Fertility rates – worldwide

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Abstract

Dataset

World Development Indicators

Question

How have fertility rates evolved in the past decades and how can countries be organized based on fertility rates?

Methods

Multilinear regression
Clustering

Findings

1. The data collection methodology has probably changed overtime.
2. Fertility rates have been decreasing globally (between 1972 and 2012).
3. The indicators I choose to relate with fertility rates explain about XXX of the variance
4. The fertility rate in time seems to be bi-modal, applying clustering shows that there are multiple modes and those seem somewhat related to my ad-hoc understanding of fertility changes globally.

Motivation

I am exploring population growth, from the perspective of fertility rate.

Part 1, how does the proportion of rural population, GDP and energy use can be used to predict fertility rate. There are known relationships between all these indicators. Here, I am trying to understand what the most valuable contributions are within this subset of indicators.

Part 2, the data showed a bimodal distribution of fertility rates. Hence the second step involved clustering the evolution of fertility rates for the different countries. Though I didn’t expect it to cluster into two well isolated clusters, analyzing the clusters can help understand the effects of culture and policies.

Though it is not very easy to design policy to mostly positively influence these indicators, it is relevant to understand what can contribute to reducing overall fertility rates and hence population growth.

Dataset

- World Development Indicators Dataset

  "The World Development Indicators (WDI) is the primary World Bank collection of development indicators, compiled from officially-recognized international sources. It presents the most current and accurate global development data available, and includes national, regional and global estimates." – From the World Bank website.

- Relevant indicators for this exercise:
  - Fertility rate, total (births per woman)
  - GDP per capita (current US$)
  - Rural population (% of total population)
  - Energy use (kg of oil equivalent per capita)

Data Preparation and Cleaning

The data was mostly organized.

I wanted to use information relative to countries only, I removed data relative to regions.

As I wanted to understand trends in time, I wanted to include as much data in time as possible. From looking at the data it became apparent that something had changed in the data collection, and I decided to focus on a subset of years.

Finally only a subset of countries had data for the selected years and indicators.

It was not a lot of data, but hopefully enough to illustrate the points I explored.

Research Question

Part 1. What is from the subset of indexes (GDP per capita (current US$), Rural population (% of total population) and Energy use (kg of oil equivalent per capita)) the best predictor for fertility rate? How much variance could such an approach explain?

Part 2. Given that the fertility rates across countries are not uniformly distributed, how many clusters would be appropriate to break the data into? In this case, looking at evolution of fertility rates in time.

Methods

Correlation: Explore relationships between GDP, Rural Population, Fertility Rate, Electricity Consumption, Energy Use, and Climate.

Data Regularization: Prepare data for following steps.

Multivariate Regression: Predict fertility rate using the selected indicators.

Dynamic Time Warping (DTW): Explore time evolution using DTW.

Cluster Analysis: Test different cluster sizes and apply Time Series KMeans clustering.

Findings (I)

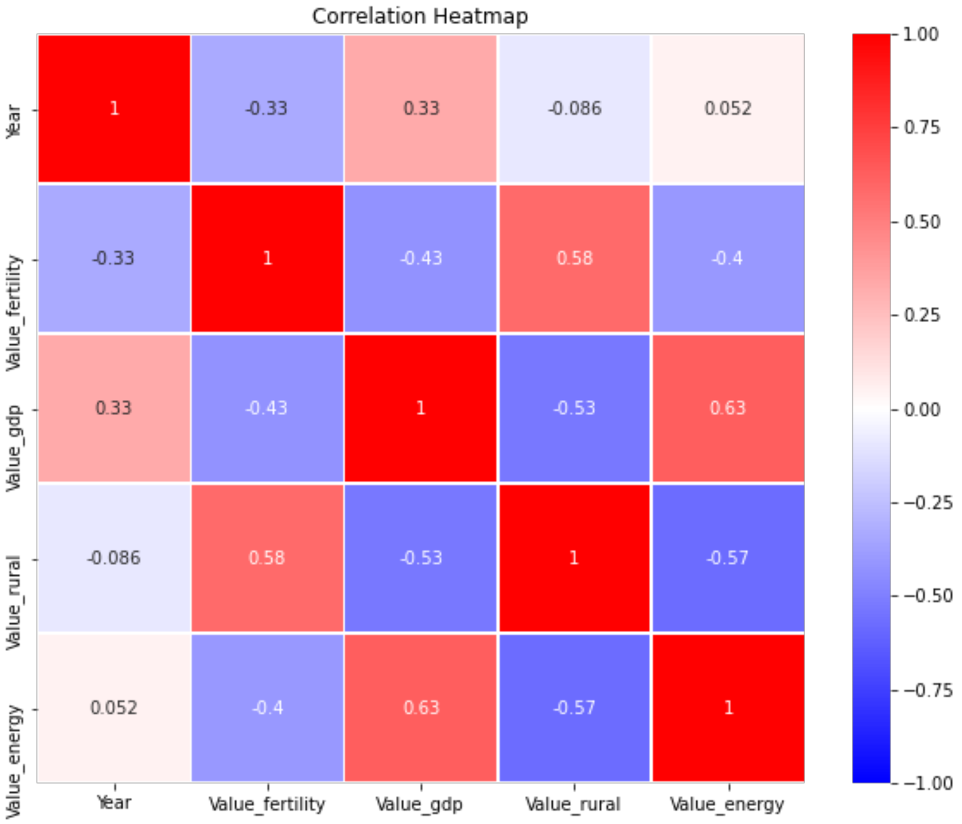
Observable correlations:

Fertility rate: decrease of fertility in time, decrease of fertility with increase in GDPs, increased in fertility for more rural populations, and decrease in fertility with increase is energy use.

GDP per capita: increase in GDP with increased energy use, increase of GDP in time (note: not inflation adjusted), decrease of GPD with increase of rural population

Rural: decrease in rural population with increase in energy use, and with time

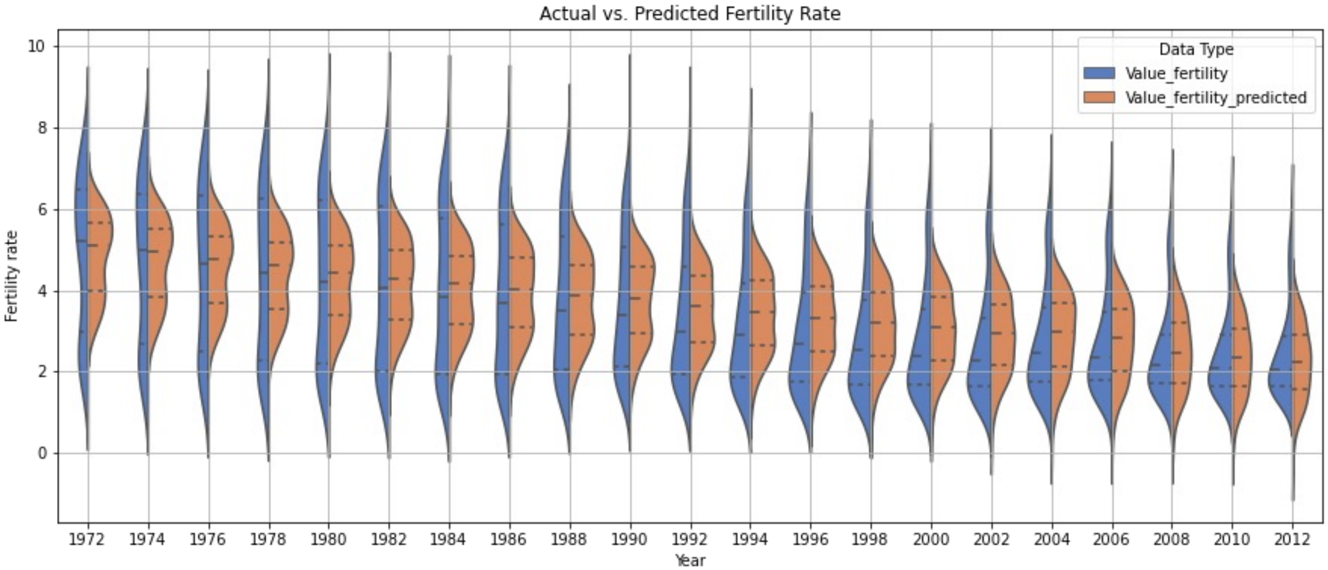
Energy: slight increase in energy use with time



Findings (II)

The first interesting observation is that in 1972 the world (in terms of fertility rates) seem to have two gears, a cluster around 2.5 and another around 6 and in 2012 there is mostly a single group around 2.

Around 40% of the variability in the data can be explained by this model (R-squared ~0.4)



The proportion of rural population is the strongest predictor of fertility rate (not GDP)

Predictor	Coefficient
GDP	−0.045
Rural Pop%	0.847
Energy Use	−0.163
Time	−0.590

Findings (III)

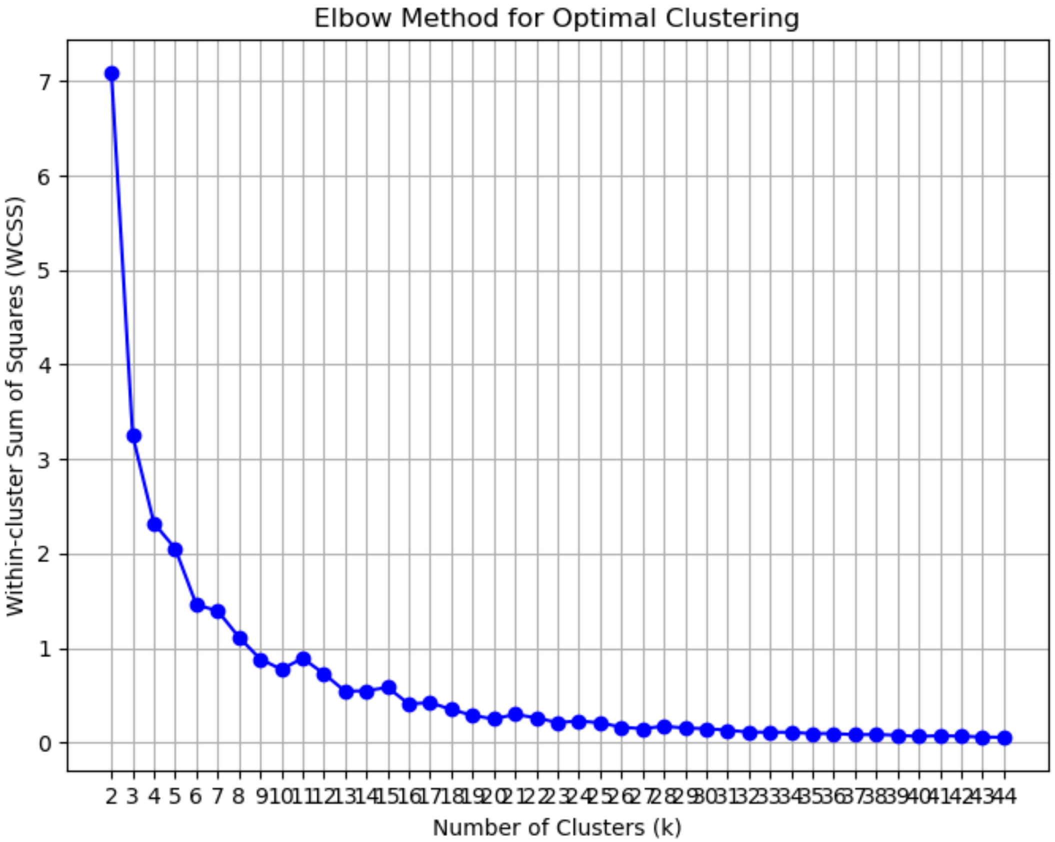
Though we tend to consider GDP a strong predictor of fertility rate, there are other factors, probably more related to livelihood, cultural habits, education, health care access that influence fertility rates.

In this toy exercise, I limited the question to rural populations (%) for the sake of having enough years/countries data.

Next, after noting that the fertility data seems to evolve from a bimodal to a unimodal distribution, I try to cluster the countries based on how fertility rates have evolved during this time (1972-2012).

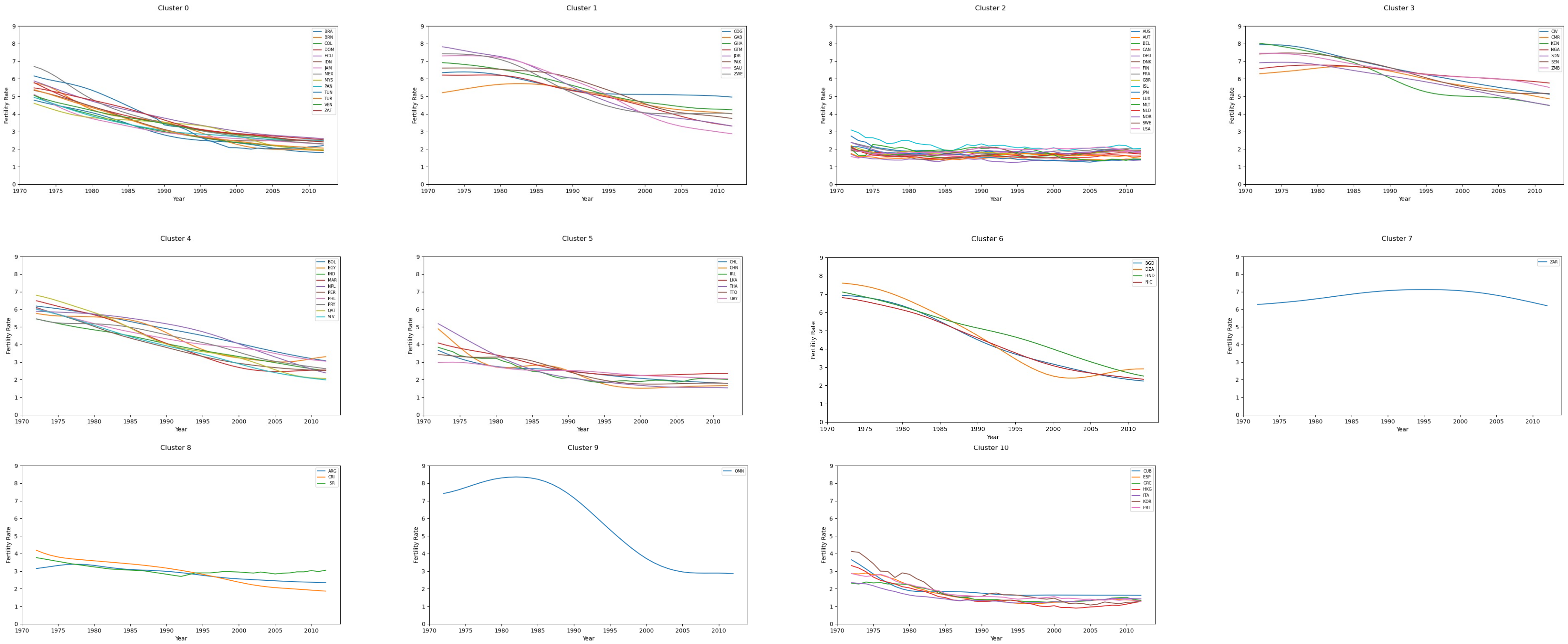
Findings (IV)

Using an elbow method for optimal clustering, given the data either the dynamic time warping or k-means clustering didn't result in a clear cluster cut off I decided on using 11.



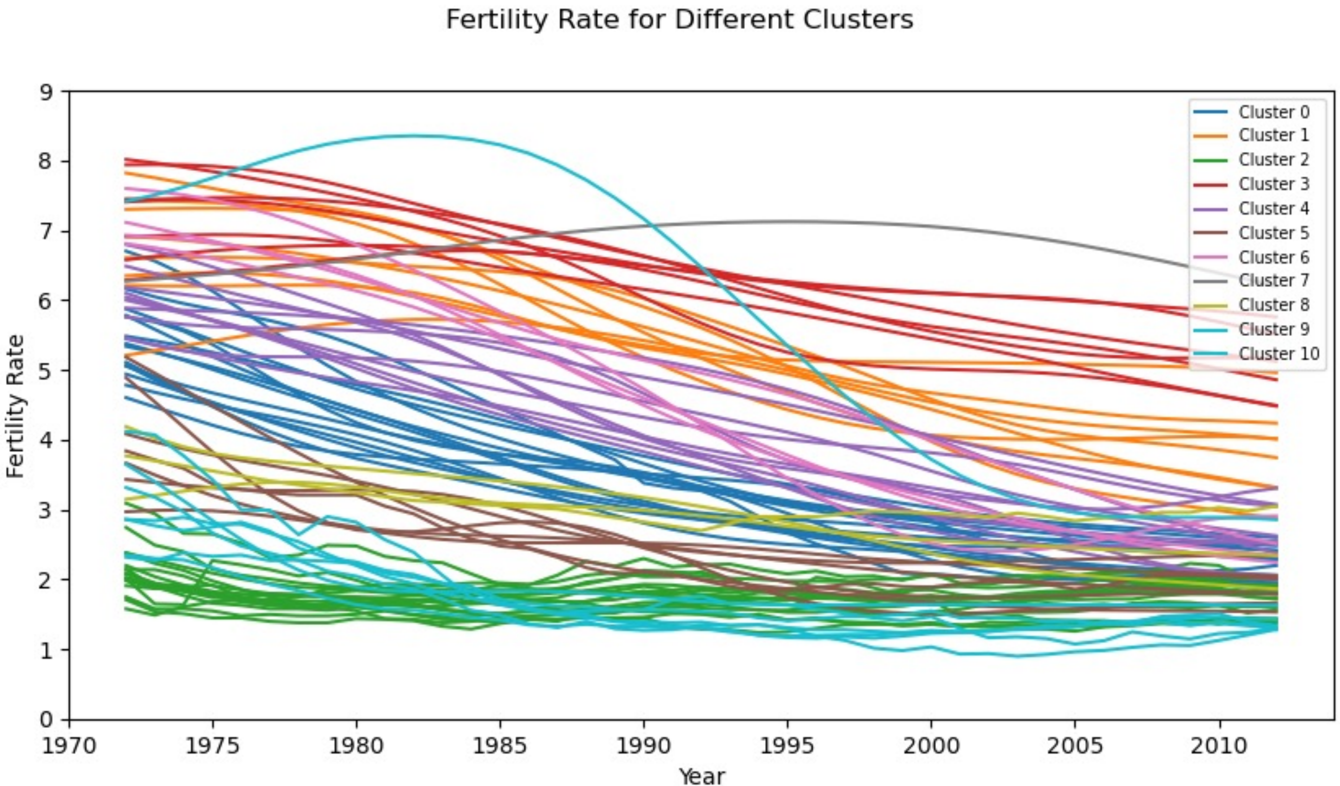
Findings (V)

Apologies for the dense visuals. Overview of all the clusters.



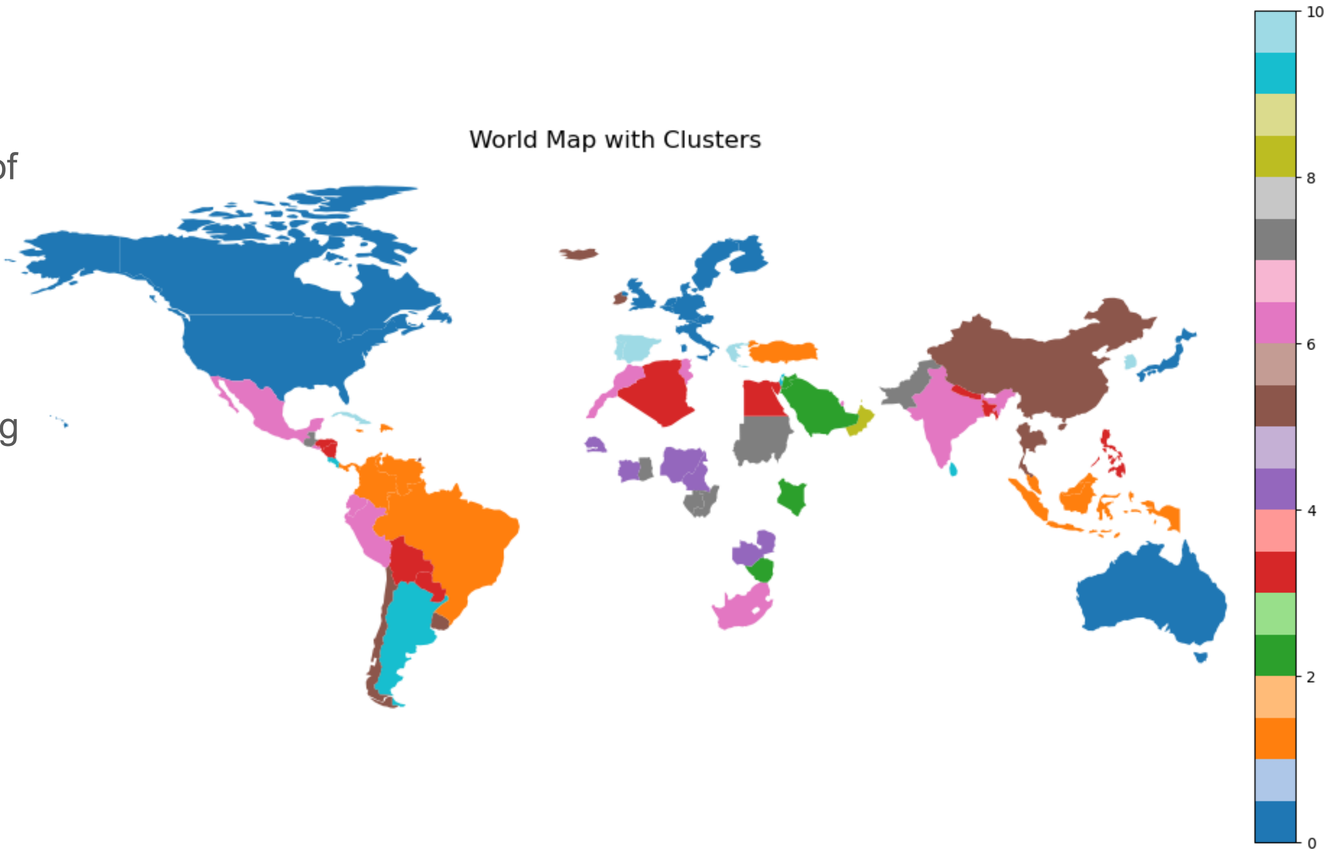
Findings (VI)

For the most part the different clusters tend to capture somewhat different modes of how the fertility rates have been trending. Mostly differentiating the rate of change in fertility rates across different countries.



Findings (IV)

The map, though with a lot of countries missing, is still shows some geographical relationships that seem to make sense. For example, “Western countries” including parts of northern Europe, North America, Australia belong to the same cluster. Sub-Saharan countries also organize in their own clusters.



(Apologies, I couldn’t find a way to make the cluster legend better.)

Limitations

To start with I used only a subset of the data, both in time and included countries. This was somewhat out to my control; it was related to the dataset I used.

The multilinear regression, assumes a linear relationship between the considered indicators, and that does not have to the correct. Have a better understanding of the indicators and how the data was collected could have helped in using more complex relationships and a better explanation of the data.

Regarding the clustering, I tried a few things that didn't generate stable clusters. My solution is stable, but probably not very generalizable. I tied it to 'culture' or 'policies' that would allow to 'validate' the clustering results.

Conclusions

Fertility rate trends: from 1972 to 2012 fertility rates have been decreasing. The earlier data showed more of a bimodal distribution that with time has been diluting and converging to a unimodal distribution. This might be related to a more global transition from rural and agricultural societies to more industrialized and service-oriented societies where families decide to have less children. This is supported by the fact that rural population is a better predictor of fertility rates and GDP.

When trying to understand how fertility rates compare across different countries one notices that there are adjacent countries that fall into similar clusters, or countries that have similar ‘societies’ (Western societies).

Looking that this rich data and a few indicators, for a few years in a few countries one can already notice patterns that seem to differentiate so much of our global landscape. Moving forward it would be relevant to tie this work to policy changes and expand it to explore more indicators.

Acknowledgements

No real acknowledgement to do here, other to the web browsing I did to fix issues with my script and learn about different packages.

References

I don’t have references to cite.

Project_2

November 14, 2023

1 Project: Working with World Development Indicators Dataset try understading the how different indicators cluster different countries together

Data Source: https://www.kaggle.com/worldbank/world-development-indicators

(Folder: 'world-development-indicators')

1.0.1 Part 1: predict fertility rate from a few other indicators

Step 1: Clean the data (confirm the same numbers of entries for all datasets)
Step 2: Correlations
Step 3: Multivariate regression

1.0.2 Part 2: cluster countries based on a subset of indicators

Step 4: Regularize the data
Step 5: Use Dynamic Time Warping to find the best match between time evolution of the group of different indicators in different countries
Step 6: Try clustering of single versus groups of indicicators
Step 7: Plot the clusters on a map to try to illustrate what might be happening (culture, policy)

[1]:
```
# Import the relevant libraries:

import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
import seaborn as sns
import geopandas as gpd
```

[2]:
```
# Load the data:
data = pd.read_csv('/Users/mariana/Documents/Classes/PythonForDataScience/
↪Week-5/Week5-Visualization/world-development-indicators/Indicators.csv')
```

```
print(data.shape)

# Need to select data from countries only, exclude regions:
countries = pd.read_csv('/Users/mariana/Documents/Classes/PythonForDataScience/
↪Week-5/Week5-Visualization/world-development-indicators/Country.csv')

print(countries.shape)
```

```
(5656458, 6)
(247, 31)
```

[3]:
```
# Clean the indicators' data frame, based on the country names/codes.
# We want to look only at countries and not regions.
# Country codes (Alpha2Code) with numbers correspond to regions: remove those.

# Filter the country codes to exclude things with numbers &
# Remove also 'countries' with no region associated.
# The regular expression \d matches any digit (0-9)
countries_filtered = countries[(~countries['Alpha2Code'].str.contains(r'\d',␣
↪na=False)) &\
                               (countries['Region'].notna())]

countries_filtered
countriesToKeep = countries_filtered['CountryCode'].unique().tolist()
data_clean1 = data[data['CountryCode'].isin(countriesToKeep)]

data_clean1
```

[3]:
```
          CountryName CountryCode  \
3492      Afghanistan         AFG
3493      Afghanistan         AFG
3494      Afghanistan         AFG
3495      Afghanistan         AFG
3496      Afghanistan         AFG
…              …           …
5656453      Zimbabwe         ZWE
5656454      Zimbabwe         ZWE
5656455      Zimbabwe         ZWE
5656456      Zimbabwe         ZWE
5656457      Zimbabwe         ZWE

                                            IndicatorName      IndicatorCode  \
3492     Adolescent fertility rate (births per 1,000 wo…        SP.ADO.TFRT
3493     Age dependency ratio (% of working-age populat…        SP.POP.DPND
3494     Age dependency ratio, old (% of working-age po…     SP.POP.DPND.OL
3495     Age dependency ratio, young (% of working-age …     SP.POP.DPND.YG
```

```
3496           Arms imports (SIPRI trend indicator values)     MS.MIL.MPRT.KD
…                                                         …                 …
5656453          Time required to register property (days)         IC.PRP.DURS
5656454           Time required to start a business (days)         IC.REG.DURS
5656455              Time to prepare and pay taxes (hours)         IC.TAX.DURS
5656456                 Time to resolve insolvency (years)         IC.ISV.DURS
5656457           Total tax rate (% of commercial profits)  IC.TAX.TOTL.CP.ZS

         Year         Value
3492     1960  1.453210e+02
3493     1960  8.171773e+01
3494     1960  5.086254e+00
3495     1960  7.663147e+01
3496     1960  4.000000e+07
…         …           …
5656453  2015  3.600000e+01
5656454  2015  9.000000e+01
5656455  2015  2.420000e+02
5656456  2015  3.300000e+00
5656457  2015  3.280000e+01

[4926334 rows x 6 columns]
```

2 Part 1 - multi variate regression

Explore the relationship between:

GDP: 'GDP per capita (current LCU)'

Rural pop: 'Rural population (% of total population)'

Fertility rate: 'Fertility rate, total (births per woman)'

Electriticy: 'Electric power consumption (kWh per capita)'

Energy use: 'Energy use (kg of oil equivalent per capita)'

Climate: 'Droughts, floods, extreme temperatures (% of population, average 1990-2009)"

[4]:
```
# Select indicators and find the current years and countries



# Select relevant indicators
indicators = [r'Fertility rate, total \(births per woman\)',\
              r'GDP per capita \(current US\$\)',\
              r'Rural population \(% of total population\)',\
              r'Electric power consumption \(kWh per capita\)',\
              r'Droughts, floods, extreme temperatures \(% of population,␣
 ↪average 1990-2009\)',\
              r'Adult literacy rate, population 15\+ years, both sexes \(%\)']
```

```
indicator_data = {}

# Extract data for selected indicators
for indicator in indicators:
    pattern = indicator
    indicator_data[indicator] =\
    data_clean1[data_clean1['IndicatorName'].str.contains(pattern, case=False,␣
↪regex=True)]

# Confirm size/shape
for indicator, data in indicator_data.items():
    print(indicator)
    print(data.shape)

# fertility = r'Fertility rate, total \(births per woman\)'

# gdp = r'GDP per capita \(current US\$\)'
# rural = 'Rural population \(% of total population\)'
# electricity = r'Electric power consumption \(kWh per capita\)'
# energy = r'Energy use \(kg of oil equivalent per capita\)'
# climate = r'Droughts, floods, extreme temperatures \(% of population, average␣
↪1990-2009\)'
# literacy = r'Adult literacy rate, population 15\+ years, both sexes \(%\)'

# fertility_data = data_clean1[data_clean1['IndicatorName'].str.
↪contains(fertility, case=False, regex=True)]

# gdp_data = data_clean1[data_clean1['IndicatorName'].str.contains(gdp,␣
↪case=False, regex=True)]
# rural_data = data_clean1[data_clean1['IndicatorName'].str.contains(rural,␣
↪case=False, regex=True)]
# electricity_data = data_clean1[data_clean1['IndicatorName'].str.
↪contains(electricity, case=False, regex=True)]
# energy_data = data_clean1[data_clean1['IndicatorName'].str.contains(energy,␣
↪case=False, regex=True)]
# climate_data = data_clean1[data_clean1['IndicatorName'].str.contains(climate,␣
↪case=False, regex=True)]
# literacy_data = data_clean1[data_clean1['IndicatorName'].str.
↪contains(literacy, case=False, regex=True)]
```

```
Fertility rate, total \(births per woman\)
(10484, 6)
GDP per capita \(current US\$\)
(8752, 6)
Rural population \(% of total population\)
(11600, 6)
Electric power consumption \(kWh per capita\)
```

```
(5473, 6)
Droughts, floods, extreme temperatures \(% of population, average 1990-2009\)
(168, 6)
Adult literacy rate, population 15\+ years, both sexes \(%\)
(653, 6)
```

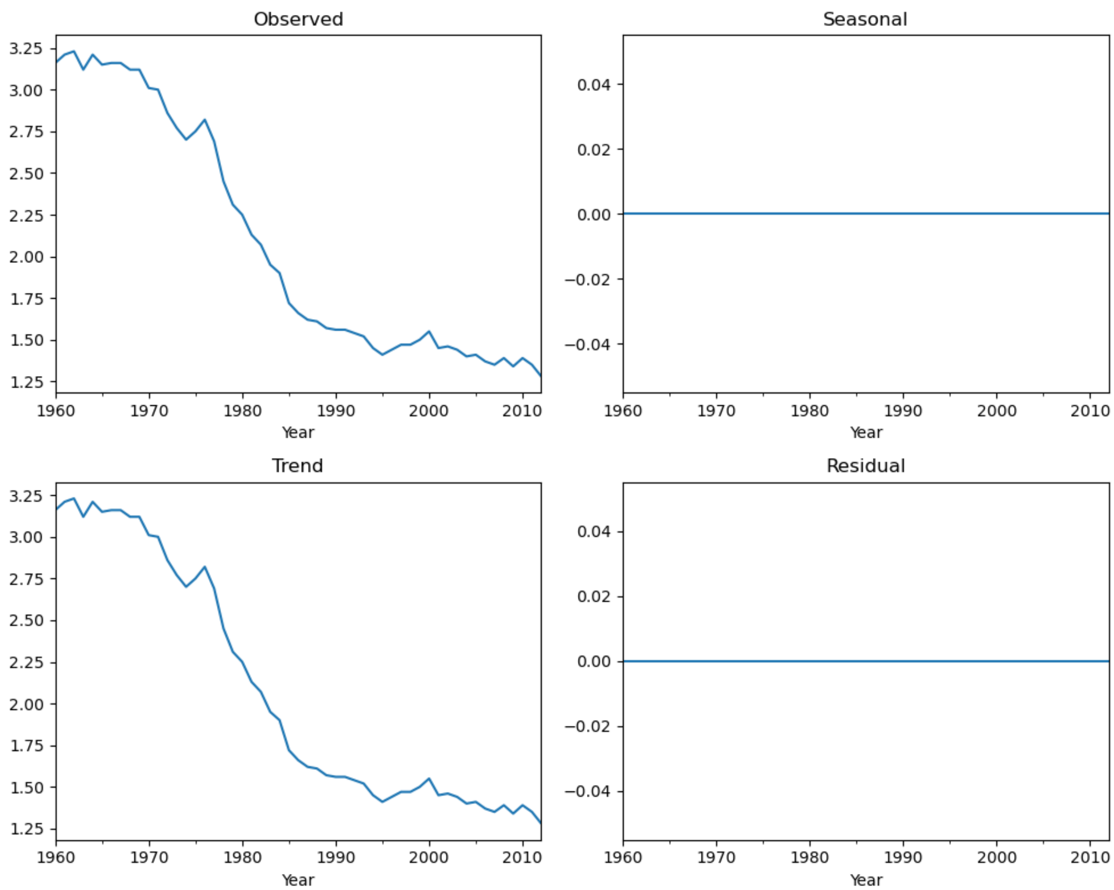
[5]:
```python
# Merge the data into a single dataframe
# Data will be completed relative to the data available on the corresponding␣
↪years/countries

columns_keep = ['CountryCode', 'IndicatorCode', 'Year', 'Value']

# 0 - fertility
# 1 - GDP
# 2 - rural
# 3 - energy
# 4 - doughts
# 5 - education

merged_df_1 = pd.merge(indicator_data[indicators[0]][columns_keep],\
                       indicator_data[indicators[1]][columns_keep],\
                       on=['CountryCode', 'Year'], suffixes=('_fertility',␣
↪'_gdp'))

merged_df_2 = pd.merge(merged_df_1,\
                       indicator_data[indicators[2]][columns_keep],\
                       on=['CountryCode', 'Year'])

dataIn = pd.merge(merged_df_2,\
                  indicator_data[indicators[3]][columns_keep],\
                       on=['CountryCode', 'Year'], suffixes=('_rural',␣
↪'_energy'))

# columns_keep = ['CountryCode', 'IndicatorCode', 'Year', 'Value']
# merged_df_1 = pd.merge(indicator_data[indicators[0]][columns_keep],\
#                        indicator_data[indicators[1]][columns_keep],\
#                        on=['CountryCode', 'Year'], suffixes=('_fertility',␣
↪'_gdp'))

#dataIn.head(5)
```

3 Note:

Below is a test to understand if the data could be easily decomposed into a linear trend. Using the library below it does not seem to be condusive to that.

[6]:
```python
from statsmodels.tsa.seasonal import seasonal_decompose

# Select data from a single country:
# PRT - Portugal
dataSingleCountry = dataIn.loc[dataIn['CountryCode'] == 'PRT']


# Create a time series using 'Year' as the index
dataSingleCountry['Year'] = pd.to_datetime(dataSingleCountry['Year'],␣
↪format='%Y')
dataSingleCountry.set_index('Year', inplace=True)

# Run seasonal decomposition on the 'Value_fertility' column
result = seasonal_decompose(dataSingleCountry['Value_fertility'],␣
↪model='additive', period=1)

# Plot the decomposed time series
fig, axes = plt.subplots(2, 2, figsize=(10, 8))
result.observed.plot(ax=axes[0,0], title='Observed')
result.trend.plot(ax=axes[1,0], title='Trend')
result.seasonal.plot(ax=axes[0,1], title='Seasonal')
result.resid.plot(ax=axes[1,1], title='Residual')

plt.tight_layout()
plt.show()

# result = seasonal_decompose(dataSingleCountry['Value_fertility'],␣
↪model='additive', period = dataSingleCountry['Year'])
# result.plot()

result.seasonal
# dataSingleCountry
```

```
/var/folders/w8/cndzxznj0dn45fvjfnjq7dl80000gn/T/ipykernel_60038/294880856.py:9:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dataSingleCountry['Year'] = pd.to_datetime(dataSingleCountry['Year'],
format='%Y')
```




```
[6]: Year
1960-01-01    0.0
1961-01-01    0.0
1962-01-01    0.0
1963-01-01    0.0
1964-01-01    0.0
1965-01-01    0.0
1966-01-01    0.0
1967-01-01    0.0
1968-01-01    0.0
1969-01-01    0.0
1970-01-01    0.0
1971-01-01    0.0
1972-01-01    0.0
1973-01-01    0.0
1974-01-01    0.0
1975-01-01    0.0
1976-01-01    0.0
1977-01-01    0.0
```

```
1978-01-01    0.0
1979-01-01    0.0
1980-01-01    0.0
1981-01-01    0.0
1982-01-01    0.0
1983-01-01    0.0
1984-01-01    0.0
1985-01-01    0.0
1986-01-01    0.0
1987-01-01    0.0
1988-01-01    0.0
1989-01-01    0.0
1990-01-01    0.0
1991-01-01    0.0
1992-01-01    0.0
1993-01-01    0.0
1994-01-01    0.0
1995-01-01    0.0
1996-01-01    0.0
1997-01-01    0.0
1998-01-01    0.0
1999-01-01    0.0
2000-01-01    0.0
2001-01-01    0.0
2002-01-01    0.0
2003-01-01    0.0
2004-01-01    0.0
2005-01-01    0.0
2006-01-01    0.0
2007-01-01    0.0
2008-01-01    0.0
2009-01-01    0.0
2010-01-01    0.0
2011-01-01    0.0
2012-01-01    0.0
Name: seasonal, dtype: float64
```

[7]:

```
# Decide on the time window to use:
# Create the violin plot for actual data only

# Fertility rate plot
plt.figure(figsize=(30, 6))
sns.violinplot(x='Year', y='Value_fertility', data=dataIn, inner="quart",␣
 ↪palette="muted")
plt.xlabel('Year')
plt.ylabel('Fertility rate')
plt.title('Fertility rate in Time')
```

```
plt.grid(True)
plt.show()

# GDP plot
plt.figure(figsize=(30, 6))
sns.violinplot(x='Year', y='Value_gdp', data=dataIn, inner="quart",␣
↪palette="muted")
plt.xlabel('Year')
plt.ylabel('GDP')
plt.title('GDP in Time')
plt.grid(True)
plt.show()

# Rural population (%) plot
plt.figure(figsize=(30, 6))
sns.violinplot(x='Year', y='Value_rural', data=dataIn, inner="quart",␣
↪palette="muted")
plt.xlabel('Year')
plt.ylabel('Rural population (%)')
plt.title('Rural population in Time')
plt.grid(True)
plt.show()

# Energy use (kg of oil equivalent per capita)
plt.figure(figsize=(30, 6))
sns.violinplot(x='Year', y='Value_energy', data=dataIn, inner="quart",␣
↪palette="muted")
plt.xlabel('Year')
plt.ylabel('Energy use kg of oil equivalent per capita)')
plt.title('Energy use in Time')
plt.grid(True)
plt.show()
```

```
/Users/mariana/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498:
FutureWarning: is_categorical_dtype is deprecated and will be removed in a
future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
/Users/mariana/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498:
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```

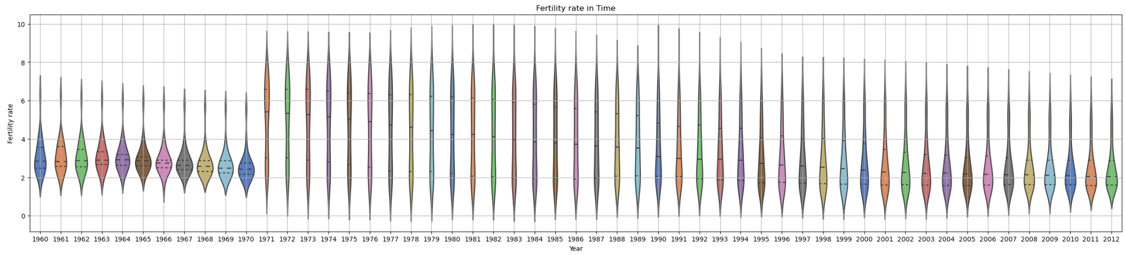


```
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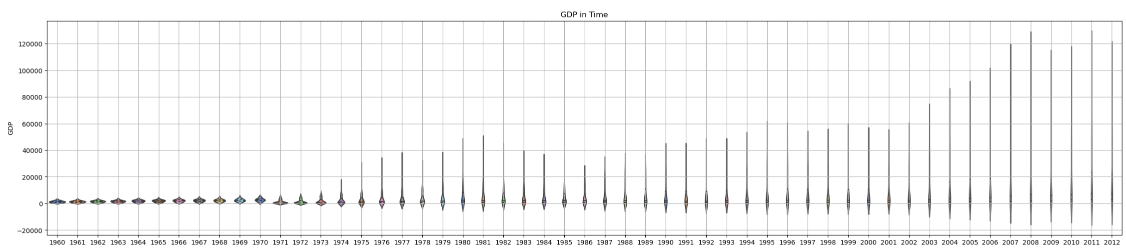


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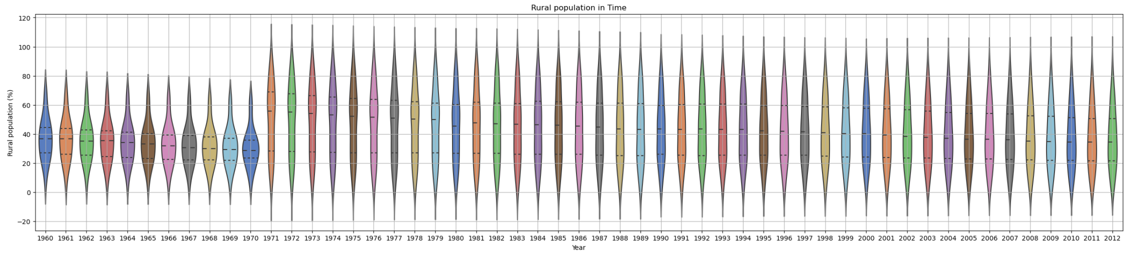


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  if pd.api.types.is_categorical_dtype(vector):
/Users/mariana/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498:
FutureWarning: is_categorical_dtype is deprecated and will be removed in a
future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
/Users/mariana/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498:
FutureWarning: is_categorical_dtype is deprecated and will be removed in a
future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
```
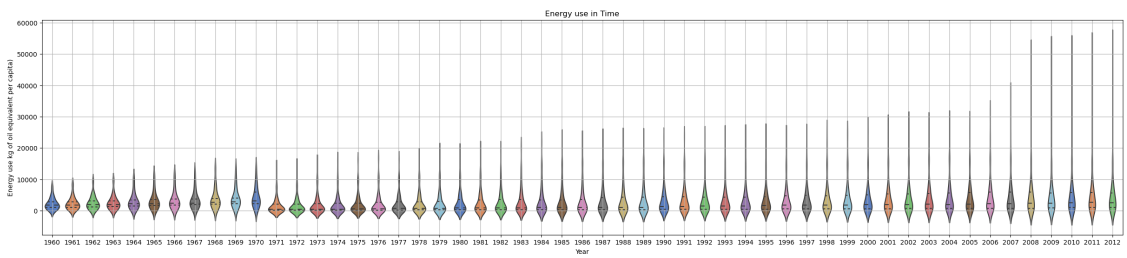



4 NOTE:

It looks like after 1971 some countries got included into the equation. - Maybe something changed in the way data was collected. I'll be excluding data prior to 1972.

And something might have happened in 2013 as well, exclude that year, as I don't have 2 of those years for test and control groups.

[8]:
```
# Exclude here some data in time (prior to 1972 and after 2012).

dataForMod = dataIn[(dataIn['Year'] > 1971) & (dataIn['Year'] < 2013)]



# Data in format for correlation
```

```
dataForModRelevantColumns = dataForMod[['Value_fertility', 'Value_gdp',␣
 ↪'Value_rural', 'Value_energy']]

dataForModRelevantColumns
```

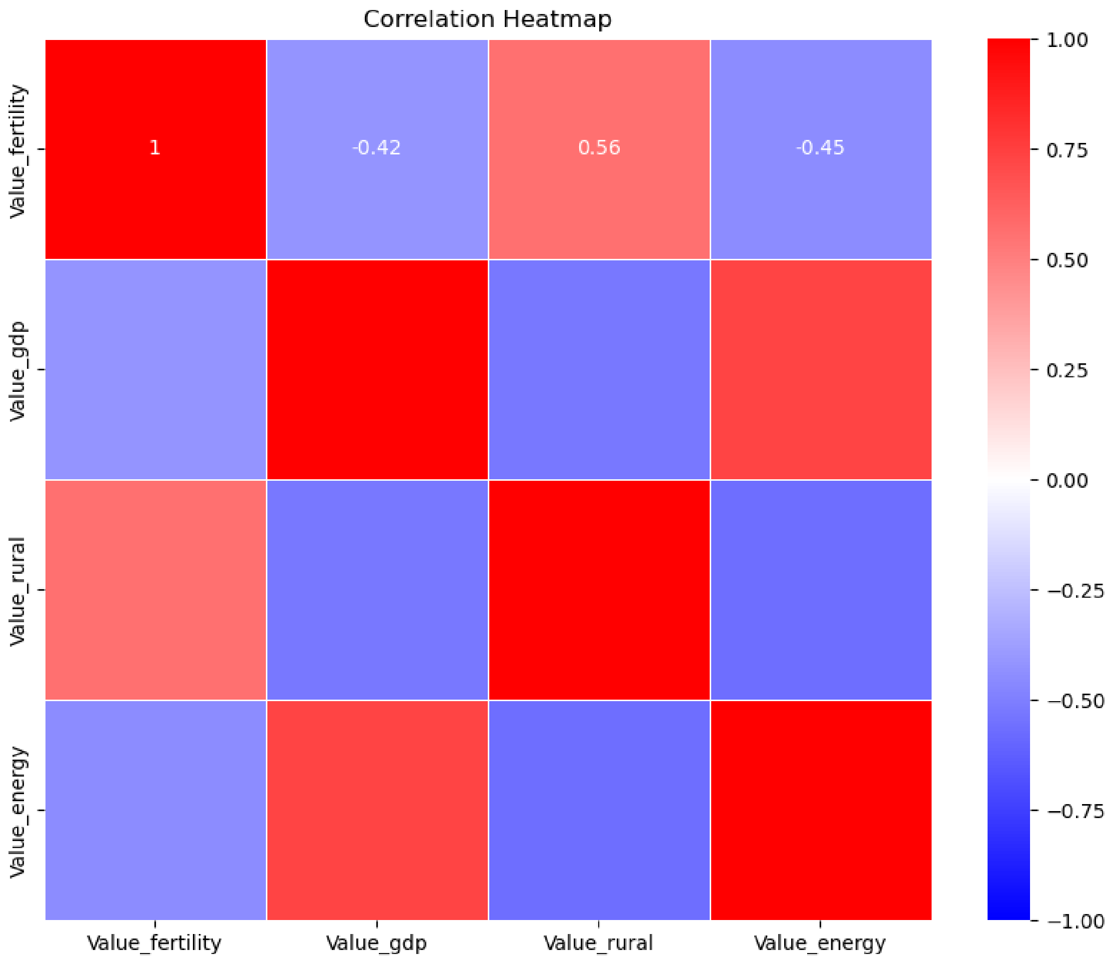
[8]:

	Value_fertility	Value_gdp	Value_rural	Value_energy
337	7.597	439.731073	60.169	142.029428
338	3.148	1401.487738	20.257	920.471534
339	2.744	3940.861981	14.319	3880.928891
340	2.080	2917.004844	34.689	3404.469208
341	6.928	93.051002	91.779	10.506302
…	…	…	…	…
4996	2.417	12771.595036	11.149	3412.681308
4997	1.768	1755.265424	68.332	1272.539255
4998	4.416	1289.034078	67.126	170.077377
4999	5.511	1686.618024	60.413	571.261200
5000	4.016	850.827694	67.166	561.807704

[4664 rows x 4 columns]

[9]:

```
# Check the correlation between inputs
# Test the correlation with a heatmap visulization

# Assuming 'dataForMod' is your DataFrame with numeric columns
correlation_matrix = dataForModRelevantColumns.corr()

# Create a heatmap to visualize the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='bwr', linewidths=0.5,␣
 ↪vmin=-1, vmax=1)
plt.title('Correlation Heatmap')

# plt.savefig('correlation_heatmap.png', format='png')

plt.show()
```



[10]:
```python
# Create a fit and test groups.
# Use all odd years for the fit and all even years for the test:

auxData_fit = dataForMod[dataForMod['Year'] % 2 != 0] # The odd numbers
y_fit = auxData_fit['Value_fertility']
X_fit = auxData_fit[['Value_gdp', 'Value_rural', 'Value_energy', 'Year']]


auxData_test = dataForMod[dataForMod['Year'] % 2 == 0] # The even numbers
y_test = auxData_test['Value_fertility']
X_test = auxData_test[['Value_gdp', 'Value_rural', 'Value_energy', 'Year']]


# Do some regularization before inputing it into the model
# Create a StandardScaler instance
scaler = StandardScaler()
```

```python
# Fit and transform the feature matrix X
X_scaled = scaler.fit_transform(X_fit)

X_test_scaled = scaler.fit_transform(X_test)

# The model (fit)

model = LinearRegression()

model.fit(X_scaled, y_fit)

model


mse = mean_squared_error(y_fit, model.predict(X_scaled))

print("MODEL Mean Squared Error:", mse)

# Calculate R-squared
r2 = r2_score(y_fit, model.predict(X_scaled))
print("MODEL R-squared:", r2)

# Access the coefficients (weights) and intercept
coefficients = model.coef_
intercept = model.intercept_

# Print the coefficients and intercept
print("MODEL Coefficients:", coefficients)
print("MODEL Intercept:", intercept)

# Test the model/prediction

predictions = model.predict(X_test_scaled)

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y_test, model.predict(X_test_scaled))

# Calculate R-squared
r2 = r2_score(y_test, model.predict(X_test_scaled))
print()
print(f'TEST Mean Squared Error: {mse}')
print(f'TEST R-squared: {r2}')
```

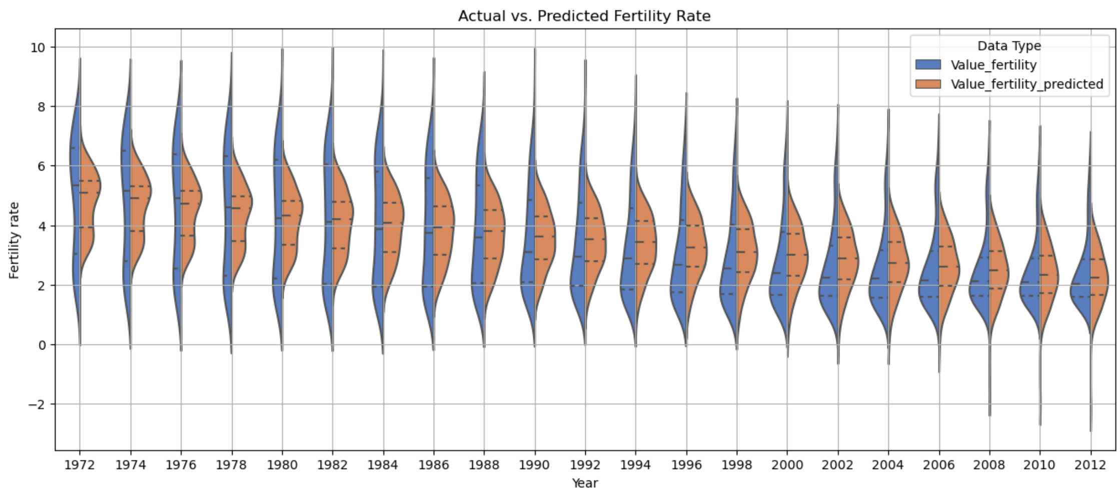
```
MODEL Mean Squared Error: 1.8609606082837478
MODEL R-squared: 0.4414748256975858
MODEL Coefficients: [ 0.09003101  0.80469139 -0.33581143 -0.59752481]
MODEL Intercept: 3.3539458901098924
```

```
TEST Mean Squared Error: 1.8575909423559192
TEST R-squared: 0.4459023947245544
```

[11]:
```python
# Visualize data: actual and prediction from multilinear regression model.

data_test_toplot = auxData_test[['Year', 'Value_fertility']]

data_test_toplot.loc[:, 'Value_fertility_predicted'] = predictions

df_melted = pd.melt(data_test_toplot, id_vars=['Year'], var_name='Data_Type',␣
 ↪value_name='Value')

# Create the violin plot
plt.figure(figsize=(15, 6))
sns.violinplot(x='Year', y='Value', hue='Data_Type', data=df_melted,␣
 ↪split=True, inner="quart", palette="muted")
plt.xlabel('Year')
plt.ylabel('Fertility rate')
plt.title('Actual vs. Predicted Fertility Rate')
plt.legend(title='Data Type')
plt.grid(True)

plt.savefig('violin_actual_predicted.png', format='png')

plt.show()
```

```
/var/folders/w8/cndzxznj0dn45fvjfnjq7d180000gn/T/ipykernel_60038/1972097548.py:5
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data_test_toplot.loc[:, 'Value_fertility_predicted'] = predictions
/Users/mariana/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498:
FutureWarning: is_categorical_dtype is deprecated and will be removed in a
future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
/Users/mariana/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498:
FutureWarning: is_categorical_dtype is deprecated and will be removed in a
future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
/Users/mariana/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498:
FutureWarning: is_categorical_dtype is deprecated and will be removed in a
future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
/Users/mariana/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1498:
FutureWarning: is_categorical_dtype is deprecated and will be removed in a
```

```
future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
```



[12]:
```python
# Make model output into a pretty table:
# pip install PrettyTable
# conda install -c conda-forge prettytable

from prettytable import PrettyTable

# Create a PrettyTable object
table = PrettyTable()

# Add columns to the table
table.field_names = ["Predictor", "Coefficient"]

# Add rows to the table
table.add_row(["GDP", f"{coefficients[0]:.3f}"])
table.add_row(["Rural Pop%", f" {coefficients[1]:.3f}"])
table.add_row(["Energy Use", f"{coefficients[2]:.3f}"])
table.add_row(["Time", f"{coefficients[3]:.3f}"])

# Print the table
print(table)
```

```
+------------+-------------+
| Predictor  | Coefficient |
+------------+-------------+
|    GDP     |    0.090    |
| Rural Pop% |     0.805   |
| Energy Use |    -0.336   |
|    Time    |    -0.598   |
```

```
+-----------+------------+
```

Based on the fact that there are significant correlations between the different variables/columns, I want to try seeing if there are meaningful ways to cluster these data in time.

The plan will be to use dynamic time warping and try to do classification based on the similarities across indicators in time to separate different countries into clusters. And finally plot it on a map.

5 Part 2: Clustering

[13]:
```
from tslearn.datasets import CachedDatasets
from tslearn.preprocessing import TimeSeriesScalerMeanVariance
from tslearn.clustering import TimeSeriesKMeans
```

[14]:
```
# Convert the DataFrame into a pivoted format

# Do some regularization before inputing it into the model
# Create a StandardScaler instance
scaler = StandardScaler()

# Fit and transform the feature matrix X
X_scaled = scaler.fit_transform(X_fit)

X_test_scaled = scaler.fit_transform(X_test)


dataForDTW = dataForMod[['CountryCode', 'Year', 'Value_fertility', 'Value_gdp',␣
 ↪'Value_rural', 'Value_energy']]

pivoted = dataForDTW.pivot(index='CountryCode', columns='Year')
pivoted.columns = [f"{col[0]}_{col[1]}" for col in pivoted.columns.
 ↪to_flat_index()]

auxUniqueCountries = dataForDTW['CountryCode'].unique().tolist()
len(auxUniqueCountries) # 165 countries
pivoted.shape
auxUniqueYears = dataForDTW['Year'].unique().tolist()
len(auxUniqueYears) # 41 years

len(pivoted.columns) # This is 4 indicators * 41 years - should be 164
```

[14]: 164

[15]:
```
# Extract values and reshape for clustering

reshaped_array = pivoted.values.reshape(\
                                        pivoted.shape[0],\
```

```
                                                len(pivoted.columns) //␣
 ↪len(auxUniqueYears),\
                                                len(auxUniqueYears))

# Transpose the array
reshaped_array = np.transpose(reshaped_array, axes=(0, 1, 2))

# Check the shape of the reshaped array
print('(countries, indicators, years): ', reshaped_array.shape)
```

```
(countries, indicators, years):  (135, 4, 41)
```

[16]:
```
dataForDTW

# Data preparation for clustering in time:
dataForDTW = dataForMod[['CountryCode', 'Year', 'Value_fertility']]

# Pivot the data to a time series format suitable for DTW
pivoted = dataForDTW.pivot_table(index='CountryCode', columns='Year',␣
 ↪values='Value_fertility')
# Remove countries with NaNs
pivoted.dropna(axis=0, how='any', inplace=True)

# Extract the values
X = pivoted.values

# Fill NaN values with the mean of each column
imputer = SimpleImputer(strategy='mean')
X_imputed = imputer.fit_transform(X)

# # Normalize the data
# scaler = StandardScaler()
# X_normalized = scaler.fit_transform(X_imputed)
X_normalized = X_imputed
```

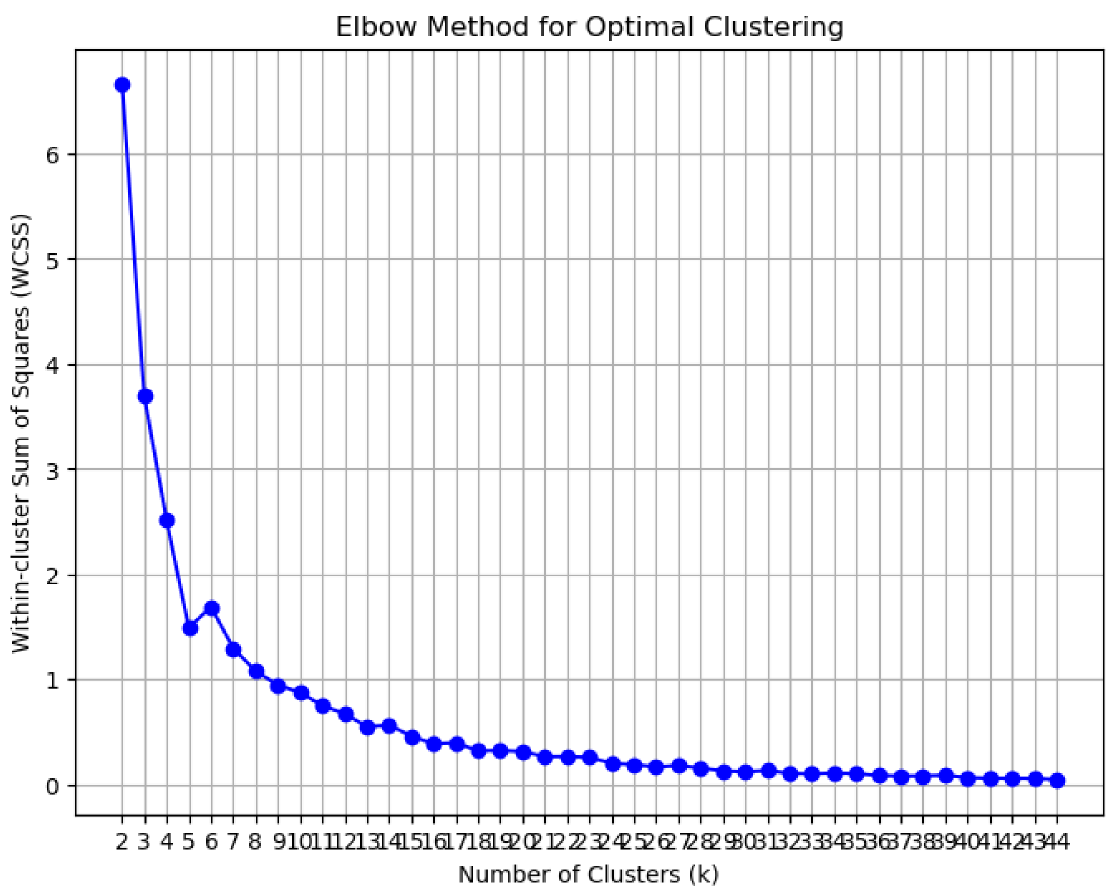
Problem: the clusters are not stable accross iterations.

[17]:
```
# Analysis for different cluster sizes to find the 'best' number of clusters:

cluster_min = 2
cluster_max = 45

# Loop through different cluster counts
centroid_errors = []  # Create an empty list to store centroid errors
for n_clusters in range(cluster_min, cluster_max):  # Considering clusters from␣
 ↪2 to 10
    model = TimeSeriesKMeans(n_clusters=n_clusters, metric="dtw") # No verbose␣
 ↪this time
```

```
    y_pred = model.fit_predict(X_normalized)


    # Get the sum of the within cluster squared error
    sum_centroid_error = model.inertia_

    centroid_errors.append(sum_centroid_error)  # Append the error to the list

    print(f"For {n_clusters} clusters, WCSS: {sum_centroid_error}")


plt.figure(figsize=(8, 6))
plt.plot(range(cluster_min, cluster_max), centroid_errors, marker='o',␣
 ↪linestyle='-', color='b')
plt.title('Elbow Method for Optimal Clustering')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Within-cluster Sum of Squares (WCSS)')
plt.xticks(range(cluster_min, cluster_max))
plt.grid(True)

plt.savefig('ClusteringSize.png', format='png')


plt.show()
```

```
For 2 clusters, WCSS: 6.665905402522037
For 3 clusters, WCSS: 3.693186260690312
For 4 clusters, WCSS: 2.5160314350339386
For 5 clusters, WCSS: 1.4922200117728124
For 6 clusters, WCSS: 1.6903441008034583
For 7 clusters, WCSS: 1.295169581351241
For 8 clusters, WCSS: 1.081128334166747
For 9 clusters, WCSS: 0.9474379690130366
For 10 clusters, WCSS: 0.8771970152761386
For 11 clusters, WCSS: 0.7498564858558089
For 12 clusters, WCSS: 0.6752411129003572
For 13 clusters, WCSS: 0.5522943893585808
For 14 clusters, WCSS: 0.566490468076903
For 15 clusters, WCSS: 0.4612144175915803
For 16 clusters, WCSS: 0.38827716969013354
For 17 clusters, WCSS: 0.3971811450006798
For 18 clusters, WCSS: 0.32262058847070496
For 19 clusters, WCSS: 0.32647366413553286
For 20 clusters, WCSS: 0.31569287157057274
For 21 clusters, WCSS: 0.2664863136284591
For 22 clusters, WCSS: 0.26871014234865725
For 23 clusters, WCSS: 0.26008382707618527
For 24 clusters, WCSS: 0.20383692377277848
```

```
For 25 clusters, WCSS: 0.1895813219429657
For 26 clusters, WCSS: 0.16700657679605355
For 27 clusters, WCSS: 0.18026804070537666
For 28 clusters, WCSS: 0.1569839252578643
For 29 clusters, WCSS: 0.13034629473710238
For 30 clusters, WCSS: 0.12118728618332911
For 31 clusters, WCSS: 0.13321475341304892
For 32 clusters, WCSS: 0.10759123030540266
For 33 clusters, WCSS: 0.10188050661671795
For 34 clusters, WCSS: 0.1105550830525412
For 35 clusters, WCSS: 0.1041787798096672
For 36 clusters, WCSS: 0.08603176314318738
For 37 clusters, WCSS: 0.08071322008698897
For 38 clusters, WCSS: 0.08236894521051115
For 39 clusters, WCSS: 0.08774281138195698
For 40 clusters, WCSS: 0.06664334989825438
For 41 clusters, WCSS: 0.06016334275268078
For 42 clusters, WCSS: 0.06086464866019627
For 43 clusters, WCSS: 0.05912127475182438
For 44 clusters, WCSS: 0.049351858147328974
```

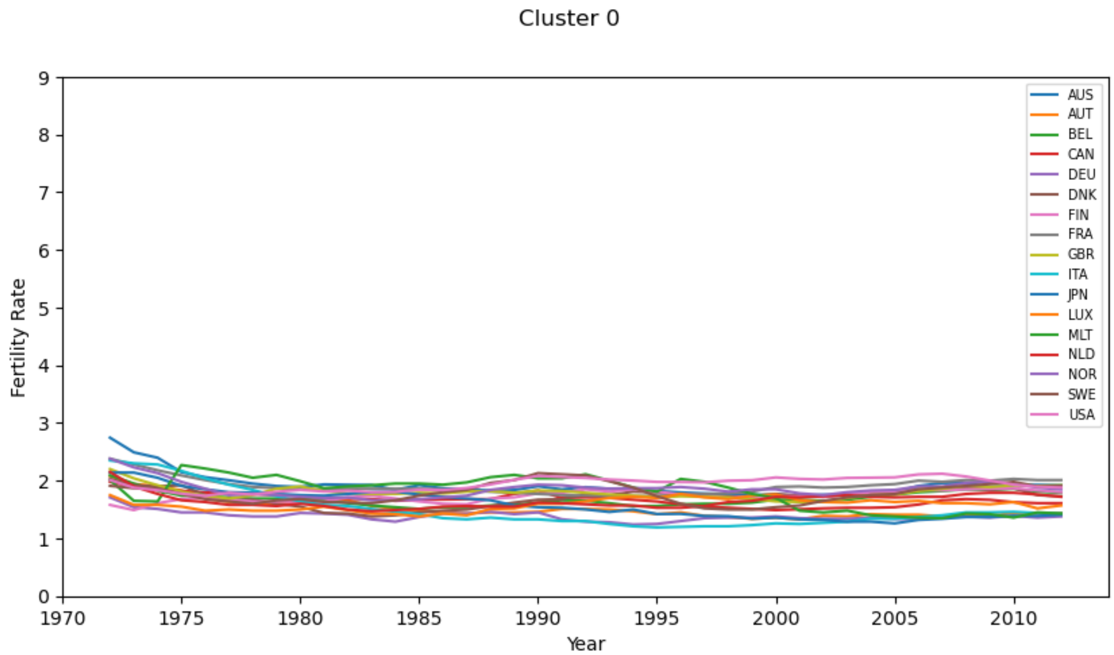


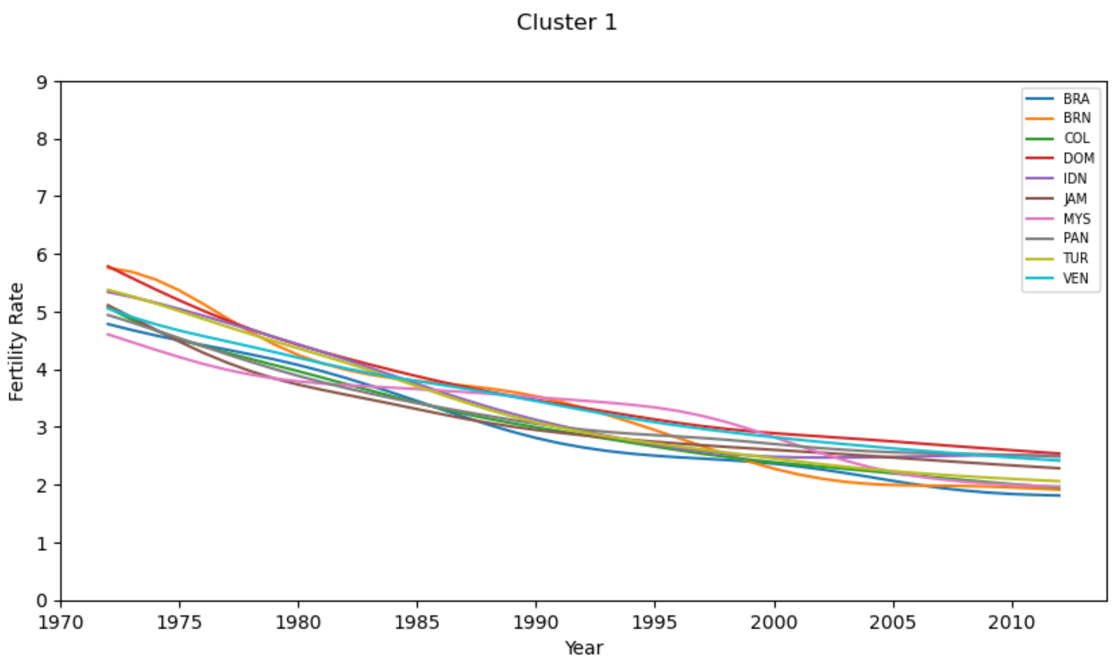
[18]:
```
# Perform Time Series KMeans clustering using Euclidean distance
n_clusters = 11  # Set the number of clusters
model = TimeSeriesKMeans(n_clusters=n_clusters, metric="euclidean",␣
↪verbose=True)
# model = TimeSeriesKMeans(n_clusters=n_clusters, metric="dtw", verbose=True)

y_pred = model.fit_predict(X_normalized)
sum_centroid_error = model.inertia_
centroid_positions = model.cluster_centers_

# Display the predicted clusters
print(y_pred)
```

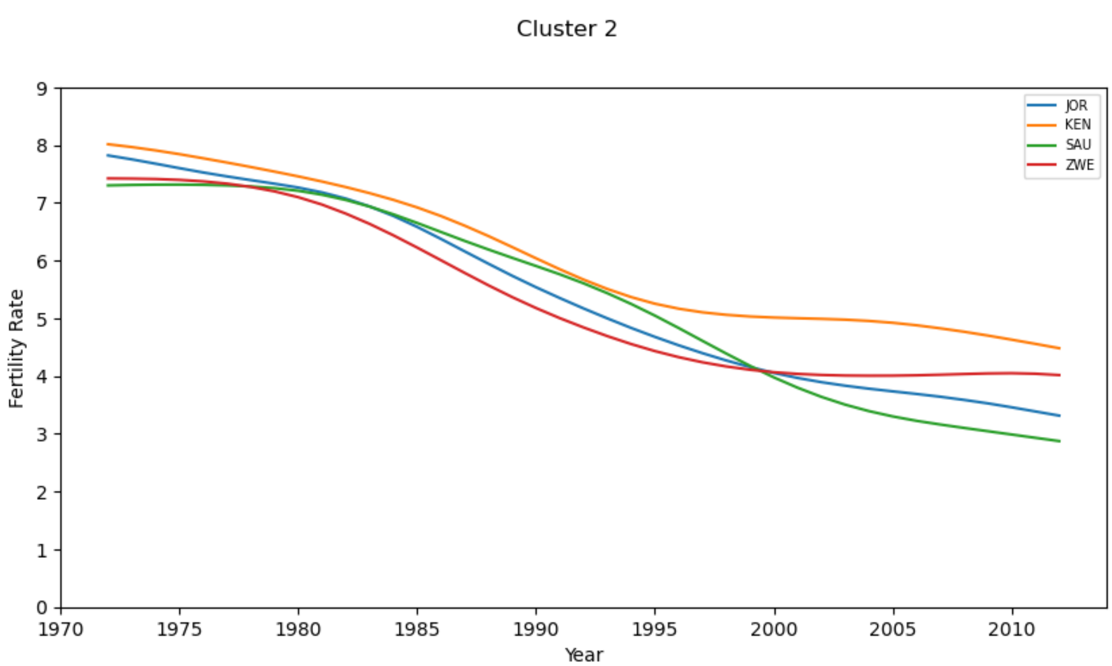
```
6.196 --> 4.361 --> 4.263 --> 4.263 -->
[ 9  0  0  0  3  3  1  1  0  5  5  4  4  7  1  9 10  0  0  1  3  6  3 10
  0  0  7  0  7 10  7 10  3  1  6  5  5  9  0  1  2  0  2 10  9  0  6  6
  0  1  4  3  0  0  3  8  7  1  6  3 10  3  6  2  7  4  6  0  5  5  6  1
  5  0  1  6  4  4  2]
```

[19]:
```
# Assuming 'data_with_clusters' is a DataFrame containing CountryCodes and␣
↪their respective clusters

data_with_clusters = pd.concat([pivoted, pd.Series(y_pred, name='Cluster',␣
↪index=pivoted.index)], axis=1)
# Display the 'pivoted' table along with the 'Cluster' column
# print(data_with_clusters)


min_fertility = min(0, data_with_clusters.iloc[:, :-1].values.min())  #␣
↪Excluding the 'Cluster' column
max_fertility = max(9, data_with_clusters.iloc[:, :-1].values.max())  #␣
↪Excluding the 'Cluster' column


# Grouping data based on clusters
for cluster in range(n_clusters):
    cluster_data_loc = data_with_clusters[data_with_clusters['Cluster'] ==␣
↪cluster]

    countries = cluster_data_loc.index.tolist()

    plt.figure(figsize=(10, 5))
    plt.suptitle(f'Cluster {cluster}')

    for country in countries:
```

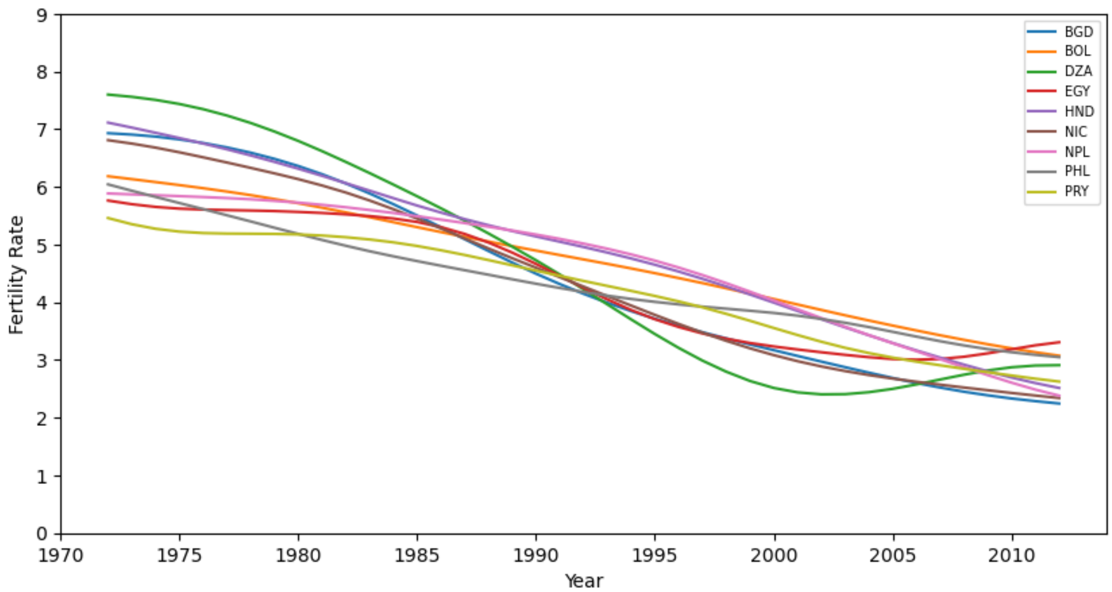
```
        country_data = cluster_data_loc.loc[country][:-1]
        # Extract fertility data, excluding the 'Cluster' column

        plt.plot(country_data.index, country_data, label=country)

    plt.xlabel('Year')
    plt.ylabel('Fertility Rate')
    plt.legend(loc='upper right', fontsize='x-small')
    plt.ylim(min_fertility, max_fertility)

    plt.savefig("Cluster_" + str(cluster) + ".png", format='png')

    plt.show()
```



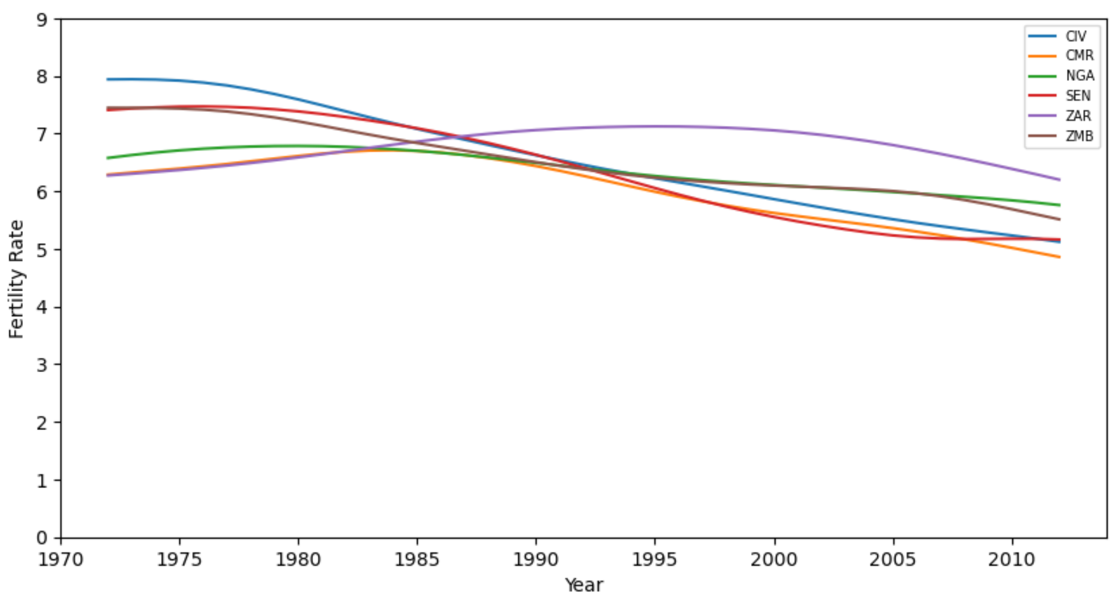

Cluster 1
Fertility Rate
Year
BRA
BRN
COL
DOM
IDN
JAM
MYS
PAN
TUR
VEN
0
1
2
3
4
5
6
7
8
9
1970
1975
1980
1985
1990
1995
2000
2005
2010


Cluster 2
Fertility Rate
Year
JOR
KEN
SAU
ZWE
0
1
2
3
4
5
6
7
8
9
1970
1975
1980
1985
1990
1995
2000
2005
2010

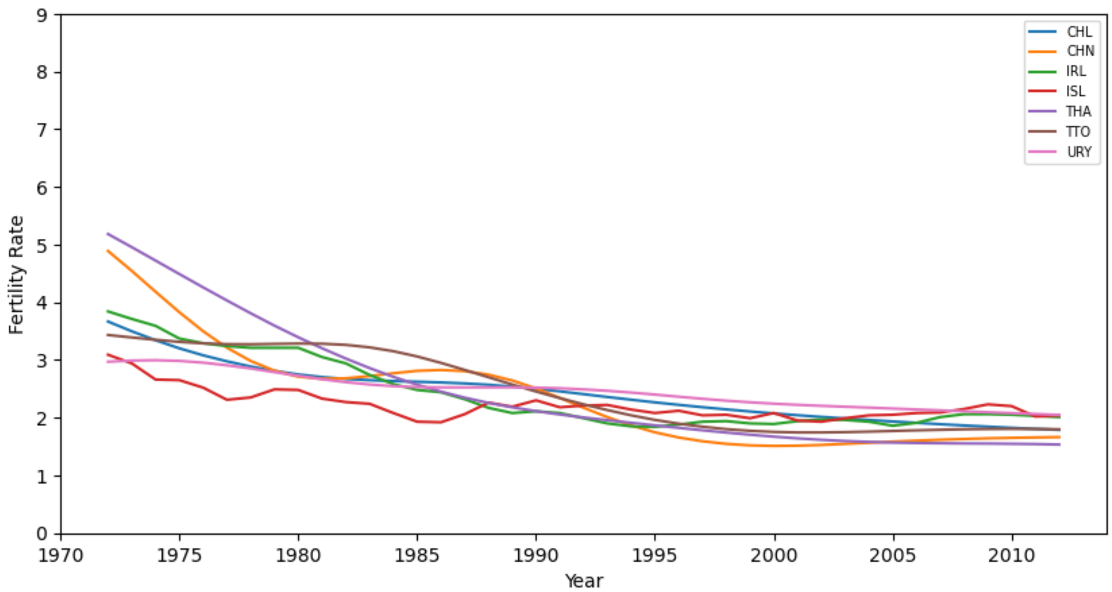
Cluster 3



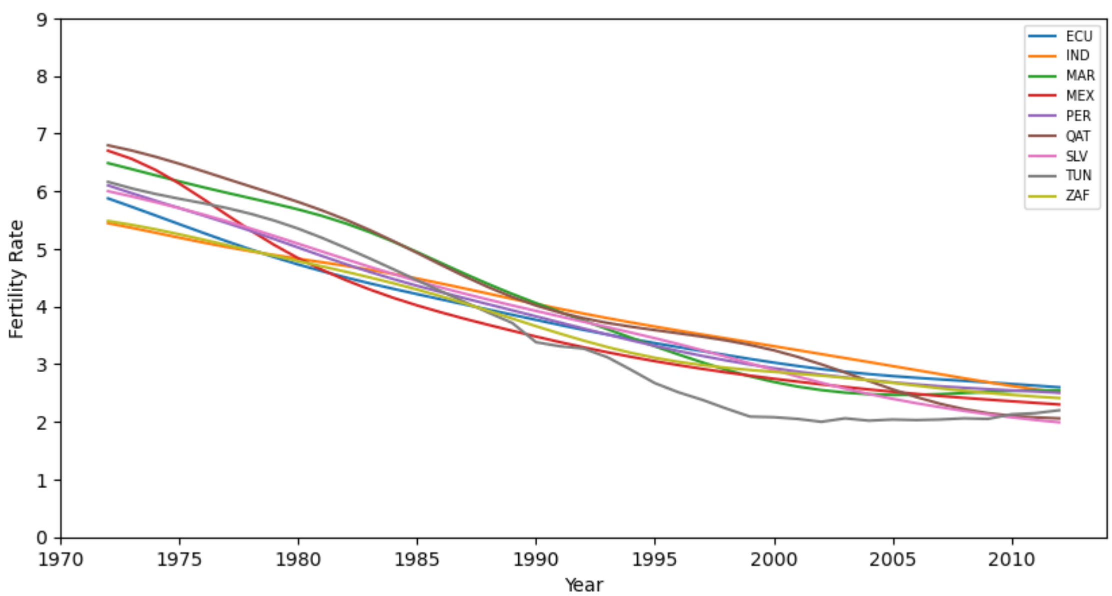
Cluster 4



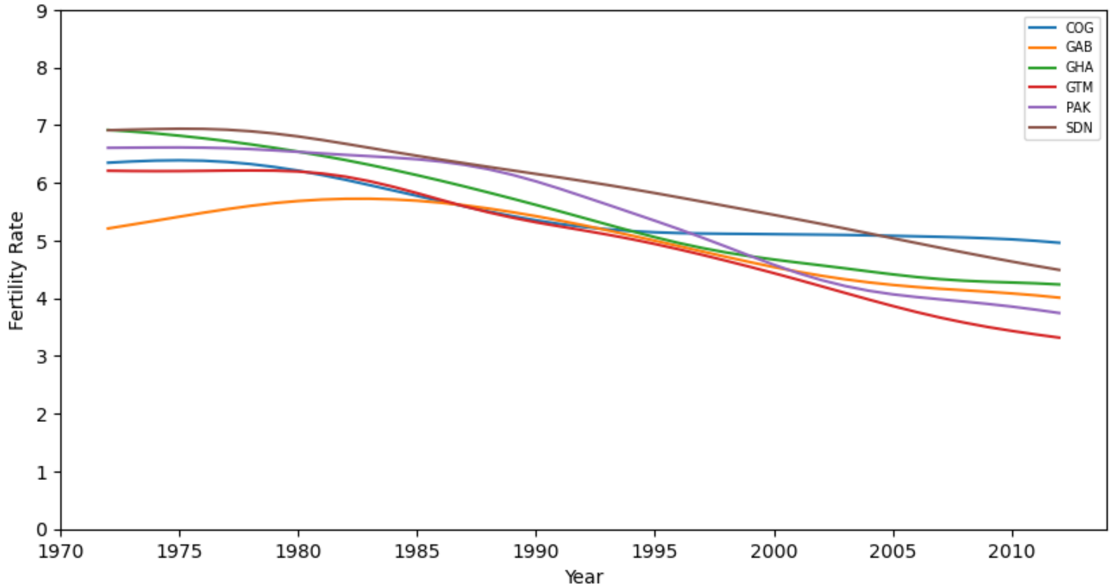
Cluster 5



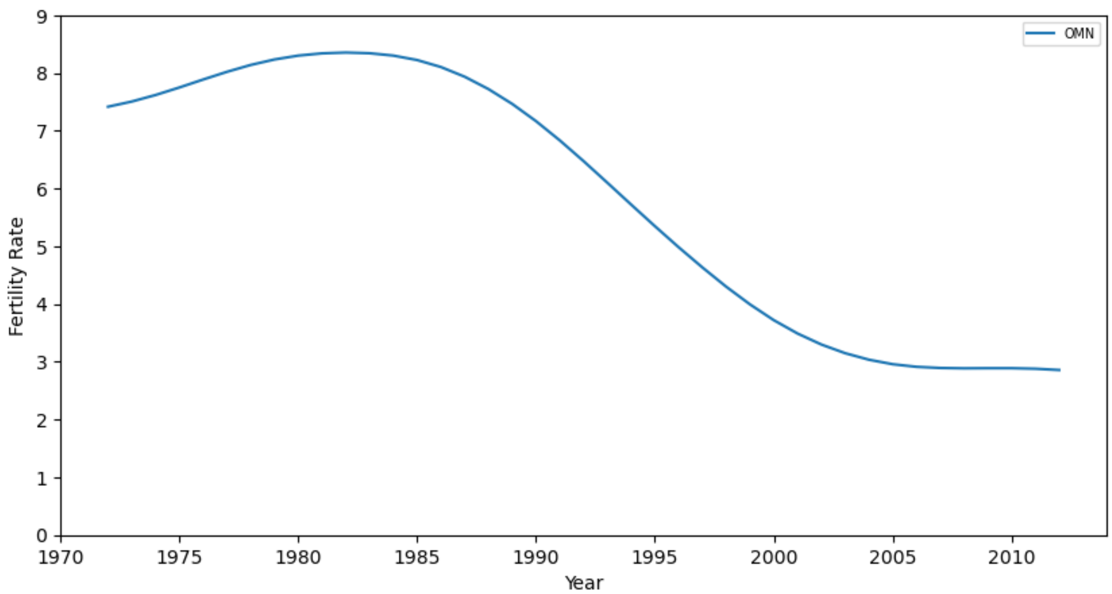
Cluster 6



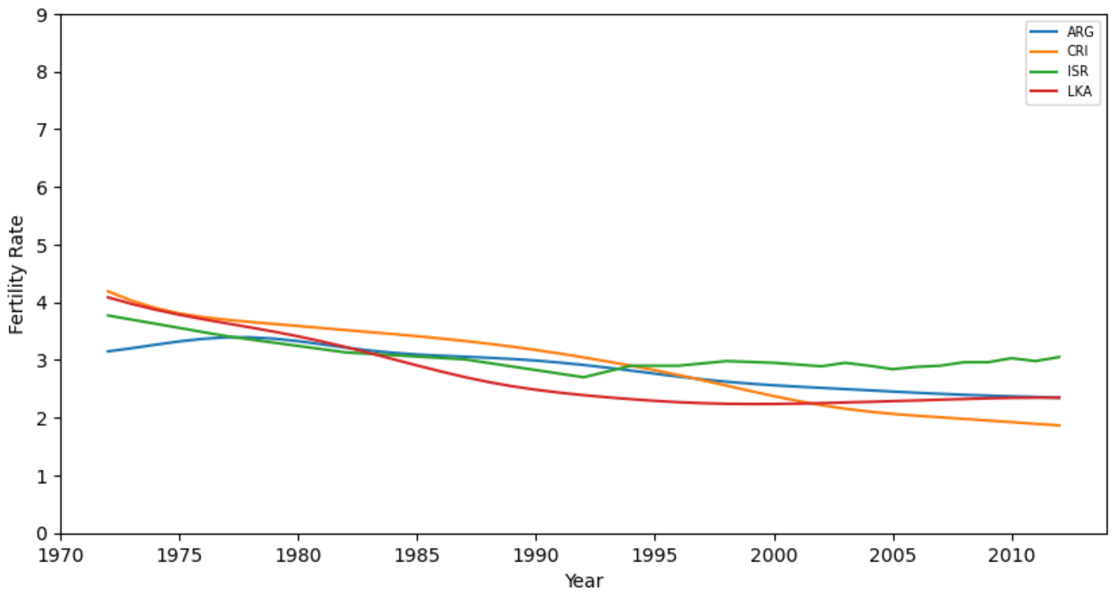
Cluster 7



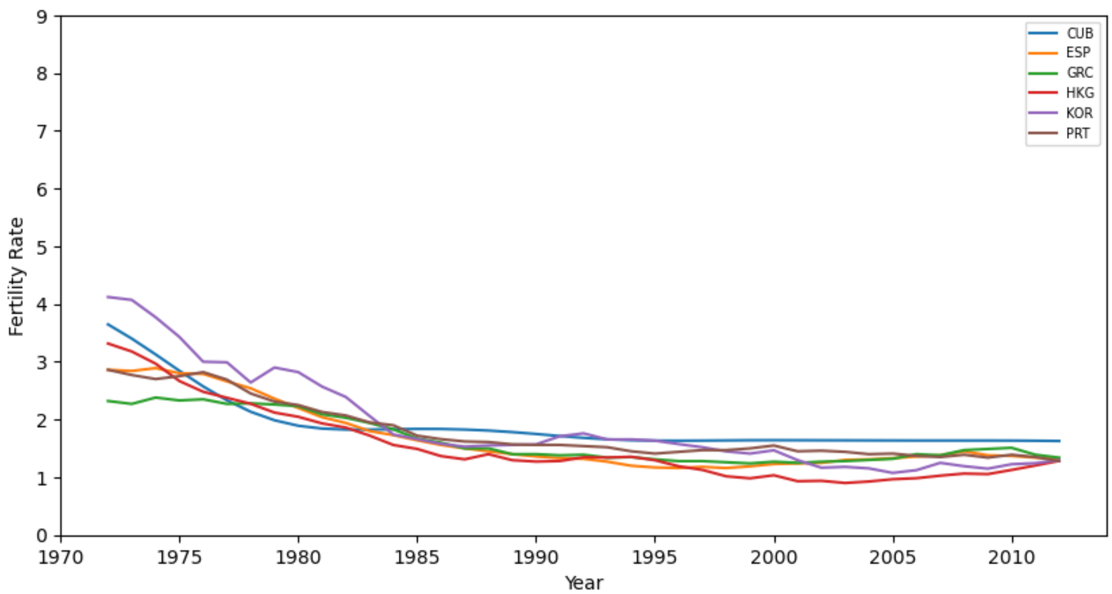
Cluster 8



Cluster 9

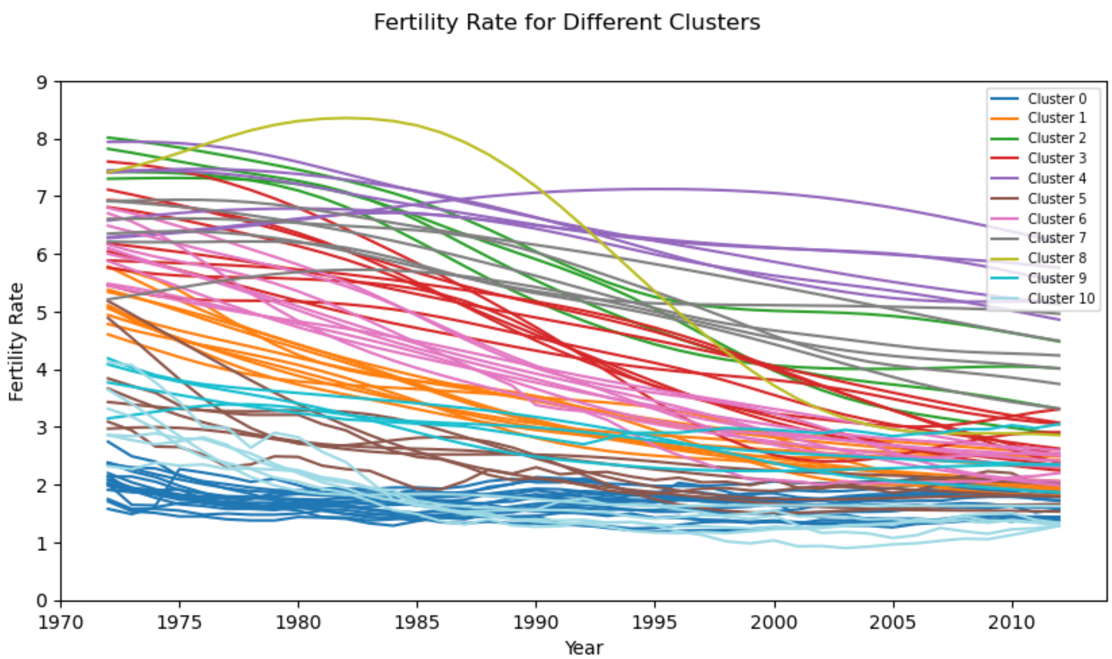


Cluster 10



[21]:
```
# Grouping data based on clusters - all in the same plot
# n_clusters = 11  # Update the number of clusters
```

```
colors = plt.cm.tab20(np.linspace(0, 1, n_clusters))  # Use tab20 colormap

plt.figure(figsize=(10, 5))
plt.suptitle('Fertility Rate for Different Clusters')

# Create lists to store legend handles and labels
legend_handles = []
legend_labels = []

for cluster in range(n_clusters):
    cluster_data_loc = data_with_clusters[data_with_clusters['Cluster'] ==␣
 ↪cluster]

    countries = cluster_data_loc.index.tolist()

    for country in countries:
        country_data = cluster_data_loc.loc[country][:-1]  # Extract fertility␣
 ↪data, excluding the 'Cluster' column

        line, = plt.plot(country_data.index, country_data, label=f'Cluster␣
 ↪{cluster}', color=colors[cluster])

    # Add the line handle and label to the legend lists only once
    legend_handles.append(line)
    legend_labels.append(f'Cluster {cluster}')

plt.xlabel('Year')
plt.ylabel('Fertility Rate')

# Create the legend using the custom handles and labels
plt.legend(handles=legend_handles, labels=legend_labels, loc='upper right',␣
 ↪fontsize='x-small')

plt.ylim(min_fertility, max_fertility)

plt.savefig("Clusters_overlaid.png", format='png')

plt.show()
```



From the geopandas data there are a few datasets that are useful. On the loaded repository of maps, the 'iso_a3' matches the 'CountryCode'. Hence, merging the dataframe containing that map with the clusters should produce something useful.

Available geopandas maps: 'naturalearth_cities', 'naturalearth_lowres', 'nybb' (run: gpd.datasets.available)

[22]:
```
centroid_positions.shape

dataForDTW
```

[22]:
```
     CountryCode  Year  Value_fertility
337          DZA  1972            7.597
338          ARG  1972            3.148
339          AUS  1972            2.744
340          AUT  1972            2.080
341          BGD  1972            6.928
…             …    …                …
4996         VEN  2012            2.417
4997         VNM  2012            1.768
4998         YEM  2012            4.416
4999         ZMB  2012            5.511
5000         ZWE  2012            4.016

[4664 rows x 3 columns]
```

[26]:

```
# Load world map data
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

# Assuming 'cluster_data' is a DataFrame containing CountryCodes and their␣
↪respective clusters
# Join world map with cluster data
cluster_data = data_with_clusters
world = world.merge(cluster_data, left_on='iso_a3', right_on='CountryCode',␣
↪how='left')

# Plot world map with country colors based on clusters
world.plot(column='Cluster', cmap='tab20', figsize=(15, 10), legend=True)  #␣
↪Use the tab20 colormap
plt.title('World Map with Clusters')

# Remove the axis labels, ticks, and spines
plt.xticks([])
plt.yticks([])
plt.axis('off')

# plt.savefig('map_clusteringAll_noRegularization.png', format='png')
plt.savefig('map_clusteringFertitilyOnly_withRegularization_euclideanDistance.
↪png', format='png')

plt.show()
```

```
/Users/mariana/anaconda3/lib/python3.11/site-packages/geopandas/plotting.py:715:
FutureWarning: is_categorical_dtype is deprecated and will be removed in a
future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(values.dtype):
/Users/mariana/anaconda3/lib/python3.11/site-packages/geopandas/plotting.py:48:
ShapelyDeprecationWarning: The 'type' attribute is deprecated, and will be
removed in the future. You can use the 'geom_type' attribute instead.
  if geom is not None and geom.type.startswith(prefix) and not geom.is_empty:
```

[24]:
```
# The maps available with geopandas

world

gpd.datasets.available
```

[24]: ['naturalearth_cities', 'naturalearth_lowres', 'nybb']