Evolving Geopolitics: Network Analysis of UN General Debate Speeches Across Decades

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International relations encompasses a broad array of relationships between global actors with the United Nations (the UN) serving as a notable decision-making body within this sphere. This study seeks to analyze these relationships through General Debate speeches from the 1950s, 1980s, and 2010s using computational methods that include social network analysis and natural language processing (NLP). Utilizing NLP, we construct networks based on references to countries in speeches, aiming to uncover trends in global diplomacy. The analysis focuses on network metrics such as node centrality, modularity, and the Friendship Paradox, and content analyses, notably TF-IDF scores, sentiment analyses and word embeddings. Our results display a distinct transformation in the diplomatic landscape, shifting from a post World War II context with broad debates and fewer countries involved to more versatile communities and nuanced discussions. Previously, we assumed countries formed communities based on geographical location as the majority of countries are typically most interested in advocating their own issues in an international forum. However, our findings suggest different results for many of the communities across the decades seen by, for example, primarily European and South American countries forming one community together. This indicates a move away from a more hierarchical, limited-focus international dialogue to a more egalitarian and multifaceted global conversation. This shift has significant implications for understanding current and future trends in international relations.

network analysis | natural language processing | united nations | united nations general debate | foreign policy

Since the UN's establishment in 1945, representatives from the member states annually gather for General Assembly sessions, with the highlight being the General Debate (UNGB). The UNGB serves as an important forum for member states to present their perspectives on key global issues. Typically delivered by heads of state, government leaders, or foreign ministers, the speeches cover a spectrum of international concerns, providing an unparalleled and unfiltered insight into nations' foreign policy stances and priorities (1). The significance of investigating these debates lies in their unique features: offering comparable textual data, including the voices of smaller nations, presenting justifications for policy positions, and operating independently of formal decision-making processes, thereby fostering candid expressions on diverse and often contentious issues in global politics.

Our research explores the nuances of discourses in the UNGD through text data, revealing interesting patterns indicative of the geopolitical landscape throughout time. Our primary focus lies on three pivotal decades—the 1950s, 1980s, and 2010s—strategically chosen to encapsulate a broad temporal spectrum while ensuring analytical depth. Through network analysis, we identify countries at the nexus or periphery, thereby exposing geopolitical dynamics shaping global conversations within the UNGD. Additionally, employing automated text analysis, we dissect the evolving language, key topics, and sentiments across the dataset. Ultimately, from community-based visualizations of the networks to word frequency analyses and sentiment mapping, our research presents a multifaceted exploration of UNGD, illuminating evolving diplomatic narratives and their implications for global governance and decision-making.

Significance Statement

Our project seeks to use computational methods to uncover patterns and shifts over time in international relations through the framework of UN General Debate speeches. In a landscape where global diplomacy shapes the course of world events, understanding these speeches is crucial. With the geopolitical context in mind, we examine the dialogue between countries, particularly which countries are referenced and which are making references most. This insight is pivotal for grasping how nations navigate complex geopolitical landscapes and how diplomatic ties evolve. This research provides insights into the world's political shifts and equips policymakers with a data-driven compass, enhancing their ability to navigate the dynamic terrain of international discourse. Focus is not only placed on past and present diplomatic strategies but also aids in mapping future trends in international relations.

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Results

In order to capture and analyze country mentions in the UN discourse across time, we created three separate networks, one for each decade as outlined above. We treated each country as a node; if that country mentioned the name of another country in any of their speeches from the decade, an edge was created between the two countries. We also incorporated variations of the country name that would still represent a reference to the country such as using the adjective to describe the people of that country ("Ukrainian" for people living in Ukraine). The directional network extends from the speech holder to the mentioned country. Nodes and edges deriving from a given node are color-coded based on community affiliation. Additionally, node size is proportional to the in-degree of the node, meaning the countries with the most mentions have the largest node size. We chose to scale our network based on in-degree as this represents the countries that are central to the discourse, suggesting significant geopolitical events.

Next, to discern the central actors within the diplomatic discourse, we analyzed the attributes of each network, considering several different measures. We started by enumerating the nodes and edges to gauge the network's scale. We also identified the nodes with the highest in-degree and out-degree to pinpoint the most referenced and referencing countries. Further, we utilized the Louvain method for community detection, enabling us to uncover the underlying modular structure and quantify it through modularity scores. Finally, we examined the extent to which our networks exhibited the Friendship Paradox, a phenomenon where most nodes have fewer connections than their neighbors, by calculating the proportion of nodes that meet this criterion, thereby offering insight into the networks' hierarchical tendencies (2).

Fig. 1. The network graph illustrates the connections among countries mentioned by speech holders. Each node symbolizes either a speech holder or a mentioned country, with edges extending from the speech holder to the mentioned country. Node sizes correspond to in-degree connectivity, while nodes and edges deriving from a given node are color-coded based on community affiliations. In the 1950s network graph four communities are revealed: 1) The brick red cluster encapsulates the intense dialogue between war-recovering Europe and South America, focusing on reconstruction and shared economic goals within the UN framework. 2) The orange red cluster of African nations reflects their concerted push for independence and self-determination. 3) The orange cluster of Asia and Europe denotes negotiations around decolonization and Cold War alignments. 4) The light coral group represents a miscellany of nations, possibly engaged in individual issues or forming nascent alliances that don't follow the predominant geopolitical divides.

In considering the networks' shapes and characteristics, we can observe several patterns indicative of the geopolitical landscape at the time. The 1950s has considerably less nodes (117) and edges (2143) than its counterparts, which makes sense given the post-World War II context where fewer nations were independent and were members of the UN. During this time many countries were still under colonial rule or within spheres of influence that limited their participation in international forums like the United Nations. France, China, and Egypt have the highest in-degrees, suggesting these countries were central to the discussions of the decade. This could be due to France's colonial engagements, China's emergence on the world stage post-civil war, and Egypt's strategic role in Middle Eastern politics. The modularity score (0.125) is on the lower end, and there are a total of four communities, suggesting the network is more integrated than it is split into distinct groups. During the 1950s, the world was divided into two major bloc powers rather than several groups of distinct governing bodies. This bipolar structure potentially led to a network where discussions were not confined within isolated communities but were more global in nature, as countries interacted within the framework of these two large, influential blocs. Additionally, the emergence of newly independent states from colonial rule might have not yet formed distinct geopolitical groups or communities, further contributing to the lower modularity. Over half of the nodes (53.85%) satisfy the Friendship Paradox, showing a tendency towards a core-periphery structure in the network.

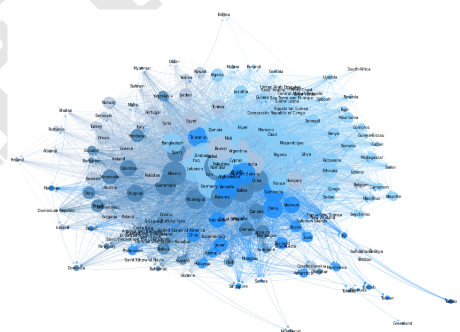

Fig. 2. The above mentioned network structure also applies here. The 1980s network graph reveals four communities: 1) The steel blue cluster reveals focused discussions within the Americas on Cold War impacts and regional economic policies, likely influenced by U.S. diplomacy. 2) The light sky blue cluster indicates Africa's dialogue on developmental challenges and conflict resolutions. 3) Bright blue captures Asia's rising global presence, underscored by economic expansion and political assertion. 4) The grey cluster reflects Europe and the Middle East's strategic dialogues on security and peace, possibly linked to the era's significant geopolitical shifts.

Transitioning to the 1980s, the network becomes visibly more complex with an increased number of nodes (183) and a significant rise in edges (6374), reflecting intensified diplomatic activity. The top nodes with the highest in-degree, Afghanistan, Namibia, and Iran, indicate the countries positions as key geopolitical hotspots, as a result of being marked by either ongoing conflicts or struggles for sovereignty. Despite the larger number of nodes, the modularity is slightly decreased (0.100), and the number of communities remains at five, suggesting a persistent pattern of global discourse. Notably, the percentage of nodes satisfying the Friendship Paradox increased to 73.22%, emphasizing a more pronounced hierarchical network structure.

The 2010s network shows further expansion with the highest number of nodes (214) among the three decades, yet fewer edges (5416) compared to the 1980s, possibly indicating more

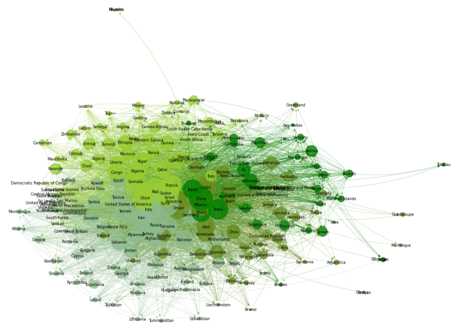

Fig. 3. The above mentioned network structure also applies here. The 2010s network graph reveals four communities: 1) The olive cluster suggests collaboration between the Caribbean and Europe on pressing issues like climate change and sustainable development within the UN. 2) The dark green cluster signifies Asia's enhanced role in international discourse, leveraging economic strength for greater geopolitical influence. 3) Lime green highlights Africa's unified voice on development and peace. 4) The sage green might indicate newer, less defined geopolitical alliances or issue-based partnerships.

bilateral rather than multilateral interactions. The dominant in-degree of countries like Syria, Israel, and Mali could be attributed to their significant roles in defining the decade's geopolitical issues—Syria with its civil war drawing global attention, Israel due to its central position in Middle Eastern conflicts, and Mali as a focus of international efforts against regional terrorism and instability. The network's modularity has increased to 0.173, and the number of communities has decreased to four, which may suggest emerging regional blocs or alignments. The highest percentage of nodes that satisfy the Friendship Paradox (81.31%) in this decade reflects the stark contrast between highly connected and less connected nodes, indicative of a distinct hierarchy within the network.

Thus, the network attributes from the 1950s to the 2010s reveal a transformation in international discourse, from a less fragmented Cold War era to a contemporary landscape marked by complex bilateral relations and distinct geopolitical clusters. The usage of network metrics—such as node centrality, modularity, and the Friendship Paradox reflects the changing dynamics of global diplomacy over time, with specific countries rising to prominence in response to the pressing issues of their respective decades.

Now, we move on to investigate the speeches on a content and sentiment basis in order to gain a deeper perspective in the geopolitical dynamics between 1946 and 2022. By preprocessing the text data, which included removing stop words, punctuation, tokenizing and lemmatizing, to maintain the contextual significance of the words, we prepared and ensured standardized corpora for following text analyses.

By calculating the TF-IDF score, we located the most significant and decade-specific words. We chose the TF-IDF score over the TF-TR score, as the former focuses on the importance of a term compared to the entire corpus, while considering term frequency and document frequency. Additionally, we created a custom stop word list to sort out more obvious words such as 'united', 'nations', 'country', 'people', 'international', 'world', 'states', that were all highly present across the corpora, as well as common words such as ' 'would', 'also', 'must'. This helps to highlight words that are particularly significant in a specific decade as well as locate significant themes for further analyses. To visualise these patterns and highlight the decade specific themes, we created word clouds in corresponding colours with the networks.

Fig. 4. Word clouds of the speech content from the three decades, a) 1950s, b) 1980s, and c) 2010s. Popular words across the decades are sorted out based on a custom stop word list. Word clouds show consistent word usage related to peace, conflicts, governments, etc. and more decade-specific topics such as war in the 1950s, economy in the 1980s, and climate in the 2010s.

'Peace' has the highest TF-IDF score in the 1950s (0.226), 1980s (0.237), and still places within the top three words in the 2010s (0.199). This reflects the UN's mission to maintain "international peace and security", coincides with the establishment of the first peace-keeping force in 1956 and the creation of the UN being a direct result of the Second World War (3). Consequently, the speeches held during the 1950s, reflect these beginning years with 'assembly' (0.184), 'general' (0.155) and 'problem' (0.177) ranking high. Against the backdrop of the Cold War ending, the speeches of the 1980s the most significant words are 'economic' (0.19) and 'problem' (0.153) echoing the severe recessions, the debt crises in African and Latin American countries and the long term consequences of high inflation due to the oil price shock of 1973 (3). For the 2010s, 'development' (0.291) is the most notable word, which we chose to inspect more closely in the word frequencies over time. Around the middle of the decade, 'development' peaked coinciding with speeches from the UN Sustainability Development Summit, which was adapted in 2016 in the Paris Climate Agreement. Moreover, with the population surpassing seven billion people in 2011, the most refugees and displaced people in 2014 in UN history, words such as 'human', 'global' and 'support' were among the most noteworthy and decade-specific words (3).

In order to go deeper into affective tone we conducted sentiment analysis on the speeches to infer the international community's tone and mood over time. Peaks and troughs in sentiment scores correspond to periods of global optimism or

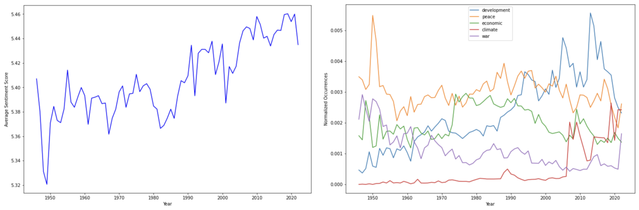

Fig. 5. Sentiment (left) and word frequencies (right) over time (per year). On the left, the change in sentiment in the speeches over time is visualized. While the changes in sentiment are not dramatic (ranging from 5.32 to 5.46 out of 10), it is visible that the sentiment slowly rises over time, however with a gap down in 2022. On the right, the normalized word frequency over time are visualized so fluctuations in length and amount of speeches are ignored. The two graphs could be reflective of each other, with the years mentioning words related to 'war' and 'peace' being less positive in sentiment, and topics related to 'development' and 'climate' being more positive. This is, however, not a causal claim and as only five words have been investigated for the word frequency and many other topics could have influenced the changes in sentiment.

tension, such as the end of the Cold War or the post-9/11 era. Notably, the overall sentiment steadily increases, suggesting the speeches got more positive over time. However every 15 to 20 years, pits occur and the sentiment scores rapidly fall. This could be due to specifically negative events occurring in this rhythm, such as speeches leading up to the 2000 "UN Peacekeeping Reform" addressing the shortcomings of the task force or a limitation of the word list.

We started out hoping to conduct the sentiment analysis by decades but we noticed that annual sentiment scores showed minimal variation. Thus we shifted our approach, and calculated the sentiment on a yearly basis, which yielded the following meaningful results. Additionally, when sentiment analysis was conducted on a decadal basis, the detailed changes seen in the yearly data became less apparent. As a result, this broader, decade-focused analysis did not reveal any notable differences in sentiment patterns, with each decade displaying remarkably similar trends.

The findings from the word clouds align with the visualization of word frequencies over time, whilst adding more detailed insights into the temporal shifts. It is visible that "peace" has been a central word in the establishment of the UN, but over time has been overtaken by "development". Likewise, we see that "war" was previously a more commonly used word, whereas "climate" has entered the debate drastically since the end of the millennium. It is notable, that many of the word frequency patterns switched in the last year (2022) of the dataset, where "war" and "peace" again are going up, and the other words are decreasing in frequency. This undoubtedly points to the major influence that the Russian annexation of Ukraine had on global discourses in the UNGD.

Finally, we investigate meaning associations in the speeches from the three decades and compare them to each other to explore indications of changes in discourses. Using word embeddings, we examine contextual relationships among words and identify similarities and differences in their usage. Word embeddings operate on the premise that similar words occur in similar contexts (4). Unlike traditional methods, modern models like Word2Vec (5) focus on local word contexts rather than the entire document, efficiently projecting words into a vector space (4). Word2Vec does not rely on predefined context words but leverages natural co-occurrence to compute vectors. This approach proves valuable for studying speeches at the UN meeting. For the word embeddings, we investigated the five words from the word frequency analysis to see how the discourse around the words have changed in the three decades. While there are many notable findings, 'climate' especially stands out as it has moved from being related to atmosphere and relaxation in the 1950s and 1980s to being associated to (climate) change, warming and disaster-risk in the 2010s. 'Peace', on the other hand, seems stable in discourse throughout the three decades, continuously being semantically related to harmony, stability and lasting (peace), implying this being a constant aim within the UN. Lastly, a surprising finding was the dominance of 'holocaust' in relation to 'war' in the 1980s. After a further inspection of the corpus, it is however clear that holocaust in this period is used in relation to 'nuclear holocaust' and, thus, showcasing the conversation in the UNGD evolving around of the cold war in this period.

1950s	
climate	easing, atmosphere, aggravation, lessening, relaxation, relaxing, equilibrium, ease, deterioration, propitious
war	wars, unleashing, outbreak, catastrophe, horrors, defeat, warfare, cold, conflagration, brink
peace	lasting, tranquillity, maintenance, concord, enduring, harmony, amity, endangered, strengthening, stability
1980s	
climate	atmosphere, détente, relaxation, conducive, healthier, favourable, favorable, conditions, normalcy, predictability
war	wars, outbreak, horrors, holocaust, fratricidal, conflagration, eruption, specter, catastrophe, carnage
peace	harmony, tranquility, concord, tranquillity, unison, stability, desirous, prosperity, sanity, amity
2010s	
climate	change, desertification, climate-change, sendai, adverse, mitigating, 2015-2030, warming, impacts, disaster, risk
war	wars, bipolar, cold, ruins, victors, tyranny, horrors, shadow, colonialism, ashes
peace	prosperity, stability, tranquillity, indivisible, harmonious, lasting, concord, furthering, equilibrium, unification

Table 1. Word embeddings on the words 'climate', 'war', and 'peace' across decades. While there are rhetorical shifts in the word usage related to climate, peace remains stable in its semantic patterns over the three decades. Word usage related to war also remains consistent, yet with some context specific variations.

In delving into the content and sentiment of UNGB speeches, our analysis unveils evolving geopolitical priorities. From the prominence of 'peace' during the establishment years in the 1950s to the contemporary focus on 'development', our exploration, aided by sentiment analysis, word frequencies, and embeddings, illuminates the dynamic nature of global discourses within the UNGD moving from a war-focus to a sustainability oriented focus.

Discussion

While having gained insights into the development in the UNGD over time, we recognize that there are several limitations to this study. In terms of the network analysis, one limitation is that while an edge is added for every country mention, we do not have a way in this study to measure the "strength" of the mention. We cannot distinguish between a passing reference versus a substantive discussion of a country. Future iterations could benefit from a weighted approach, where edges are assigned varying strengths based on the context and frequency of mentions. Implementing advanced NLP methods, such as contextual embeddings or topic modeling, could enable us to assign such weights accurately. Additionally, a next step on the network analysis could be to map the network of each year to gain more granularity in the networks and capture the nuances over time.

In our NLP analysis, although we computed sentiment scores annually, the variations in sentiment were not substantial. Similarly, when we initially performed sentiment analysis by decade, the nuanced fluctuations observed in yearly sentiment were smoothed out, leading to a decade-based sentiment analysis that did not yield significant distinctions, as each decade exhibited very similar sentiment patterns. This lack of granularity could be due in part to the limited nature of the labMT word list, which may not adequately capture the diverse and complex linguistic nuances typical in diplomatic language.

While these limitations are acknowledged, our research prompts new avenues for exploration. Future studies could broaden the scope by incorporating speeches from additional diplomatic forums like NATO, WHO, or the EU. This expanded dataset would offer richer insights, enabling a comparative analysis of connections and attention across various international institutions.

Materials and Methods

The Dataset. Our research is anchored in a comprehensive and open-source dataset from Harvard Dataverse (1). The dataset has a temporal breadth and volume in content, as it spans from 1946 to 2022, covering 10,575 speeches. The richness of the data enables the extraction of meaningful insights over time.

Network Analysis Methods. We used the Python package NetworkX to create the graph after loading in the speech text data from our internal files. After specifying the data and parameters in NetworkX we used the Louvain community algorithm to detect country groupings and color code the network. In addition to network analysis, we leveraged the Matplotlib package in Python for visualization purposes. This enabled us to create comprehensive network visualizations, illustrating the complex interconnections and community structures within the UNGD network.

Decade-based Text Analysis. To prepare for the decade analysis, we aggregated all the text files corresponding to the respective decade, then cleaned, tokenized, and removed stop words and punctuation in each decade corpora. For the NLP, we used several text processing tools. The TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer measures the importance of terms by considering both their frequency in a document (TF) and their uniqueness across the entire corpus (IDF). By multiplying these metrics, TF-IDF assigns numerical weights to words, highlighting their significance in a document while downplaying common terms. In our study, TF-IDF scores were then visualised by wordclouds, highlighting nuanced patterns in global diplomatic discourse over the three decades. For the sentiment analysis, we used the Language Assessment by Mechanical Turk (LabMT) Wordlist and the AFINN lexicon. LabMT is a curated word list rated by human evaluators on their happiness scores, providing a baseline for assessing the sentiment of written content (6). AFINN, developed by Finn Årup Nielsen at DTU, is a lexicon-based tool that provides sentiment scores between -5 (negative) and +5 (positive)

We wanted to expand on the semantic relationships, by diving deeper into contextual meanings of the speeches. Thus, we used Gensim Word2Vec, utilizing neural networks to learn vector representations of words based on their co-occurrence patterns in a given text corpus to create word embeddings (7).

Modularity. Modularity is a measure assessing community detection algorithms and identifying cohesive groups within a network. It gauges the extent to which nodes in the same community are more interconnected compared to random communities (2).

The formula for modularity ($\bar{M}$), where ($\bar{n_c}$) are the communities stemming from a full network with complete partition, ($\bar{L_c}$)is the total number of links within the community ($\bar{C_c}$) and ($\bar{k_c}$) is the total degree of the nodes in this community, is expressed as:

$$M = \frac{1}{n_c} \sum_{c=1}^{n_c} \left(\frac{L_c}{L} - \left(\frac{k_c}{2L} \right)^2 \right) \qquad [1]$$

(2)

The Friendship Paradox. The Friendship Paradox is a phenomenon in social networks where individuals, on average, have fewer friends than their friends do (2). This can be formulated as follows:

Let N be the total number of individuals in a network, k_i the number of friends of the i-th individual, and f_i the average number of friends that the friends of the i-th individual have. The paradox is represented by the inequality:

$$\bar{f} = \frac{1}{N} \sum_{i=1}^{N} \frac{\sum_{j \in \text{friends}(i)} k_j}{k_i} > \bar{k} = \frac{1}{N} \sum_{i=1}^{N} k_i \qquad [2]$$

(2)

This indicates that the average number of friends of friends ($\bar{f}$) is generally greater than the average number of friends per individual ($\bar{k}$) in the network, emphasizing the skewed distribution of social connections.

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