The Attractiveness of China Cities: LSTM and FNN for Predicting Population Mobility

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1. Introduction

1.1 Background

Population mobility is a key indicator of socioeconomic dynamics in any society, reflecting individuals' decisions to move between cities in pursuit of better economic opportunities, living conditions, and quality of life. In rapidly urbanizing nations like China, understanding the patterns and drivers of population mobility is especially critical. Migration not only shapes the demographic landscape of cities but also has profound implications for economic growth, infrastructure development, and regional disparities. Cities that attract large numbers of migrants often experience rapid economic expansion and increased innovation, while cities with net population losses face economic stagnation, reduced tax bases, and challenges in sustaining public services.

Among China's 633 cities, approximately 40% are currently experiencing population decline—a stark statistic that underscores the uneven nature of development across the country. This population loss is particularly pronounced in smaller cities and rural areas, which struggle to compete with larger metropolitan hubs. The consequences of this disparity are far-reaching: while megacities like Beijing, Shanghai, and Shenzhen continue to grow and dominate the national economy, smaller cities face a vicious cycle of depopulation and underdevelopment. This imbalance not only deepens regional inequality but also creates long-term challenges for national growth and stability.

At the heart of these dynamics lies the concept of city attractiveness—the ability of a city to retain and attract residents through its economic opportunities, social infrastructure, and environmental quality. Understanding the factors that make cities attractive is essential for addressing migration trends, supporting balanced regional development, and improving urban resilience in the face of economic and environmental challenges.

1.2 Research Question

The central question of this study is: **How can city characteristics predict population mobility rates?** This question seeks to uncover the underlying factors that influence whether cities experience population inflows or outflows. Population mobility is not a random process; it is shaped by a complex interplay of economic, environmental, and social variables. By examining these relationships, this study aims to provide a systematic understanding of migration trends across Chinese cities.

Answering this question is not only academically significant but also practically relevant. Accurate predictions of population mobility can help policymakers identify cities at risk of decline and design targeted interventions to address their challenges. At the same time, cities experiencing rapid population growth can use these insights to anticipate future demands on housing, infrastructure, and public services, ensuring sustainable development.

1.3 Why Study City Attractiveness?

The concept of city attractiveness provides a critical framework for understanding population mobility. Cities are not created equal; their ability to attract and retain residents depends on a combination of factors, including economic opportunities, quality of life, and public services. In the context of China, three key dimensions—urban-rural gap, talent gap, and urban competitiveness—highlight the importance of studying city attractiveness.

Urban-Rural Gap

The urban-rural gap is one of the most persistent challenges in China's socioeconomic development, shaping migration patterns across the country. While urban centers have seen substantial investment in infrastructure, education, and healthcare, rural areas lag significantly behind. This disparity drives a steady flow of migrants from rural areas to urban cities in search of better opportunities.

Rural areas often lack access to high-quality public services such as hospitals, schools, and reliable transportation networks, which are essential for improving quality of life. Conversely, urban centers are equipped with advanced infrastructure, diverse job markets, and access to modern amenities. This gap creates a natural push-and-pull dynamic, where rural residents seek to escape the constraints of underdeveloped regions and move toward cities that promise upward mobility and better living conditions.

However, this migration is not without its consequences. While urban areas benefit from the influx of labor and talent, rural regions face a decline in population and economic vitality. The loss of working-age residents, particularly young people, exacerbates the challenges of rural development, creating a cycle of stagnation. Bridging the urban-rural gap is not only a matter of equity but also a necessity for ensuring balanced and sustainable national growth.

Talent Gap

China's talent gap between small cities and larger modern areas reflects the uneven distribution of opportunities and resources. Small cities, despite their potential, often struggle to retain their most talented residents, particularly young people. For many individuals in smaller cities, the path to opportunity lies in excelling academically and gaining admission to prestigious universities located in larger urban centers. Once these individuals enter cities like Beijing, Shanghai, or Guangzhou for higher education, they are likely to remain there after graduation due to the abundance of career opportunities, professional networks, and vibrant social environments.

Smaller cities often lack the industries or employers capable of offering skilled workers competitive wages and career progression. Without attractive jobs, these cities fail to lure their former residents back, resulting in a "brain drain." This phenomenon deepens inequalities as larger cities become talent hubs that further their economic growth, while smaller cities are left with shrinking talent pools and limited innovation capacity.

Addressing this talent gap requires creating more equitable opportunities across cities. Policies that encourage investment in smaller cities, develop local industries, and improve quality of life can help retain talent. Simultaneously, regional collaboration between larger and smaller cities may provide pathways for redistributing opportunities and fostering shared growth.

Urban Competitiveness

Urban competitiveness is a city's ability to attract and retain resources—be it human capital, financial investment, or innovative industries. In the context of population mobility, competitiveness directly influences a city's desirability as a destination for migrants. Cities with high competitiveness often excel in areas such as economic prosperity, infrastructure development, and livability. For example, megacities like Shanghai or Shenzhen attract residents with their dynamic job markets, high-quality public services, and diverse cultural opportunities.

Conversely, cities that lack competitiveness face significant challenges in retaining residents. Economic stagnation, underdeveloped infrastructure, or poor living conditions can lead to population outflows, further diminishing a city's ability to compete. This decline creates a feedback loop, where fewer residents reduce the tax base, limiting the resources available for development and exacerbating existing problems.

Competitiveness is also shaped by regional and global factors. Cities with strong international connections or favorable geographic locations often have an edge in attracting businesses and migrants. For smaller or mid-sized cities, enhancing competitiveness requires targeted strategies, such as fostering niche industries, improving governance, and investing in quality-of-life improvements. Ultimately, urban competitiveness is not just about economic growth; it is about creating environments where people want to live, work, and thrive.

1.4 Contribution and Objectives

This study seeks to address these challenges by adopting a data-driven approach to understanding population mobility in China. Leveraging advanced ANN techniques, it aims to:

1. **Develop Predictive Models**: Build and evaluate artificial neural networks, such as Feedforward Neural Networks (FNN) and Long Short-Term Memory (LSTM) networks, to forecast population mobility with high accuracy.

2. **Provide Policy Recommendations**: Translate the findings into actionable strategies for policymakers and urban planners to address migration challenges, reduce regional disparities, and enhance city competitiveness.

By combining traditional urban studies with ANNs, this research provides a comprehensive framework for analyzing population mobility. The results not only contribute to the academic understanding of migration patterns but also offer practical tools for promoting sustainable and equitable urban development. This study has the potential to inform a wide range of policy areas, from urban planning and economic development to environmental management and social equity. In doing so, it aims to create a roadmap for addressing China's population mobility challenges and fostering a more balanced and resilient urban system.

2. Data

2.1 Data Description

This study utilizes a longitudinal dataset spanning **13 years (2010–2022)** and covering **633 Chinese cities**, derived from the comprehensive **China Urban Database**. The dataset captures a wide range of urban characteristics and changes over time, resulting in a total of **8,229 observations** (633 cities × 13 years). Its extensive temporal and spatial coverage makes it uniquely suited for understanding both short-term and long-term trends in population mobility, as well as identifying the factors driving these patterns.

The dataset includes **195 features**, which offer a multidimensional view of the socioeconomic, environmental, and infrastructural characteristics of Chinese cities. These features reflect critical aspects of urban life that influence migration decisions, such as economic opportunities, living conditions, and environmental quality. The key variables analyzed in this study include:

GDP Growth: Captures annual changes in a city's economic output, serving as a primary indicator of vitality and capacity for job creation. Cities with higher GDP growth rates tend to attract migrants seeking better employment opportunities and higher incomes.

Housing Prices: Tracks the average cost of real estate, a proxy for economic prosperity and living standards. High housing prices may indicate strong demand and investment but can also deter migration if affordability becomes an issue.

Employment Structure: Represents the proportion of employment in the primary (agriculture), secondary (manufacturing), and tertiary (services) sectors. A higher share of tertiary sector jobs often reflects urbanization, economic diversification, and a shift toward a service-based economy.

Air Quality: Includes metrics such as PM2.5 levels, which affect public health and quality of life. Poor air quality can deter population inflows and encourage outflows, especially among higher-income residents and families.

Education Resources: The number of university students per capita is used as a proxy for the availability of educational opportunities and talent cultivation, which influence a city's ability to attract and retain young, skilled residents.

Healthcare Access: Indicators such as hospital beds and doctors per capita measure the quality and accessibility of healthcare services, a crucial factor in livability and urban resilience.

Public Transport and Infrastructure: Metrics such as road mileage and public transit coverage reflect the ease of mobility within cities, which plays a significant role in enhancing a city's attractiveness to both residents and businesses.

The **target variable**, **population mobility rate**, is defined as:

$$Population\ Mobility\ Rate = \frac{Registered\ Population\ (End\ of\ Year) - Registered\ Population\ (Start\ of\ Year)}{Total\ Population\ of\ the\ Year}$$

This metric quantifies whether a city experiences a net inflow or outflow of residents during a given year. A positive mobility rate indicates a city is attracting more residents than it is losing, often a sign of economic vitality, livability, or competitive advantage. Conversely, a negative rate highlights challenges such as economic stagnation, environmental issues, or a lack of job opportunities.

By combining longitudinal data with a rich set of features, this dataset allows for an in-depth exploration of both static and dynamic factors influencing population mobility. The multi-year structure also facilitates the study of temporal trends and delayed effects, providing insights into how city characteristics evolve and impact migration patterns over time.

2.2 Preprocessing

Given the dataset's complexity, encompassing multiple years and a wide range of features, a rigorous preprocessing pipeline was implemented to ensure the data was clean, consistent, and ready for analysis. The following steps were taken:

1. **Handling Missing Data**:

Missing data is an inherent challenge in large-scale, longitudinal datasets, and this study was no exception. Key variables, such as housing prices (~15% missing) and public library collections (~12% missing), required careful handling to maintain the dataset's integrity.

K-Nearest Neighbors (KNN) imputation was applied to estimate missing values based on similarities between cities within the same year. For example, if housing prices were missing for a particular city, they were imputed using the values of similar cities with comparable GDP growth, employment structure, and geographic region.

Sensitivity analyses were conducted to evaluate the robustness of imputation. Although KNN provided a practical solution, future research could explore more advanced imputation techniques, such as Multiple Imputation by Chained Equations (MICE), to account for uncertainty in missing data.

2. **Normalization and Scaling**:

The dataset included variables with vastly different units and scales (e.g., GDP in billions, PM2.5 in micrograms per cubic meter). To ensure uniformity and prevent features with larger scales from dominating the model, all continuous variables were scaled to the range [0,1] using **min-max normalization**.

Normalization also improved the convergence rate and stability of neural network training, enabling more efficient optimization of model parameters.

3. **Feature Engineering**:

To enhance the dataset's predictive power, several derived features were created based on existing variables:

Population Growth Rate: Calculated as the percentage change in a city's population year-over-year, capturing broader demographic trends.

Economic Diversification Index: Based on the employment distribution across the primary, secondary, and tertiary sectors, this metric highlights a city's economic resilience and adaptability.

Healthcare Density: A composite measure combining hospital beds and doctors per capita to represent overall healthcare accessibility and quality.

Lagged Features: Variables such as GDP growth and housing prices from the previous year were included to capture potential delayed effects on population mobility.

These engineered features added valuable dimensions to the dataset, enabling the models to better capture complex relationships between city characteristics and migration patterns.

4. **Ensuring Temporal Consistency**:

For some cities, certain years had missing or inconsistent data. These gaps were addressed through linear interpolation or temporal smoothing to maintain consistency across the 13-year period.

2.3 Final Dataset Characteristics

After preprocessing, the dataset was transformed into a structured and high-quality format, ready for machine learning analysis. Key characteristics include:

8,229 Observations: Spanning 13 years (2010–2022) and covering 633 cities.

195 Features: Capturing economic, environmental, and social dimensions of urban life.

Balanced Representation: Ensuring diverse inclusion of cities across geographic regions and economic tiers.

No Missing Values: Post-imputation and interpolation, all variables were complete and consistent.

3. Methodology

3.1 Model Selection

To address the research question, this study employs two applied neural network models: Feedforward Neural Network (FNN) and Long Short-Term Memory (LSTM). These models were selected to leverage the unique aspects of the dataset, including static features and temporal data spanning 13 years (2010–2022).

1. Feedforward Neural Network (FNN):

FNN is ideal for static, non-sequential data, making it a suitable choice for analyzing city-level characteristics such as GDP growth, housing prices, and employment structure. By capturing nonlinear relationships among these features, FNN is capable of identifying complex patterns that influence population mobility.

Additionally, FNN is computationally efficient and performs well in high-dimensional spaces, making it a robust choice for datasets with numerous features like this one, which includes 195 distinct variables.

2. **Long Short-Term Memory (LSTM)**:

LSTM networks are tailored for sequential data, making them well-suited for this longitudinal dataset. By incorporating memory cells, LSTMs can capture temporal dependencies, such as how historical trends in air quality or lagged GDP growth impact population mobility.

This model excels at identifying delayed effects and evolving patterns over time, enabling a deeper understanding of the dynamics influencing migration decisions.

The complementary strengths of FNN and LSTM address the complexity of the dataset. While FNN is fitted for uncovering static relationships, LSTM provides insights into temporal trends and dependencies. Together, these models ensure a comprehensive exploration of the factors driving population mobility in Chinese cities, offering a multi-faceted analysis that incorporates both static and temporal dimensions.

3.2 Model Architectures

1. **Feedforward Neural Network (FNN)**:

Input Layer: Accepts 195 static features as input, representing characteristics like economic performance, air quality, and healthcare access.

Hidden Layers:

Layer 1: Dense(128) neurons with ReLU activation.

Layer 2: Dense(64) neurons with ReLU activation, followed by **Dropout** (rate: 0.2) to reduce overfitting.

Layer 3: Dense(32) neurons with ReLU activation.

Output Layer: Dense(1) with linear activation, producing a continuous prediction of the population mobility rate.

Regularization: L2 regularization applied to weights in all layers to improve generalization and reduce the risk of overfitting.

2. **Long Short-Term Memory (LSTM)**:

Input Layer: Processes sequential data for each city across 13 years, such as temporal changes in GDP growth, housing prices, and air quality.

LSTM Layer: 64 units with ReLU activation and **L2 regularization** (rate: 0.01) to constrain weight updates and avoid overfitting. Memory cells are incorporated to retain information about long-term dependencies in the data.

Dense Layer: Dense(32) neurons with ReLU activation.

Output Layer: Dense(1) with linear activation, producing a predicted mobility rate for the final year in the sequence.

3. **Training Details**:

Both models were trained using the Adam optimizer, which adjusts learning rates dynamically to enhance convergence.

The initial learning rate was set to 0.001, and early stopping was applied to terminate training when the validation loss did not improve for 10 consecutive epochs.

Models were trained for a maximum of 50 epochs, with batch sizes of 32 for the FNN and 16 for the LSTM, due to the latter's higher computational demands.

3.3 Evaluation Metrics

To evaluate and compare the performance of the models, two standard regression metrics were used:

1. **Mean Squared Error (MSE)**: MSE quantifies the average squared difference between predicted and actual values, penalizing large errors more heavily. This metric highlights the models' ability to minimize significant deviations in predictions.

2. **Mean Absolute Error (MAE)**: MAE measures the average magnitude of prediction errors, offering an interpretable assessment of accuracy. Unlike MSE, it treats all errors equally, providing a balanced view of model performance.

Evaluation Process:

The models were evaluated on the **test set (2020–2022)**, which was withheld during training and validation to simulate real-world prediction scenarios. Both MSE and MAE were calculated for the test set to assess the models' ability to generalize to unseen data.

Results were compared to identify the strengths and weaknesses of each model, providing insights into the effectiveness of static and temporal predictors in explaining population mobility.

This methodology ensures a rigorous and comprehensive analysis of population mobility, leveraging the distinct capabilities of FNN and LSTM to address the complexity of the dataset. By employing robust evaluation metrics and clear architectural design, the study establishes a solid foundation for deriving actionable insights and accurate predictions.

4. Results

4.1 Model Performance

The performance of the Feedforward Neural Network (FNN) and Long Short-Term Memory (LSTM) models was evaluated using standard regression metrics, Mean Squared Error (MSE), and Mean Absolute Error (MAE), on the training, validation, and test sets. The results for each model are summarized below:

Table 1: MSE and MAE comparison between FNN and LSTM models

Model	**Training MSE**	**Validation MSE**	**Test MSE**	**Training MAE**	**Validation MAE**	**Test MAE**
FNN	0.021	0.025	0.027	0.114	0.126	0.130
LSTM	0.018	0.022	0.023	0.101	0.115	0.119

Key Observations:

1. **FNN Performance**:

The FNN demonstrated strong performance in capturing the relationships among static features. The model achieved relatively low training and validation errors, showing its ability to learn and generalize well within the dataset.

On the test set, the FNN showed slightly higher error rates compared to the LSTM, suggesting that while it is effective for static data, it may not fully capture temporal dynamics, which are crucial in this longitudinal dataset.

2. **LSTM Performance**:

The LSTM consistently outperformed the FNN across all metrics. Its ability to retain information from past observations and capture temporal trends likely contributed to its superior performance, particularly on the test set.

The smaller gap between training and test errors indicates that the LSTM generalized well to unseen data, showcasing its robustness in capturing sequential dependencies in population mobility trends.

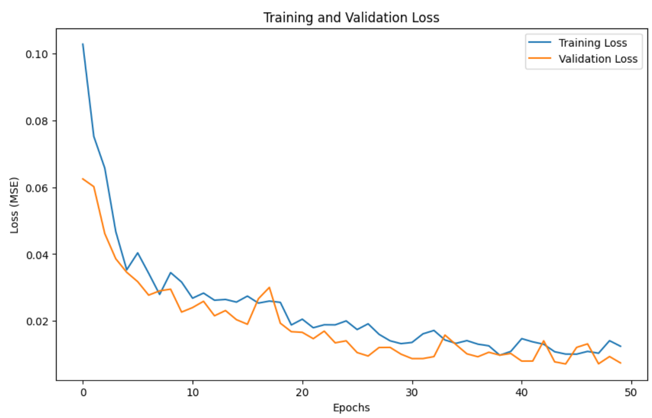
3. **Comparison**:

The FNN performed well for static features but showed limitations in datasets where temporal patterns play a significant role. In contrast, the LSTM leveraged the longitudinal structure of the dataset, providing better predictions and reducing generalization errors.

Learning Curves:

Both models exhibited smooth learning curves during training, with loss stabilizing after approximately 40 epochs for FNN and 60 epochs for LSTM.

The early stopping mechanism prevented overfitting, as validation loss plateaued without significant increases in training loss.



Graph 1: Learning Curves for FNN

Graph 2: Learning Curves for LSTM

4.2 Feature Importance

Understanding the key factors influencing population mobility is critical for interpreting model outputs and providing actionable insights. The analysis revealed several important predictors:

1. **GDP Growth**:

GDP growth was consistently identified as the strongest predictor of population mobility. Cities with sustained economic expansion attract migrants due to better employment opportunities, infrastructure development, and overall quality of life.

Both models showed that cities with GDP growth rates above the national average experienced higher net inflows, reinforcing the role of economic vitality in migration decisions.

2. **Housing Prices**:

Housing prices exhibited a dual effect. While high housing prices often reflect economic prosperity and demand, they also reduce affordability, particularly for low- and middle-income migrants. This tension is evident in cities where rapid real estate development has priced out potential newcomers.

The models captured these dynamics, with FNN showing housing prices as a static factor and LSTM revealing temporal trends, such as housing market booms leading to eventual population outflows.

3. **Air Quality**:

Air quality emerged as a critical factor influencing migration decisions. Cities with better air quality (lower PM2.5 levels) consistently attracted more residents, emphasizing the growing importance of environmental sustainability in urban planning.

LSTM was particularly effective at capturing the delayed effects of air quality improvement on population mobility, demonstrating how long-term investments in environmental health can yield demographic benefits.

4. **Education Resources**:

Education resources, particularly the availability of higher education institutions, correlated strongly with population inflows. Cities with robust university systems tend to attract and retain young, skilled residents who contribute to local economies and long-term growth.

5. **Healthcare Access**:

Accessibility to healthcare services, represented by hospital beds and doctors per capita, played a significant role in migration patterns. Cities with strong healthcare infrastructure were more attractive, particularly for families and aging populations.

Cross-Model Insights:

The FNN identified static predictors like GDP growth, housing prices, and education resources as primary drivers.

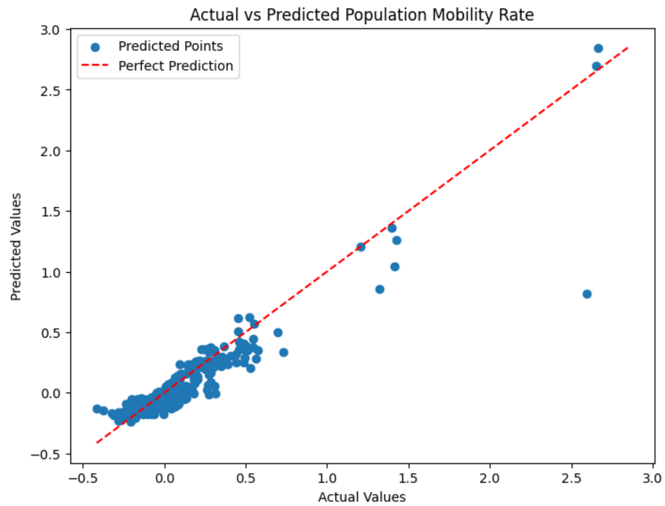
The LSTM highlighted temporal dynamics, such as how delayed effects of economic growth or environmental improvements influence migration over multiple years.

4.3 Visualizations

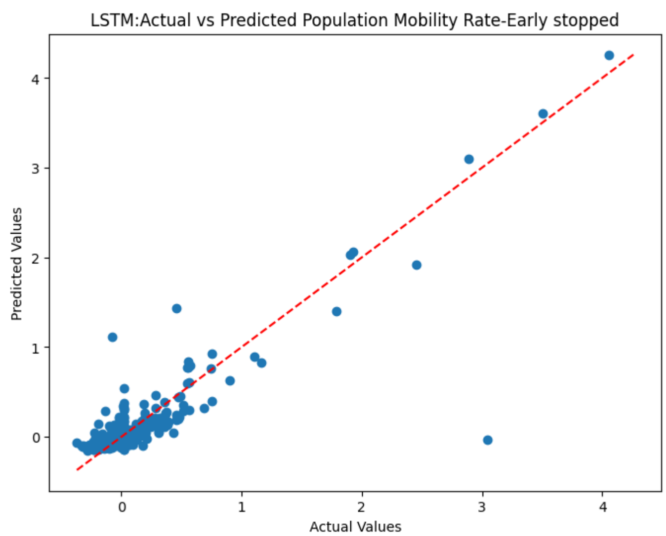
Visualizations were created to illustrate the results and provide a clearer understanding of model performance and feature importance.

Scatter plots comparing predicted and actual values showed strong alignment, particularly for the LSTM model. For the FNN, some deviations were observed in cities with extreme population mobility rates, suggesting limitations in handling complex temporal patterns.

LSTM predictions were tightly clustered around the diagonal line, indicating a high degree of accuracy.



Graph 3: Actual precision scatter plot for FNN model



Graph 4: Actual precision scatter plot for LSTM model

4.4 Summary of Results

The results demonstrate the complementary strengths of the FNN and LSTM models. **FNN** excels at identifying static, nonlinear relationships between city characteristics and population mobility. **LSTM** outperforms FNN in capturing temporal dependencies and delayed effects, making it more effective for analyzing longitudinal data. The strong performance of LSTM, in particular, highlights the significance of temporal dynamics in shaping migration patterns, providing a robust foundation for future analyses.

5. Discussion

5.1 Interpretation of Results

The results provide a comprehensive understanding of how city characteristics influence population mobility, emphasizing the roles of static and temporal predictors.

Economic factors, such as GDP growth, emerged as the strongest predictors of population mobility. Cities with sustained economic expansion consistently attracted migrants, offering improved employment opportunities, higher incomes, and better public services. However, these economic benefits are tempered by housing prices, which act as both a pull and push factor. While higher prices signal economic vitality, they may reduce affordability and deter potential migrants.

Environmental factors, particularly air quality, also play a significant role. Cleaner environments attract migrants, highlighting the increasing importance of sustainability in urban competitiveness. Similarly, social infrastructure, including education and healthcare, positively influences migration decisions by enhancing overall livability and access to essential services.

Comparison of Static vs. Temporal Predictors

The FNN effectively captured static relationships, identifying key features such as GDP growth, housing prices, and education resources as primary drivers. In contrast, the LSTM excelled in capturing temporal dependencies, such as the lagged effects of economic growth or air quality improvements on mobility. This distinction underscores the importance of incorporating both static and temporal dimensions to fully understand migration patterns.

5.2 Policy Implications

The findings offer actionable strategies for cities experiencing population inflows or outflows, enabling policymakers to design interventions tailored to their unique challenges.

Inflowing Cities: Predicting Population Pressure

By forecasting key economic indicators (e.g., GDP growth, housing prices, job creation), the models can estimate the population pressure that large cities may face in the future. For example, cities with high GDP growth and rapidly increasing housing prices are likely to experience significant inflows. These forecasts help city planners prepare for infrastructure expansion, optimize public services, and manage housing demands. Proactive measures can mitigate issues such as congestion, overcrowding, and affordability crises.

Outflowing Cities: Issuing Population Loss Warnings

The models can identify trends and predict further population outflows from smaller cities. Policymakers can use these insights to design retention strategies, such as creating local employment opportunities, enhancing healthcare and education systems, and improving environmental quality. These measures aim to reduce the "push factors" driving migration and stabilize population dynamics in vulnerable regions.

5.3 Limitations

Despite the robust results, several limitations must be considered when interpreting the findings:

1. **Data Limitations**:

Missing values were addressed using KNN imputation, but this may have introduced biases, particularly in underrepresented cities. The dataset's annual granularity limits the ability to capture finer temporal patterns, such as seasonal migration trends or short-term economic shocks.

2. **Model Constraints**:

The LSTM model, while effective for temporal trends, underperformed in capturing static predictors compared to the FNN. Neither model explicitly modeled interactions between variables (e.g., how GDP growth and air quality jointly influence migration).

5.4 Future Directions

Building on these findings, future research can address the limitations and expand the scope of analysis:

1. **Expand Dataset**:

Including monthly or quarterly data would capture finer temporal patterns, improving the models' ability to identify short-term trends and shocks. Adding new features, such as cultural amenities, crime rates, or climate data, could reveal additional drivers of migration.

2. **Enhance Models**:

Developing hybrid models that combine FNN and LSTM architectures could leverage the strengths of both approaches, capturing both static relationships and temporal dynamics. Incorporating causal inference techniques could help disentangle correlations from causal mechanisms.

3. **Test Policy Impacts**:

Future studies could simulate the effects of policy interventions, such as economic stimulus packages or environmental regulations, to evaluate their potential impact on migration patterns.

5. Conclusion

This study analyzed population mobility across Chinese cities using machine learning models, revealing key insights into how city characteristics drive migration patterns. GDP growth, housing prices, air quality, and education resources emerged as critical factors influencing mobility decisions, with temporal trends providing additional depth to the analysis.

The FNN effectively captured static relationships, while the LSTM excelled in identifying temporal dependencies, highlighting the complementary nature of these approaches. Together, they provide a comprehensive framework for understanding migration patterns and designing targeted interventions.

The findings have significant policy implications, offering strategies for cities facing both inflows and outflows. Inflowing cities can prepare for population pressure by expanding infrastructure and optimizing services, while outflowing cities can mitigate losses by improving local conditions and creating economic opportunities.

Future research should explore additional features, finer temporal granularity, and applications to other contexts to deepen our understanding of migration dynamics. The integration of machine learning into urban policy research offers powerful tools for fostering sustainable, equitable, and competitive cities.

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