Temporal Network Analysis of International Trade Flows

Ben Hinshaw
Umut Ozturk
Harsh Choudhary
Kevin Cao

Outline

1. Overview
2. Network Analysis: Basics
3. Literature Review
4. Time Series Analysis
5. Random Failure
6. Community Detection

Overview

Why Trade?

- Globalized World
- GDP Growth
- International Relationship Evolution

Our Network

Our network is a temporal bilateral trade network from 1948-2020. It was sourced from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII).

We thought this dataset was particularly interesting as the temporal network will allow us to examine how things change over time.

Our Network: By the Numbers

2M+
Total Data Points

73
Years of Data

100+
Countries

Year

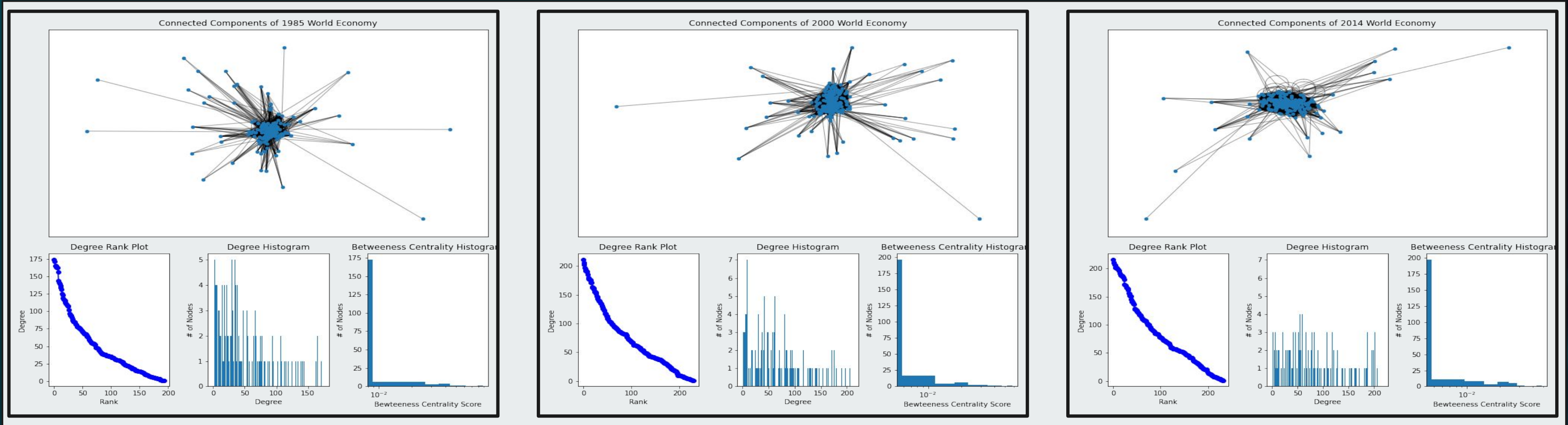
Importer

Exporter

Trade Volume

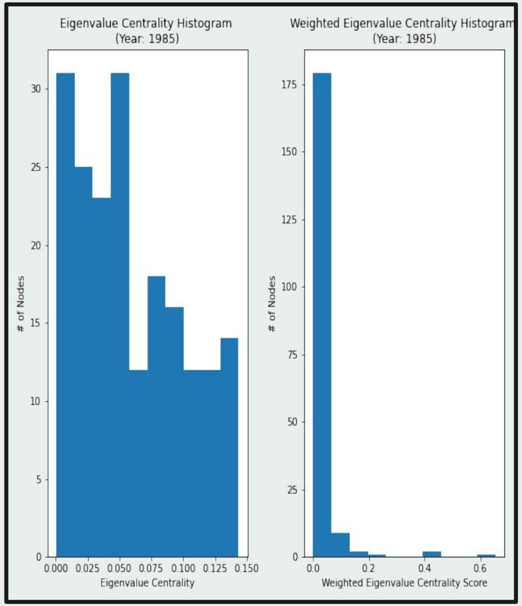
Network Analysis: Basics

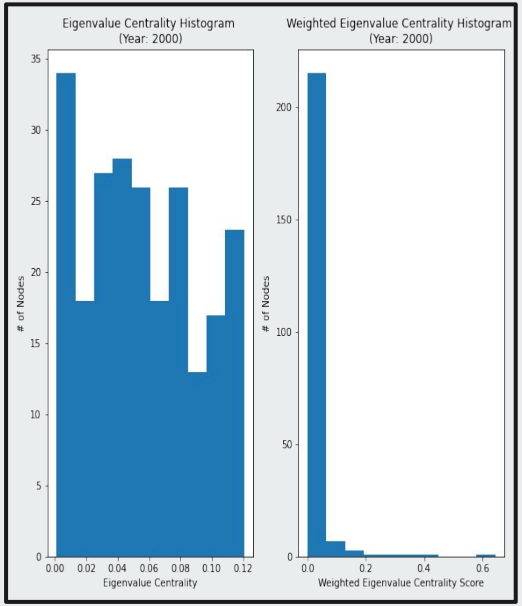
Network Characteristics

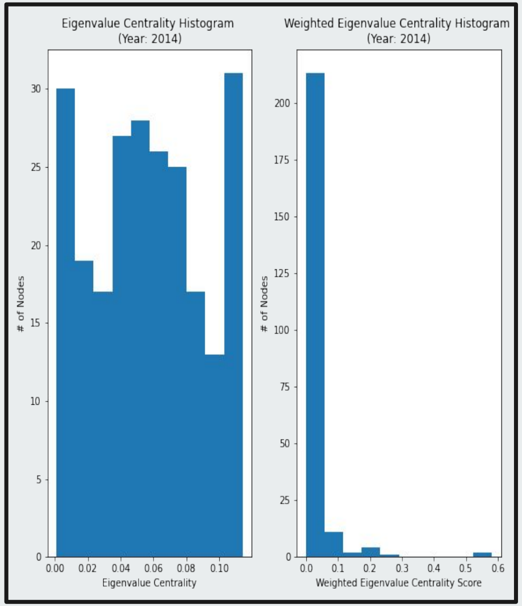


Over time, we can observe how the distributions of the degree and betweenness centrality histograms shift right as countries become more connected in an increasingly globalized world

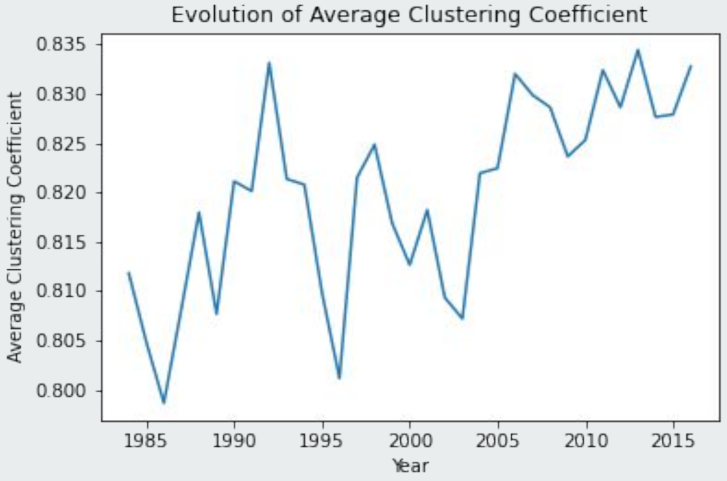
Network Characteristics Cont.

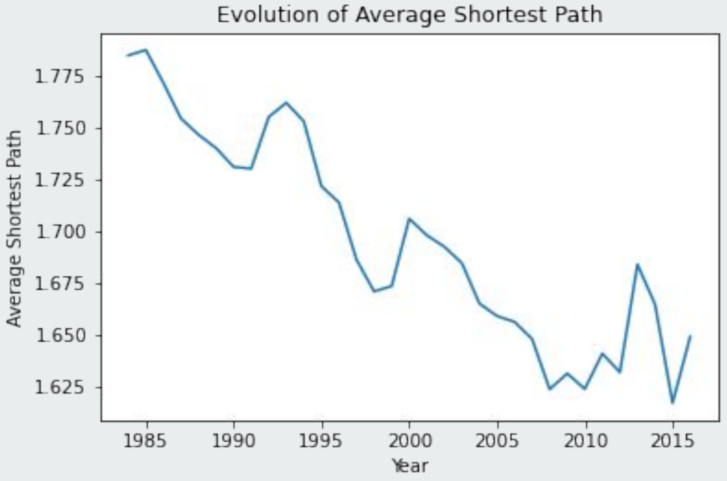






Network Characteristics Cont.





Literature Review

Weighted Network Analysis

The International Trade Network: weighted network analysis and modelling (2008)

Uses scaled link weight distribution to assess the growth of trade strength and its relation to GDP of the corresponding countries.

“a large fraction of the global trade is controlled by a club of a few rich countries which shrinks in size as time goes on”

Uses a time-series weighted network analysis on international trade

Dynamics and Evolution of the International Trade Network

“This paper studies how the distributions of the most important network statistics measuring connectivity, assortativity, clustering and centrality in the international-trade network have co-evolved over time.”

This paper analyzes node statistic distributions and their correlation for the past 20 years, seeing no significant change.

Our project employs similar network statistics measurements, but for a broader time horizon (84 years).

Forecasting International Trade: A Time Series Approach

This paper developed a model to predict the imports of major advanced economies for the upcoming 2-6 quarters.

It uses multivariate structural time series models, creates a regression model to represent the imports and uses ARIMA to forecast the future imports.

Our project also utilizes ARIMA for similar purposes, where we forecast eigenvector centrality for some of the advanced countries to see if there is an expected difference in their importance in global trade network.

Attack Vulnerability of Complex Networks

Uses complex networks to identify methods in network attacks and their effectiveness.

It uses four different strategies: attacks by descending order of degree and betweenness centrality, as well as implementing these strategies by recalculating those values after each node removed.

Results suggest that attacks that use recalculation of centrality and degrees have more damage to the network in most cases.

Our paper uses eigenvector centrality instead of betweenness centrality as our network is perfectly connected, yet eigenvector centrality values might change drastically as major economies are removed.

We also compared the results of the random attacks and targeted attacks, where targeted attacks employ the strategy of attacking nodes in descending order of eigenvector centrality as described in this paper.

We do not think recalculation of eigenvector centrality will change the results of targeted attacks drastically as trade networks often have correlated edge weights.

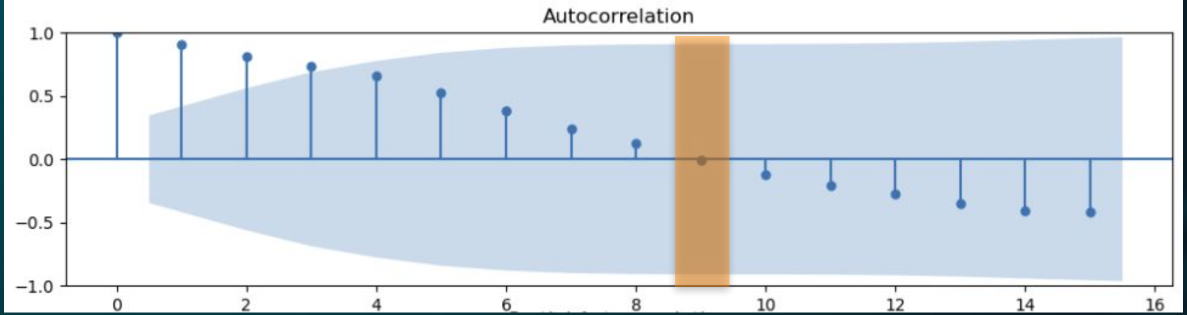
Time Series Analysis

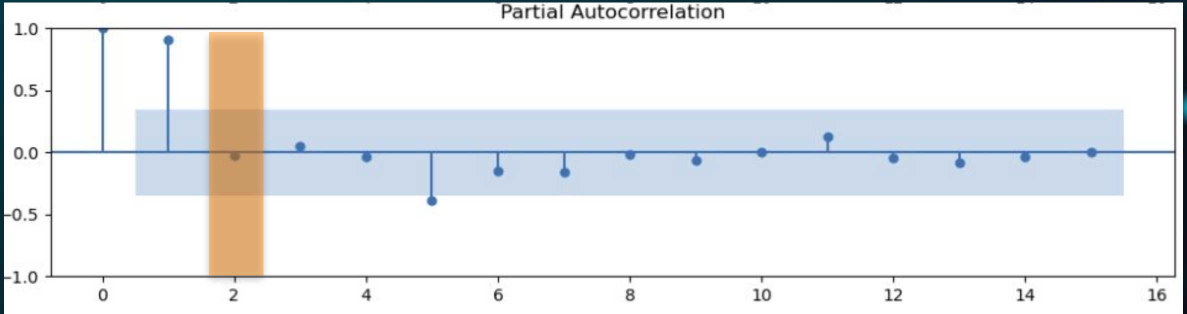
Applying the ARIMA model

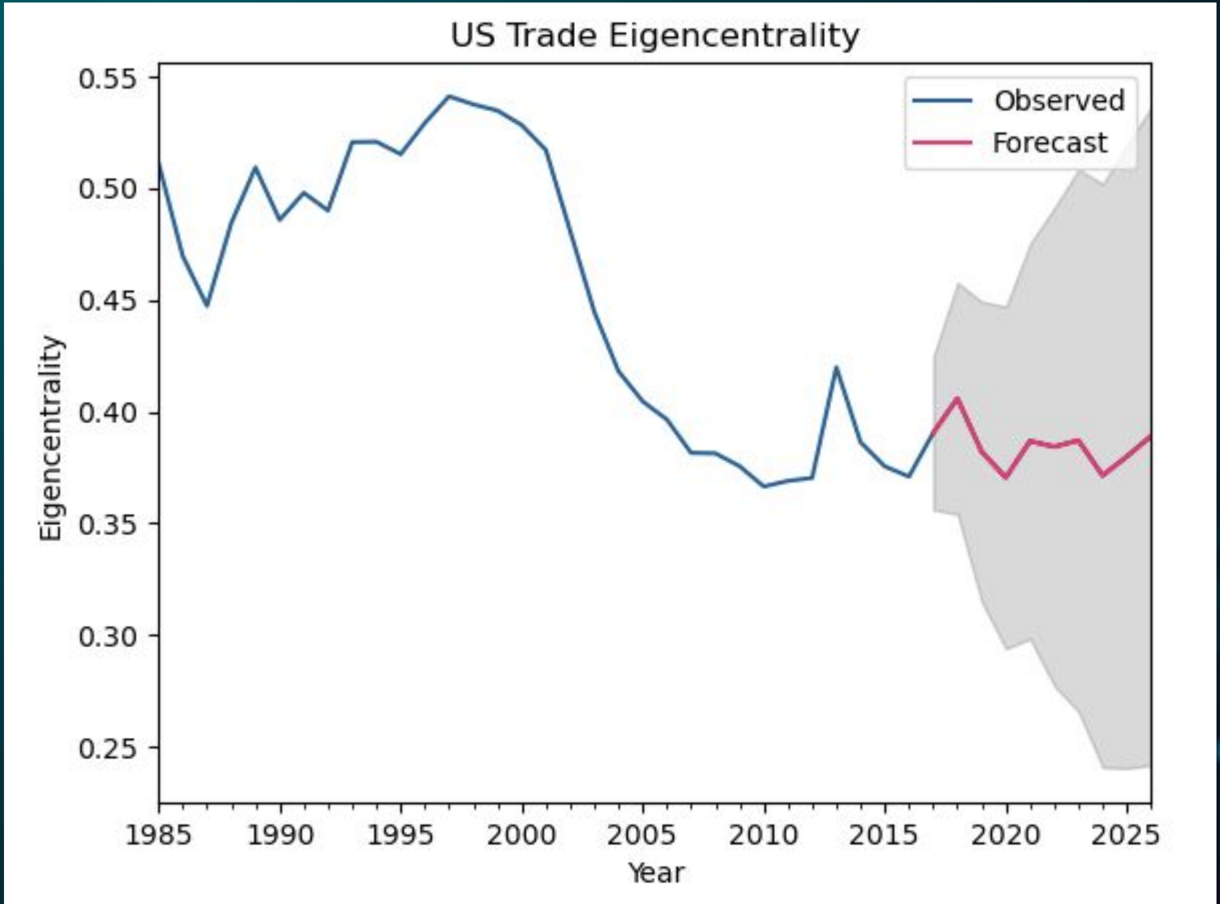
- ARIMA is a popular method for univariate time-series data forecasting
- We examine and predict the change in trade eigen centrality scores for specific countries over time
  - USA
  - China
- Procedure:
  - Obtain a dataframe with the index as year and one column as the eigen centrality scores of the country
  - Use Dickey-Fuller to find the appropriate differencing (d) such that series is stationary
  - Autocorrelation Function (ACF) to identify the order of the moving average term (q)
  - Partial Autocorrelation Function (PACF) to identify the order of the autoregressive term (p)
  - Use ARIMA with the derived (p, d, q) values

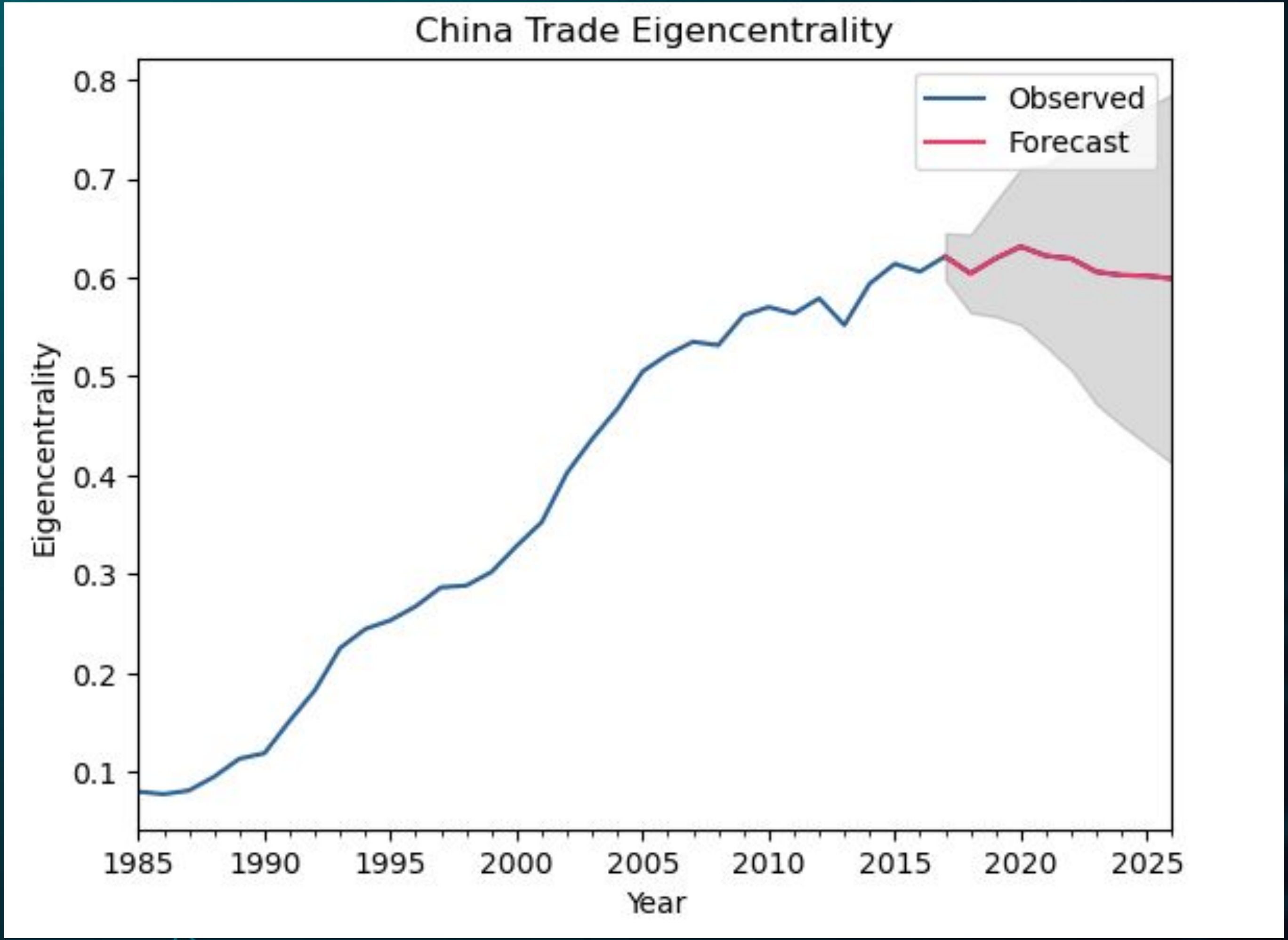
```
Results of Dickey-Fuller Test:
Test Statistic                 -0.803718
p-value                         0.818027
#Lags Used                      0.000000
Number of Observations Used    32.000000
Critical Value (1%)            -3.653520
Critical Value (5%)            -2.957219
Critical Value (10%)           -2.617588
dtype: float64
```

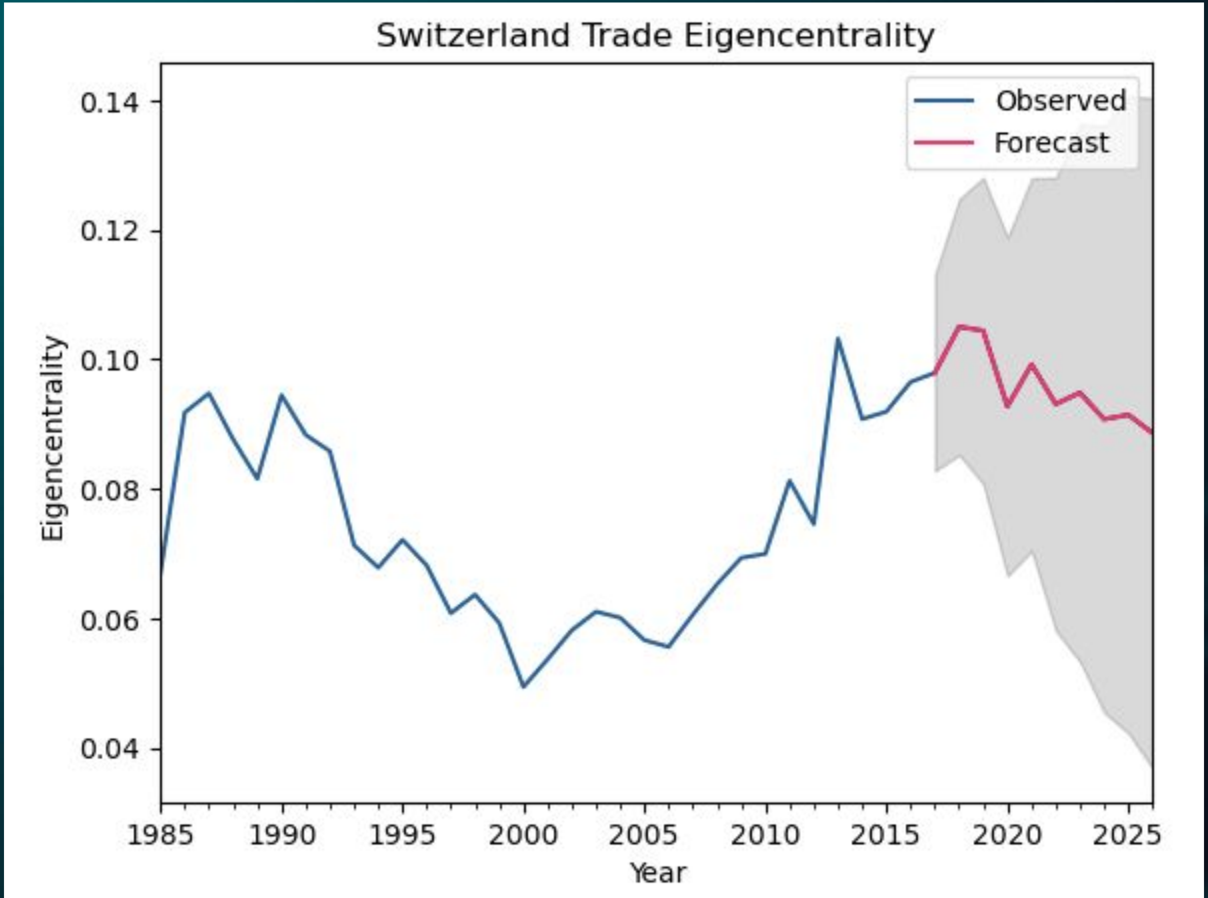
```
Results of Dickey-Fuller Test:
Test Statistic                 -4.596405
p-value                         0.000131
#Lags Used                      0.000000
Number of Observations Used    31.000000
Critical Value (1%)            -3.661429
Critical Value (5%)            -2.960525
Critical Value (10%)           -2.619319
dtype: float64
```





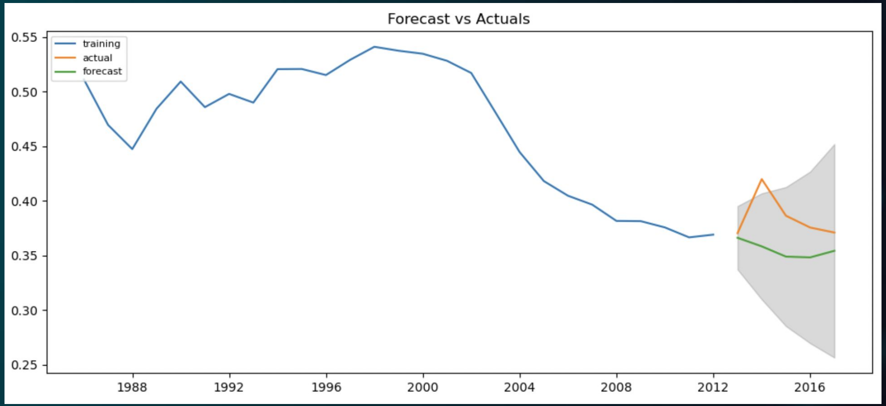

US Trade Eigencentrality
Observed
Forecast
Eigencentrality
0.55
0.50
0.45
0.40
0.35
0.30
0.25
1985
1990
1995
2000
2005
2010
2015
2020
2025
Year


China Trade Eigencentrality
Observed
Forecast
Eigencentrality
Year
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
1985
1990
1995
2000
2005
2010
2015
2020
2025

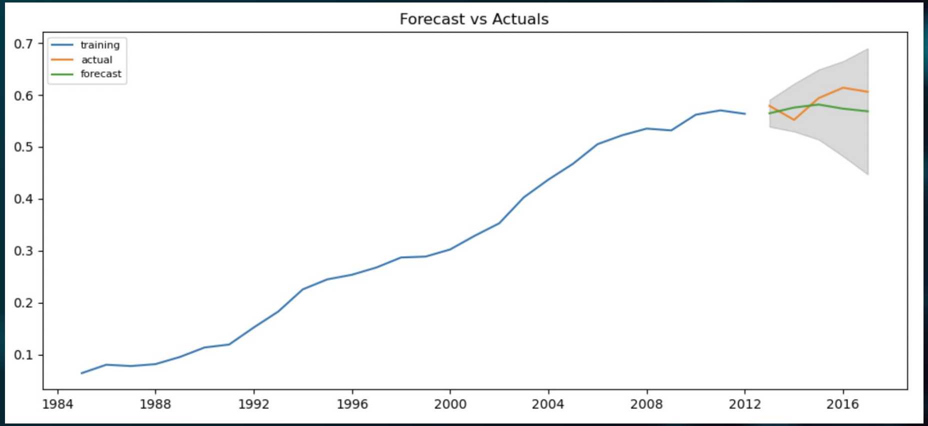

Switzerland Trade Eigencentrality
Observed
Forecast
0.14
0.12
0.10
0.08
0.06
0.04
Eigencentrality
1985
1990
1995
2000
2005
2010
2015
2020
2025
Year

ARIMA robustness

- Train-test split using final 5 years of data
- USA MSE: 0.035
  - 2013 eurozone crisis
  - 2013 QE/financial crisis recovery
- China MSE: 0.023



United States



China

Network-based Theory of the Exchange Rate?

- Current exchange rate theory is the IS/LM/UIP model
    - Not a “perfect” model because you need to somehow calculate the expected future exchange rate before being able to calculate the present exchange rate
- However, according to pure economic intuition, we can break the exchange rate down to 3 factors
    - Interest rates: higher interest rates make investing in a country’s bonds more attractive due to greater returns, so more people would want to buy the country’s currency in order to be able to invest
    - Investment flows: economic growth attracts foreign capital as it increases the perceived returns on any investment (also decreased risk of expropriation)
    - Trade desirability: if a country exports more to other countries, that means many global consumers will need to buy the country’s currency in order to be able to purchase the country’s products

Exchange Rate Regression

- Predict exchange rate from interest rate, investment flow (annual growth in real GDP), trade desirability (eigencentrality)
- Use historical interest rate, growth, and exchange rate data
  - World Bank
  - Bank for International Settlements (BIS)

$$Y_{ER\_it} = \beta_0 + \beta_1 \ln(X_{eigencentrality\_it}) + \beta_2 \ln(X_{interest\_it}) + \beta_3 X_{growth\_it} + \mu_{it} + \lambda_{it} + \varepsilon_{it}$$

- Country fixed effects to control all time-invariant characteristics of each country
- Year fixed effects to account for global economic fluctuations that affect each country
- Clustered standard errors (on country) to account for the fact that observations in the same country but in different years aren't independent (e.g. an economic shock can have lasting effects)

Regression Output and Results

ln_e_usd	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ln_eigen	.15005	.0838148	1.79	0.075	-.015355	.315455

ln_e_usd	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ln_eigen	.0798518	.2067055	0.39	0.701	-.3345678	.4942714
ln_interestrate	.1160977	.1109365	1.05	0.300	-.1063166	.338512
gdpgrowth	.0179409	.0106487	1.68	0.098	-.0034084	.0392902

- At least for this simple model, there probably is a relationship between trade dominance and weaker currencies (but no statistically significant slope coefficient)
- A machine learning forecasting model would probably be better for forecasting exchange rates

Trade Network Centrality and Growth

- We want to capture the relative importance of trade "dominance" on annual growth in real GDP
- The relationship between export-driven centrality scores on growth can inform economic policy
- Establishing this relationship can be helpful when assessing the economic distress caused by a random failure in a trading network

$$Y_{growth\_it} = \beta_0 + \beta_1 \ln(X_{eigencentrality\_it}) + \text{controls} + \mu_{it} + \lambda_{it} + \varepsilon_{it}$$

Regression Output and Results

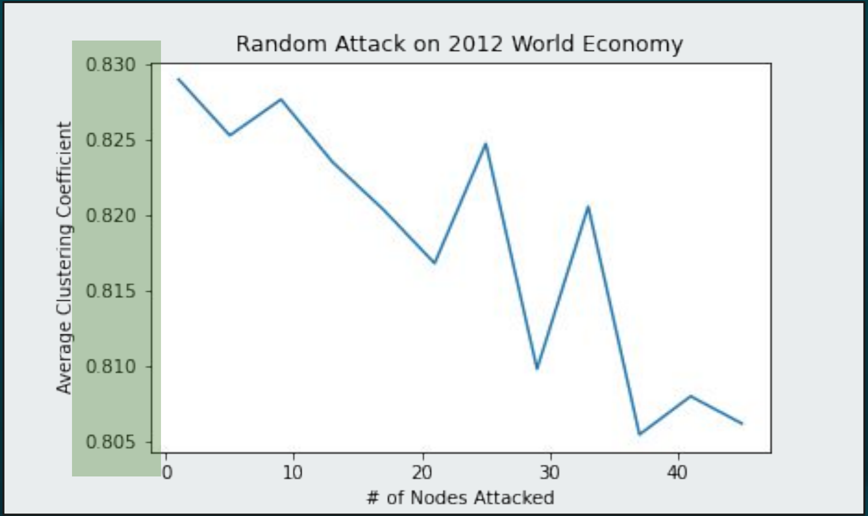
gdpgrowth	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ln_eigen	.934423	.2669208	3.50	0.001	.4076662	1.46118

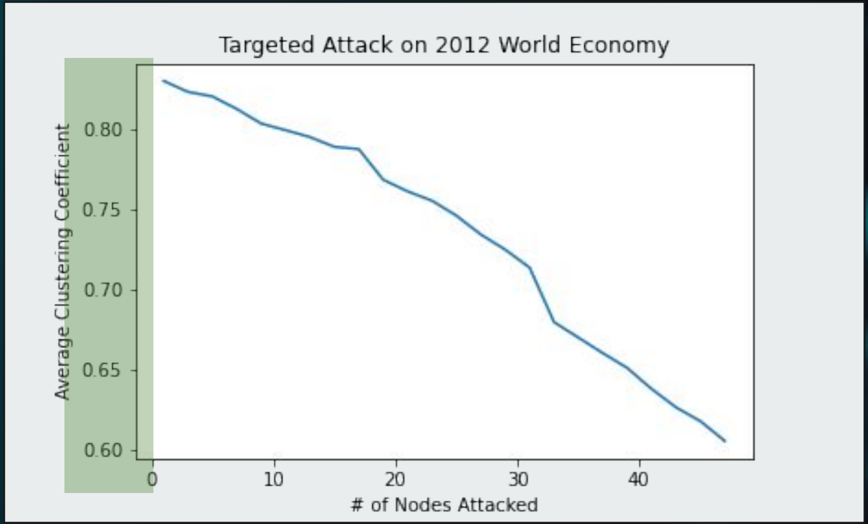
gdpgrowth	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ln_eigen	1.36918	.4531004	3.02	0.004	.460768	2.277591
ln_e_usd	.184214	.1293275	1.42	0.160	-.0750719	.4435
ln_interestrate	-.1410645	.1537765	-0.92	0.363	-.4493678	.1672388

- A 1% increase in trade eigencentrality yields a 1.369% increase in annual growth of real GDP.
- Trade dominance leads to increased economic growth

Attacks

Random Attacks/Failure





Targeting Based on Node Degree

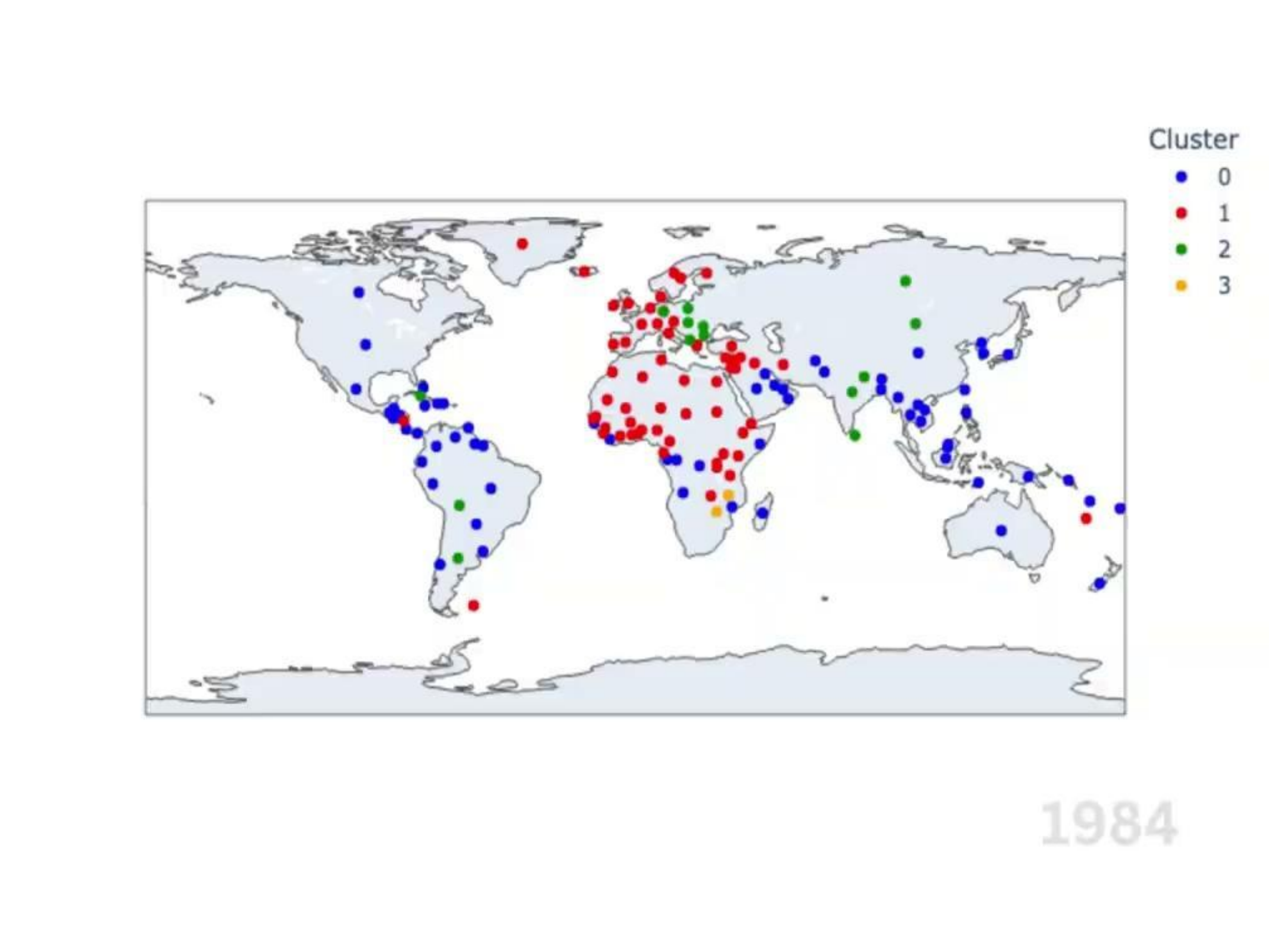
Community Detection

Community Detection

Procedure

- Treated each year of data as a separate Networkx graph
- Leveraged Louvain Best Partition to identify trading clusters for each year
- Utilized Plotly Express Scatter Geo package to visualize the clusters on a world map

Visualizing Trade over Time

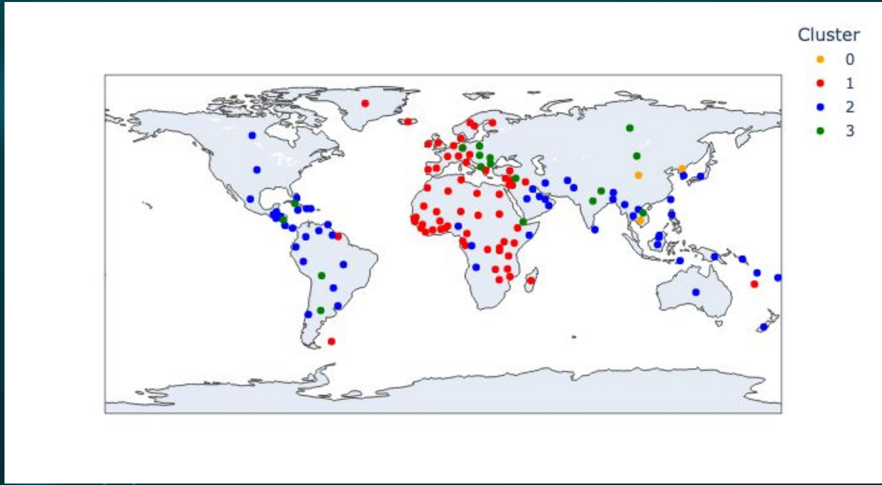


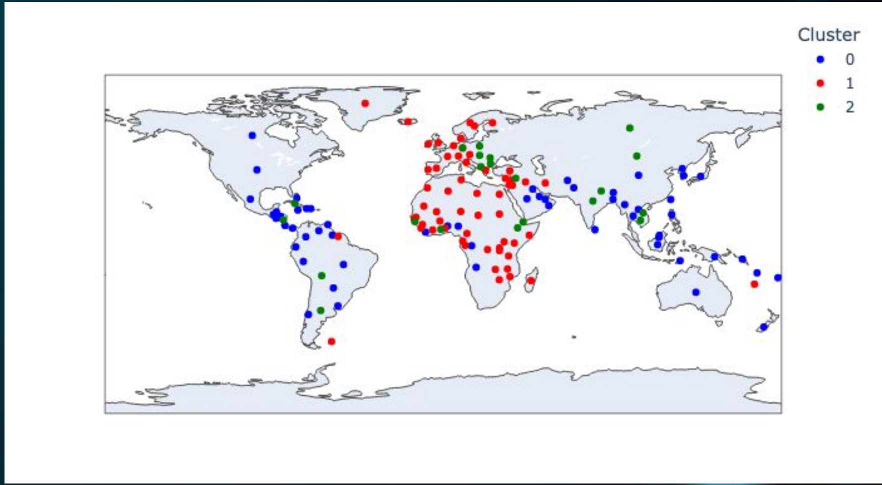
Key Shifts

- ❖ 1986 → 1987
- ❖ 1990 → 1991
- ❖ 1997 → 1998
- ❖ 2000 → 2001
- ❖ 2008 → 2009

1986 → 1987 (4 Clusters to 3 Clusters)

IMF Structural Rebalances, Deng Xiaoping's Economic Liberalization, and Collapse of Oil Prices due to OPEC policy

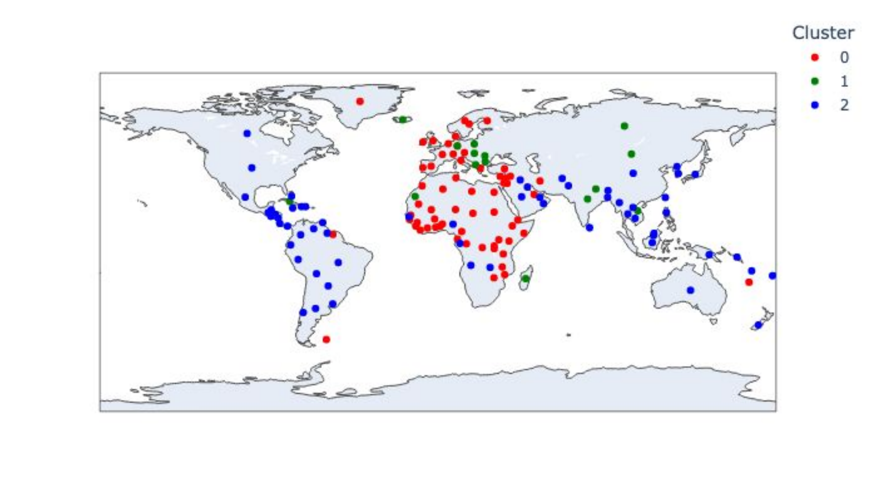


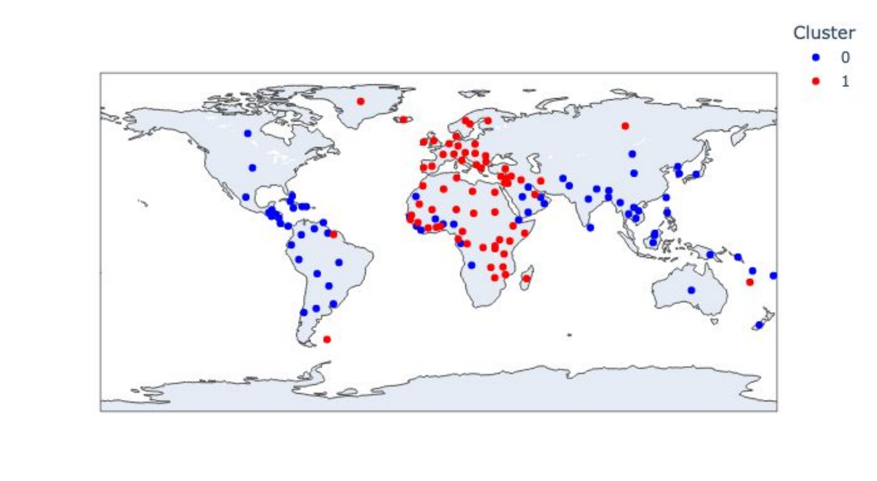


China joins cluster with most of Americas + S. Asia

1990 → 1991 (3 Clusters to 2 Clusters)

Collapse of the Soviet Union, the 1991 Indian Financial Crisis, and the Global Recession from the Savings and Loans Crisis

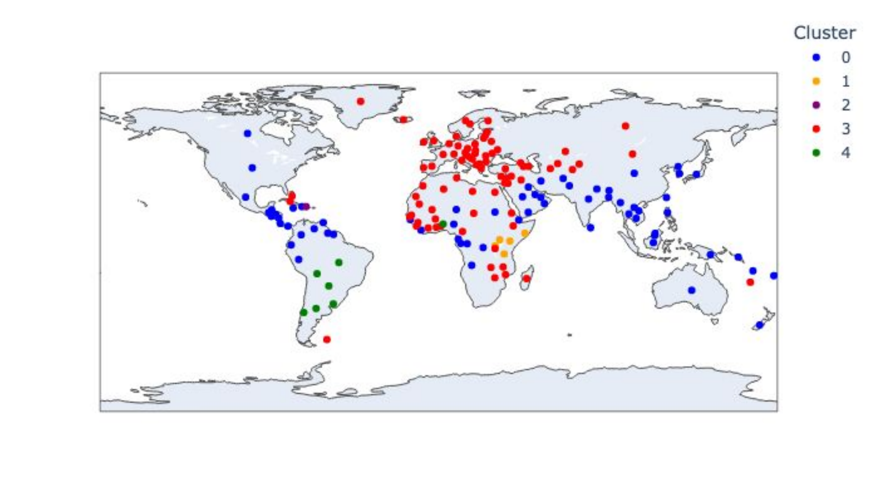


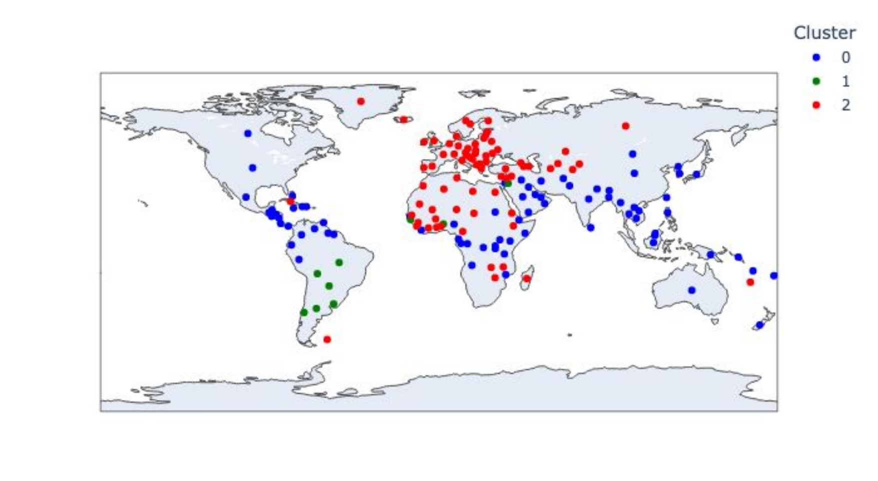


Europe unifies, Russia joins Europe + Africa cluster, India joins Americas + S. Asia cluster

1997 → 1998 (5 Clusters → 3 Clusters)

Asian Financial Crisis

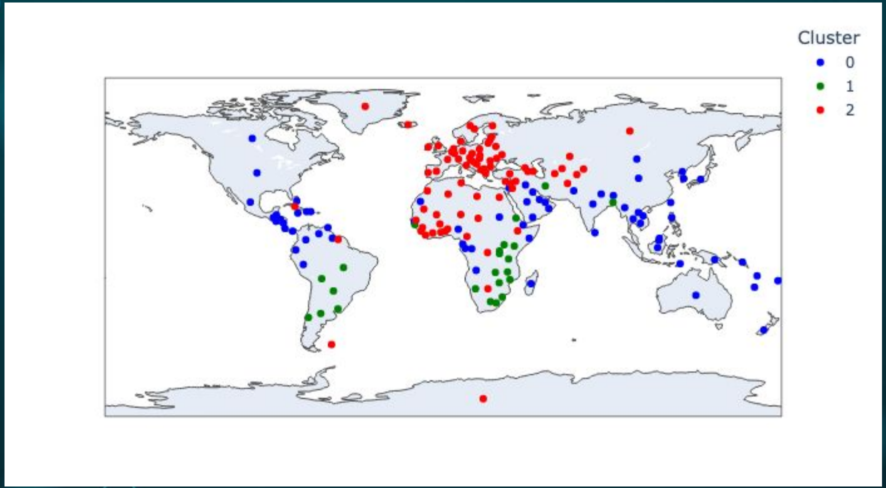


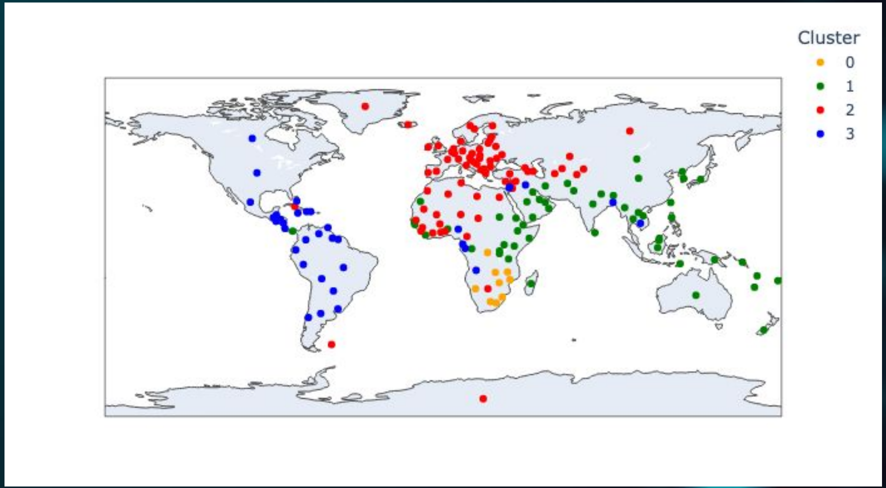


SE African countries join S. Asia + N. America cluster

2000 → 2001 (3 Clusters to 4 Clusters)

Recovery from Asian Financial Crisis and post-9/11 economic slowdown

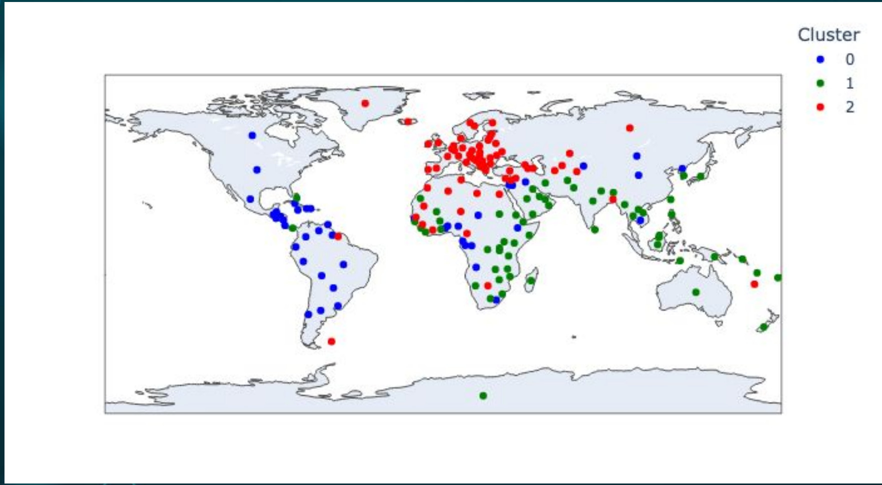


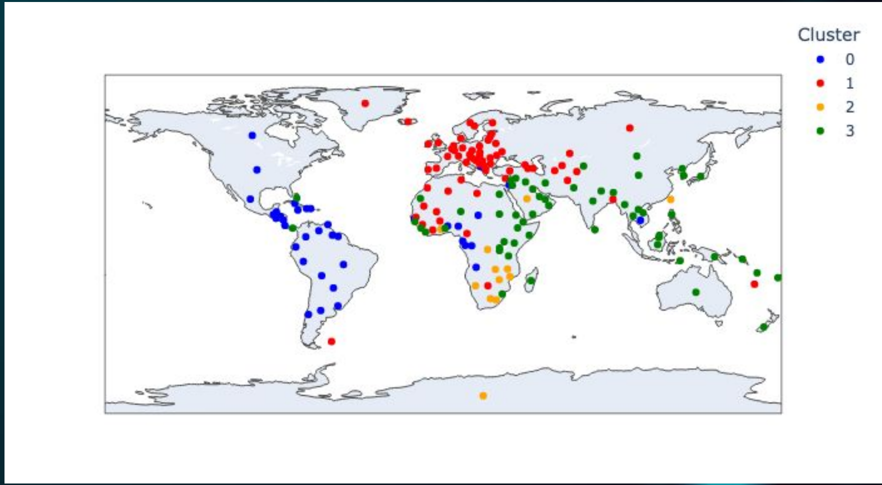


S African countries break apart from countries in S. America , Americas unify

2008 → 2009 (3 Clusters to 4 Clusters)

2008 Financial Crisis





S African countries break apart from countries in NE Africa + S Asia, China joins cluster w/India

Future Directions

- Explore how tradeflow and economic growth may evolve following random failure or targeted attacks on a network using ARIMA predictive model
- Apply LSTM for more robust, flexible predictive models
  - Might especially be useful for exchange rate forecasting
- Network link prediction for new nodes or after attacks
  - May require more granular data

Thank you.