Internacia

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1 Project Description

1.1 Introduction, Motivation and Hypothesis

The measurement of a country's status is a crucial aspect of international relations, but it poses a significant challenge due to its complex nature. Typically, conventional approaches rely on material attributes such as wealth and military capability to determine a state's status ranking. In such an approach, the higher a state's score is on specific attributes, the higher its status is assumed to be (see for example: Gilpin, 1981; Paul et al., 2014; Wohlforth, 2009). However, reducing status to a function of attributes is inconsistent with the social nature of status. To address this issue, we propose an alternative approach to measuring status that leverages networks of diplomatic exchange. By using diplomatic exchanges as a metric, we can determine which countries are more socially recognized and thus have higher status ranking. Weber defined status as "an effective claim to social esteem in terms of positive or negative privileges" (Weber, 1978, p. 305). Therefore, according to this definition of status, the mere aspiration to have status doesn't create it, nor are particular attributes sufficient. For an actor to achieve a particular status, others need to recognize it. For example, a state may claim to be a great power and have great power attributes, but its great-power status depends on whether other states consider that claim to be legitimate. In light of this definition we will use a measure of status that is sensitive to social recognition: diplomatic exchanges. The decision to allocate an ambassador to another country can be considered as a vote for the importance of the receiving country since each country has limited diplomatic resources and therefore must prioritize where to send its diplomats. Using data on diplomatic exchange we could distinguish which countries receive more ambassadors and consider those countries as the ones with more status.

There are two distinctive advantages of using diplomatic exchange networks to measure a country's status over other approaches. First, it considers the collective judgment of the international community, not merely the claims of individuals or groups. Second, diplomatic exchanges hold importance across time periods, unlike state attributes such as possession of colonies or nuclear weapons. Thus, this measure of status is less restricted by temporal considerations than other methods since there has always been a relationship between diplomacy and status. For instance, after the Japanese defeat of Russia in 1904–5, Japan's missions in the West and those of the principal Western powers in Tokyo were progressively upgraded to the rank of embassies—a move which immensely enhanced Japan's prestige and cemented its status as a great power (Anderson, 2014, p. 109), or as early as the year 2010, the former Chief of Diplomatic Protocol for the US stated that ”the presence of a diplomatic mission in a foreign country lends credibility or prestige to both sending and receiving states” (Mel, 2010, p. 279).

If our measurement of status is valid, it should correlate better with foreign travels made by heads of states compared to material attributes. This means that the higher a country is in the ranking, the more likely it is to receive foreign chiefs of states. Our working hypothesis is that a country’s status correlates with the likelihood of a US president visiting it.

1.2 Pipeline description

A diagram of our data collection, analysis, and modeling processes can be seen in Figure 1. First we collect data about US presidential visits to foreign countries by web-scraping “The Office of the Historian” Html websites (United States Department of State, 2019a). Additionally, we analyze existing datasets of diplomatic exchange information, particularly the Correlates of War (COW) ”Diplomatic Exchange” dataset (Bayer, 2006). We transform the diplomatic dataset to a network (nodes: countries, edges: diplomatic connections) and we further compute various centrality measures. Furthermore, we apply record linkage techniques to connect our web-scraped dataset with the diplomatic COW data as well as other pre-existing data sources: (1) the “Penn World Table dataset” (Feenstra et al., 2015), which contains various economic information at the country level, and (2) the ”National Material Capabilities” COW dataset, which has various measures of material attributes at the country level (Singer, 1987). Note that data collection, cleaning, transformation and record linking is conducted using an SQLite database and relevant Python modules (requests, beautifulsoup, pandas, sqlite3, jellyfish, networkx), Thus, the final datasets used for the modelling part of our project (regression analysis and network visualizations) are stored in a database.

2 Data

In the following we will take a closer look at our collected data.

2.1 Correlates of War Dataset

2.1.1 Diplomatic Exchange

The first dataset we are using is diplomatic exchange data from the Correlates of War project (Bayer, 2006). The dataset captures diplomatic relationships between countries at the following levels: chargé d’affaires, minister, and ambassador. Information is available for the following years: 1817, 1824, 1827, 1832, 1836, 1840, every five years between 1844 and 1914, every five years between 1920 and 1940, and every five years between 1950 and 2005. The variables present in the dataset can be seen in Table 1. The dataset consists of 310820 diplomatic connections between 213 countries.

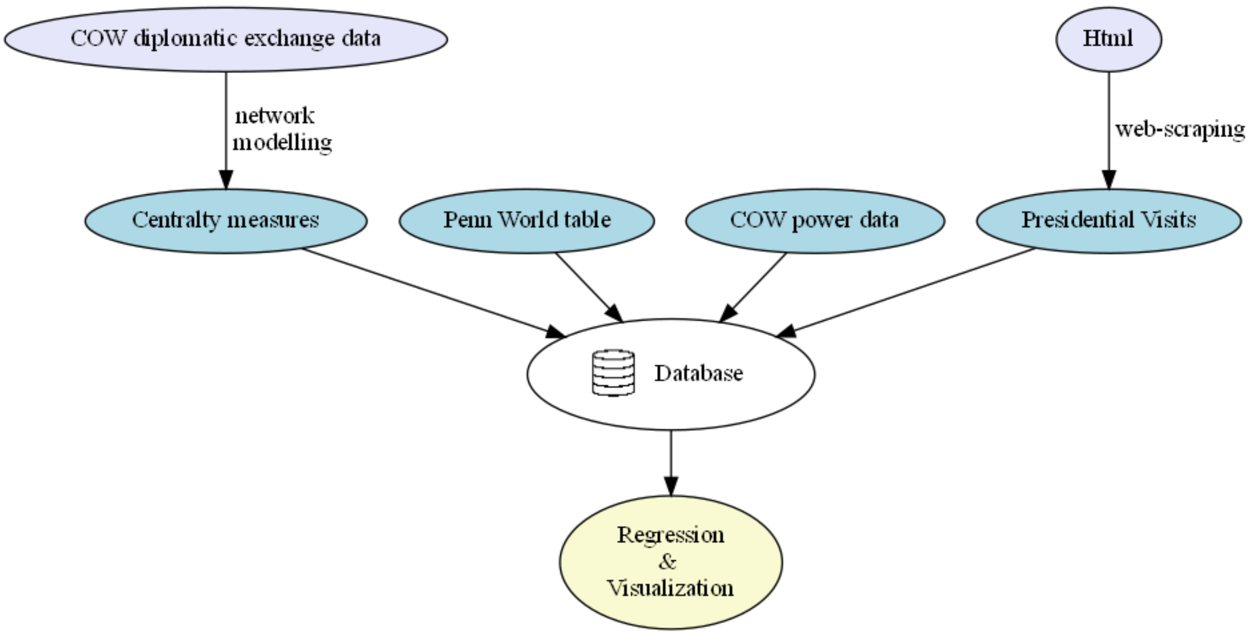

Figure 1: Diagram showing the complete pipeline of data collection, transformation, storage and analysis.

Columns	Column Description	Type
ccode1	Correlates of War state number of country 1	integer
ccode2	Correlates of War state number of country 2	integer
year	Year of observation or period of years	integer
DR_at_1	Diplomatic representation level of side 2 at side 1	ordinal
DR_at_2	Diplomatic representation level of side 1 at side 2	ordinal
DE	Any diplomatic exchange between side 1 and side 2	categorcal
Version	Current version of the data set	string

Table 1: Variable names and descriptions for the COW diplomatic dataset.

2.1.2 Variable explanation

Variables `DR_at_1` and `DR_at_2` have the following encodings:

- `0=no evidence of diplomatic exchange`
- `1=chargé d'affaires`
- `2=minister`
- `3=ambassador`
- `9=other`

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Charge d'affairs, counselor, and ambassador expelled, recalled, or withdrawn, result in an encoding of 1. Category 1 is the least significant category of diplomatic connection.

Minister, minister plenipotentiary, minister resident, and envoy correspond to an encoding of 2. Category 2 is also a category of low importance.

Ambassador, high commissioner, secretary of Libyan People's bureau and similar labels, high commissioner or ambassador resident elsewhere, and ambassador, high commissioner or secretary vacant, correspond to an encoding of 3. It is worth noting that category 3 signifies the strongest type of diplomatic connection which we will extensively use in comparing status measurements.

Interest sections, interests served by another country, address only (without indication whether there was any diplomatic staff occupying it), temporary embassy closings, and consulate-generals, result in an encoding of 9. Note that in the analysis of the data we are disregarding category 9 as it points to a weak diplomatic link.

Variable DE can have two values: 0, signifying that both sides do not have any kind of diplomatic connection (types 1, 2 and 3), or 1, signifying that there is at least one diplomatic relationship between the two countries.

2.1.3 Power of Nations

Although power and material capabilities are not identical, given their association it is essential that we try to define the latter in operational terms so as to understand the former. The power dataset of material capabilities (Singer, 1987) takes the total population, urban population, military personnel, military expenditures, primary energy consumption, and iron and steel production for each country and combines them into the Composite Index of National Capability (CINC) score. The CINC reflects an average of a state's share of the system total of each element of capabilities in each year, weighting each component equally. In doing so, the CINC will always range between 0 and 1. Descriptions of the variables in this dataset can be found in Table 2.

Variable name	Description	Type	Example
stateabb	Abbreviation of country name	string	USA
ccode	Country code	integer	2
year	Year of observation	integer	1816
milex	Military Expenditure	integer	3823
milper	Military personnel	integer	17
irst	Iron and steel production	integer	80
pec	Primary energy consumption	integer	254
tpop	Total Population	integer	8659
upop	Urban population	integer	101
cinc	Composite Index of National Capability	float	0.0396975

Table 2: Description of COW power of nations data.

2.1.4 Country Code

This table is part of the COW dataset and provides a mapping from country codes to country names. This mapping is subsequently used to link the different datasets containing country level information. The description of the columns in this dataset can be found in Table 3

Variable name	Description	Type	Example
StateAbb	Abbreviation of country name	string	PER
ccode	Country code	integer	135
StateNme	Country name	string	Peru

Table 3: Description of COW country codes data.

2.1.5 Example

In the following we examine a few rows of the COW dataset for the year 2005 (Figure 2). The first row means that country 2 (`ccdode1=2`) is connected to country 20 (`ccode2=20`) with a diplomatic relationship of type 3 (`DR_at_1=3`) while the reciprocal connection between the two countries (20 to 2) is also of type 3 (`DR_at_2=3`). The third row, on the other hand, means that there is no diplomatic relationship between country 2 and country 40. From the COW country codes table we check that country 2 corresponds to the U.S.A., country 20 to Canada and country 40 to Cuba. Therefore, the U.S.A. and Canada are connected with a strong diplomatic relation while the U.S.A. and Cuba do not have diplomatic relations for the year 2005 (5 year period 2001-2005).

2.2 Presidential Visits

We scrape data about the US president's visits to foreign countries. The data is scraped from `https://history.state.gov/departmenthistory/travels/president` (United States

ccode1	ccode2	year	DR_at_1	DR_at_2	DE	version
2	20	2,005	3	3	1	2,006.0999755859
2	31	2,005	3	3	1	2,006.0999755859
2	40	2,005	9	9	0	2,006.0999755859
2	41	2,005	3	3	1	2,006.0999755859
2	42	2,005	3	3	1	2,006.0999755859

Figure 2: Screenshot of the diplomatic exchange dataset.

destination country	destination city	description	time	year
Panama	Colon, Panama City	Inspected construction of Panama Canal. Met with Presiden	January 29–February 7, 1909	1,909
United Kingdom	Bermuda	Vacation. [Visit made as President-elect.]	November 18–December 13, 1912	1,912
France	Paris, Chaumont	Attended Preliminary to the Paris Peace Conference. Depar	December 14–25, 1918	1,918
United Kingdom	London, Carlisle, Manchester	Met with Prime Minister Lloyd George and King George V.	December 26–31, 1918	1,918
France	Paris	Stopover en route to Italy.	December 31, 1918–January 1, 1919	1,918
Italy	Rome, Genoa, Milan, Turin	Met with King Victor Emnanuel III and Prime Minister Orlan	January 1–6, 1919	1,919

Figure 3: Screenshot of the scraped presidential visits data.

Department of State, 2019b). The time frame of presidential visits is from 1906 (President Theodore Roosevelt) to 2020 (President Donald J. Trump). Our dataset consists of 775 presidential visits to 120 different countries. The web-scraped data includes the following information: destination country, destination city, brief description of the visit, datetime of the visit. A description of the dataset columns can be seen in Table 4 and example values can be found in Figure 3.

Columns	Column Description	Type
Destination country	Country the president visited	string
Destination city	City the president visited	string
Description	Description of the visit	string
Time	Date of the visit	datetime
Year	Year of the visit	integer

Table 4: Description of Presidential Visits

2.3 Penn World Table

Penn World Table is a dataset which contains information on relative levels of income, output, input and productivity, covering 183 countries between 1950 and 2019 and hosted by the University of Groningen (Feenstra et al., 2015). Its size is 12810 rows. This dataset includes 53 variables such as population, real GDP adjusted for PPP for each year, consumption and output based GDP and economic structure. The Penn World Table will enable us to control for the effect of economic growth on a country's status in international relationships.

2.4 Data validity

We are interested in examining alternative network-based measures of country status in international relations and thus the US presidential visits can be a great example of how a country of high status allocates its diplomatic resources through presidential visits. The scraped data can provide a way to validate our hypothesis that network measures of country status in international relations are more important than material or other attributes. In the analysis part of the project we will compare different measures of status as predictors of the US president's visits. Since the US is a country that is considered as a high status regardless of the way status is measured, the visits of the president can be a good way to compare the different measurements of status.

2.5 Data limitations

One of the most important limitations is that our analysis focuses on US presidential visits. It would be useful to have information of high-ranking state officials (president, prime minister etc.) for multiple countries. However, information for other countries is not always readily available or easily web-scraped. We will evaluate our hypothesis on US presidential visits, keeping in mind the unknown generalizability of our results. If our hypothesis is validated, we could expand evaluations of visits for other countries as well. To our knowledge, the relevant data is already available for China and can also be scraped through wikipedia pages for a variety of countries.

A second limitation is that when linking presidential visits with the COW dataset we are compelled to limit examining presidential travels for the years between 1970 and 2005, since that is the overlapping time frame between the two datasets[1]. Further data collection of diplomatic relation data could be implemented in the future to enrich the datasets.

3 Data Cleaning, Wrangling and Methodology

3.1 Data cleaning/processing and linking

First, we reformulate the COW diplomatic data as a directed network for each year or time period of diplomatic information. Each node of the network represents a country, while each edge corresponds to different types of diplomatic relations (different coding for `DR_at1`/`DR_at_2`). An example graph can be seen in Figure 4, where we can see that the network of connections changes over time. Subsequently network centrality measures are computed for every country-node and aggregated in a table in the database (Figure 5).

We are subsequently merging the web-scraped data on presidential visits to the centrality measures table. In order to link the two tables, further cleaning is required on the scraped data. First, we extract the year of each visit. Note that we are only focusing on presidential visits between 1950-2005 since that is the data available on the COW tables. The visits are then matched to five year periods to match the year column of the COW table with the

[1] The actual overlap is 1950-2005. However, the COW dataset does not contain information for the year between 1950-1965. Hence we limit our analysis to year after 1965.

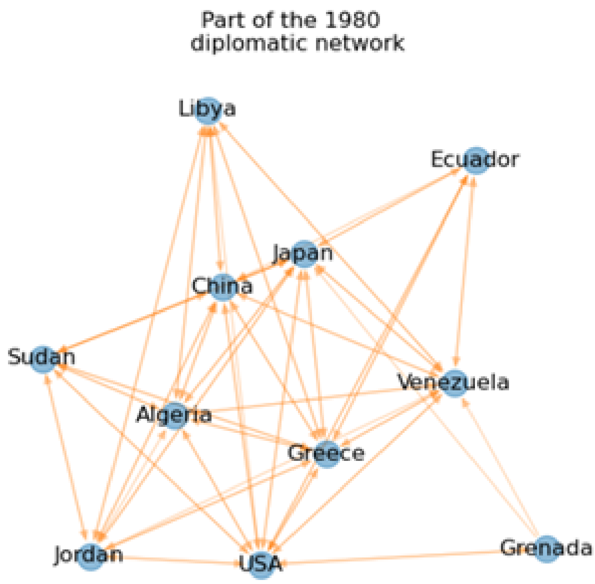


Figure 4: Part of the diplomatic networks (subgraphs) for years 1980 (left) and 2005 (right). The edges correspond to diplomatic relations of type 3. Note that Yemen is not present in the 1980 subgraph but has connections with the rest of the countries in the 2005 network. Hence, it is worth noting that diplomatic networks are temporal.

scraped data (for example a visit on 2004 is matched to year 2005 in the COW dataset since year 2005 refers to the time period between 2001 and 2005).

In addition, country names between the two datasets slightly vary. For example, the scraped dataset refers to China as "China, People's Republic of " whereas the COW dataset as "China". We are thus linking the two tables by translating every country name to the COW dataset country code.

Further matching between countries and years in the economic info dataset and the web-scraped visits is required. Similarly to the matching applied to connecting visits with the centrality table, we are linking Penn World Table countries to the COW integer country codes. However, the economic data table also contains countries not present in the rest of the datasets. These country names are left untouched for now. In the future, we plan to further encode them with a new integer value to facilitate matching between our tables.

As for the years, since economic information of each country remains relatively stable in a time period of 5 years, we will use the economic data for each year instead of aggregating years to 5-year periods. For example, for linking presidential visits from 2001 to 2005 codes as year=2005 to aggregated economic data for the same period we will directly link them to economic data for the year 2005. This approximation is conducted for simplicity and can be enriched in the future.

3.2 Database description

In the following we will provide a brief description of the final database. The database contains a `president_visits` table containing all the information from the web-scraped

pagerank	betweenness	closeness	degree	in_degree	out_degreee	node_id	year
0	0	0	1	0	1	220	1,854
0.4235238894	0	0.6470588235	0.44	0.4444444444	0.4	2	1,894
0.5234933317	0	0.6666666667	0.4545454545	0.3333333333	0.5	200	1,859
0.5300632844	0.0151515152	0.6666666667	0.5405405405	0.5	0.4	200	1,844
0.5364407725	0	0.3968253968	0.5714285714	0.5714285714	0.5714285714	2	1,899
0.5566945533	0.4318181818	1	0.6129032258	1	0.5	200	1,824
0.6322968577	0.2875	0.6666666667	0.7878787879	0.5	1	200	1,840
0.6794660946	0.0217391304	0.7	0.7142857143	0.5714285714	0.6666666667	200	1,836
0.7280589529	0	0.8333333333	0.8095238095	0.75	0.8333333333	200	1,884
0.7400458491	0.0291262136	0.8333333333	0.8095238095	0.75	0.8333333333	200	1,879
0.7468987698	1	0.8235294118	0.7777777778	0.8	0.8888888889	2	1,909
0.7955516458	0.5492957746	0.8571428571	0.8387096774	0.75	0.75	200	1,827
0.7957552883	0.1111111111	0.9090909091	0.8235294118	0.8333333333	0.8	200	1,874

Figure 5: Example rows of the centrality measure table. Each row corresponds to a specific country (*node_id*) at a specific year (*year*) and contains different centrality rankings for this country.

data enriched with a column matching years to their 5-year periods (`year_aggregate`) and a column specifying the integer country code (`ccode`). It also contains a table containing centrality measures for each country and year/period (`all_centralities`). Furthermore, it contains a `diplomatic_exchanges` table containing the COW diplomatic exchange data. Finally, the database includes an `economic_data` table containing all the information available in the Penn World table also matched to the country codes (`ccode`) as well as the "power" data of material capabilities as a `power_data` table.

The tables are linked with the connections seen in Figures 6 and 7. Note that the economic data table contains countries not present in the rest of the datasets. These countries are, for now, encoded as strings in the `ccode` column of the `economic_data` table and hence we cannot set foreign key connections with the rest of the tables. We will further encode those countries with a new integer value to facilitate linking between tables.

3.3 Descriptive Network Analysis

There are multiple ways to model the COW diplomatic dataset as networks. As previously discussed we will model the COW dataset as a directed graph. Nodes of the network correspond to countries and edges to diplomatic relationships. However, the diplomatic connections are of various types and hence we could model connections using different combinations of relationships (e.g. type 1 for ij and 1 for ji or type 1 for ij and type 2 for ji).

We propose the following simplifying approach of modeling the network as a directed weighted graph:

$$G = (V, E, W) \tag{1}$$

where V the node set of countries, $E \subseteq [V]^2$the edge set and W an edge-weight set.

Each edge e_{ij} of the network, denoting a link from country i to country j, is identified by two criteria: (a) there exists a diplomatic exchange between the two countries, denoted as

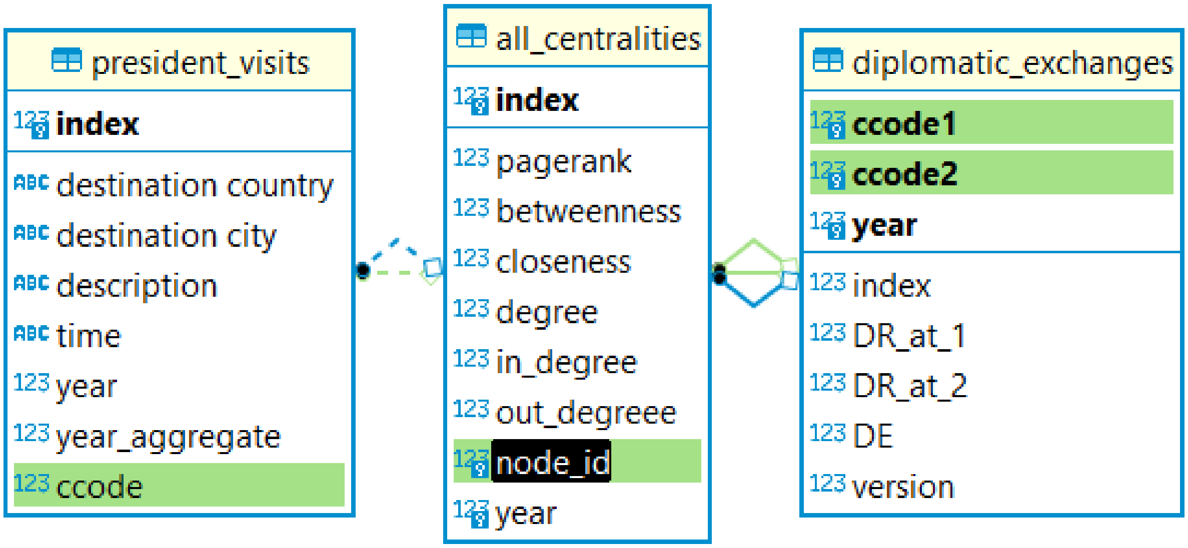


Figure 6: Foreign key relations for matching countries between president visit, centrality and diplomatic exchange data). As similar relation is enforced on both the economic data and the power tables. The visualization of links is possible through the DBeaver database management interface.

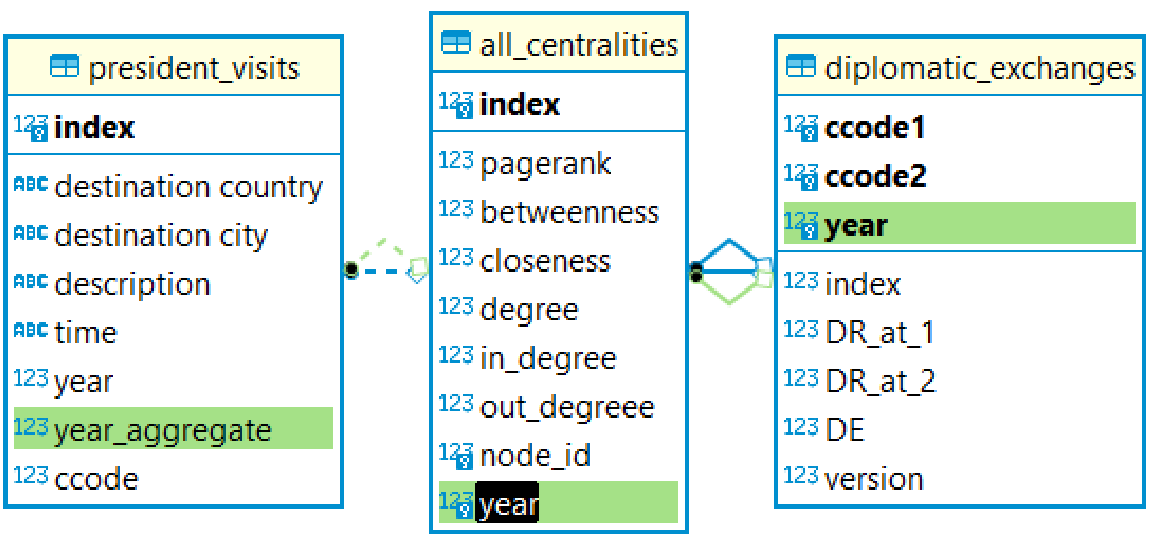


Figure 7: Foreign key relations for matching years/periods between president visit, centrality and diplomatic exchange data). As similar relation is enforced on both the economic data and the power tables. The visualization of links is possible through the DBeaver database management interface.

$DE = 1$ in the diplomatic_exchanges table, and (b) the diplomat sent from country i to j is an ambassador, denoted as $DR\_at\_1 = 3$ in the same table.

We will also weight the edges using the reciprocal relation, i.e. the edge type for $e_j i$(edge from j to i), which can be either $0, 1, 2, or 3$. The relevant information is stored in the DR_at_2 column of the diplomatic_exchanges table.

The intuition for using this network-formulation of diplomatic relationships is that diplomatic relationships could be common yet ambassador level relationships are not. Selecting only ambassador level diplomats can illustrate how countries distribute their most important resources in diplomatic relationships. Moreover, if we want to analyze the network-"status" level of a node, it seems intuitive to analyze how other nodes favor the node of our interest. Then, DR_at_2, reflecting how country j values the relationship with country i is taken into account as the weight of the edge e_{ij}. In $G = (V, E, W)$ "status" can be quantitatively measured as the centrality of each node. Six centrality measures will be examined in the following.

3.3.1 Eigenvector

The rationale of eigenvector centrality is that one node's centrality is determined by the centrality of its connected nodes. Suppose we allocate the centrality value on each node and diffuse it around the network, then we will expect the centrality of each node converges to a certain value. Suppose we have a transition matrix characterized by the network, then the convergence point can be characterized as (Newman, 2010):

$$\mathbf{x} = c\mathbf{A}\mathbf{x} \tag{2}$$

where $\mathbf{x}$ is our centrality measure, $\mathbf{A}$ is the transition matrix and c is the term representing the diffusion. Since $\mathbf{x}$ is also the eigenvector corresponding to the eigenvalue c^{-1}, it is also called the centrality eigenvalue centrality measure.

3.3.2 PageRank

The PageRank algorithm was proposed by Brin and Page, aiming to rank websites by their importance (Brin & Page, 1998). PageRank is a variant of eigenvalue centrality and measures the importance of a node inside a network based on the following simple principle (Langville & Meyer, 2006):

A node is considered important if other important nodes point to it.

We assume the diplomatic exchange as a type of "voting" for a country's importance. Suppose there is a "vote" from country i to country j, then country j can pass down such "vote" to other countries. With the direction and weight of the edges inside the network defined, a transition matrix can be obtained to illustrate the dispatch of diplomats. Iterating this transition matrix, we will eventually converge to a stationary distribution on the probability that each country receives such "vote" in importance. Such probability is our quantitative measure of a country's status.

3.3.3 Katz

Katz centrality is an alternative reformulation of eigenvector centrality giving a starting value which is independent of their position in the network and the position of their neighbors. It can be represented in matrix form as follows (Newman, 2010):

$$\mathbf{x} = (\mathbf{I} - \alpha\mathbf{A})^{-1}\mathbf{b} \tag{3}$$

where α is a decay term and $\mathbf{b}$ the assigned values.

3.3.4 Degree, In Degree and Out Degree

The degree centrality is the simplest centrality measure, as it measures the number of nodes that each node connects to, i.e. the number of neighboring nodes. In an directed graph it is defined as:

$$\deg(i) = |E(i)| \equiv \deg_{in}(i) + \deg_{out}(i) \tag{4}$$

where: $|E(i)|$ is the number of neighbors to node i, $\deg_i n(i)$ is the in-degree of the node i (number of edges pointing to node i) and $\deg_{out}(i)$ is the out-degree of i (number of edges pointing out of i).

Hence, in our network, $\deg_{in}(i)$ refers to the number of ambassadors received by country i from other countries and is indicative of the country's "popularity" or "importance". On the other, hand, $\deg_{out}(i)$ refers to the number of ambassadors country i dispatches to other countries. Note that for simplicity, we calculate degree in the undirected graph.

3.3.5 Betweeness and Closeness

We also calculate betweeness and closeness centrality for undirected versions of our temporal networks. However, as we will see in the following, those centrality measures are excluded from the analysis.

3.4 Methodology

3.4.1 Principal Component Analysis

Even though six centrality measures will be used in our analysis(eigenvector, PageRank, Katz, in degree, out degree and degree), it is worth noting that they provide the same information: the centrality of a node in the network. Indeed, the centrality measures in our temporal networks are highly correlated with each other (Figure 8). This forbids us from applying regression models directly using centrality measures as the data show severe multicollinearity.

One solution to this problem would be to keep only one of the measures in the analysis. However that could lead to loss of information, omitted variable bias and measurement error problems, which will decrease efficiency and induce inconsistencies. Therefore, we alternatively choose to aggregate the information offered by various centrality measures conducting principal component analysis.

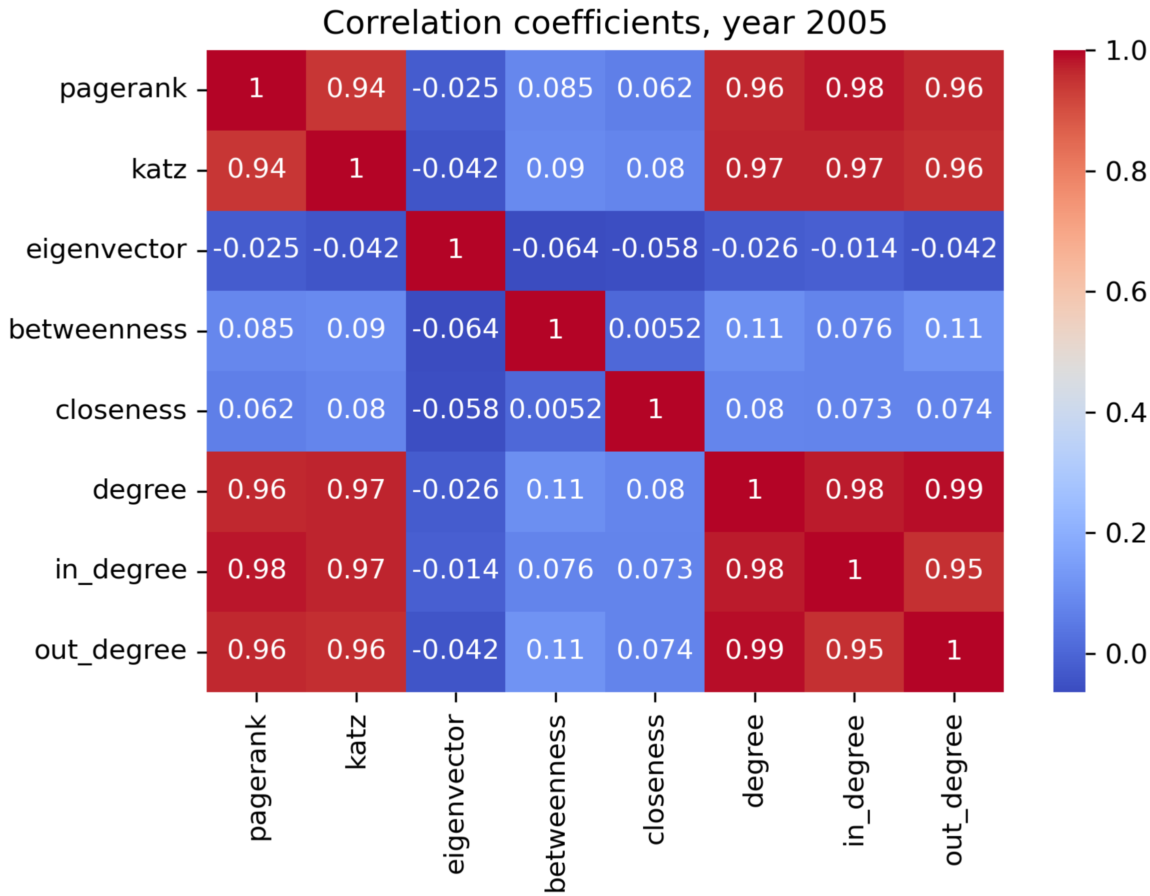


Figure 8: Correlation coefficients for the centrality measures of table *all_centralities* for year period 2005. Note that we are mainly interested in the PageRank, Katz, Eigenvector, Degree, In-degree and Out-degree measures. We observe that the table is suffering from severe multicollinearity in the measures of interest.

Taking the product of the centrality measure matrix for each country and its transpose, we calculate its eigenvalues and eigenvectors and select the vector with the largest eigenvalue (principal component). Such a component will efficiently combine the information of these variables, explain most of their variance, reduce dimensionality and alleviate the multicollinearity problem.

3.4.2 Logsitic Regression

As previously mentioned, our working hypothesis is that network-based measures better capture status as they take into account its relational character, compared to material or other attributes. We will try to validate this hypothesis by comparing different measures of status as predictors of the US president's visits to other countries. Our hypothesis is that a country's status as measured through network metrics better correlates with the likelihood of a US president visiting it compared to other attributes.

The dataset to analyze is created by connecting the US presidential visits dataset with the centrality and other measures (per year and per country). Since all our data are part of an SQL database this step can be easily conducted by applying multiple `JOIN` statements between the `all_centralities`, `president_visits`, `power_data` and `economic_data` tables for each year and a `GROUP BY` statement on countries (`node_id`).

The Python modules we will be using for this part of the project include: sqlite3, pandas, numpy, statsmodels, and scikit-learn.

We will apply a simple logistic regression model to validate our claim. The dependent variable is a dummy variable signifying whether a US president or secretary of state visits that country during a given time span and the independent variables include: the first principal component of the centrality measures, GDP per capita of destination countries, political features, and military advances. Note that the coefficient of the first principal component reflects how a country's network-based status affects the probability of U.S. presidential visits.

3.4.3 Violations of OLS assumptions

It is worth noting that we have to deal with some violations of OLS assumptions. Since our data are relational, we are not dealing with independent observations. However, as we will discuss in the following, the use of Katz and Pagerank results in a less severe violation of independence.

In addition, as previously discussed our data suffer from multicollinearity (8) while the distribution of each measure violates the normality assumptions. In Figure 9 we can see the distributions of various centrality measures for a sample year. We observe that all the measures (with the exception of eigenvector) violate the normal distribution assumption of OLS. We believe that applying PCA and aggregating centralities in the first principal component, although not a complete solution, provides a significant improvement.

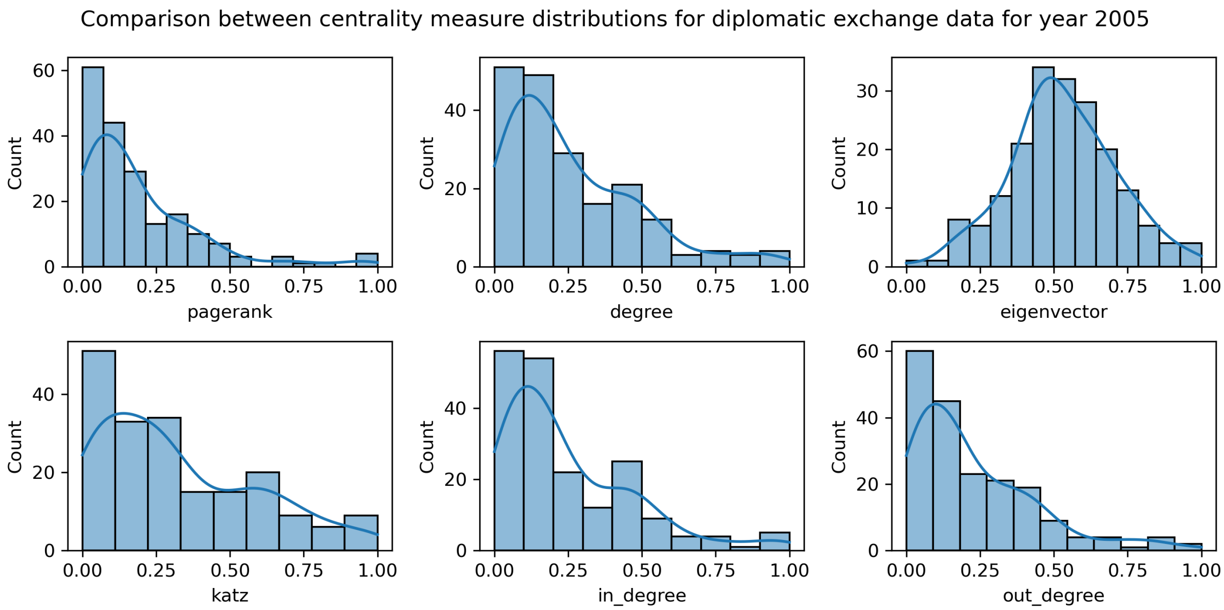


Figure 9: Distributions of various centrality measures for the year 2005. We observe that all except eigenvector have left skewed distributions and thus violate OLS assumptions.

4 Results

4.1 Centrality Measures

We obtained six centrality measures: PageRank, Katz, eigenvector, degree, in degree and out degree. We futher normalize these measures to a $0 \sim 1$ range (most central countries correspond to a score of 1). The top 20 countries according to each centrality measure in the 2005 temporal network are presented in Figure 10.

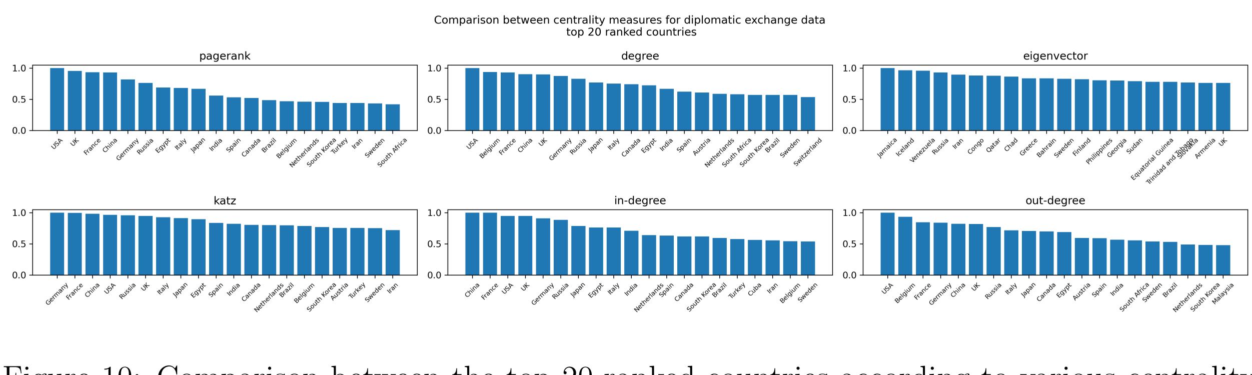
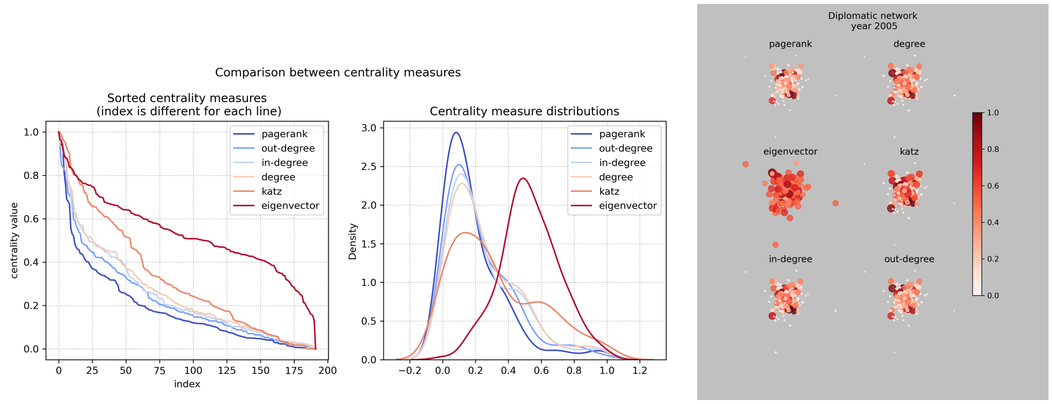


Figure 10: Comparison between the top 20-ranked countries according to various centrality measures in the temporal network of year 2005. We observe subtle changes to the top nodes.

Although in network analysis betweenness and closeness centralities are often used, here the two measures are not adopted for two reasons: (1) the network of interest is a directed graph and hence the two measures not easily defined, and (2) even if we compute them for an undirected version of the graph, their distributions are close to the degenerate distributions (with many 1- or 0-values). Therefore, betweenness and closeness are not considered suitable for our analysis.

A comparison between different ranking in the 2005 graph can be seen in Figure 11.



(a) Comparison of Centrality Measures

(b) Centrality-Weighted Network

Figure 11: A comparison of centrality measure distributions and centrality-weighted networks can be seen for year 2005.

In order to test how these centrality measures affect the probability of a U.S. presidential visit, we run a regression model with the U.S. president visit dummy variable (1 for visit, 0 for non-visit) on the six centrality measures. The results can be seen in Table A1. From the table, it can be directly observed that PageRank, Katz, degree, in degree, out degree are statistically significant predictors. We also observe that the eigenvector centrality measure does not provide statistically significant regression coefficients. Moreover, comparing the results in Figures 8, 9 and 11, we can directly observe that eigenvector centrality differs significantly from other centrality measures. As a result of this observations, in the following analysis section, we drop eigenvector centrality measure from the set of independent variables.

Moreover, despite the degree, in-degree and out-degree measures being not equivalent in our directed graph, they appear to be highly correlated with the dependent variable of presidential visits. The regression results indicate that all degree measures can help significantly predict the probability of a U.S. president visit to a certain country. Even perceiving the network as an undirected graoh with degree centrality, the results are persistent. An intuitive explanation is that in the international diplomatic network, it is common that diplomatic relationships are bi-directional.In rare cases, there can be cases that one country will terminate its diplomatic relationship with another (for example Australia and North Korea). Therefore, our diplomatic network is highly symmetric with some directional relationships as exceptions. Therefore, the directed and undirected network measures yield little differences.

4.2 Principal Component

After, droping eigenvector centrality as previously discussed, we have now a set of 5 different centrality measures. We have already discussed the problems of multicollinearity in our dataset. In Figure 12 a correlation study for our independent variables is conducted.

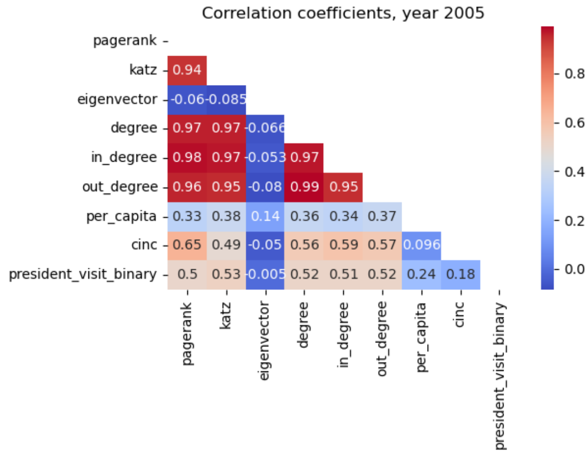


Figure 12: Correlation coefficients for the independent variables (centralities, economic and power measures) for the year 2005.

It can be directly observed from the correlation graph that the five centrality measures: PageRank, Katz, degree, in-degree and out-degree are highly correlated and cause multicollinearity issues and violations of OLS assumptions. Meanwhile, we also observe correlations between centrality measures and our control variables: economic variable (GDP per capita) and national power (CINC). Comparing with the extremely high correlations within the set of centrality measures, the correlation between centralities and control variables is relatively mild. VIF values for each of variable can be seen in Table 5.

Variable	VIF	Multicollinearity
PageRank	570.447	YES
Katz	201.129	YES
Degree	1512.329	YES
In Degree	1452.316	YES
Out Degree	1810.207	YES
GDP per capita	2.040	NO
National power	2.442	NO

Table 5: VIF of Variables before PCA

Therefore, it is legible for us to use economic (GDP per capita) and national power (CINC) as control variables. After conducting the principal component analysis, we find that the first two largest eigenvalues explain over 99% of the centralities' variance and we therefore select the first two principal components. Checking again the VIF values for the transformed dataset (Table 6) we validate that the multicollinearity has been significantly improved.

We further run logistic regression models using the first two principal components and only the first principal component (Table A2). It can be directly observed that introducing a second principal component will not increase the $pseudo - R^2$ while coefficients of other variables remain unaffected. Moreover, the coefficient of the second principal component

Variable	VIF	Multicollinearity
PC1	1.540	NO
PC2	1.224	NO
GDP per capita	1.119	NO
National power	1.770	NO

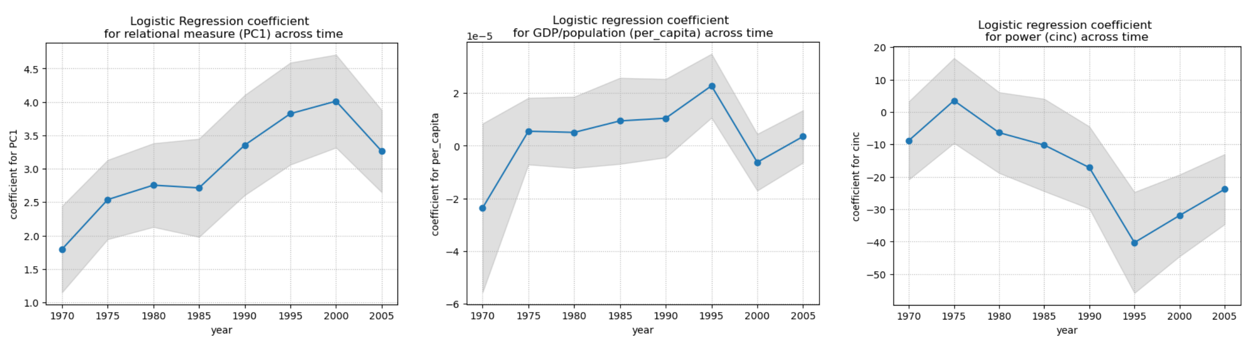
Table 6: VIF of Variables after PCA

appears to be not statistically significant. Therefore, we decide to apply regression models keeping only the first principal components in our dataset.

4.3 Logistic Regression

We have already obtained the principal component of diplomatic centrality measure as well as the GDP per capita and CINC and thus proceed in running logistic regression for each 5-year period from 1970 to 2005. Even though our data are relational with each node being connected to each other, Katz and PageRank (our iteration-based centrality measures) posses the ergodic distribuition and are unconditional (You et al., 2017; Dasaratha, 2020). Therefore, we can assume the independence of Katz and PageRank on the network structure. We can also use the value obtained from the network analysis as an asymptotic approximation to their true value. And therefore, eventually the independent observation assumption for regression analysis is not severely violated.

In table A3 we can see the effect of centrality measure, economic development and national power on the probability that United States president will visit one country during that 5-year period. We can see that over these years, the coefficient of centrality is always significant. Meanwhile, the economic development coefficient appears to be not statistically significant in most years, while the effect of national power becomes significantly negative after 1995.



(a) Centrality (b) Economic (c) National Power

Figure 13: Regression coefficients for our three independent variables (first principal component, economic measure and power measure).

The regression results show that every 0.01 increase in PC1 will increase the probability of a U.S. president visit by 4% in 2005. Figure 13 can provide more information on the dynamics of the effect of centrality, economy and national power. The effect of centrality measures keeps increasing until 2000 and it suddenly drops afterwards. This pattern shows that the international diplomatic network is playing an increasingly important role in the diplomatic policy of United States. The sudden drop in 2005 might indicate a change in U.S. foreign policy after 9/11, the Iraq war or other exogenous shocks. Validation of these observations would require more data across year periods. Meanwhile, the effect of national power becomes significantly negative after 1995. We hypothesize that this might be related to the deformation of USSR. The factors affecting the dynamics of both centrality and national power effect will require more data to further validate.

4.4 Network visualization

Finally, we provide a preliminary network visualization for a subgraph of diplomatic exchanges in Figure 14. We can see traces of small communities forming according to their connections to central nodes.

5 Conclusions and Future work

In this research project, we propose a network-based model to measure the status of countries in international relations. We further use the probability of U.S. presidential visit to validate that the network-based status measure reflects the importance of a country from the perspective of the US foreign policy. The results indicate that a country's centrality level in international diplomatic exchange network can reflect a country's status. Comparing with an economic development indix and a traditional national power index, the centrality performs better in predicting the probability that a U.S. president will pay a visit. Note that economic and material attributes can also be of relational nature. However, our network-based measure seems to capture better the relation information of international relations.

Moreover, our regression results indicate ways for future work: we observe that the effect of centrality decreases after 2000 and that national power plays a negative role in how the U.S. president decides which country to visit after 1995. As the data is only available from 1970 to 2005, we would need more data to validate the mechanism of such dynamic.

Further future work could also include applying community detection algorithms to the diplomatic networks, examining number of visits of the president to countries, patterns of repetition in presidential visits, validation of results in secretary of state visits and comparison of results for visits of high ranking officials or important bussiness figures of other countries other than the US.

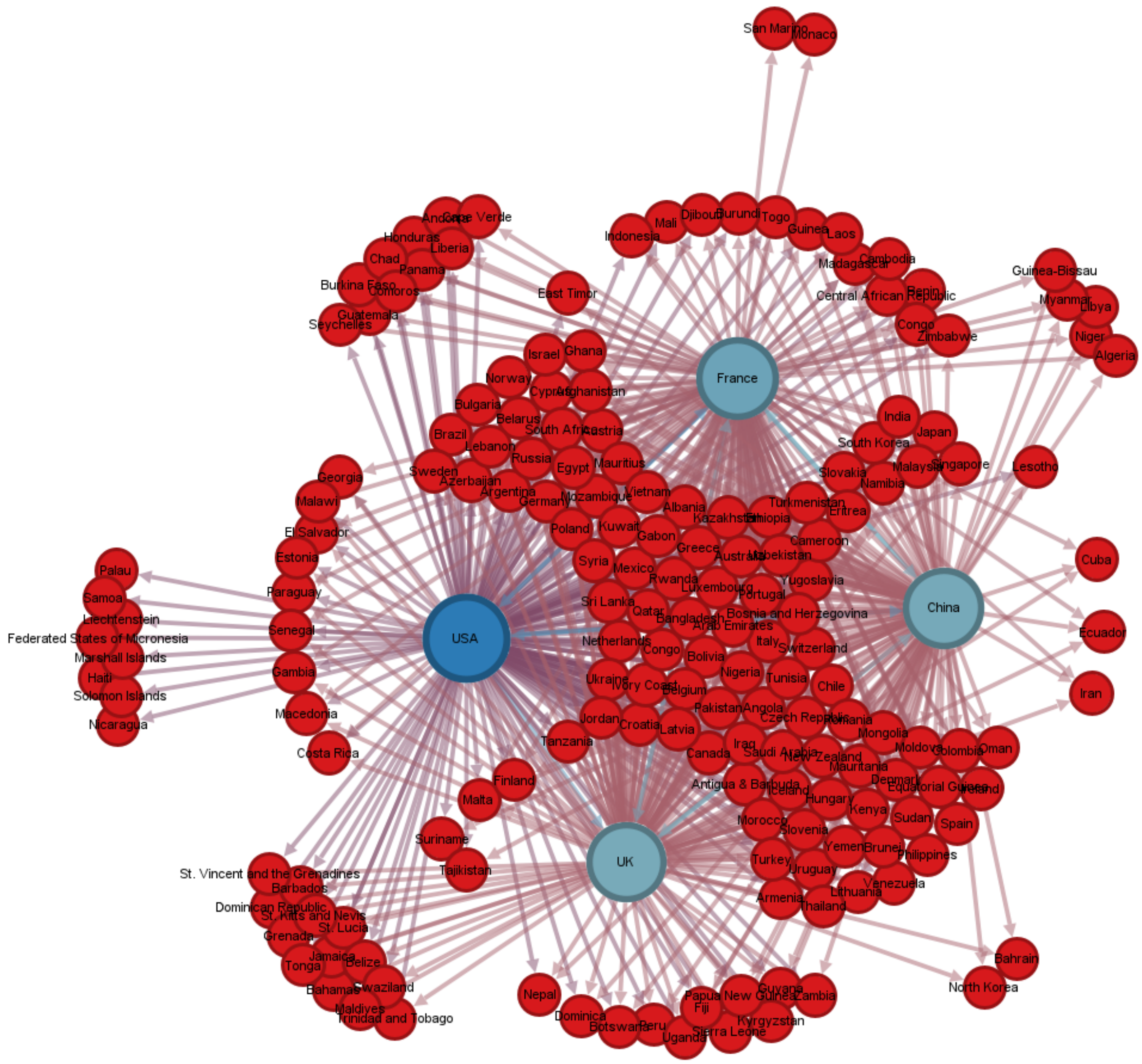


Figure 14: Visualization of the 2005 diplomatic exchange network. The network is actually a subgraph of the connections of the top 4-ranked countries according to Pagerank (blueish colored nodes). The US receives the highest score and is followed by France, the Uk and China. We can see that the Atlas-2d visualization algorithm positions nodes in communities according to their connections to the US, France, China and the UK. Nodes at the center of the graph are highly connected to the top-4 nodes while as we move outwards, countries connect with less and less central nodes. Note that edges in the graph correspond to our simplifying definition of ambassador relations previously presented.

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Appendix

Table A1: Regression Results

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	President	*President*	*President*	*President*	*President*	*President*
PageRank	9.555***					
	(1.863)					
Katz		5.575***				
		(1.027)				
Eigenvector			-0.384			
			(0.962)			
Degree				7.076***		
				(1.381)		
In Degree					7.155***	
					(1.375)	
Out Degree						7.553***
						(1.486)
Economics	4.368e-06	3.751e-06	2.371e-05***	4.055e-06	5.531e-06	4.08e-06
	(9.9e-06)	(9.84e-06)	(8.7e-06)	(9.95e-06)	(9.92e-06)	(9.79e-06)
Military	-38.564***	-14.388	19.378	-22.152**	-25.082**	-23.243**
	(13.148)	(9.607)	(12.189)	(10.938)	(10.877)	(11.534)
Const	-2.939***	-3.198***	-1.271**	-3.087***	-3.031***	-2.954***
	(0.431)	(0.469)	(0.549)	(0.455)	(0.443)	(0.435)
Observations	164	164	164	164	164	164
Pseudo-R^2	0.262	0.256	0.064	0.246	0.249	0.246
LL-Null	-98.247***	-98.247***	-98.247***	-98.247***	-98.247***	-98.247***

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2: Regression Results

	Dependent variable:	
	(1)	(2)
	President Visit	President Visit
Centrality (PC1)	3.23***	3.265***
	(0.663)	(0.616)
Centrality (PC2)	-0.519	
	(4.110)	
Economics	3.528e-06	3.519e-06
	(9.96e-06)	(9.96e-06)
Nation Power	-22.947*	-23.924**
	(13.223)	(10.818)
Const	-1.100***	-1.088***
	(0.305)	(0.289)
Observations	164	164
Pseudo R^2	0.2580	0.2580
LL-Null	-98.247***	-98.247***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A3: Regression Results

	Dependent variable:							
	(1) Visit(1970)	(2) Visit(1975)	(3) Visit(1980)	(4) Visit(1985)	(5) Visit(1990)	(6) Visit(1995)	(7) Visit(2000)	(8) Visit(2005)
Centrality (PC1)	1.796***	2.538***	2.754***	2.714***	3.354***	3.825***	4.0112***	3.262***
	(0.647)	(0.593)	(0.626)	(0.735)	(0.749)	(0.763)	(0.695)	(0.616)
Economics	-2.364e-05	5.525e-06	5.071e-06	9.448e-06	1.046e-05	2.279e-05*	-6.286e-06	3.517e-06
	(3.21e-05)	(1.27e-05)	(1.36e-05)	(1.64e-05)	(1.49e-05)	(1.22e-05)	(1.08e-05)	(9.96e-06)
Nation Power	-8.794	3.499	-6.385	-10.204	-17.149	-40.283***	-31.936***	–23.836**
	(12.058)	(13.097)	(12.463)	(14.248)	(12.664)	(15.573)	(12.611)	(10.805)
Const	-1.312***	-2.182***	-2.394***	-2.556***	-2.143***	-2.127***	-0.490*	-1.265***
	(0.361)	(0.392)	(0.413)	(0.439)	(0.386)	(0.355)	(0.262)	(0.288)
Observations	118	127	137	140	144	164	164	164
Pseudo R^2	0.092	0.269	0.276	0.238	0.310	0.330	0.277	0.258
LL-Null	-58.206***	-58.543***	-58.686***	-53.713***	-70.935***	-83.702***	-108.75***	-98.247***

Note: *p<0.1; **p<0.05; ***p<0.01

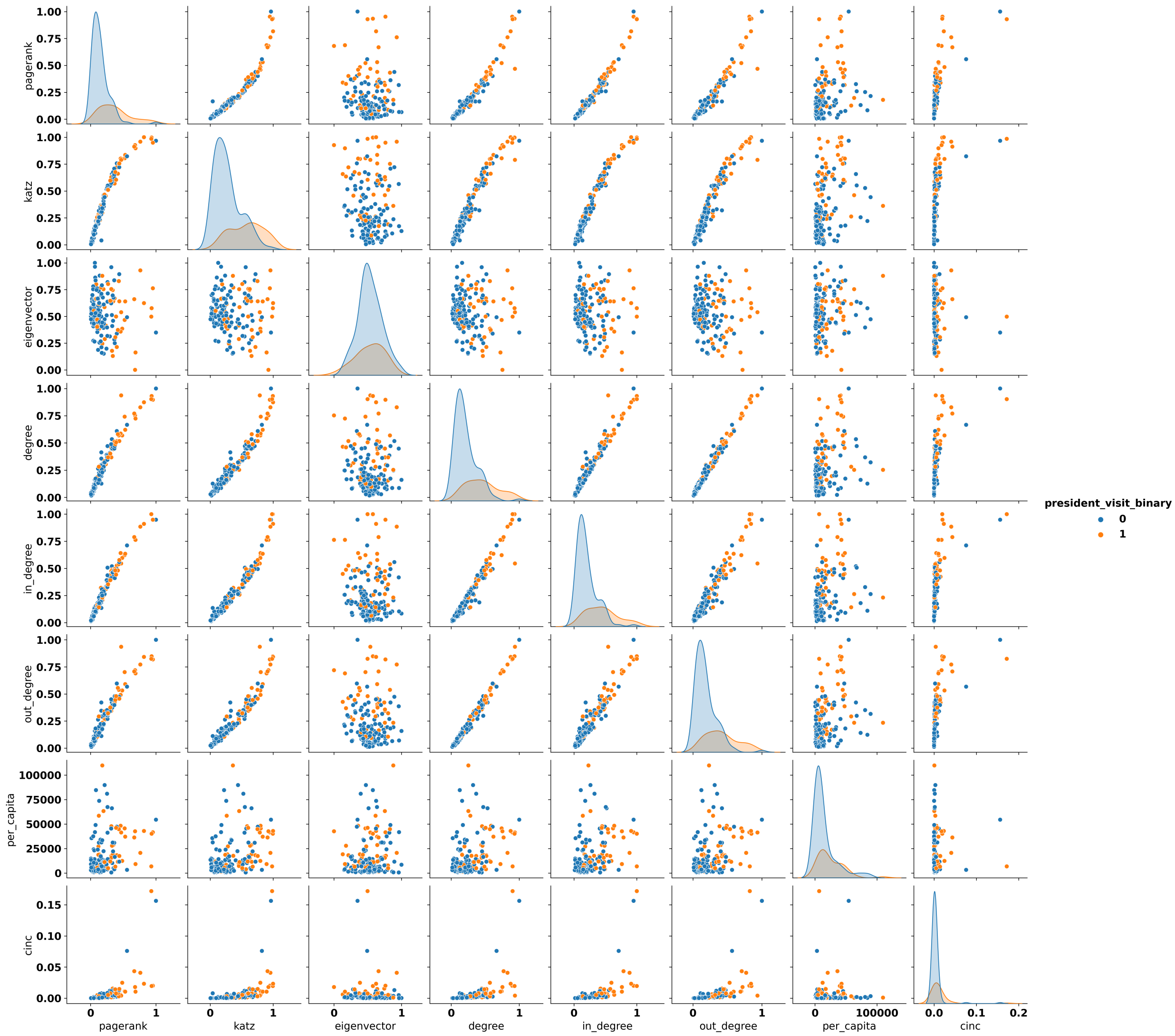

Figure 15: Scatter plot of independent variables for year 2005. Blue points correspond to countries not-visited by the US president while orange points correspond to presidential visits.