be made is all the major donors are in the same community i.e. Community 2 in red.

An additional visualisation from which observations can be made is generated for community detection over the years from 2017 to 2021 (Fig. 4.). One interesting observation that can be made here is the growth in the community where China is a part. Starting from 2017 where it was part of a very minor community to 2021 where the country tends to be part of major community.

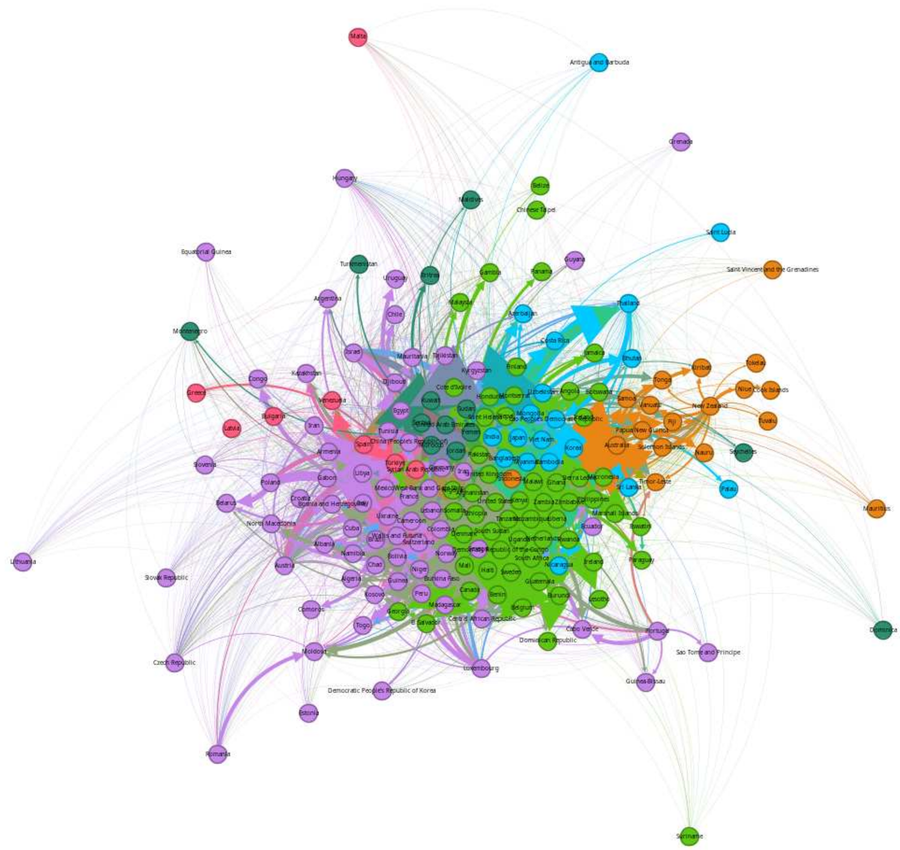

Fig. 2. Community detection in Gephi

3.2. Centrality measures

Centrality measures are vital in understanding the importance of the nodes in a network and applying them after community detection can offer additional insights about the communities which they are part of.

In the scope of this work, the focus was put on Degree centrality and Pagerank algorithm. Although, betweeness and closeness centralities could have been tired, a straightforward implimentation of those centralities doesnt suit the bipartite weighted directional graphs type networks. All the analysis regarding centralities was done in Gephi.

3.2.1. Degree Centrality

From (Fig. 5.) which represents degree centrality, it is intuitive to observe that the donors are highlighted, since they donate to multiple countries which translates to higher degree. In-degree and out-degree provides more clearer insights, where in-degree denotes taking aid and highlights the recipients and so the high number of recipients is reflected in the sizes of many nodes being bigger. In case of out-degree, since only the donations made are considered as out-degree, all the highlighted nodes are donors.

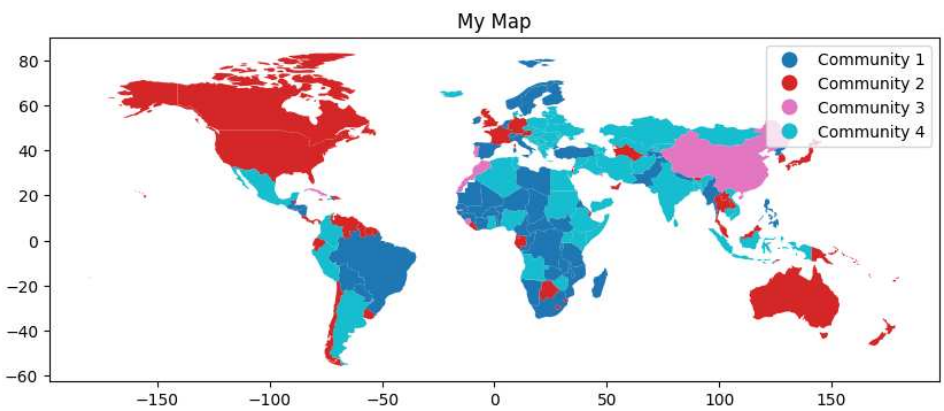

Fig. 3. Community detection in NetworkX

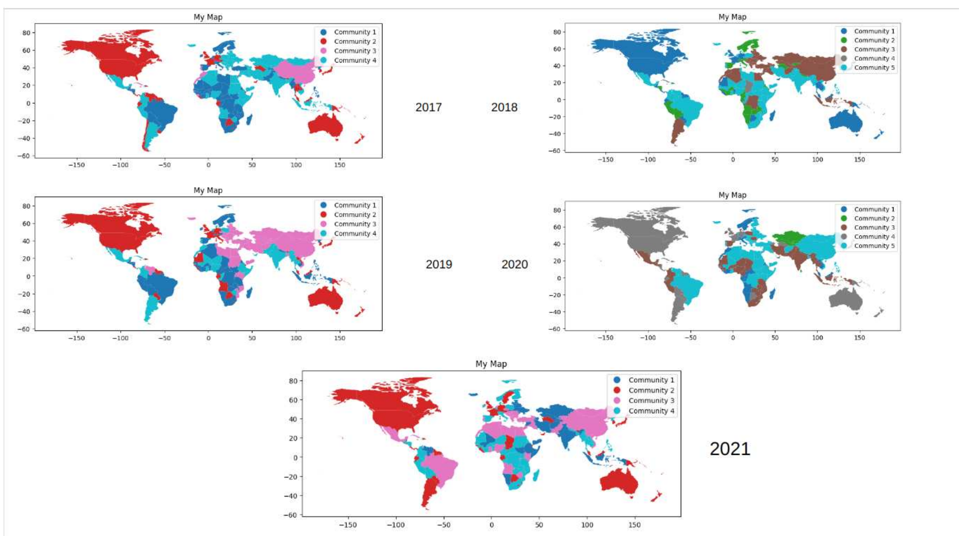

Fig. 4. Community detection in NetworkX over the years

3.2.2. Pagerank

The more interesting centrality was PageRank, as this centrality considers the importance of the connections node rather than just based on degree of a specific node. Applying this centrality highlighted Afghanistan and Paraguay (Fig. 6.), interestingly enough this coincided with the crisis the countries were going through in the year 2021. Afghanistan was dealing with a Taliban offensive that changed the course of their future forever and Paraguay was filled with protests on the ruling government, this disturbances might have disrupted a lot of respective country's resources, which probably resulted in additional donations in the development category and that explains their bigger node size.

4. Discussion

Community detection has led to many observations for making real life inferences, but there is a lot of improvements that can be done to make this study more effective. Finding one or a combination of real-life metrics to understand the community detection has not been done, although various ways like geography was put into the perspective, it was not broad enough to generalise for the

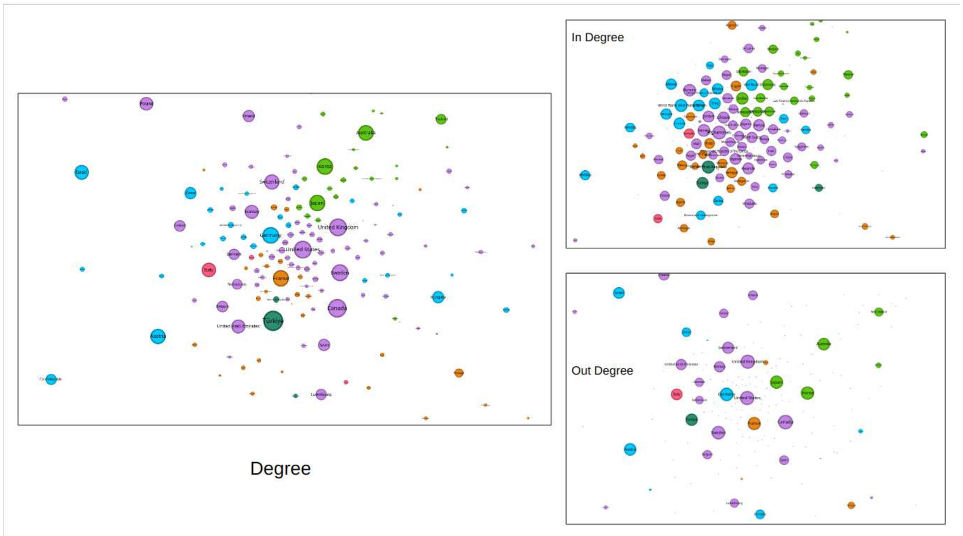

Fig. 5. Degree centrality

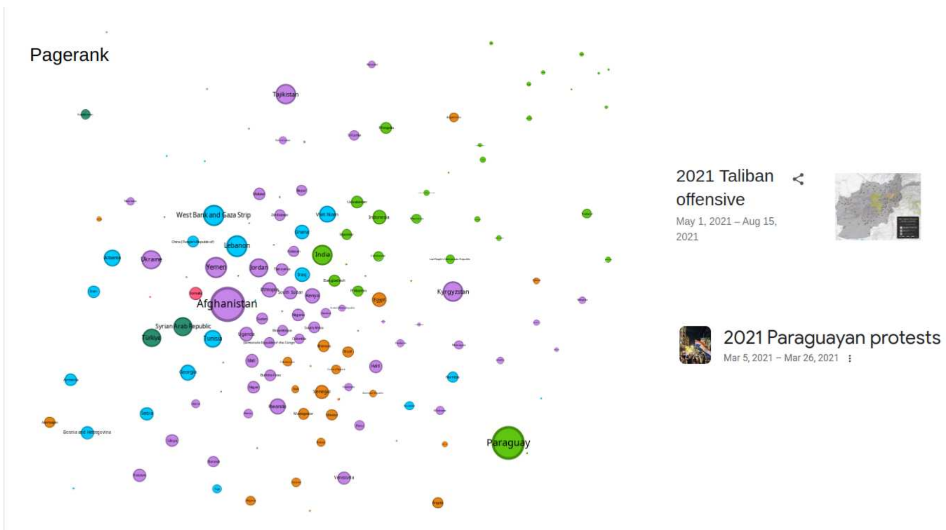

Fig. 6. Degree centrality

data. Gross Domestic Product (GDP) of the countries was also looking into to see if the GDP range can define the community participation of a country, but it was not entirely clear on how to design a tangible way to define that. International connections, strategies and policies can also be brought into the spectrum to understand the community detection more.

Exploring of more robust ways of community detection and centrality measures should have been done[6] to make more concrete conclusions about the potential of this data and how network science can augment the analysis of this sort of data. Another community detection algorithm in addition to Louvain is using Link Communities [7]. The algorithm focuses on community detection based on edges, upon implementing this on the data at question, the community detection was not easy to interpret in the default setting. Upon more experimenting with the attributes the algorithm might have lead to interesting observations

The future expansions for the work to expand the data taking into consideration Other Official

Flows (OOF) and Private funds. The data can also be expanded on include public and private organisations for the analysis. On top of all this going into the depths of separating the analysis for each sector would essentially be opening up of new paths of exploration.

5. References

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