Geopolitical Relationships Visualization

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1 Abstract

Monitoring and interpreting political relationships between nation-states is of critical value to nations, analysts and researchers. Existing literature highlights the importance of understanding these relationships through United Nations (UN) voting records. Visualizations within this literature vary in their ability to effectively communicate the data. Additionally, established voting coincidence metrics, such as W-NOMINATE, require complex data preparation and are primarily designed for domestic legislative bodies. This project addresses these challenges by creating an accessible visualization tool that allows users to explore geopolitical relationships as signaled by UN General Assembly (UNGA) and UN Security Council (UNSC) voting data over selected time periods without requiring complex data preparation. The tool provides scatter plots, tree maps, and statistics tables to visualize voting coincidence and clusters of nations, enabling users to explore international relations (IR) and test their own hypotheses about geopolitical relationships.

2 Introduction

Monitoring and interpreting political relationships between nation-states is of critical value to nations seeking to prioritize their own foreign interests. The United States (US) Department of State's annual report, "Voting Practices in the United Nations" (Bureau of International Organization

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Affairs, 2024), highlights the importance of understanding these relationships through UN voting records. Additional work, including Voeten's (2012) analysis of UNGA voting records and Binder and Payton's (2021) study of rising powers blocs, demonstrates the potential value of visualizing UN voting data for IR analysis. However, the established voting coincidence metric (W-NOMINATE) is primarily designed for domestic legislative bodies and requires complex data preparation (Binder & Payton, 2021). An alternative IRT-based method developed by Bailey et al. (2017) and used by Binder and Payton also requires specific data preparation.

The data preparation needs represent a barrier for ingesting and manipulating UN voting data for visualization. By extension, rapidly preparing visualizations for IR analysis is hindered. This project has created an accessible visualization tool based on blind vote data preparation using a simple correlation metric to calculate voting coincidence. The tool allows users to explore geopolitical relationships through UN voting data over selected time periods without requiring complex data preparation. As such, the tool provides a means for users to explore IR and test their own hypotheses about geopolitical relationships.

In the following sections of this report, further background on the topic is provided to establish context for the reader. Within the background, a case study is selected to demonstrate the metrics and visualization techniques developed in this project. Next, the approach section describes the dataset processing, voting coincidence calculation, clustering, dimensionality reduction, visualizations, and the tool's dashboard. Finally, the results section uses the case study to demonstrate the tool's capabilities and the consistent results with Binder and Payton's (2021) analysis.

3 Background

As previously noted, The US Department of State's report (Bureau of International Organization Affairs, 2024) highlights the importance to nations-states of monitoring geopolitical relationships. Voeten (2012) provides a background in academic analysis of UNGA voting records indicating that the modern IR community employs this practice minimally. While Voeten's paper provides evidence to warn against drawing conclusions from general UNGA voting trends, it also includes guidance and examples to interpret historic trends through the data. In a more recent study, Binder and Payton

(2021) use the UNGA voting records to analyze rising powers blocs, BRICS and IBSA, that challenge the established powers bloc, the G7. Among this work, visualizations are used to communicate the findings, indicating the potential value of UN voting records visualization for IR analysis.

3.1 Visuals Employed in Previous Work

The US Department of State (2024) report almost exclusively employs tables to present voting data with one line plot to show voting coincidence between the US and all UNGA member states in a single trace. The line plot provides minimal information as it aggregates all voting coincidence data. The tables provide detailed information on voting coincidence but are multi-page and require reading the text to capture insight. Overall, the report uses visualization but does not employ it effectively to communicate the data.

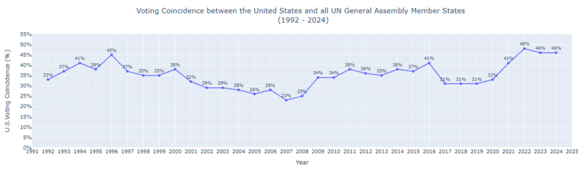
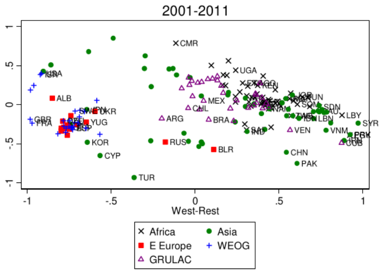
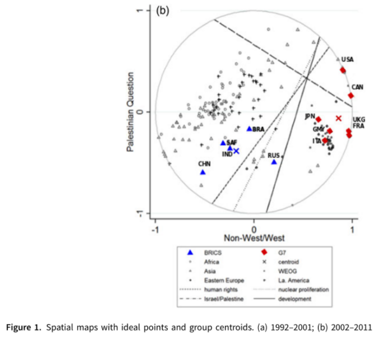


Figure 1: Voting coincidence between the US and UNGA member states Bureau of International Organization Affairs (2024)

Voeten (2012) and Binder and Payton (2021) use scatter plots to visualize voting coincidence between nations. In Voeten's plots, markers and color are used to visualize the continent or region of the nations. In Binder and Payton's scatter plots, markers are used to visualize the continent or region while color is used to indicate membership in a international organization (IO) such as BRICS or IBSA. Binder and Payton also use a an "x" mark to indicate the centroid of the IOs. Additionally, Binder and Payton use lines to show ideological "cutting lines" between nations.



(a) Voeten's scatter plot of voting coincidence (Voeten, 2012)



(b) Binder and Payton's Scatter plot of voting coincidence (Binder & Payton, 2021)

Figure 2: Previous work scatter plots of voting coincidence

Binder and Payton also use a table to show dispersion and distance among IOs. The table is included here for reference as Binder and Payton provide a valuable case study for testing this project's visualization. Note that the dispersion of BRICS is significantly reduced in the second decade of interest.

Table 1. Measures of dispersion and distance in UNGA voting models

	Model 1 W-NOMINATE[a]			Model 2 IRT-Abstentions as nays[b]			Model 3 IRT-Abstentions as midpoint[c]		
	1992–2001	2002–2011	% change	1992–2001	2002–2011	% change	1992–2001	2002–2011	% change
Dispersion									
BRICS	0.509	0.257	−49.51%	0.543	0.208	−61.69%	0.114	0.026	−77.19%
IBSA	0.362	0.131	−63.81%	0.395	0.095	−75.95%	0.088	0.056	−36.36%
G7	0.273	0.248	−9.16%	0.464	0.444	−4.34%	0.376	0.334	−11.17%
Distance									
BRICS-G7	1.067	1.090	+2.16%	1.898	1.772	−6.64%	0.921	0.911	−1.09%
IBSA-G7	1.149	1.079	−6.09%	2.014	1.783	−11.47%	0.986	0.940	−4.67%
μ distance	0.760	0.746	−1.8%	0.883	0.893	+1.02%	0.366	0.349	−4.64%

Notes: Dispersion is the average of the absolute values of the distance from the centroid. 'μ distance' is the average distance between any two ideal points in the UNGA.
[a]Ideal point values between [−1, 1].
[b]Ideal point values between [−1.47, 1.67].
[c]Ideal point values between [−1.90, 3.01].

Figure 3: Table of Voting Coincidence Metrics (Binder & Payton, 2021)

3.2 Voting Coincidence Metrics

Both Voeten (2012) and Binder and Payton (2021) use the W-NOMINATE metric (Poole, 2005) to calculate the voting coincidence between nations. The NOMINATE metric or its variants, specifically W-NOMINATE in this material, are a well-established method in political science for measuring the ideological distance within roll-call voting. However, W-NOMINATE is primarily designed for legislative bodies with domestic parties that vote along party lines, such as the US Congress. The absence of established political parties in international politics poses challenges for applying W-NOMINATE (Binder & Payton, 2021). Given this limitation, Binder and Payton also use the IRT based method developed by Bailey et al. (2017).

Bailey et al. (2017) contrast the simpler S score metric with their IRT based method. In this case, Bailey et al. demonstrate that their ideal point model provides a more accurate representation of voting coincidence than the S score metric. However, the IRT based method is more complex and also requires more data preparation to produce accurate results. Based on the scope of this project and the data needs of W-NOMINATE and the IRT based methods, a simpler S score-like correlation metric is used to calculate voting coincidence.

3.3 Case Study: BRICS Bloc

The BRICS bloc, comprising Brazil, Russia, India, China, and South Africa, has emerged as a notable IO in IR, challenging the traditional dominance of Western powers. Binder and Payton's (2021) analysis of UNGA voting records have revealed that BRICS countries have increasingly aligned their geopolitical activity since the end of the Cold War. This is contrasted against the G7, where BRICS and G7 are disjoint sets. Binder and Payton's visuals are used to better communicate this theory. By calculating the dispersion among IOs, they show a significant increase in alignment within BRICS while the G7 experiences a slight increase in alignment.

Binder and Payton's analysis of BRICS voting coincidence is used as a case study for this project. The BRICS bloc is selected as it is an established IO with a clear geopolitical significance. With the same justification, the G7 is selected as a contrasting IO. The BRICS and G7 blocs are used to demonstrate the visualization techniques and metrics developed in this project.

4 Approach

4.1 Dataset Processing

The UNGA voting dataset (United Nations Dag Hammarskjöld Library, 2024a) is first read from the provided CSV file into a Pandas dataframe. The date of resolutions is then converted from a YYYY-MM-DD string to discrete year, month, and day integer columns. The remaining columns remain unchanged.

The UNSC voting dataset (United Nations Dag Hammarskjöld Library, 2024b) is then read from the provided CSV file into a Pandas dataframe. The data is converted to the same format as the UNGA dataset. The columns are then refactored to match the UNGA dataset. Specifically, the "permanent_members" and "modality" columns are dropped, and the "description" column is renamed to "title". The "agenda" column is also renamed to "agenda_title". The UNSC dataset is then reindexed to match the UNGA dataset columns before being merged with the UNGA dataframe.

4.2 Mapping Votes to Numerical Values

Voting records are "Y", "N", "A", "X" for "Yes", "No", "Abstain", and "Absent" respectively. These values are mapped to numerical values for processing. Specifically, "Y" is mapped to 1, "N" is mapped to 0, and "A" and "X" are mapped to 0.5. This mapping allows for the calculation of voting coincidence between nations.

4.3 Voting Coincidence Calculation

The user provides a range of dates to bound the analysis. The voting records are then filtered to only include votes within the specified date range. A pivoted dataframe is then created with nations as rows, resolutions as columns, and the mapped voting values as the data. Nations that were absent for all votes in the specified date range are dropped from the pivoted dataframe. This filter is specifically targeted to remove nations that are absent from the UN over an extended time period, such as Afghanistan in 2024. Using the pivoted dataframe, the voting coincidence between nations is calculated. The voting coincidence is calculated as the Pearson correlation coefficient between the voting records of each nation pair. The correlation coefficients are placed in a correlation matrix.

The coincidence calculation approach was chosen as a similar method to the S score metric described by Bailey et al. (2017).

4.4 Clustering Nations

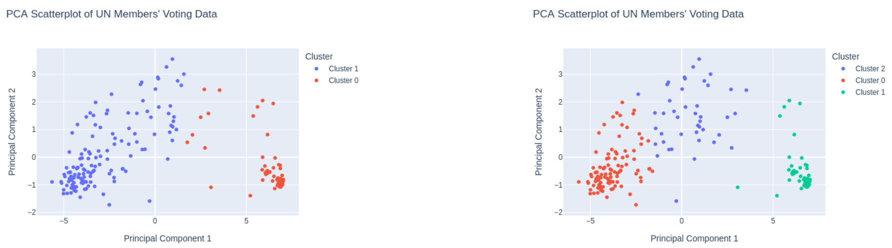
Using the correlation matrix, nations are clustered using the K-means clustering algorithm. The number of clusters is determined by the user with a default value of 2. The clustering results are stored in a separate cluster dataframe. The clustering algorithm selection was based on evaluation of various clustering algorithms, including DBSCAN, OPTICS, HDBSCAN and Affinity Propagation. Given the expected audience, K-means was selected as it provided an explainable approach to produce visually interpretable clusters.

4.5 Dimensionality Reduction

To visualize the clusters, the high-dimensional correlation matrix is reduced to two dimensions with Principal Component Analysis (PCA) using Singular Value Decomposition (SVD). The PCA results are stored in a separate PCA dataframe. The PCA approach was selected as it is a well-established method for dimensionality reduction. The PCA results are used to visualize the clusters in a scatter plot.

4.6 Scatter Plot Visualization

The scatter plot is created using the PCA results, with each point representing a nation and its position determined by the two principal components. The points are colored according to their cluster assignment from the K-means algorithm. This visualization allows for an intuitive understanding of the relationships between nations based on their voting behavior. The scatter plot visualization is created using Plotly. The scatter plots provides panning, zooming, an interactive legend to isolate clusters, and hover text to show the nation name, cluster, nation code and PCA coordinates.



(a) PCA scatter plot of UN voting data with two clusters

(b) PCA scatter plot of UN voting data with three clusters

Figure 4: PCA ccatter plot of UN voting data

4.7 Tree Map Visualization

The tree map visualization is created using the clusters as the top level of the hierarachy. Binder and Payton (2021) discuss the Global South as a potential cluster in opposition to Western nations. As the Global South roughly correlates with continents, the continent of each nation is determined using the Python pycountry and pycountry_convert packages. The second level of the tree map hierarchy is the continent with the nation being the lowest level. This mirrors the marker scheme used by Voeten (2012) and Binder and Payton (2021). Additionally, it provides a visual correlation of cluster membership by Global South and Western nations.

The tree map visualization is created using Plotly. The tree map provides drill-down, drill-up and hover text that varies by level. The top level shows cluster country count and ID. The second level shows continent name, country count and parent cluster ID. The lowest level shows the nation name, nation code, continent and cluster ID.

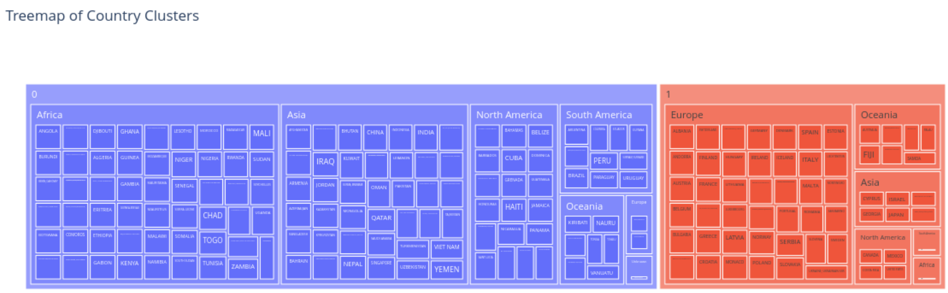


Figure 5: Tree map of UN voting data clusters

4.8 Country Group Highlights

Following the Binder and Payton (2021) example, a country group highlight feature was developed. This feature allows the user to enter semicolon separated groups of countries to highlight in the scatter plot. The countries are entered by country code and comma separated. The highlights can be enabled and disabled to allow toggling of the visuals. The group colors can also be disabled to revert back to cluster colors.

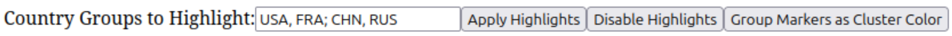
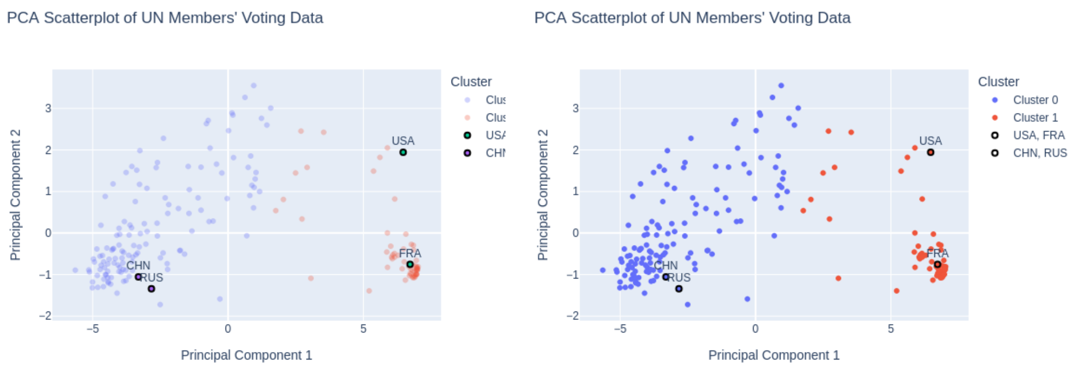


Figure 6: Country group highlight controls

When highlights are applied to the scatter plot, the opacity of the cluster points is reduced to allow the highlighted points to stand out. By default, the groups are assigned their own color. The user can switch the marker colors off and retain the country label to visualize the cluster assignment of each highlighted country.



(a) Highlighted scatter plot where country groups have unique color

(b) Highlighted scatter plot where countries have their cluster color

Figure 7: Scatter Plot with Country Group Highlights

4.9 Statistics Table

A table containing the country count and dispersion of each cluster and country group is provided. The dispersion is calculated as the mean Euclidean distance between each nation in a category and the centroid of the category. The table mirrors the table used by Binder and Payton (2021) to show the voting coincidence metrics. The table's interactions are based on the country group highlight and number of clusters inputs.

index	Dispersion	Size
Cluster 0	2.559	132
Cluster 1	1.593	60
CHN, RUS	0.673	2
USA, FRA	1.464	2

Figure 8: Voting Coincidence Metrics Table

4.10 Dashboard

A Plotly Dash dashboard was developed to provide an interactive user interface for exploring the UN voting data. The dashboard layout was motivated by Binder and Payton's (2021) work. The dashboard uses two sets of all described visuals in a side-by-side layout to facilitate comparison and analysis.

Specifically, the side-by-side layout was needed to overcome the typical processing time for calculating the correlation matrix for a time period. Benchmarking of the processing time found that new time period requests required approximately 4 to 10 seconds to initialize the correlation matrix. With 10 seconds being a significant threshold for user visual memory, the dashboard had to be designed to allow the user to retain prior results while adding a new time period. While the time windows are provided as independent controls, the country group highlights and number of clusters are shared between the two time windows.

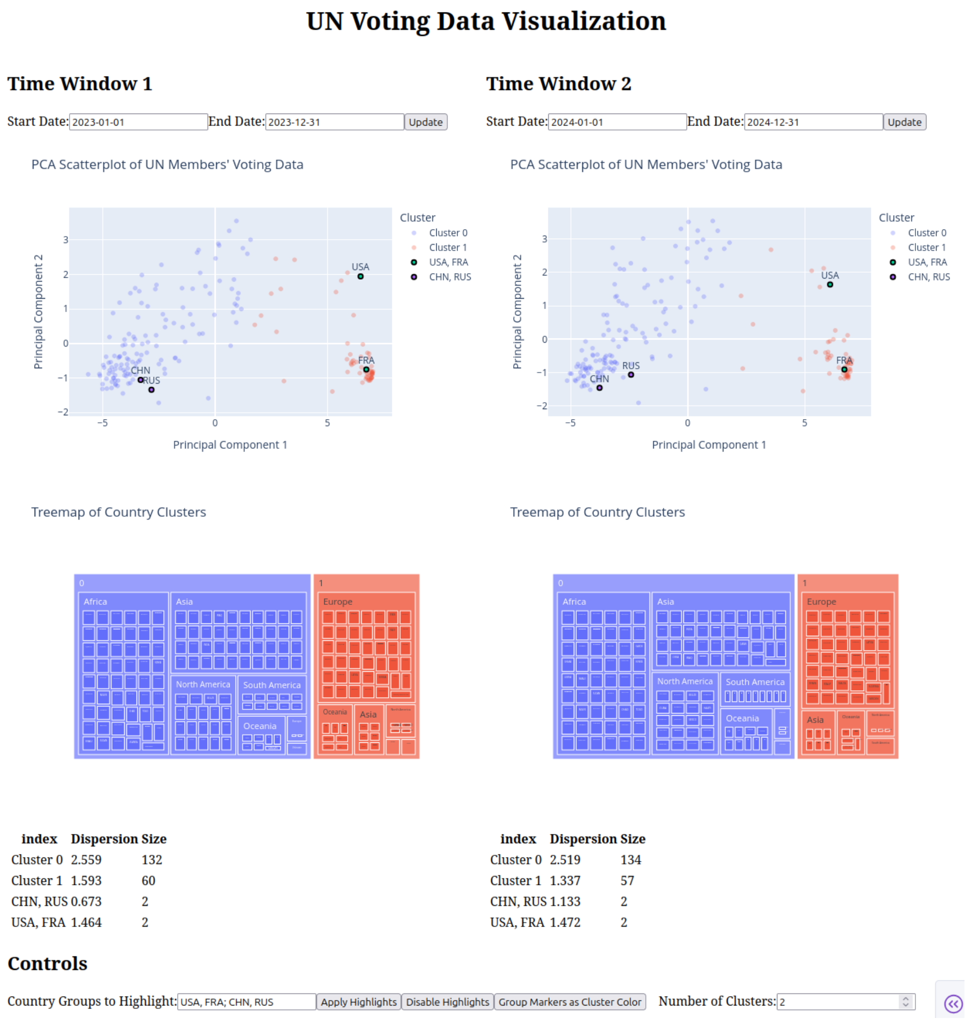
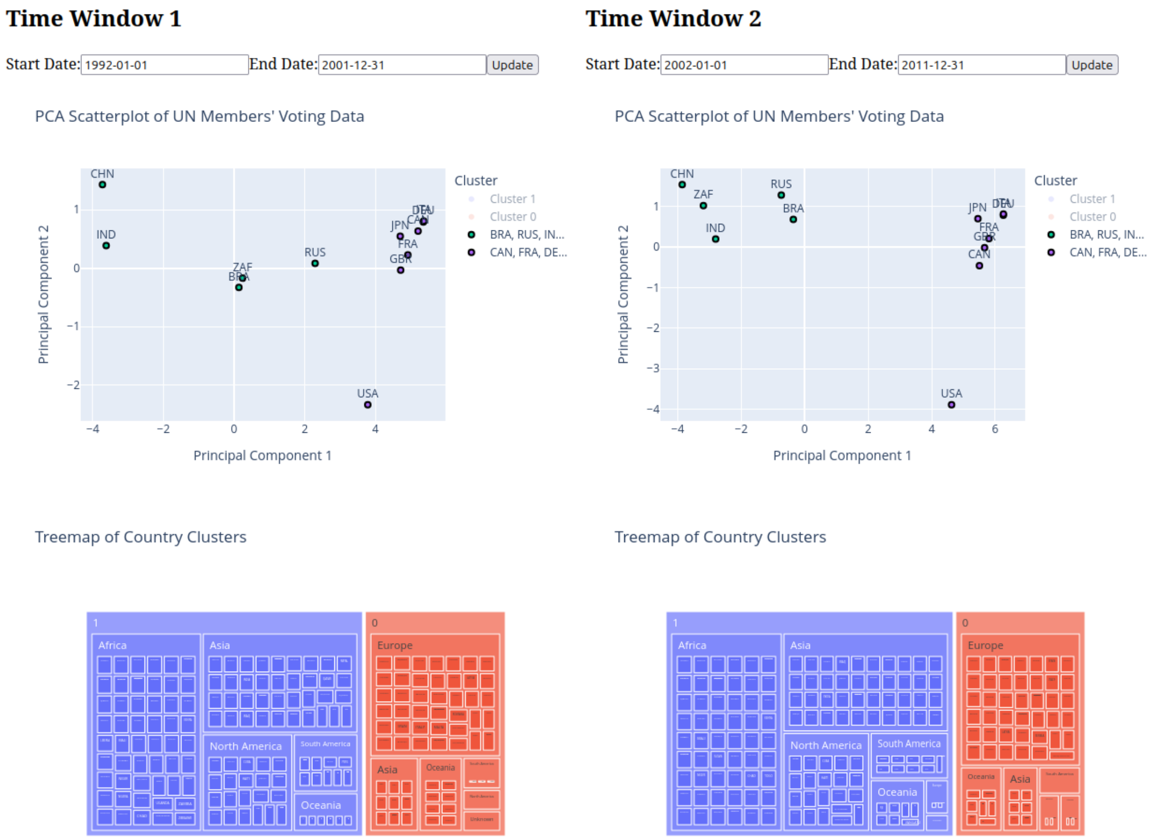


Figure 9: UN Voting Data Dashboard

5 Results

To demonstrate the results of the project, the dashboard was tested by analyzing the BRICS and G7 blocs in the same manner as Binder and Payton (2021). Binder and Payton compared the periods of 1992-2001 and 2002-2011. The dashboard was used to compare the same periods. The country groupings for BRICS and the G7 were then highlighted. In the scatter plots, the BRICS bloc looks more dispersed in the earlier period then more cohesive in the later period. This mirrors the scatter plots presented by Binder and Payton. Additionally, the table shows that the BRICS dispersion decreased from 2.584 to 1.641 while the G7 dispersion increased from 1.086 to 1.429. This indicates that the BRICS bloc has become more cohesive while the G7 bloc has become more dispersed.



index	Dispersion	Size
Cluster 0	1.744	64
Cluster 1	2.090	125
BRA, RUS, IN...	2.584	5
CAN, FRA, DE...	1.086	7

index	Dispersion	Size
Cluster 0	1.460	61
Cluster 1	2.105	134
BRA, RUS, IN...	1.641	5
CAN, FRA, DE...	1.429	7

Figure 10: BRICS and G7 clusters in 1992-2001 and 2002-2011

Enabling the clusters on the scatter plot shows that in 1992-2001, most BRICS members belong to cluster 1 while in the 2002-2011 period, BRICS members all belong to cluster 1. During both periods, the G7 members belong to cluster 0. Looking at the tree map, cluster 1 is populated by African, Asian and South American nations. Drilling down into the North American container, the nations are found to be Latin American and Caribbean nations. The composition of cluster 1 closely matches the Global South composition. Cluster 0 is populated primarily by European nations and in North America, the US and Canada. This indicates that cluster 0 closely matches the Western or Global North nations.

From these observations, it appears that the BRICS bloc is not only within the Global South but may be actively increasing their alignment with Global South countries as the USSR had done with former colonies in the 1960s (Voeten, 2012). As BRICS is a competing IO to the G7, this is consistent with Binder and Payton's observation that, within the context of IR, the Global South may also be a potential cluster in opposition to Western nations.

6 Conclusion

This report has presented the UN voting data visualization tool developed using Plotly Dash. Introduction of a Pearson correlation coefficient based voting coincidence metric allows for the calculation of voting coincidence between nations without the complex data preparation required by W-NOMINATE or the Bailey et al. (2017) IRT based method. The tool provides scatter plots, tree maps, and statistics tables to visualize voting coincidence and clusters of nations. Interactions include time period selection, country group highlights, and number of cluster selection.

Once developed, the tool was used to analyze the BRICS and G7 blocs in the same manner as Binder and Payton (2021). The results showed that the BRICS bloc has become more cohesive when compared between the 1992-2001 and 2002-2011 periods. These observations aligns with Binder and Payton's findings, demonstrating that the tool is capable of producing consistent results with existing literature.

Overall, the UN voting data visualization tool provides an accessible means for users to explore geopolitical relationships through UN voting data over selected time periods without requiring complex data preparation. As such, the tool allows users to test their own hypotheses about geopolitical relationships and provides a valuable resource for IR analysis.

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