# Predicting Changes in Global Military Alliances Using Social Balance Theory

https://github.com/hziegel/Alliances
Heron Ziegel
Temple University
hziegel@gmail.com

## Abstract

**Objective**: During times of major global conflict such as world wars, changes in alliances between countries can appear to be random. The purpose of this study was to look for patterns in these changes in order to determine whether they can be predicted and at what times it is possible to make these predictions.

**Methods**: A Python script was written to visualize major powers within historical global conflicts as nodes on an undirected signed graph. A partitioning algorithm was used to show what each graph would look like as it trended toward balance. Data from the Correlates of War project between 1946 and 1999 was used to train a Long Short-Term Memory (LSTM) deep learning model on the trend of balance and imbalance over time. The model was then used to forecast future balance trends and compared to a more current dataset.

**Results**: First the LSTM model was trained on time series data from 1946-1999. The Root Mean Squared Error (RMSE) of the LSTM model after 2000 epochs was 10.48. The mean of the data was 55.88. The Mean Absolute Percentage Error (MAPE) of the testing data was 25.72%. The trained model was then applied to the past 10 year timeline data which I created and used to forecast 3 steps into the future. The RMSE was 10.82. The MAPE was 13.67%. The mean of the data was 85.58.

**Conclusions**: The partitioning algorithm cannot be applied to current data in order to predict and visualize a more balanced network over the next several years. This is because, based on the LSTM predictions, the current network is trending toward further imbalance. Furthermore, more robust data is needed. The most valuable discovery was that a LSTM model can be used to analyze and predict trends in balance among global military alliances over time. We may think of global conflicts and alliances as random, or as the result of individual decisions by the leaders of nations. But what this project has indicated is that periods of global instability are cyclical, and that cycle can be analyzed and understood using machine learning.

# Introduction

Understanding changes in military alliances between countries is a complex topic which has often puzzled researchers. As noted by Doriean and Mrvar, many methods have been proposed to understand why countries change alliances with conflicting or poor results. For example, countries which share a border are more likely to have border disputes leading to conflict. However, these countries are also more likely to share cultural values which could influence their decision to join forces against foreign powers. Furthermore, many such methods rely on the notion that political leaders make decisions based on the rational interests of their countries, which is not always the case. Rather than trying to view this problem through the lens of the numerous potential variables from religion to historical disputes to economic ties, they suggested using a more high level approach (Doriean and Mrvar 2015).

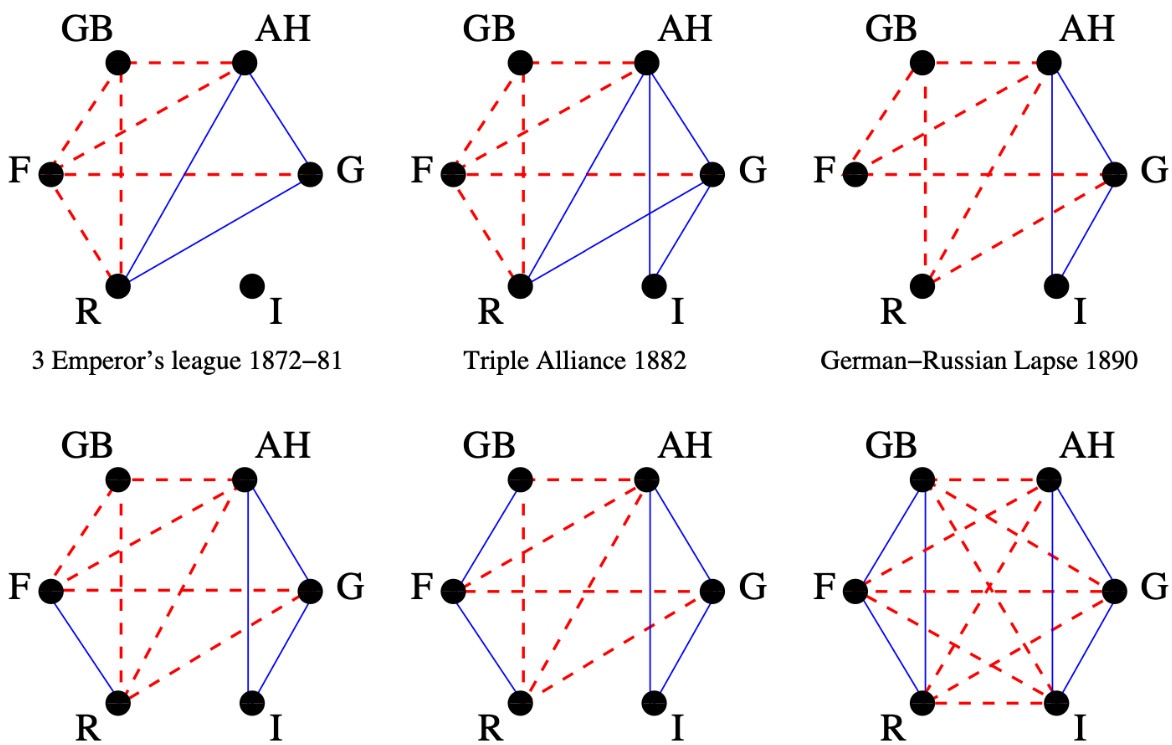
In 1946 psychologist Fritz Heider proposed a theory as to why human relationships change over time which he called “balance theory.” He conceptualized groups of three people, called triads, striving toward social balance. If all three people were friends, the triad was considered balanced. However, if two people became enemies, this created an imbalanced triad which could be balanced again if the third person chose to become enemies with one of the other two. Furthermore, a triad in which all three people are enemies is imbalanced and will likely result in two of the three people becoming friends. In short, the enemy of my enemy is my friend (Caffrey 2023).

In 1953, Cartwright and Harary generalized Heider’s theory to apply to other types of networks using graph theory. They visualized the “people” as nodes on an undirected signed graph with the positive edges representing allies and the negative edges representing enemies. This was then applied to international military alliances by Antal, T., Krapivsky, P. L., and Redner, S in their 2006 paper, using the example of data from World War 1.

Much of my research focused on the work of Antal et al. as well as Doriean and Mrvar. However, they only attempted to use Heider’s balance theory to explain in retrospect the changes over time in network balance. I wanted to determine whether their findings in combination with modern computer programming techniques such as machine learning could be used to predict these changes in the future.

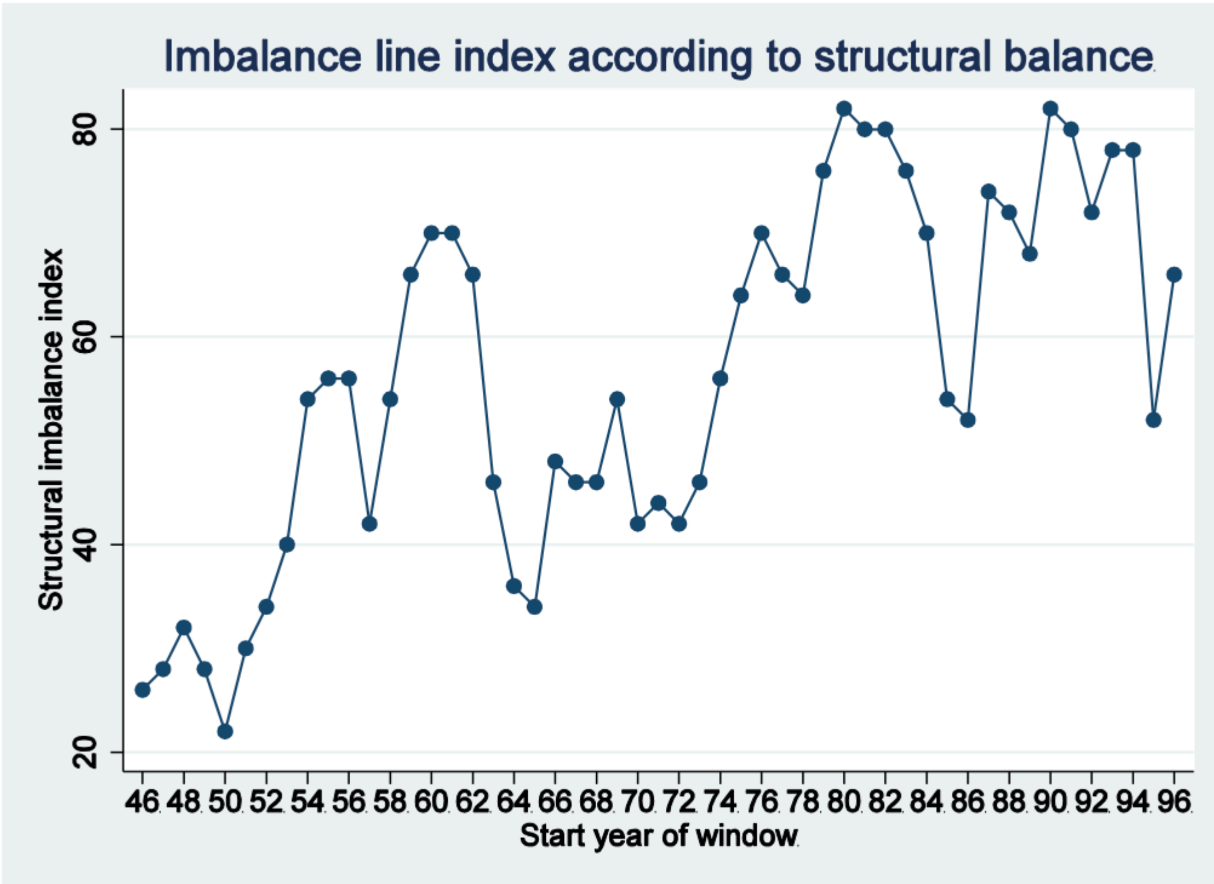
# Related Work

Antal et al. created the visualization below to explain how balance theory relates to the changes in military alliances between major powers during World War 1. The changes between the three networks in the top row don't strongly trend toward balance. How could we predict that Italy would join the war, or that Russia would break from a balanced triad and go to war with its two allies? But after 1890 the network does trend toward balance, resulting in an even partition of two sides - the Central Powers and the Allied Powers. This suggests that there may be a specific window of time during which international alliances trend toward balance.




3 Emperor's league 1872–81 | Triple Alliance 1882 | German–Russian Lapse 1890

This concept was further explored by Doreen and Mrvar in 2015. They used the Correlates of War dataset of international military alliances (Gibler) to generate what they called the "structural imbalance index" of the network of all international relations between the years 1946 and 1999. This index is a simple proportion of the number of imbalanced triads over the total number of possible triads in the network. They created the below line graph of the structural imbalance over time:

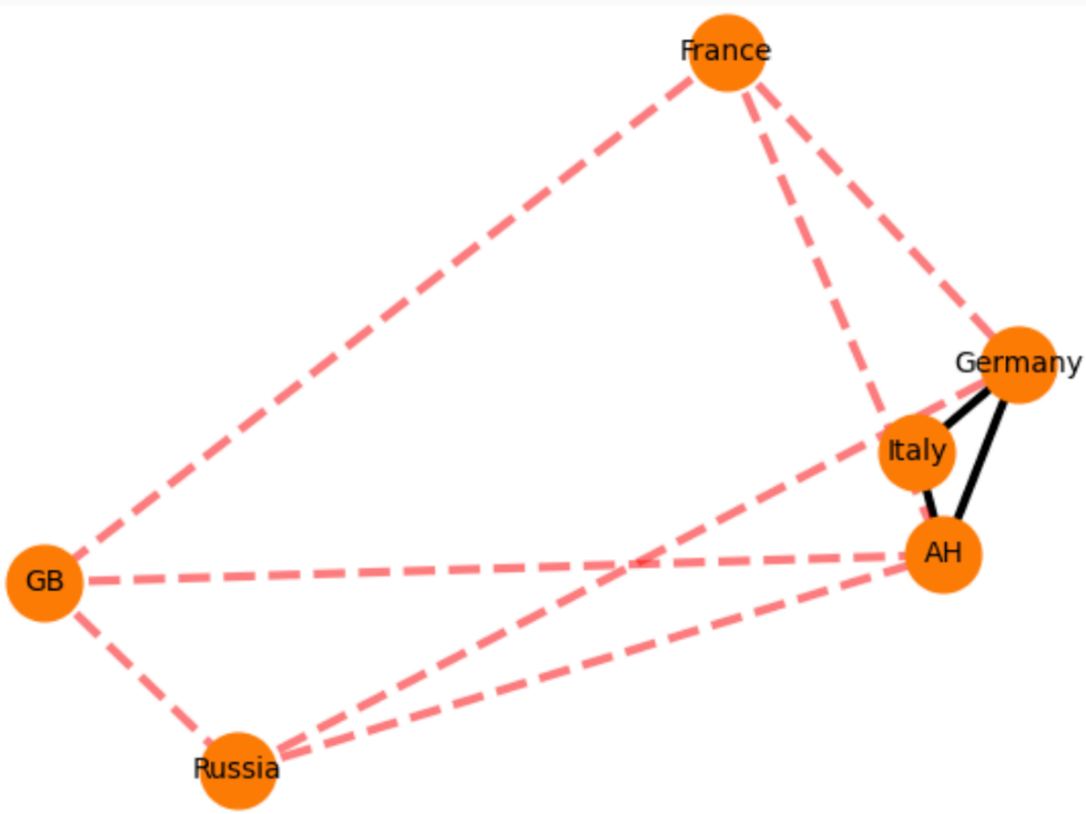



The graph is non-linear and not quite sinusoidal. However, intuitively it does seem to show a trend over time. Using a deep learning method called a Long Short-Term Memory model, it is possible to make predictions on this trend which are more accurate than traditional methods such as sine wave fitting or Fourier transform.

# Methodology

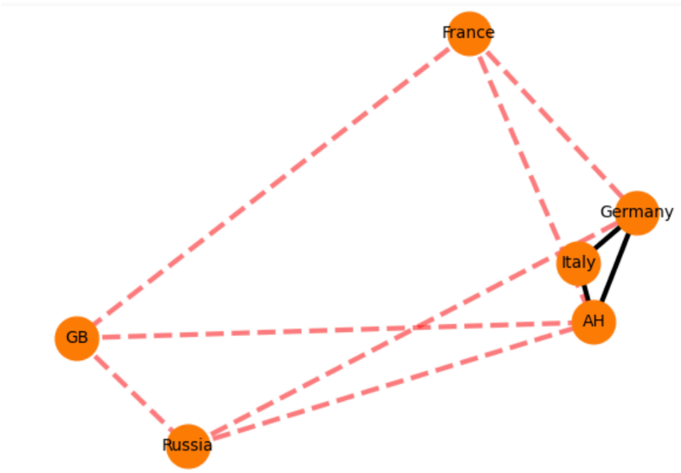
## 1. Visualizing Alliances as Graphs

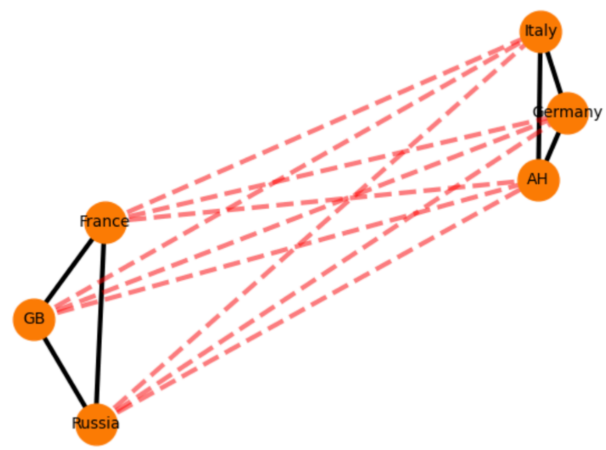
I wrote a script using Python and the networkx library which takes an input of an adjacency matrix in a CSV file and generates a visualization of the countries and military alliances as nodes and edges of a graph. Notice the below graph, which resembles the graph from Antal et al. It depicts the major global powers during World War 1 in 1890. I generated the CSV manually, along with another CSV of the World War 2 data from 1940. These years were specifically chosen because the global network was known to trend toward balance for several years after each.

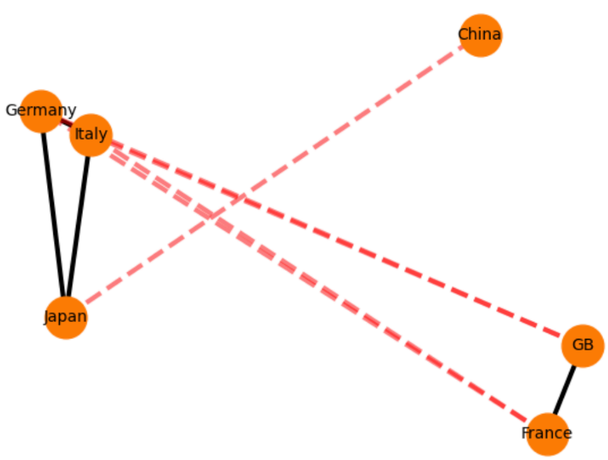


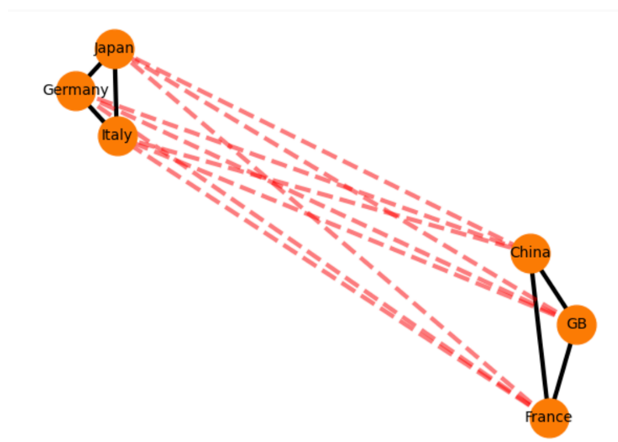

## 2. Partitioning Network

Then I created a “Divide and Conquer” method to partition the countries into two likely sides and show how their alliances might change over time, assuming the network is trending toward triadic balance. First the Louvain algorithm was used to detect clusters among countries with positive edges. Next, a list of all clusters detected was sorted in descending order. Finally, the clusters were iteratively placed into two new lists based on which list was smallest. This algorithm could likely be improved in many ways, but for the purpose of visualizing WW1 and WW2 data it was sufficient. Another limitation of this algorithm is that it cannot account for countries which joined the war at a later date, such as the United States during World War 2. See examples below.



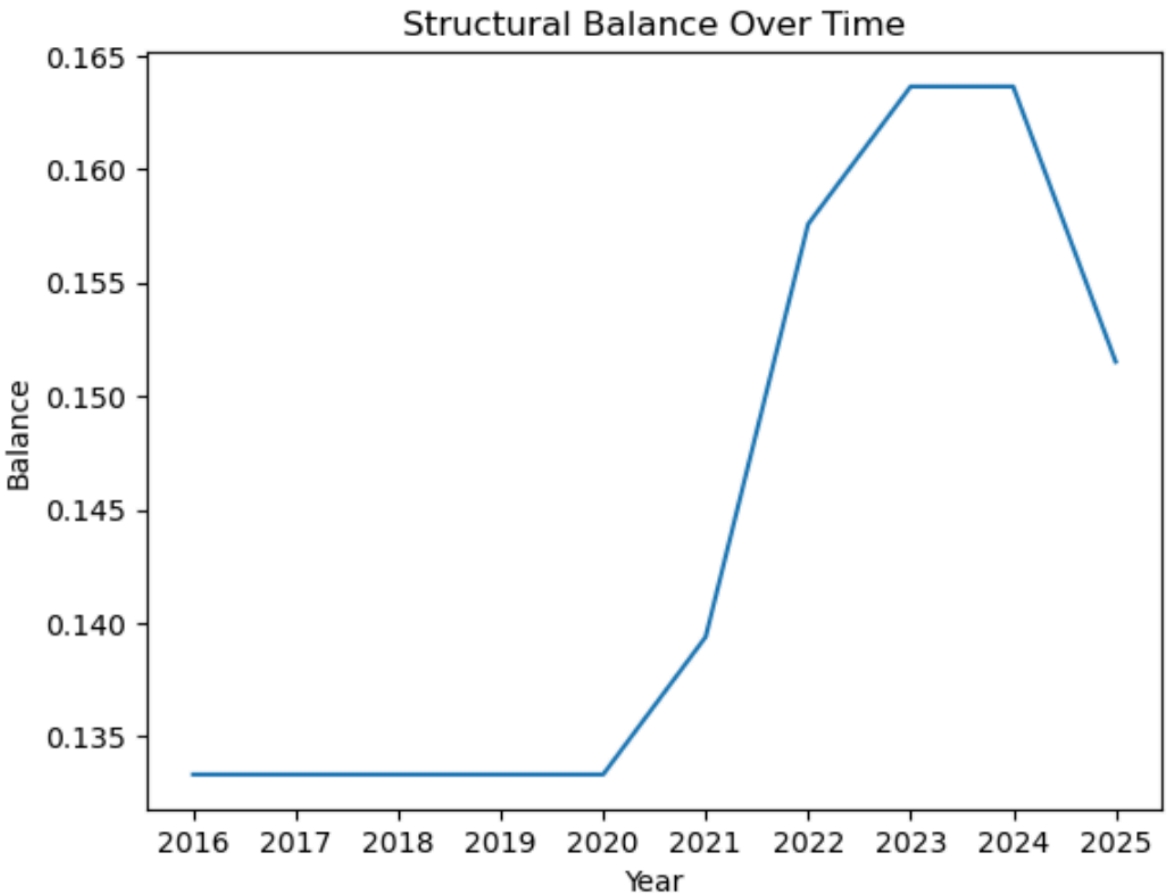




## 3. Past 10 Year Timeline Data

Generating data for current military alliances proved to be the most difficult and time consuming part of this project. The Correlates of War datasets end roughly ten years prior to when I began my research (2025). Determining which countries are allies, enemies or neutral in present day is arguably subjective. I also struggled with time constraints when it came to using methods such as block modeling to account for the entire system of 195 countries.

I spoke with local politician Lindsay Imber and we created a spreadsheet containing 11 countries which we considered major military powers. We then created an adjacency matrix of their alliances based on participation in ongoing conflicts, military treaties, trade agreements and historical interests. This data is very limited, and is meant to be used as a loose reference for further exploration. However, when the structural balance is visualized in a line graph it does resemble the shape of the imbalance trend from Doriean and Mrvar:




## 4. Analyzing Imbalance Over Time

I used the imbalance data between 1946 and 1999 from Doreian et al. to create a time series in Python. Then I trained a Long Short-Term Memory (LSTM) model on the time series using a PyTorch library. The time series was split into 67% training data and 33% testing data with a 1 step lookback. 2000 epochs were used to test the model, which had 50 hidden layers, 1 input and 1 output layer.

After training and testing the LSTM model on the historical data, I applied the model to the timeline data which I had created based on the past 10 years of alliances. I used the inverse of my balance data, since the model had been trained on imbalance data.

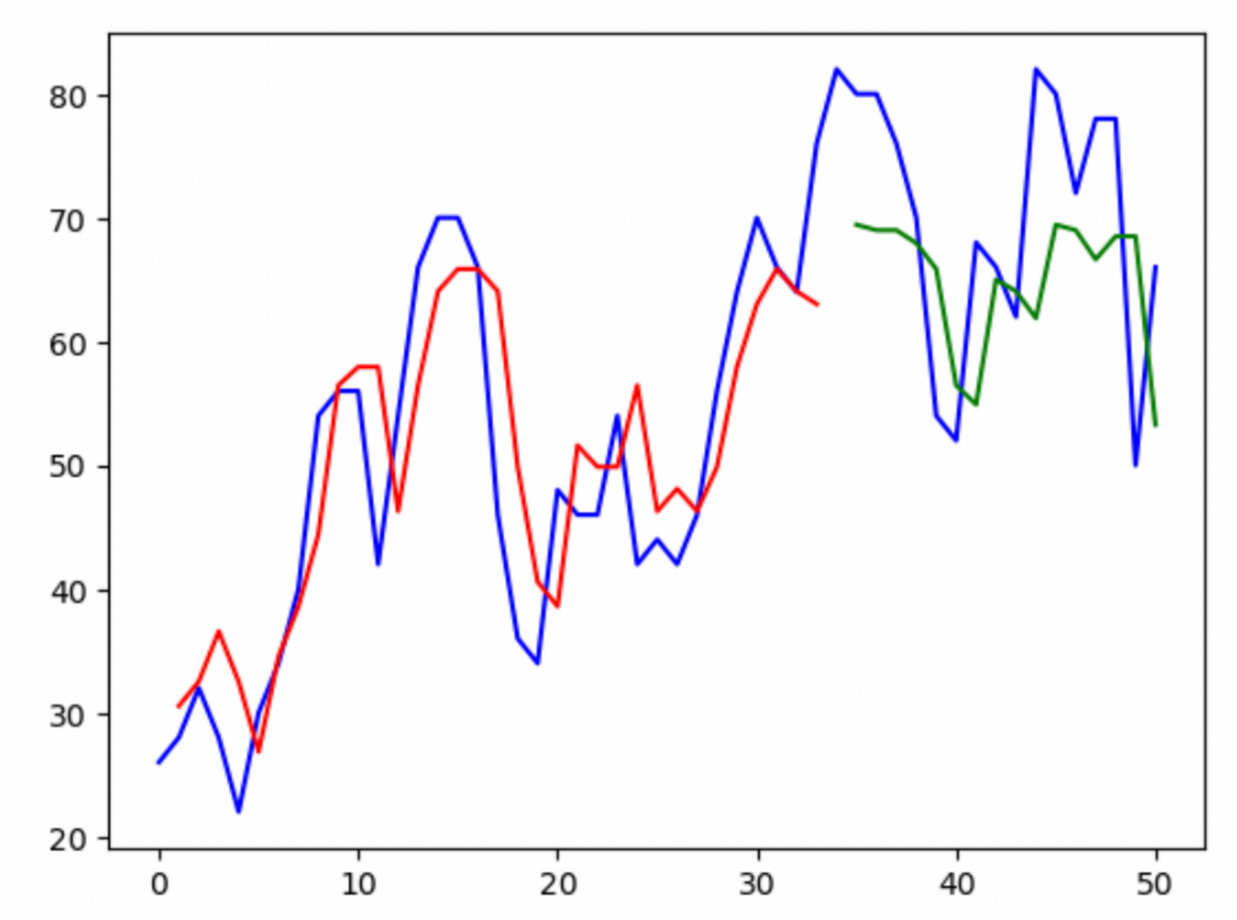
For the datasets and code used in this project, please see the public GitHub repository: [https://github.com/hziegel/Alliances](https://github.com/hziegel/Alliances)

# Results

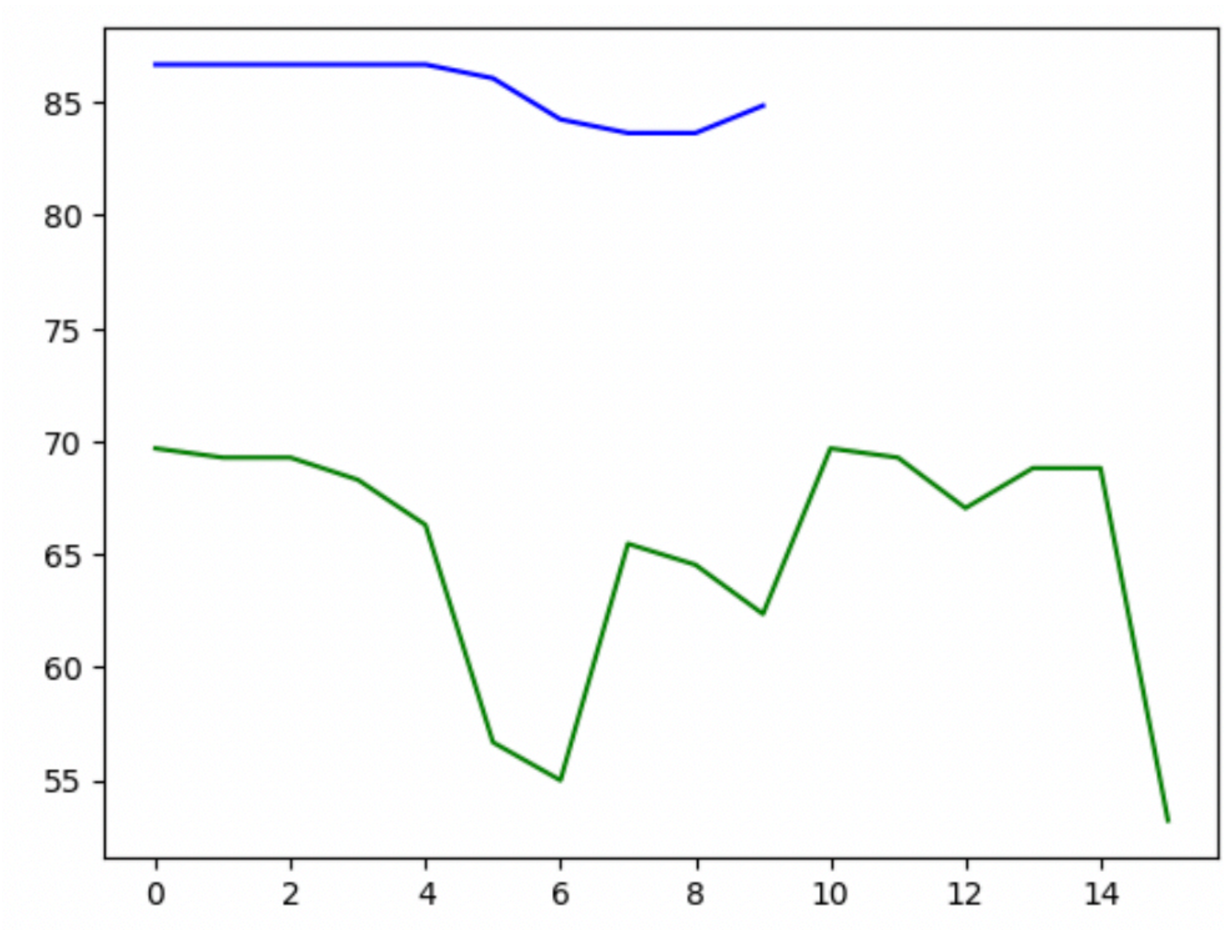
The Root Mean Squared Error (RMSE) of the LSTM model after 2000 epochs was 10.48. The mean of the data was 55.88.

The Mean Absolute Percentage Error (MAPE) of the testing data was 25.72%.

See below a visualization of the 1946-1999 time series data (blue) overlapped with the results from the training data (red) and the testing data (green):

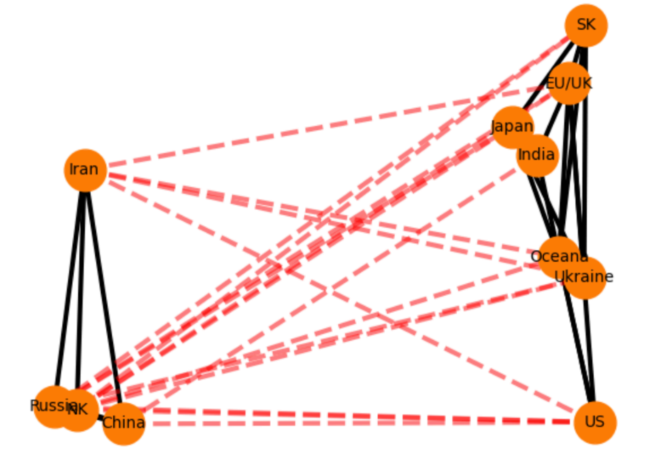


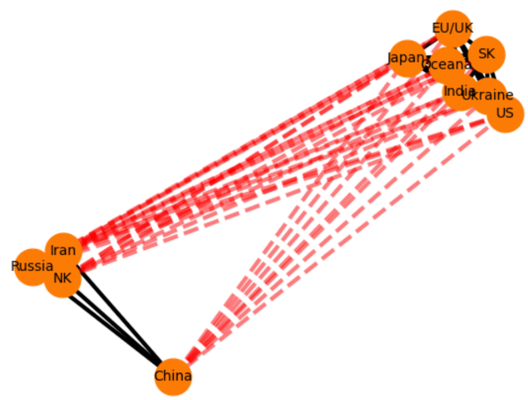
The trained model was then applied to the 10 year timeline data which I created and used to forecast 3 steps into the future. The RMSE was 10.82. The MAPE was 13.67%. The mean of the data was 85.58. See the visualization below, with the data I created in blue and the prediction in green:



# Discussion

When looking at the results of the algorithm used to partition data from WW1 and WW2, it is tempting to apply the same algorithm to current data in order to predict what future alliances will look like. For example:




However, not all networks are trending toward balance. Based on the prediction of the LSTM model, it appears that the above network of 11 countries is trending toward a period of imbalance. This method of partitioning does not apply to networks which are trending toward imbalance, so it cannot be used to predict the changes in international alliances over the next several years.

Furthermore, the data being used to predict this trend is incomplete. It only represents 11 countries out of 195, and the mean is 53% higher than the mean of the data used to train the LSTM model. More accurate and complete data would need to be generated based on the entire global network in order to compare the results to the original time series which the model was trained on.

The results of this project should not be taken to indicate what changes in military alliances will happen over the next several years, or even whether the current network will trend toward or away from balance during that time. Rather, it indicates that it is possible to use an LSTM model to predict patterns in global balance and imbalance over time.

This is significant because it indicates that there is a broad scope pattern in military alliance changes which can be analyzed exclusively using Heider's balance theory. If a simple LSTM was able to fit a 53 year time series with 74% accuracy without any additional variables used beyond structural imbalance, how much more reliable could the same method become with a larger and more comprehensive dataset?

We may think of global conflicts and alliances as random, or as the result of individual decisions by the leaders of nations. But what this project has indicated is that periods of global instability are cyclical, and that cycle can be analyzed and understood.

## Acknowledgements

I am grateful to Lindsay Imber, president of the Sherman Oaks Neighborhood Council, for helping me to generate the dataset of the past 10 years of global alliances.

I also would like to thank Dr. Alex Pang for meeting with me to discuss the use of machine learning and other methods of analyzing time series data. He recommended using a LSTM, which was vital in analyzing and understanding the trend of imbalance over time.


## References


Doreian, Patrick, and Andrej Mrvar. “Structural Balance and Signed International Relations.” *Journal of Social Structure*, vol. 16, no. 1, Jan. 2015, pp. 1–49.

Antal, T., Krapivsky, P. L., and Redner, S. "Social Balance on Networks: The Dynamics of Friendship and Enmity." *Physica D: Nonlinear Phenomena*, vol. 224, no. 1-2, 2006, pp. 130–136.

Gibler, Douglas M. *International Military Alliances, 1648–2008*. CQ Press, 2009.

Cartwright, D., & Harary, F. (1956). Structural balance: a generalization of Heider's theory. *Psychological Review, 63*(5), 277–293. https://doi.org/10.1037/h0046049

Caffrey, Cait. "Fritz Heider." *EBSCO Research Starters*, 2023, https://www.ebsco.com/research-starters/biography/fritz-heider.