
Temporal Analysis of International Relations Networks

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1 Introduction

Systems of formal alliances and wars between countries are central topics in international relations, and have influenced the lives of billions in the last few centuries. However, this field has largely been the domain of traditional historians, and very little quantitative analysis has been applied towards understanding international politics. In this project, we will use data on formal alliances and international wars provided by the Correlates of War project, which aggregates data on countries and international affairs over a period of two centuries, since 1816.

In this project, we will explore structural properties of the alliance, war, and sentiment graphs, including the roles of individual nodes, structural motifs, and graph-level communities. In contrast to most previous work, we will also explicitly analyze changes to the graphs over time.

2 Related Work

The paper *Networks of Military Alliances, Wars, and International Trade* [5] performs a similar analysis between alliances and war by investigating “the role of networks of alliances in preventing multilateral interstate wars.” It finds relevant statistics and reaches some important conclusions. For example, they notice the dramatic drop in interstate wars since 1950, and the densification and stabilization of alliances. They also conclude that increased trade between countries decreases chance of war and that countries of high levels of trade with their allies are less likely to be involved in wars with any other countries. They do so by using a logistic regression of the probability that two countries are at war with each other in a given year as a function of the level of trade between the two counties. They also analyze cliques in the graph, showing for example that multilateral wars never involved cliques.

Another paper named *Artificial Intelligence for Conflict Management* [3] employs machine learning algorithms for predicting the presence or absence of conflict edges between war nodes. The prediction task uses seven dyadic (between two countries) variables. These include, Allies, Border Contiguity, Distance, Major power, Industrial Capability Ratio, Democracy Level, and Trade. The authors achieved a prediction AUC of 0.84 for the SVM and 0.81 for the NN. They also conducted experiments to determine the relative importance of each variable for the prediction task. The first experiment consisted of setting all variables to their minimum value while setting a single one to its maximum value, and vice versa. In this case, only democracy level and capability ratio are able to produce a peaceful outcome for the majority of cases. The second experiment holds all variables constant while setting the final variable to its max or min value. This experiment shows that maximizing the democracy level avoids conflict entirely, and maximizing the capability ratio reduces conflict by 98%.

To analyze the relationships between countries, we incorporate Balance Theory [1], a seminal social psychological framework designed to interpret relationships between individuals. Its basic tenets

posit that in a triad of individuals (or countries) that each have a positive or negative opinion of each other, the triad will naturally tend towards a balanced equilibrium. Figure 1 shows the triads that are considered balanced and unbalanced. The top left is unbalanced because it is difficult for the third node to maintain a positive relationship with its neighbors when they are in a dispute. In the top right, two nodes have an incentive to settle their dispute and gang up on the third node. The bottom right is balanced because it illustrates the adage, "the enemy of my enemy is my friend."

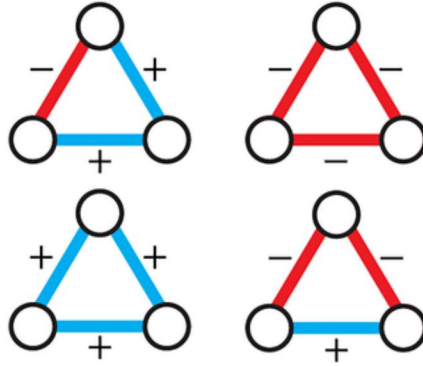


Figure 1: Balanced (top) and unbalanced (bottom) triads.

3 Data

3.1 Description of the Data

We draw our data from the Correlates of War project. The alliances and wars data can be structured as distinct graphs where a node corresponds to a country. Alliances are represented by an undirected graph, where nodes i and j have an edge if countries i and j have an alliance. In contrast, wars are represented by a directed graph, where an edge (i, j) exists if country i declared war on country j .

An additional complexity is present because the state of the world's alliances and wars change over time. Thus, we can maintain a distinct graph for each year. For the wars dataset, the graph at year t contains only edges corresponding to wars that occurred in year t . Similarly, an edge in an alliance graph for the year t is only present when the corresponding countries had an alliance in that year. (As an additional note, due to the relative sparsity of wars over time, we aggregate multiple distinct years into graphs containing wars that happened over a period of multiple decades.)

For the final portion of the paper, we also examine a "relation" graph, an undirected graph where each edge has either a positive sign if its two endpoint country nodes have a positive relationship, and a negative sign if the endpoint countries have a negative relationship. This is constructed by interpreting a formal alliance between two nations as indicating a positive relationship. Drawing on another Correlates of War dataset, we use disputes between two countries to indicate a negative relationship. Disputes may include anything from a declaration of war to a hollow territorial threat.

3.2 Preliminary Analysis

For the following section, refer to Figure 2. In the alliances graphs, when we plot year by year network average clustering coefficients we observe that this coefficient has been increasing over recent years. Also a plot in the following figures on the total number of edges to nodes ratios for alliances lets us conclude that on recent years the trend has been for this ratio to increase possibly indicating more formation of alliances per node.

A similar analysis on the wars network allows us to observe a maximum of clustering coefficient and edges to nodes ratio around the years between 1900-1925 right around the time when World War I happened.

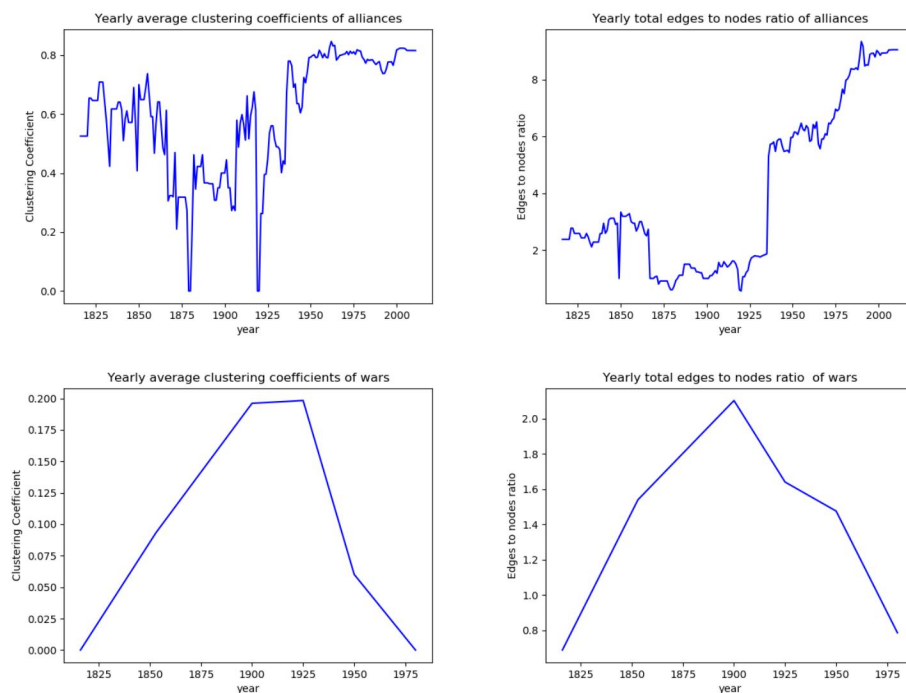


Figure 2: Plots illustrating basic properties of the graphs over time.

4 Methods

4.1 Motif Detection

To identify motifs in a network we employed the Exact Subgraph Enumeration (ESU) algorithm from Figure 3. For the alliances network, we computed the number of occurrences of undirected motifs of size three and four. Whereas for the wars network we calculated it for all directed motifs of size three. Figures 4a, 4b, and 4c show these, respectively. Note that for the directed case, bidirectional arrows are shown as undirected.

Figure 3: ESU Algorithm

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Algorithm: ENUMERATESUBGRAPHS( $G, k$ ) (ESU)
Input: A graph  $G = (V, E)$  and an integer  $1 \leq k \leq |V|$ .
Output: All size- $k$  subgraphs in  $G$ .

01 for each vertex  $v \in V$  do
02    $V_{Extension} \leftarrow \{u \in N(\{v\}) : u > v\}$ 
03   call EXTENDSUBGRAPH( $\{v\}, V_{Extension}, v$ )
04 return

EXTENDSUBGRAPH( $V_{Subgraph}, V_{Extension}, v$ )
E1 if  $|V_{Subgraph}| = k$  then output  $G[V_{Subgraph}]$  and return
E2 while  $V_{Extension} \neq \emptyset$  do
E3   Remove an arbitrarily chosen vertex  $w$  from  $V_{Extension}$ 
E4    $V'_{Extension} \leftarrow V_{Extension} \cup \{u \in N_{excl}(w, V_{Subgraph}) : u > v\}$ 
E5   call EXTENDSUBGRAPH( $V_{Subgraph} \cup \{w\}, V'_{Extension}, v$ )
E6 return

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At its core our implementation of the ESU algorithm counts the number of these motifs in the respective graph (directed or undirected).

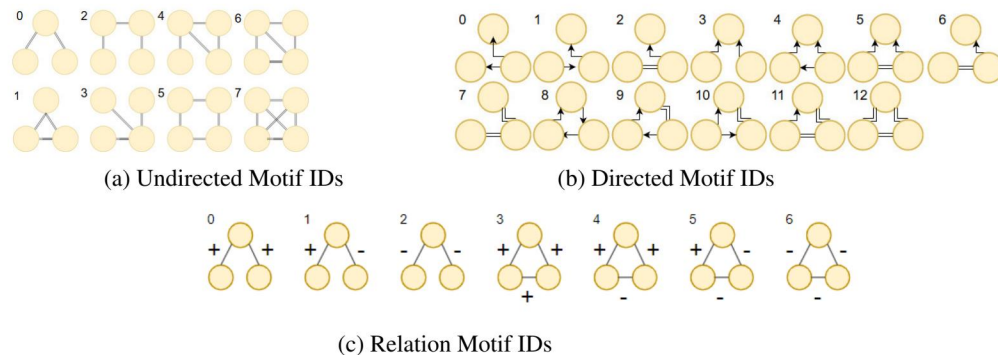


Figure 4: Motif IDs

4.2 Relation Graph Null Model

The following setup is used to build a null model for the relation graphs. The null model retains the exact same nodes and edges as the empirical graphs. The creation of the null model only involves changing the edge signs. This gives us a better idea of how the graphs evolve when countries have random sentiments towards one another. Our initial naive implementation randomly set each edge to positive or negative with equal probability. However, this reference is too distorted and unrealistic. Instead, from the empirical graphs, we can find the number of positive edges changed to negative and vice versa. Then, at each timestep, we randomly select the same number of positive edges to change to negative (and vice versa).

4.3 Community Detection

For running temporal community detection, we run different algorithms on the relations graphs, which are the graphs with + and - edges between countries.

4.3.1 Community detection with Spectral Clustering

For spectral clustering, we try different approaches. First, we try running recursive spectral clustering using the approach from Hagen et al. [4]. We also try running k-way spectral clustering [7], basing our k on the largest eigengap. We try the first approach using the signed Laplacian (negative edges have positive entries) and the regular Laplacian (all edges have negative entries), since there are arguments for both approaches [2] [6].

4.3.2 Community detection with the Louvain algorithm

The Louvain algorithm is a procedure for community detection that works for weighted graphs. It works by greedily maximizing the modularity. On each step of the algorithm, modularity is optimized by allowing local changes of communities and aggregating identified communities to build a new network.

For the relations graph, instead of weights, there are labels of whether the relationship is a friendly one or a hostile one. For this, the algorithm is tweaked to maximize modularity minus the number of negative edges maintained in each single community. This is implemented by keeping track of the negative edges in a community. More specifically, local node removals make the community the node was part of incur a cost the size of the number of negative edges the node had inside the community.

5 Results

5.1 Role Analysis

We use a feature extraction algorithm to collect vectors for nodes in each graph, where the vectors contain information about the nodes and the local substructure of the graph. These feature vectors can then be compared to a reference vector to determine trends in the node’s role over time.

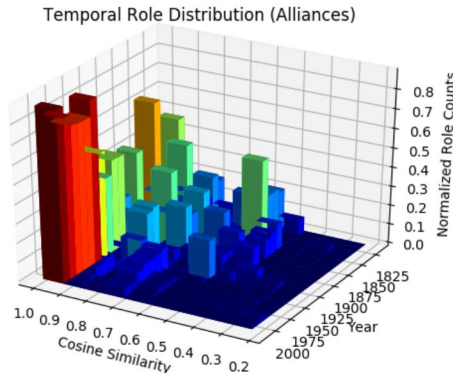
We also note that we attempted to use Principal Components Analysis (PCA) to reduce the dimensionality of the features for each country for easier visualization without resorting to the use of a ”reference country” against which to compare the feature vectors. However, the generated plots lacked any clear interpretation, and we opted to exclude them from this paper.

5.1.1 Roles in the Alliances Network

We begin with a set of features $F_t = \{V_{i,t} | i \in Nodes(G_t)\}$, where each $V_{i,t}$ is a feature vector for country i in the alliance graph corresponding to the t -th year. We can then pick some node j to serve as a baseline and compute the cosine similarity between $V_{j,t}$ and every other vector in F_t . This process is repeated for every year in the range 1816 to 2012. In particular, note that the cosine similarity for each node is computed only against the baseline node in the same year; in other words, the features of the baseline node will evolve over time.

For this analysis, we use the United Kingdom as a baseline because of its role as an important world power in the last two centuries and due to the fact that it has had an alliance with at least one other country in every year since 1816.

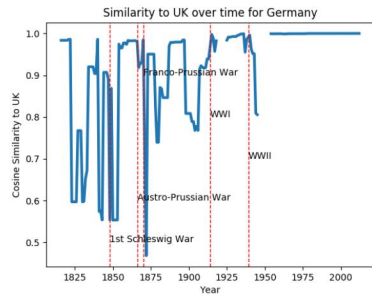
Figure 5: Distribution of roles in the alliance network over time, as measured by cosine similarity of each node’s features to those of the UK.



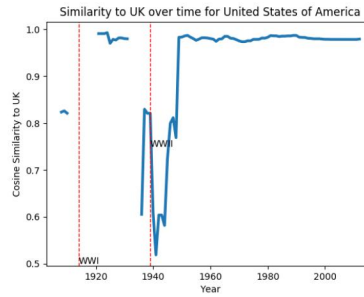
Our results for the distribution of roles in the alliances network over time is displayed in Figure 5. Observe that the horizontal axis displays the cosine similarity and the vertical axis displays the year. The z-axis displays normalized counts.

From the chart we can observe that after the Second World War, nations have largely converged towards playing the same role - that of having a large number of alliances with almost every other country. This represents a paradigm shift in international relations, since previously, we can see that roles in the alliances network were much less clustered.

Figures 6a and 6b narrow down on the role of individual nations in the alliances graph. The figures also mark the years in which major wars for the respective countries occurred. For example, we can see that for both the US and Germany, the start of a major war was often accompanied by a significant drop in similarity, as alliances were suddenly reshuffled. Interestingly, however, even when nations fight on opposite sides in wars, such as Germany and the UK in WWI, the underlying structure of their alliances may remain the same.



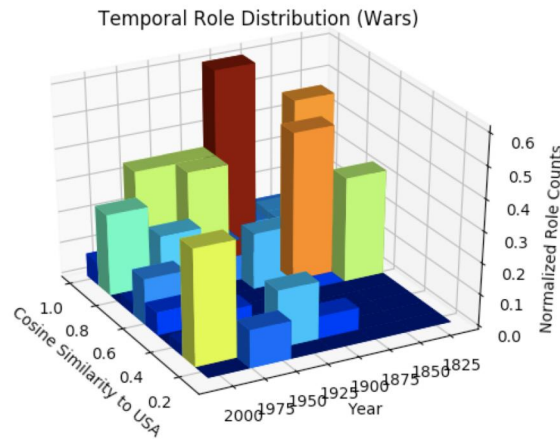
(a) A plot of the cosine similarity of Germany's features to those of the UK over time. (Note that Germany is considered to be equivalent to Prussia, the North German Federation, and West Germany in the appropriate time frames.)



(b) A plot of the cosine similarity of the USA's features to those of the UK over time.

Figure 6: Roles for individual countries over time. Gaps in the lines denote years for which the countries had no formal alliances with other countries.

Figure 7: Distribution of roles in the wars network over time, as measured by cosine similarity of each node's features to those of the USA.



5.1.2 Roles in the Wars Network

We now apply a similar analysis to the wars networks over time. For our comparison node, we have instead selected the United States, as the UK does not appear in every graph over time. In Figure 15, it is apparent that the prevalence of different types of roles in the wars network follows a pattern opposite to what we saw for alliances over time - we observe that roles were more similar in the past but in the present day have become more widely distributed.

A qualitative examination of the graph structures shows that we can attribute this to a change in the nature of wars. In the early 19th century, most wars were local and only involved two participants. In the modern era, however, we observe a mixture of strictly bilateral wars (e.g. Soviet invasion of Afghanistan) and multiparty "world" wars involving many participants (e.g. the Gulf War).

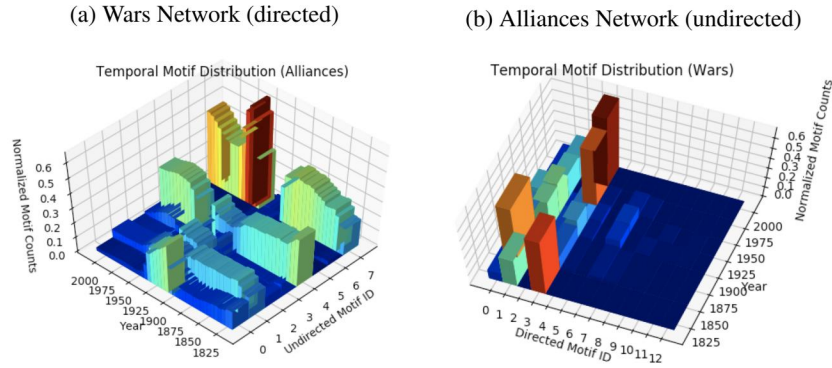


Figure 8: Distribution of motifs over time

5.2 Motif Analysis

5.2.1 Motifs in the Alliances Network

For the alliances network, the results of running ESU can be visualized in Figure 8a, which displays normalized histograms of motif counts over time.

First, we can see that there are a negligible number of occurrences of motifs with ID five and six (see Figure 4a for ID references). This makes sense and follows the structural balance theory, which suggests that four nodes should either form a clique or one should separate. This brings us to ID 7, which is the 4-clique. This is the most common motif over time in general, except for years between the two World Wars, where we see a large shift from ID 7 to ID 0, which is a simply three nodes forming a line. This shows that many strong alliances were lost after WWI. But then, right after WWII we see a huge uptick again in ID 7, which means that many strong alliances were formed and have been stable ever since.

5.2.2 Motifs in the Wars Network

For the wars network we ran a similar analysis. Note that in this case, the graph is directed, so we instead compute the motif occurrences for directed subgraphs of size three (see 4b). Also, recall that since the war graphs, we have only six graphs for that represent longer periods of time. For example, the bars bottom represent the motif counts for between years 1816 and 1853.

The results for this network are intuitive. We encounter a negligible amount of bidirectional edge, which indicates that countries do not often counterattack after a war finishes.

A very common motif in recent years is motif number 3, which represents two countries "ganging up" on another. Prior to 1950 we actually encounter more of motifs 1, which is when a country declares war on another country, and that target country declared war on a third country. Note that these wars may have happened at different times. Finally, we see a unusually high number of occurrences of motif 1 in the period between 1900 and 1953. This motif represents a country attacking two other countries, which in a sense describes a time in which countries were trying to assert domination.

5.2.3 Motifs and Balance in the Relation Graph

We now explore a similar analysis of motifs in the relation networks. The graph is undirected, but edges have signs, so there are seven isomorphic subgraphs of size 3 (see 4c). However, four of these motifs have a convenient interpretation inspired by balance theory. Note that for this section, we will neglect to consider motifs in which only two out of three edges are present, since these triads do not have a clear balance theory interpretation.

We first note the proportion of balanced triads over time in the empirical graphs and null model graphs in Figure 9. At first glance, without the null model, we believed the surge of imbalance from around 1870-1945 was due to rising tension that culminated in the world wars, but consideration of

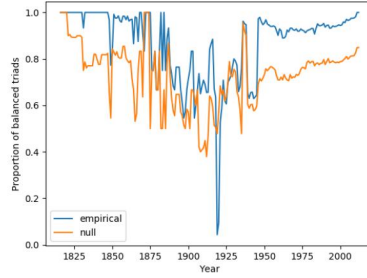


Figure 9: Proportion of balanced triads in the empirical and null graphs over time.

the null model shows this is not the case. We do however observe a sudden spike in the proportion of imbalanced triads precisely in 1914, the beginning of World War I. In general, the empirical graphs display a much higher level of balance before 1870 and after 1945. In particular, many previously unbalanced relationships suddenly became balanced after the second world war.

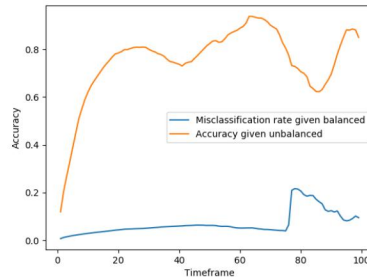


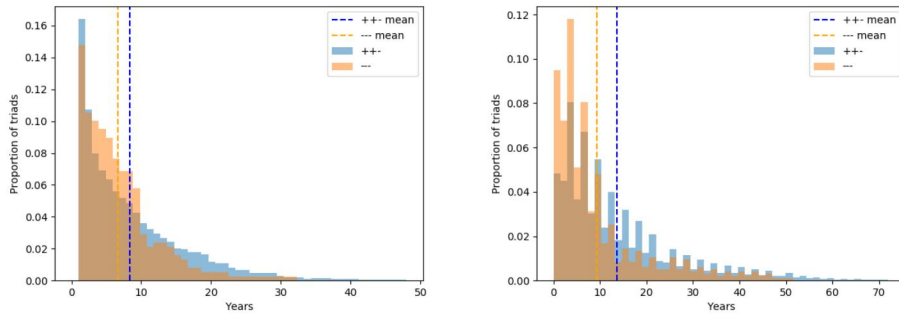
Figure 10: Given a timeframe, x , if we predict that all triads will become balanced after x years elapse, this graph displays the accuracy rate for initially unbalanced triads and the misclassification rate for initially balanced triads.

The graph in Figure 10 considers the question: given a timeframe, x , if we predict that all triads will become balanced after x years elapse, what proportion of initially unbalanced triads become balanced and what proportion of initially balanced triads are no longer balanced? We aim to maximize the former and minimize the latter. We see that the misclassification rate is always low, but this is only because most triads are always "+++". Interestingly, we observe that depending on the timeframe, the likelihood of an unbalanced triad to become resolved follows a cycle. We can interpret this as evidence of cycles in foreign relations - periodic events cause disruptions to established alliance and antagonism relationships which force countries to reshuffle their relationships, which causes imbalance for periods of time.

Additionally, we ask a question: given that an unbalanced triad eventually becomes balanced, what is the distribution of the lengths of time this change requires? Figures 11a and 11 show the normalized distributions for the empirical and null model graphs. We observe a roughly exponential distribution where the mean resolution length under the null model is about 5 years longer than the empirical resolution length, suggesting that triads do tend towards balance to some degree. Note that the histograms are colored by the class of the initial unbalanced triad (either "++-" or "--"). Interestingly, under the empirical graphs, we also observe the greater concentration of mass on the histogram corresponding to "--" in shorter time periods, which indicates that countries more strongly disprefer relationships in which all three countries are hostile.

5.3 Communities

We find that the Louvain algorithm gives better communities than our implementations for Spectral Clustering. When we used the regular Laplacian, the recursive failed to discover relevant communi-



(a) A normalized histogram of the length of time that triads take to become balanced, given that they are initially unbalanced. (b) A normalized histogram under the null model that triads take to become balanced, given that they are initially unbalanced.

Figure 11: Resolution time histograms. The histograms are separated by the type of the initial unbalanced triad (either ++ or —).

ties. It worked better with the signed Laplacian, but it was able to find more than two communities in just eight of the graphs (out of 196) since the Laplacian of the communities did not have a matrix inverse. K-way clustering did work well on all graphs, but after manual inspection we found that the Lovain approach gave better results. We recommend exploring k-way clustering on the signed laplacian for future work, noting that standard implementations do not work for this case. Please see the Appendix for the Spectral Clustering results.

The figures below compare the results of running the classic Louvain without taking sign of conflict into account on 12 and the results for the implementation taking relationship type into account on 13.

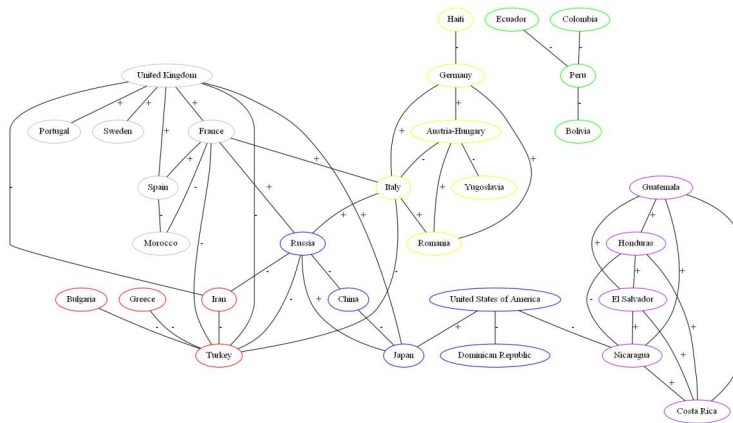


Figure 12: Communities for normal Louvain for year 1910

6 Conclusion

In this paper we have seen that we can frame the study of international relations over time as an analysis of network evolution for alliance, war, and relation graphs. By applying motif, community, and feature detection algorithms we observe many results that confirm our intuition about how countries interact and provide data-driven support for our historical preconceptions. Our other important contribution has been to examine the evolution of these relationships over a period of nearly 200 years.

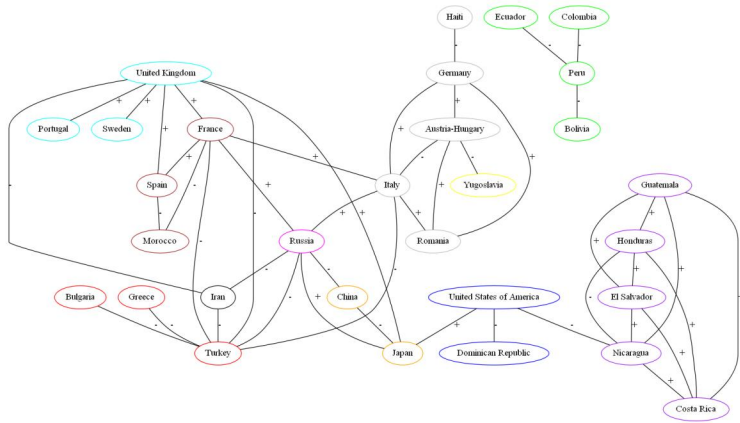


Figure 13: Communities for Louvain taking relationship type into account for year 1910

7 Future Work

For some years, there is not enough data with respect to the type of relationships that countries may have. For example there might not be an edge between two countries marking whether they are enemies or allies because their actual relationship is something in between. In real life politics are more complicated than just a division between friends or enemies. As such future work consists of improving the available dataset to be able to extract more fine-grained information about the relationships between countries. Moreover, another issue with respect to temporal comparisons is what to do with countries that go out of existence and form new ones, should they inherit relationships similar to the ones of its predecessors or completely different ones if it is a conquered nation. Furthermore, thus far we have ignored the individual properties of each country like size and geography which clearly play a role in political negotiations. In short much remains to be done because in real life when it comes to relationships, “its complicated.”

8 Notes

Our code, data, and graphs can be found at github.com/lfvarela/nation-networks.

References

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9 Appendix

Figure 14: k-way Spectral Clustering (1916): Does not incorporate edge signs (standard implementations fails with signed Laplacian)

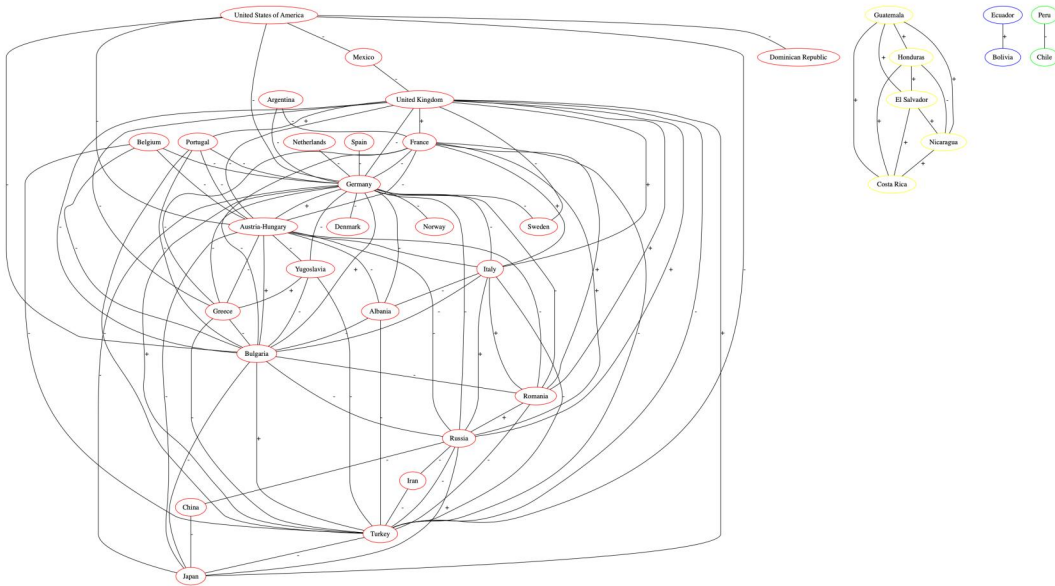


Figure 15: Recursive Spectral Clustering (1916): Communities make little sense

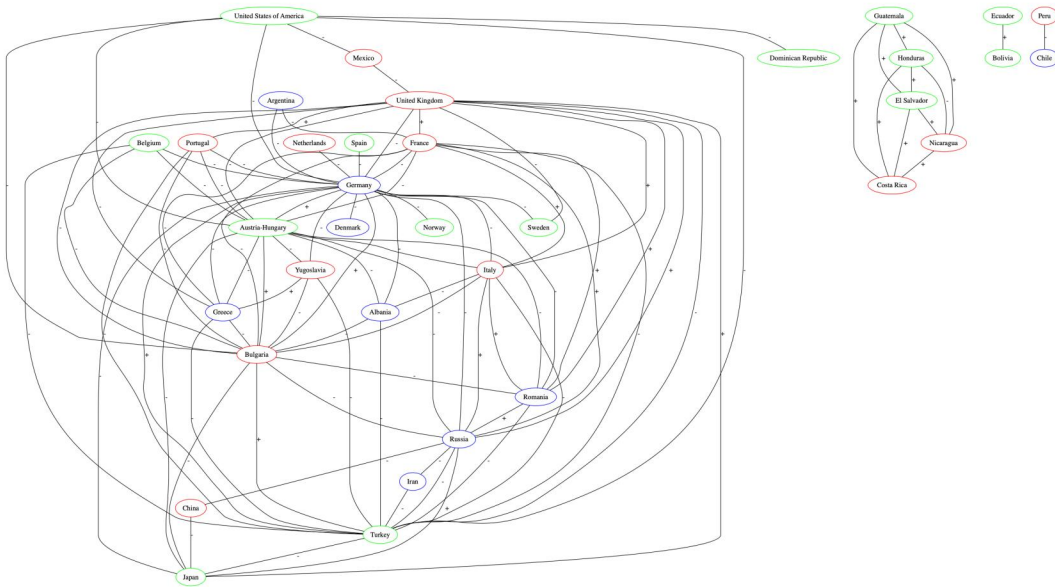


Figure 16: Communities for Louvain taking relationship type into account for year 1916

