A Discourse-Driven Intervention Recommendation Framework for United Nations Peacekeeping in Post-Colonial Africa

Brian Zhou[1] and Alvan Caleb Arulandu[2]

[1]Thomas Jefferson High School for Science and Technology, Alexandria, Virginia, USA
[2]Harvard University, Cambridge, Massachusetts, USA

ABSTRACT

The United Nations (UN) is the foremost international body helping uphold world peace through peacekeeping missions, ranging from deployments that enforce peace treaties, monitor conflicts, and protect civilians; However, determining when and how to intervene is complex. The updated UN General Debate Corpus (UNGDC), cataloging every speech from the UN's inception in 1946 to 2022, is a treasure trove of national policy, as the UNGD is the only body where every country can speak. We propose a discourse-driven intervention recommendation framework that categorizes ongoing conflicts based on UN precedent and recommends the magnitude of funds and forces that should be committed to addressing a conflict. We employ natural language processing techniques to tokenize, preprocess, and analyze word stem frequencies in the UNGDC, generating a timeseries of the number of UN mentions for any given country. Paired with historical analysis, we show that debate in the UNGDC is a potent indicator to determine UN intervention and response mechanisms for conflicts in Africa; further, by aggregating mention statistics across periods of active conflict, we provide quantitative backing for the correlation of mention dynamics and the presence of an active conflict, for a given country. Finally, we present and test an interpretable, shallow decision tree model that can perform intervention type classification and response magnitude recommendation with 91.7% accuracy. Our results, established by computational experiments and statistical testing, suggest that corpus analysis and broader computational diplomacy methods can drive intervention recommendations to improve the UN's decision-making.

KEYWORDS

United Nations, conflict resolution, natural language processing, decision trees, computational diplomacy, UN peacekeeping, UN General Assembly General Debate, UN General Debate Corpus, political communication

1. Introduction

United Nations (UN) peacekeepers, run by the UN Peacebuilding Commission, operate around the world to assist in humanitarian interventions, protect civilians and refugees in civil war and conflict, and promote post-war peace and peaceful transitions. Peacekeepers operate as a representation of the international community's will to protect and uphold human rights while promoting and overseeing demobilization and transitions to peace [1].

David C. Wyld et al. (Eds): SIPR, NCWC, BIBC, SOFEA, DSML, ARIA, NLP, CSEN -2023
pp. 349-369, 2023. CS & IT - CSCP 2023 DOI: 10.5121/csit.2023.131927

UN peacekeepers operate around the world with varying levels of success. In Rwanda and Bosnia [2], UN peacekeepers failed to protect civilian lives in devastating massacres and genocides, but UN peacekeepers saw success in other operations such as the UN Interim Administration Mission in Kosovo and the UN Transitional Administration in East Timor (UNTAET) [3]. The efficacy of individual peacekeeping missions, alongside the overall efficacy of the UN peacekeeping body, has been disputed by various scholars and researchers. Scholars and activists have called out varying forms of human rights violations conducted by UN peacekeepers against civilians [1], including sexual exploitation by UN peacekeepers [4]. Scholars also dispute the effectiveness peacekeepers bring, drawing various conclusions on the effects of peacekeeping deployments:

- Prior and in early stages of a conflict, increased budget for UN peacekeeping operations (PKOs) reduces armed conflicts by up to two thirds in a simulation against an alternative without early peacekeeping action [5].
- During conflicts, UN operations are more effective compared to operations conducted by countries to reduce civilian casualties [6], but often hinge on cooperation from actors inside the state [7]. Other scholars dispute the effectiveness of non-UN peacekeepers, finding that non-UN operations are often effective at limiting civilian violence [8] and are similarly effective to mitigate violence [9]. Literature usually agrees that the UN is significantly more effective in creating treaties and agreements for peace [8].
- After a conflict happens, UN peacekeepers increase the likelihood that combatants agree to negotiate and a cease-fire [10]. UN peacekeepers are effective at short-term achievement of peace; longer deployments increase the chance a peace continues [11], and similarly, UN peacekeeping missions are effective at enforcing rule of law in times of peace when reforms are being implemented [12].

In this environment, knowing when, where, and how peacekeeping forces will be deployed is critically important for promoting peace and security in war torn regions. International organizations (IOs) such as the United Nations with peacekeeping capacities are not only more effective at creating and enforcing peace agreements, but create forward-facing effects that the discourse of a potential peacekeeping force creates a credible commitment, a theory in conflict resolution demonstrating that discourse surrounding UN interventions helps bring peace and create more effective conflict resolutions [10]. Thus, predicting a UN Security Council (UNSC) decision to deploy peacekeepers can shine light into evaluating the credible commitment theory and serve as an effective push to promote peace in emerging conflict zones. This knowledge of future operations can assist other humanitarian organizations and allow researchers to compare the effectiveness between an implemented UN PKO scale and a predicted need, allowing future missions to adapt and commit a credible force to promote peace.

Fortunately, linguistics is a flexible tool that is able to turn qualitative data into quantifiable data for data science in the field of international relations and politics, and has the potential to be able to detect and predict discourse surrounding ongoing and future UN peacekeeping deployments. Historically, linguistics and Natural Language Processing (NLP) has been applied to a variety of applications in international relations using a variety of Corpora (compilations of text), including diplomatic documents [13], real-world conflict detection using news [14], and foreign influence from social media [15], to name a few. The growing popularity of data science and NLP approaches in social science allows the use of these Corpuses to answer important questions. One such Corpus is the UN General Debate Corpus (UNGDC) created by A. Baturo [16]. We utilize this corpus to answer questions about how post-independent states in the Global South emerge on the international stage, including their prevalence in UN discourse and distinguishing factors between African regions. The UNGDC is comprised of speeches from the representatives of all 193 UN member states given each year in an address to the UN General Assembly (UNGA) discussing a state’s stance on global issues, outlining the issues they deem most important, and laying out their national and international agendas. These speeches are important, as the UNGA is often referred to as a ”barometer of international opinion” [17]. By being text-based, the UNGDC offers a promising solution to the large gap of quantitative data that existed within the social sciences just decades prior, and which continues to persist today. Notably, the broad nature of the dataset allows for a variety of quantitative studies to emerge.

For example, prior studies with the UNGDC have researched how specific world leaders, countries, or supranational bodies engage or utilize rhetoric at the UNGA, like Pakistan [18] and the speeches given by the former Prime Minister of Pakistan Nawaz Sharif [19] or the European Union [20]. Studies include a wide range of topics, including rhetoric, Islamophobia, organizational management, gender, language policy, and economic theory, respectively:

- Evaluating the impact of cross-cultural differences on the explicitness and persuasiveness of rhetoric between cultures at the UN [21]
- Utilizing Critical Discourse Analysis to study the portrayals of Islam and Muslims in UN speeches [22]
- Studying benign neglect in an organization’s rhetoric [23]
- Examining trends in gender representation in policymakers as well as gender representation and linguistics in topic discourse at the UNGA [24]
- Highlighting language policy and ideology of UN members [25]
- Analyzing how economic scarcity between lower-income and higher-income countries influences narratives of want and wealth in speeches given at the UN [23]

Many studies have also expanded the UNGDC dataset to new parts of the UNGDC, including:

- UNSCdeb8, a corpus containing all verbatim statements of permanent and non-permanent members of the UNSC by [26]
- spaceTexts, a corpus containing all speeches related to the UN Committee on the Peaceful Uses of Outer Space including state and nonstate actors by [27]
- UNSC Afghanistan, a corpus combining quantitative and qualitative approaches to analyze dynamic topics in Afghanistan from UNSC speeches conducted by [28]

We study only the UNGDC, where new novel areas of study have been created by the expansion of the dataset. The most recent dataset created by [29] extends the original UNGDC, which covered all speeches from 1970 to 2017, to the first UNGA session, now covering from 1946 to 2022. With over 10,000 speeches from more than 193 countries, the updated UNGDC is a treasure trove of linguistic data.

Uniquely, the expanded UNGDC dataset allows us to study the complete history of post-colonial states such as Nigeria or Algeria. These post-colonial states often emerged beginning in the 1950s and joined the UN the same year as their independence. All of them joined after the formation and establishment of the UN, meaning that for the entirety of the nation's existence, they have been UN members. This uniquely allows us to examine and catalog the development of these independent states as they develop economically, gain footing on the global stage, and also observe how the international community reacts and resolves turmoil in these new states.

In Materials and Methods, we discuss the composition of the UNGDC dataset, the advantages of using the UNGDC dataset for mapping the shift of a country's national priorities over time, and the specific coverage that the UNGDC dataset offers for representing lower-income countries. We use the UNGDC dataset to first develop a time series of the 'relevance' of a nation in UNGDC speeches, based on the number of references a country receives in a given UNGD. We explain the novel ways that the UNGDC dataset is able to explain trends such as UN involvement in the peacekeeping and conflict resolution process. Computational Experiments and onward detail how we extract features and tokenize speeches to conduct our experiment, as well as the conditions validated to conduct our statistical tests.

In Results, we conduct a select review of certain UN PKOs in Africa alongside compute differences in discourse between various conflicts, evaluating determining factors to develop an interpretable machine learning model that can predict the type of peacekeeping operation and magnitude of committed funds and forces throughout the length of the operation. We discuss the implications of our analysis and review future work that can develop a multimodal model including other sources of information such as UNSC data and large datasets from traditional press and social media platforms.

2. MATERIALS AND METHODS

2.1. Advantages of the UNGDC Dataset

Every September, the heads of state and other high-level country representatives gather in New York at the start of a new session of the United Nations General Assembly (UNGA) and address the Assembly in the General Debate (GD). The GD provides the governments of the almost 200 UN member states with an opportunity to present their views on international conflict and cooperation, terrorism, development, climate change and other key issues in international politics. As such, the statements made during the GD are an invaluable and largely untapped source of information on governments' policy preferences and global involvement across a wide range of issues over time. Thus, statements made during the GD can roughly approximate the relevancy of African nations, but conflicts take center stage, dominating discourse rates.

Uniquely, the UNGD provides a platform for all member states to deliver addresses, including smaller nations otherwise unrepresented [16], with the intention of all speeches being to justify their stance on foreign policy and persuade other UN states to adopt positions similarly [29]. This updated corpus contains over 10,000 speeches from more than 193 countries, making it the most comprehensive collection of global political discourse. This corpus can facilitate further research on a range of issues in international relations – from looking at different influences on state preferences to understanding the spread of ideas and norms in international politics.

2.2. Feature Extraction

Before using the UNGDC, we first perform feature extraction to generate metrics for further statistical analysis. Firstly, we generate a number of characteristics describing each speech by segmenting the speech text according to stopwords provided by Python's Natural Language Toolkit [30]. Doing so, we characterize each speech according to its character count, word count, sentence count, average word length, and average sentence length.

After generating these summary statistics, we tokenize each piece of speech text. In the English language, words can be modified in a number of ways while preserving meaning. For example, the words "nation", "nations", and "national" all *stem* from a common linguistic concept though they have different spellings. In order to perform an accurate linguistic analysis of UNGDC speeches, multiple variations of a single word stem must be consolidated. To execute this, we use WordNet's [31] morphological processing capabilities to isolate the stems of each word, removing affixes and other lexicographic nuances.

3. COMPUTATIONAL EXPERIMENTS

After the data has been sufficiently pre-processed in the above manner, we conduct multiple computational experiments to address the discussion of African regions in the UN.

3.1. Frequency Analysis

We begin by aggregating the number of mentions for each word temporally segmented by year. Sorting words by total frequency across the temporal span of the dataset, we can compute the most common words used. The results in Figure 1 are quite intuitive, as the most popular words strongly relate to international relations and government structure. Cross-referencing these tokens with a database of countries from Python's pycountry package, we can compute the number of mentions over time for any given country.

From Figure 2, the most discussed countries are those heavily involved in international conflicts. Using a database of African regions and the nations which consist of them, we aggregate the net number of mentions for each region over time. From Figure 3, we see that nations in Eastern Africa seem to receive the most attention followed by Western, Northern, Southern, and Central Africa. Regions are segmented using the UN Geoscheme for Africa from the UN M49 [32]. Dependencies or overseas territories of European countries are excluded in this data, and the disputed territory of Western Sahara is included.

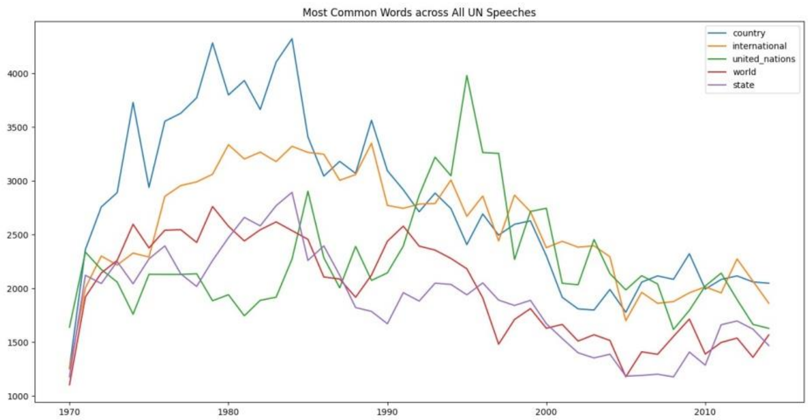


Figure 1. Most Mentioned Words in UNGDC Speeches

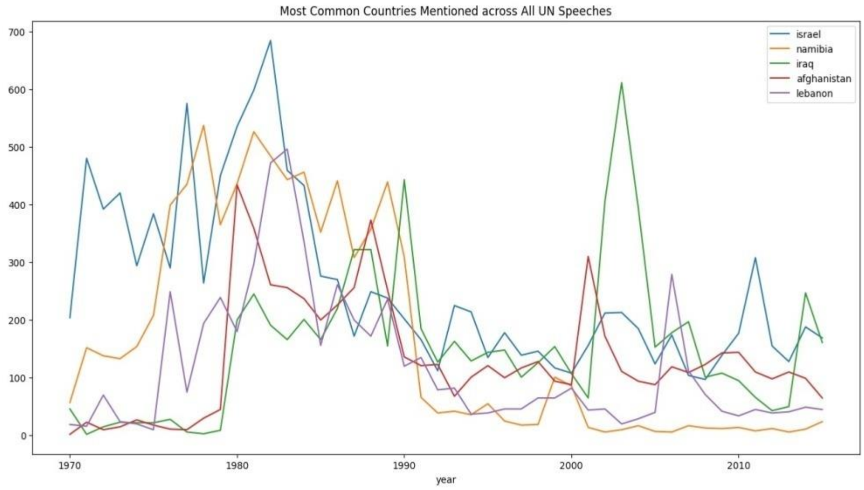


Figure. 2. Most Mentioned Countries in UNGDC Speeches

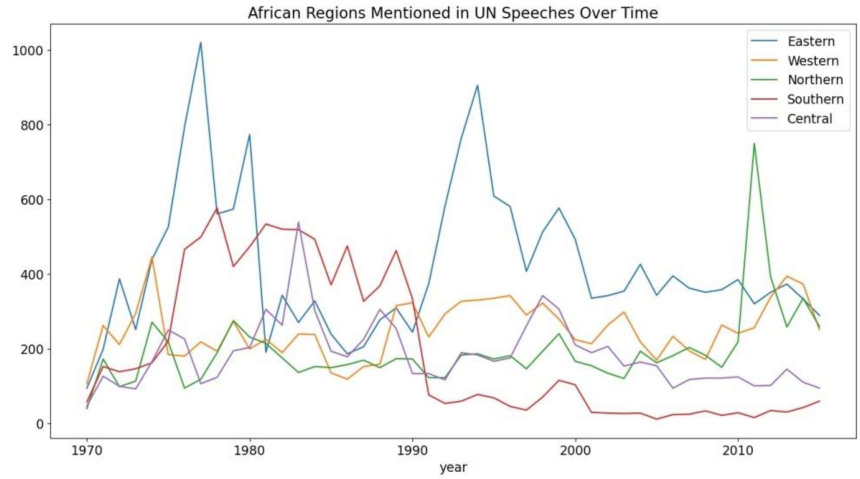


Figure. 3. Mentions of African Regions in UNGDC Speeches

3.2. Summary Statistics

We migrate the time series data from Figure 3 from Python to R for further analysis. We begin by transforming the time series data into a linear regression problem, viewing the quantitative response variable, the total Count of mentions, as a function of the quantitative explanatory variable Year and the categorical explanatory variable Region. Grouping this rearranged data by region, we compute summary statistics.

Table 1. Summary Statistics for African Region Mentions

Region	**min**	**Q1**	**median**	**Q3**	**max**	**sd**
Eastern	94	311.8	360.0	523	1021	195.3
Central	46	121.0	165.5	221	539	88.1
Northern	39	149.0	172.5	211	750	104.5
Southern	11	76.5	76.5	370	577	194.8
Western	106	195.2	240.0	297	446	73.9

From Table I, we see that the medians differ between each region, suggesting a potentially significant result.

3.3. Diagnosing Condition Violations

A priori, we propose and fit a multiple linear regression model with $n - 1 = 4$ indicator variables to account for the Region. From the Q-Q plot in Figure 4, the majority of the data adheres to normality, but there is concave curvature indicating a short tail on the right-hand side of the distribution. Further, we analyze the deviation in spread according to region.

$$Count = \beta_0 + \beta_1 \cdot Year + \sum_{k=1}^{4} \beta_{k+1} I_k \quad Count \approx +- 3315170. .152017 \cdot I - _W 1.453 \cdot Year - 237.652 \cdot I_C - 227.522 \cdot I_N - 228.022 \cdot I_S$$

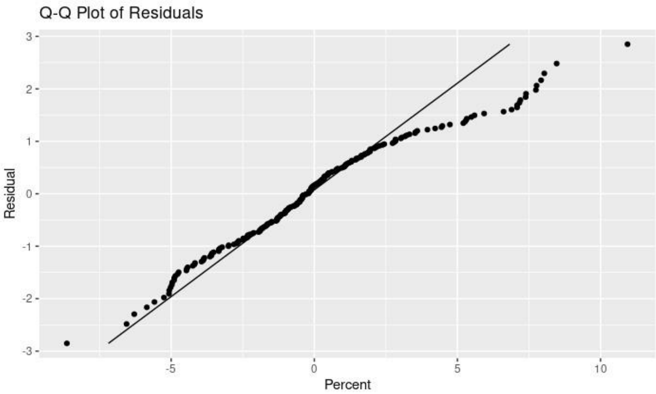


Fig. 4. Q-Q Plot for A Priori Model

From Table I, $\frac{max(\sigma_i)}{min(\sigma_i)} = \frac{195.3}{73.9} = 2.64 > 2$.

This violation of normality and equal spread is enough to consider a data transformation.

3.4. Power Transformation

Since our data is grouped by species, we construct a diagnostic plot for computing the ideal exponent for a power transformation using the regression: $log(\sigma) = \beta_0 + \beta_1 \cdot log(\mu)$.

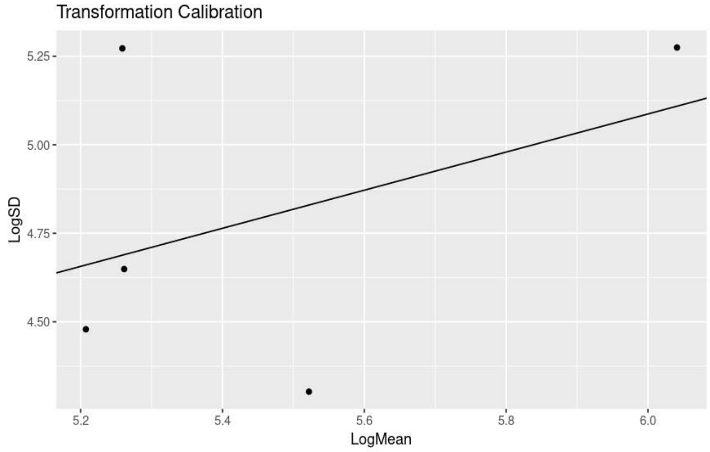


Fig. 5. Diagnostic Plot for Equalizing Spreads

Fitting this model, we find $\beta_1 = 0.538$, so we use the following transformation:

$$x \rightarrow f(x) = x^p = x^{1-\beta_1} = x^{0.462}$$

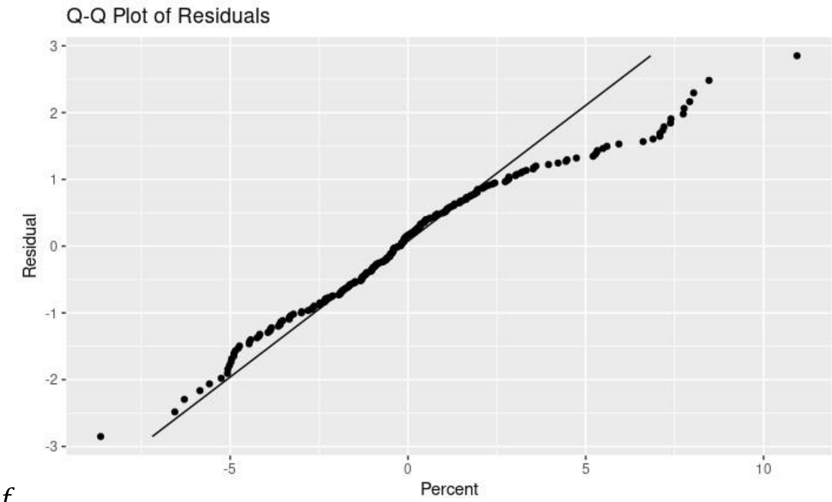
While this transformation is similar to, $\sqrt{x}$ we use this more accurate form in order to maximally adhere to normality.

3.5. Validating Conditions

Applying $f(x)$ to both $Count$and $Year$, we fit the following regression model.

$$f(Count) = \beta_0 + \beta_1 \cdot f(Year) + \sum_{k=1}^{4} \beta_{k+1} I_k$$

$$f(Count) \approx + 188.329 - 5.157 \cdot f(Year) - 5.086 \cdot I_C - 4.810 \cdot I_N - 6.082 \cdot I_S - 3.218 \cdot I_W$$



f

Fig. 6. Q-Q Plot for Transformed Model

From the Q-Q plot in Figure 6, we see that while the normality condition is not perfectly satisfied, the data adheres enough to satisfy the condition. From the residual plot in Figure 7, we see that the variance across regions is sufficiently similar for the equal variance condition and note that the residuals have zero mean.

Since the entire population of UNGDC debates is used, the randomized and independent conditions are independently satisfied. We also assume that the data is approximately linear. With these conditions met, we continue to a significance test.

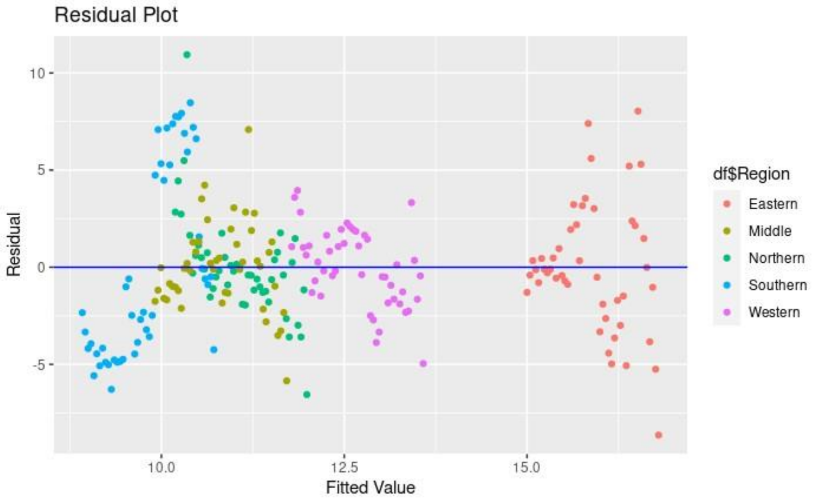


Fig. 7. Residual Plot for A Priori Model

$= 1.2 \times 10^{-12}$; $p_N = 1.4 \times 10^{-11}$; $p_S = 2 \times 10^{-16}$; $p_W = 3.4 \times 10$

p-values for each indicator are all significant.

3.6. Significance Testing

We t-test the indicator weights where $H_0 : \beta_i = 0$ and $H_a : \beta_i \neq 0$ for $2 \leq i \leq 5$.

p_{C-6}

These resulting

$$p_C, p_N, p_S, p_W < \alpha = 0.05$$

These indicator variable t-tests suggest that $\beta_i \neq 0$ for $2 \leq i \leq 5$, rejecting the null hypothesis and suggesting the validity of the alternate hypothesis. This is statistically significant evidence that the mean number of mentions after accounting for time is significantly pairwise different between all five African regions.

3.7. Complementary Correlation Analysis

Given that the conditions for multiple linear regression were not satisfied perfectly, we also analyze the Pearson correlation coefficient between each region. From Table II, most regions are weakly associated with one another. The most associated pair is Southern and Central Africa, and yet, even for this pair, $r = 0.466 < 0.5$ which is not large. This result further supports the conclusion from significance testing.

Table 2. Pairwise Pearson Correlation Between Regions

Region	*Eastern*	*Western*	*Northern*	*Southern*	*Central*
Eastern	1.000	0.228	-0.032	0.068	0.004
Western	0.228	1.000	0.293	-0.344	-0.043
Northern	-0.032	0.293	1.000	-0.176	-0.138
Southern	0.068	-0.344	-0.176	1.000	0.466
Central	0.004	-0.043	-0.138	0.466	1.000

4. RESULTS

Understanding the timing and method by which the UN acts during crises is key to understanding the effectiveness of UN solutions, such as peacekeeper deployments in Africa [33]. The UNGD is key to facilitating these understandings, as it has primarily served as a vehicle to formulate multilateral action and dialogue.

Table III demonstrates trends with UN discourse for all conflicts collected in our data. We select civil wars and conflicts that have lasted 3+ years (a shorter conflict will still be included if a UN peacekeeping action was taken), and compare the average mentions during the conflict with the average of the state(s) throughout its history.

Figure 8 demonstrates a spike in discourse regarding Chad during the Chad-Libyan war. Notably, the selected word matters, as “Chad” was a preferred term by UN delegates to refer to the “Chadian-Libyan War” overall. Although Table III finds discourse trends up during conflict, two general exceptions exist. First, some states have conflicts that dominate UN discussion, such as Libya, which has a high peak due to the Libyan Civil War that overshadows other conflicts involving Libya. This is best demonstrated through Figure 8, which shows that discourse for Libya remained low. Second, some conflicts did not last long enough or were not severe enough to attract discourse, such as Kenya and Uganda’s border conflict.

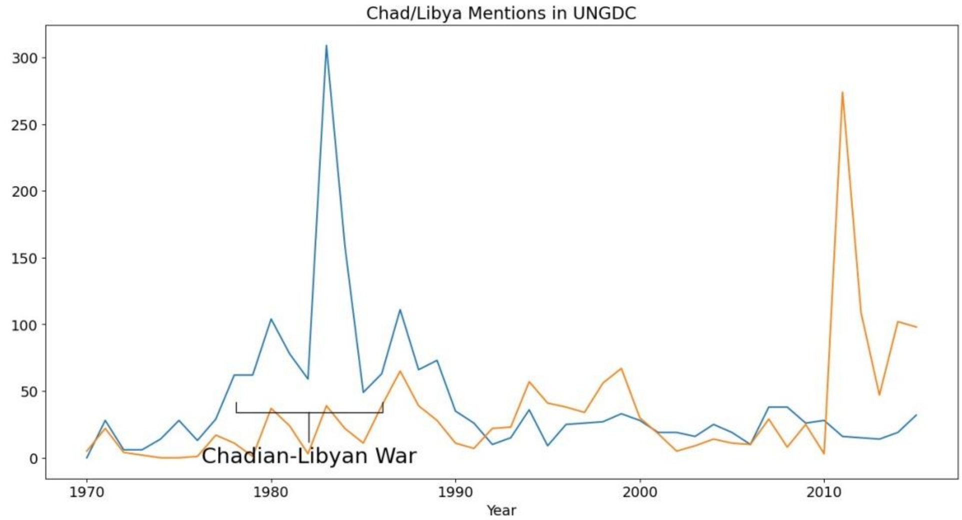


Fig. 8. Mentions of Chad during the Chad-Libyan War. Blue indicates any references to Chad, Orange indicates any references to Libya.

4.1. UN Peacekeeping Missions

The UN Charter authorizes the UN Security Council to take collective action to maintain international peace and security. This is carried out through UN peacekeepers and UN peacekeeping missions, the primary instrument by which the United Nations decides to intervene to preserve or create conditions for peace in hostile conflicts and environments. Although the UN primarily describes peacekeepers as vehicles to create conditions for lasting peace, various UN peacekeeping missions are dependent on the context of the mission and regional background; missions range from protecting demilitarized or arbitrated ceasefire borders and stabilizing nations post-conflict to preventative missions to ensure peaceful transitions or observe developing conditions on the ground.

In total, more than 1 million personnel including military, police, and civilians from 125 countries have served in 71 peacekeeping missions worldwide [34]. In Africa, the UN has authorized 29 total peacekeeping missions. Of these, 23 missions are complete, and 6 missions are currently ongoing. Of the 29 missions, we did not analyze the United Nations Operation in the Congo (ONUC), as the Congo Crisis (1960-1965) fell outside of the range of the UNGDC dataset.

The UN are good recordkeepers of quantitative counts of past peacekeeping operations. Data on UN PKOs sourced in Table III can be found at [35], but the depth of data differs between each mission; historic missions lack the same level of depth when having exact numbers for military or civilian forces provided by each participating country, for example, while still ongoing missions lack a final expenditure count as budgets are revised and annual expenditures often go below the allocated annual budgets.

Table 3. Discourse Surrounding Conflicts in Africa Including UN Intervention and PKO Statistics

State	Conflict	Period	Base Rate	Conflict Rate	% Chg. of Rate	UN Action	Budget (USD)	Military Strength	Civilian Strength
NAM	Namibian War for Independence	1966-1990	169.4	**339.5**	**100.5**	UNTAG(1989-1990)	368.6mil	6993/7500	00, 00 ring ction
ETH	Ethiopian Civil War	1974-1991	28.2	**28.4**	**0.71**	The UN did not intervene with PKO(s) in this conflict.			
AGO	Angolan Civil War	1975-2002	79.1	**109.5**	**38.43**	UNAVEMI(1989-1991) UNAVEMII(1991-1995) UNAVEMIII(1995-1997) MONUA(1997-1999)	16.4mil 175.2mil 752.2mil 293.7mil	70 304 4220 3568	0 ~365 Unknown Unknown
ESH	Western Sahara War	1975-1991	45.0	**70.9**	57.4	MINURSO(1991–)[1]	Ongoing	202	226
MOZ	Mozambican Civil War	1977-1992	41.1	**43.9**	**6.81**	ONUMOZ(1992-1994)	492.6mil	5063	861, ~1561 during election
SOM	Ethio-Somali War	1977-1978	59.4	44.5	-25.08	The UN did not intervene with PKO(s) in this conflict.			
UGA	Uganda-Tanzania War	1978-1979	22.5	18.5	-17.78	The UN did not intervene with PKO(s) in this conflict.			
TCD	Chadian-Libyan Conflict	1978-1987	41.8	**105.6**	**152.6**	UNASOG(1993-1995)[2]	64,471	9	6
ERI	Second Eritrean Civil War	1980-1981	14.4	1.5	-89.6	The UN did not intervene with PKO(s) in this conflict.			
UGA	Ugandan Bush War	1980-1986	22.5	15.1	-32.88	The UN did not intervene with PKO(s) in this conflict.			
SDN	2nd Sudanese Civil War	1983-2005	50.5	43.7	-13.47	The UN did not intervene with PKO(s) in this conflict.			
LBR	First Liberian Civil War	1989-1997	36.0	**86.2**	**139.4**	UNOMIL(1993-1997)	103.7mil	368	284
RWA	Rwandan Civil War	1990-1994	37.7	**112.4**	**198.14**	UNOMUR(1993-1994) UNAMIR(1993-1996)	2.3mil 453.9mil	81 2548	Unknown Unknown
NER	Tuareg Rebellion	1990-1995	15.9	**24.0**	**50.94**	The UN did not intervene with PKO(s) in this conflict.			

[1] The United Nations Mission for the Referendum in Western Sahara (MINURSO) is the longest ongoing PKO. Figures are from December 2019.

[2] The United Nations Aouzou Strip Observer Group (UNASOG) was resolved the dispute between Chad and Libya over the Aouzou Strip after decades of fighting.

State	Conflict	Period	Base Rate	Conflict Rate	% Chg. of Rate	UN Action	Budget (USD)	Military Strength	Civilian Strength
DJI	Djiboutian Civil War	1991-1994	11.7	10.2	-0.1282	The UN did not intervene with PKO(s) in this conflict.			
SIL	Sierra Leone Civil War	1991-2002	24.7	**51.9**	**110.1**	UNOMSIL(1998-1999) UNAMSIL(1999-2005)	12.4mil 2.8bn	209/245 max 17455/17500 max	~176 max 874 max
DZA	Algerian Civil War	1991-2002	18.7	16.7	-10.7	The UN did not intervene with PKO(s) in this conflict.			
SOM	Somali Civil War	1991–	59.4	**96.2**	**62.0**	UNOSOMI(1992-1993) UNOSOMII(1993-1995)	42.9mil 1.6bn	947/4269 max 28000 max	Unknown max ~2800 max
BDI	Burundian Civil War	1993-2005	35.3	**64.2**	**81.87**	ONUB(2004-2006)	678.3mil	5,665/5650 max	885/1170 max
NAM	Caprivi Conflict	1994-1999	169.4	42.3	-75.0%	The UN did not intervene with PKO(s) in this conflict.			
COD	1st Congo War	1996-1997	38.3	**107.2**	**179.9**	The UN did not intervene with PKO(s) in this conflict.			
COD	2nd Congo War	1998-2003	38.3	**112.0**	**192.4**	MONUC(1999-2010)	8.73bn	20586/22016 max	4397, no max
ERI	Eritrean-Ethiopian War	1998-2000	14.4	**73.0**	**406.9**	UNMEE(2000-2008)	1.32bn	4154	473
LBR	2nd Liberian Civil War	1999-2003	36.0	**58.8**	**63.33**	The UN did not intervene with PKO(s) in this conflict.			
CIV	1st Ivorian Civil War	2002-2007	Requires collocations in NLTK, disrupting format			MINUCI(2003-2004) UNOCI(2004-2017)	29.9mil 153.0mil	75/76	109, “small” max
SUD	War in Darfur	2003-2020	50.5	**108.7**	**115.2**	The UN did not intervene with PKO(s) in this conflict.			
CAF	Central African Republic Bush War	2004-2007	Requires collocations in NLTK, disrupting format			MINURCAT(2007-2010)[3]	1.39bn	3814/5525	1089, “as approp.”
COD	Kivu Conflict	2004–	38.3	**63.3**	**65.4**	MONUC(1999-2010) MONUSCO(2010–)[4]	Ongoing	14475/16316 max	3278, “as approp.
TCD	Chadian Civil War	2005-2010	41.8	26.5	-36.6	MINURCAT(2007-2010)[2]	1.39bn	3814/5525	1089, “as approp.”
CIV	2nd Ivorian Civil War	2010-2011	Requires collocations in NLTK, disrupting format			UNOCI(2004-2017)	Ongoing		

[3] The United Nations Mission in the Central African Republic and Chad (MINURCAT) operated simultaneously in both regions.

[4] Figures for military strength are from February 2023, and civilian strength is from May 2018

State	Conflict	Period	Base Rate	Conflict Rate	% Chg. of Rate	UN Action	Budget (USD)	Military Strength	Civilian Strength
LBY	Post-Civil War Violence	2011-2014	33.0	**133.0**	303.0	The UN did not intervene with PKO(s) in this conflict.			
SDN	Sudan-South Sudan Border War	2012-2012	50.5	**162.0**	**220.8**	UNISFA(2011–)[2]	Ongoing	3786, 3890 max	232, "as approp."
CAF	Central African Republic Civil War	2012–	Requires collocations in NLTK, disrupting format			MINUSCA(2014–)[3]	Ongoing	16363	1662
MLI	Mali War	2012–	22.5	**107.8**	**379.1**	MINUSMA(2013–2023)[4]	Ongoing	12193/15209 max	3586, "as approp."
SSD	South Sudanese Civil War	2013-2020	50.5	**88.0**	74.26	UNMIS(2005-2011)[5]UNMISS(2011–)[6]	5.76bn	10352/10519 max 15078/19101 max	4099/4280 max 2876, "as approp."
LBY	2nd Libyan Civil War	2014-2020	33.0	**100.0**	203.0	The UN did not intervene with PKO(s) in this conflict.			

UN data is historically well kept, especially with recent operations that include tallies of forces each year and even including a breakdown of which countries provide forces and how many. In some cases, we made exceptions based on the conditions of the data. In cases where there was a temporary increase in civilian strength for operations including overseeing elections, we included the temporary civilian personnel and indicated as such under Civilian Strength. Old operations where civilian strength is reported 'unknown' on the UN report are left out of regressions. Other operations only had approximate counts accurate to the hundreds, which we entered assuming the numbers were correct.

Notable exceptions to the observed trends are the UNASOG, which had a historically low expenditure of $64,471 in total supporting 9 armed and 6 civilian staffers. Another is Namibia, which up until its independence in 1990, dominated discussion in the United Nations. Namibia's War for Independence had been going on and off since it became a League of Nations mandate overseen by South Africa following World War I. Discourse over Namibia reached upwards of a

[2] Figures are from December 2019

[3] Figures are from February 2023

[4] The United Nations Multidimensional Integrated Stabilization Mission in Mali (MINUSMA) is coming to an end in July 2023.

[5] The UN Mission in the Sudan (UNMIS) took place before the South Sudanese Civil War, and was the peacekeeping force sent to ensure the peaceful creation of South Sudan. This was then followed with the UN Mission in South Sudan (UNMISS), which operated during the South Sudanese Civil War.

rate of 580 at its peak over a two-decade span, making it the second-most mentioned country in the UN just below Israel. This is an example of when one conflict significantly undercuts a later one, in this case, the Caprivi Conflict.

4.2. An Interpretable Machine Learning Model for Intervention Recommendation

Given the clear correlation in Table III between the percent increase in yearly UN corpus mentions of a particular country and the presence of an active military conflict within the country, we create an interpretable framework for UN officials to leverage the presented analysis of their rhetoric to suggest data-driven intervention recommendations. In particular, we present a two-pronged approach that not only categorizes on-going conflicts according to the UN's existing conflict classification system but also forecasts the required bulk budget, strength of deployed military troops, and strength of civilian personnel to address the conflict in accordance with the UN's behavior historically.

To optimize the interpretability of our framework, we utilize a decision tree with a fixed maximal depth d, there are at 2 most +1 = 17 + b + b^2 + ⋯ + 2 2 b^d = 4 b d b + − 1 − 1 1 nodes. Thus, for b our maximal depth of two and a branching factor of two. For, any tree with branching factor and decision tree, there are at most 3 nodes, at most of which are leaf nodes. This significantly bounds the number 2 − of 1 nodes in the tree to an extent that any user, such as a government official, can manually interpret the nodes and employ their own decision making.

Our framework uses the discourse of a given country to calculate the Base Rate and Conflict Rate:

1. *Base Rate:* The mean number of annual mentions across the temporal span of the UNGDC database.
2. *Conflict Rate*: The mean number of annual mentions within the target time period of active conflict. We alternatively coin this the *active rate*.

Both rates are helpful, as beyond just the percent change as calculated in Table III, the Base Rate and Conflict Rate provide context into the overall count of how many times a country is mentioned, providing context that helps the decision tree make the right classification.

4.2.1. A Decision Tree Classifier for Intervention Classification

The most important classification to determine is whether the UN decides to intervene based on the knowledge that we have about discourse rates. After we classify a binary yes/no in terms of UN intervention, we then classify the *type* of UN intervention based on Fortna's four classifications of Peacekeeping Operations [36]:

1. Observation Missions, which are small contingents of usually unarmed military/civilian observers that monitor ceasefire agreements and conditions, observing and reporting on conditions to the UN. UNAVEM II in Angola is one example.
2. Interpositional Missions, which are traditional peacekeeping operations where large contingents of armed military forces serve as a buffer after two sides in a conflict. UNAVEM III in Angola is one example.
3. Multidimensional Missions, which are large operations carried out by military and police personnel that engage in various tasks outside of the historical understanding of PKOs, including supervising elections, building institutions, developing economies, and overseeing human rights reports. ONUMOZ in Mozambique is one example.

4. Peace Enforcement Missions are substantively different from the three prior missions. Each of these missions invoke Chapter VII of the UN Charter, allowing PKOs to operate in the region without the consent of either side. The prior three classifications, which invoke Chapter VI, depend on the consent of factions on either side to operate, which has led to some to be preemptively canceled when consent is revoked. These missions are authorized to use force beyond self-defense and take an active role in enforcing peace and protecting civilians. UNAMSIL in Sierra Leone is one example.

This is key to understanding UN interventions, as actions differ based on the classification.

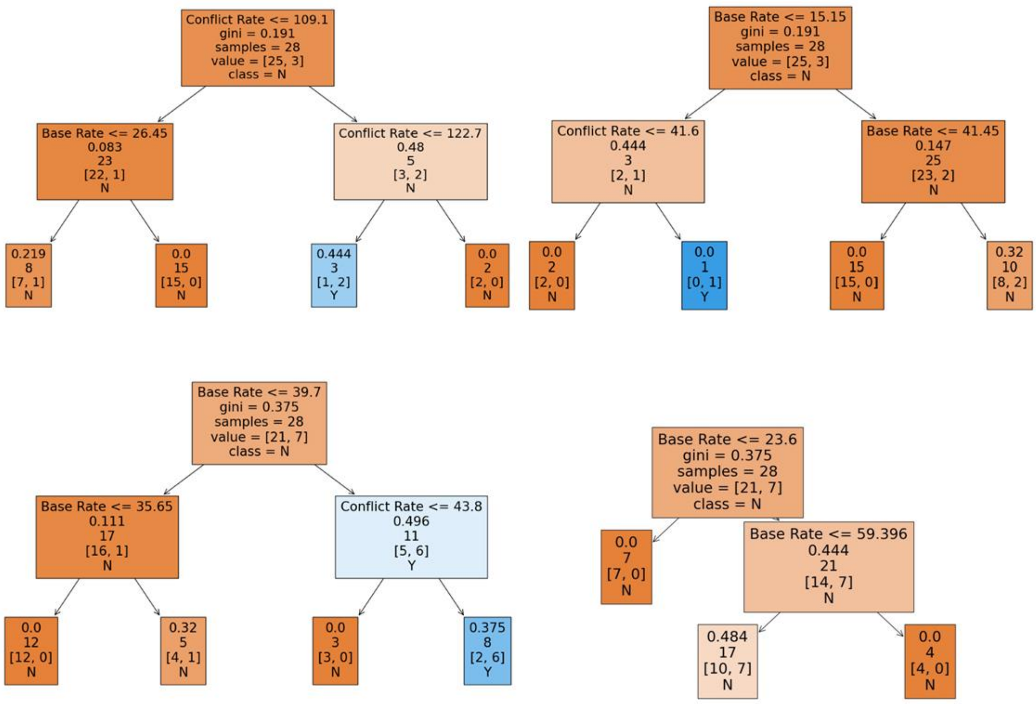


Fig. 9. Decision trees for all four indicator variables, in the order: OBS, INT, MUL, ENF/VII.

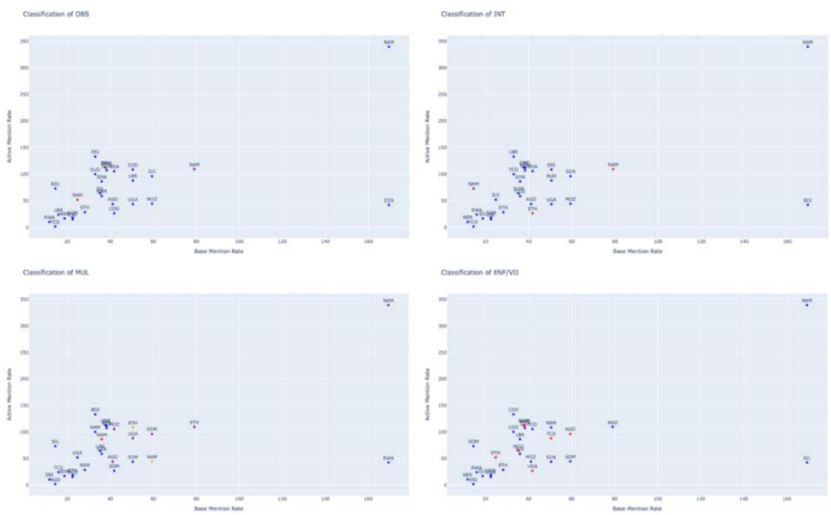


Fig. 10. Decision tree classification for intervention types, in the same order as Figure 9.

Blue is N/N, **Red** is N/Y, **Orange** is Y/N, and **Purple** is Y/Y for Truth/Predicted Intervention.
We introduce four binary indicator variables (OBS, INT, MUL, ENF/VII) corresponding to whether the UN has authorized an observation, interpositional, multidimensional, or enforcement PKO. We proceed to fit our decision tree using Gini impurity [37] as our splitting criterion, resulting in the following models shown in Figure 9 yielding the respective classifications shown in Figure 10. The classification accuracies of each decision tree are: OBS: 92.9% | INT: 92.9% | MUL: 89.3% | ENF: 75%

Given the high classification accuracy from the shallow tree, any UN official can predict the classification type to at least 75% accuracy within two questions regarding the base and conflict mention rate of a particular country.

4.2.2. A Regression for Quantitative Intervention Factors

Once an intervention is classified, we explore if discourse serves as a determining factor to see the overall expenditure, military strength, and civilian strength of a mission. These correlate heavily with the type of intervention; for example, an observer mission will have low-forces and subsequently low expenditures, while an enforcement mission will have expenditures in the billions and a large active military force with a similarly large civilian supplement. We study the following three quantitative metrics of a UN response:

1. The total expenditure of a PKO
2. The maximum military strength of a PKO throughout the mission
3. The maximum civilian strength of a PKO throughout the mission

Numbers like the expenditure and maximum strengths are useful quantifiable metrics of the size and scope of a UN intervention. Helpfully, the UN provides total expenditure and maximum strength of military and civilian forces for almost every prior PKO, but more expansive statistics such as the contribution of forces from each participating country is limited to more recent conflicts with better data and recordkeeping. Additional data, such as the difference between armed police, civilian police, and military officers are recorded for many, but are still not present in most PKOs. Thus, these three metrics serve as useful baselines which can explore the evolution and types of PKOs throughout the past 50 years.

We use mean squared error as our splitting criterion, and do not perform minimal cost-complexity pruning [37] given that the number of analyzed countries is within reason. Fitting our regression model on the historical PKO and UNGDC data detailed in Table III, we obtain the following regression predictions:

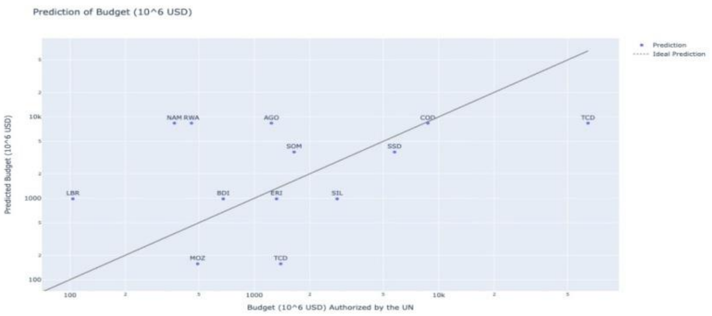


Fig. 11. Regression predictions for total mission expenditure (in millions USD).

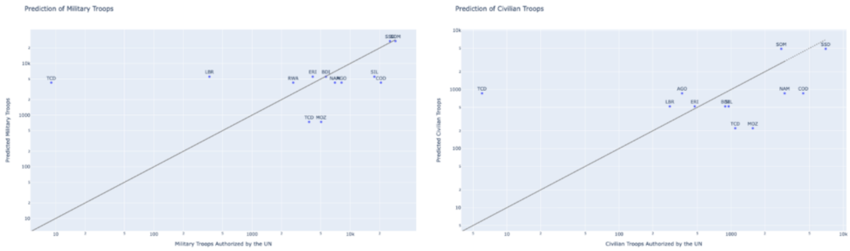


Fig. 12. Regression predictions for maximum military/civilian strength.

As with classification, with a shallow tree of depth 2, this approach is able to reasonably recommend the maximum military/civilian strength that the UN should authorize given the base and conflict rate of a given country during a conflict. The United Nations Aouzou Strip Observer Group (UNASOG) is a notable outlier; the regression correctly predicts a much higher estimated force count in the thousands, but there were only 9 military troops and 6 civilian forces deployed. Other cases lie much closer to the regression, with a maximum deviation of approximately 2,000 in extreme cases.

5. CONCLUSION

While this work uses a representative span of UN discourse via the UNGDC, our framework provides an end-to-end solution for transforming discourse during an on-going conflict into actionable intervention recommendations and classifications using natural language processing and interpretable machine learning. After computational experimentation and statistical testing, we show to significance that the timeseries of mentions for African regions varies region to region based on the time period's conflict landscape, suggesting that regions with differing mention dynamics may require differing intervention strategies. We identify multiple wars where discourse in the UNGD prerequisites intervention of UN actors and peacekeeping forces, especially in conflicts that lasted more than three years and with significant violence. In general, higher UN discourse in a particular conflict is correlated with the magnitude of the UN's crisis resolution response, and we aim to rigorously explore various response mechanisms in future work.

This correlation allows us to develop a framework which validates that, presented with any given conflict, a decision tree is accurate in predicting the classification of a Chapter VI UN Charter mission (observation, interpositional, and multidimensional) with a ~91.7% accuracy. Our decision tree to predict a Chapter VII UN Charter Mission (enforcement) is less accurate at 75%, indicating the difficulties of predicting when the UN decides to authorize use of force beyond self-defense in PKOs, which is understandable given the qualitative nuances required to authorize force in any given PKO. With these accuracies, we conclude that shallow decision trees are an effective, accurate, and interpretable method to use base and conflict discourse rates to not only determine not only if the UN will intervene, but also the type of a forecasted intervention. This is incredibly important to create qualitative analysis of UN effectiveness and forecast when and what types of aid will be provided by the UN during the conflict.

An important benefit of validating decision trees as an accurate predictor is that while alternative machine learning methods such as deep neural networks may achieve higher accuracies, shallow decision trees do not black box decision making from the policy maker. A fitted depth-two decision tree, such as our proposed classifier, reduces the intervention categorization problem to an interpretable two-step question-and-answer process that provides accurate conclusions; in practice, computational diplomacy must be actionable by policymakers.

5.1. Future Work

Given the large amount of time series data being used, techniques such as multiple linear regression and Pearson correlation can not detect complex temporal correlations. Even if two random temporal variables are not directly correlated, there may be time-lagged cross-correlation during which changes in one variable correlate with the other after some amount of delay. Similarly, variables may temporally react in a non-Euclidean way detected by more advanced techniques such as dynamic time warping and instantaneous phase synchrony. Measuring autocovariance could also inform the prediction of long-term mention growth trends.

Given the breadth of the UNGDC dataset, we aim to expand our experiments to consider international relations, forecast economic growth, and network relations between countries. Other combinations of statistical analysis, NLP, and ML for speech analysis could be invaluable for computational approaches to diplomacy for other areas the UNGDC covers such as the UN's Sustainable Development Goals.

To augment our recommendation framework, we aim to include other modes of data, including other text sources such as social media feeds from UN ambassadors on the UNSC and conventional media reporting on conflicts for more accurate and informed recommendations for modern PKOs. We believe that integrating other sources of data can create a novel quantitative algorithm and process to forecast and predict future conflicts alongside effective responses from UN PKOs alongside qualitative analysis.

Beyond the decision trees we created, we hope to use modern time-series classifications techniques that can provide UN intervention recommendations as a foreign conflict progresses across multiple years and perhaps finer-grained temporal resolutions; this is especially helpful to classify between interventions that often happen when a conflict concludes and other intervention types that happen during a conflict. Furthermore, we believe that modern time-series classifications can allow us to segment the interventions for countries such as Angola which had different interventions at different times, helping us gain a more nuanced understanding of each individual conflict for review.

6. Availability of Data and Material

Our work uses Python, R, and associated packages to analyze the open-source UNGDC dataset. Please contact authors for access to the implementation.

Acknowledgements

We would like to thank Professor Catherine Scott at the University of North Carolina Chapel Hill for her guidance.

References

[1] F. Lewis, "Human Rights Abuses in U.N. Peacekeeping: Providing Redress and Punishment while Continuing Peacekeeping Missions for Humanitarian Progress," *Southern California Interdisciplinary Law Journal*, vol. 23, no. 3, pp. 595-626, Spring 2014.

[2] K. J. Campbell, "Clausewitz and genocide: Bosnia, Rwanda and strategic failure," *Civil Wars*, vol. 1, no. 2, pp. 26–37, 1998. doi:10.1080/13698249808402372

[3] D. Silander, "The United Nations and Peace Building: Lessons from the UN Transitional Administrations in East Timor and Kosovo," *Social Alternatives*, vol. 28, no. 2, pp. 23-28, 2009. Available: https://search.informit.org/doi/10.3316/ielapa.201000290.

[4] C. Mudgway, "Sexual exploitation by UN peacekeepers: the 'survival sex' gap in international human rights law," *The International Journal of Human Rights*, vol. 21, no. 9, pp. 1453-1476, 2017. https://doi.org/10.1080/13642987.2017.1348720

[5] H. Hegre, L. Hultman, and H. M. Nygård, "Evaluating the Conflict-Reducing Effect of UN Peacekeeping Operations," *The Journal of Politics*, vol. 81, no. 1, pp. 215-232, 2019. Available: https://doi.org/10.1086/700203

[6] L. M. Howard, *Power in Peacekeeping*. Cambridge, U.K.: Cambridge University Press, 2019.

[7] D. Pushkina, M. B. Siewert, and S. Wolff, "Mission (im)possible? UN military peacekeeping operations in civil wars," *European Journal of International Relations*, vol. 28, no. 1, pp. 158-186, 2022. Available: https://doi.org/10.1177/13540661211046602

[8] W. Kim and T. Sandler, "Non-UN Peacekeeping Effectiveness: Further Analysis," *Defence and Peace Economics*, vol. 33, no. 5, pp. 511-533, 2022. Available: https://doi.org/10.1080/10242694.2021.1882280

[9] C. Bara and L. Hultman, "Just Different Hats? Comparing UN and Non-UN Peacekeeping," International Peacekeeping, vol. 27, no. 3, pp. 341-368, 2020. Available: https://doi.org/10.1080/13533312.2020.1737023

[10] M. Lundgren, "Which type of international organizations can settle civil wars?," *Rev. Int. Organ.*, vol. 12, pp. 613–641, 2017. Available: https://doi.org/10.1007/s11558-016-9253-0

[11] N. Sambanis, "Short- and Long-Term Effects of United Nations Peace Operations," The World Bank Economic Review, vol. 22, no. 1, pp. 9–32, 2008. Available: https://doi.org/10.1093/wber/lhm022

[12] R. A. Blair, "UN Peacekeeping and the Rule of Law," Am. Polit. Sci. Rev., vol. 115, no. 1, pp. 51–68, Feb. 2021, doi: 10.1017/S0003055420000738. Available: https://doi.org/10.1017/S0003055420000738.

[13] M. J. Connelly, R. Hicks, R. Jervis, A. Spirling, and C. H. Suong, "Diplomatic documents data for international relations: the Freedom of Information Archive Database," *Conflict Management and Peace Science*, vol. 38, pp. 762–781, Nov. 2021. Publisher: SAGE Publications Ltd.

[14] B. O'Connor, B. M. Stewart, and N. A. Smith, "Learning to Extract International Relations from Political Context," in *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, (Sofia, Bulgaria), pp. 1094–1104, Association for Computational Linguistics, Aug. 2013.

[15] S. Kreps, "Social Media and International Relations," *Elements in International Relations*, July 2020. ISBN: 9781108920377 9781108826815 Publisher: Cambridge University Press.

[16] A. Baturo, N. Dasandi, and S. J. Mikhaylov, "Understanding state preferences with text as data: Introducing the UN General Debate corpus," *Research & Politics*, vol. 4, p. 2053168017712821, Apr. 2017. Publisher: SAGE Publications Ltd.

[17] C. B. Smith, *Politics and Process at the United Nations: The Global Dance.*, vol. 44. 2006.

[18] S. Khan, F. Ahmed, and M. Mubeen, "A Text-Mining Research Based on LDA Topic Modelling: A Corpus-Based Analysis of Pakistan's UN Assembly Speeches (1970–2018)," *International Journal of Humanities and Arts Computing*, vol. 16, pp. 214–229, Oct. 2022. Publisher: Edinburgh University Press.

[19] A. Sultan, A. Afsar, and M. A. Lashari, "Nawaz Sharif's Speeches to the United Nations General Assembly: A Corpus-Based Analysis," June 2019.

[20] M. O. Hosli and J. Kantorowicz, "The European Union in the United Nations: An Analysis of General Assembly Debates," 2022.

[21] L. Shen, "Culture and Explicitness of Persuasion: Linguistic Evidence From a 51-Year Corpus-Based Cross-Cultural Comparison of the United Nations General Debate Speeches Across 55 Countries (1970-2020)," *Cross-Cultural Research*, vol. 57, pp. 166–192, Apr. 2023. Publisher: SAGE Publications Inc.

[22] K. A. N. Al-Anbar, *The representations of Islam and Muslims at the United Nations General Assembly 2013-2016: a corpus-assisted critical discourse analysis*. phd, University of Southampton, Nov. 2018.

[23] L. McEntee-Atalianis and R. Vessey, “Using corpus linguistics to investigate agency and benign neglect in organisational language policy and planning: the United Nations as a case study,” *Journal of Multilingual and Multicultural Development*, vol. 0, pp. 1–16, Feb. 2021. Publisher: Routledge eprint: https://doi.org/10.1080/01434632.2021.1890753.

[24] N. Brun-Mercer, “Women and men in the United Nations: A corpus analysis of General Debate addresses,” *Discourse & Society*, vol. 32, pp. 443–462, July 2021. Publisher: SAGE Publications Ltd.

[25] L. McEntee-Atalianis and R. Vessey, “Mapping the language ideologies of organisational members: a corpus linguistic investigation of the United Nations’ General Debates (1970–2016),” *Language Policy*, vol. 19, pp. 549–573, Nov. 2020.

[26] P. J. Kohlenberg, N. Godehardt, S. Aris, F. S ̈undermann, A. Snetkov, and J. Fall, “Introducing UNSCdeb8 (beta): A Database for Corpus-Driven Research on the United Nations Security Council,” *SWP Working Paper: Research Division Asia*, p. WP 01, June 2019. Accepted: 202209-30T13:04:03Z Publisher: Stiftung Wissenschaft und Politik (SWP), Deutsches Institut f ̈ur Internationale Politik und Sicherheit.

[27] C. Pomeroy, “spaceTexts: A new corpus of speeches in the UN committee on the peaceful uses of outer space,” in *2017 International Conference on the Frontiers and Advances in Data Science (FADS)*, pp. 41–46, Oct. 2017.

[28] M. Schoenfeld, S. Eckhard, R. Patz, and H. van Meegdenburg, “Discursive Landscapes and Unsupervised Topic Modeling in IR: A Validation of Text-As-Data Approaches through a New Corpus of UN Security Council Speeches on Afghanistan,” Oct. 2018. arXiv:1810.05572 [cs].

[29] N. Dasandi, S. Jankin, and A. Baturo, “Words to Unite Nations: The Complete UN General Debate Corpus, 1946-Present,” May 2023. Publisher: Open Science Framework.

[30] S. Bird, E. Klein, and E. Loper, *Natural language processing with Python: analyzing text with the natural language toolkit.* ”O’Reilly Media, Inc.”, 2009.

[31] Princeton University, “About WordNet,” 2010.

[32] United Nations Contributors, “Un M49: Standard Country or Area Codes for Statistical Use.,” Dec 2021.

[33] A. Ruggeri, T.-I. Gizelis, and H. Dorussen, “Managing Mistrust: An Analysis of Cooperation with UN Peacekeeping in Africa,” *Journal of Conflict Resolution*, vol. 57, no. 3, pp. 387–409, 2013

[34] Better World Campaign, "UN Peacekeeping," Better World Campaign, 2023. [Online]. Available: https://betterworldcampaign.org/un-peacekeeping

[35] United Nations Peacekeeping, "Past peacekeeping operations," United Nations. [Online]. Available: https://peacekeeping.un.org/en/past-peacekeeping-operations.

[36] P. Fortna, *Does Peacekeeping Work?: Shaping Belligerents’ Choices after Civil War.* Princeton, NJ, USA: Princeton University Press, 2008, ch. 7.

[37] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, *Classification and Regression Trees.* Belmont, CA, USA: Wadsworth, 1984.