Article

Causal Model

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Abstract: The impacts of mass migration, such as crises induced by climate change, extend beyond environmental concerns and can greatly affect social infrastructure and public services, such as education, healthcare, and security. These crises exacerbate certain elements like cultural barriers and discrimination by amplifying the challenges faced by these affected communities. This paper proposes an innovative approach to address migration crises in the context of crisis management through a combination of modeling and imbalance assessment tools. By employing deep learning for forecasting and integrating causal reasoning via Bayesian networks, this methodology enables the evaluation of imbalances and risks in the socio-technological landscape, providing crucial insights for informed decision-making. Through this framework, critical systems can be analyzed to understand how fluctuations in migration levels may impact them, facilitating effective crisis governance strategies.

Keywords: Migration, Forecasting; Deep Learning; Machine Reasoning; Bayesian Network

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1. Introduction

Mass migration, the movement of large groups of people from one region or country to another, is a pressing global challenge that has escalated in recent years due to factors such as conflict, climate change, economic disparities, and political instability.

There a numerous causes of mass migration with mainly 2 types, forced displacement and economic migration [1]. Some key drivers include conflicts, climate change, economic disparities, and demographic factors. Armed conflicts, civil wars, and political instability drive millions of people to flee their homes in search of safety. Rising sea levels, extreme weather events, and environmental degradation force communities to relocate in search of a more suitable environment. Economic inequality and lack of opportunities in certain regions compel individuals to seek better prospects elsewhere. Population growth and demographic shifts can lead to mass movements in search of resources and better living conditions.

The impact of mass migration is in four main areas, particularly social/cultural, economic, environmental, and security [2]. Mass migration often leads to cultural exchanges, integration challenges, and potential tensions between host and migrant communities. Migrants can contribute positively to host economies through labor and skills, but they may also strain resources and welfare systems. Mass migration can lead to overexploitation of natural resources and increased pressure on ecosystems. Inadequately managed migration can raise security issues for both host and origin countries.

Several challenges arise when dealing with mass migration: policy, infrastructure, services, and discrimination. Inconsistent and inadequate migration policies can hinder the effective management and protection of migrants' rights. Host regions may face difficulties in providing adequate housing, healthcare, and education to a sudden influx of migrants. Deep-rooted prejudices can exacerbate tensions between local communities and migrants. Limited access to accurate migration data hampers evidence-based policymaking.

2. Problem Formulation and Related Work

There are many studies on the problem of migration [3–6]. One particular study by Andersson [3] mentions that the mass migration crisis in Europe contains many challenges, in particular, how Europe's attempt to secure the border is a repetition of the same response resulting in a perpetual cycle. The solution proposed is to break this vicious cycle by encouraging policymakers to directly address the underlying problems.

Various solutions have been proposed to alleviate the problem of migration [7–11]. With the recent rise of artificial intelligence, [7] examines the increasing use of digital and AI technologies in the context of migration and evaluates the challenges and opportunities to migration due to these technologies. In another case, [8] examines the use of 'self-sovereign identity' (SSI), a user-controlled and decentralized form of digital identification, for border/migration management. SSI is closely tied to blockchain technologies where [9] reviews the use of blockchain technology in migrant systems to address problems of transparency and data consolidation. A cognitive checkpoint has been proposed by [10] as an emerging technology that makes use of a biometric-enabled watchlist screening to fortify border control and security measures.

This paper seeks to delve into the underlying impacts of mass migration, centering particularly on the potential impact of increased migration influx into Canada on the infrastructure and services of each province. The objective is to leverage machine learning models to predict future migration patterns, subsequently employing these projections to infer the implications for government infrastructure. We aspire to provide a comprehensive understanding of the interplay between migration dynamics and provincial capabilities, ultimately contributing to informed policy decisions and effective resource allocation.

3. Dataset

The data used in this paper is sourced from the Government of Canada [12] and is based on immigration/permanent resident data from 2016 to 2023. The data contains monthly data starting Jan 2016 to March 2023 (updated monthly). The data includes immigration/permanent resident categories such as economics, sponsored family, and refugees for each province and territory. For each category, there are subcategories such as worker program and provincial nominee program for economics.

The distribution of the data is heavily dependent on the year and the province with a trend of growing immigration year-over-year. An exception is for the year 2020 where due to the COVID lockdown, the level of immigration is greatly reduced. On average, Ontario receives the most immigration while the territories receive the lowest.

The UN Refugee Agency (UNHCR) [13] demographic data where the country of asylum is Canada. Demographic data includes age and sex distributed from the year of 2001 to 2023. Data includes population figures such as refugees and asylum seekers.

StatCanada's Labour force characteristics by educational attainment, monthly, unadjusted for seasonality [14], reports the number of population with a certain level of education and the employment rate from the1 1990 to 2023 for different sexes, age groups, and provinces.

4. Proposed Approach

In this paper, we propose an innovative approach that combines machine learning and machine reasoning techniques. Our approach leverages machine learning models to predict forthcoming migration trends by analyzing patterns within 7 years of Canada's historical migration data [12]. Concurrently, we employ machine reasoning models based on causality networks, with a specific emphasis on Bayesian Networks. These reasoning models enable us to uncover the intricate distribution of current infrastructure and migration patterns across each province within Canada. Moreover, they facilitate an examination of how individual provinces provide support to migrants in various ways, encompassing economic aspects, sponsorships, and refugee assistance.

By combining these machine learning and machine reasoning models, our methodology yields unique insights into the impacts of migration on each province. As migration numbers surge, our approach reveals the potential strain on existing infrastructure and services. In particular, we delve into scenarios where certain provinces may encounter challenges in accommodating heightened migration flows due to limitations in their infrastructure capacities.

5. Machine Learning Architecture for Forecasting

5.1. Recurrent Neural Network

LSTM, a type of Recurrent Neural Network, is another deep learning architecture for analyzing time series data. In this paper, we used two different LSTM networks, one which consists of 2 LSTM layers (Table 1) and another that consists of 2 Bidirectional LSTM layers (Table 2), both network is connected to a fully-connected layer for classification.

Bidirectional LSTM extends traditional LSTM by processing input sequences in both forward and backward directions. This bidirectional processing helps capture both past and future context for each time step in the input sequence.

Table 1. Structure of LSTM network

	Output Shape	Parameters
Input	30×30	-
LSTM	30×128	66,560
LSTM	128	131,584
Batch Normalization	128	512
Fully-Connected	2	258
Sigmoid Activation	2	-

Table 2. Structure of BiLSTM network

	Output Shape	Parameters
Input	30×30	-
BiLSTM	30×256	133,120
BiLSTM	256	394,240
Batch Normalization	256	1024
Fully-Connected	2	514
Sigmoid Activation	2	-

5.2. Temporal Convolutional Network

Temporal convolution network (TCN) is one of the proposed networks to extract and classify time-series data.

The TCN (Table 4) is composed of four blocks of residual units. Each residual unit (Table 3) is composed of three sets of sub-blocks where each sub-block is the combination of Batch Normalization (BatchNorm), Rectified Linear Unit (ReLu), 1D Convolution, and residual connection. For the 1D convolution, different dilation parameters ($d = 1, 2, 4$) are used to expand the receptive field of the convolution process to capture long-range dependencies.

5.3. Metrics

In this paper, we characterize the performance of each of the forecast models in terms of Mean Squared Error (MSE), Root Mean Squared Logarithmic Error (RMSLE), and R2. These three metrics are commonly used to measure the forecasting performance of models in time-series forecasting tasks.

Table 3. Structure of Residual Unit

Input	
Conv1D	Batch Normalization ReLU Activation Conv1D ($d = 1$)
Add	
Conv1D	Batch Normalization ReLU Activation Conv1D ($d = 2$)
Add	
Conv1D	Batch Normalization ReLU Activation Conv1D ($d = 4$)
Add	
Output	

Table 4. Structure of TCN

	Output Shape			Parameters
Input	30	×	1	-
Conv1D	30	×	8	56
Residual Block	30	×	8	1520
Residual Block	15	×	16	4768
Residual Block	8	×	32	18496
Residual Block	4	×	64	72832
Batch Normalization	4	×	64	256
Global Average Pooling		64		-
Fully-Connected		2		130
Sigmoid Activation		2		-

MSE (Eq. 1) is an error metric that measures the accuracy of a model's predictions relative to a naive baseline forecast. It is useful for evaluating the forecast accuracy when dealing with non-seasonal time-series data.

$$MSE = \frac{1}{T} \sum_{t=1}^{T} (y_t - y'_t)^2 \tag{1}$$

where T is the number of time steps in the test period, y_t is the actual value at time step t in the test set, and y'_t is the predicted value at time step t in the test set.

RMSLE (Eq. 2) measures the accuracy of predictions, and it is especially useful when the predicted values and actual values have a significant spread or when you want to penalize underestimations and overestimations differently.

$$RMSLE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (log(y_t) - log(y'_t))^2} \tag{2}$$

where T is the number of time steps in the test period, y_t is the actual value at time step t in the test set, and y'_t is the predicted value at time step t in the test set.

6. Causal Network

Historically, significant disruptive events, such as the 2008 financial crisis, the 2016 EU migration crisis, the 2019 pandemic, and most recently the Russian-Ukraine conflict, have reshaped the socio-technological landscape, resulting in fluctuations in migration patterns. We provide a demonstrative experiment in order to understand and model the behavior of migration in response to these events.

6.1. Immigration/Permanent Resident Network

We accomplish this by using a causal network (Fig. 1) comprising five nodes arranged with one parent, one child, and three grandchild nodes. At the core of the network lies a unique hidden state representing the crisis event's impact, influencing changes in migration levels. While this hidden state is believed to influence sponsor, refugee, and economic nodes, its precise mechanism remains undisclosed due to the lack of comprehensive documentation. Through this causal network, we seek to shed light on the underlying dynamics that drive migration patterns during these disruptive events.

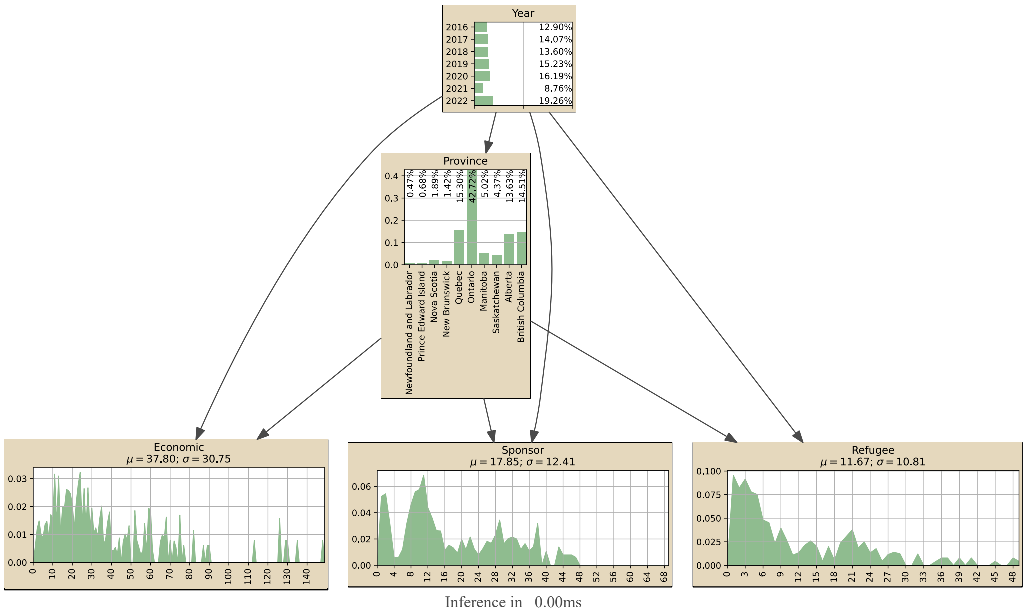

Figure 1. The proposed causal network consists of a hidden crisis node that influences the degree of migration, specifically impacting migration levels to 'Sponsor', 'Refugee', and 'Economic'.

This paper employs a probabilistic causal network to model patterns in Canadian provinces based on the number of permanent resident data from 2016 to 2023. The structure of the causal network is inspired by the categories (sponsor, economic, and refugee) within the Canadian immigration/PR dataset [12]. The focus of this study is on the 10 provinces in Canada, while data from the territories is excluded due to relatively low levels.

The network comprises four key nodes: 'Year', 'Province', 'Sponsor', 'Refugee', and 'Economic'. The 'Year' node serves as the parent node, encompassing prior probabilities representing each level of immigration in each province by year.

The remaining nodes, 'Sponsor', 'Refugee', and 'Economic', quantify the average monthly migration (per 100 individuals) to each province. Specifically, 'Sponsor' represents migration resulting from family sponsors, including children, spouses, and parents. 'Refugee' denotes migration due to refugees or protected persons in Canada. 'Economic' captures migration for economic reasons, such as worker programs, business ventures, or provincial nominee programs. These economic reasons can also be used to create a smaller network to describe the intricate details of 'Economic' but in this paper, we chose to focus on the macro elements.

To represent the uncertainty associated with migration estimates, we employ probability distributions for each node, denoted by μ for average migration and σ for one standard unit of standard deviation. For example, an $\mu = 10$ in the 'Economic' node indicates that, on average, 1000 (10*100) individuals migrate to the province monthly for economic reasons.

By employing this probabilistic causal network, we aim to gain valuable insights into the dynamics of immigration patterns across Canadian provinces, facilitating informed decision-making and policy formulation in migration management.

6.2. Immigration Status-Employment Rate Network

We proposed a causal network (Figure 2) consisting of 3 nodes to model the relationship between immigrant status and the employment rate for each province in Canada. The 2 parent nodes in the network are the Immigration Status and Province, and the child node is the Employment Rate.

From the Labor statistics from the Government of Canada [14], we obtain the following prior values for Immigration Status and Province. Table 5 indicates the population in each group. For example, in the first row of *Status*, there is a monthly average of 21,906 total population that join the "Born in Canada" status. Similarly, for the last row in *Province*, there is a monthly average of 4,189 people joining British Columbia. Note that both these tables are conditioned on the age group: "15 years and over". This represents that the "Born in Canada" category is not newborn babies but people who have aged from age 14 to age 15.

Table 5. The prior values corresponding to Figure 2, monthly average from 2015-2022.

Status	*Population*
Born in Canada	21,906
Immigrants, landed 5 or less years	1,008
Immigrants, landed more than 10 years	5,580
Immigrants, landed more than 5 to 10 years	1,142

Province	*Population*
Newfoundland and Labrador	447
Prince Edward Island	128
Nova Scotia	802
New Brunswick	641
Quebec	6,946
Ontario	11,893
Manitoba	1,027
Saskatchewan	877
Alberta	3,430
British Columbia	4,189

Figure 2 illustrates the marginalized probabilities of the relationship between "Immigration" and "Province" to "Employment Rate". The probabilities represent Canada's monthly average from 2015 to 2022. For example, in Figure 2, "Employment Rate" reports a $\mu = 61.52$ which represents Canada's monthly employment rate from 2015 to 2022 is 61.52% weighted on the "Sex", "Education" and "Province" parent nodes.

6.3. Education-Employment Rate Network

Another causal network of interest is the relationship between education level and employment rate. For this network, we propose a 4-node causal network (Figure 3) that uses the information about education level and sex for each province to determine its effect on employment rate.

Similarly to the previous network, we obtain the prior values of Sex, Education, and Province from the labor statistics [14]. Each element in Table 5 reports the population for each group. For example, in the *Sex* table, there are on average $15,401$ females and $15,011$ males on a monthly basis that are eligible for employment. Similar to the previous section, the tables are conditioned on the age group: "15 years and over". This represents that the "Born in Canada" category is not newborn babies but people who have aged from age 14 to age 15.

Figure 3 illustrates the marginalized probabilities of the relationship between "Sex", "Education" and "Province" to "Employment Rate". The probabilities represent Canada's

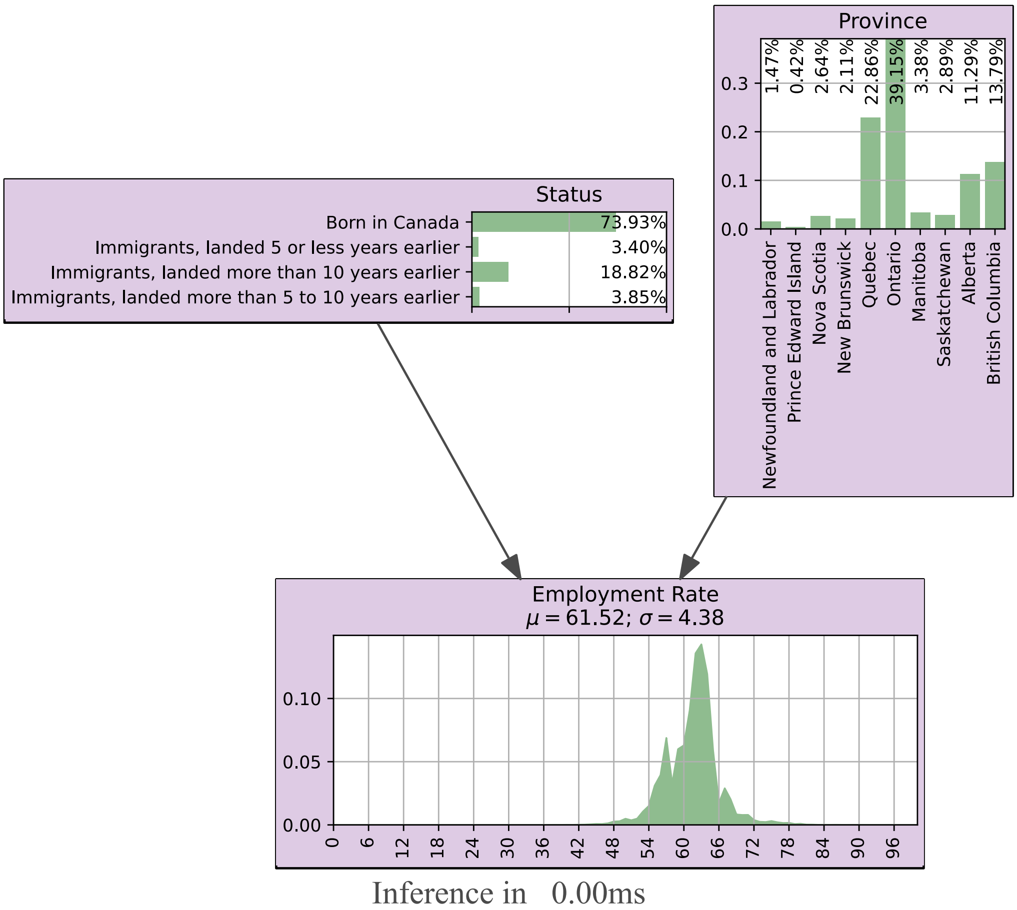

Figure 2. The proposed causal network consists of immigration status and employment rates.

monthly average from 2015 to 2022. For example, in Figure 3, "Employment Rate" reports a $\mu = 61.24$ which represents Canada's monthly employment rate from 2015 to 2022 is 61.24% weighted on the "Sex", "Education" and "Province" parent nodes.

6.4. Refugee Network

Lastly, a causal network of interest is the relationship between Country of Origin and Age/Sex. For this network, we propose a 3-node causal network (Figure 4) that uses the information about a refugee's Country of Origin and their sex/age.

Similarly to the previous network, we obtain the prior values of Country of Origin from the UNHCR [13]. In Table 7, the top 10 countries of origin arriving in Canada are shown with the relative population amount on a yearly average from 2015 to 2022. For example, Ukraine has on average 10,708 people coming every year to Canada. Note that the yearly average is calculated from the period of 2015 to 2022 and the migrants from each country are not uniform, particularly, looking at Ukraine's case, a vast majority, 75,294, arrived in the year 2022.

Figure 4 illustrates the marginalized probabilities of the relationship between "Origin" to "Sex" and "Age". The probabilities represent Canada's yearly average from 2015 to 2022. For example, in Figure 4, "Age' reports a 75.99% for the 18-59 age group, which represents 75.99% of Canada's yearly incoming migrants are between the ages 18 and 59.

7. Experimental Results

In this section, we present the experimental results of our study, which focuses on evaluating the performance of different deep learning architectures for time-series forecasting

Table 6. The prior values corresponding to Figure 3, monthly average from 2015-2022.

Sex	*Population*
Female	15,401
Male	15,011

Education	*Population*
0 to 8 years	1,386
Some high school	3,295
High school graduate	6,060
Some postsecondary	1,953
Postsecondary certificate or diploma	9,702
University degree	8,016

Province	*Population*
Newfoundland and Labrador	447
Prince Edward Island	129
Nova Scotia	803
New Brunswick	641
Quebec	6,951
Ontario	11,908
Manitoba	1,028
Saskatchewan	877
Alberta	3,434
British Columbia	4,194

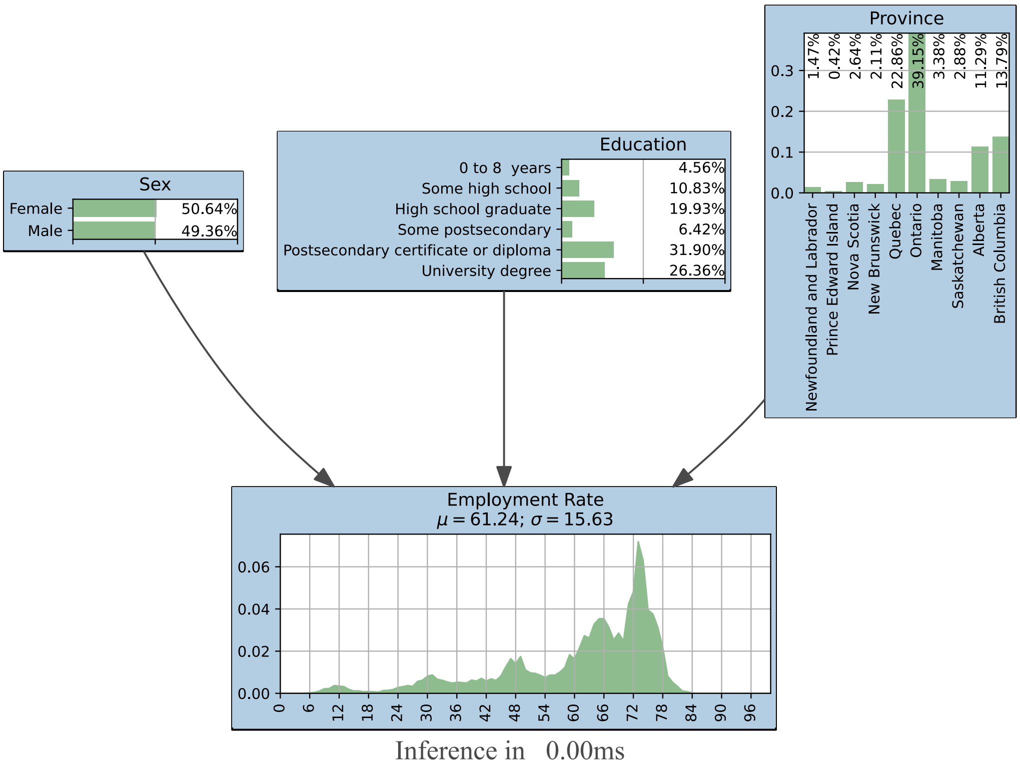

Figure 3. The proposed causal network consists of education and employment rates.

using the Mean Square Error (MSE) and Root Mean Squared Logarithmic Error (RMSLE) 218
metrics. 219

Table 7. The prior values corresponding to Figure 4 from 2015-2022.

Origin	*Population*							
	2015	2016	2017	2018	2019	2020	2021	2022
China	12,483	9,466	9,396	9,570	8,933	7,861	7,243	3,457
Colombia	14,123	9,185	9,616	10,562	9,783	9,078	9,541	13,297
Haiti	9,012	7,161	13,971	14,187	11,928	9,249	7,352	14,798
India	4,050	1,741	3,048	6,979	10,941	11,714	12,360	13,878
Iran	2,746	2,274	2,844	5,085	7,216	7,511	8,556	9,790
Mexico	6,471	4,402	5,254	7,270	10,035	9,943	9,821	23,916
Nigeria	5,125	5,594	10,432	18,532	19,468	17,230	14,019	6,930
Pakistan	7,753	5,640	6,962	8,508	8,742	8,826	8,660	5,436
Türkiye	2,239	2,607	4,611	6,169	7,266	7,361	8,013	11,278
Ukraine	1,550	1,415	1,558	1,617	1,506	1,395	1,326	75,294

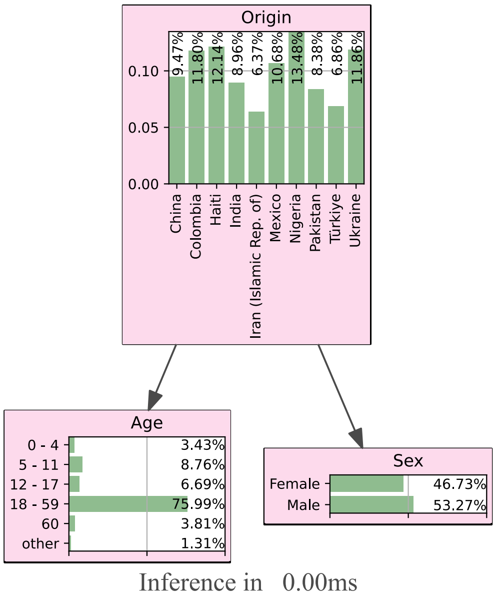

Figure 4. The proposed causal network consists of origin country, age, and sex.

8. Causal Analysis

9. Discussion and Conclusion

In this study, we proposed a comprehensive approach to forecast migration patterns and analyze their causal relationships using deep learning models and Bayesian networks. We focused on three state-of-the-art Transformers: the original Transformer, Informer, and AutoFormer, to forecast migration trends in response to historical events during various context lengths. Additionally, we employed a Bayesian network to investigate the causal impact of immigration on specific provinces, shedding light on the factors influencing migration patterns.

The experimental results demonstrated the effectiveness of the different Transformers in forecasting migration trends. While all models exhibited competitive performance across various context lengths, Informer marginally outperformed the others. Furthermore, our causal analysis using the Bayesian network provided valuable insights into the relationships between historical events and migration dynamics. The analysis revealed the significant impact of economic factors, refugee crises, and government policies on migration patterns. These findings are crucial for policymakers and stakeholders in developing targeted interventions and crisis governance strategies.

Table 8. Forecast Performance for TCN, LSTM, and BiLSTM.

Test Frames	BiLSTM MSE	BiLSTM RMSLE	BiLSTM R2	LSTM MSE	LSTM RMSLE	LSTM R2	TCN MSE	TCN RMSLE	TCN R2
Employment									
12	0.0369	0.1377	0.3246	0.0158	0.0917	0.7103	0.0106	0.0743	0.8059
24	0.0131	0.0776	0.7959	0.0119	0.0752	0.8146	0.0682	0.1823	-0.0657
36	0.0186	0.0931	0.7596	0.0153	0.0853	0.8030	0.0206	0.0995	0.7340
48	0.0377	0.1223	0.4852	0.0223	0.0914	0.6955	0.1509	0.2614	-1.0588
60	0.0176	0.0933	0.7003	0.0272	0.1161	0.5366	0.0059	0.0589	0.8998
Economic									
12	0.0265	0.1133	0.5319	0.0199	0.0995	0.6491	0.0103	0.0730	0.8177
24	0.0187	0.0933	0.7129	0.0192	0.0946	0.7064	0.0784	0.1946	-0.2010
36	0.0244	0.1038	0.6734	0.0241	0.1048	0.6774	0.0215	0.1015	0.7115
48	0.0298	0.1136	0.5038	0.0916	0.2002	-0.5243	0.1455	0.2564	-1.4205
60	0.0747	0.1796	0.0311	0.0372	0.1306	0.5171	0.0202	0.0970	0.7382
Refugee									
12	0.0101	0.0732	0.7611	0.0126	0.0809	0.7019	0.0081	0.0668	0.8089
24	0.0128	0.0832	0.7315	0.0155	0.0911	0.6746	0.0443	0.1543	0.0705
36	0.0172	0.0912	0.6711	0.0191	0.0950	0.6359	0.0518	0.1606	0.0101
48	0.0252	0.1093	0.5719	0.0237	0.1050	0.5974	0.0954	0.2200	-0.6228
60	0.0244	0.1088	0.6128	0.0275	0.1158	0.5637	0.0409	0.1370	0.3509
Sponsor									
12	0.0205	0.0988	0.6115	0.0209	0.0991	0.6040	0.0208	0.0969	0.6056
24	0.0187	0.0942	0.6522	0.0198	0.0994	0.6306	0.0679	0.1835	-0.2661
36	0.0149	0.0813	0.7250	0.0184	0.0893	0.6613	0.0215	0.0970	0.6039
48	0.0268	0.1034	0.2961	0.0215	0.0916	0.4364	0.1358	0.2541	-2.5637
60	0.0405	0.1269	0.1769	0.0502	0.1400	-0.0207	0.0613	0.1553	-0.2473

Our research contributes to the field of migration forecasting and crisis management by offering interpretable models and causal analysis. The integration of deep learning models and Bayesian networks provides a powerful framework for understanding migration patterns and their drivers, facilitating more informed decision-making in migration governance.

While our study presents promising results, there are still opportunities for future research. Exploring the incorporation of additional features, such as geographical and climate data, or more developed machine learning models could further enhance the forecasting accuracy of the models. Moreover, expanding the scope of the Bayesian network to include more factors and provinces would deepen our understanding of migration dynamics on a larger scale.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript.", please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

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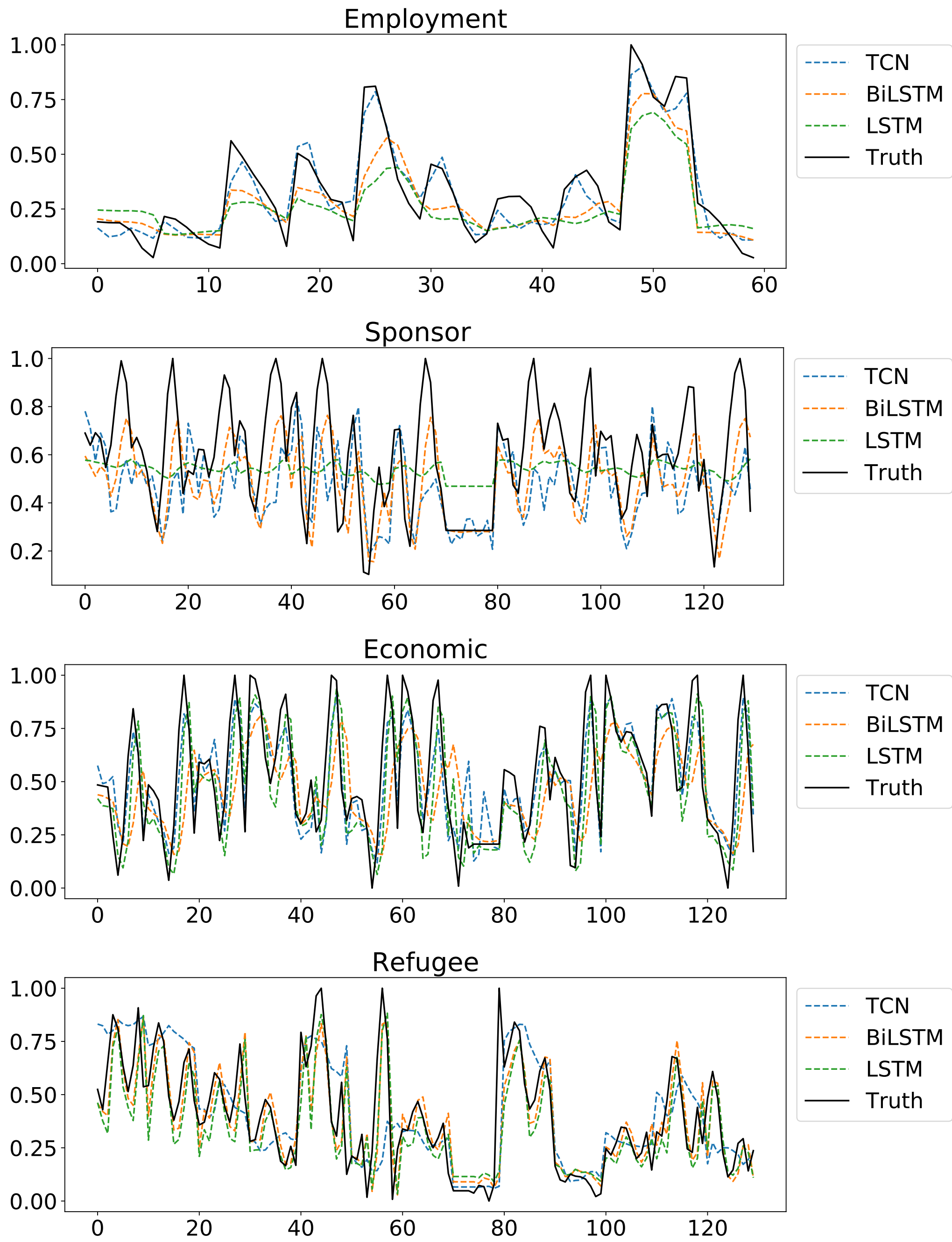

Figure 5. Prediction Plot.

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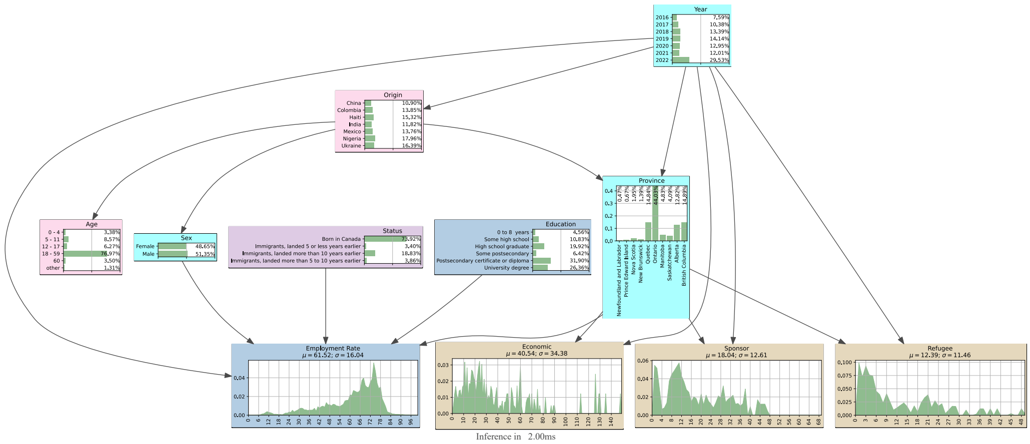

Figure 6. The proposed causal network.

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