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COMPGW01: Complex Networks and Web
Coursework Project (2016-2017)
Analysis of International Relations through Opinion Network

1 Abstract

Traditional social science collect data from controlled environments such as surveys and they typically represent a subset as determined by the researchers. On today's new media, data collected in uncontrolled environment are made available as Big Data repositories and can be organised for analysis. This study attempt to generate an international opinion network from news collected across the globe. The study showed potential for creating an opinion network using large news datasets. The opinion network can then be used for research in domains such as international relations. As a proof of concept, the opinion network was used to answer three basic questions related to international relations.

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2 Introduction

With the advent of the World-Wide-Web (WWW), all sorts of news could be digitalized and disseminated via the WWW, and their opinions of the world projected in real-time. Often, the opinions projected by these news media could reflect the voices of their own nations in international relations.

The goal of this study was to demonstrate the creation and analysis of a network of directed international opinions from news consolidated across the world. The study then sought to answer the following questions on International Relations.

1. What characteristics would such a network follow?
2. Who are the top players and what is the perception of them?
3. What is the relationship between the top players?

The consolidated world news was extracted from The Global Database of Events, Language and Tone (GDELT) Project. An International Opinion network was created from news embedded with metadata such as actors (person or organisation) and the sentiments of the event covered in the news. As far as this study was aware, there were no prior network research on such dataset. The opinion network was analysed using both customised software (Python script with NetworkX) and commercial tools such as Powerlaw, Excel, Gephi, Cytoscape and Tableau.

The study showed that relevant metrics in complex network analysis could be applied in this network to answer real world questions. It also highlighted shortcomings and potential future work that could answer more sophisticated questions. Finally, this study showed its potential to be used as complementary research in domains such as international relations.

Although the author had minimal statistical and research background, he enjoyed the whole process of deriving research questions, building datasets, finding and learning new tools, to the analysing and validation of generated results. He was proud to have completed a small research project in the given time frame. Some challenges he encountered during the study include finding and validating explanations to unexpected results, managing the scale of data collected and handling noise and potential bias in datasets collected.

3 Background

3.1 News as an opinion network

News, it is information about current events. It reaches out to every society on the planet, by form of conversation, print, broadcasting, digital media and more recently social media. Each piece of news would detail information such as the actors and the event that brought about the news. An actor in the news can be an entity such as a person or an organisation. In some cases, the actors and their roles can be linked to entities such as organisations or countries. An event in the news hold the core information and can convey subtle opinions in the form of a positive, negative or neutral tone.

If a news article contained two actors and the affiliated countries of these actors were available, a directed opinion between the countries could be established. For example, in the article “Barack Obama used nuclear ‘red phone’ to warn Putin about Russian hacking of US election’”, there were two actors Barack Obama and Putin. These actors could be affiliated to USA and Russia respectively. Thus, a directed negative opinion could be established from USA to Russia. Most of the times, the opinion offered by the news media is not too different from the host government’s. By consolidating news on a very large scale, a network of International Opinion could be built. This would in turn provide a real-time alternative to analyse international relations.

With the advancement of database, language translation and natural language processing technologies, it is now possible for news to be digitised, pre-processed and archived online along with important metadata. The GDELT Project is an example of such technology advancement.

3.2 International Relations

International relation is defined as a wide-ranging field that encompasses political science, global studies, social science and even humanities. It focused on relationships between sovereign states, non-government organisations, multinational corporations, and the wider world-systems[1] produced by this interaction. This study would apply the results of the international opinion network to this field.

[1] A world-system is a socioeconomic system, under systems theory, that encompasses part or all the globe, detailing the aggregate structural product of the sum of the interactions between polities.

4 Literature Survey

Emilie, Miles and Alexander [1] performed a literature review of researches on International Relations using network analysis. The authors positioned the network in the form of official diplomacy between the nations and focused network analysis in the context of power. The review highlighted problems with testing the network theory in international relations and the availability of suitable data for network analysis. Another problem was the clash between traditional international relations study and network analysis, which means network analysis had yet to be as proliferated as hoped.

The review associated degree centrality, between-ness centrality and closeness centrality with international relations but offered little explanation beyond the scientific definition for between-ness (brokerage) and closeness centrality. Emilie, Miles and Alexander positioned the network as dynamic, since nations could choose to form or sever diplomacy as it wished. The review attempted to form a prediction of alliance by reviewing the structural balance of a subset of the network, asserting that it could in turn be used by world actors to enhance or exploit their network positions.

Emilie, Miles and Alexander performed a great deal of research into the topic and provided an insight on how network analysis of their dataset could be applied on international relations. However, insufficient studies were made into close to real time international exchanges.

Doreian and Mrvar [2] used balance theoretic ideas to study the dynamics of the international system of nations in a network of signed relations. Their research considers negative ties in conflicts and territorial exchanges and positive ties in the form of alliances. Their findings implied that the structural balance theory do not apply to international relations as they asserted the level of imbalance changed too dramatically through time.

The results from Doreian and Mrvar used data from the Correlates of War project and their research used a sliding window of four-year width in their study. No experiments were carried out for shorter temporal windows to map the structural balance in smaller granularities.

5 Methodology

5.1 Datasets

5.1.1 Raw Datasets

The Global Database of Events, Language and Tone (GDELT) is a Big Data repository that collects the world's news media from nearly every country in print, broadcast and web formats. The dataset collected information from 1st January 1979, through present days with daily updates.

For the goal of this study, a dataset that would portray country to country sentiment was required. The GDELT 2.0 Event database is a global catalogue of worldwide activities ('events') in over 300 categories from protests and military attacks to peace appeals and diplomatic exchanges. Each event record details 58 fields capturing different attributes of the event. A detailed explanation of the data format was available in GDELT Project Data Format Cookbook [3].

The records retrieved ignored whether it is originating from ethnic, religion, cultural, business or government context (E.g. CAMEO Event and ActorType codes). The country affiliated to the Actors of the article and the tone were extracted for each article. Reposted articles were excluded from the dataset. Table 5-1 showed the extracted fields from the GDELT 2.0 Event database. Noting the results generated from Doreian and Mrvar, this study used a smaller sliding window of a calendar month.

Field	Description	Remarks
Actor1CountryCode	The country affiliation of Actor1, following the UN country code.	The record would be retrieved if and only if there were an interaction between Actors with affiliated countries. In a single month, all events unique to an Actor1, Actor2 pair are grouped into a single record with the tone summed. YearMonth, NoOfEvents and ToneCount are author generated fields (Aggregated from original table fields).
Actor2CountryCode	The country affiliation of Actor2, following the UN country code.	
YearMonth	The month and year that this event occurred.	
NoOfEvents	The number of events that occurred in this grouping. This is to be used as a measure to assess if abnormal results could be skewed by a very small number of events.	
ToneCount	The average tone of the interactions in the grouping. Normalised from -10 to 10. 10 being most positive and -10 most negative.	

Table 5-1 - Fields extracted from the GDELT Event database.

A simplified example to demonstrate the dataset would be to consider the following to be the only article published in Dec 2016, "*The President of Russia is visiting Washington, DC in the United States*". If GDELT categorised the tone of this article to

be positive eight, Table 5-2 would be generated. Note that the country referred to the Actor1's affiliation (RUS), not Actor1's physical location (Washington DC, USA).

Field	Value
Actor1CountryCode	RUS
Actor2CountryCode	USA
YearMonth	201612
NoOfEvents	1
ToneCount	8

Table 5-2 - Example of dataset

5.1.2 Data Processing

The generated raw dataset was good for most of the study, however, there were a few problems. First, the raw data set lacked geographical information of the Actors' affiliated countries. Although not critical, this limited the capability in presenting the results. To resolve this, all the country codes were geocoded and added into the dataset. Second, the correctness of the data was not guaranteed. One issue was the country code listed could not be found in the UN country code list. To avoid unnecessary noise in the data, such records were detected and removed. Table 5-3, Table 5-4 and Table 5-5 showed the breakdown of the processed datasets to be used in this work.

Field
UNCountryCode
CountryName
Latitude
Longitude

Table 5-3 - Nodes

Field	Description
Actor1CountryCode	From Node. The country affiliation of Actor1, following the UN country code.
Actor2CountryCode	To Node. The country affiliation of Actor2, following the UN country code.
ToneCount	Weight of edge. The average tone of the interactions in the grouping. Normalised from -10 to 10. 10 being most positive and -10 most negative.

Table 5-4 - Edges

Field	Description
YearMonth	The month and year that this event occurred.
NoOfEvents	The number of events that occurred in this grouping. This can be used as a measure to assess if abnormal results could be skewed by a very small number of events.

Table 5-5 - Auxiliary data

5.2 Methods and tools

The extracted dataset was depicted as an opinion network where countries were the nodes and the weighted links being the sentiment(tone) between them. Thus, a weighted directed graph was generated with the direction of the edge represented by an Actor1-Actor2 interaction and a signed weight represented by the tone.

In the first part of the study, a network statistical analysis was performed on a global scale on an unweighted graph. This was followed by a structural balance analysis of the weighted graph on a sub-regional scale.

In this work, NetworkX [4], a python library was used along with Excel and Google Big Query SDK [5] to retrieve and manipulate the datasets. A batch geocoding tool [6] was used to geocode the entire list of country codes. Gephi [7], NetworkX and Powerlaw [8] were used to perform network statistical computation. Much of the visualisation in this study were generated using Tableau [9], Cytoscape [10, 1] and Python Matlibplot.

6 Results

It was mentioned that the raw data set contained a time element which sets apart every single event. It sufficed at this point to note the importance of this component although the temporal element was not discussed in detail. Instead, the data was partitioned into 12 calendar months across the year 2016. The first part of this study focus on data retrieved from the eighth calendar month of 2016, the choice was made randomly to avoid bias.

6.1 Nature of network

6.1.1 Small-World

	Opinion network (s)
Number of nodes (N)	198
Number of edges (E)	6989
Average path length (L)	1.881
Average clustering coefficient (C)	0.641

Table 6-1 - Average path length and clustering coefficient

Using Gephi, the statistics in Table 6-1 was computed and showed an apparent low average path length and a high average clustering coefficient which appeared to present a small world model. However, there was no comparison on whether the results were indeed high or low as stated. As such, an Erdos-Renyi random network with the same number of nodes and edges was generated with NetworkX and computed in Gephi. The results were presented in Table 6-2.

	Opinion network (s)	Random network (r)
Number of nodes (N)	198	198
Number of edges (E)	6989	6989
Average path length (L)	1.881	1.643
Average clustering coefficient (C)	0.641	0.179

Table 6-2 - Comparison of opinion network with random network

Random models were characterised by low shortest path lengths and low clustering coefficient while Small-World networks were characterised by low shortest path length like random models but with higher clustering coefficient [11] as represented in Equation 6-1.

$$L_s \approx L_r$$
$$C_s \gg C_r$$
$$\sigma = (C_s/C_r)/(L_s/L_r) > 1$$

Equation 6-1 - Small-World conditions

The result of $\sigma = 3.13$ showed that the opinion network was a small world network.

6.1.2 Not Power Law

Next was the analysis of degree distributions of the network. The number of 13 bins was chosen to remove significant noises and yet retain observable characteristics of the network. Figure 6-1 and Figure 6-2 showed the degree distributions created with Matplotlib. The distribution is undoubtedly exponential, however at the end of long tail showed the existence of some-what rare hubs in the network. This could also imply a Power Law network.

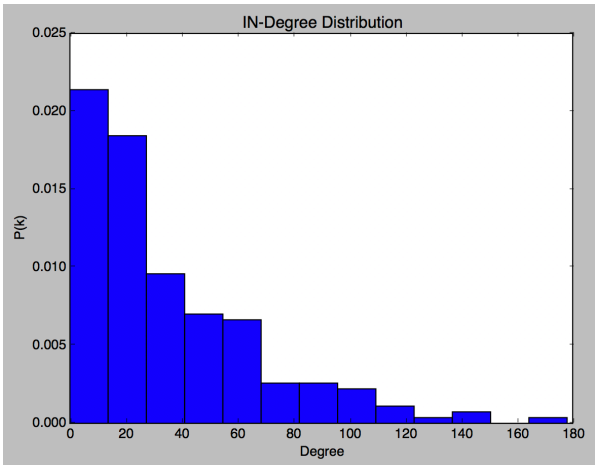


Figure 6-1 - In Degree Distribution

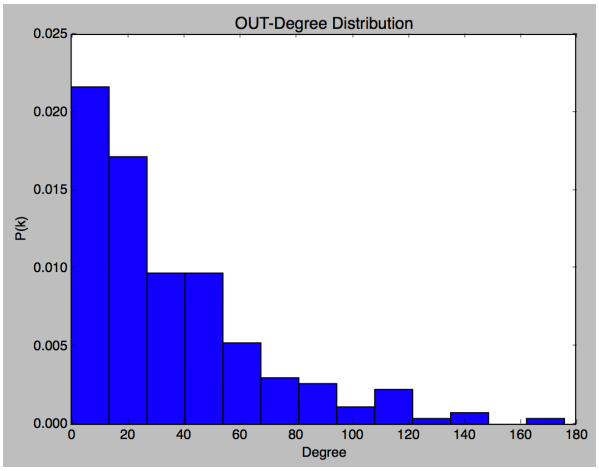


Figure 6-2 - Out Degree Distribution

To investigate if the network was Power Law, the distribution was plotted on log-log scale as shown in Figure 6-3 and Figure 6-4. The powerlaw python tool plotted a best fit for a Power Law for comparison. For a network to be Power Law, the plot would be a negative gradient line on the log-log scale (Green-Dashed line). It was clear that the resulting plot was not a line in the log-log scale, thus the opinion network was not Power Law.

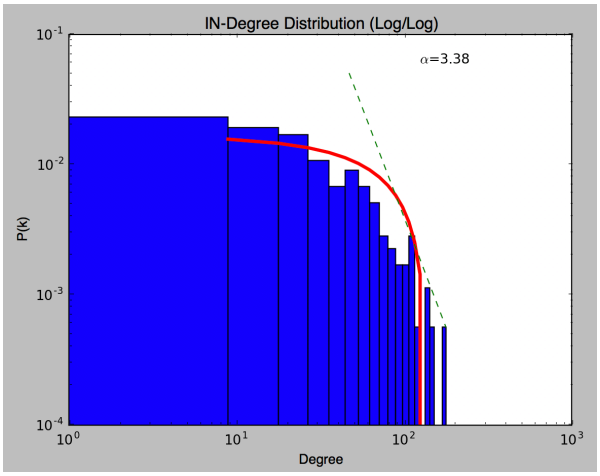


Figure 6-3 - In Degree Distribution (Log-Log scale). The red line is fitted to the data. The green dashed line is what would be a best fitted Power Law for comparison.

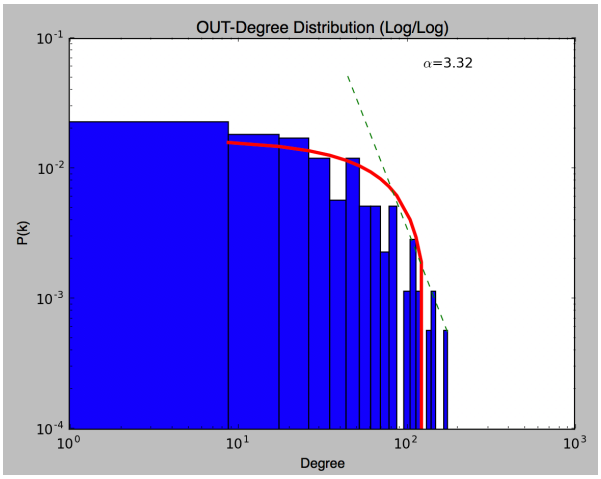


Figure 6-4 - Out Degree Distribution (Log-Log scale). The red line is fitted to the data. The green dashed line is what would be a best fitted Power Law for comparison.

6.1.3 Centrality

Centrality metrics offer a characterisation of an important node. However, a centrality metric suitable for one application may not be suitable for another. This section determined which metrics were most suitable for the analysis of the opinion network in this study.

6.1.3.1 Global Status

Figure 6-5 showed the Tableau results of unweighted in-degree and out-degree centrality for all the countries in the network. Having a lot of countries talking about a single country, it implied that country held a higher global status. If a country made mentions to a lot of other countries, it would imply its influence. The Gephi statistics results showed that United States of America (USA), Great Britain(GBR) and China (CHN) had the highest in-degree of 90%, 73% and 70% respectively on a global scale. This showed the three countries' higher global status in the timeframe that was studied. Interestingly, the same countries held the highest out-degree as well.

The above assertion was challenged by the thought that not all countries are the same, some countries are more important than the others. If a country was projected by another important country, that would elevate its status. To this assertion, Figure 6-6 showed the Eigenvector centrality of the nodes and noted slight changes in the ranking. France was moved up to the third rank while Japan was dropped from the top ten. Although the impact is subtle but it showed that having good connections matters.

The 2016 Best Countries report and rankings [12] listed the top four most influential countries to be USA, United Kingdom, Germany and China. This corresponds closely to the assertions made in this section.

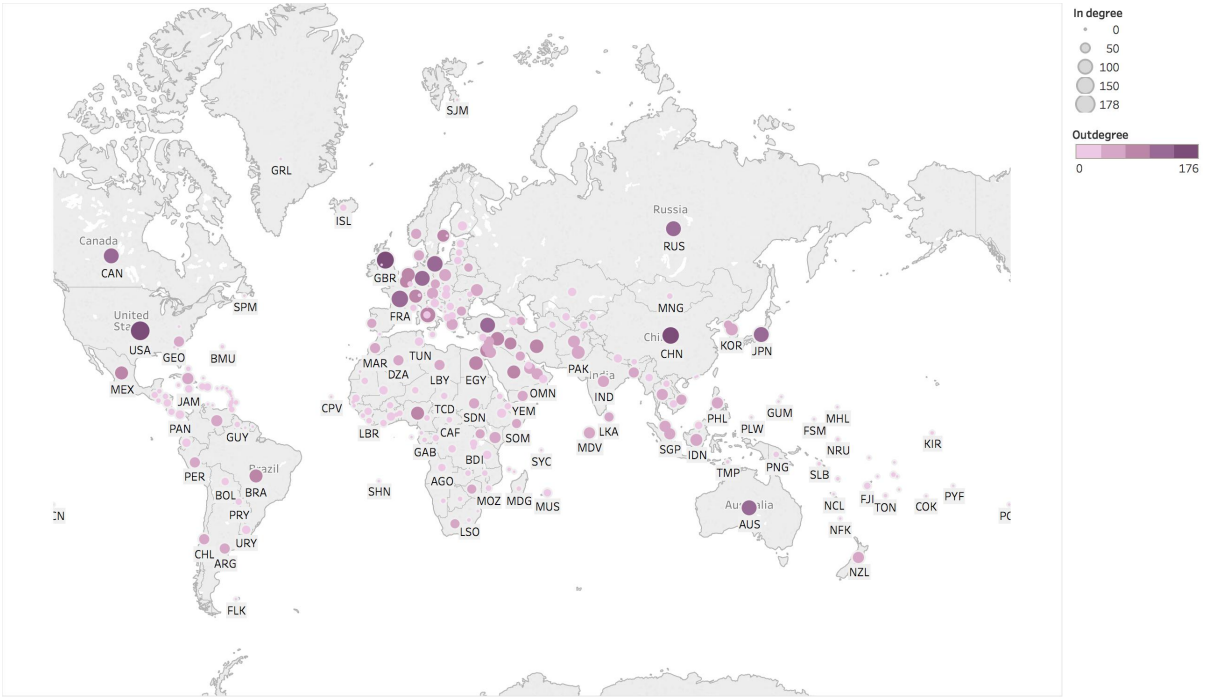


Figure 6-5 – Unweighted Degree Centrality of nodes

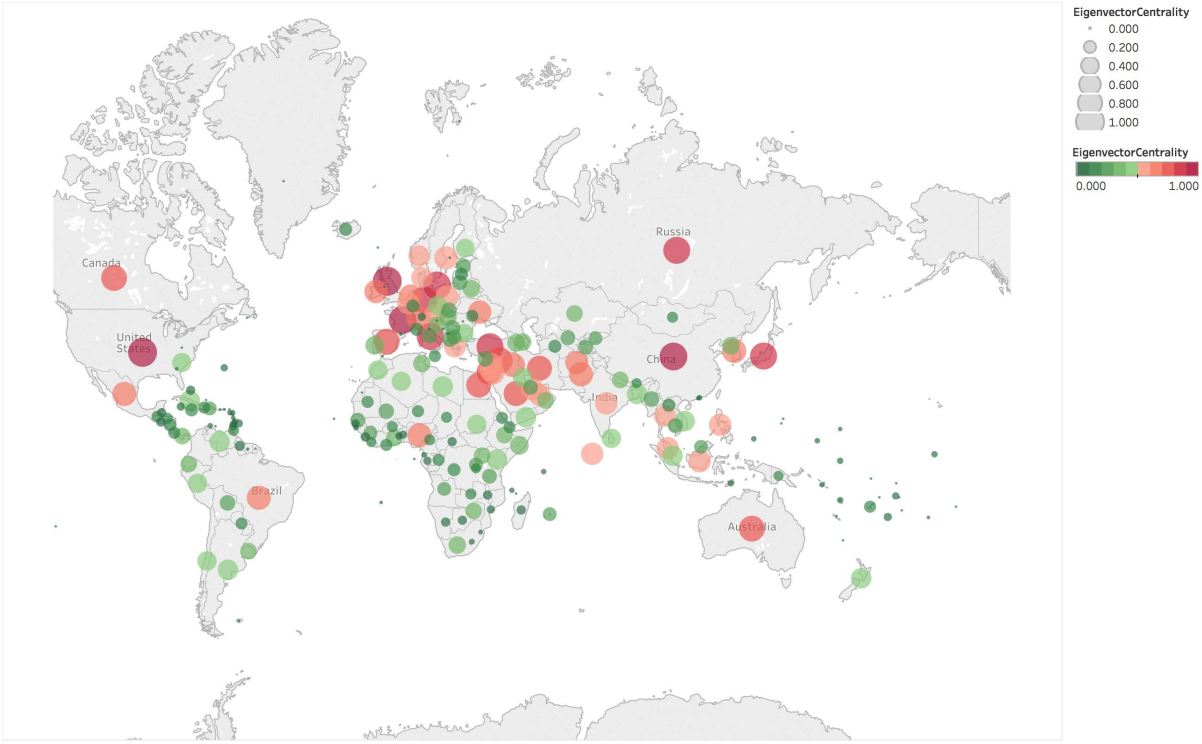


Figure 6-6 - Eigenvector centrality

6.1.3.2 Opinion reciprocal

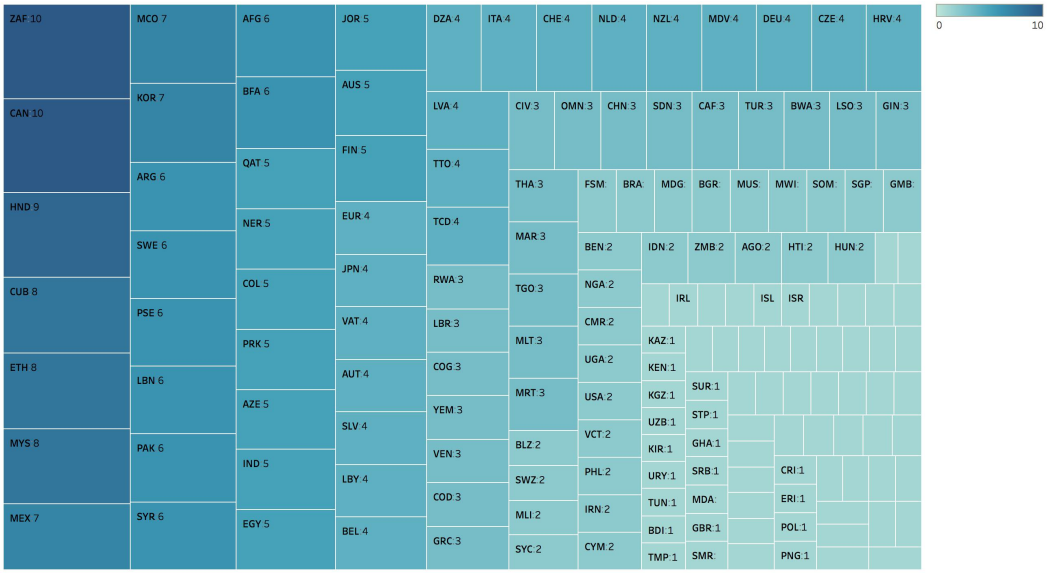


Figure 6-7 – Absolute differences of In-degree and Out-degree

Figure 6-7 created by Tableau showed that there was little difference between In-Degree and Out-Degree. To investigate, a python function was created to probe into nodes with more than thirty in and out degrees. It showed over 95% of them have up to 80% of their successor nodes sharing the same predecessor nodes and vice versa. This showed that if an opinion was projected at a country, there was a high likelihood that an opinion would be reciprocated.

6.1.3.3 Global Sentiments

Recall that the weight of the opinion network represented a tone on the opinion projected. A negative and positive tone represented a negative and positive sentiment respectively. Using Tableau, Figure 6-8 showed the Gephi computed weighted in-degree of each node. The results showed that Syria, USA, and Turkey had the most negative sentiments (Red dots) towards them in the timeframe studied, with USA scoring -306.99. A referral made back to the GDELT database for the articles that generated the negative sentiments for these countries in that period and most of them referred to the ongoing Syria war. China, Ghana and Japan had the most positive sentiments (Green dots) towards them with China ahead by double of that of its runner ups at +47.41. Interestingly, most of the negative sentiments were focused on Europe, Middle East and North Africa.

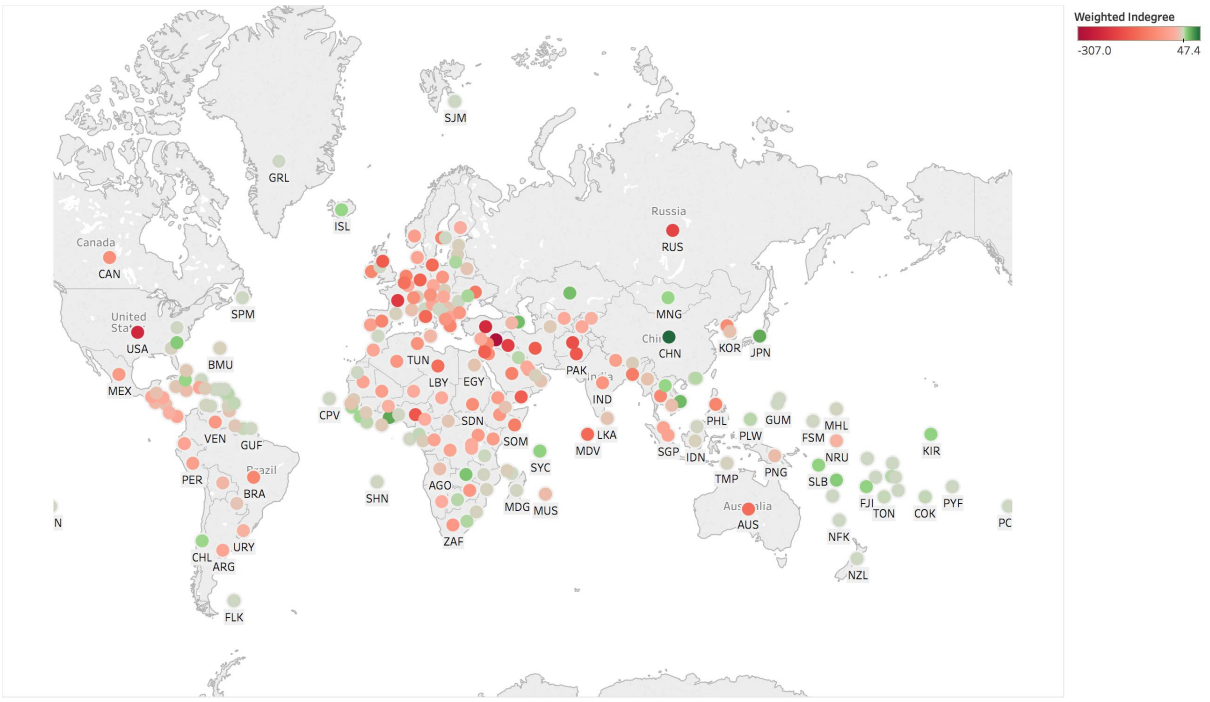


Figure 6-8 - Weighted In-Degree Centrality

6.1.3.4 Antagonist versus Endorser

it was possible to determine if the country was antagonising or endorsing in its projection of opinions by summing the sentiments projected towards other countries. Figure 6-9 showed the Gephi computed weighted out-degree of the nodes in the network. Syria, USA and Turkey topped the list of antagonists (Red dots) while China, Japan and Fiji was listed as top endorsers (Green dots) to which China was three times ahead of its runner ups.

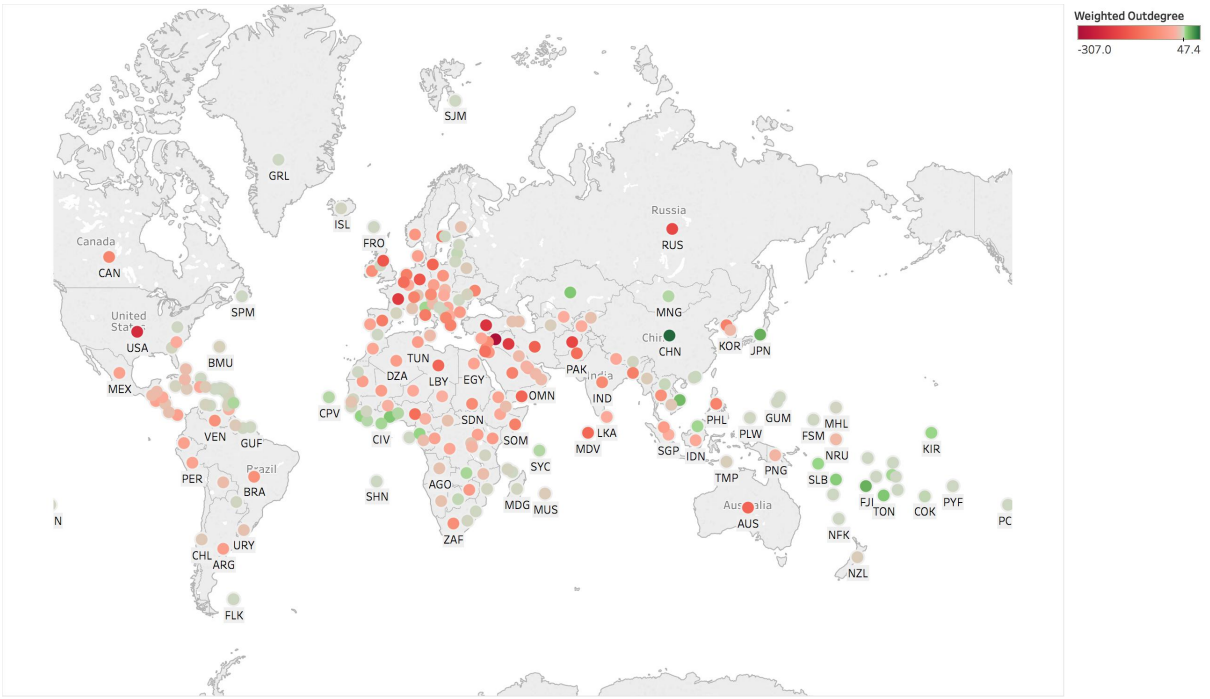


Figure 6-9 - Weighted Out-Degree Centrality

6.1.3.5 Between-ness and Closeness

Between-ness can be used to determine if a node is a conduit to reach another set of nodes. Figure 6-10 showed that the Gephi computed between-ness in all the nodes were relatively low, with USA topping at 0.13 despite having very high degrees. One explanation was that there was no advantage in projecting an opinion of a country via another country. An online news website could project its opinion to another country simply by posting the article and let it be viewed online.

Closeness was used to determine if a node can quickly spread information through a network. In the results, the closeness centrality was closely correlated to the strength of their degrees with a gentler rate of change. However, there were no useful insights that could be retrieved based on this metric.

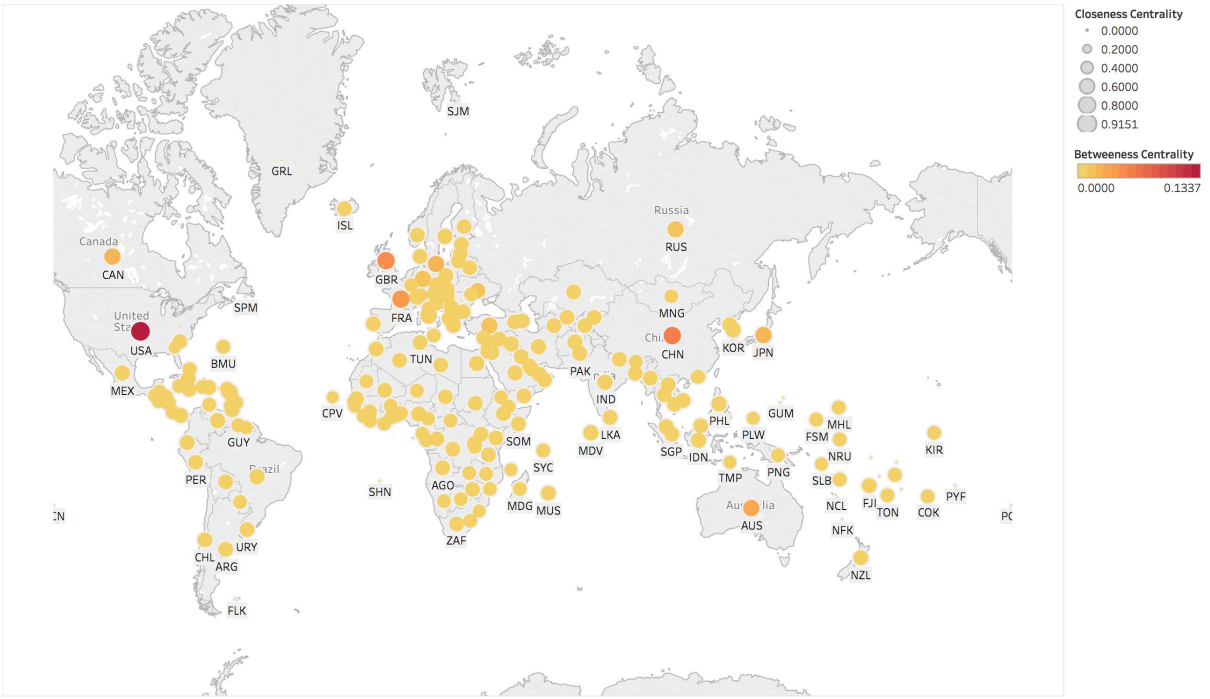


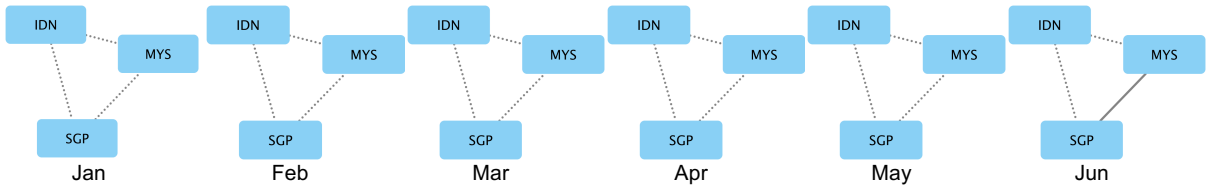
Figure 6-10 - Closeness and Between-ness Centrality of nodes

6.2 Structural Balance

Structural balance theory theorises that “Friend of my friend is my friend”, “Enemy of enemy is my friend”, “Enemy of friend is my enemy”. In the context of this study, it allowed a test of the balance of the countries over time. This section computed the results using NetworkX on a regional scale and reviewed below.

6.2.1 Suitability of dataset

Singapore, Malaysia and Indonesia were the main players and most closely situated countries in SEA. They had enjoyed a balance of ties over decades despite vast differences in geographical size, economy and demographics. As such, they were most suitable for testing the structural balance theory in this dataset. The original graph was partitioned as above and the weights of the dataset refined to only a sign, where -1 represented a negative tone and +1 represented a positive tone. The data was fed to Cytoscape for visualisation. Figure 6-11 depicted the structural development of the above three countries over a course of the first eleven months in 2016. The results defied the structural balance theory in that it hardly stabilises, were Doreian and Mrvar right?



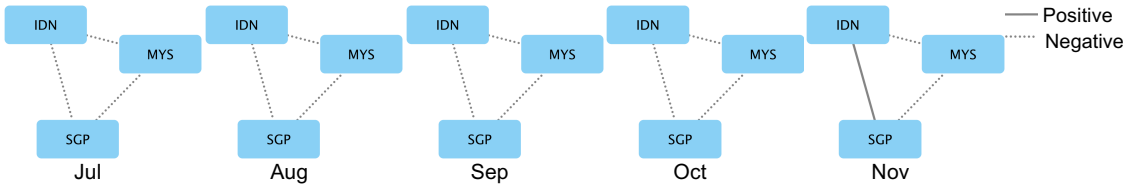


Figure 6-11 - SEA Structure development across 11 months (Tone)

This results could however be explained by two reasons. First, recall that the dataset consisted of unfiltered type of articles, thus there were significant noise when it comes to evaluating stability. Second, tone was an emotional measure which tends to go out of control in society [13] and thus not suitable for stability measures.

To test the above reasoning, a second subset of data from the same source using Goldstein scale [3] instead of tone and limited the articles to Actors with government roles. This dataset removed noise and unreliable weights for stability measures. The new results in Figure 6-12 showed that the three main players in SEA did strive to reach stability across time, albeit with bits of de-stabilisation in 2016. Those could be explained by alleged involvement of Malaysians in the Jakarta bombings in Jan 2016 and the regional air pollution created by Indonesia in Aug 2016.

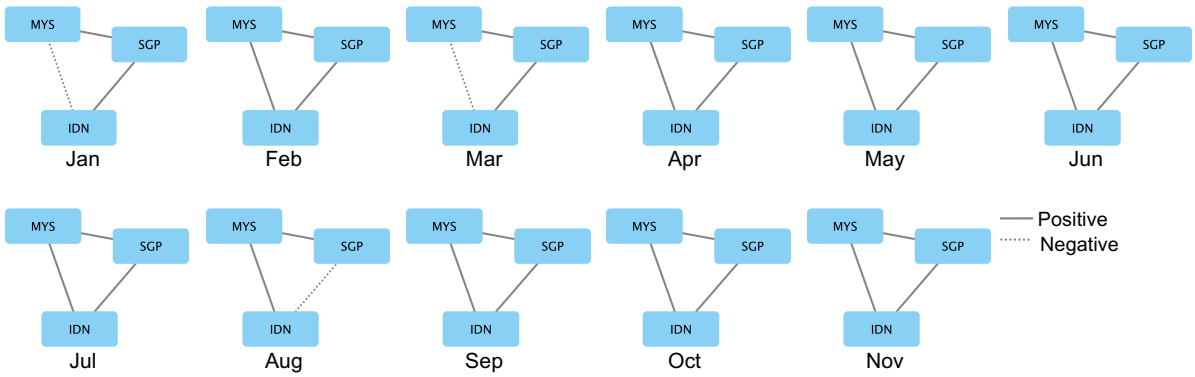
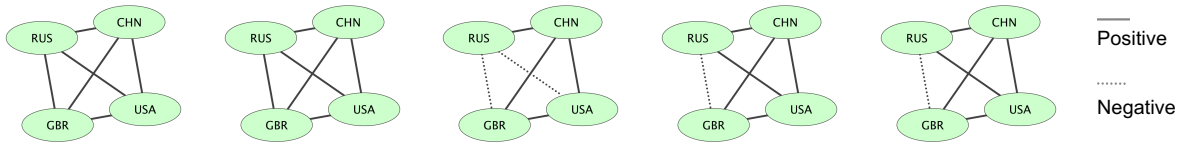


Figure 6-12 - SEA Structure across 11 months (Goldstein Scale and GOV roles)

6.2.2 Global top nations balance

The insight from section 6.2.1 was applied to discover the structural balance of the global top countries in the past five months. A graph is balanced if every set of three nodes within is balanced. The study determined the current state of balance in the global top countries, namely USA, GBR, CHN and Russia (RUS). Figure 6-13 showed the structural balance of the partitioned graph over the past five months. The results showed that the top powers were in a state of balance until events in Oct 2016 triggered a shift in balance. This was correlated to the Russian's friction with NATO[2] during that period. The figure also showed that the structural balance was in a state of shift.

[2] The North Atlantic Treaty Organization (NATO) is an intergovernmental military alliance based on the North Atlantic Treaty. The organization constitutes a system of collective defence whereby its member states agree to mutual defence in response to an attack by any external party. United Kingdom is one of the founding members.



Aug (Balanced) Sep (Balanced) Oct (Unbalanced) Nov (Unbalanced) Dec (Unbalanced)

Figure 6-13 - Global top powers structural balance Aug to Dec 2016

The results suggested that the partitioned network strived towards balance, however, the achieved balance was not permanent and subjected to shifts and potentially re-balance over time.

7 Discussion

7.1 Scientific approach

The GDELT events database contained translated natural language analysed articles accumulated over decades and thus was a unique form of dataset to approach. In this study, it was affirmed that a network analysis approach could be taken for the chosen subset of data retrieved from this non-conventional dataset.

In general, this study identified the global top nations of status and influence. It also identified the global perception of China as an endorser whilst the USA generally being an antagonist towards the world. The study also identified a shift in balance in the ties between the top global countries. Interestingly, the findings of opinion reciprocal could be a cheap alternative to elevate a relatively unknown country's exposure to the world for tourism purposes.

The study determined that the nature of the opinion network was not random, which means projected opinions were made with logic. The Degree centrality and Eigenvector centrality were successful in probing of the nature of each country. The influential countries on a global scale using centrality metrics and their current state of ties using structural analysis was identified. There was no significant advantage in reaching a country via another country on the opinion network (between-ness) and the close-ness centrality would not offer new insight to the opinion network. It was shown in this study that adopting shorter temporal windows would demonstrate structural balance theory but balance shifts should not be a surprise.

This study used International Relations to deliver the opinion network's plausibility in real-life applications but it could be extended to sophisticated questions outside of International Relations.

7.2 Lessons learnt

An unexpected set of results first came about while analysing the current state of ties using structural balance. Much thought and detailed analysis was put into understanding the results and an explanation was derived and tested. The experience taught was that there should not be too much judgement and assumptions made during a study, and irregularities of results should be investigated to uncover new insights.

As expected from real world data, there were significant noise to contend with during this study. Obvious erroneous data could be removed while other options include binning of data to suppress some of the noise. However, binning should be experimented with caution to avoid losing important information.

7.3 Limitations

7.3.1 Strength of dataset

In this study, the GDELT database provided very interesting datasets that could be analysed to produce plausible results. However, the strength of the datasets largely depended on the accuracy of the language translation and natural language processing backend used to generate the tone and Goldstein scale on the dataset. Tone, which was commonly aligned to sentiments can be an unreliable metric at times, this was shown in Section 6.2.1.

7.3.2 Structural balance on a larger scale

This study corrected the validity of parameters used for testing against structural balance using a known three nation ties. It further tested the theory against the top global nations identified in the study. To test on a global set, it would require an NP-Hard task to determine all cycles in large signed network to compute structural balance for a large network.

7.3.3 Multi-dimensional approach

Changes in world events could affect the outcome of this study and these changes could also be studied from other dimensions, such as psychology, traditional international relations and even modern history. Thus, the results from this study worked best as a complement to other studies in international opinion or relations.

7.4 Future work

7.4.1 Communities and coalitions

Upon completing the main objectives of this study, an attempt was made in analysing the communities of the global network. The objective was to analyse similarities between communities generated by modularity, and the coalitions generated by structural balance analysis. The results could be used to address the large scale structural balance limitation detailed in section 7.3.2.

7.4.2 Temporal and Spatial network analysis

This study focused on foundation metrics of network analysis and did not explore in detail on the temporal and spatial analysis aspects that was readily available in the dataset. The temporal and spatial element was only utilised for analysing changes in the metric of the network analysis and visualisation respectively. The positive outcome of this study provided a basis for a detailed study in the temporal and spatial aspects of the network analysis in the topic.

8 Reference

[1] M. H.-B. Emilie , K. Miles and A. H. Montgomery , “Network Analysis for International Relations,” *International Organization,* vol. 63, no. 3, pp. 559-592, 2009.

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