Global Migration Patterns with Spatio-Temporal Graph Convolutional Networks

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Abstract

This paper presents an innovative study on the application of Graph Neural Networks (GNNs), specifically Spatio-Temporal Graph Convolutional Networks (STGCN), in the analysis of global migration patterns. Recognizing the limitations of conventional methods in capturing the complex spatial and temporal dynamics of migration, we propose a novel approach that utilizes the advanced capabilities of STGCN to model the multifaceted nature of migration flows. Our methodology integrates spatial interconnectivity and temporal evolution, to provide a comprehensive analysis of migration patterns across 195 countries and territories. Employing datasets from the United Nations World Population Prospects and the Global Migration Database, we demonstrate the model's ability to accurately predict net migration flows and immigration patterns. The results underscore the potential of GNNs in enhancing predictive accuracy and offering deeper insights into migration dynamics. Through this study, we contribute to the advancement of migration research methodologies, showcasing the applicability of GNNs in addressing complex societal challenges.

Keywords: Graph Neural Networks, Migration Patterns, Spatio-Temporal Analysis, Predictive Modeling.

1. Introduction

Migration patterns play a pivotal role in shaping numerous socio-economic aspects, including urban planning, environmental sustainability, public health, and more. Traditional methods for predicting international migration have relied on theoretical network models such as Convulational Neural Networks (CNN) that does not simulatenousely capture the spatial and temporal properties. Other traditional theoretical network models, such as exponential graph models and quantitative social network models, offer insights into migration patterns but are constrained by strict assumptions, such as homophily, but in essence emigration and immigration are unpredictable.

The primary challenge in predicting international migration lies in the complexity of spatial and temporal dynamics, which are typically treated independently in current models. Existing approaches fail to account for the interconnected nature of how and why people move across different regions over time. The limitations of existing approaches underscore the need for a more holistic modeling framework that can capture the multifaceted nature of migration patterns. Over this challenge, we have adopted a deep learning model that has been used to predict traffic flow patterns that takes into account spatio-temporal into consideration to predict the migration patterns around the world.

Graph-based models have attracted a lot of attention due to the effective representation for the graph structure data. Our proposed approach involves an incorportation of Spatio-Temporal Graph Convolutional Network (STGCN) which offers a unified framework capable of capturing the intricate interplay between various influencing factors driving migration patterns. By simultaneously analyzing spatial and temporal data, our model mirrors the real-world process of migration, where decisions are influenced by both current conditions and evolving trends over time.

2. Related Work

The study of migration patterns necessitates a sophisticated understanding of both spatial and temporal dynamics. Recent advancements in spatio-temporal graph convolutional networks (STGCNs) have shown promising results in capturing these dynamics in various domains, including traffic flow prediction and urban planning, which share underlying similarities with migration pattern analysis.

Temporal Convolutional Networks (TCN): This is a neural network proposed in by Bai et al (1) which utilizes dilated convolutions to efficiently capture long-range dependencies in sequential data while maintaining a constant computational cost. TCN has demonstrated effectiveness in various sequence modeling tasks such as language modeling, time series prediction, and speech recognition, making it a versatile and promising architecture in the field of sequential data analysis. TCNs can be helpful in our investigations of immigration patterns over the course of a number of decades to understand the immigration flow patterns. However, the TCNs are only limited to the Temporal domain.

Attention Enhanced Graph Convolutional LSTM: Graph-based methodologies have also emerged as a powerful framework for understanding relationships within diverse data structures. GNNs have been leveraged to interpret complex motion dynamics in the context of skeleton-based action recognition considering parts as a set of joints that reflect spatio-temporal dynamics of human body movement. Skeleton-based action recognition methods have relied on hand-crafted features. However, recent advancements have seen a shift towards deep learning approaches. For example, Du et al. (5) partition the human skeleton into distinct parts and process them individually through a hierarchical recurrent neural network. The spatio-temporal deep learning approach has been the inspiration for Spatio-Temporal GCNs model which can be effectively utilized to model spatio-temporal of global human migration.

Spatio-Temporal Graph Convolutional Networks (STGCNs): STGCNs represent a significant step forward in analyzing data with inherent spatial and temporal relationships. Yu et al. (8) pioneered the application of STGCNs to traffic forecasting, demonstrating the model's capability to capture complex spatio-temporal dependencies through a graph convolutional network combined with gated temporal convolutional layers. Their work underscores the potential of STGCNs in understanding dynamic systems, laying a foundation for its application in migration studies.

Dynamic Modeling of Spatio-Temporal Graphs: The dynamic nature of population migration, characterized by evolving spatial interactions and temporal patterns, calls for models that can adapt to changes over time. Li et al. (3) introduced a diffusion convolutional recurrent neural network (DCRNN) that models traffic networks as diffusion processes, allowing for the prediction of traffic flow with high accuracy. This approach to modeling dynamic spatio-temporal graphs can be directly relevant to predicting migration flows, where both spatial proximity and temporal evolution play critical roles.

Graph Neural Networks (GNNs) for Non-Euclidean Data: Migration data, represented through networks of countries or regions, does not conform to traditional Euclidean spaces, making GNNs an ideal tool for analysis. GNNs, as reviewed by Wu et al. (6), have been applied across various domains, including social network analysis and biological data interpretation, to model relationships and interactions within data. Their application to migration studies can offer insights into the complex network of factors influencing migration decisions.

External Factors in Spatio-Temporal Predictions: Understanding migration also requires considering external factors that influence movement patterns, such as economic conditions, policy changes, and environmental factors. Ali et al. (9) developed the DHSTNet, which integrates external factors into spatio-temporal predictions. This model's ability to incorporate additional dimensions of data highlights the importance of a multifaceted approach to migration pattern analysis, acknowledging that factors beyond spatial and temporal dependencies affect migration.

In summary, the methodologies and insights from STGCN applications in traffic flow prediction and other domains provide a valuable framework for analyzing migration patterns. By adapting these approaches to the unique challenges of migration studies, researchers can uncover the multifaceted dynamics driving population movements across spatial and temporal dimensions.

3. Proposed Method

Our approach to forecasting global migration patterns encompasses meticulous data preprocessing followed by the application of a hybrid model architecture. This section elaborates on the comprehensive methodology, underpinned by mathematical formulations, designed to enhance predictive performance.

[CL] Our project encompassed two Aims. The first aim focused on analyzing the overall migration trends, with the ultimate objective of forecasting the net migration flow (immigration minus emigration) between countries. For this part, we employed an integrated approach that combines LSTM networks with GCN, leveraging their strengths to enhance the accuracy and reliability of our predictions.

The second aim was dedicated to understanding the immigration patterns, specifically aiming to predict the inflow of travelers among key hub countries. This aspect of the project is crucial for grasping how major countries attract individuals from various regions, assisting in the planning and management of resources, and policy-making in these countries. To achieve this, we implemented the cutting-edge Spatio-Temporal Graph Convolutional Network (STGCN) model, as proposed by Yu et al (7).

3.1. Data Preprocessing Techniques

3.1.1. Data Cleaning and Normalization

To ensure model efficacy, initial preprocessing steps include rigorous data cleaning, notably the exclusion of records with missing values in critical fields, such as 'Net Number of Migrants (thousands)'. Numerical features undergo normalization to facilitate model training:

$$x_{\text{norm}} = \frac{x - \mu}{\sigma}$$

where x_{norm} denotes the normalized feature, x the original value, μ the mean, and σ the standard deviation of the feature.

3.1.2. Construction of Time Series

In Aim 2, we consider each hub country and its corresponding immigration figures as individual observations in a time series analysis. To minimize the occurrence of missing data, we selected a continuous span of 18 years, specifically from 1995 to 2013, despite having access to data starting from 1980. Furthermore, we narrowed our focus to 29 countries, each exhibiting fewer than 5 instances of missing data throughout the 18-year period. Despite these precautions, the issue of missing values is unavoidable. To address this, we employed a multiple imputation technique as suggested by Li et al (2). This approach involves conducting multiple regression analyses on the incomplete data and substituting the missing values with those derived from a consistent and reliable model. A subset of the data, post-imputation, is illustrated in Figure 1.

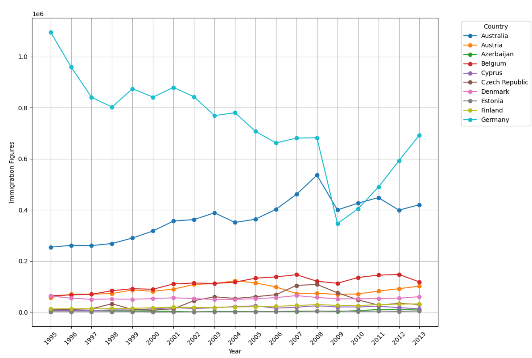

Figure 1. Time series of the immigration counts for the first 10 immigration hub countries after multiple imputation

3.1.3. Construction of Countries Network

Additionally, we must develop a network representation of countries anchored in their geographical positioning. The inter-country distances were gauged utilizing a dataset from Google Maps, which designated either the countries' centroids or their principal cities (typically capitals) as the nodes for connection. Subsequent to acquiring the latitude and longitude of these points, we computed the distances employing the great-circle distance method, which accounts for the Earth's curvature. An exemple of this network is depicted in Figure 2, where the nodes' sizes correspond to the immigration counts.

3.2. Model Architecture

3.2.1. Aim 1 Model Architecture

In Aim 1, our model synergistically combines Long Short-Term Memory (LSTM) units for temporal data analysis with Graph Convolutional Networks (GCN) for spatial data interpretation.

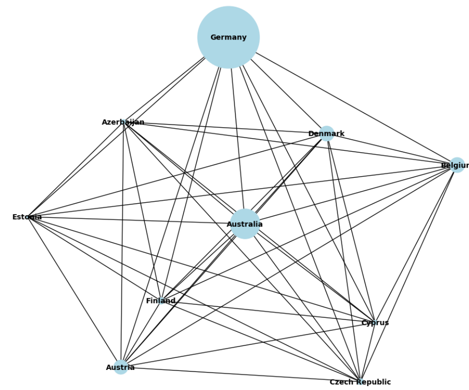

Figure 2. Subgraph of the first 10 immigration hub countries in 1995

The LSTM component processes sequential migration data, capturing long-term temporal dependencies. For a sequence of migration data $X = \{x_1, x_2, ..., x_T\}$, the LSTM updates its hidden state h_t and cell state c_t at each time step t:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
$$c_t = f_t * c_{t-1} + i_t * \tilde{C}_t$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(c_t)$$

To incorporate the effects of spatial interconnectivity among regions, we apply a GCN layer, updating node features as follows:

$$H^{(l+1)} = \sigma(\hat{D}^{-\frac{1}{2}} \hat{A} \hat{D}^{-\frac{1}{2}} H^{(l)} W^{(l)})$$

where $\hat{A} = A + I_N$ denotes the adjacency matrix with self-connections, $\hat{D}$ the degree matrix of $\hat{A}$, $W^{(l)}$ the weight matrix for layer l, and σ a nonlinear activation function.

The final predictive model integrates outputs from both LSTM and GCN components via a fully connected layer, generating forecasts for net migration figures. This comprehensive model architecture, combining temporal and spatial analyses, aims to markedly improve the accuracy of migration predictions.

3.2.2. Aim 2 Model Architecture

In Aim 2, we utilized the advanced STCGN model for predicting immigration flows. Echoing our methodology in Aim 1, the STGCN model is a sophisticated composite framework designed to analyze spatio-temporal graphs. This model is structured around two spatio-temporal convolutional blocks (ST-Conv blocks) followed by a fully-connected layer that produces the output. Each ST-Conv block is composed of two temporal gated convolution layers flanking a central spatial graph convolution layer. These blocks incorporate residual connections and a bottleneck approach to enhance processing efficiency. The input $v_{t-M+1}, \ldots, v_t$ is uniformly processed by ST-Conv blocks to explore spatial and temporal dependencies coherently. Comprehensive features are integrated by an output layer to generate the final prediction $\hat{v}$.

Graph convolution is applied directly to data with graph-based structure, enabling the extraction of significant patterns and features within the spatial domain. This process typically involves kernel computation, which is computationally intensive. To efficiently manage this, we employed an approximation method known as the Chebyshev Polynomials Approximation, specifically designed to streamline and optimize the computational demands of graph convolutional operations.

For an in-depth examination and mathematical formulation of the Chebyshev Polynomials Approximation, we refer readers to the foundational paper (4). The Chebyshev Polynomials Approximation is a refined mathematical technique adept at functionally approximating within the context of graph signal processing. It can effectively approximates spectral filtering operations related to the graph Laplacian. Utilizing a truncated set of Chebyshev polynomials, this method avoids the computationally demanding eigendecomposition of the Laplacian, presenting a viable and scalable solution for analyzing large graphs. The technique involves a sequence of orthogonal polynomials truncated at a chosen degree, concisely encapsulating the spectral filter's characteristics and thereby enabling efficient and memory-conservative graph convolution computations.

In order to fuse features from both spatial and temporal domains, the spatio-temporal convolutional block (ST-Conv block) is constructed to jointly process graph-structured time series. The block itself can be stacked or extended based on the scale and complexity of particular cases. The input and output of ST-Conv blocks are all 3-D tensors. For the input $v^l \in R^{M \times n \times C^l}$ of block l, the output $v^{l+1} \in R^{(M-2(K_t-1)) \times n \times C^{l+1}}$ is computed by

$$v^{l+1} = \Gamma_{1*\mathcal{T}}^{l} \operatorname{ReLU}\left(\Theta^l *_{\mathcal{G}} \left(\Gamma_0^l * \mathcal{T} v^l\right)\right)$$

where Γ_0^l, Γ_1^l are the upper and lower temporal kernel within block l Θ^l is the spectral kernel of graph convolution using Chebyshev Polynomials approximation method. A graph representation of the method can be found in Figure 3.

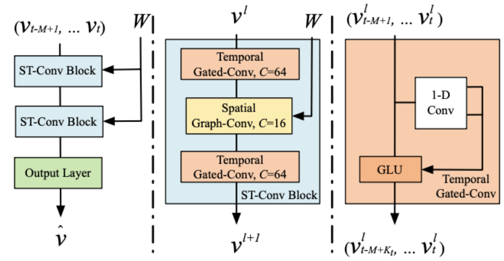

Figure 3. Architecture of spatio-temporal graph convolutional networks

4. Experiments and Analyses

4.1. Data Description

4.1.1. Net Migration Flow Data

Our analysis leverages the Net Migration Flow data from the United Nations World Population Prospects (WPP), which is a pivotal component of the extensive dataset provided by the United Nations Department of Economic and Social Affairs (UN DESA). The World Population Prospects dataset offers an in-depth view of global demographic changes, with projections that are essential for planning and analysis by governments, international organizations, and researchers across various disciplines.

The Net Migration Flow data, specifically, captures the estimated net number of migrants for each country, accounting for both the inflows and outflows, spanning from 1950 to 2020. This dataset encompasses 195 countries and territories, ensuring a comprehensive global coverage. Each entry in the dataset represents the net migration rate, which is calculated as the difference between the number of immigrants (people moving into a country) and the number of emigrants (people moving out of a country) over a specified period.

This crucial dataset assists in understanding the dynamic nature of global migration patterns, highlighting trends such as increasing international migration, shifts in migration destinations, and the implications of such movements on national and international policies.

4.1.2. Immigration Data

Our dataset is derived from the United Nations Global Migration Database, an extensive repository of empirical data detailing international migrants, segmented by country of origin, citizenship, gender, and age. To ensure clarity and reliability, our selection criteria included only countries with complete datasets, free from territorial disputes or changes, and recognized internationally. This stringent selection process resulted in a refined dataset comprising 29 countries across 18 years. The dataset is publicly accessible and can be found at the following link: United Nation Development Programme.

4.2. Results

4.2.1. Prediction Accuracy of Aim 1

Model	MAE	MAPE(%)	RMSE
TimeSeriesGCN	4.73	8.54	8.73

Table 1. TimeSeriesGCN prediction Accuracy

Based on the presented results in the table detailing the prediction accuracy of Aim 1, we have conducted a thorough evaluation of our TimeSeriesGCN model's performance on net migration flow prediction. The evaluation metrics include Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE), providing a comprehensive understanding of the model's predictive accuracy and reliability.

The TimeSeriesGCN model demonstrated a MAE of 4.73. Furthermore, the MAPE value of 8.54 reflects the model's prediction error in terms of percentage, offering insight into the error magnitude relative to the true data points. Lastly, the RMSE of 8.73 further corroborates the model's effectiveness, highlighting its ability to minimize the squared prediction errors.

4.2.2. Prediction Accuracy of Aim 2

Model	MAE	MAPE(%)	RMSE
STCGN(1 - year)	2.25	5.54	5.73
STCGN(5 - year)	4.37	10.24	7.32

Table 2. One-ear Versus Five-Year STCGN prediction Accuracy

Table 2 details the STCGN model's performance in predicting immigration counts for aim 1, assessed with MAE, MAPE, and RMSE over 1-year and 5-year periods. The 1-year results—MAE: 2.25, MAPE: 5.54%, RMSE: 5.73—suggest high accuracy, while the 5-year outcomes—MAE: 4.37, MAPE: 10.24%, RMSE: 7.32—indicate reduced precision over extended durations, emphasizing the model's superior short-term forecasting effectiveness.

Table 3 displays the predicted immigration counts for nine major countries using the STGCN model, comparing projections for one year (2014) and five years (2018) from a base year of 2013. Across all listed countries, the trend shows an increase in predicted immigration counts from 2014 to 2018, indicating that the model forecasts a consistent growth in immigration numbers over the five-year span.

Countries	2014 (1 year)	2018 (5 year)
United States	1107177	1112708
United Kingdom	590325	596499
Spain	599148	605683
Russia	281681	288040
Netherlands	143528	143630
Italy	534809	539667
Germany	682178	689368
Czech Republic	108361	117860
Australia	536024	543363

Table 3. One-Year Versus Five-Year STCGN prediction results for nine selected counties (round to the closest integer)

5. Conclusions

Our research and experiments have been dedicated to the development of a comprehensive framework for predicting migration patterns, covering both emigration and immigration dynamics. We utilized Spatio-Temporal Graph Convolutional Networks (STGCN) to leverage the complex interplay of spatial and temporal factors inherent in migration trends. Originally designed for forecasting traffic flow patterns, STGCN was adapted to address the intricacies of global migration.

Our investigation focused on two fundamental aspects of migration patterns worldwide: the net migration flow across 195 countries and territories, and immigration patterns within a subset of 29 countries. To ensure clarity and reliability, we omitted countries with missing data from our analysis. We evaluated the performance of our STCGN model using metrics such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). Our findings suggest that the time series GCN yielded satisfactory approximations for the net migration flow. However, we observed significantly larger values for MAE, MAPE, and RMSE over a 5-year period compared to 1 year. This discrepancy implies the inherent unpredictability of immigration patterns over longer durations, likely influenced by external factors that fluctuate over time.

In summary, our study underscores the complexities of migration dynamics and highlights the challenges in accurately predicting long-term immigration trends. Despite the limitations encountered, our framework provides valuable insights into global migration patterns.

6. Division of work and individual contributions

Shitong: Developed ideas, preprocessed data, implemented the methodology, and authored the manuscript for Aim 1.

CL(Chuanling): Developed ideas, preprocessed data, implemented the methodology, and authored the manuscript for Aim 2.

Abdibaset: Worked on gathering and curating information about other related works to this project, and coauthored the manuscript for conclusion.

Samuel: Worked on outlining and defining the research problem and coauthored the manuscript for the introductory section.

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