State Preferences for Political Agendas and Policy Position Proximity: A Computational Content Analysis Project on the United Nations General Debate Corpus*

Luxin Tian, Heather Chen

MA Program in Computational Social Science

The University of Chicago

Abstract

Quantitative revelations of political agents' preferences are of substantial interest in the field of political science. In this project, we employ computational methods to perform a content analysis of the United Nations General Debate Corpus (UNGDC). We infer state preferences for political agendas through features embedded in text data and topic modeling, and we examine policy position proximity between states based on our measurement. We embed the documented statements delivered by countries into a semantic space and infer state blocs based on their policy positions represented by document vectors. We also present the topics that the states are concerned about over the past half-century and investigate international relations in terms of common concerns. Finaly, we evaluate the validity and reliability of our methods and results.

Keywords: natural language processing, international relations, united nations

1. Introduction

There has been a growing interest in quantitatively measuring preferences of political agents in the field of political science. While qualitative approaches through case studies or historical analyses have been canonical in this field for centuries, quantitative measurement provides a more comprehensive and systematic framework in which the characteristics and dynamics revealed by actions of political agents can be identified, tracked, and analyzed. In the digital age, actions of political agents, such as parties, governments, and international organizations, can be traced in miscellaneous forms, and the development of data mining techniques and the computation capability unlocks new possibilities for researchers to reveal preferences of political agents through documented actions.

In this project, we perform an exploratory computational content analysis on the United Nations General Debate Corpus (UNGDC) to extract insights into state preferences for political

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agendas and positions from documented speeches. The UNGDC, which has been introduced and maintained by Baturo et al. (2017) and Jankin Mikhaylov et al. (2017), currently consists of 8093 statements made by state governments or heads of state at the annual General Debate of the United Nations General Assembly from 1970 to 2018. All the statements have been processed and converted to text files and organized by countries and sessions. Incorporating several prevailing techniques in Natual Language Processing, we make inference about international politics on two dimensions. First, we investigate the preferences for political agendas of international political agents, or, more specifically, the variation and dynamics of states' emphasis on certain topics of their concerns. Second, we extract position information of each state from the statements and quantify the dynamic similarities between sates in political position space. As we will show in section 4, benefited from the inclusiveness and completeness of the UNGDC corpus, we can examine several aspects of contemporary international politics from a comprehensive perspective. Most of our data processing and computational analysis work is performed in Python.

As is argued by Baturo et al. (2017), using the General Debate statements data has several favorable properties than using voting records or military allies for comparative political analysis. For one thing, the lack of military allies for some states and the limited number of issues that are voted on in international conferences make such indicators incomplete and biased for measuring political preferences. In contrast, the General Debate provides all the member states of the United Nations an equal opportunity to address their positions on issues of their concerns to the international society. For another thing, due to loose institutional connection to the decision-making process, the General Debate statements are less constrained by external pressures from other states than voting actions are so that the contents would reflect more about the real interests and positions of states. These features make it more reliable and comprehensive to use the UNGDC for revealing and measuring political preferences than using military alliances or voting records as proxy indicators.

In light of the advantages of the UNGDC, we assume through the whole analysis that the UNGDC is complete and unbiased for revealing political preferences and ideologies in a way that it contains semantically meaningful sentences that address political positions and concerns. This assumption may not be completely true. First, as we will show, the lengths of statements become more and more limited as the number of participating states increases over the years. As a result, since states may have priorities on elaborating certain issues over others, the compressed content may not represent the complete ideologies on all issues, and the distribution of emphasis on each topic can also vary across states and sessions. Second, the states may still face external pressures from other states when delivering the statements even though the opportunity is institutionally equal for all member states. This can result that the semantic meaning of one state's expressions is not independent but correlated to other states. If it is the case, the robustness and reliability of our inference would be contaminated. However, for the reasons mentioned above, we argue that the UNGDC still outperforms many other data sources for empirical analysis of state political preferences, and we will address potential drawbacks and our reflections of this research in sections 5 of this report.

In section 3, we review the computational methods that we employed in this project and evaluate the fitness of each method to our research question. For some of the methods, we also introduce our implementation of the algorithms and evaluate the computational performance of the program.

In section 4, we present our findings and relate some of the results to historical events and contexts. Finally, in section 5, we assess the reliability and validity of our analysis, clarify potential drawbacks, and propose future extensions of our research.

2. Data

The United Nations General Debate Corpus (UNGDC) has been published and maintained by Jankin Mikhaylov et al. (2017). The latest update of the corpus consists of 8093 statements delivered by 200 states on the annual sessions of the United Nations General Assembly from 1970 to 2018. The comprehensive historical miscellaneous data for each session, based on which this corpus was built, is published on the website of the General Assembly of the United Nations in the forms of full-text `.pdf` documents, audio, video, and summary text in all the six official working languages. The UNGDC incorporates all the English version documents that record the statements made by state leaders or government representatives. Each document has been converted to a `.txt` file and categorized and labeled by an alpha-3 country code (ISO 3166), the session number, and the year.

The number of states that deliver the statements on each session varies across years, but overall it has been gradually increasing from 71 in 1970 to 200 in 2018. We identify these changes and include a table showing the change of participating states for each year in the appendix.

We preprocess the corpus by tokenizing the words in each document into lists of tokens, normalizing the tokens, removing digits, punctuations, non-Latin characters, and English stop words, and then lemmatizing. For some of the modeling procedures that we introduce in the next section, we also perform stemming on the normalized tokens, which simplifies the tokens into their base forms. For tokenization and normalization, we take advantage of the helper functions from the `lucem_illud_2020` package. For stemming we use the `PorterStemmer` implemented by the `NLTK` package.

After tokenizing, we count the number of tokens in each document and calculate the mean token count per statement. As is shown by figure 1, with the number of participating states increasing over years, the mean token count steadily reduced almost in half, indicating the speakers face more and more rigorous time limitation when delivering the statement speech. However, the mean token count remains as high as around 2,000.

We arrange this corpus and organize it into the following format. For each document, we label it with a three-letter country code, an integer indicating the session, and another integer indicating the year. We save the results of tokenization and normalization into two separate columns for future use. Note that in the original UNGDC corpus one text document `URY_40_1985.txt` was mistakenly named as `URY_49_1985.txt`. We have corrected it by hand.

3. Methods and Implementations

The UNGDC corpus contains rich information about national political positions on a wide range of issues and topics. In this section, we briefly review the methods we employ to gain insights into the social mechanism underlying the data generating process of the text. First, we examine word frequency. On this basis, we identify the most common words conditional on their

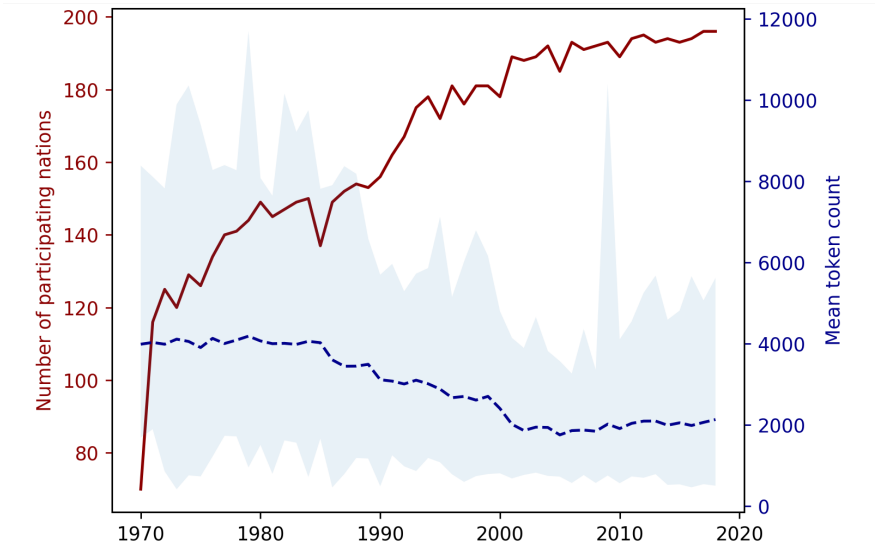


Figure 1: Number of Participating Nations and Mean Token Count per Statement (1970-2018)

functions as parts of speech to reveal the most significant object being discussed in recent decades. We also try to directly quantify the proximity of state positions by extracting the principal components of the word frequency vectors as well as performing a K-means clustering on the vector space. Second, we embed the tokens onto a semantic space using the techniques named Word2Vec and Doc2Vec, based on which we investigate position proximity between states from a semantic perspective. Third, we turn to topic modeling and employ the Latent Dirichlet Allocation model to figure out the topics that the states concerned across years. Finally, we also construct international networks based on mutual information revealed by topic modeling to measure position proximity in terms of topics of common interests.

3.1. Word Frequency: Term Frequency - Inverse Document Frequency (TF-IDF)

The Term Frequency - Inverse Document Frequency (TF-IDF) measures the frequency of a word in a document normalized by the importance of documents in the whole corpus. Intuitively, it reduces the weights of the words in a document that occur very frequently in the whole corpus. To characterize this normalized measurement of word frequency, for each token t in a document d, the formula of TF-IDF is given by:

$$\begin{aligned} \text{TF-IDF}(t, d) &= \text{Term Frequency (TF)} \times \text{Inverse Document Frequency (IDF)} \\ &= \frac{\text{count of } t \text{ in } d}{\text{number of tokens in } d} \times \ln\left(\frac{\text{count of t in corpus} + 1}{N}\right) \end{aligned} \tag{1}$$

We use `sklearn.feature_extraction.text.tfidfvectorizer` to extract the word frequency features for each token in each document of our corpus, which gives a document-token

Table 1: Preview of the UNGDC corpus

filename	country_code	session	year	text
ALB_25_1970.txt	ALB	25	1970	33: May I first convey to our President the co...
ARG_25_1970.txt	ARG	25	1970	177.\t : It is a fortunate coincidence that pr...
AUS_25_1970.txt	AUS	25	1970	100.\t It is a pleasure for me to extend to y...
AUT_25_1970.txt	AUT	25	1970	155.\t May I begin by expressing to Ambassado...
BEL_25_1970.txt	BEL	25	1970	176. No doubt each of us, before coming up to ...
BLR_25_1970.txt	BLR	25	1970	\n71.\t. We are today mourning the untimely de...
BOL_25_1970.txt	BOL	25	1970	135.\t I wish to congratulate the President o...
BRA_25_1970.txt	BRA	25	1970	1.\tMr. President, I should like, first of all...
CAN_25_1970.txt	CAN	25	1970	\nThe General Assembly is fortunate indeed to ...
CMR_25_1970.txt	CMR	25	1970	: A year ago I came here as the Acting Preside...

TF-IDF matrix. Each row of this matrix can be viewed as a feature vector characterizing each document in terms of the relative significance of its tokens.

We assume that the content of a statement can be represented by its TF-IDF vector, which is expected to contain multidimensional information about the topics that the state concerns and their position and ideology on the topics. Even though the topics are not directly observable nor identifiable by the TF-IDF vector, we can compare any two documents by comparing the two TF-IDF vectors to infer the similarity of the content in the normalized word frequency space.

Based on the TF-IDF matrix, we perform two analyses. First, we reduce the dimensionality of the vectors using Principle Component Analysis (PCA) to unidimensional scalars. We expect this to abstractly represent the content of the statements in the TF-IDF space, which is equivalent to project multi-dimensional state preference to one single visible dimension. Then, we take several countries as examples and visualize the revelation of several countries' preferences across years. Second, we perform K-means clustering using the TF-IDF vectors associated with each document. We review and evaluate the K-means Clustering method in section 3.4

3.2. Part-of-Speech Tagging

Part-of-Speech (POS) Tagging is to parse a document of natural language and tag the grammatic role of each token in a sentence. Since it depends on the grammatic context to disambiguate the word category, we use the `SpaCy`'s implementation of POS tagging to parse our documents using the original text without lemmatization or normalization. Note that one of the most frequent words "cooperation" is commonly written as "co-operation" in our corpus, and the POS tagger fails to identify it as a single word, we have corrected it to "cooperation" by hand before performing POS tagging. Conditional on word categories, we can count token frequency and figure out the most frequently-used word of certain grammatic category in our corpus, which can reflect the general topics and the main content of this international politics corpus.

3.3. Word Embeddings and Semantic Space: Word2Vec and Doc2Vec

Word embedding is a language modeling technique that maps words to vectors in a semantic space, of which `Word2Vec` and `Doc2Vec` are two computational implementations. In the resulting

vector representations of words, similar words with similar semantic meanings turn out to be close to each other (Mikolov et al., 2013). While `Word2Vec` embeds each token into a semantic space and represents tokens as numeric feature vectors, `Doc2Vec` enables us to label each document as a set of tokens and create numeric representations of documents in the same semantic space where the words are embedded. As a result, the word vectors can be thought of as representations of the semantic meaning of every single word, and the document vectors represent the meaning of each document.

In our analysis, we train a `Doc2Vec` model with our corpus using the implementation by `gensim.models.doc2vec`. Based on the resulting semantic space, we can quantify the proximity of any two states' position by calculating the cosine similarity of their document vectors. We can also assign hierarchical labels to the documents to integrate the features of all the documents of one state across years into a single vector. On this basis, we can project the states onto certain dimensions we define to answer our research question, for example, the Cold War dimension specified by the differences between the vectors of the NATO and the WTO states as well as 'capitalism' and 'socialism'. Furthermore, we perform K-means clustering using the documentation vectors to identify state blocs in terms of their overall standpoints of the Cold War extensive issues.

To verify that our corpus is complete and rich enough to construct a semantic space with meaningful results, we pre-train a `Word2Vec` model and experiment with several vector operations. We can find the most semantically similar words to a word. We can also perform vector operations to find the most matching word to an equation such as king – queen = man – women, which is one of the examples presented by Mikolov et al. (2013). We have many interesting results (shown in Table 2 and 3).

Table 2: Examples of finding the most similar words

target word	similar words
economic	socioeconomic, macroeconomic, economy, economies
political	institutional, geopolitical, politico, civic
socialism	communism, revolution, militarism, fascism

Table 3: Examples of vector operation in the semantic space

token1	–	token2	=	token3	–	token4
american	-	america	=	korean	-	korea
islamabad	-	pakistan	=	bangkok	-	thailand
oppose	-	support	=	reject	-	welcome

We can also visualize the semantic space where the words or documents are embedded. Since the vectors are high dimensional, we perform dimension reduction using the Principle Component Analysis (PCA) implemented by `sklearn.decomposition.PCA` and the t-distributed Stochastic Neighbor Embedding (tSNE) implemented by `sklearn.manifold.TSNE`. While PCA is a technique for linear dimensionality reduction, tSNE is a specific tool to visualize high-dimensional

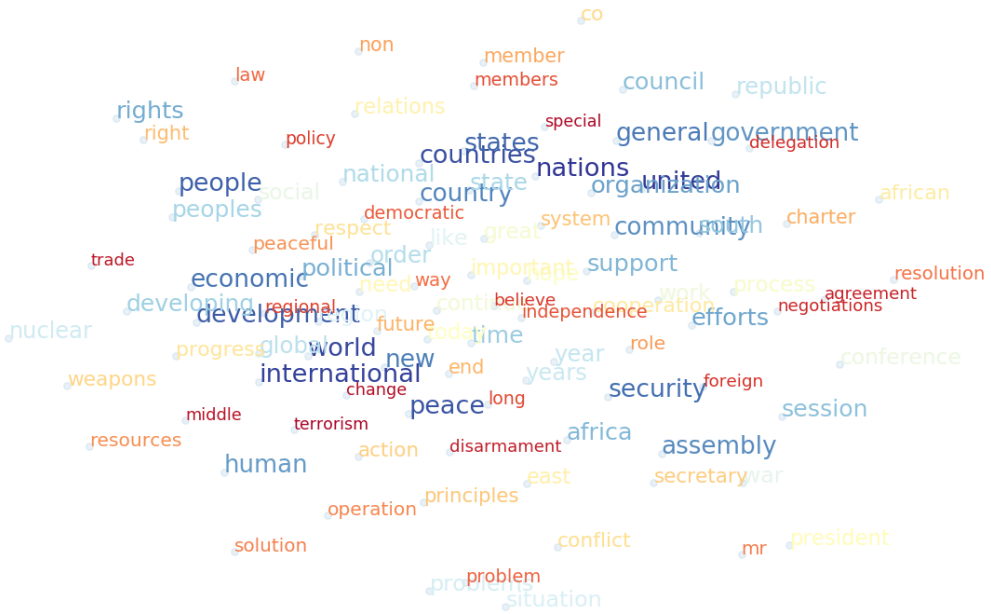


Figure 2: Top 100 words in the Word2Vec semantic space (dimension-reduced)

data (Maaten and Hinton, 2008). Since PCA is computationally efficient, we use PCA decomposite the vectors in the semantic space to 100 dimensions before using tSNE to project the vectors onto a two-dimensional space. Note that `gensim.models.word2vec.Word2Vec` sorts the vocabulary by descending frequency by default, we selected the first 100 most frequent words in the corpus and visualize their positions in the semantic space in Figure 2. We can observe, for example, 'state', 'states', 'country', 'countries', 'nations', and 'national' are located close to each other. Note that colors are proportional to the font size from blue to red, which reflects the frequency of a word in the whole corpus.

Similar results can be found in the `Doc2Vec` semantic space. For example, we find that the most similar states in terms of text content to 'USA' are 'GBR', 'CAN', 'ISR', 'AUS', 'NOR', 'NZL', 'NLD', etc, which are consistent to the reality that the UK, Canada, Norway, and the Netherlands are member states of the North Atlantic Treaty Organization (NATO), and Israel, Australia, and New Zealand are designated by the US government as Major non-NATO Allies (MNNA).

Such evidence shows the UNGDC corpus contains information that is complete and rich enough to construct a meaningful semantic space, from which we can make inferences about the relations between countries in terms of political positions and opinions on issues and the dynamics over years.

3.3.1. Cosine Similarity

With the vectors representing the documents in the semantic space, we can evaluate the similarity between any two vectors by calculating the cosine similarity. The formula is given by:

$$\cos(\boldsymbol{a}, \boldsymbol{b}) = \frac{\boldsymbol{a} \cdot \boldsymbol{b}}{\|\boldsymbol{a}\| \cdot \|\boldsymbol{b}\|} \in [0, 1] \tag{2}$$

, where $\boldsymbol{a}$ and $\boldsymbol{b}$ are any two vectors in the corpus. The higher the cosine similarity, the more similar the two vectors are in terms of semantic meanings.

We perform two analyses. First, we examine the similarities between states across years by calculating pairwise cosine similarities of the state vectors. We visualize the result in a heatmap. To alleviate noisy variations across years, we also show the average cosine similarities between states every five years to detect the most significant dispute and consensus. We will give the standard deviation of the cosine similarities at the end of the analysis, which indicates the variation of international relations in terms of policy proximity.

Second, we investigate the dynamics of international attention paid on specific policy areas by calculating the cosine similarities between the year vectors and the vectors representing the keywords of several policy topics. For the topics characterized by more than one token, we use the mean of multiple vectors to construct the basis vector. We can also observe the attention to such topics paid by specific states and evaluate to what extent these states are leading the international discussion of the policy issues in the United Nations.

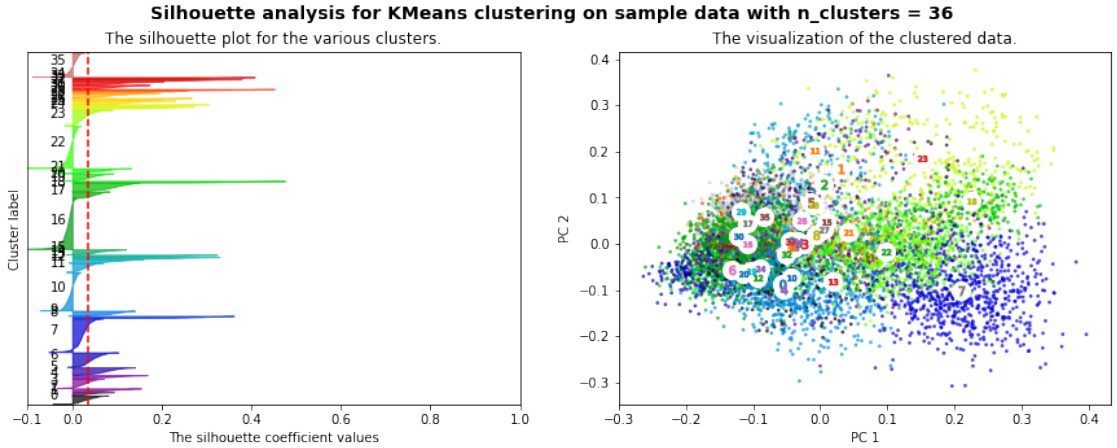
3.4. K-means Clustering

K-means clustering is an unsupervised learning method that partitions feature vectors into k clusters aiming at minimizing the sum of squared distance from each observation to the centroid with each cluster. We fit the model implemented by `sklearn.cluster.KMeans` using both the TF-IDF vectors and the `Doc2Vect` vectors as the features.

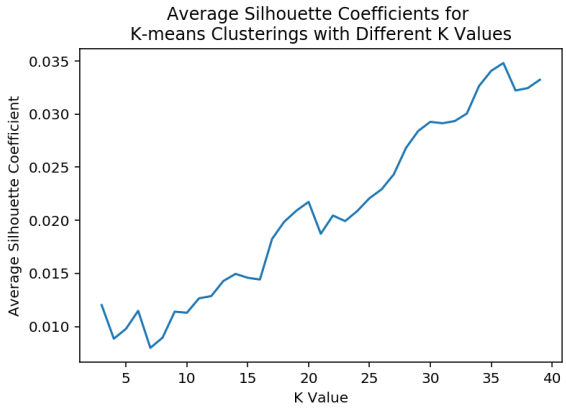
Fitting with the TF-IDF vectors, we cluster the single documents featured by distributions of normalized word frequency. We assume documents with similar TF-IDF vectors are likely to elaborate state positions about similar political agendas. On this basis, we can reveal the topics within each cluster by querying the most distinguishing words, in terms of TF-IDF scores, of the cluster centroids. Although this analysis reveals very limited information about the preference for political agenda of any specific state, it can help us with an overall impression about what the topics are discussed in the UN General debate in the past half-century.

Using the state vectors in the `Doc2Vec` semantic space, we are to identify state blocs in the semantic space, respectively. Since each vector represents the content of all the statements of one state as a whole, partitioning such vectors can reveal the state blocs in terms of position proximity. We also experiment by fitting the model using a subset of the corpus during the Cold War period, trying to identify state blocs in the Cold War years.

To tune the parameter k, the number of clusters, we use `Silhouette` coefficient as a metric. The Silhouette is a measure of the extent to which an observation is similar to its cluster compared to it is to other clusters. The higher the Silhouette is, the more coherent and less separative the observations within each cluster are. For our clustering model using TF-IDF vectors, the optimal k value is 36 (shown in Figure 3). For the model using Doc2Vec vectors, the optimal k value is 5 (shown in Figure 4).



(a) Silhouette Coefficient for $k = 5$



(b) Silhouette Coefficients for different k values

Figure 3: Parameter tuning for K-means Clustering using Doc2Vec vectors

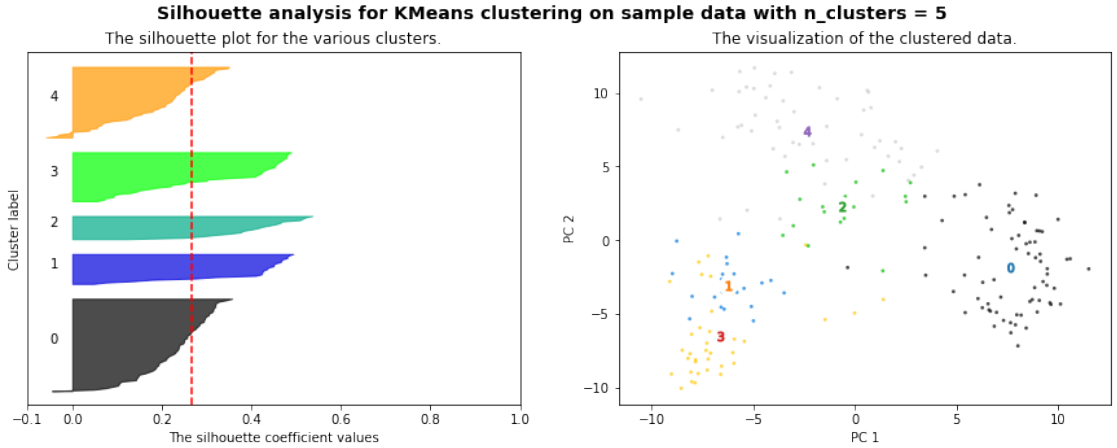
3.5. Topic Modeling

Topic Modeling is a method used for extracting abstract topics in a set of documents. In topic modeling, a document is represented by a distribution of topics, while a specific topic is represented by a probability distribution over a set of words. Words that are assigned with higher probability can better reflect the main ideas in this topic (Griffiths et al., 2007). In this paper, we use two different methods, The Latent Dirichlet Allocation model and Dynamic Topic Modeling[1], to address this issue from different perspectives.

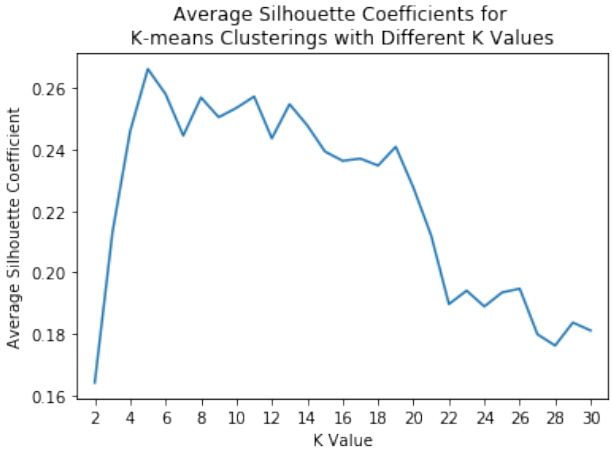
3.5.1. Latent Dirichlet Allocation (LDA) Model

We reveal state preferences for political agendas by revealing the topics in the corpus. By examining the distribution of probabilities of a certain speech on different topics, we can discover what issues the state that proposed this speech is putting spotlights on. This information is then

[1]Dynamic Topic Modeling is requires substantial computating, we only provide the code in our notebook.



(a) Silhouette Coefficient for $k = 5$



(b) Silhouette Coefficients for different k values

Figure 4: Parameter tuning for K-means Clustering using Doc2Vec vectors

utilized to construct network analysis in the following section. Furthermore, generalized from a larger perspective, we may conclude the most heated topics on UNGA throughout the past half-century.

The Latent Dirichlet Allocation (LDA) model is one of the most widely used techniques for topic modeling. In this model, topics are presented as latent variables that cannot be observed. In the first two steps, θ_i, the topic distribution for the document i in the corpus and ϕ_k, the word distribution for the topic k, are characterized by two separate Dirichlet distributions at given Dirichlet prior parameters α and β. Then it supposes that $z_{i,j}$, the topic for the j-th word in document i can be expressed by a multinomial distribution of θ_i. Given the conditions above, a specific word at position j at a specific document i can, therefore, be represented by a multinomial distribution with the topics as an embedded layer (Blei et al., 2003).

The first step of LDA topic modeling in this paper is choosing the optimal parameters to obtain the most meaningful and interpretable topic results. Before conducting LDA analysis, we restrict

the vocabulary using TF-IDF measures to ignore words that appear too frequently in the corpus. In the TF-IDF measure, we also set up a tokenizer to stem words whose length is less than 4 letters. To acquire the optimal results of topics, we choose different levels of `max_df` [2] parameter to compare the performance of the LDA model under different TF-IDF filtering standards.

The number of topics is another factor that we take into consideration when selecting the best LDA model. A satisfying topic number can capture the most information in the corpus and produces the most meaningful topic results. Given the two parameters of interest stated above, we use the UMass coherence score to evaluate the performance of the LDA model. UMass is an intrinsic measurement of topic coherence, which captures how well the topic model 'explains' our corpus of interest. The less the UMass coherence score is the better interpretability of the model. Figure 5 below illustrates the coherence score under these different `max_df` level against different number of topics.

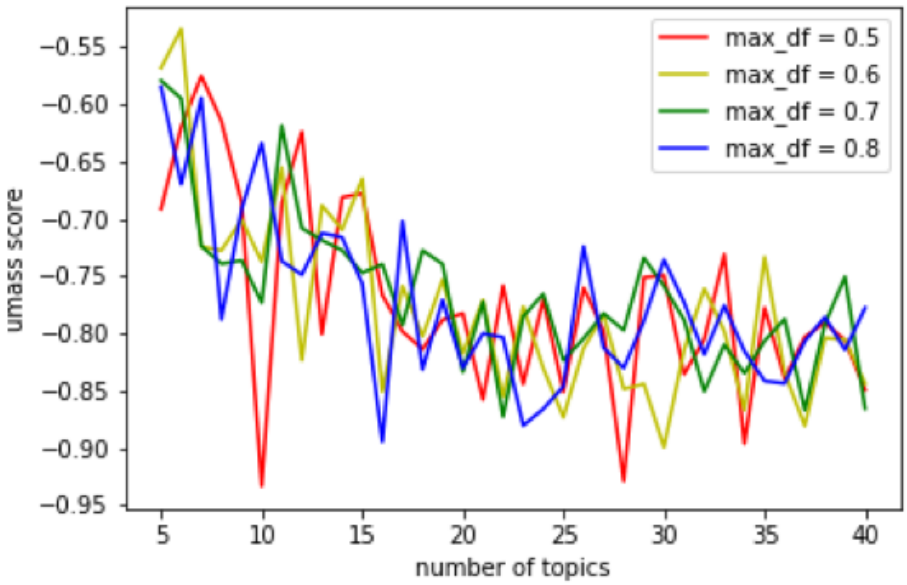


Figure 5: UMass coherence scores for different number of topics

As is shown in Figure 5, the LDA model has the best interpretability when setting `max_df = 0.5` and choosing the number of topics equal to 10 or 28. After printing out the top feature words in each topic under these two topic numbers, we use `num_topic = 28` for further analysis as it captures more information.

Using LDA topic modeling alone, we present the top 10 words with the highest probability in each topic. For some of these topics, we can interpret their practical contents. Besides, we use a Python package called `pyLDAvis` to visualize our topic model generated above. Other applications of the LDA model are stated in Section 3.6.

[2] A float between 0 and 1, which is used to indicate a proportion of documents, and words that have term frequency higher than that value is ignored.

3.6. Network Contraction: Mutual Information

Semantic networks are representations of semantic relationships between concepts of interest in the corpus. A semantic network has two key elements: nodes that represent concepts and edges, which can be directed or undirected, that represent the semantic relationship between linked concepts.

Based on the argument of Gurciullo and Mikhaylov (2017), we can regard topics extracted from the LDA model as having semantic values. Countries whose speeches cover similar topics show their overlying interest in similar political issues. In the last section, we use the LDA model to construct a vector that constitutes of topic probabilities of the 28 topics for each country each year. Therefore, in each of these 49 years, if we view each country (represented by a topic probability vector) as an individual semantic entity, we can build a semantic network based on the similarity of their topics of interest. The similarity is measured in normalized mutual information score, which will be introduced in detail in the following section.

In this paper, we construct 49 networks based on mutual information. We first investigate several statistics, which reveal the overall structure of the network such as density, average shortest length path, and diameter. Further on, by looking at the individual nodes of the graph, we can make inquiries about which countries are in the center of this network, which countries are on the border, and which countries are usually linked with one another. At the end of our network analysis, we go on to explore how a country's 'position' in the network evolves over years through different measurements of centrality.

3.6.1. Mutual Information

In the LDA model, for each country that has given a speech in each year, we obtain a vector of topic prevalence that describes the probability that the speech might load on each of the 28 topics. These can be intercepted as probability distributions, whose similarities between one another can be measured using the mutual information coefficient.

Mutual information captures the mutual dependence of two random variables. Since vectors here can be interpreted as discrete probability distributions, we might write the mutual information measurement as the following:

$$I_{X;Y} = \sum_{y \in Y} \sum_{x \in X} p_{X,Y}(x, y) \ln \frac{p_{X,Y}(x, y)}{p_X(x) p_Y(y)}$$

, where X and Y is the random variable of interest, $p_{X,Y}(x, y)$ is the joint probability density function of X and Y, and $p_X(x)$ and $p_Y(y)$ are the marginal probability density functions of X and Y, respectively.

The value of mutual information indicates how much the two random variables share information. In this case, a low mutual information score that close to zero denotes the two countries are focusing on different topics, while a relatively high mutual information score can be viewed as the two countries are paying attention to similar topics in that year. For comparison, we normalize the mutual information score computed above to a float between 0 and 1. The normalized mutual information score is what we used to construct edges in the semantic network.

3.6.2. Construct Networks using Mutual Information

After obtaining the normalized mutual information score between any two countries that have delivered a speech in a given year, we establish a semantic network whose nodes are countries. This network is completely linked at the first place, where the weight of the edge between two nodes is defined by the normalized mutual information score.

For the simplicity and interpretability of the network, we remove edges whose weights are below the median weight of the network. This step ensures that our networks only retain semantic relationships between countries above a certain threshold. Also, for years between 1970 and 1991, we assign different colors to nodes that represent NATO countries and WTO countries. An example of the network is shown in Figure 6.

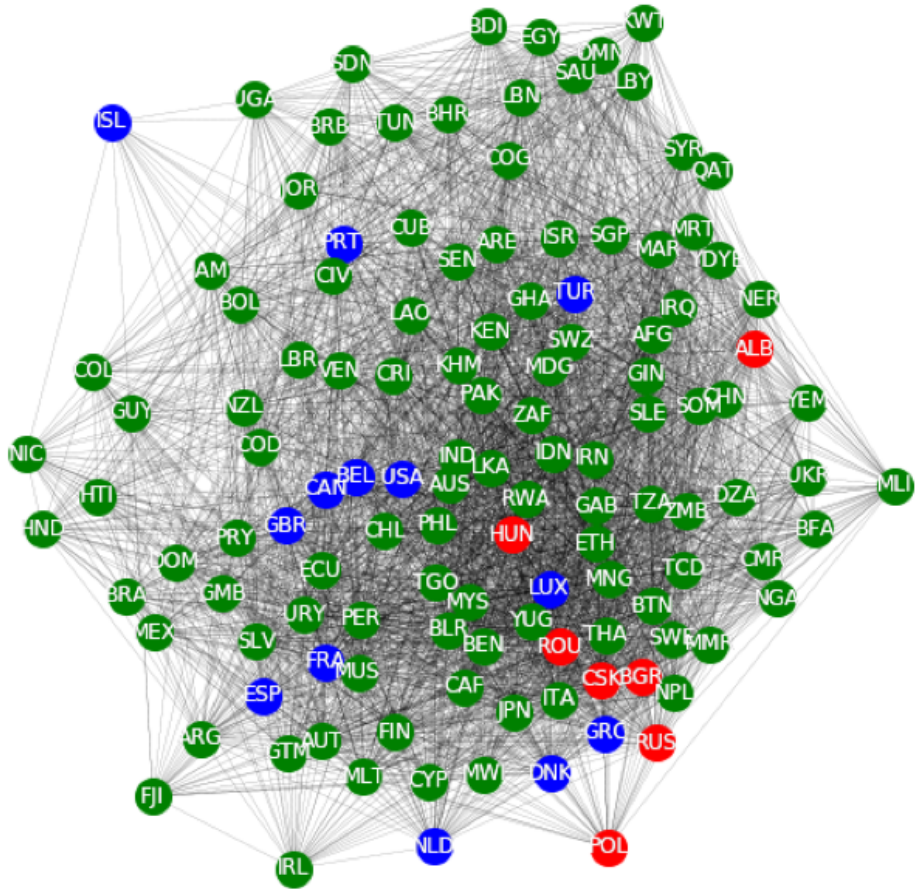


Figure 6: State Network of Mutual Information (1972; NATO states in blue and WTO states in red)

3.6.3. Network Statistics

The network statistics that we examine in this paper can be categorized into statistics that reveal general characteristics of the network and statistics that indicate features of individual nodes.

For the first category, we mainly examine density, average shortest path length, and diameter as indicated by Gurciullo and Mikhaylov's paper in 2017. Density is a proportion of the actual number of edges over the total amount of possible edges. During the 49 years in our analysis, the average density is about 0.495, and its variance is about 0.004, which implies the network density is quite stable over the years.

As for average shortest path length and diameter, the networks of the years 1990 and 1993 do not have these features since these two networks are not connected. For other networks, the average shortest path length is about 1.508 and the average diameter is about 2.936.

For the second category, we mainly focus on degree centrality. Degree centrality indicates how 'central' a node is compared with other nodes, based on how many connections (edges) it has. Here in our analysis, degree centrality captures how similar a country's speech is in topic comparing with the statements of other countries. The country with the highest degree centrality made a speech that covers the most heated topics discussed this year.

3.7. Topic summarization using BERT Text Generation

BERT (Bidirectional Encoder Representation from Transformers) is first introduced by . Pre-training unlabeled texts from two directions (left and right) at all layers allows it to overcome the drawbacks of traditional unidirectional fine-tuning methods such as ElMo. This method has its unique advantages when conducting researches related to text generations and question answering.

Text generation has been widely used in indicative summary generations (Kan and Mckeown, 2002)[5], which is an unbiased way to derive the condensation of a corpus as well as extract its important features. In our analysis, we utilize this method to generate the summaries of certain topics of interest. Furthermore, through the automatic generation of texts, we try to examine the linguistic standard of a formal speech in the United Nations General Debate. To be specific, we endeavor to investigate what the topics are about in the language of the states addressing their opinions on UNGA.

4. Results

Employing the methods introduced in the previous section, we try to answer two research questions. First, we examine what topics states are concerned about and how the attention paid to specific issues evolve over the years. Second, we examine the patterns in which the states are related to each other in terms of topics of common concerns, political positions, and policy preferences, and the dynamics of the relationship.

4.1. State Preferences for Political Agenda

The most frequent words in this corpus hint us with an overall impression of the general topics being discussed on the UNGA in the past half-century. While, peace and development are the theme of the era, economic development, nuclear security, human rights, etc, are the common issues concerned by international society.

We try to gain further insights into agenda topics by performing K-means clustering on the TF-IDF matrix. We query the most distinguishing patterns of each cluster centroids, which is, equivalently, the words with the highest TF-IDF scores associated with each cluster centroid. The

(a) The most frequent nouns

(b) The most frequent adjectives

Figure 7: The most frequent words in the corpus

clustering result is shown in Table B.9, B.10, B.11, and B.12. Unfortunately, the result shows no coherent topic within each cluster, but we still pick up some meaningful topics from the results: terrorism, nuclear weapons, disarmament, climate change, drug abuse, poverty alleviation, etc. Such results help us as evidence to validate the result of our subsequent topic modeling analysis. However, the clusters are less meaningful in revealing agenda topics due to transparent fallacy, which we discuss in Section 5.

We use topic modeling to gain more sophisticated insights into the corpus. We examine the generated topics according to the method discussed in the former section. In the beginning, we attempt to identify these topics and hand-classify them into several interpretable categories. Then, for some of these topics, we go on to show how their popularity has evolved, and whether the trend reveals the true story. At last, for countries whose GDP ranks top 20 in 2019, we list the most discussed 5 topics across all years to investigate their political preferences.

Table 4 demonstrates the top 10 words with the highest probability in each topic. And Figure 8 is the visualization of this LDA model if reduced to two dimensions. The area of the circle is proportional to the proportion of the topic across total tokens in the corpus. In other words, the larger the circle is, the more salient the topic is in the corpus. The distance between any two circles captures the similarities between the two topics.

Aside from words that indicate the themes of the topics, there are a few words in the table above that serve functional purposes and do not have conceptual meanings. The words “unite” and “nation” are the top two words of 19 topics among all the 28 topics. Other functional words include “operation”, “principle”, “relation”, “power”, “strengthen”, “initiative”, “lead”, “determination” and so on.

Based on the feature words shown above, we can hand-classify these topics into 9 categories:

Table 4: Top 10 feature words in 28 topics

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
unite	unite	unite	unite	nation	unite	unite	nation	nation	iraq
nation	nation	nation	nation	unite	nation	nation	unite	unite	unite
determination	sustainable	union	afganistan	sustainable	live	small	terrorist	romania	nation
power	challenge	reform	principle	challenge	society	climate	pakistan	operation	iran
self	reform	strengthen	affordable	goal	fight	sustainable	terrorism	relation	arab
operation	strengthen	european	secretary	reform	women	challenge	stand	arab	iraqi
principle	goal	secretary	lebanon	address	challenge	tobago	live	power	palestinian
relation	include	weapon	terrorism	climate	cent	trinidad	attack	principle	principle
measure	terrorism	programme	challenge	strengthen	child	caribbean	want	regime	kuwait
regime	address	challenge	meet	secretary	sustainable	address	power	mean	relation
Topic 11	Topic 12	Topic 13	Topic 14	Topic 15	Topic 16	Topic 17	Topic 18	Topic 19	Topic 20
nation	nation	unite	chad	unite	nation	unite	unite	nation	unite
unite	unite	nation	nation	syria	unite	nation	nation	unite	venezuela
suriname	sustainable	mongolia	paraguay	israel	island	sahel	ukraine	malawi	nation
poland	include	relation	unite	nation	climate	sudan	weapon	weapon	nicaragua
principle	japan	principle	guinea	palestinian	pacific	mali	ukrainian	power	bolivarian
panama	challenge	increase	live	terrorism	sustainable	tanzania	russia	canada	america
base	live	initiative	principle	syrian	small	lake	central	delegation	latin
power	reform	operation	solidarity	yemen	challenge	niger	crimea	operation	american
weapon	climate	area	principe	arab	ocean	hold	principle	reform	attempt
relation	goal	reform	lead	terrorist	address	refugee	strengthen	initiative	sovereignty
Topic 21	Topic 22	Topic 23	Topic 24	Topic 25	Topic 26	Topic 27	Topic 28		
unite	nation	unite	unite	sudan	unite	morocoo	malta		
nation	solomon	nation	nation	unite	korea	nation	nation		
viet	unite	turkey	mauritius	nation	korean	unite	unite		
china	nation	leste	philippines	lead	peninsula	albania	mediterranean		
asean	tonga	timor	live	drug	nation	mohammed	ethiopia		
singapore	ireland	greece	increase	libya	statement	kingdom	power		
power	weapon	determination	ocean	terrorism	relation	king	principle		
korea	principle	european	principle	democracy	build	relation	relation		
chinese	climate	union	chagos	initiative	joint	union	delegation		
korean	small	portugal	lead	arab	bulgaria	european	operation		

- **Climate Change (Topic 5, 7, 12, and 16):** These topics contain words such as "climate" and "sustainable", which indicates a focus on climate change and sustainable development. Topic 5 and 12 discuss the general issues regarding climate change, while topic 7 and 16 put a special emphasis on marine countries.

- **Terrorism (Topic 4, 8, 10, 15 and 25):** The five topics all consist of keywords such as "terrorism" or "terrorist" while underscoring different perspectives individually. Topic 4 contains the word "afghanistan", where the Taliban is founded. Topic 8 is related to terrorism in Pakistan. Its northern part borders with Afghanistan, where terrorist activities are mostly conducted by religious extremists. Topic 10 focuses on terrorism in Iraq, which might have a relationship with Iraq War which started in 2003. Topic 15 is concerned with terrorism in Syria, which is still on the U.S. list of State Sponsors of Terrorism. Syria is accused of sponsoring weapons and providing political support for terrorists in Palestine and intervening in Iraq Conflicts, which corresponds to our results found in the LDA model. Topic 25 reveals terrorism issues in Sudan, where members of Hamas (Islamic Resistance Movement) are allowed to live and fundraise.

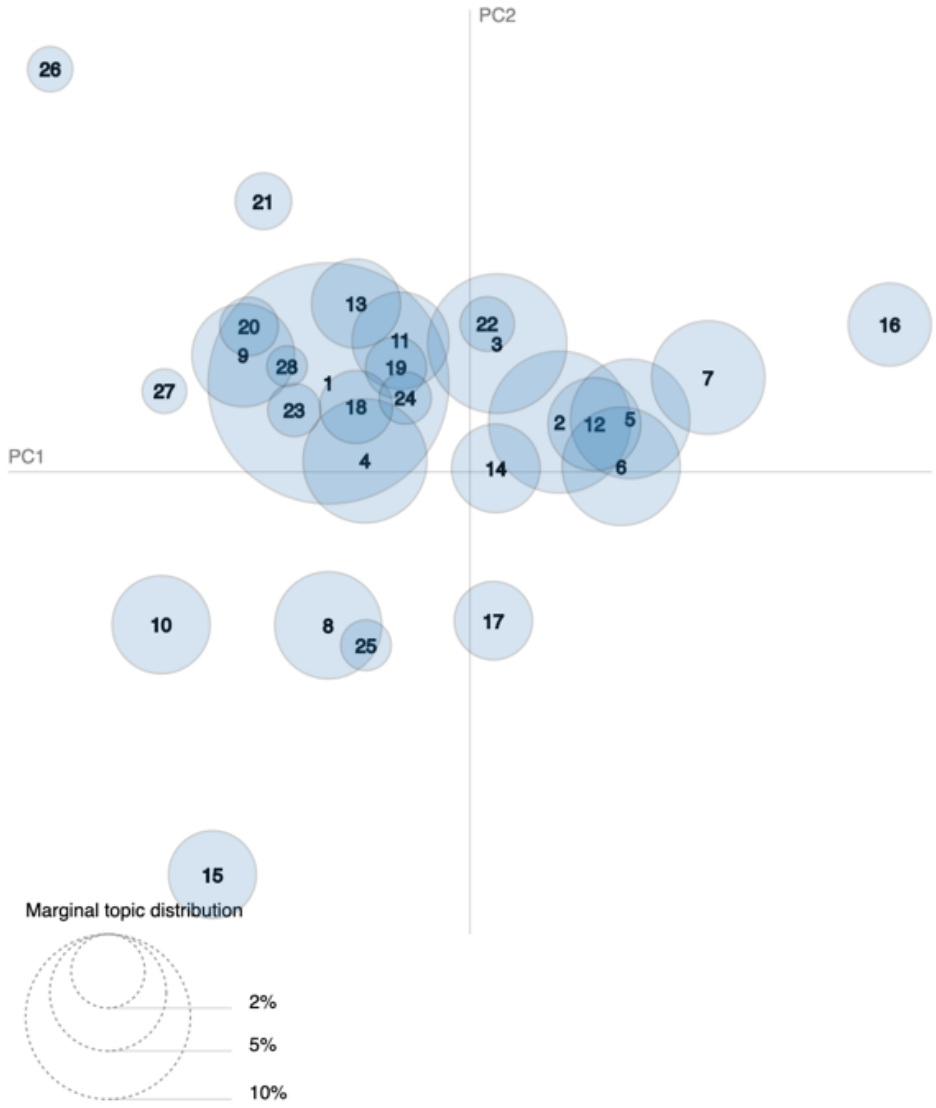
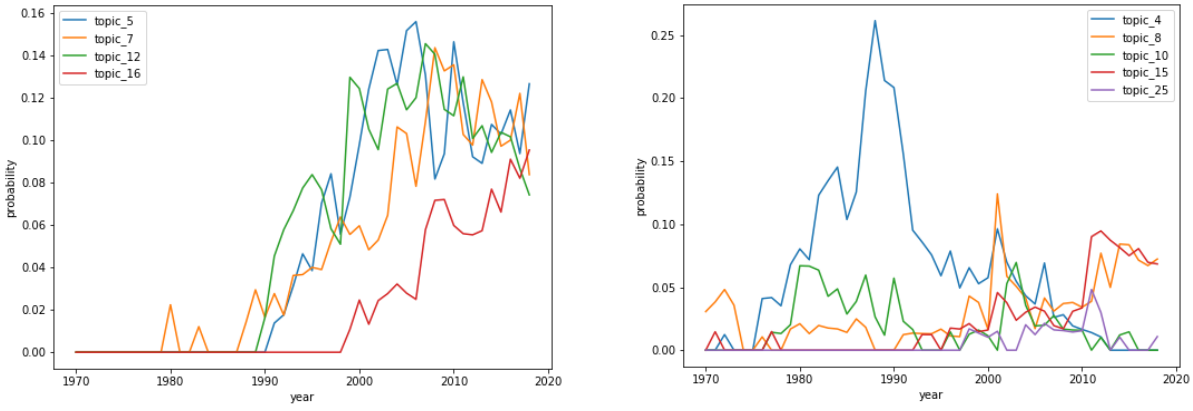


Figure 8: Intertopic Distance Map (after multidimentional scaling)

- **Issues in Asian (Topic 21 and 26):** Topic 21 and 26 indicate issues in Asia. Topic 21 is related to general affairs in Asia since it incorporates words such as 'viet' (Vietnam), 'china' (chinese), 'korea' (korean), 'singapore', and 'asean' (Association of Southeastern Asian Nations). Topic 26 points to Korean issues in particular. This topic also includes other distinctive words like "peninsula", "statement", and "joint", demonstrating the ongoing negotiation of reunification problem in this area.
- **Issues in Latin America (Topic 20):** Topic 20 deals with issues in Latin America, which includes highly identifiable words such as 'latin', 'america' (american), along with country names such as 'venezuela' and 'nicaragua'. There are still areas in Latin America whose

sovereignty is still in dispute, which has been a subject discussed in the 1980s.

- **Issues in Europe (Topic 23):** Having words such as "european", "union", "greece", and "turkey", Topic 23 reveals a clear indication of its focus in European issues.
- **Issues in Africa (Topic 17):** Topic 17 addresses issues, especially refugee problems, in Africa. It also shows the most discussed countries in Africa, which are countries in Sahel, Sudan, Mali, and Tanzania.
- **Crimea Crisis (Topic 18):** Topic 18 mainly discusses war and conflicts in Crimea. After the dissolution of the Soviet Union, Crimea was formed as a constituent entity of Ukraine. After several conflicts, the sovereignty of Crimea was passed to the Russian Federation in 2014.
- **Human Rights (Topic 6):** Topic 6 differs from other topics in that it contains words like 'women', 'child', 'society', and 'fight', which might indicate its focus on human rights issues.
- **Others (Topic 1, 2, 3, 9, 11, 13, 14, 19, 22, 24, 27, and 28):** The 12 topics remaining cannot be easily categorized into any of the classifications above. They are also not identifiable enough to be regarded as an independent category. Some of these topics, such as topic 1, 2, 3, 9, and 13 include words that are mostly functional and do not have discernible political indications. Topic 11, 14, 19, 22, 24, 27 and 28 contain few incompatible feature words so that they cannot be assigned into any of the categories above.



(a) How topics on climate change have evolved over time

(b) How topics on terrorism have evolved over time

Figure 9: Time trend of topics on certain issues

After deducing the meanings and categories of the 28 topics, we can examine how a topic's probability has evolved by aggregating the texts of the same year. As is shown in Figure 9, topics related to climate change and terrorism reveal different time patterns. Issues regarding climate change and sustainable development gradually receive global attention since 1990, and ascend

their peaks between 2005 and 2010. Topic 4, which discusses terrorism in Afghanistan, attracts more global attention than other topics. This topic is at its peak around 1990. Issues about terrorism in Pakistan comes to a climax after 2000, and its probability has increased in current years after a partial decline. Topic 10 (terrorism in Iraq) has two peaks. One starts at 1980 and ends at 1990, and another starts after 2000, which correspond to the period of Iraq War. Topic 15 (terrorism in Syria) gains increased attention after 2010, while topic 25 (terrorism in Sudan) is the least discussed one among all issues about terrorism.

Table 5: Top 5 topics discussed over years (20 states)

Country	Top 1	Top 2	Top 3	Top 4	Top 5
USA	8	12	1	18	6
CHN	21	1	13	9	10
JPN	12	13	3	1	26
IND	1	4	8	5	3
GBR	1	8	12	4	2
FRA	1	3	6	13	14
ITA	22	3	1	2	18
BRA	11	1	6	3	5
CAN	19	2	12	1	3
RUS	18	13	1	3	26
KOR	5	26	2	12	13
ESP	1	14	3	11	22
AUS	3	1	2	16	4
MEX	11	6	1	3	2
IDN	4	5	1	3	24
NLD	2	1	3	19	18
SAU	10	4	15	1	8
TUR	23	4	1	15	2
CHE	2	6	12	3	28

Now we turn to state preferences revealed by LDA topic modeling. Table 5 illustrates the top 5 topics across all years for countries whose GDP ranks top 20 in 2019. The United States has a special interest in issues about terrorism, as they discuss terrorism in Pakistan more than any other topics, followed by topics about climate change, Crimea crisis, and human rights. China focuses on Asian issues (Topic 21). The result for all states is presented in Table B.13, B.14, B.15, B.16, B.17, and B.18.

We turn to the analysis based on the Doc2Vec semantic space. Recalling that we have labeled the documents with year and country code, we can examine the cosine similarity of the year vectors and other vectors representing specific issues. This allows us to reveal the dynamics of attention paid on the issues over the years. We choose the issues in Table 6 and select the corresponding keywords to construct the basis vectors. Note that our result is robust against slightly different keywords. We also measure the attention paid by the US and China on the same topics

by calculating the cosine similarity of the country vectors representing the US for each year and the basis vectors.

Table 6: Selected topics and corresponding key words

Topic	Key words
anti-terrorism	terrorism
nuclear weapons	nuclear
health	health
education	education
climate change	climate, environment
economic development	economic, development

Figure 10: Dynamics of attentions on specific policy issues over years (1970-2018))

As is shown in Figure 10, health, education, climate change, and economic development received substantial attention from the international society in recent decades. This can be largely explained by the efforts promoted by the United Nations on these issues. The graph shows a sharp increase in the international attention on terrorism in the year of 2001, suggesting the escalated concerns and tensive discussions about this topic after the September 11 attack happened in New

York. As for the nuclear weapon issue, the international attention calmed down after 1991 when the Soviet Union collapsed and the Cold War terminates.

Among these topics, there is no significant emphasis put by the US or China. Even though the international society has shown constantly increasing concerns about health, education, climate change, and economic development, the attention paid by the US and China shift back and forth around zero cosine similarity on these topics. However, this may not necessarily suggest that the US and China do not prefer discussions or international efforts on such topics. On the contrary, this may be explained by the diversity of the statements made by the two countries each year. Due to time limitations on the General Debate section, states concerning a wide range of issues must have shortened the length of speech on specific topics. We can verify this by looking back at the original scripts of US statements. Nevertheless, it is still obvious that the dynamics of the US and China's concerns on these topics are highly correlated to that of the international society, which indicates the significant role played by the two countries in the UNGA conference.

Finally, we present the result of topic summarization using BERT Text Generation. Table7 shows four examples of using BERT to generate texts based on General Debate Corpus. As we can see, formal speeches in the United Nations General Debate tend to focus on the global effect of a specific issue. It means a country is inclined to emphasize on how an issue will influence the world when talking about its topics of interest. Also, the countries also highlight a lot about the important role the United Nation plays from a global perspective.

Table 7: Examples of topic summarization using BERT Text Generation

Initial tokens	Generated Text
Climate change is...	Climate change is a major challenge for the world. The world is facing a new challenge, one that is not only global, but also global in scope. The United Nations is the only global organization that can effectively address the challenges of climate change.
Terrorism is...	Terrorism is a threat to international peace and security. It is a threat to the stability of the region and to the stability of the world. It is a threat to the stability of the world.
The Syrian conflict has...	The Syrian conflict has been a source of great concern to the international community. The Syrian people have suffered a terrible loss of life and have suffered a great loss of property.

4.2. Policy Position Proximity and International Relations

Given the complexity of state policy objectives and international relations, it is beneficial to investigate state policy positions in high dimensions. We first assume that the policy positions are expressed in the General Debate statements and can be represented by the TF-IDF matrix. Then we turn to more sophisticated models to reveal similarities and discrepancies between state policy positions including the Doc2Vec semantic space and the LDA topic modeling.

To characterize high-dimensional state policy positions, we perform Principal Components Analysis on the TF-IDF matrix, which decomposes the TF-IDF vectors for each document to a

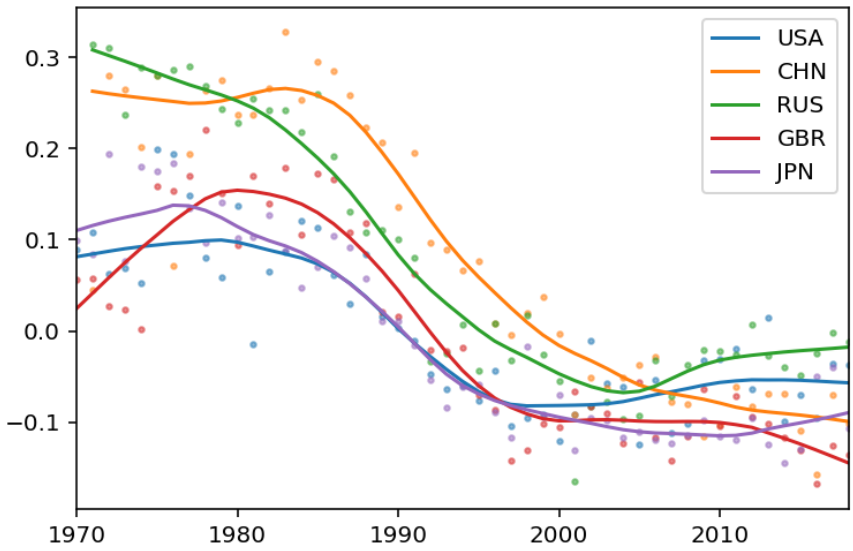


Figure 11: Multi-dimensional policy position revelation: principle component of the TF-IDF matrix (1970-2018))

scalar that accounts for the most variation in the data. In Figure 11, we visualize the results for the US, China, Russia (previously the Soviet Union), the UK, Japan, Korea, and the European Union to make a shallow observation of the international relations revealed by the TF-IDF matrix. It is obvious that, before 1990, China and Russia are similar to each other in terms of policy positions, and the US is closer to the UK and Japan. This is consistent with the historical context. While the Sino-soviet split from 1956 to 1966 is not captured by our data, the improvement of the bilateral diplomatic relationship after that period can be observed from the converging curves of China and the Soviet Union (labeled by RUS) in the figure. The consistency of our results with history increases our confidence in the validity of our analysis.

We investigate the policy position proximity during the Cold War period. This geopolitical tension mainly between the US and the Soviet Union spaned 45 years before its termination marked by the 1991 dissolution of the Soviet Union (Plan). We plot the PCA results for all the member states of the North Atlantic Treaty Organization (NATO) and the Warsaw Treaty Organization (WTO in Figure 12. The NATO and WTO member states are labeled by the real lines and the dashed lines, respectively. It is a significant pattern that the NATO states and the WTO states show similar policy positions to each other within the organizations before the year of 1990. While the Soviet Union is located in the most extreme position in the figure among other WTO members, the US is laid in the middle of other allies in NATO. It is also obvious that the discrepancies decrease over years before the dissolution of the Soviet Union.

Furthermore, we can also conclude that the state policy positions have shown an overall trend of converging in recent decades, especially by the middle of the 2000s. However, discrepancies seem to have gradually escalated after 2008, the year of the international financial crisis.

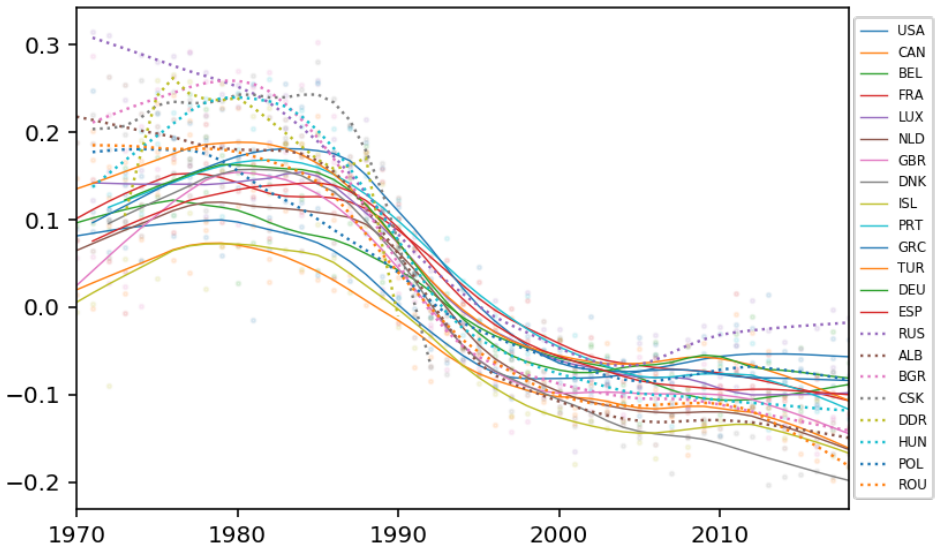


Figure 12: Multi-dimensional policy position revelation: NATO and WTO states (1970-2018)

We now turn to the analysis based on the Doc2Vec semantic space. We examine the cosine similarities between state vectors with the assumption that the policy positions are meaningfully underlying the vector representations of the document in the semantic space.

In Figure 13, we visualize the pairwise cosine similarities of the 20 states that have the highest nominal GDP by 2020, according to the IMF. Red cells indicate significant dissimilarities between two states in terms of the meaning of their General Debate statement, and blue cells indicate similarities. Under our assumption, these are equivalent to dispute or disagreement and consensus or proximate policy positions, respectively, on policy issues. However, given that international relations can vary dramatically across time, merely the overall cosine similarities cannot capture the dynamics of policy position proximities.

To examine the dynamics of policy position proximities over years, we calculate the cosine similarities between the state vectors each year. As is shown in Figure B.16, we take the average of the results within every five years from 1970 to 2015 to cancel out noisy variations. The dynamics of recent years are shown individually in Figure B.17. We also visualize the standard deviations of the cosine similarities in Figure B.18.

Several observations can be made from the figures. First, the UK and the US are consistently similar to each other in terms of policy positions, which conforms to our findings in the previous analysis. Second, the cosine similarity between the US and China increase from 1971-1975 to 1976-1980. This can be explained by a series of historical events that mark the improvement of the US-China relations in the 1970s. Starting from 1971, the tension of the US-China relations had been alleviated by a series of civic exchange activities including the well-known Pingpong diplomacy. In February of 1972, President Nixon's visit to Beijing marks the resumption of the

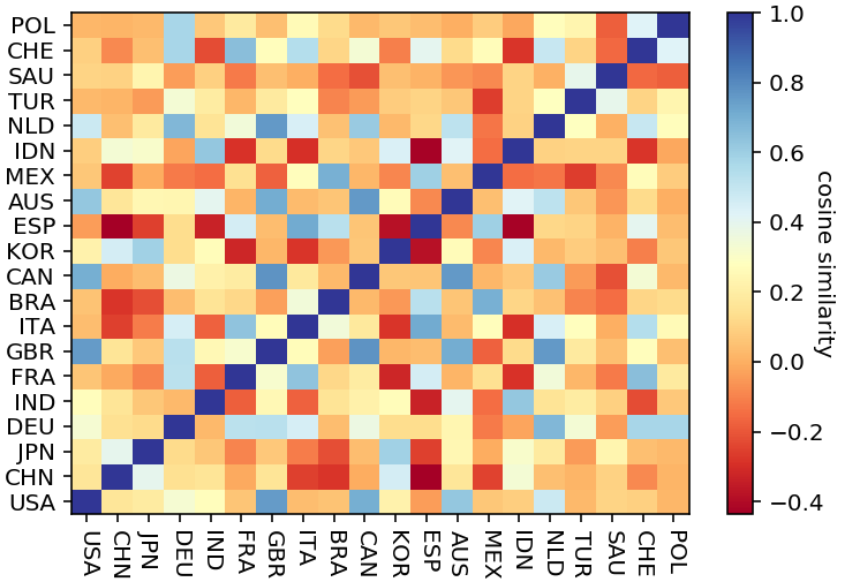


Figure 13: Pairwise cosine similarities of 20 states (1970-2018)

harmonious relations between the two countries, and the US officially changed its diplomatic recognition of China from Taipei to Beijing on January 1, 1979. Besides, there are also significant results that can hardly be explained by history. For example, while the figure suggests significant dissimilarities between Spain and French, and French and India, we cannot match any important historical events to the analytical results.

Again, we apply this analysis to examine the Cold War period. We train the Doc2Vec model again using the 1970-1991 subset of the UNGDC corpus (see Figure B.20). In Figure B.19, all the states in our corpus are projected onto a basis vector constructed by the difference of the mean of the NATO state vectors and the WTO state vectors as well as the tokens ”capitalism” and ”socialism”. NATO and WTO member states are indicated by bigger labels. Blue labels indicate proximity to the NATO camp, and red labels indicate proximity to the WTO camp. Only the related positions on the north-to-south direction are meaningful, and horizontal variations are randomly assigned to make a clear visualization. This result is a simple prediction of whether a state is closer to the NATO camp or to the WTO camp before the dissolution of the Soviet Union.

We finally perform K-means clustering on the Doc2Vec state vectors. The result is shown in 14. After tunning the parameter, the optimal number of clusters is 5, which means the states can be optimally partitioned into five state blocs. As is shown in Table B.19, the top states listed in cluster 0, Australia (AUS), Canada (CAN), the UK (GBR), Ghana (GHA), the Gambia (GMB) are members of the Commonwealth of Nations. The top states in cluster 2 are mostly South American countries, and cluster 3 mainly involves middle eastern countries. The result is correlated to the status quo of the geopolitical structure of the world. It identifies latent state blocs in terms of policy position proximities.

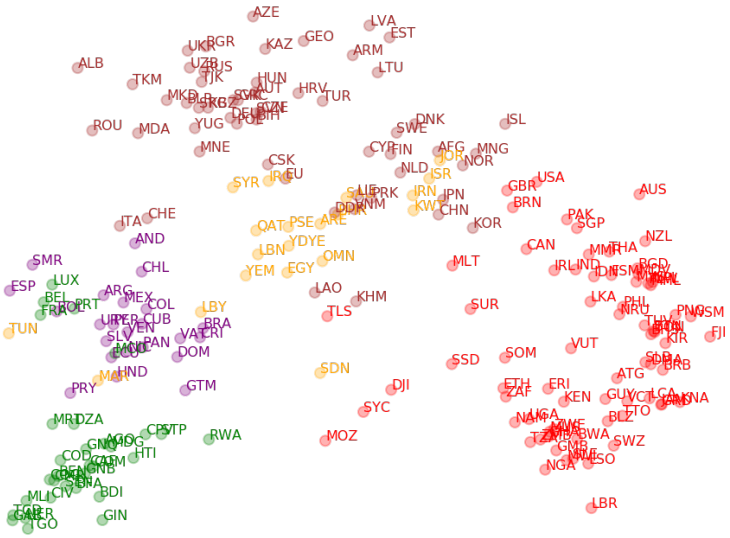


Figure 14: K-means clustering of Doc2Vec state vectors

All 49 networks constructed by normalized mutual information score is presented in the appendix due to the limitation of space in the main body. By examining networks from 1970 to 1991, we can discover that NATO countries and WTO countries are generally close to countries within the same camp, even though countries of the same organization may not necessarily gather in a cluster. Moreover, there is not much distance between NATO countries and WTO countries. There are two possible explanations for this phenomenon. The first one is that there are indeed few divergences in opinions about topics between these countries. As we can see from our analysis on topic modeling in the former section, the most discussed topics across all years are those about climate change, terrorism, and other functional topics with no intelligible political implications. Possibilities are strong that these countries agree to each other on these overall topics in spite of their difference in ideology. Another plausible explanation of the proximity is that mutual information only captures the similarity between topics included in two countries' speeches, not the opinions underlying these speeches. Therefore, chances still exist that countries with different ideologies take different stands on political issues, even though they are focused on the same topic.

Another insight worth noting is that networks of the year 1990 and 1993 have subgraphs that are not connected. In the network of the year 1990, the country East Germany is an isolated node. In 1993, the isolated node is Cambodia. It implies that these two countries talk about topics differed from all other countries in that year.

Now we turn to network statistics mentioned in Section 3.6.3. Figure 15 below illustrates

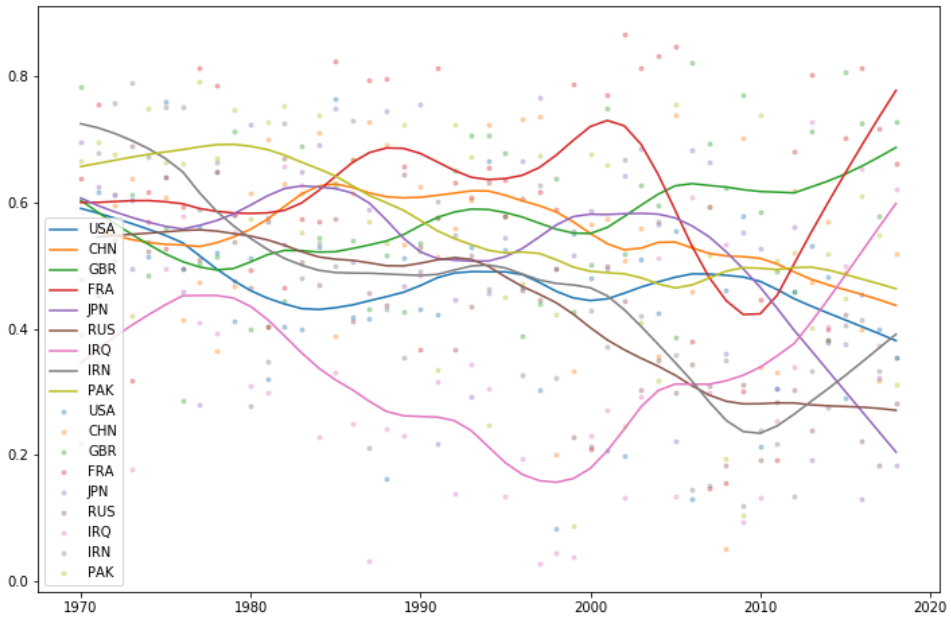


Figure 15: Degree centrality from 1970 to 2018

how several countries' degree centrality has changed over time. As introduced in the former section, degree centrality captures how similar a country's speech is compared with those of other countries in topic distribution. It is shown in the figure that France generally has the highest degree centrality score across the 50 years, and Iraq has the lowest. For most of the countries in the figure above, their degree centralities have decreased since 2000. Generally speaking, as demonstrated in the graph, developed countries (here we have USA, GBR, GRA, JPN) are more central than developing countries and third World countries (here we have CHN, RUS, IRA, IRN, PAK) in networks.

5. Conclusions and evaluations

K-means clustering using TF-IDF. No time slice, features are assoicated with single document, which is the distinguishing features of the specific state in the specific year.

In this project, we employ a series of content analysis methods such as TF-IDF feature extractions, principle component analysis, K-means clustering, Doc2Vec word embeddings, LDA topic modeling, and network contractions. Our study contributes to the current literature of quantitative measurements of political preferences by synthesizing prevalent methods to explore the United Nations General Debate Corpus. Throughout the analysis, we answer two questions: state preferences for political agendas and international policy position proximity. We validate our findings by relating some of the results to the historical events, which suggests the potential of using text data in revealing complicated internatioanl political interactions in a quantitative perspective.

However, our current analysis is far from robustness and accurate to reveal the whole story. First, no political inferences can be made for years before 1970 due to the limitation of the UNGDC

corpus. Second, most of the models employed are subject to strong assumptions. For example, we assume the semantic meaning of the documents can be represented by the TF-IDF matrix and the Doc2Vec word embedding space, which requires further evaluation. We also assume in the K-means clustering model that features of state preference are associated with single document, but they can be dramatically varing across years. It is worth noting that failure of our assumptions may lead to significant error in our inference. Third, more accurate models such as Dynamic Topic Modeling requries substantial computing resources and can take very long time to run. Due to limitations of our computation capacity, we only provide the notebook in the online appendix.

Further efforts can be made to specify more sophisticated probability models to identify features embedded in the text data and integrate political science methods into the computational analysis. Our project offers an exploratory analysis into the newly published UNGDC corpus. We believe that more potentials of this corpus are for researchers within the political science field to discover.

References

Baturo, A., Dasandi, N., Mikhaylov, S.J., 2017. Understanding state preferences with text as data: Introducing the un general debate corpus. Research & Politics 4, 2053168017712821.

Blei, D.M., Ng, A.Y., Jordan, M.I., 2003. Latent dirichlet allocation. Journal of machine Learning research 3, 993–1022.

Griffiths, T.L., Steyvers, M., Tenenbaum, J.B., 2007. Topics in semantic representation. Psychological review 114, 211.

Gurciullo, S., Mikhaylov, S., 2017. Topology analysis of international networks based on debates in the united nations. arXiv preprint arXiv:1707.09491 .

Jankin Mikhaylov, S., Baturo, A., Dasandi, N., 2017. United Nations General Debate Corpus. URL: `https://doi.org/10.7910/DVN/0TJX8Y`, doi:`10.7910/DVN/0TJX8Y`.

Maaten, L.v.d., Hinton, G., 2008. Visualizing data using t-sne. Journal of machine learning research 9, 2579–2605.

Mikolov, T., Chen, K., Corrado, G., Dean, J., 2013. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781 .

Plan, M., . Marshall plan. Public law 80, 472.

Appendix A. Online resources

- Project website: `https://luxintian.com/UNGDC`
- Reproducible notebooks: `https://luxintian.com/UNGDC`
- Topic Modeling visualization - Interactive intertopic distance map: `http://luxintian.com/UNGDC/pylda_topic.html`

Appendix B. Tables and graphs

Table B.8: Changes of participating states over years

year	plus	minus
1971	IRL LUX POL CHL MLI CHN YDYE CAF BFA MUS PAN M...	HND CRI GMB
1972	MWI HND SWZ CRI DNK ARE BTN GMB BHR OMN BRB PRT	PAN NOR TTO
1973	PAN DEU BHS LSO DDR NOR	MWI DOM SWZ GMB CIV UGA TGO MLT CMR TCD BRB
1974	DOM SWZ GMB BGD GRD CIV GNQ UGA BWA TGO MLT CM...	PAN FJI ZAF BHS MDG
1975	MOZ PAN MWI FJI MDG	LBN LUX SWZ GMB HTI CIV EGY MLT
1976	LBN CPV SWZ MDV PNG COM GNB STP EGY MLT SUR	MWI GNQ THA
1977	MWI LUX AGO WSM GMB TTO HTI CIV SYC THA	GUY DOM GAB MLT
1978	DOM GNQ GAB VNM MLT GUY	MWI SWZ PRY GIN SAU
1979	DJI MWI DMA PRY VAT GIN SAU	GMB DNK SWE AGO
1980	SWZ LCA VCT AGO DNK SWE GMB BHS ZWE	KWT WSM DMA VAT
1981	KWT WSM DMA	NOR MWI SWZ MMR GMB TTO LSO
1982	NOR ATG MMR GMB TTO BLZ LSO	LBN DMA WSM CIV SYC
1983	LBN VUT SLB WSM SYC	PAN LCA GMB
1984	PAN SWZ LCA DMA GMB ZAF	VCT WSM GRD SYC ZMB
1985	MWI WSM BRN KNA	LBN CPV ATG SEN LCA DMA MDV BTN GMB GNB FJI GN...
1986	LBN CPV ATG SEN VCT MDV BTN GMB GNB GRD FJI GN...	MDG UGA BEN KNA
1987	BEN LCA KNA GAB MDG	STP ATG
1988	STP ATG UGA	GUY
1989	GUY CIV SYC DMA	LBN SLE WSM BTN CAF
1990	LBN SLE WSM BTN LIE CAF NAM	YDYE STP KHM CIV
1991	EST KOR PRK LTU LVA FSM CIV STP MHL KHM	COD DDR NER SOM
1992	TJK BIH KGZ MDA HRV SVN NER GEO SMR ARM UZB AZ...	LCA WSM TTO CAF KHM ZMB GUY YUG THA
1993	LCA WSM TKM MKD CZE TTO CAF SVK KHM ERI GUY MC...	VUT GEO STP CSK MDG
1994	GEO ZAF ZMB MDG AND	WSM TKM
1995	WSM TKM	CPV DMA COM CIV UZB SYC ZWE SAU
1996	CPV VUT DMA COM PLW CIV UZB SYC ZWE SAU	CMR
1997		WSM PLW FSM KHM SAU
1998	WSM FSM PSE STP CMR SAU	MHL
1999	PLW KHM MHL	CAF SYC STP
2000	CAF NRU SOM	MOZ WSM BTN CMR UZB ZMB
2001	MOZ WSM TON BTN STP ZMB CMR UZB TUV SYC YUG	
2002	CHE	LBY SYC
2003	KIR TLS SYC	DJI TKM
2004	DJI VAT TKM LBY	SOM
2005	SOM	DJI HND MLI LBR BWA SYC SAU OMN
2006	SRB HND MNE MLI LBR BWA SYC SAU OMN	YUG
2007		SAU MLI
2008	MLI	
2009	DJI	
2010		DJI MDG UZB TKM
2011	DJI SSD TKM UZB EU MDG	SYC
2012	SAU SYC	GNB
2013	GNB	DJI KEN SAU
2014	KEN	
2015	DJI SAU	SGP CMR UZB
2016	SGP CMR UZB	DJI BRN
2017	DJI BRN	
2018		

Table B.9: Distinguishing features of K-means cluster centroids

Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8
iraq	terrorism	soviet	morocco	bahamas	africa	guatemala	sudan	ecuador
kuwait	reform	socialist	algeria	drug	south	belize	malawi	peru
lebanon	cooperation	nuclear	mauritania	haiti	african	guatemalan	somalia	latin
iraqi	nuclear	republic	arab	caribbean	namibia	american	ethiopia	peruvian
lebanese	afghanistan	disarmament	maghreb	small	independence	central	kenya	american
arab	weapon	relation	african	traffic	regime	guatemalans	eritrea	america
iran	millennium	weapon	sahara	island	struggle	america	somali	democracy
aggression	terrorist	imperialist	africa	illicit	apartheid	caribbean	africa	drug
israel	poverty	detente	kingdom	commonwealth	delegation	drug	african	andean
islamic	sustainable	union	palestinian	south	republic	democracy	igad	power

Table B.10: Distinguishing features of K-means cluster centroids (continued)

Cluster 9	Cluster 10	Cluster 11	Cluster 12	Cluster 13	Cluster 14	Cluster 15	Cluster 16	Cluster 17
japan	south	african	korea	chad	azerbaijan	latin	guinea	sustainable
nuclear	delegation	africa	lao	chadian	armenia	chile	equatorial	climate
japanese	africa	congo	korean	african	karabakh	argentina	papua	agendum
assistance	operation	republic	republic	libya	armenian	venezuela	bissau	goal
operation	nuclear	burundi	peninsula	africa	azerbaijani	brazil	pacific	tobago
weapon	power	reform	democratic	libyan	nagorny	mexico	african	woman
reform	disarmament	democratic	nuclear	republic	nagorno	american	republic	trinidad
disarmament	relation	liberia	north	delegation	minsk	america	africa	2015
korea	namibia	continent	cooperation	idriss	osce	uruguay	south	poverty
intend	independence	delegation	reunification	darfur	armenians	power	delegation	mdgs

Table B.11: Distinguishing features of K-means cluster centroids (continued)

Cluster 18	Cluster 19	Cluster 20	Cluster 21	Cluster 22	Cluster 23	Cluster 24	Cluster 25	Cluster 26
european	island	ukraine	operation	israel	ireland	arab	panama	latvia
kosovo	marshall	georgia	europe	arab	irish	yemen	canal	baltic
union	barbuda	ukrainian	nuclear	palestinian	northern	terrorism	panamanian	reform
bosnia	antigua	georgian	european	israeli	nuclear	emirate	latin	latvian
herzegovina	small	abkhazia	disarmament	palestine	european	bahrain	american	european
europe	pacific	russian	weapon	jordan	operation	egypt	panamanians	sustainable
cooperation	caribbean	russia	negotiation	territory	unionist	palestinian	america	afghanistan
moldova	climate	european	south	aggression	british	syrian	treaty	union
croatia	nuclear	europe	soviet	occupy	weapon	stability	republic	europe
albania	test	chernobyl	arm	zionist	violence	israeli	oceanic	syria

Table B.12: Distinguishing features of K-means cluster centroids (continued)

Cluster 27	Cluster 28	Cluster 29	Cluster 30	Cluster 31	Cluster 32	Cluster 33	Cluster 34	Cluster 35
turkey	pacific	spain	pakistan	paraguay	caribbean	tunisia	myanmar	honduras
cyprus	island	spanish	india	bolivia	saint	arab	drug	nicaragua
turkish	fiji	gibraltar	sri	bolivian	barbados	tunisian	rakhine	costa
greece	zealand	operation	lanka	latin	grenada	maghreb	narcotic	haiti
greek	solomon	european	kashmir	america	small	african	opium	salvador
cypriots	small	mediterranean	nuclear	american	island	solidarity	poppy	rica
cypriot	climate	europe	afghanistan	drug	dominica	palestinian	nuclear	dominican
european	samoa	possible	terrorism	democracy	lucia	mediterranean	reform	central
settlement	tuvalu	crisis	indian	coca	kitts	ben	constitution	el
union	sustainable	terrorism	south	paraguayan	haiti	stability	democratic	american

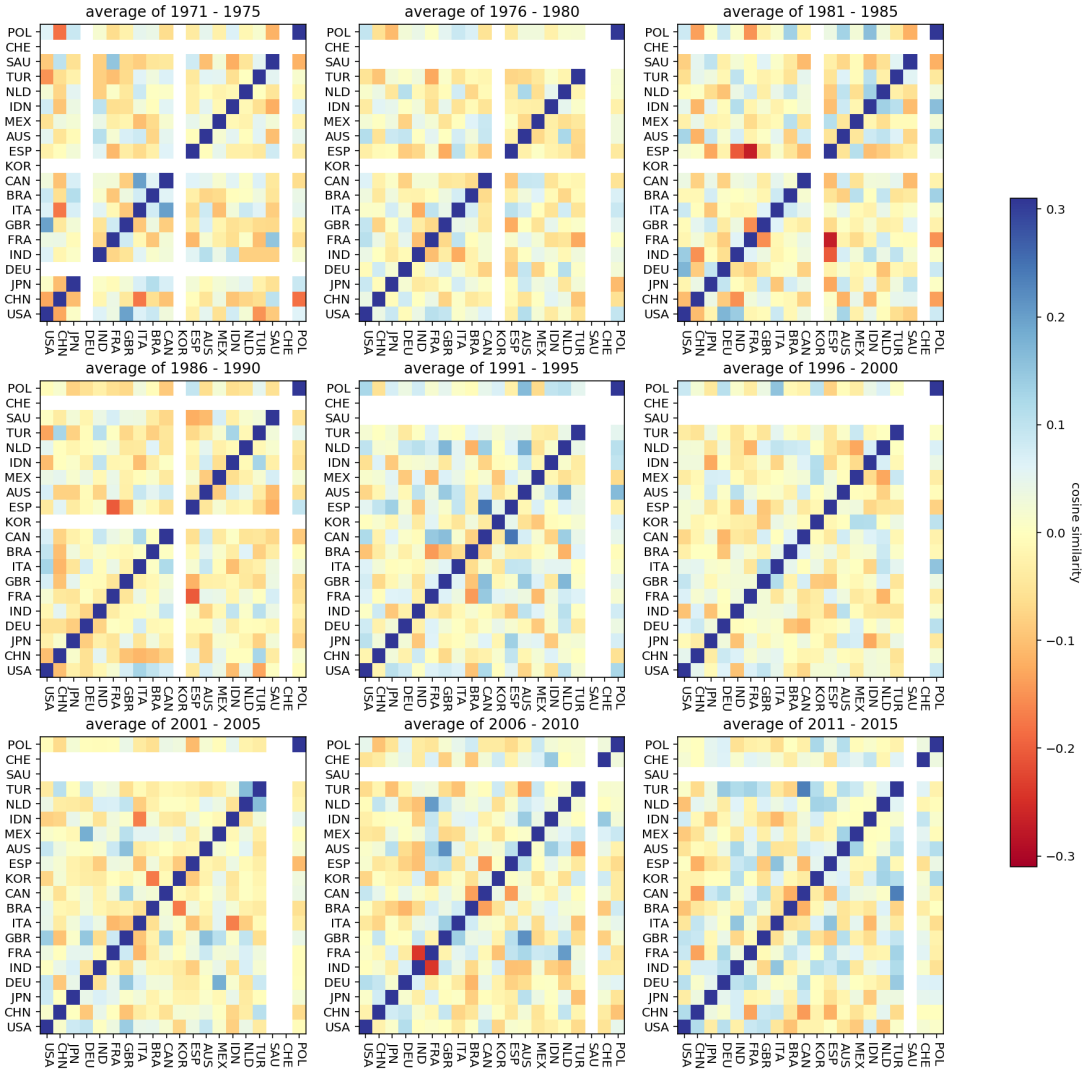


Figure B.16: Average pairwise cosine similarities of 20 states every five years (1970-2015)

Table B.13: Top 5 topics discussed over years

Country	Top 1	Top 2	Top 3	Top 4	Top 5
AFG	4	8	1	18	3
AGO	1	17	23	3	9
ALB	27	1	9	18	8
AND	6	12	2	8	1
ARE	10	4	15	1	5
ARG	11	1	20	14	6
ARM	2	8	1	23	3
ATG	7	1	6	8	12
AUS	3	1	2	16	4
AUT	2	13	3	18	22
AZE	2	13	10	18	15
BDI	1	17	6	3	14
BEL	3	1	18	2	6
BEN	1	6	3	14	5
BFA	1	6	5	17	3
BGD	4	3	5	24	7
BGR	3	26	2	18	13
BHR	10	15	4	1	12
BHS	7	1	4	2	3
BIH	2	8	3	1	18
BLR	1	13	3	9	18
BLZ	7	16	1	6	4
BOL	6	14	25	11	1
BRA	11	1	6	3	5
BRB	7	4	1	12	16
BRN	12	5	1	4	13
BTN	19	5	7	1	4
BWA	1	5	4	7	12
CAF	1	14	3	17	18
CAN	19	2	12	1	3
CHE	2	6	12	3	28
CHL	11	1	6	3	14
CHN	21	1	13	9	10
CIV	1	3	14	6	17
CMR	1	14	3	19	4
COD	1	17	6	14	10

Table B.14: Top 5 topics discussed over years (continued)

Country	Top 1	Top 2	Top 3	Top 4	Top 5
COG	1	17	6	14	3
COL	6	11	1	25	14
COM	14	1	10	4	24
CPV	1	14	6	5	3
CRI	11	6	1	12	14
CUB	1	20	6	8	21
CYP	1	23	4	2	13
CZE	2	18	3	12	13
DEU	3	18	13	1	2
DJI	1	4	17	15	7
DMA	7	16	12	4	1
DNK	2	3	18	1	4
DOM	14	1	6	11	7
DZA	1	27	10	5	4
ECU	11	6	1	14	12
EGY	15	1	10	4	25
ERI	1	8	17	28	7
ESP	1	14	3	11	22
EST	2	18	12	3	8
ETH	1	28	17	5	4
EU	2	8	6	15	18
FIN	2	3	1	19	18
FJI	12	16	1	22	7
FRA	1	3	6	13	14
FSM	16	12	22	7	3
GAB	1	14	3	17	5
GBR	1	8	12	4	2
GEO	2	8	18	6	13
GHA	1	4	7	5	12
GIN	1	14	17	3	5
GMB	4	7	1	5	12
GNB	14	1	3	5	17
GNQ	14	1	3	6	28
GRC	23	1	3	2	4
GRD	7	1	6	4	8
GTM	11	14	6	3	1

Table B.15: Top 5 topics discussed over years (continued)

Country	Top 1	Top 2	Top 3	Top 4	Top 5
GUY	1	7	4	3	16
HND	18	6	14	11	1
HRV	2	1	18	3	13
HTI	1	6	7	14	4
HUN	3	1	18	13	2
IDN	4	5	1	3	24
IND	1	4	8	5	3
IRL	22	1	2	4	8
IRN	10	8	1	4	18
IRQ	10	1	8	15	28
ISL	24	2	1	12	16
ISR	8	15	1	10	18
ITA	22	3	1	2	18
JAM	7	1	3	4	16
JOR	15	1	4	10	8
JPN	12	13	3	1	26
KAZ	2	13	3	18	12
KEN	1	17	4	7	3
KGZ	2	3	13	5	6
KHM	13	21	1	8	24
KIR	16	12	7	5	6
KNA	7	12	4	6	5
KOR	5	26	2	12	13
KWT	10	4	1	15	8
LAO	21	1	9	5	3
LBN	4	15	8	1	10
LBR	1	5	3	12	7
LBY	1	25	10	15	8
LCA	7	1	12	8	4
LIE	2	1	12	18	3
LKA	4	1	8	3	7
LSO	1	4	5	7	19
LTU	2	18	3	12	8
LUX	3	1	2	18	15
LVA	2	18	3	12	5
MAR	27	1	10	4	15

Table B.16: Top 5 topics discussed over years (continued)

Country	Top 1	Top 2	Top 3	Top 4	Top 5
MCO	2	6	3	7	12
MDA	2	3	18	13	5
MDG	1	3	6	24	4
MDV	7	4	1	24	5
MEX	11	6	1	3	2
MHL	16	12	22	7	2
MKD	2	23	3	1	6
MLI	1	17	3	6	4
MLT	28	1	2	3	12
MMR	3	4	1	5	13
MNE	2	5	3	28	28
MNG	13	3	5	2	9
MOZ	1	5	9	17	3
MRT	1	25	10	17	4
MUS	24	1	5	7	4
MWI	19	5	7	12	3
MYS	4	8	1	12	5
NAM	5	1	7	4	17
NER	1	17	3	14	6
NGA	1	5	4	3	7
NIC	20	6	1	11	14
NLD	2	1	3	19	18
NOR	2	3	1	4	19
NPL	5	4	1	19	13
NRU	16	12	7	2	28
NZL	16	1	12	13	3
OMN	10	4	15	1	24
PAK	8	4	1	13	3
PAN	11	6	1	20	2
PER	6	11	3	1	14
PHL	24	1	12	5	6
PLW	12	16	7	28	28
PNG	16	12	1	3	14
POL	11	3	13	1	2
PRK	26	13	1	12	21
PRT	1	23	3	2	14

Table B.17: Top 5 topics discussed over years (continued)

Country	Top 1	Top 2	Top 3	Top 4	Top 5
PRY	14	1	6	11	19
PSE	15	8	12	28	28
QAT	10	15	1	4	12
ROU	9	3	2	13	1
RUS	18	13	1	3	26
RWA	1	17	6	14	3
SAU	10	4	15	1	8
SDN	25	1	4	15	10
SEN	1	6	14	3	17
SGP	1	12	21	8	7
SLB	22	16	12	7	5
SLE	1	5	16	4	7
SLV	6	1	11	14	3
SMR	2	6	3	5	12
SOM	1	17	8	15	12
SRB	2	6	27	8	12
SSD	25	17	12	5	2
STP	1	14	6	5	12
SUR	11	7	3	1	4
SVK	2	3	18	13	12
SVN	2	3	1	12	18
SWE	2	3	1	18	19
SWZ	5	12	1	4	19
SYC	1	16	24	6	7
SYR	15	1	10	8	4
TCD	14	1	17	25	10
TGO	1	3	14	17	6
THA	7	4	21	1	5
TJK	3	2	13	4	5
TKM	13	2	3	28	28
TLS	23	6	12	5	8
TON	16	22	12	5	7
TTO	7	1	4	3	5
TUN	1	10	15	3	5
TUR	23	4	1	15	2
TUV	16	12	5	7	28

Table B.18: Top 5 topics discussed over years (continued)

Country	Top 1	Top 2	Top 3	Top 4	Top 5
TZA	1	17	5	4	7
UGA	1	12	17	4	5
UKR	18	13	3	9	1
URY	1	11	6	3	14
USA	8	12	1	18	6
UZB	2	3	13	4	8
VAT	6	2	12	1	8
VCT	7	1	8	4	6
VEN	6	1	20	11	8
VNM	21	1	5	13	3
VUT	16	1	12	8	7
WSM	16	1	12	4	7
YEM	15	10	1	4	9
ZAF	1	5	12	6	3
ZMB	1	5	4	9	7
ZWE	1	5	4	7	8

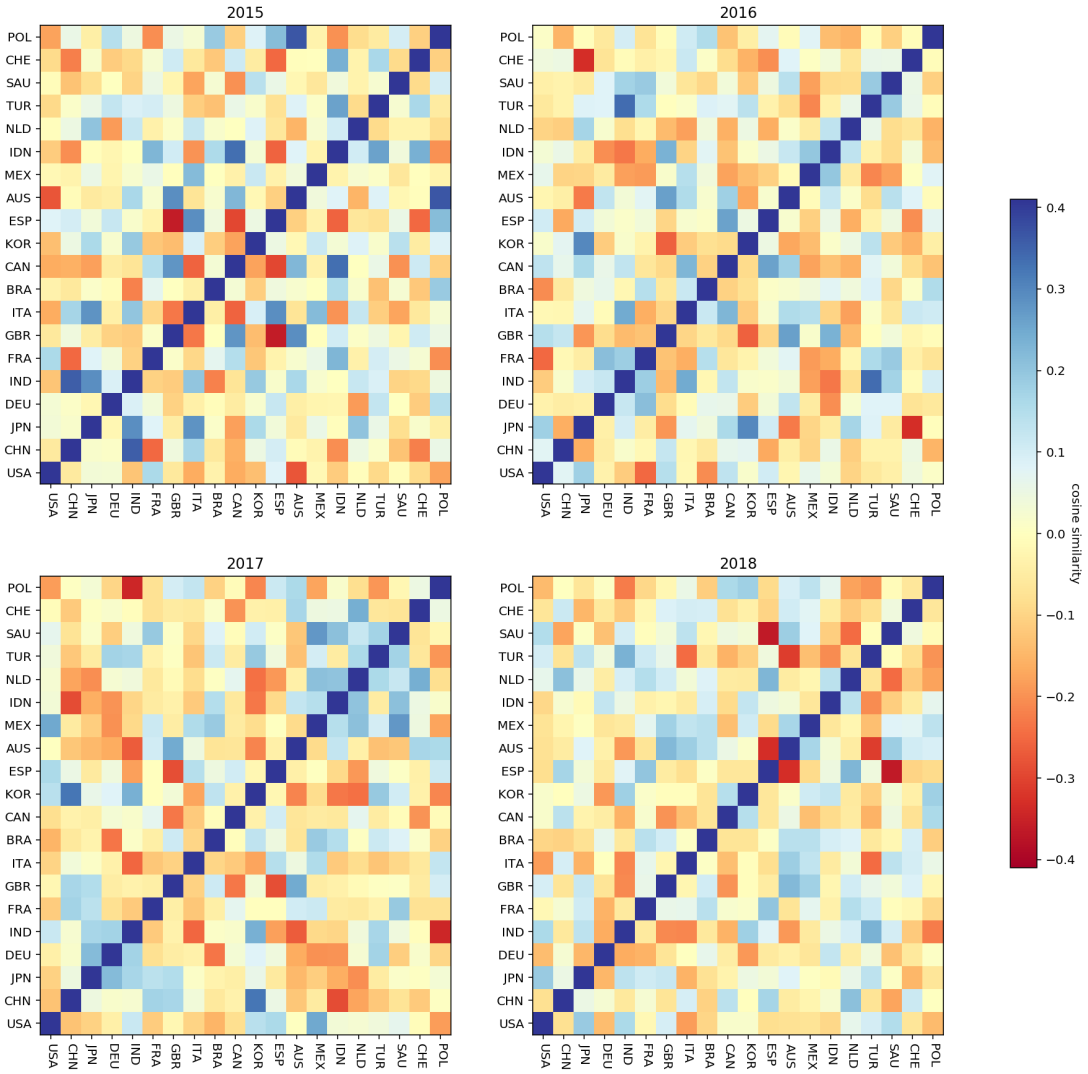


Figure B.17: Pairwise cosine similarities of 20 states in recent years (2015-2018)

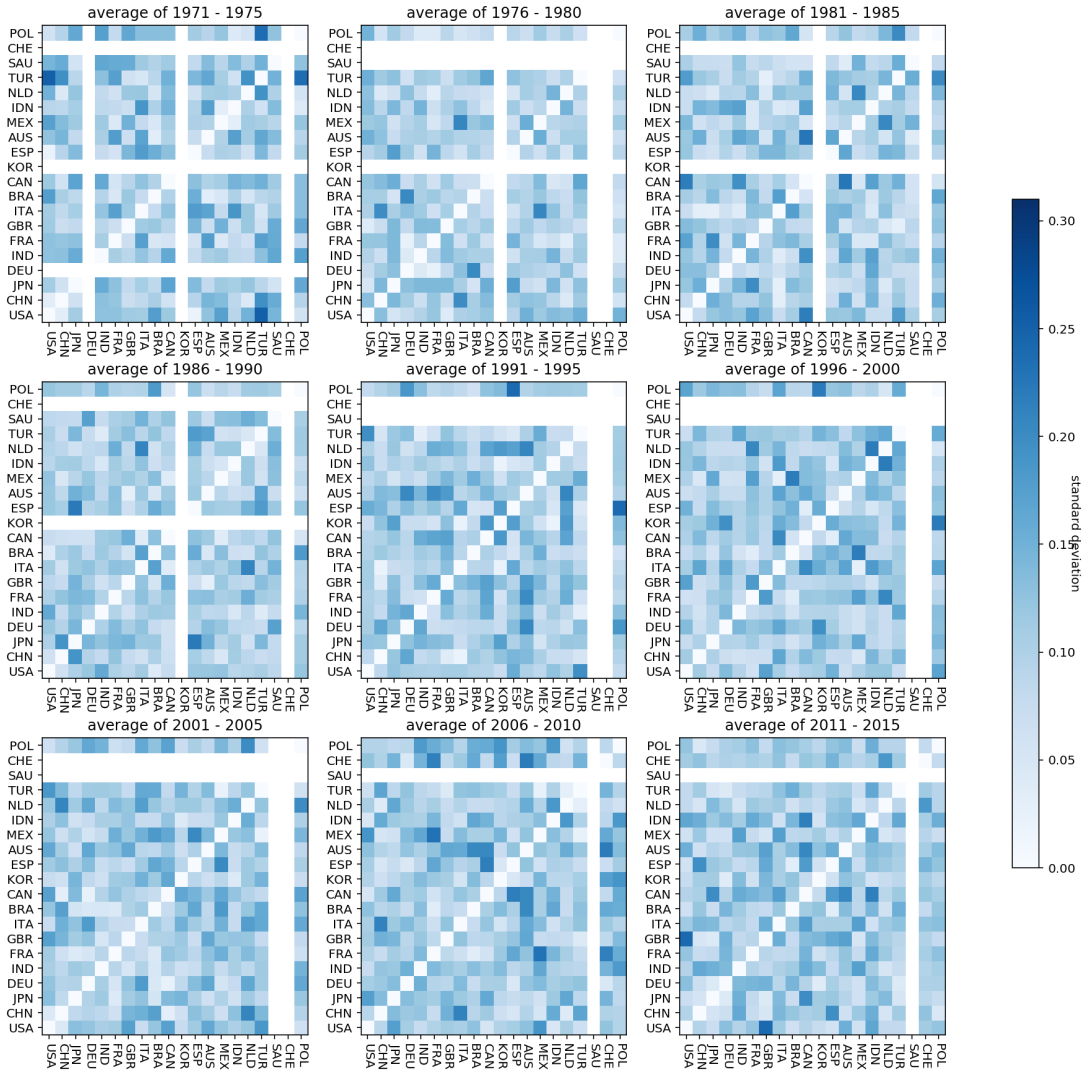


Figure B.18: Standard deviation of pairwise cosine similarities of 20 states every five years (1970-2015)

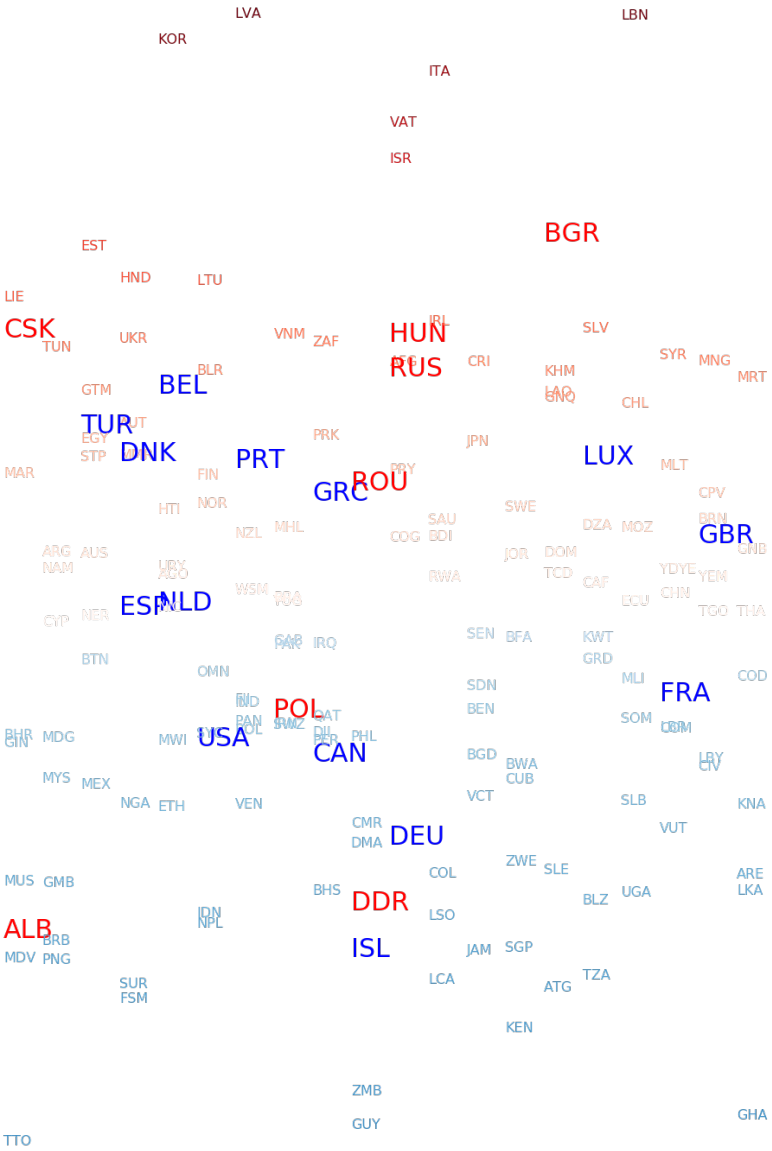


Figure B.19: Projection of states vectors onto the Cold War dimension (1970-1991)

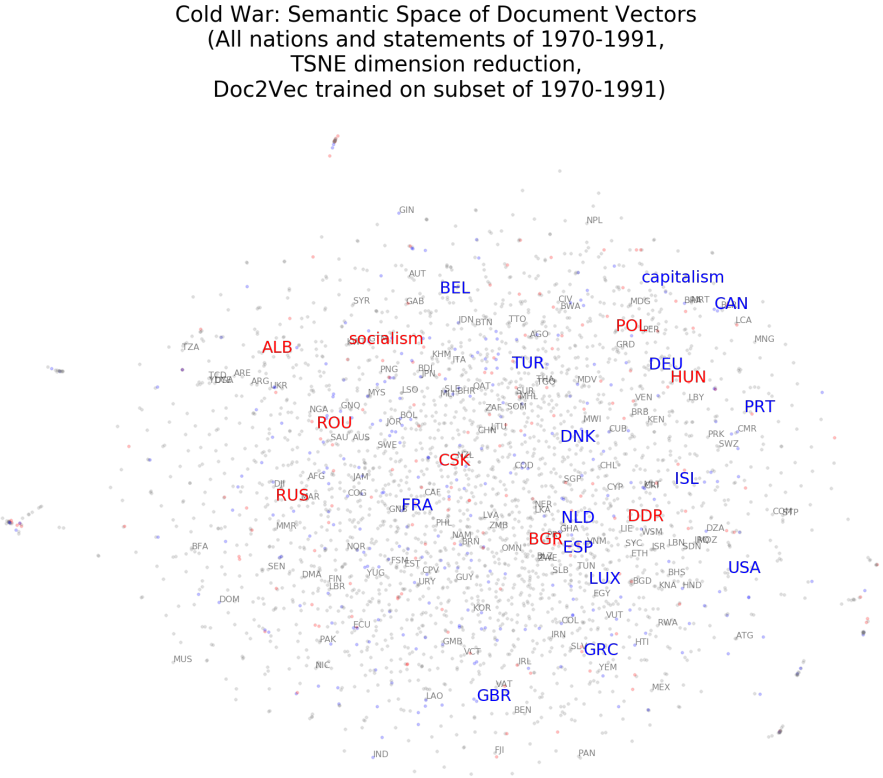


Figure B.20: Semantic space of document vectors (1970-1991)

Table B.19: K-means clustering of Doc2Vec state vectors

cluster 0	cluster 1	cluster 2	cluster 3	cluster 4
AUS	ALB	ARG	IRN	BEL
CAN	AUT	BOL	IRQ	CMR
GBR	BLR	BRA	ISR	COG
GHA	ISL	COL	KWT	DZA
GMB	ITA	CRI	LBN	FRA
IDN	JPN	CUB	LBY	GIN
IND	KHM	DOM	MAR	HTI
KEN	NLD	ECU	SDN	MDG
LBR	NOR	GTM	SYR	RWA
LKA	TUR	HND	TUN	TGO
MMR	UKR	MEX	EGY	BDI
NZL	YUG	PER	JOR	BEN
PAK	AFG	PRY	QAT	BFA
PHL	BGR	SLV	SAU	CAF
SGP	CHN	URY	YDYE	CIV
SLE	CSK	VEN	YEM	COD
SOM	CYP	CHL	ARE	GAB
THA	FIN	ESP	BHR	LUX
TTO	GRC	NIC	OMN	MLI
USA	HUN	PAN	PSE	MRT
ZAF	LAO	VAT		NER
ZMB	MNG	SMR		SEN
ETH	POL	AND		TCD
FJI	ROU			PRT
GUY	RUS			GNQ
IRL	SWE			COM
JAM	DNK			CPV
MLT	DDR			GNB
MUS	DEU			STP
MYS	VNM			AGO
NGA	LIE			MCO
NPL	EST			
TZA	KOR			
UGA	LTU			
BRB	LVA			
BTN	PRK			
MWI	ARM			
...	...			