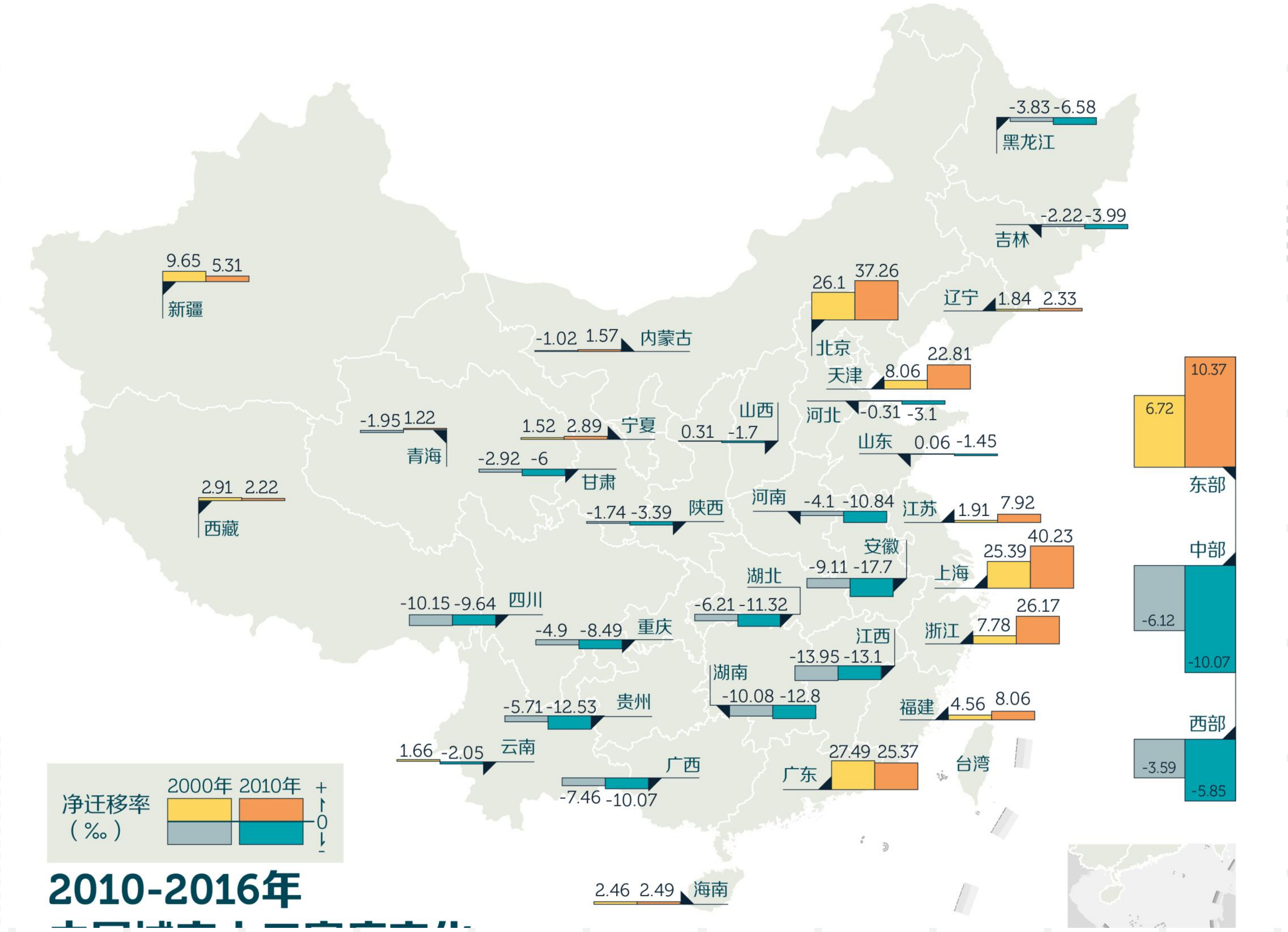
THE ATTRACTIVENESS OF CHINA CITIES: LSTM AND FNN FOR PREDICTING POPULATION MOBILITY

Presentation by Chuchu Wan

633 Chinese cities, 40% are losing population



WHY POPULATION MOBILITY?

- Why Attractiveness?
  - Urban-Rural Gap
  - Talent Gap
  - Urban Competitiveness

- What Does Population Mobility Data Represent?

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

MODEL Design

Target: Population Mobility Rate

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

- A positive value indicates a net inflow of residents (population leaving the city).
- A negative value reflects a net outflow (population entering the city).

Features: Data from the China Urban Database

195 Key Prediction Features to Picture a City’s Characteristic

- Population density
- Employment by sector (primary, secondary, tertiary)
- GDP and GDP growth rate
- Housing prices
- Number of university students per capita
- Hospital beds and number of doctors
- Air quality (e.g., PM2.5 levels)
- Road and highway mileage

……

METHODOLOGY

FNN

- Efficient for structured, non-sequential data.
- Captures non-linear relationships between input features and outcomes.
- Simpler architecture with faster computation compared to LSTM.

RNN ：LSTM

- Designed for sequential data, such as population mobility trends.
- Retains temporal dependencies using memory cells.
- Suitable for capturing long-term patterns and changes over time.

Prediction Model ： FNN

Input Layer:

- Dense(128) with ReLU activation and input shape matching the feature count.

Hidden Layers:

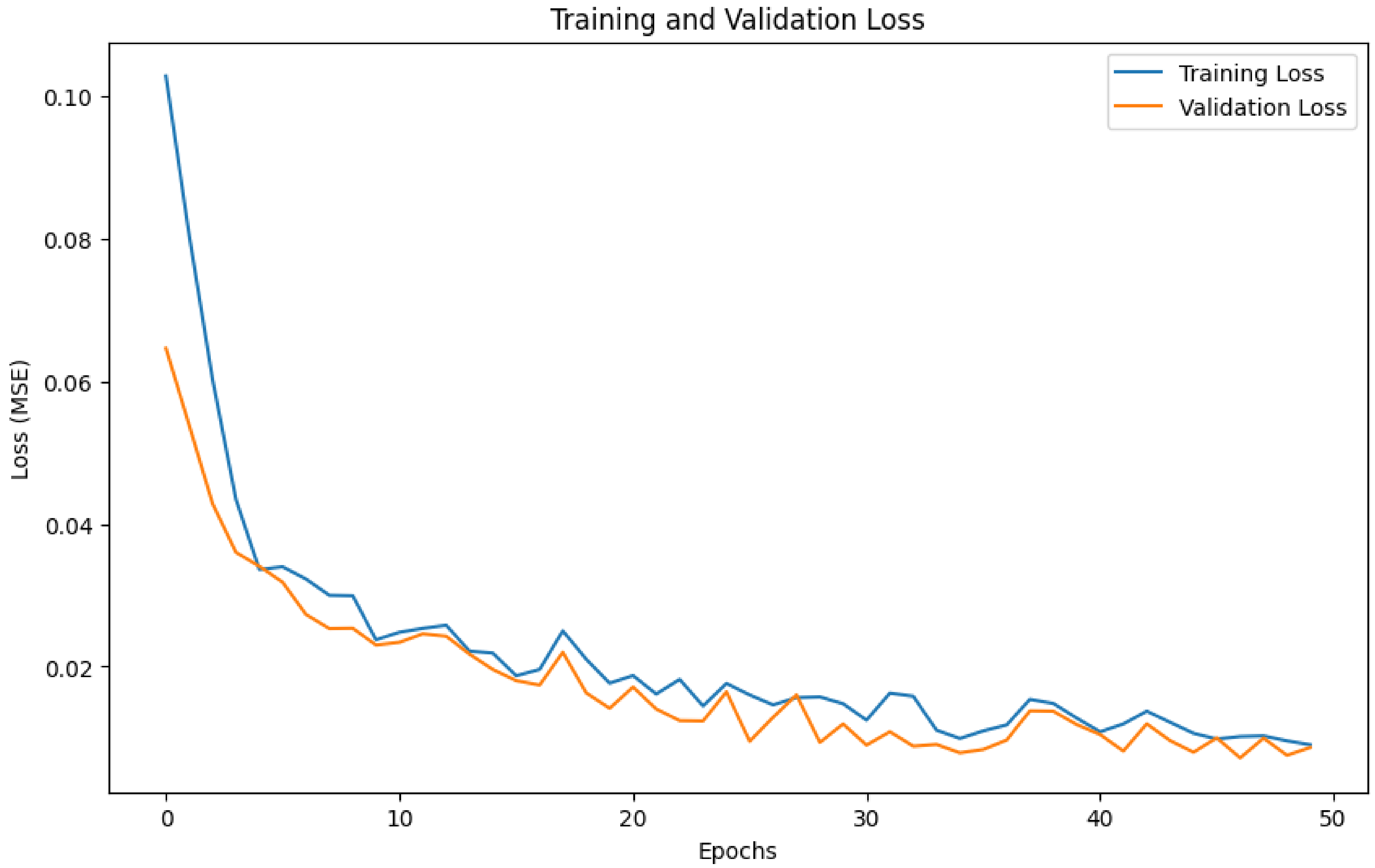
- First Hidden Layer: Dense(64) followed by Dropout(0.2) to prevent overfitting.
- Second Hidden Layer: Dense(32)

Output Layer:

- Dense(1) for the final prediction.

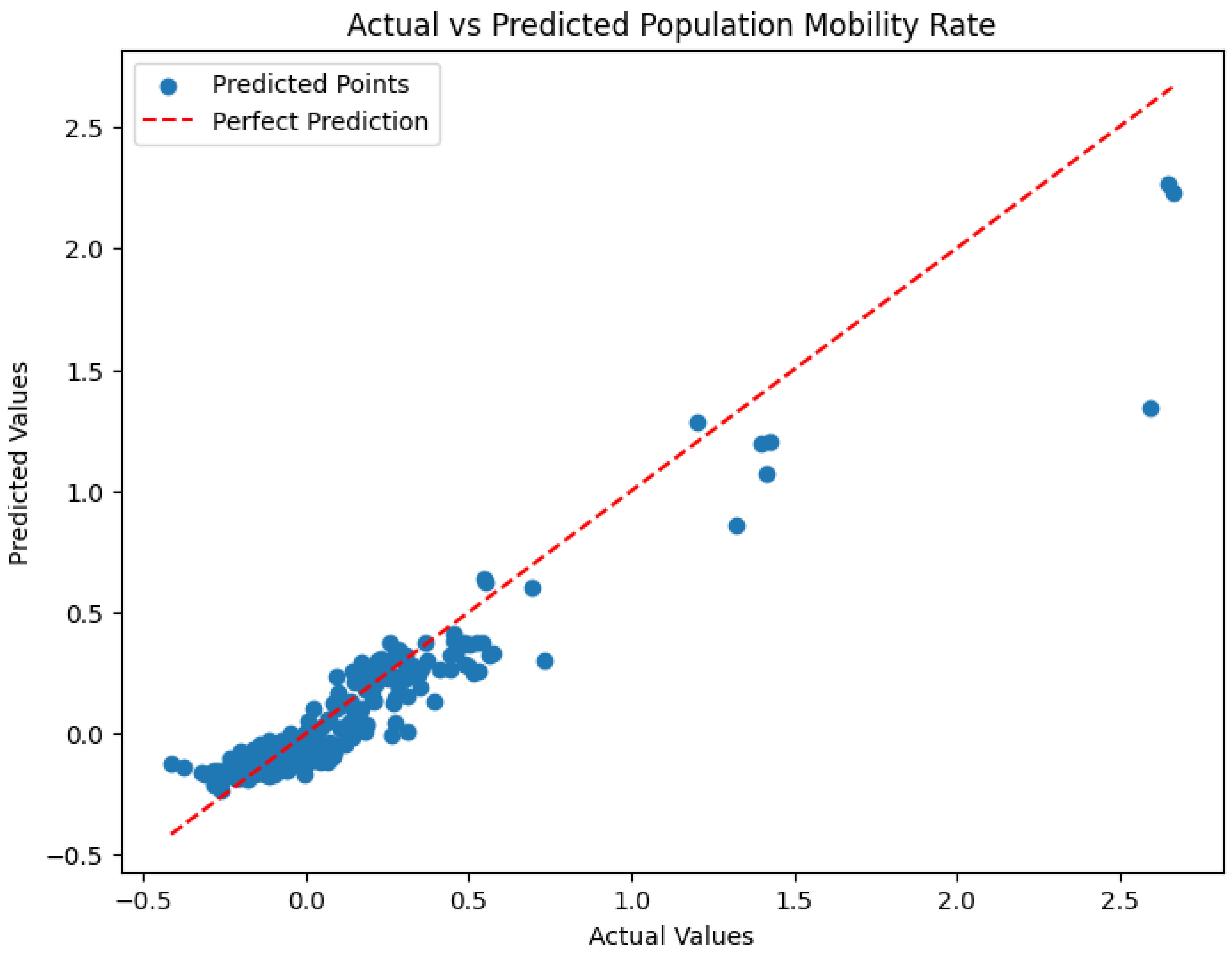
Training Parameters:

- 50 epochs with a batch size of 32.



Prediction Model ： FNN

Test MSE	Test MAE
0.01115	0.065375



Prediction Model ： LSTM

Input Layer:

- LSTM layer with 64 units
- Regularization: l2(0.01) kernel regularizer

Hidden Layers:

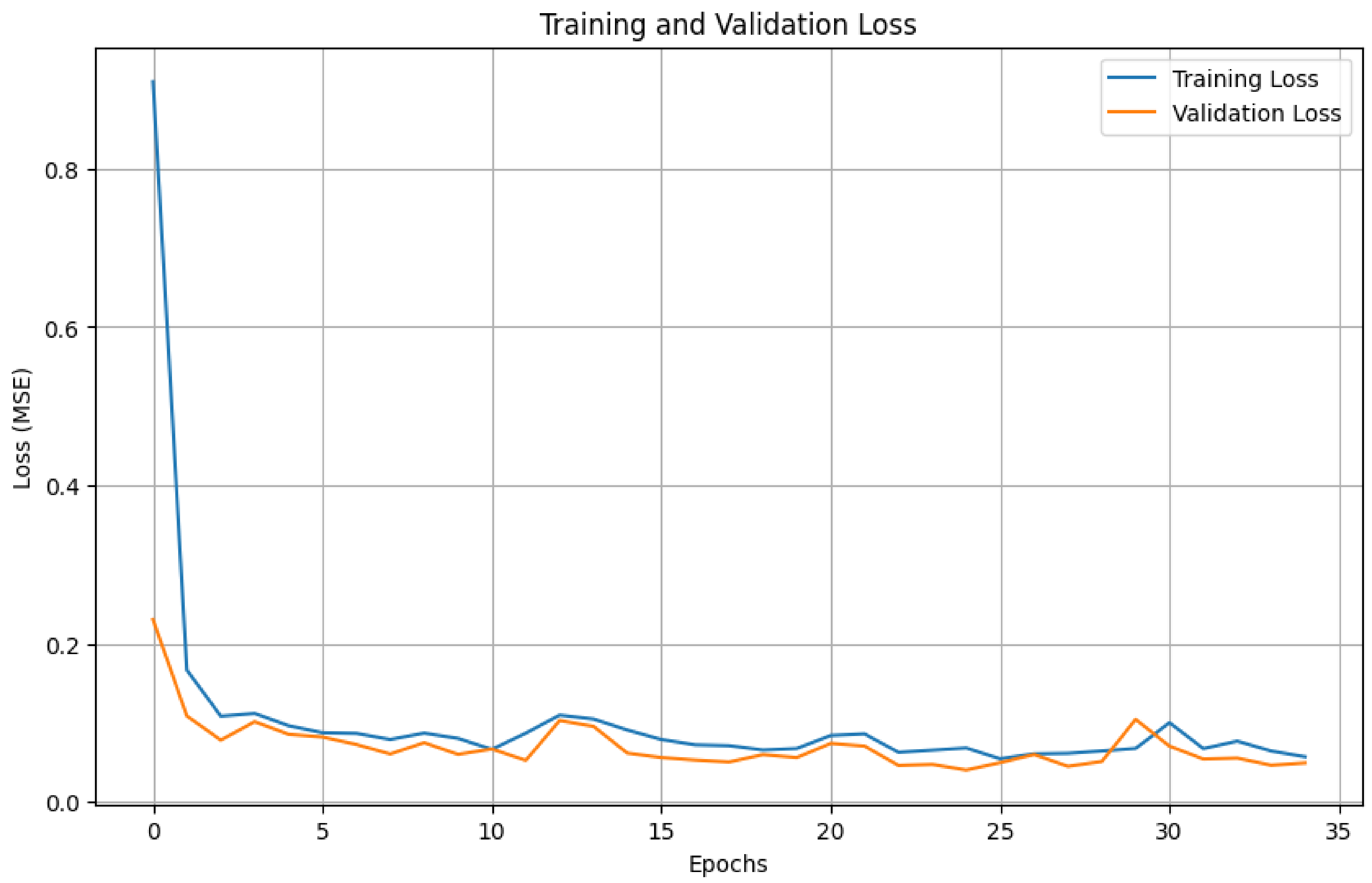
- One dense(32) is followed by dropout layers with a dropout rate of 0.5.

3. **Output Layer**:

- Dense(1) for the final prediction.

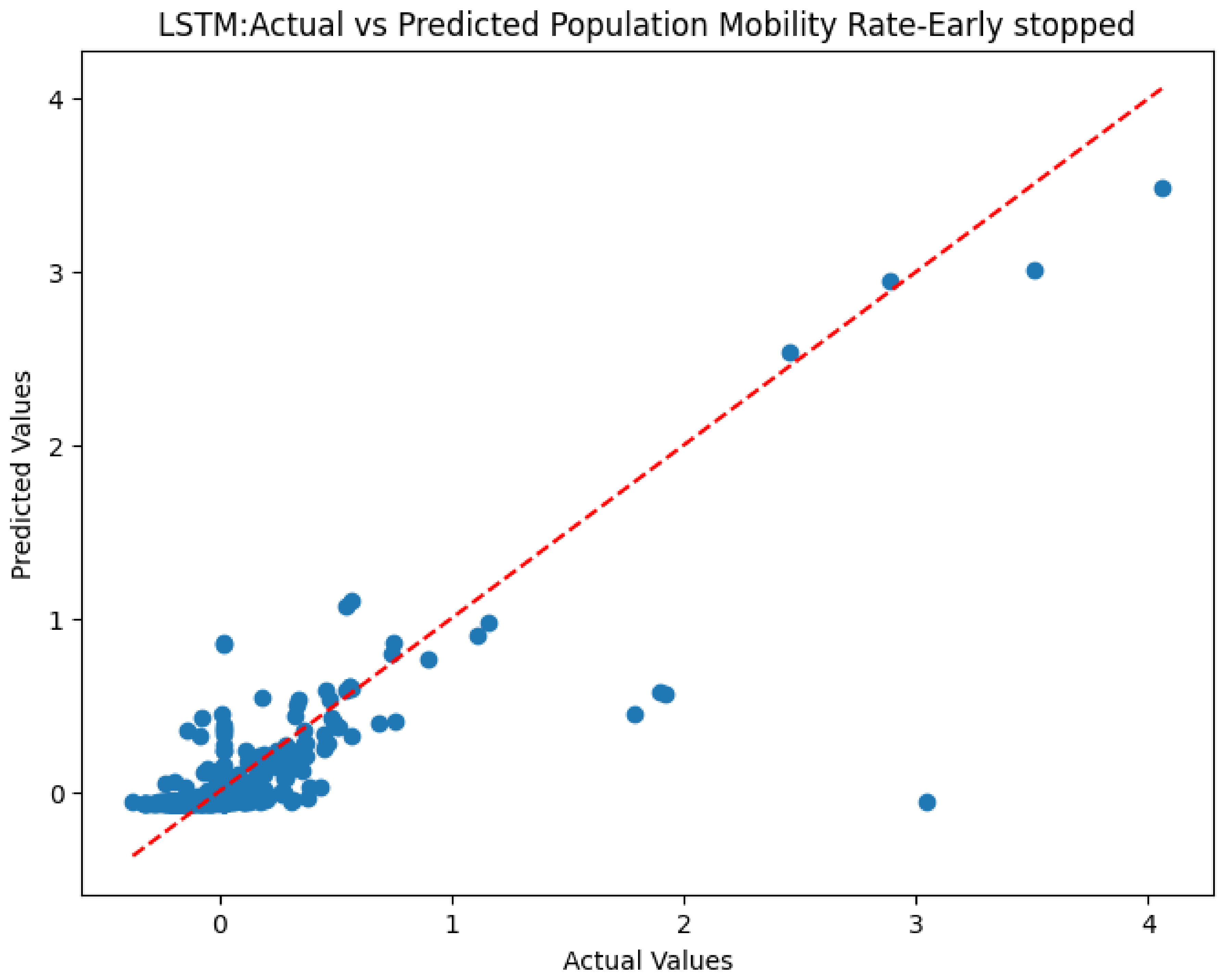
4. **Additional Details**:

- Early Stopping: Stops training when validation loss does not improve for 10 consecutive epochs, restoring the best model weights.



Prediction Model ： LSTM

FNN:	Test MSE 0.01115	Test MAE 0.065375
LSTM:	Test MSE 0.0391	Test MAE 0.10365



Practical Use

Inflowing Cities: Predicting Population Pressure

• By forecasting key economic indicators (e.g., GDP growth, housing prices, job creation), the model can estimate the population pressure that large cities may face in the future. This helps city planners prepare for infrastructure expansion, housing demands, and public service optimization.

Outflowing Cities: Issuing Population Loss Warnings

- The model can identify trends and predict further population outflows from smaller cities. Policymakers can use these insights to implement retention strategies, such as improving local employment opportunities and living conditions.

Things to do Next

Missing Data:

- Housing Prices: ~15% missing.
- Public Library Collections: ~12% missing.
- Currently using KNN imputation for handling missing values.
- Future Plan: Explore detailed city-level data from government portals for more accurate imputation.

REFERENCES

1. **Zhejiang University Population Research Center.** (2021). *The impact of population mobility on regional relationships in China*. Retrieved from https://www.ggzc.zju.edu.cn/2021/0312/c54184a2266429/page.htm

2. **CSDN Blog.** (2022). *Implementing LSTM neural networks with PaddlePaddle for predicting China's population*. Retrieved from https://blog.csdn.net/m0_63642362/article/details/128327594

3. **Wang, Y., & Li, Z.** (2020). Analyzing the economic factors influencing population mobility in China. *Journal of Regional Economics*, *12*(3), 45–59.

4. **Chen, H., & Zhou, X.** (2019). Predicting migration trends using neural network models. *International Journal of Population Studies*, *8*(2), 100–115.

THANK YOU

Presentation by Chuchu Wan