# Modelling and Assessing the Relations of Power Between Worldwide Countries' Foreign Affairs.

github: `https://github.com/gzemo/relations-of-powers-between-countries`

***Abstract*—Social Science research is currently living an unprecedented golden era due to the availability of maintained high quality open platforms that allows to exploit massive historical data to shed lights on nowadays existing assets between communities of countries. The present work provides an evaluation on events data to detect whether the leading role of the most influential countries over the past 5 years can be predicted by competitors and allied changes in centrality by implementing a community detection approach and a graph-based measure time series analysis.**

***Index Terms*—Goldstein Scale, Granger Causality, Community Detection Algorithm, Betweenness Centrality**

## I. Introduction

With the recently increased amount of big data sources which are currently allowing to gather close-to-real-time information on ongoing events occurring between countries, crucial inights on relations of power between states are on the verge to be studied in a unprecedent manner. Significant efforts are therefore striving to exploit such data with the purpose of predicting close to real time warning systems that may allow national policy makers to tackle future crises by forecasting resources to be allocated in advance [8].

Graph-learning technique is nowadays considered the state-of-the art statistical method fulfilling such predictive tasks by estimating the confidence of a given event by training a deep learning architecture on graph-based relational structures [3].

Although the current interest in this social science field seems to be focused more on forecasting future changes in countries foreing exchange, less attention had been paid on explaining emerging trends in the alliance builing process through time. Moreover with such a consistent amount of publicy available information, the evolving pattern of influence within the closest countries' neighbours for which an extensive social and economic trade occurred can be studied dynamically exploring historical records.

With this in mind, the current project aims at unravelling the past 5 years information on worldwide event and foreign policy exchange in order to map inter-state relationships as fully connected graphs to further address how the most central actors had been mutually influenced themselves through time in their community of interest. By doing so, a community detection approach has been set to take trace of the emerging cluster of countries whose exchange pattern had been found to be more segregated for further investigate the mutual influence of the leading communities' nodes over time.

### A. Hypothesis

It can be advanced the assumption for which the higher the centrality measure of a given node within it's own community of reference the more likely that country is to behave like the leading entity within the circle of its closest partners.

The more centrality the top centered node gains through time, the more is expected to centralize the closest neighbours by ensuring most distal nodes in the community to converge towards itself rather than adhering to other most influential top centered nodes within the remaining communities. Besides, if any given leading node within a community tends to lose centrality one can state that the less involved it becomes in countries information exchange the more the distal nodes are likely to be influenced by other communities.

The resulting scenario may be set by considering either as composed by completely segregated communities which are highly persuaded to exchange information towards the current head of the countries alliance or by widely spread set of communities for which top centered nodes are playing a minor role in the alliance attraction. In other terms, the trend of a given countries'community to caslte itself should be enhanced and, eventually, forecasted by the tendency of a competitor cluster to merge client states and segregate them. By contrast the lower the inter-countries clashes the lower the need for relying to the most leading node by countries belonging to each factions involved, yielding therefore a set of less centered countries alliances. The *hypothesis* can be formalize as: the higher the centrality measure over time of a node the higher the competitors nodes' centrality within their relative communities and viceversa.

## II. Methods

### A. Data source description

The GDELT project is a massive data-coding service that monitors the latest world-wide events by a comprehensive system that collects, translates and processes relevant web news into codified categories [5]. In it's most recent distribution (v. 2.0) it provides event updates by gathering all relevant information in the latest 15 minutes time-span and codifies them according to the *Conflict and Mediation Event Observations* (CAMEO) framework which allows to ubiquitously translate the principal actors involved and the action performed in the current event between them into a pre-defined schema [7]. Any event instance can be defined by a pair of actors ($Actor_1$ and $Actor_2$), an event occurring between them and a list of event attributes that seek to quantify the relevance of the current fact by measuring how many times it had been cited or how many articles had been written about the topic during the time-span in which it was first noticed; moreover, the project automatically provides a *tone* score that suggest an insight on the average tone used by the first news published on that specific event which may further help to better filter and cohomprehend the context (*see "Edge estimation" section*).

Each event classified in a specific category is associated to a *score* which defines the degree to which an alliance or a conflict between actors is occurring, ranging from a maximum positive score (+10) to a minimum (-10) respectively (Goldstein, [4]). This codification aims at providing an ordered set of categories of international affairs sorted by relevance which may in principle define either cooperation or crisis between actors in either "verbal" or "material" manner. Therefore the higher the Goldstein score ($G$), the higher the actor engagement in activities such as "Promising poilicy support" ($G$ = 4.5), "Promising material support"($G$ = 5.2) or "Extend military assistance" ($G$ = 8.3) meaning that it is more likely that a positive international relation is occurring between those actors and, consequently a mutual alliance regulates their affairs. Besides, negative scores codifies events that points towards a verbal and material clash between countries such as "Halt negotiation" ($G$ = -3.8), "Treat with specific negative non-military sanctions" ($G$ = -5.8), "Break diplomatic relation" ($G$ = -7.0), or "Military attack, clash, assault" ($G$ = -10.0) that suggest the international policy deterioration and, thus, material and potential military hostility between a pair of countries.

### B. Data selection and filtering

The present work takes into account the amount of international events recorded from January 2018 to June 2023 for a total of 5 years and 6 months (66 months overall). This time-span has been chosen to comprehend the degree to which the aforementioned hypothesis can be addressed in light of the events occurring between these years, including, to cite few, the United States – North Korea crisis (2018), the latest year and the aftermath of US Army Afghanistan occupation (2021), the COVID-19 pandemic (2020-2022), Taiwan riots against China repression and the Russia – Ukrainian conflict (February 2022-ongoing).

Each set of records referring to the latest 15 minute interval GDELT update have been filtered to retain entries whose Actor fields codifies a country entity in order to retain only those events that specifically decoded a fact occurring between nations rather than sub-national entities like single government parties, religious communities or public individual figures.

### C. Edge estimation

The way in which the countries' relationships had been formalized relies on a composite score which takes into account the information available from the list of filtered event features. The resulting edge value between nodes $(i, j)$ that defines the degree to which an alliance is occurring between that pair of countries mostly depends on $G$. Minor relevance is given by the news coverage information such as the *a)* number of sources, *b)* number of articles and *c)* the average tone (formalised respectively by $(s, a, T)$ in the equation below) by tuning their weighting factors $\{\theta_1, \theta_2, \theta_3\}$ in a $[0, 1]$ range:

$$w_{i,j} = \begin{cases} \text{sign}\,(T) \times (\theta_1 s + \theta_2 a) + \theta_3 T & \text{if } G\text{=0} \\ \text{sign}\,(G) \times (\theta_1 s + \theta_2 a) + \theta_3 T + G & \text{otherwise} \end{cases}$$

for which $s, a \in \mathbb{N}$ and $T \in [-100, 100]$.

In the case in which $G$ is equal to 0, the $w_{i,j}$ sign will be defined by the $\text{sign}(T)$ besides, while considering an event marked by $G$ score different from zero instead, it will be ruled by the current $\text{sign}\, G$. This implies that the greater the magnitude of a given fact, the higher the score will be and, again, the more likely that event will influence the current alliance or hostility between those actors through the whole monthly averaged time-period.

### D. Time points graph estimation

The process of estimating a single month undirected weighted time-step graph has been computed by the following process:

1) *Single-update graph estimation:* the single 15 minute interval update graph is estimated by assigning to each pair of countries involved in each entry the corresponding weight as defined in the previous section generating the $G_k^{[update]}$ graph with $k = 1, .., N_{updates}$.
2) *Daily-updates graph estimation:* the complete set of 15 minutes time interval updates of a given day (as in Point *1*) is processed and the edgewise values are summed, yielding the $G_d^{[day]}$ graph with $d = 1, .., N_{days}$.
3) *Monthly time step graph estimation:* Point *2* is performed for all days in a month and the amount of daily graphs generated by excluding those edges whose value is zero (meaning that no information exchange between those countries was found so far in the past records) is averaged in order to achieve the $m - th$ monthly time-step which will be further considered as single time-point instance in the time-series analysis ($G_m^{[month]}$). Therefore each edge weight $w_{i,j}^{[month]} \in G_m^{[month]}$ of a given month $m$ between $(i, j)$ actors is estimated by:
$$w_{i,j}^{[month]} = \frac{1}{N_{days}} \sum_{d=1}^{N_{days}} w_{i,j}^{[day]} \in G_d^{[day]}$$
that represents the averaged cell-wise value of all past $w_{i,j} \in G_d^{[day]}$ daily-updates graphs considering exclusively those countries in that month.
4) Once the whole set of 12 averaged monthly graphs had been completed, each positive and negative edge is resized by the yearly highest or lowest value respectively in order to normalize the edges' values range between $(-1, 1)$.

Each normalized monthly time-step can be splitted into two sub-graphs according to the edge values sign which namely define the alliance and hostility network by considering the undirected graph built exclusively from positive or negative values respectively. For the current project purpose the set of the monthly "alliance" graphs over time will be considered to test the aforementioned hypothesis.

### E. Community detection

The global network of countries alliance over time is then processed in order to detect sub-set of countries showing some clusterized trends in sharing information while interacting with other members belonging to the same cohesive subgroup. A community detection algorithm had been applied on each monthly alliance time-step graph to detect and store *a)* which elements had been grouped into communities and *b)* the most centered node showing the highest Betweenness Centrality (BC) value with respect to its own community. For this purpose the *a)* Louvain optimization-based algorithm [2] and *b)* random-walk-based community detection method [6] had been tested and compared. The top five countries which are found to play a leading role by showing the highest centrality measure within their community in the time span under examination are then saved and condidered for the following analysis.

### F. Statistical analysis

*1)* ***Augmented Dicker-Fuller test****:* In order to evaluate the mutual $top_5$ centered countries' centrality Granger causation through time, each time-series needs to be evaluated by testing whether it is stationary or not. The *Augmented Dicker-Fuller (ADF)* statistical test aims at verifing whether the current set of data can be described by an unit root (which yields the vector of observations to spread through time according to some trend) or follows a "stationary" trend, which namely implies the current time series to evolve through time with constant mean, variance and covariance over periods with identical distance. It works by considering an Auto-regressive model (AR) defined as:

$$y_t = \rho y_{t-1} + \mu_t$$

for which the resulting observation $y$ at time $t$ is defined by the product of an AR parameter $\rho$ with the observation at timestep $(t-1)$ plus an error term $u_t$ which depends on the current time-step.

According to the original Dicker-Fuller test, the regression model of the whole time-series is defined by expressing the AR model equal to the *finite difference operator*[1] $\Delta$ over the $t$-observation:

$$\Delta y_t = (\rho - 1) y_{t-1} + \mu_t$$

The ADF test improves the initial hypothesis by defining the following model:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + ... + \delta_{p-1} \Delta y_{t-p+1} + \epsilon_t$$

for which an improved set of parameters is added: the Null and Alternative hypothesis are then defined by:

- $H_0 : \gamma = 0$ The time-series has an unit root and any $\gamma$ is ineffective in the prediction of the current time-step observation $y_t$.
- $H_1 : \gamma < 0$ The time-series is stationary and $y_t$ can be predicted by the lagged value of the past $(t-1, ..., t-p+1)$ observations and, consequently, it converges to the mean of the series.

Finally, the aim of the current test is to evaluate the Dicker-Fuller estimate defined by:

$$DF_\gamma = \frac{\hat{\gamma}}{SE(\hat{\gamma})}$$

meaning that the lower the Dicker-Fuller estimate the higher the chance of rejecting the Null hypothesis.

*2)* ***Granger Causality****:* it had been originally proposed to explain whether a time-series may be used to forecast the observations that occur in another set of observations given a fixed time-lag parameter.

It relies on the assumption that a variable $X$ is said to Granger Cause another time-series $Y$ when

$$\mathbb{P}[Y(t+1) \in M \mid I(t)] \neq \mathbb{P}[Y(t+1) \in M \mid I_{-x}(t)]$$

that can be read as: the probability of having a forecasting prediction of $Y(t+1)$ for all elements of a given set $M$ given a set of available information $I(t)$ is different with respect to the same probability considering the set of all available information $(I_{-x}(t))$ excluding the time-series $X$.

The initial auto-regression model on $y$ can be written as:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + ... + \beta_m y_{t-m} + \epsilon_t$$

for which the present $y_t$ observation is explained by all the previous $(t-m)$ observation weighted by a factor $\beta = (1, ..., m)$ plus an error term $\epsilon_t$.

The model is then enhanced by including the information from the first variable $x$

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + ... + \beta_m y_{t-m} + \lambda_p x_{t-p} + ... + \lambda_q x_{t-q} + \epsilon_t$$

for that all lagged values of $x$ for a given $p$ (shortest) and $q$ longest lag length, that were found to be significant according to their t-statistic are included right after having tested that all newly added variables are improving the explanatory power to the current model by an F-test.

The null and alternative hypothesis given two time series $(X, Y)$ are defined as follows:

- $H_0 : X$ does not Granger Cause $Y$
- $H_1 : X$ Granger Causes $Y$

and the Null hypotesis is confirmed only if no lagged values are retained in the regression, meaning that no F-test yielded any significant result for each lag involved.

*3)* ***Benjamini-Hochberg multiple comparison correction****:* defines the False Discovery Rate (FDR) approach which implies a weak control over Family Wise Error Rate (FWER) and a less conservative rate of rejecting the *Null* hypothesis $(H_0)$ with respect to the *Bonferroni* procedure given a multiple comparison scenario [1].

[1] $\Delta$ maps a function $f$ to $\Delta[f]$ such that: $\Delta[f] = f(x+1) - f(x)$ an expression that is usually used to approximate the derivatives of a given function in points where a change in sign occurs and, consequently, a negative change in trend is observed after reaching a local maximum or, by contrast, a positive change in trend can be seen right after the observation at time $(t-1)$ reached a local minimum.

## III. Results

The Louvain algorithm found crucial international actors in the $top_5$ most central nodes within their community including USA, China and Russia, historically thought to be competitors in foreing policies (see *Figure 1*).

Besides, with the walktrap method such countries failed to be recognized by the community building procedure (*see Table 1,2*). The overall 66 months BC time series over time of the $top_5$ countries have been tested to check the stationarity assumption (*see Table 3,4*). All countries displayed a stationary time-series meaning that their centrality fluctuation over time is not affected by any significant trend: no further data transformation is needed to evaluate the mutual Granger causality.

From *Table 5,6* it can be pointed out how some combinations of countries' centrality measures tested by Granger Causality turned out to be significant. Specifically, while extracting communities with the Louvain algorithm, the China's centrality series seems to significantly Granger cause the United States centrality role (*p-value <0.05*) and Australia was found to significantly Granger cause the Russian influence over its alliance (*p-value <0.05*); the United States centrality time-series failed to Granger cause the China's one with $alpha = 0.05$ (*p-value = 0.0518*). No significant result was found by considering the combination of $top_5$ countries from the Walktrap algorithm apart from those previously discussed.

After correction for multiple comparison by FDR any Granger-causality-related result turned out to be not significant.

## IV. Discussion

The work here presented aims at providing an insight on most centered countries influence over competitors through time. The initial hypothesis was presented to address whether some variation in the position of an influential international actor can have an impact on centrality roles from others players. The Graph building process had been designed to address the need for a fine-grained interval of time-steps that could have best represented a sufficient number of positive $G$ event and thus an ongoing network of alliances.

The random-walk algorithm tested so far was supposed to better capture more meaningful overall community structures given the high matrices' edges sparsity over time. This could have been explained by the walktrap algorithm tendency to compute communities according to the random flow of information between pre-existing relationships that could have been bounded by the absence of edges occurring between countries with no formal exchange. By contrast, a set of more politically relevant countries had been found by the aforementioned optimization-based method allowing to better depict the nowadays trends in international foreing policies.

Although no significant result survived after the FDR correction, meaningful trends are still providing some insights on the mutual relationships between the $top_5$ countries. The higher (or, the lower) the influence of China's foreign policy within its neighbouring countries the higher (or the lower) the centrality role of US with respect of its own allied members and viceversa. Unfortunately, without a sufficient statistically significance level, any conclusion provided so far is limited to the extent of mere speculations. Future works will further address whether the lack of significant evidences could be motivated by the limited amount of events gathered from the time-interval considered.

### A. Limitation and future improvements

The design choice to weight each edge value by weighting factors $\{\theta_1, \ldots, \theta_3\}$ had been arbitrarily set to enhance the contribution of some event features rather than others without any additional tuning procedure.

Networks and communities are varying over time meaning that a more exhaustive analysis on which subset of countries were found to belong to the same community at each processed month would have better helped to disetangle and define alliances.

The period under examination does not delve into the Israeli – Hamas conflict which started on October, 7th , 2023 that could have further enriched the present dataset: further project updates may improve on this subject.

## References

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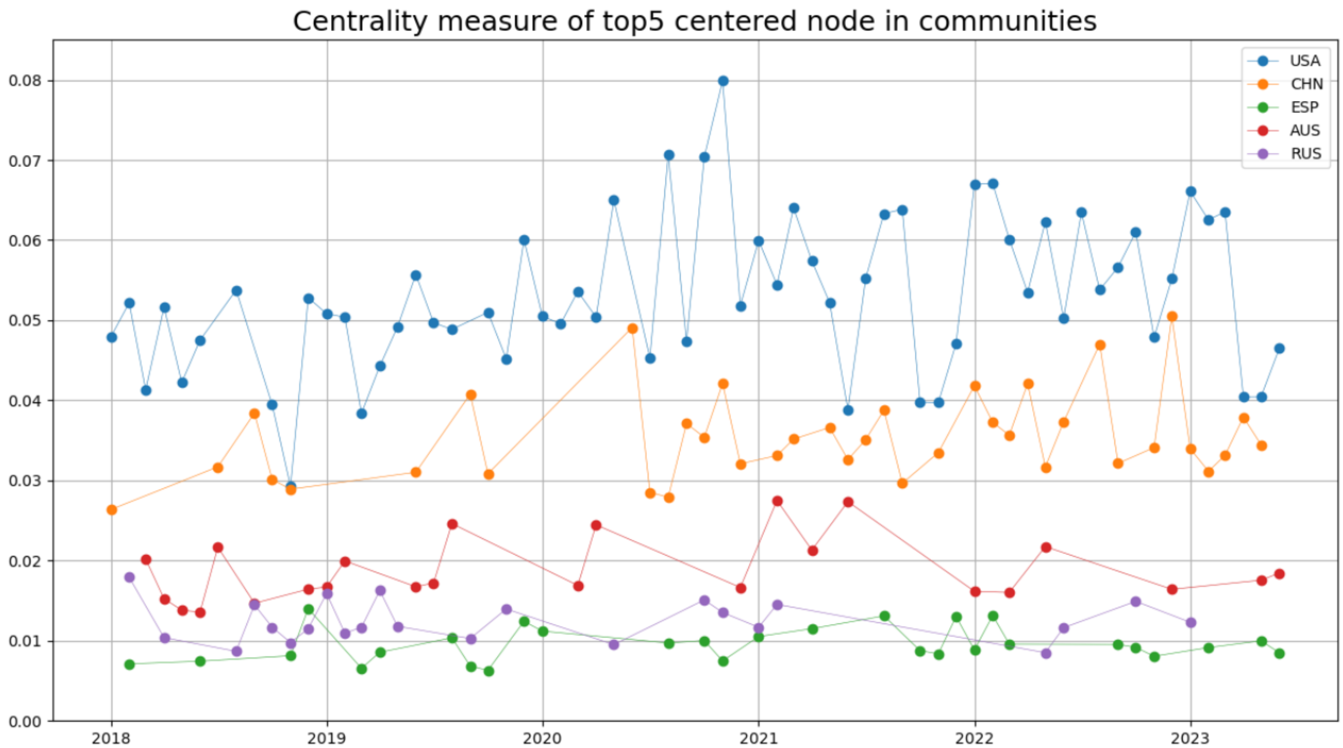


Fig. 1. Distribution of Betweenness Centrality measures over time according to the most centered countries found to have the highest centrality value within their reference community estimated through the Louvain algorithm. Each solid dot represents the month in which that country had the highest centrality (see Table 1)

## APPENDIX A

| Country code | Number of months |
|---|---|
| USA | 62 |
| China | 38 |
| Espana | 29 |
| Australia | 24 |
| Russia | 23 |

TABLE I
LOUVAIN ALGORITHM MOST CENTERED NODES

| Country code | Number of months |
|---|---|
| USA | 63 |
| Nigera | 40 |
| Fiji | 34 |
| China | 16 |
| Cuba | 15 |

TABLE II
WALKTRAP ALGORITHM MOST CENTERED NODES

| Country codes | ADF Estimate | p-value |
|---|---|---|
| USA | -6.018 | 1.52e-07 *** |
| China | -5.465 | 2.46e-06 *** |
| Espana | -6.391 | 2.10e-08 *** |
| Australia | -8.505 | 1.20e-13 *** |
| Russia | -7.902 | 4.17e-12 *** |

TABLE III
LOUVAIN, AUGMENTED DICKER-FULLER RESULTS

| Country codes | ADF Estimate | p-value |
|---|---|---|
| USA | -6.018 | 1.52e-07 *** |
| Nigeria | -6.855 | 1.65e-09 *** |
| Fiji | -1.666 | 0.44 |
| China | -5.465 | 2.46e-06 *** |
| Cuba | 23 -6.701 | 3.88e-09 *** |

TABLE IV
WALKTRAP, AUGMENTED DICKER-FULLER RESULTS

| | USA | China | Espana | Australia | Russia |
|---|---|---|---|---|---|
| **USA** | 1 | 0.051889 | 0.481439 | 0.719154 | 0.151406 |
| **China** | 0.025322 | 1 | 0.190428 | 0.192034 | 0.632014 |
| **Espana** | 0.141286 | 0.079211 | 1 | 0.464461 | 0.659098 |
| **Australia** | 0.089469 | 0.940279 | 0.584269 | 1 | 0.016820 |
| **Russia** | 0.915289 | 0.975822 | 0.384792 | 0.347994 | 1 |

TABLE V
LOUVAIN, MUTUAL GRANGER CAUSALITY TEST PROBABILITY RESULTS

| | USA | Nigeria | Fiji | China | Cuba |
|---|---|---|---|---|---|
| **USA** | 1 | 0.709037 | 0.910231 | 0.051889 | 0.399108 |
| **Nigeria** | 0.347007 | 1 | 0.824654 | 0.529230 | 0.630569 |
| **Fiji** | 0.315894 | 0.924442 | 1 | 0.202219 | 0.452977 |
| **China** | 0.025322 | 0.759407 | 0.317460 | 1 | 0.340701 |
| **Cuba** | 0.018504 | 0.082733 | 0.547841 | 0.348538 | 1 |

TABLE VI
WALKTRAP, MUTUAL GRANGER CAUSALITY TEST PROBABILITY RESULTS