Understanding the Global Arms Trade Network

Analysis of Different Community Detection Methods

Comp 479 - Network Science

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1. Introduction

Great power rivalries do not seem to end after the conclusion of the Cold War. Intense military races have been worrying the world in Middle East, the South China Sea, the Middle East, and Kashmir between India and Pakistan, and many other places. The growing armed conflicts were partly supported by the thriving arms trade industry. It is estimated that the total international trade in arms now is worth about $100 billion per year [1]. The Arms Trade Treaty, which was signed in 2014 to regulate the international trade in conventional weapons, has not had any visible impact on the overall trade in arms. China is seeking to transform into a military power and export to form stronger alliance. The US accounts for 34% of all global arms sales, and the weapons which flowed into the Middle East led to increasing regional instability [1]. Light weapons continue to flow in Africa, causing relentless fightings in South Sudan. In such an arms exchange system, several questions are worth of considerations: who are the major suppliers and recipients of major conventional weapons? Can we observe communities from the trade network itself? What are missing in the initial network? In the international military world, does a certain community pattern persist if we consider characteristics of the country in the network? To answer these questions, we turn into network science, which will offer a special view on the global military partnership and power dynamics. In addition to using applied graph theory to analyze the network structure itself, we explored node attributes in the network. The diverse methods in this paper will help us understand a social network from different perspectives.

2. Previous Work

Previous research on this specific subject of arms trade has been employed purely with the network structure to study the arms trade. Kinsella has studied the global illicit small arms transfers in Africa. He argues that the arms trade resembles an informal organizational environment and the forces of supply and demand are mediated by the forces of trust, loyalty, and mutual commitment that govern the flow of information within a social network [7]. He concludes that this network is highly related to the shared interests and ongoing relationships between countries by analyzing the betweenness centrality. However, as he recognized in his work, the illicit dataset he used was still in its early development stage and future research with more thorough data was needed.

Anders and Seim studied the relationship between differences in polity and arms trade from the arms trade network 1950-2007 [5]. They found a negative relationship between differences in polity and the likelihood of arms trade. The network grows more dense, clustered and decentralized over time. The influence of USSR and NATO still influence the network structure, though the impact was less strong compared to that during the Cold War. However, their work was mainly a descriptive overview of the network over half of a century. They did not exert emphasis on a particular year and explore different potential clustering methods in one network. Their analysis also relied primarily on the topological structure of the network itself. Nevertheless, both Kinsella's and Anders' piece helped us decide to use countries' freedom scores and membership in various treaties, which will be detailed in the Data and Method section.

De Andrade, *et al.* tried to combine the topological information and node attributes to analyze international trade network of 2015. They constructed their network by assigning a weight to the edge connecting two countries (nodes) based on the trade amount. They considered GDP as the node attribute for each country. They redefined the edge weights by adding the nodes attribute weights into the scheme: $Z(v_i, v_j) = w(v_i, v_j)(\frac{s(v_i)+s(v_j)}{2})$, where Z is the new weight, w is the original weight, $s(v_i)$ is the node attributes. This approach is similar to Liu's work on combining both information in a Erdos co-author community [8]. In addition, Zhou, *et al.* developed a *SA-Cluster* algorithm through a unified distance measure [9]. It essentially augments the initial network by adding new attribute vertices and attribute edges based on both the topological and attribute similarity in a network. However, all these approaches destruct the original structure we are concerned about. Thus, we need a way to take both factors into consideration without altering the original network.

Falih, *et al.* compared seven community detection algorithms with both synthetic and real data [10]. They tested if the results produced by the algorithms preserve high dense connectivity, modularity, conductance, but low entropy. The authors reported an algorithm called *Attributed Network Clustering Algorithm* (ANCA), which incorporates the topological and attribute information, led to the best performance in the community detection task. In this report, we will analyze the applicability of this algorithm on our specific network. We thought that the result of this clustering did not offer any useful insight on our specific network perhaps because of scarcity of data. We propose an adjustment to this method and found a more contextually reasonable result.

3. Data and Methods

To answer the above questions and extend the existing research on arms trade social network, we look at both the intial network and node attributes. At first, we used the Louvain algorithm to calculate the modularity to grasp insights from the communities from the network structure. After that, we used the hierarchical clustering and a revised minimum spanning tree (MST)-based segmentation algorithm to detect new communities, both of which utilize the node attributes we assigned. Finally, we incorporate two information with an revised ANCA with the MST-based method.

3.1. Data

First of all, We built our initial network from the of the global arms trade information from the Stockhold International Peace Research Institute (SIPRI) database [2]. The database contains the suppliers and recipients of all transactions in history. It offers a good objective pricing system to measure the volume of deliveries indicators of each weapon transfer, which is referred as the trend indicator values (TIV). High TIV corresponds with high volume of each transfer or high military capability of each transfer. This network is a directed graph G, where each country is a node N and an edge is drawn from a supplier s to a recipient r. A weight is assigned to this edge based on the TIV score of this transaction. We normalized the weights because of its original skewness. We built trade network from 2016 to 2018, which contains 147 countries and 2681 transactions.

In this paper, we also assign several attributes to each node to provide complementary information to the initial network. The first attribute is the military spendings which we obtained from SIPRI database for the military expenditure of each country in 2017. All spending values have been converted to constant US dollar. We also estimated missing data based on the military expenditure share of national GDP and GDP value in 2017 from the World Bank [3]. Another attribute is the aggregate freedom scores from the Freedom House which offers comparative assessment of political rights and civil liberties that covers 195 countries. We used this score under the assumption that arms trade usually associates with allies. Allies tend to have similar political system (democracy vs. authoritarianism) which permits different levels of freedom. For example, the US and China have different political ideologies and form different allies. This was also the case during the Cold War. We also consider each country's membership in intergovernmental organizations and treaties, which are related to arms trade and weapon regulations. They include the Geneva Convention Protocol I, II, III, and memberships in the NATO, the ATT, the OPANAL, and the UNRCPD.[1] We would expect countries who have formed an alliance in a regional community share characteristics of that organization. To sum up, we construct a feature space with 9 variables of all the countries which appear in the trade network. We standardize the arms production and freedom scores throughout the analysis.

3.2. Method

3.2.1. The Topological Structure

We used the Louvain Algorithm, which was developed by Blondel *et al.* from the University of Louvain in 2008, to optimize the modularity [6]. A modularity score is defined as

$$Q = \frac{1}{2m} \sum_i \sum_j (A_{ij} - \frac{k_i k_j}{2m}) \delta(C^{(i)}, C^{(j)})$$

[1]The organizations stand for the the North Atlantic Treaty Organization (NATO), the Arms Trade Treaty (ATT), the Agency for the Prohibition of Nuclear Weapons in Latin America and the Caribbean (OPANAL), and the United Nations Regional Center for Peace and Disarmament in Asia and the Pacific (UNRCPD)

where A is the adjacency matrix; $m = |E|$, the number of edges; k_i is the degree of vertex i; $C^{(i)}$ is the type of vertex; $\delta(C^{(i)}, C^{(j)}) = 1$ if $i \in C$, 0 otherwise. This greedy algorithm was implemented in Gephi. We take advantage of this method to analyze the structure of the original arms trade network. In the network, we identify important vertices by looking at the centrality measures including hubs and authority scores and reversed PageRank and Eigenvector centrality measures.

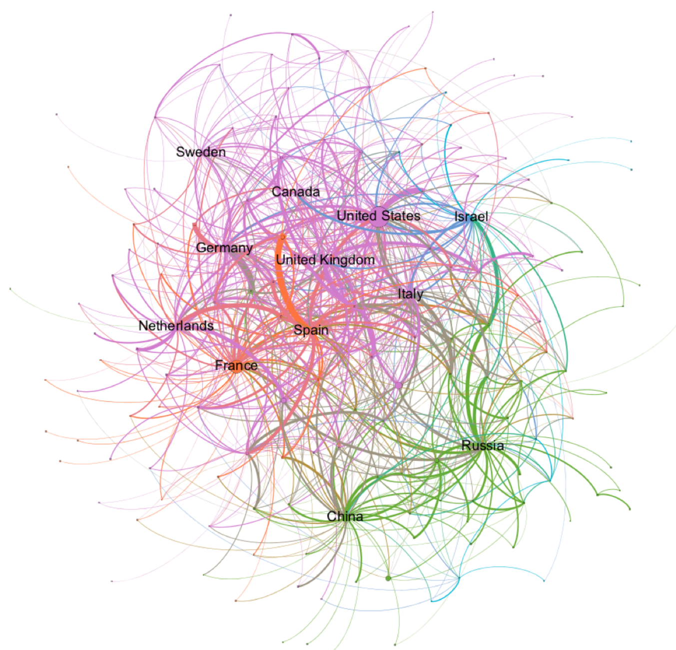

Figure 1: Global arm trade in 2016 - 2018. Each node is a country, and node size is determined by the Hub Score (by HITS algorithm) of each country. Edges are weighted based on the TIV values designed by Stockhold International Peace Research Institute to measure the trade volumns. Communities are detected based on modularity scores (0.28).

3.2.2. The Nodes Attributes Clustering

We used hierarchical clustering, a bottom-up greedy algorithm which group similar objects together so that each cluster is a collection of objects with similar properties [11]. In this case, we created a 9-dimensions feature space by the arms production, freedom scores, and membership of treaties described in the Data section.

Then, we used an MST-based algorithm to test if geographically closer countries are in a community in terms of some arms features. It was called graph-based segmentation algorithm proposed by Felzenszwalb and Huttenlocher [12]. The algorithm was designed to segment an image that consists of components with a wide range of noisy intensities. It constructs a 5-dimensional feature space which contains the coordinates and RGB values of a pixel. After calculating the Euclidean distance, the algorithm builds an initial network by k-nearest neighboring pixels in the feature space. In the network, each node is set to be a component of itself and agglomerate different components by comparing the a component's internal difference and external difference. The authors defined that an internal difference is the largest weight of the minimum spanning tree of a component:

$$Int(C) = \max_{e \in MST(C,E)} w(e)$$

They also define the minimum weight edge connecting the two components as the external difference:

$$Diff(C_1, C_2) = \min_{v_1 \in C_1, v_2 \in C_2, (v_1, v_2) \in E} w(v_i, v_j)$$

If the external difference is smaller than the internal difference, the algorithm merges the two components together. To make the first of partition possiblem, the algorithm sets a threshold function of updating the internal difference. $Int(C) = Int(C) + \tau(C)$ where $\tau(C) = \frac{K}{|C|}$. The higher the constant K, the more likely a larger communities will be found. In our case, we converted the latitude, longitude to $x = cos(latitude)cos(longitude)$, $y = cos(latitude)sin(longitude)$, and $z = sin(latitude)$ to represent the geographical distance in 3 dimensions (the globe). Then we added two variables in the feature space, the arms production and freedom scores. We can observe if, for instance, European countries are really "European" in the world of arms trade.

3.2.3. Combining Topological Structure and Nodes Attributes

We adopted the aforementioned ANCA method. ANCA can be divided into three steps: seed selection, matrices building, and clustering.

Step 1: Seeds characterize the overall structure of the network. The algorithm picks the union set of the top 20 percent and the bottom 15 percent of the countries in terms of the eigenvector centrality, the degree centrality, and the closeness centrality. The diverse set of seeds all over the network captures the most picture of the topological information.

Step 2: This step reduces the dimension of both topological and attribute information. The algorithm calculates (1) the shortest paths from each node to the seeds, and (2) the Euclidean distance between each node to the seeds. The two steps result in two $N \times M$ matrices, where N is the number of nodes and M is the number of seeds. Then we choose the largest left singular vector from both matrices and stack them together to be our new feature space. We disregard the author's original method by which he picked k left singular vectors and run a k-means clustering. The original ANCA algorithm provides us with 8 communities, the largest of which includes 85.03% (125) of the 147 countries. This indicates that the this community contains very high internal difference. When we keep adding k for the rank-k approximation, more isolated community occurs. The high k results in a relatively high-dimensional vector for the 147 countries, even though it reduces the dimension of the original matrix. The dimension is $2k$, because it stacks the topological and attribute matrices. This is prone to curse of dimensionality, which means that the available data become sparse as the volumes of space increases. Simply put, 147 countries might not be enough for this method which he considered a network with thousands of nodes [10]. A network of this result can be found in the Appendix.

Step 3: Instead of using k-means clustering, we revised the original ANCA algorithm to our specific problem. After obtaining the topological vector and attribute vector, we used the MST-based clustering method. The highlight of the algorithm is that it keeps track of a varying threshold for merging two components by adjusting the threshold according to the size of the component. For our purpose, this permits a large community which has high variations among its members, and leave the communities that are adjacent to those high energy communities intact. In our analysis, we use $K = 30$.

4. Results

4.1. Topological Structure

4.1.1. Community

The 6 communities are colored by Louvain Community detection, that we utilized Gephi to obtain. The modularity score $Q = 0.235$. Label and nodes are sized proportional to its Hub score.

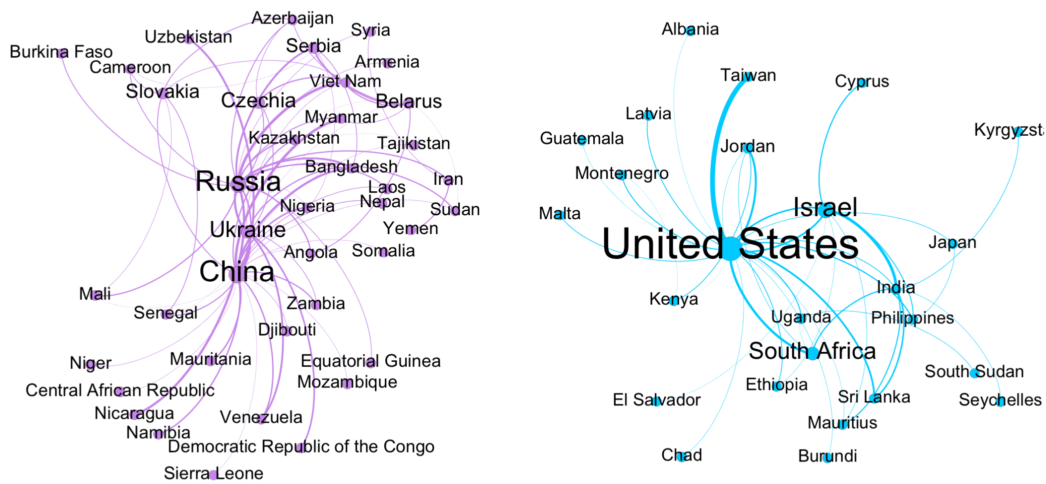

Figure 2: Communities led by Russia and the US

We observe that each community has one to a few protagonists who stood out by its high hub score. This first observation leads to a hypothesis that a weapon trade community is often characterized by a few powerful sellers and lots of buyers who do not have much inner connections (the average cluster coefficient is 0.161).

In Figure 2, Russia and China dominate this community. The other members of this community cover countries in Africa such as Angola, Democratic Republic of Congo, and countries in east Europe such as Ukraine. We find Russia and China share similar customers. The similarity might result from the historical alliance of the two countries and other communist countries such as Venezuela. Political cooperations are foreign strategies might also be a reason. For example, China's One Belt and One Road Initiative makes China form closer relationship with countries which were part of the Soviet Union.

It is evident that the US is the super protagonist in the blue community. We find Japan and Philippines are unsurprisingly clustered into the community with the US, in spite of the geographic distance. It is also not surprising that Israel is the second biggest node in this graph because they are two firm ally and Israel has been investing on its military arsenal. Interestingly, India is clustered with the US, even though it is one of Russia's largest clients (35% of all sales) [13]. This suggests that there might exist a group of countries who trade universally which are less restricted by geography, political ideology and international relations. From the two subgraph, we can observe a growing competition between the US and Russia and China in Africa in terms of arms trade. From the dense connection between the US and other African countries, we are worried about potential tensions between two forces in Africa. In fact, it's reported that China and US have been increasingly competing for political and commericial influence in Africa recently [14].

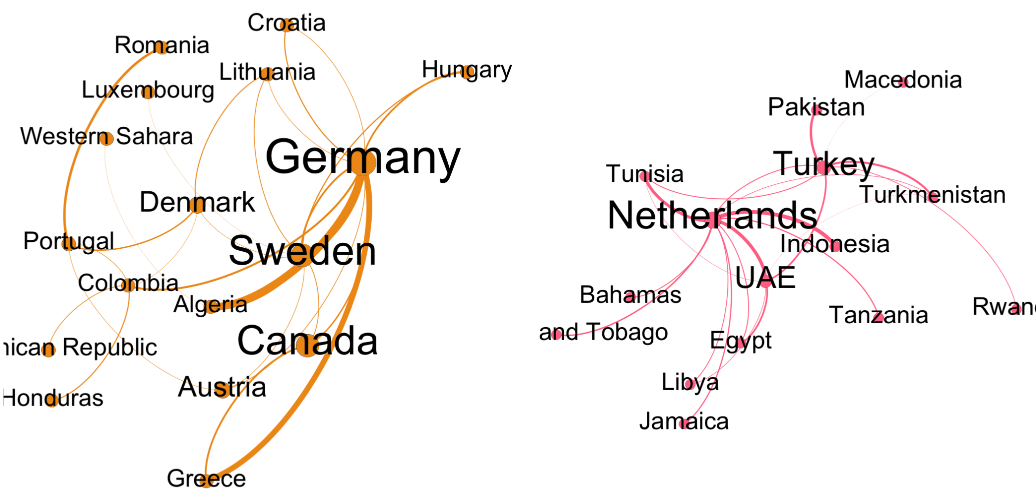

Figure 3: Communities led by Germany and the Netherlands

The European countries are generally categorized into two communities: one is led by Germany, anther is led by Netherlands. It is surprising to see Canada is not categorized with the US, despite the geographical closeness and cooperations in various occasions. However, according to a report, we realize the the US really does not have frequent arms trade history with Canada [15]. Noticing the overlap between Canada's clients, we suggest that Canada might be retained in this community more as a seller.

In the other community, the Netherlands is a surprising protagonist which stood out from the graph. The close relationship with Indonesia agrees with the result that the Netherlands' largest clients is Indonesia [15]. However, the other large client, Jordan, which constitutes 15% of the sales, does not show up in this community. Later, when we find Jordan in the community of the US who sells 15% of its export amount to Jordan. We think this is reasonable because considering overall hub score, the US is a stronger competitor than Netherlands. the Netherlands's largest clients are UAE and

Turkey. We find that Netherlands has been strengthening its cooperation with UAE from 2013 [16]. The news matches up with our observation that the Netherlands is getting involved into the Middle East export market in which one of the led country is UAE followed by Turkey. Therefore, the expansion of the community to Middle East sheds lights on the Netherlands' political plan.

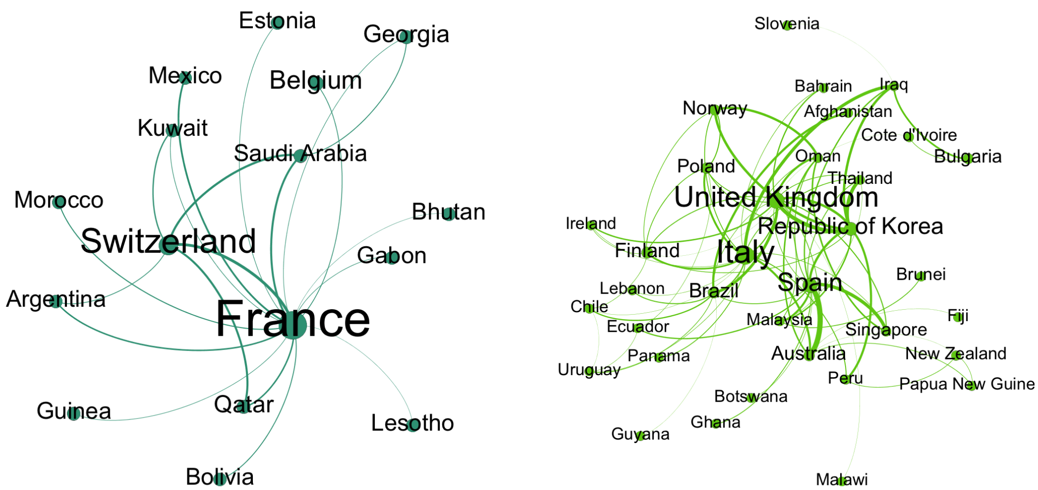

Figure 4: Communities led by France and the UK

In Figure 4, we observe France to be the protagonist of the this community. France exerted similar impact on Middle East as the Netherlands. It opens the market in Saudi Arabia and Bolivia, both of which we confirm are main import country from France. For both communities where France and the Netherlands occur, these two countries are the only power center of the community. The networks are relatively sparse, comparing to the community centered by United Kingdom, Italy, and Spain.

Also as an European countries, United Kingdom, Italy, and Spain are three major actors in this community. According to the 2017 report, United Kingdom was ranked 6th, while Spain and Italy are 7th and 9th in terms of the amount of weapon exports. We find a similar emphasis on the market of South America (an inner small community centered at Brazil), and the direction of Southern Malay (Oman, Singapore, Australia). An interesting country to look at is Republic of Korea. It is a larger buyer from European countries such as United Kingdom and Spain, but also a seller to Southern

Malay countries such as Thailand and Malaysia.

The potential partition of European countries to three communities was perhaps because they target different market. The Netherlands target more Middle East countries. France target the Middle East countries and some Latin American countries. The UK, Spain and Italy primarily target the Latin American and some Asian countries.

4.1.2. Centrality

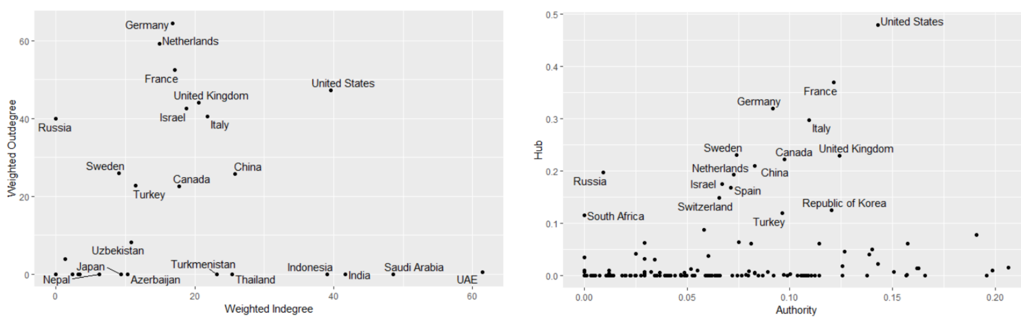

Figure 5: Weighted Indegree - Outdegree and Hub-Authority Comparison

In Figure 5, we compare the weighted in-degree/weighted out-degree with Authority/Hub. As expected, we observe consistent distribution of states. In both graphs, most data points are gathered at the low out-degree area, especially at low indegree area. This indicates that the majority of the countries depend the military supply from other countries. Other large states, such as the US, the UK, China, France, Germany, Russia, and Italy have higher weighted out-degree and hub score. Their hub scores are twice as greater than their authority score. Therefore, the apparent centrality difference indicates a clear demands of ammunities from "weaker" countries from a few powerful states.

To further explore the dynamic of those large countries, we obtained the reversed eigencentrality and reversed PageRank by reverse the edge direction. In our case, a high PageRank entails more interactions with important countries, while high Eigencentrality entails selling to other important countries. A country with high PageRank should have higher Authority Score in the reversed network. The interesting observation is that, while the US, Germany, France, Italy, Republic of Korea maintain high authority, high pagerank, and high eigencentrality, China and Russia, while maintain relative high pagerank, receive very low eigencentrality. Our theory is that western countries

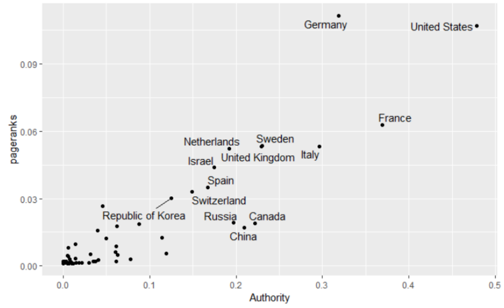

Figure 6: Authority and PageRank centrality

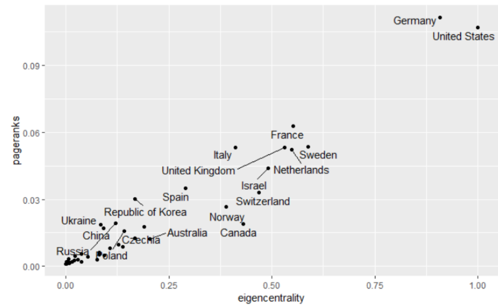

Figure 7: Eigenvector and PageRank centrality

tend to sell to other important countries, so they main balanced eigencentrality and pagerank, but the most buyers of Russia and China are countries that are further from the center of international trade, such as Nepal, Bangladesh, Myanmar, Laos.

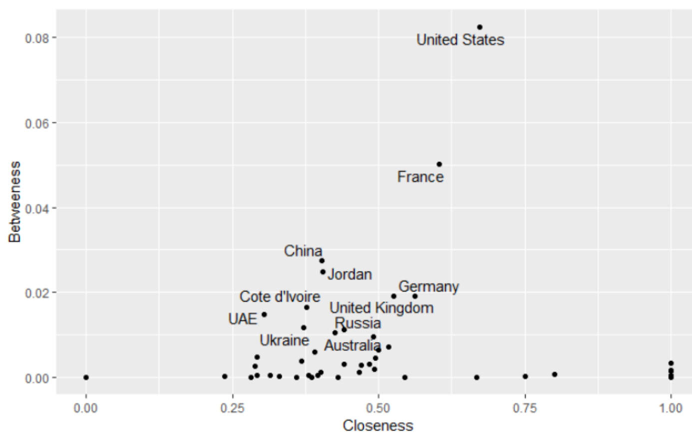

Figure 8: Betweenness centrality and Closeness

To explore the important broker countries and countries that are placed at well informed positions, we plot the relation between closeness centrality and betweenness centrality. We observe that countries are evenly spaced on x axis. the US, France, and China have positions at middle of closeness scale, but have extremely large betweenness. We recognize the countries with high betweenness are large countries that export a lot. The fact that all of them have high betweenness imply that each of them has its own community where they are the power center. For the countries have high closeness, such as Algeria, Oman, Indonesia, it implies that they might import from multiple large countries, which means they have close access to multiple communities. For example, we check the connection of Indonesia, and found that some of its large sellers include China, Korea, Australia, France, and the US. We think the roles of these countries play in the cluster are interesting.

4.1.3. Degree Distribution

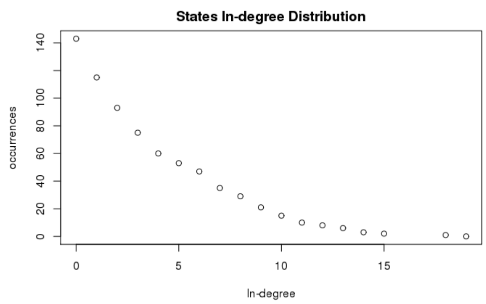

Figure 9: Authority and PageRank centrality

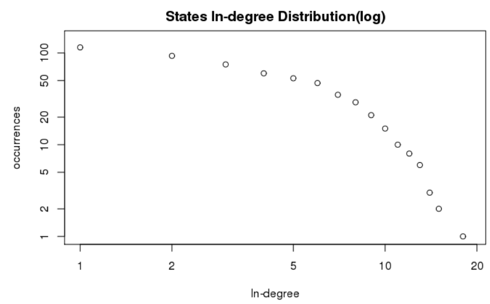

Figure 10: Eigenvector and PageRank centrality

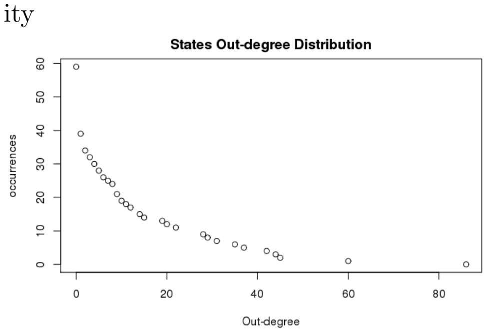

Figure 11: Authority and PageRank centrality

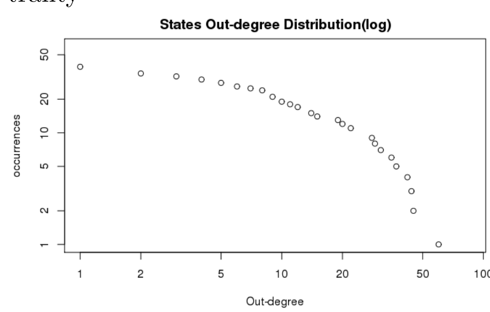

Figure 12: Eigenvector and PageRank centrality

We further explore the degree distribution of the network to see if there is a potential power law phenomenon. We plot for both indegree and outdegree. The apparent information are: 1) Although it qualifies the criteria of 'many small and a few large', we doubt we observe a power law distribution. We use the Maximum Likelihood Calculator.

$$\alpha = 1 + N[\sum_i lnK_i/(K_{min} - 0.5)]^{-1}$$

where K_{min} is the value where power law seems to hold.

For out-degree, we use $K_{min} = 6$ and obtain 1.83627 to be alpha of the best fitted powerlaw. For in-degree, we use $K_{min} = 7$ obtain 4.6799 to be the estimated alpha, which clearly indicates that in-degree distribution of the network does not conform with power law. 2)the degree range of out-degree is far more wider than in-degree range. This confirms our previous analysis that most countries heavily rely on the importing weapons from a few countries who have super high out-degree. For example, the US has out degree as high has 86, while most countries have out-degree 0.

4.2. Nodes Attribute Clustering

4.2.1. Hierarchical Clustering

The dendrogram below shows the clusters produced at each step of the agglomeration. The corresponding height of each branch is the distance at which two groups joined together. We used a complete linkage which measures the maximum difference between two potential groups.

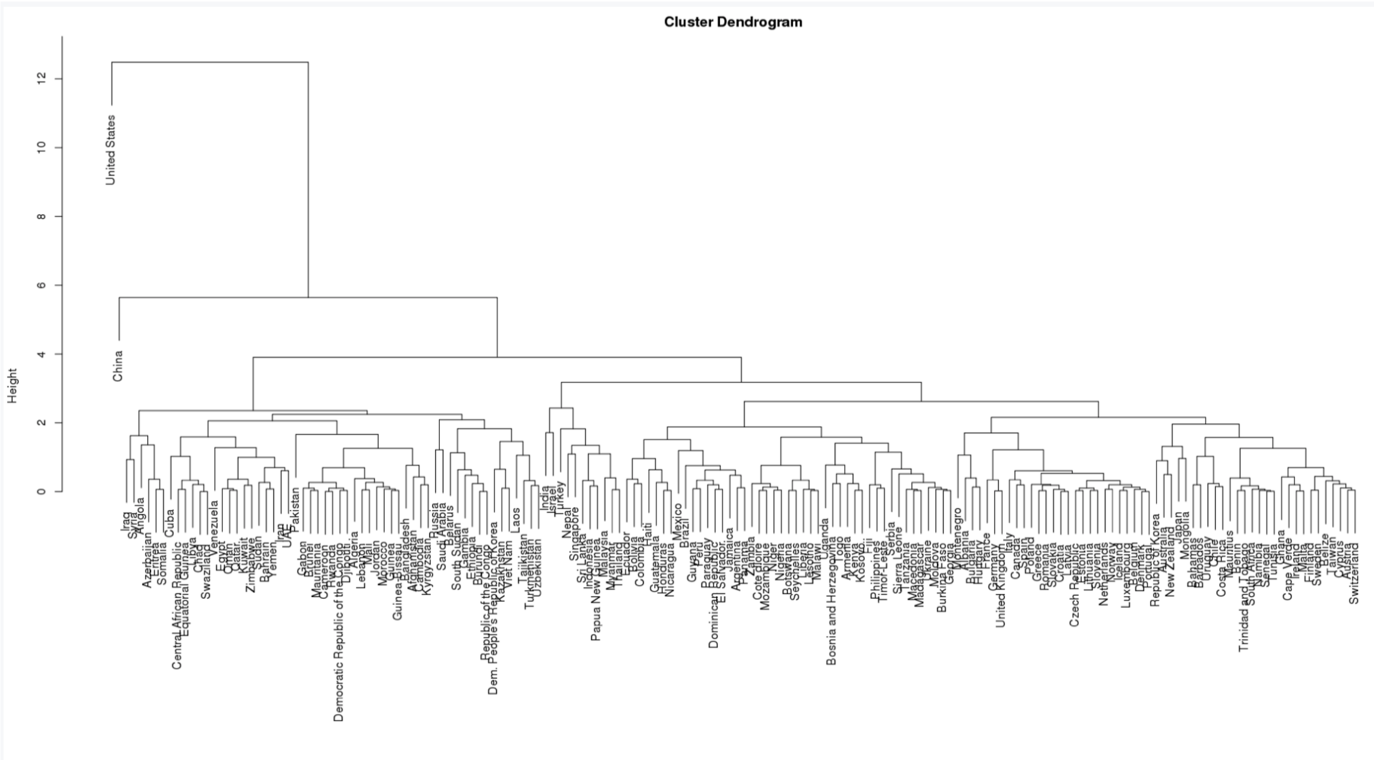

Figure 13: Dendrogram constructed with 9-variable feature space: arms production, freedom scores, and membership in organizations

The advantage of a dendrogram is that we can "cut" the tree at any height to help us visualize a reasonable community. We can clearly tell that China and the US are separate from the rest of the world. African and Central Asian countries are approximately on the left. Asian and South American countries are in the middle. European countries are on the right. From the perspective of arms production, political ideology, and membership in treaties, countries in the world can be roughly clustered based on their locations, a fact which may make us think of geopolitics in international relations. This observation makes intuitive sense because closer countries tend to join a regional organization, such as the NATO. Closer countries who join a same military organizations might have strong alliance. Their political ideology scores should also be similar, for example, in Europe, Africa, and southeast Asia. The result of MST-based partition algorithm seems to support such claim.

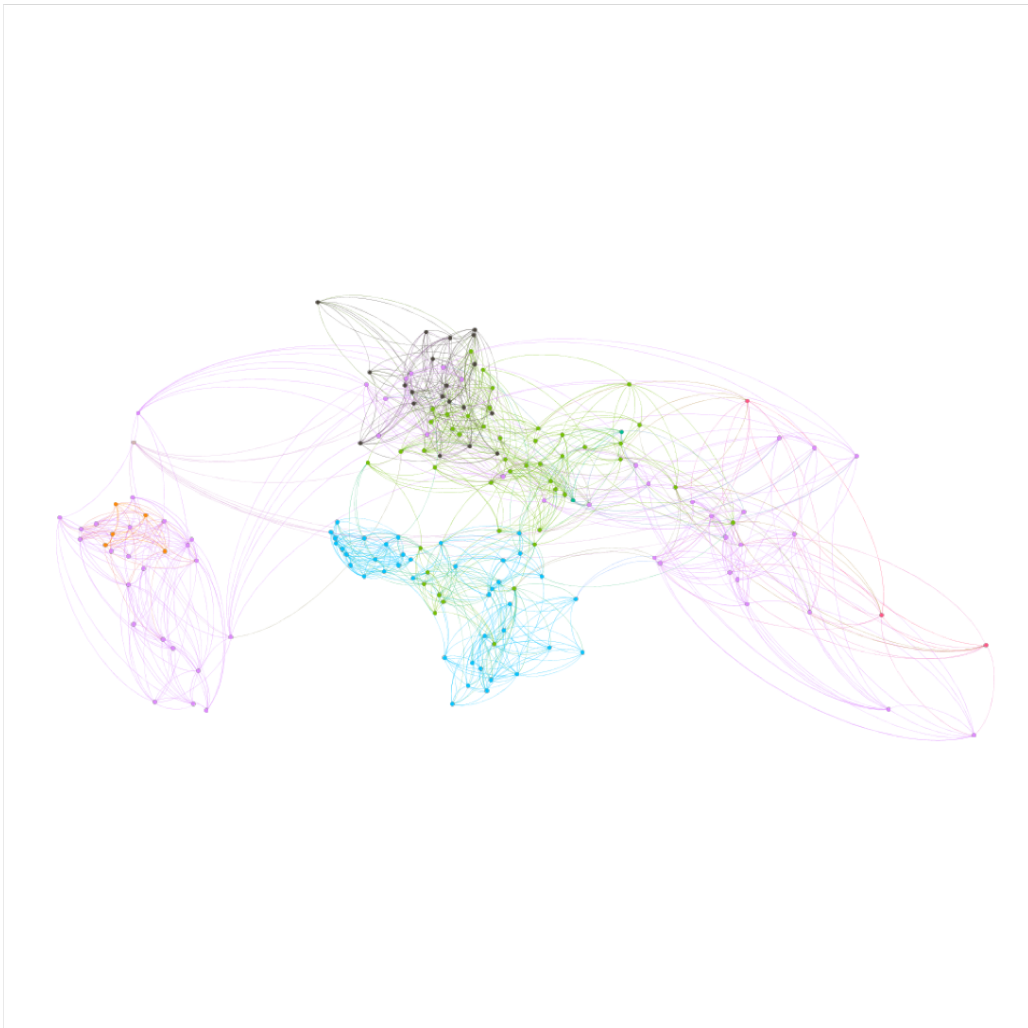

Figure 14: MST-based Partition with locations, arms production, and freedom scores. The layout corresponds to geographical locations of countries

Figure 14 gives an interesting partition of the world based on location and their qualities in terms of arms and political ideology. We can tell an interesting community spanning from Central Asia to Africa. For example, Angola, Republic of Congo, and other countries in the green community have very similar freedom score (21-26). Countries with high freedom scores around the Middle East, such as Bosnia and Herzegovina and Croatia, are incorporated into a same community. The advantage of this image processing algorithm carries itself to a world-partition problem. It detect a potentially noisy part in a lower-dimensional space, such as Middle East, after grasping more information from higher-dimensional space. We can tell in terms of arms production and political ideologies, Europe, South America, and Southeast Asia have a consistent community. Middle East and Central Africa has its interesting pattern in lieu of pre-existing delineation on a map. This coincides with the fact that this part of the world was divided by the UK and France after the World War I and it still remains unstable today.

4.3. Combining Topological Structure and Nodes Attributes

The combined method of the ANCA algorithm and the MST-based partition algorithm puts all what we typically think of as "powerful countries" in same group.

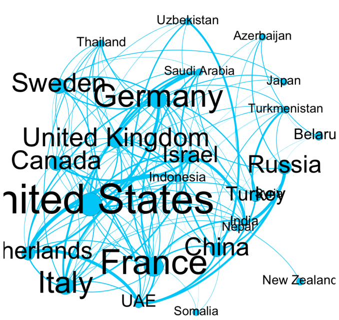

Figure 15: Community by stronger countries

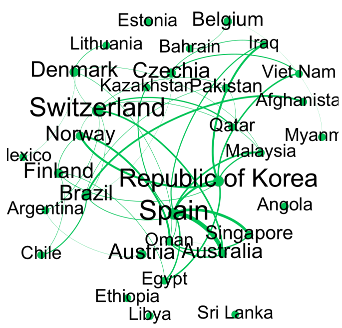

Figure 16: Community led by South Africa

Figure 17: Community led by Spain

By this combined algorithm, we can observe that the groups led by the US have very high modularity. Coincidentally, these countries all have very high hub scores, meaning that all the big weapon export countries are in the same group. The US has the highest hub score (0.478559), followed by France (0.36874) In terms of node attribute, powerful countries typically have similar stance on weapon trade. These countries have higher arms production because they are the main source of weapons. Most of the countries in this group didn't ratify the Arms Trade Treaty in 2014, including Israel, China, the US, Russia, etc. European countries are even closer because they are in the NATO and have closer political ideology. This complements the initial network community detection by including most of the western countries.

Figure 18: Community by stronger countries

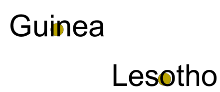

Figure 19: Community led by South Africa

Figure 20: Community led by Spain

Spain, Republic of Korea, and Switzerland in the green community might be separated because of the initial network structure and the node attribute difference. These countries, while also pretty powerful in the world, have less domestic arms production and they adovate for arms non-proliferation and usually take an opposite stance against more belligerent countries. The rest of the countries are mostly disconnected. These countries usually zero or very little arms production. Different communities among these groups were perhaps because of different ideology, as we can see the countries Figure 21 tend to have lower freedom scores. Also, Guinea and Lesotho are separated from the rest of the world perhaps because their lack of more membership in regional organization.

5. Conclusion

The node attribute and hybrid community detection algorithms depend on different input parameters very much. For example, the hierarchical clustering relies on the height at which we would like to cut the dendrogram. The MST-based method depends on a constant K threshold. It also depends how the number of nearest neighbors we would like to pick. The ANCA algorithm is dependent on the k in the rank-k approximation process. Picking a good parameter might be based on context. Our parameters in this paper might not be the best. Future work can focus on more feature space related to arms trade. (Or more feature space in other topics) In addition, the combined ANCA-MST method remains an exploratory work in this paper. The result makes some intuitive sense, but a more rigorous mathematical or accuracy proof of this method is needed. The model can be tested if it is utilized under other contexts compared to real-world network.

This paper explores four community detection methods. Each method can generate a network which offers a different insight on the power dynamics in the global arms system. By only looking at the topological structure of arms trade network, we can tell that there was a clear division between communist countries, led by Russia and China, and those led by western powers which, nevertheless, are separate into different communities. The arms trade network 2016-2018 was dominated by certain countries with high weighted out-degree and hub scores. The US dominates the arms system in that it has the highest hub score and dominate the initial arms trade network. The node attribute clustering gives us an evidence of a geopolitics in the arms trade. Considering countries' arms productions, freedom scores, and membership affiliations, the US and China are separate from the rest of the world as well. When we combine the topological information and node attributes, the new communities indicate a powerful countries might observe a particular trade pattern and share similar stance on weapon's regulation. The powerful countries tend to ally themselves with each others and leave the less stronger countries in another community. Combining all the perspective, we can reasonably conclude the way to stop regional instability is to curb the big countries, which lead different regional markets or communities, to reduce the amount of weapon export, especially to the war-torn countries. These method are certainly not the end of the story, but they provided a relatively holistic view of a given information. When we are given a network and a set of node attributes, we need to approach the problem from as many perspective as possible.

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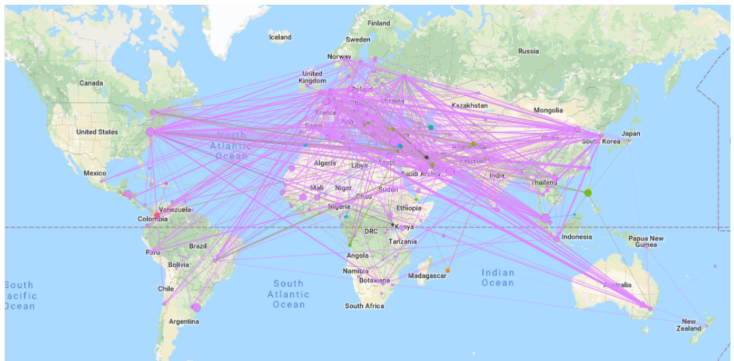

Figure .21: Arms Trade: a community resulted from ANCA, with k=8 for kmean cluster. The labels and nodes are sized proportional to Hub score, and the directed edges are weighted by the square root of trade value.