國立臺灣大學理學院地理環境資源學系

學士班學生論文

Department of Geography

College of Science

National Taiwan University

Bachelor’s Thesis

基於旅行目的的方法來預測人類移動的下一位置

Trip-purpose-based methods for predicting human mobility’s next location

劉正悅

Jeng-Yue Liu

指導教授：溫在弘博士

Advisor: Tzai-Hung Wen, Ph.D.

中華民國 113 年 04 月

April 2024

國立臺灣大學學士班學生論文
口試委員會審定書

基於旅行目的的方法來預測人類移動的下一位置
Trip-purpose-based methods for predicting human mobility's next location.

本論文係劉正悅君（B09208038）在國立臺灣大學地理環境資源學系完成之學士班學生論文，於民國 113 年 04 月 25 日承下列考試委員審查通過及口試及格，特此證明

口試委員(3 位)：

______________________（簽名）

（指導教授）

______________　______________

系 主 任 ：______________（簽名）

（是否須簽章依各院系規定）

Abstract

This study presents an innovative approach to predicting human mobility's next location, enhancing traditional methodologies with a focus on the shifts in trip purposes within time-series analysis. By integrating static background information, such as sociodemographic data, with geographic land use characteristics, the model effectively differentiates mobility behavior patterns among diverse demographic groups. This integration allows for the accurate capturing of dynamic changes in mobility while preserving the integrity of individual's background information. The development of a low-complexity hybrid model, which processes both static and dynamic features, further improves the accuracy and adaptability of predictions across various geographical areas. Employing advanced GeoAI techniques, including LSTM(Long Short-Term Memory) and GRU(Gated Recurrent Unit) models, the study aligns predictions closely with real-world dynamics and provides valuable insights for urban planning and business strategy formulation. Additionally, the evaluation of prediction performance incorporates not only "Strict Accuracy" but also a novel metric called "Adjacency Accuracy", which accommodates deviations within neighboring ranges. The model achieves a strict accuracy of 0.7927 and an adjacent accuracy of 0.9199. This approach promises to offer new perspectives and scientific support for urban economic development, paving the way for further research in applying these methodologies to specific datasets and enhancing urban planning efforts.

Keywords: Next-location prediction, Trip purpose, Human mobility pattern, GeoAI, LSTM, GRU, Deep Learning

Contents

List of Figures

List of Tables

1 Introduction

Human mobility's next location prediction represents a significant technological breakthrough pursued in the field of Urban Morphology. The regularity in human mobility patterns (Noulas et al., 2012) makes the prediction of a human's next location and the analysis of mobility patterns crucially significant from a geographical standpoint (Smolak, Kamil et al., 2022). It not only holds geographic significance for urban planning and the development of smart cities but also offers foresight for businesses formulating market strategies. However, the unpredictability of human mobility's next location across temporal and spatial dimensions, coupled with the complexity of the data, presents increasing challenges to predicting human mobility behavior.

Previous studies have achieved some success in predicting human mobility behavior, yet there remains significant room for improvement in the methodology. Firstly, regarding the temporal and spatial settings of datasets, traditional methods often utilize fixed time series intervals, which fail to accurately reflect the temporal changes in mobility behavior. The analysis of trip purposes is vital for predicting human mobility patterns (Zhu et al., 2014; Lenormand et al., 2020). The association between human mobility behavior and trip purpose is a critical consideration in this prediction task. Thus, highlighting changes in human mobility behavior based on shifts in trip purpose, and using this as the main basis for temporal segmentation, allows for the capture of mobility's next location that change with trip purpose, leading to more accurate predictions of the destinations of future trip purpose. Moreover, in terms of spatial dimensions, regional characteristics are crucial for predicting human mobility's next location. The high degree of autonomy individuals exhibit in space means regional characteristics can reflect the nature of an human's activities at any given time, incorporating this factor into the dataset can significantly enhance prediction accuracy (Shi et al., 2022).

Secondly, recent advancements in GeoAI (Geospatial Artificial Intelligence) have revolutionized the field of mobility behavior prediction. Modern models now incorporate more sophisticated temporal contexts, significantly enhancing the accuracy of predicting a person's next location. Notably, studies employing RNN-based (Recurrent Neural Network) time series models, such as LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), have demonstrated promising results in this area. However, many of these studies fail to consider critical sociodemographic characteristics such as gender, age, and occupation. This oversight leads to the assumption that all individuals' mobility patterns are universally similar, disregarding how personal background can distinctly influence movement. Indeed, mobility patterns can vary widely among different demographic groups, even when the trip purposes are identical. Incorporating these individual differences by segmenting data based on sociodemographic information could drastically improve the accuracy and applicability of predictions, aligning outcomes more closely with real-world dynamics (Montero et al., 2023).

In summary, this study improves methodologies through the training of big data, LSTM and GRU models, employing a hybrid temporal model to analyze both static and dynamic features within sequences, effectively identifying the inherent patterns of human mobility. In terms of business strategies, by analyzing the mobility trends and patterns of populations, businesses can make better decisions regarding store locations, opening hours, and the types of goods needed, thereby improving sales performance and customer visitation rates. In urban planning, human mobility's next location prediction can be utilized to optimize the planning of urban hotspots, contributing scientific foundations and innovative ideas to urban economic development.

2 Literature review

Past research on human's mobility behavior patterns has largely depended on the development of time-series forecasting models, evolving from early traditional time-series forecasting models to the widely applied GeoAI architectures of today. Despite the increasing sophistication of predictive models, prediction tasks continue to face numerous challenges, highlighting the importance of data preprocessing and model design methodology (Xie et al., 2020). In this section, we will first review prediction methods based on trip purpose, followed by an introduction to methods for predicting human's mobility behavior.

2.1 Trip purpose

Trip purpose is crucial in predicting mobility behavior, as recording specific movement trajectories and trip purposes can capture people's mobility dynamics. Zhu et al., 2014 analyzed urban features and human's mobility behavior within cities to model and infer trip purpose, confirming the correlation between mobility behavior and trip purpose through statistical analysis. Additionally, P. Wang et al., 2017 introduced the concept of synchronicity in human mobility, which can jointly capture inter-regional correlations, individual movement events, and trip purposes. It suggests that if two regions share similar geographic features and urban functions, they will exhibit similar specific trip purpose within specific time periods. By probabilistically modeling human's movement events, identifying trip purposes, and deriving spatiotemporal synchronicity rates mathematically, they have demonstrated the correlation between trip purposes and regional features. This approach can effectively predict human's mobility behavior, with spatial synchronicity providing crucial support for predictive assumptions. Utilizing probabilistic modeling methods can simulate the similarity of trip purposes in space to aid in predictive modeling.

2.2 Advancements in predicting human mobility's next location

In the realm of time series forecasting, traditional models often rely on statistical methods to handle time series data with fixed intervals, predicting future movement patterns based on past data experiences. Markov models are commonly used to analyze the stochastic changes of events over time. Gidófalvi & Dong, 2012 continuously estimated the parameters of non-homogeneous continuous-time Markov models to predict the time an individual will leave their current region and their next location in a continuous manner, while Wilinski, 2019 handled time series characteristics with complex transition matrices. However, the steady-state assumption of Markov models only holds under discrete time and states, and due to their lack of memory, these models have limited structural and accuracy capabilities in time series forecasting. Additionally, Markov models predict the next step in a probabilistic, incremental manner, where the assumption of fixed probabilities limits the independence of individual differences.

With the advancement of GeoAI technology, the trend for next location prediction is gradually shifting towards deep learning methods. This shift results from the task's involvement with highly diverse datasets that require interdisciplinary integration and models that must accommodate large variations in datasets (Zheng et al., 2018). Deep learning time series models, such as LSTM and GRU models, have been used for long-term sequence location prediction and dynamic time series behavior description, addressing deficiencies in handling continuity, accuracy, and variable diversity of past methods. Furthermore, conventional RNNs face problems with gradient vanishing and weight explosion mainly due to their handling of long-term dependencies. In RNNs, each time point's hidden state is influenced by the previous time point's hidden state, causing information to be transmitted over long time distances. This can lead to exponential increases or decreases in gradients during backpropagation, resulting in gradient vanishing or weight explosion issues. Therefore, Ke et al., 2022 integrated LSTM and GRU models for processing sequence data, utilizing location types, geographic relevance, and deep-learning-based matrix factorization to enhance human mobility predictions. However, their approach groups users solely based on their preferences for regions and location categories, overlooking crucial individual background characteristics.

Moreover, for the next location prediction task, Xie et al., 2020 emphasized that the challenge lies in handling multi-factor influences, suitable data integration methods, and overcoming data sparsity, requiring consideration of spatial and temporal scales, weather, social activities, and other factors. Luca et al., 2021 pointed out that predictive models need to capture human habitual movement patterns in both time and space dimensions and integrate heterogeneous data sources. Given this, since most AI model prediction tasks use datasets that overlook much geographic information, including environmental variables and individual background information, hybrid time series models can integrate heterogeneous datasets and incorporate individual background information, based on trip purpose prediction methodologies, to improve the accuracy and effectiveness of next location predictions.

3 Research process

3.1 Research process

The process of this study is primarily divided into two main phases (as illustrated in Figure 1). The first phase focuses on cultivating the predictive capabilities of the model, including data collection and integration, data preprocessing, selection and comparison of different models, as well as model evaluation and optimization to ensure the model can effectively train the dataset of this study. The second phase focuses on the analysis of predictive results, using strict accuracy rates and adjacent accuracy rates to assess the distribution of the model's spatial predictions, followed by an in-depth discussion on the predictive performance of the model.

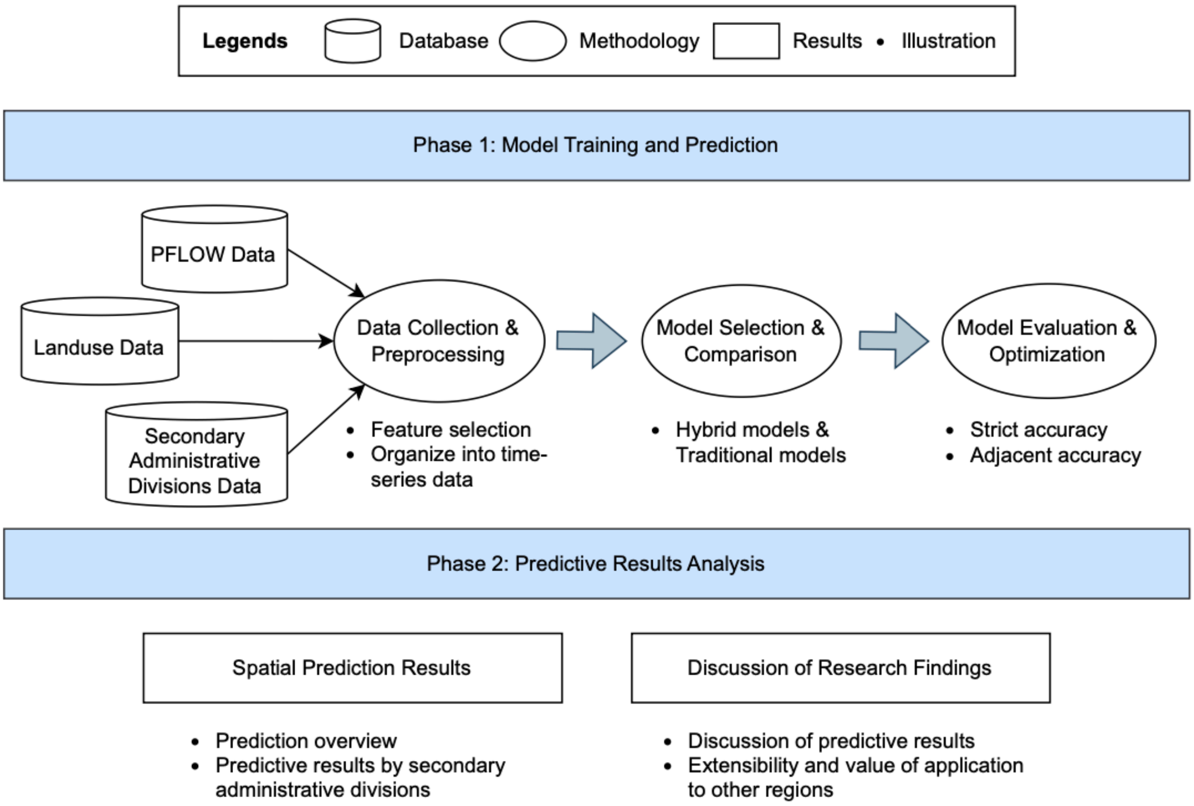

Figure 1: Research process

3.2 Research design and assumption

The training methodology of this study's model is built upon the following core assumption: Populations with similar backgrounds, if they exhibit similar patterns of mobility behavior, will also present similar trajectories in time and space dimensions. Conversely, if there are differences in an individual's background or patterns of mobility behavior, their movements may differ accordingly. Based on this assumption, when predicting human's mobility behaviors, this study considers two main influencing factors: first, individual background information (such as age, gender, occupation, etc.), and second, the characteristics of mobility behavior (including trip purposes, modes of transportation, and precise geographical coordinates). By integrating these factors and conducting cluster analysis on the feature values, our model can identify differences in mobility behaviors across various groups, thus predicting individuals' actual movement patterns more accurately.

4 Research dataset

The core dataset of this study is derived from the People Flow Data (PFLOW) in Tokyo, Japan, dated October 1, 2008. It recorded the time-series data of 576,806 participants by the minute, aiming to monitor the dynamics of people's movements. By integrating spatiotemporal information from multiple data sources, including official Person Trip Survey Data (PT Data) from various administrative districts, as well as tracking mobile individuals through Global Positioning System (GPS) and the Personal Handy-phone System (PHS), observing stationary crowds through cameras, identifying passenger flow with automatic gate IC tickets, counting people via mobile phone registrations at base stations, and department store hourly customer flow data. Initially, geographical encoding was performed on the start and end points of trips to establish their spatiotemporal positions, followed by calculating the shortest paths and using network data for minute-by-minute interpolation of locations, thus measuring people flow in multiple dimensions. The processed dataset includes de-identified basic individual data and records the geographical location, trip purpose, and transportation type at each time point, detailing people's daily movement patterns and behavioral characteristics. Figure 2 below illustrates an example of the data, while figure 3 provides a schematic of data visualization: the spatial dimension displays humans' movement trajectories, while the temporal dimension shows the variations in location over time. The movement trajectories are segmented into different sub-trips, each indicating a shift in movement segment corresponding to a change in trip purpose. Consequently, the figure illustrates three distinct sequences in the time dimension, each resulting from changes in the trip purpose segments. The four marked points along these trajectories denote the turning points where the trip purpose changes. For more details about the columns, refer to Appendix I.

Original Dataset

UserID	Trip No	Sub Trip No	Timestamp	Longitude	Latitude	Gender	Age	Address Code	Work	Trip	Transport
275176	1	1	2008-10-01 08:50:00	139.605314	35.427077	1	7	11211	49	1	1
...	1	1	2008-10-01 08:51:00	139.602041	35.422877	...	...	...	...	1	1
...	1	1	...	...	...	...	...	...	...	...	...
...	1	1	2008-10-01 09:04:00	139.602047	35.422847	...	...	...	...	1	1
...	1	2	2008-10-01 09:05:00	139.604068	35.426279	...	...	...	...	1	12
...	1	2	...	...	...	...	...	...	...	...	...
...	1	2	2008-10-01 09:24:00	139.635936	35.445625	...	...	...	...	1	12
...	1	3	2008-10-01 09:25:00	139.635925	35.445800	...	...	...	...	1	1
...	1	3	...	...	...	...	...	...	...	...	...
275176	1	3	2008-10-01 09:29:00	139.636304	35.446251	1	7	11211	49	1	1

Figure 2: Illustration of the raw dataset

To highlight the geographical characteristics of the humans' locations, this study also incorporates two datasets: one on Japan's land use types and the other on the geographical location information of Japan's secondary administrative divisions. In 2000, the National Institute for Humanities of Japan precisely annotated and delineated the land use categories in Tokyo using overlay techniques of satellite imagery, aerial photography, and a Geographic Information System (GIS) 3D earth model. This dataset divides land use categories into a grid format with a unit

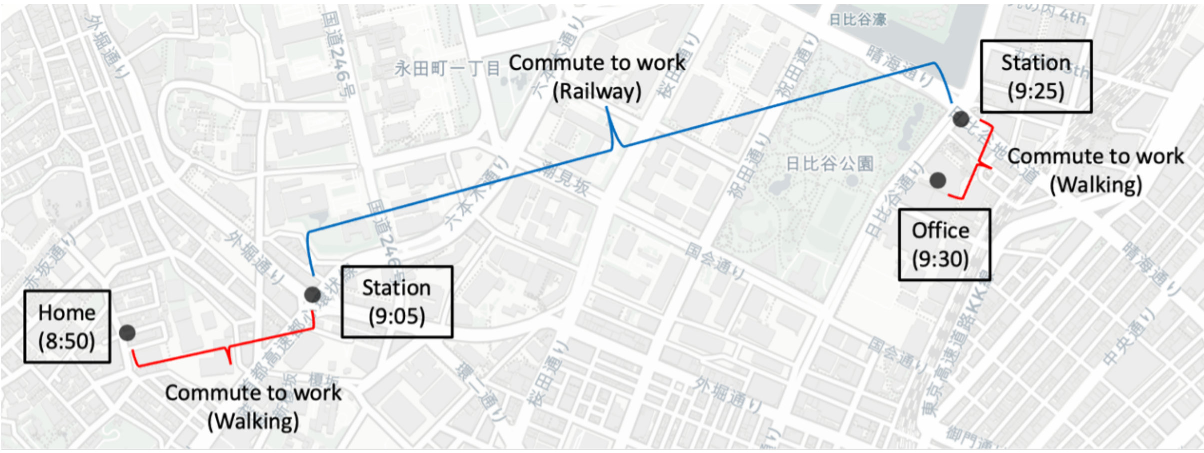

Figure 3: Schematic diagram of the research dataset

size of 500 meters, encompassing land types such as forests, grasslands, farmlands, agricultural lands, industrial areas, residential areas, aquatic wetlands, maritime areas, and other categories. As shown in Figure 4, different land use types are represented by different colored areas on the map. Integrating this dataset into the study highlights the land environmental characteristics of the human's location, providing richer geographical and environmental background information for the research.

Furthermore, this study incorporates geographical information on Japan's secondary administrative regions provided by the Global Administrative Areas (GADM) database version 4.1. This dataset offers high-resolution maps and detailed attributes of administrative divisions at all levels of a country. This study overlays the specific longitudinal and latitudinal end locations of individual time series (exact coordinates) with the polygonal maps of secondary administrative regions to determine the number of the secondary administrative division that the endpoint of the time series model prediction belongs to, serving as the predictive Y value for this study. The total number of secondary administrative divisions covered in this study amounts to 227, as illustrated in Figure 4, with black and light blue lines indicating the boundaries of primary and secondary administrative divisions, respectively.

5 Methodology

5.1 Research outline

This study introduces two key strategies to address the deficiencies of past research. First, we redefine the concept of time series, moving away from the traditional method of fixed-period time slicing. Instead, we interpret shifts in movement segments within the time dimension as changes in trip purposes, utilizing these transitions as critical elements to capture variations in mobility behavior patterns. Specifically, in the original data, we analyze both trip and transport types, defining a change in movement segment as a shift in trip purpose whenever either element varies. This approach allows us to analyze time-series data more finely, considering regional background information to delve deeper into human mobility behaviors. Second, we highlight

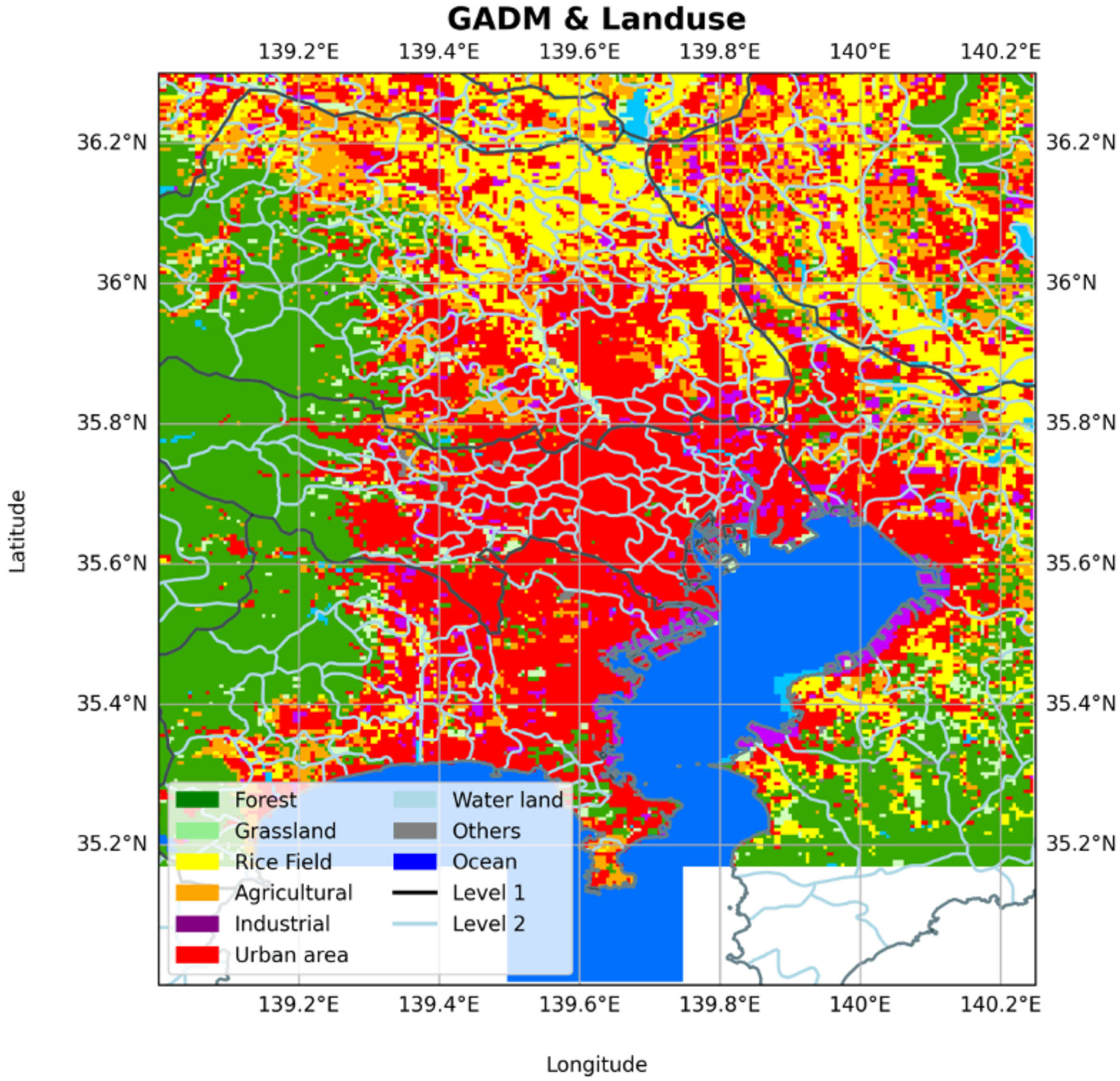

Figure 4: Schematic diagram of land use and secondary administrative divisions

the importance of static individual background information, such as sociodemographic characteristics, aiming to uncover differences in mobility behavior among different social groups. This enables our model to more accurately reflect the dynamic changes of populations within urban environments.

Methodologically, this study designs a broadly applicable human mobility prediction model. In terms of data processing, data is categorized into static and dynamic types: Static features include easily accessible and general background information, which can effectively segment individuals while ensuring de-identification. Dynamic features encompass precise geographical locations (latitude and longitude coordinates) and place-specific characteristics, as well as information describing individual movement behaviors, trip purposes, and modes of transportation, making features more aligned with actual movement patterns.

To boost the precision and applicability of predictions, this research adopts a low-complexity hybrid model, focusing on the analysis of static and dynamic features. By training neural network models on large datasets, it effectively identifies the inherent patterns of human movement, thereby increasing the accuracy of predicting future mobility trends of humans.

5.2 Data preprocessing and feature engineering

Initially, time-series data sharing the same trip purpose are regarded as part of a single mobility behavior pattern. When the trip purpose changes at a specific time point, it signifies the beginning of a new mobility behavior pattern. Thus, in the original dataset, time series under the same trip purpose are treated as a period, with a change in trip purpose marking the start of the next period.

For preprocessing the original dataset and organizing the time-series data, the starting data point of each period is used as representative data for that period. For example, as depicted in Figure 5, which is an extended version showcased in Figure 3, demonstrates how data preprocessing techniques have been applied to enhance the dataset. Different colored segments represent variations in trip purposes, each indicating a distinct sequence in the time dimension. The data at 00:00 is defined as the data for moment t_1, and when the trip purpose changes at 8:50, the initial data of that period is defined as the data for moment t_2. Based on this concept, the study defines ”Sequence Length” as predicting the Y value at the next time point through a certain number of time series. Assuming a sequence length of 3, data from t_1 to t_3 is used to predict the Y value at t_4, where the Y value is determined by overlaying the latitude and longitude at t_4 onto its corresponding secondary administrative district code. Such a set of data is called a time series data point. Subsequently, data from t_2 to t_4 is used to predict the Y value at t_5, forming the second time series data point. This preprocessing approach was applied to the 576,806 participants in the original dataset, resulting in a total of 2,626,089 data points.

As shown in Table 1, in selecting features for the time-series data, the study retains characteristics that highlight individual differences, such as gender, age group, and occupation, enabling the model to distinguish between different individual groups. Additionally, to capture humans’ mobility patterns, representative features within the time series, such as trip purpose and transportation type, are preserved. Moreover, in the temporal dimension, besides recording the hourly data of each time series, the study reveals the activity period (e.g., morning peak, evening peak, or nightlife) and its duration by calculating the time difference between time series. In the spatial dimension, geographic location latitudes and longitudes are matched with land use types through overlay analysis, thereby accentuating the geographical environmental characteristics of each location. Through a series of experiments and comparisons, the study filters out feature value fields with significant impact on model training, ensuring that the retained features maximally enhance the model's predictive capabilities.

Given the limitations of the land use classification grid resolution, integrating grids with administrative boundaries introduces certain errors, such as residential or industrial lands being mistakenly classified as maritime areas. To address this, a time correction method was adopted, reclassifying the data before 5 PM as industrial land and data after 5 PM as residential land, based on transportation type, occupation, and trip purpose at each time point.

Furthermore, to improve data quality and reliability, data from secondary administrative districts with fewer than 50 data points were removed. Also, textual feature fields were quantified and standardized to ensure data consistency and comparability.

Table 1: Data dictionary of sequence features

Column	Column name	Format	Note
x_1	Time Interval	Integer	Difference in minutes to the next time sequence.
x_2	Gender	Integer	1: Male, 2: Female, 9: Unknown.
x_3	Age Group	Integer	Divided into five-year intervals. See Appendix II.
x_4	Work	Integer	Coded by occupation. See Appendix III.
x_5	Trip	Integer	Coded by trip. See Appendix IV.
x_6	Transport Type	Integer	Coded by transportation. See Appendix V.
x_7	Longitude	Decimal	WGS84.
x_8	Latitude	Decimal	WGS84.
x_9	Land Use	Integer	Coded by land use. See Appendix VI.
x_{10}	Hour	Integer	Sequence occur time.
Y	GADM Level 2	Integer	GADM Secondary Administrative Divisions.

5.3 Model selection

This study primarily utilizes two types of time series deep learning models for exploration and comparison: the Long Short-Term Memory (LSTM) model and the Gated Recurrent Unit (GRU) model. The LSTM model is a special type of Recurrent Neural Network (RNN) architecture designed to address the gradient vanishing or exploding issues commonly encountered with traditional RNNs in processing long sequence data. Thanks to its unique structure, the LSTM is capable of effectively capturing long-term dependencies within time series data. Its core lies in the internal memory cells, each containing three main gate structures: the forget gate, input gate, and output gate, which together control the retention, updating, and retrieval of information.

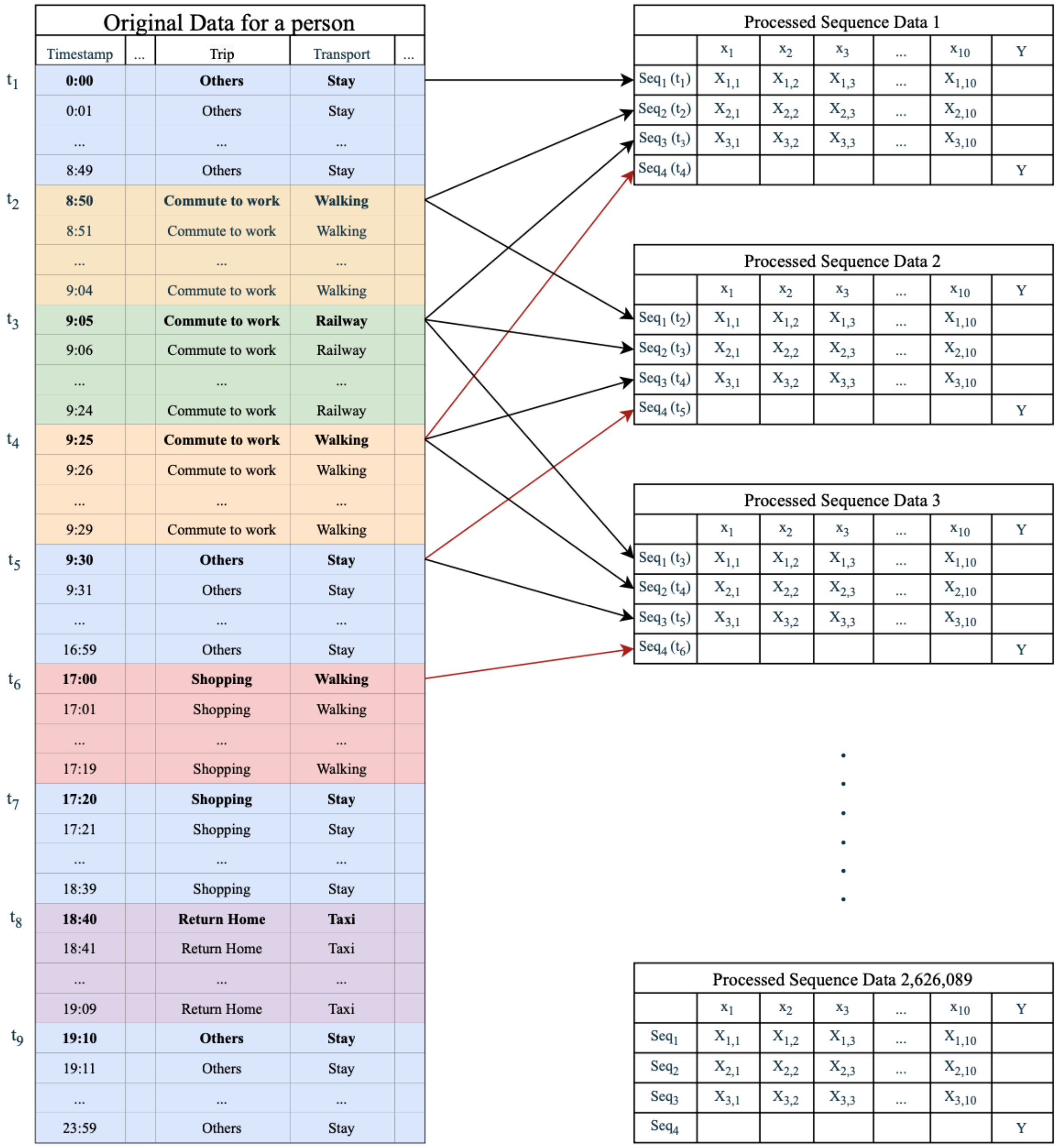

Figure 5: Illustration of data preprocessing

The GRU model simplifies the LSTM architecture, mainly utilizing two gating mechanisms to manage information retention and forgetting: the update gate and the reset gate. The update gate determines how much information from past to current hidden states needs to be updated, similar to a combination of LSTM's forget and input gates, allowing the model to retain an appropriate amount of past memory in the current state. The reset gate, on the other hand, controls the amount of past information to be discarded, enabling the model to discard state information irrelevant to the current output and thus more effectively capture short-term dependencies within the data. The design of these two gating mechanisms allows the GRU to learn long-term and short-term dependencies in time series data while maintaining computational and parameter efficiency.

The Hybrid Model time series model adopted in this study is an advanced improvement on traditional models, capable of simultaneously processing static and dynamic features, and more flexibly combining them to enhance predictive performance. This model categorizes features into two main types: individual static features and sequence dynamic features. Individual static features are personal background information that remains constant throughout the time series data, such as age group, gender, occupation, etc.; sequence dynamic features refer to changing feature values within the sequence, such as trip purpose, transportation type, and location.

In the Hybrid Model architecture, sequence dynamic features are initially trained through LSTM or GRU layers to capture temporal dependencies within the time series data. After training, the results are integrated with individual static features, and then the integrated data is processed and learned through two linear model layers to generate probability scores for all Y values, with the highest score chosen as the prediction result. This result represents the secondary administrative division where the individual is located at the last time point of the time series, as illustrated in Figure 6.

This study compares the predictive capabilities of the four aforementioned models: LSTM, GRU, Hybrid LSTM, and Hybrid GRU. The traditional models, LSTM and GRU, do not differentiate between static and dynamic features during training, treating them all as feature values of each time point. In contrast, the hybrid models, Hybrid LSTM and Hybrid GRU, specially process dynamic data during training, allowing the time series model to more easily capture the interactions between different time points.

5.4 Analysis of the impact of sequence length in experiments

Given the non-intuitive effects of sequence length choices on model predictive performance, this study conducted a series of experiments with the aforementioned four models to explore the predictive capabilities at varying sequence lengths. These experiments not only help us dissect the relationship between sequence length and model prediction outcomes but also identify the optimal sequence length for prediction tasks. This optimal length serves as a crucial parameter in subsequent research discussions and analyses, aiming to achieve higher prediction accuracy and model performance.

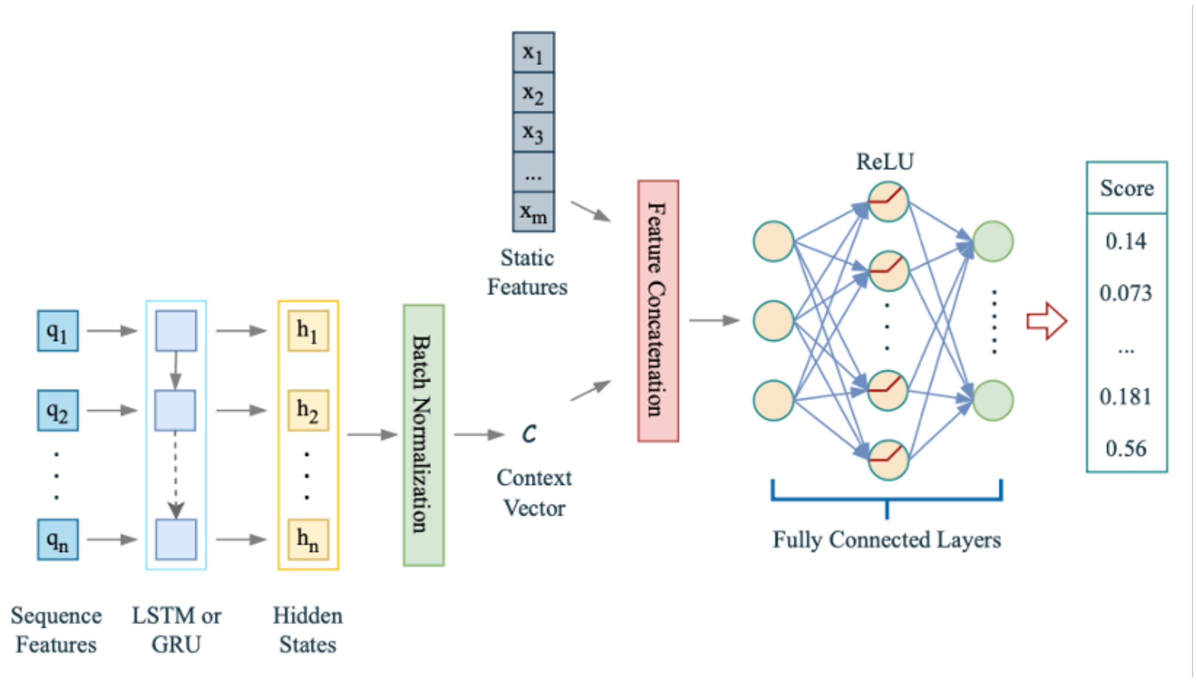

Figure 6: Illustration of hybrid model.

5.5 Model training method

Considering the characteristics of this study's dataset, where data points from the city center to the peripheral areas are relatively fewer, to prevent the model from overfitting to the features of densely populated areas while neglecting peripheral ones, this study incorporates L2 regularization (also known as weight decay) during the training process. By adding a penalty term proportional to the sum of squares of the model weights to the loss function, this method aims to encourage the model to prefer smaller weight values. This reduces the model's excessive sensitivity to minor changes in input features, thereby lowering model complexity and effectively preventing overfitting.

Moreover, to further enhance the model's generalizability and ensure the accuracy of evaluations, we divide the dataset into training, validation, and test sets with a ratio of 60:20:20, respectively, and apply the 5-fold Cross-Validation method to increase the rigor of model training and evaluation. The Cross Entropy Loss function is used to assess the training performance on the training set and is also applied to the validation set to test the model's training effectiveness. If the loss value on the validation set does not significantly decrease over 10 consecutive training epochs, an Early Stopping mechanism is triggered to terminate training and save the current optimal model. This prevents the model from overfitting to the training dataset during the training process. After training terminates, the test set is used for the final evaluation of the model's prediction accuracy to determine the actual predictive performance of the model.

5.6 Model optimization methods

The model optimization process involves adjusting multiple hyperparameters, including the size of the hidden layers, the number of hidden layers, the learning rate, the size of the fully connected layer, batch size, and the dropout rate for model layers. To optimize model performance, this study employs a grid search strategy combined with 5-fold cross-validation. Accuracy serves as the primary metric for measuring model performance during hyperparameter optimization. Through grid search, a thorough evaluation of predefined parameter combinations is conducted, filtering out the model configuration that performs best across different data subsets. These settings are then established as the final model's parameter configuration.

5.7 Evaluating spatial prediction accuracy

When assessing the accuracy of predictions in the spatial dimension, it's acknowledged that the boundaries of secondary administrative divisions might not precisely delineate the differences between areas. This suggests that adjacent districts could interact and influence each other. Therefore, this study opts not to use the top-three accuracy (Acc@3) evaluation metric commonly employed in related research. This metric deems predictions as accurate if the predicted results rank within the top three but is less effective in interpreting spatial regional characteristics. Instead, in addition to using the traditional "Strict Accuracy" evaluation standard, this research introduces a new metric - "Adjacent Accuracy." This metric allows for deviations within neighboring ranges. If the predicted secondary administrative district is adjacent to the actual value, then that prediction is considered accurate. This method places greater emphasis on the interpretability of regional characteristics in the predictions, contributing to a more precise spatial prediction assessment.

The combination of these two evaluation metrics not only showcases the model's precise prediction capabilities but also reveals mobility behavior patterns that are challenging to predict and deviate significantly from actual values, offering a comprehensive analysis of the model's predictive behavior.

5.7.1 Strict accuracy

This metric measures the proportion of predictions where the model's forecasted secondary administrative district exactly matches the actual value, reflecting the model's precise localization ability. For instance, if the actual value is represented by a green cell, the prediction must also be that green cell to be considered accurate, as illustrated in Figure 7. All other predictions are considered incorrect.

5.7.2 Adjacent accuracy

Considering the adjacency between administrative districts, this metric permits predictions to fall within the neighboring areas of the correct district, including the actual district itself. For example, as shown in Figure 7, if the actual value is a green cell, any prediction that is either in the green cell or an adjacent orange cell is deemed accurate. Predictions in the remaining light blue areas are considered incorrect.

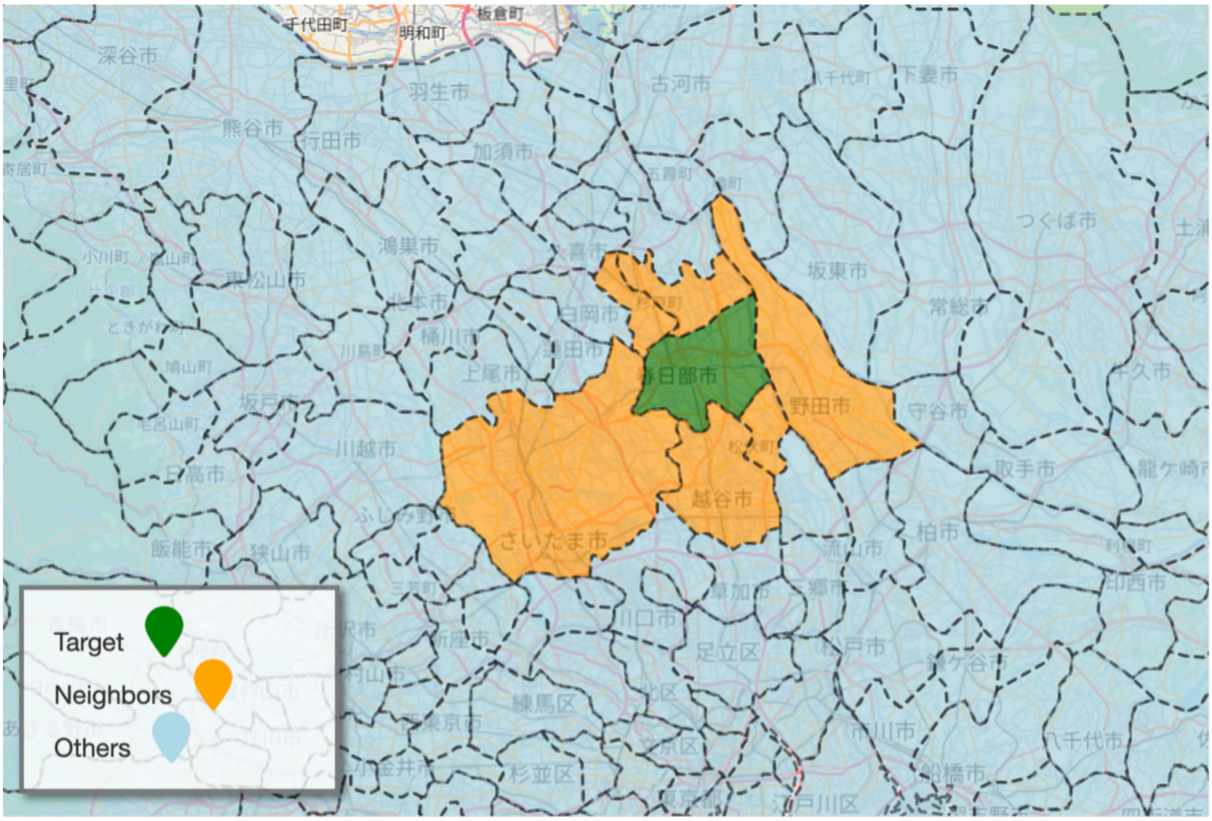

Figure 7: Illustration of accuracies.

6 Research findings

6.1 Overview

This study introduces a novel approach to human mobility's next location prediction aimed at enhancing prediction accuracy through improved time series analysis and the application of human characteristics. Instead of employing traditional fixed-period time slicing methods, we analyze mobility behaviors based on changes in trip purposes. The research emphasizes the importance of static background information, such as sociodemographic features, to highlight differences in mobility behaviors among various groups. Additionally, a low-complexity hybrid model was developed, targeting both static and dynamic features. This not only provides background data for individual segmentation but also integrates geographical location and movement behavior information, making the model more reflective of actual mobility patterns. The neural networks trained in a big data environment are capable of effectively identifying the intrinsic patterns of movement, thereby increasing the accuracy of mobility trend predictions.

6.2 Impact of sequence length in human mobility prediction

In exploring sequence length, this study preprocesses the original data to generate multiple datasets based on different sequence lengths. Each dataset was then trained and assessed for its performance. As illustrated in Figure 8, the dataset with a sequence length of 3 exhibited the best performance in terms of strict accuracy, reaching 0.7927. Consequently, this research sets the sequence length to 3 as the basis for subsequent discussions and analyses.

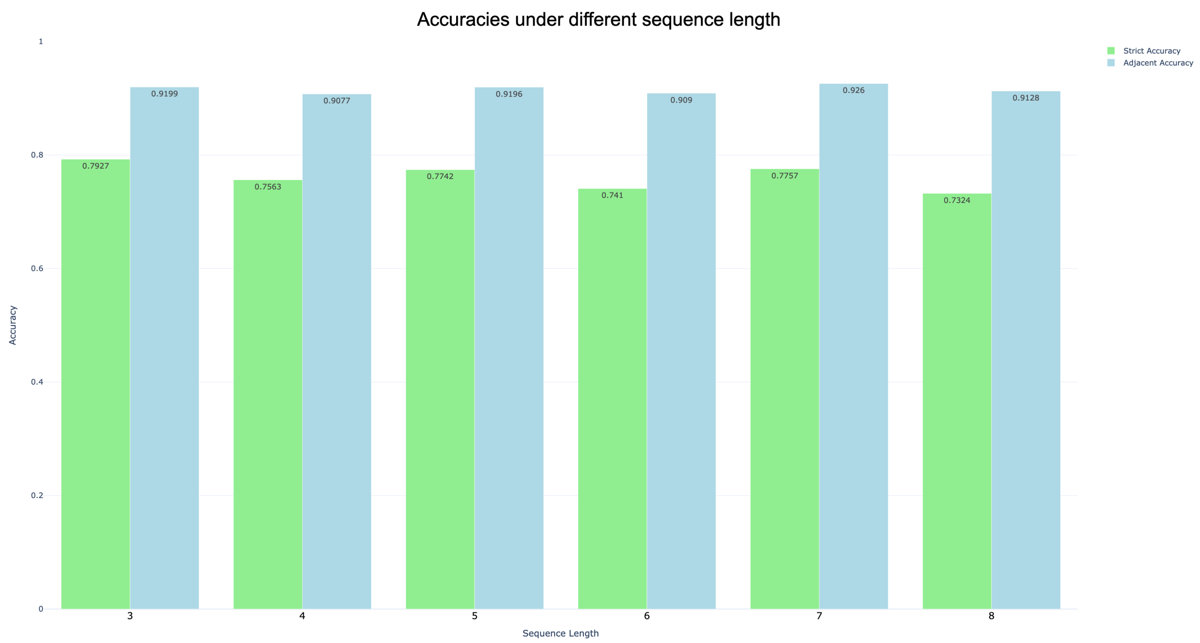

Figure 8: Predictive performance across different sequence lengths.

Furthermore, we observe that the type of movement at the final point in a time sequence significantly impacts prediction accuracy. Consider a sequence length of three, for example. The third time period can be broadly classified into two categories: stay or move. ”Move” includes all forms of transportation that do not involve remaining stationary. This distinction likely arises from patterns in human mobility behavior, particularly given the study’s approach to segmenting time series based on changes in trip purposes.

For the first category, since the predicted state’s starting position aligns with the previous moment’s stationary position, the model can more easily identify and accurately predict the outcome. However, the second category typically involves sequences that start from one location and end at another, presenting a challenge to the model’s predictive capabilities as it must discern the movement pattern from other features in the series to successfully predict the final position.

According to the statistics in Table 3, there is a positive correlation between the proportion of Category 1 and the accuracy of model predictions, with the best performance observed when the sequence length is 3. This outcome indicates the model’s varying sensitivity to capturing mobility behaviors across datasets with different sequence lengths, influencing predictive accuracy. It underscores the challenges and strengths of the model in predicting various types of mobility behaviors, reflecting its adaptability and the need for tailored approaches depending on the sequence characteristics.

6.3 Global prediction

The optimal model adopted in this research is the Hybrid GRU. As shown in the Table 4, it achieved a strict accuracy of 0.7927 and an adjacent accuracy of 0.9199. This high accuracy

Table 2: Categories of sequence movement behavior patterns

Category	Movement Pattern	Final Movement	Predictive difficulty
1	Any movement	Stay	Easy
2	Any movement	Move(Other than stay)	Hard

Table 3: Statistics table of different categories on different sequence length

Sequence Length	3	4	5	6	7	8
Category 1	31.7%	26.9%	30.6%	26.7%	30.9%	27.1%
Category 2	68.3%	73.1%	69.4%	73.3%	69.1%	72.9%

indicates that the AI model, trained on a large dataset, can effectively utilize both static and dynamic data to capture human movement patterns. The predictive results of this model not only successfully reveal the inherent regularities of human movements but also further validate the assumption of this study: groups of individuals with similar backgrounds, when exhibiting similar movement behavior patterns, also present similar movement paths in the spatiotemporal dimension.

Table 4: Model predictive accuracy

Model	Strict accuracy	Adjacent accuracy
LSTM	0.7411	0.8792
GRU	0.7488	0.8813
Hybrid LSTM	0.7887	0.9081
Hybrid GRU	**0.7927**	**0.9199**

6.4 Prediction results for secondary administrative divisions

In terms of spatial dimension, the strict accuracy rate is adopted as the evaluation metric, and the geographical distribution map of strict accuracy is visualized, as shown in Figure 9. The depth of color in each secondary administrative region block represents the proportion of successful predictions, i.e., the ratio of data points successfully predicted by the model among all data points located in that secondary administrative division. From the map, it can be observed that populations with high strict accuracy rates are mainly concentrated in the city center, indicating that the model has stronger predictive capabilities in urban areas. Conversely, populations with low strict accuracy rates are mostly distributed in peripheral areas of the study area, where limited sample size restricts the model's ability to identify patterns of mobility behavior towards these regions.

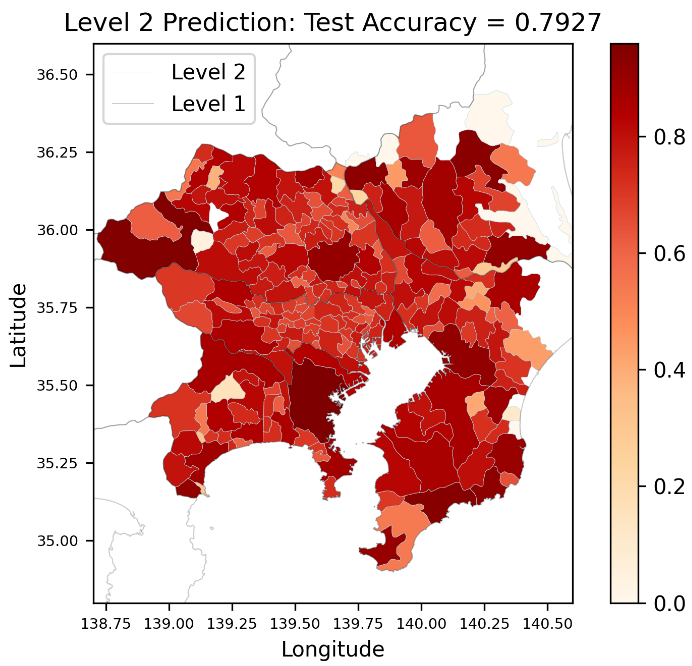

Figure 9: Strict accuracy on geographical distribution map

7 Discussion and suggestions

7.1 Impact of individual heterogeneity on predictions

Analyzing the age group adjacent accuracy chart depicted in Figure 10, we observed distinct prediction outcomes across different age groups, with accuracy displaying a V-shaped distribution. Accuracy dips from younger to middle-aged individuals and then gradually increases towards older individuals. Notably, the mobility patterns of those aged between twenty and thirty years are comparatively challenging to predict. In contrast, the prediction models perform better for the elderly and children.

This phenomenon highlights the lifestyle, activity range, and daily habit differences among various age groups. Young and middle-aged individuals, influenced by work and social interactions, possess a higher degree of movement freedom and less predictable behavior patterns. The widespread use of digital platforms has significantly impacted their mobility patterns, thereby increasing the prediction difficulty. Conversely, the elderly and children have relatively fixed and regular life scopes, making their mobility pattern behaviors easier to predict (Jamal & Newbold, 2020; Z. Wang et al., 2019).

In the transportation type adjacent accuracy analysis chart shown in Figure 11, we observed an interesting phenomenon: when the last mode of transportation in the time series is a lightweight vehicle (e.g., motorcycles or bicycles) or a public transportation vehicle with a fixed route (e.g., buses), the model's adjacent accuracy rate remains above 90%, indicating the model's higher success rate in identifying people's mobility patterns in these scenarios. However, the model struggles to accurately capture mobility patterns when the transportation type

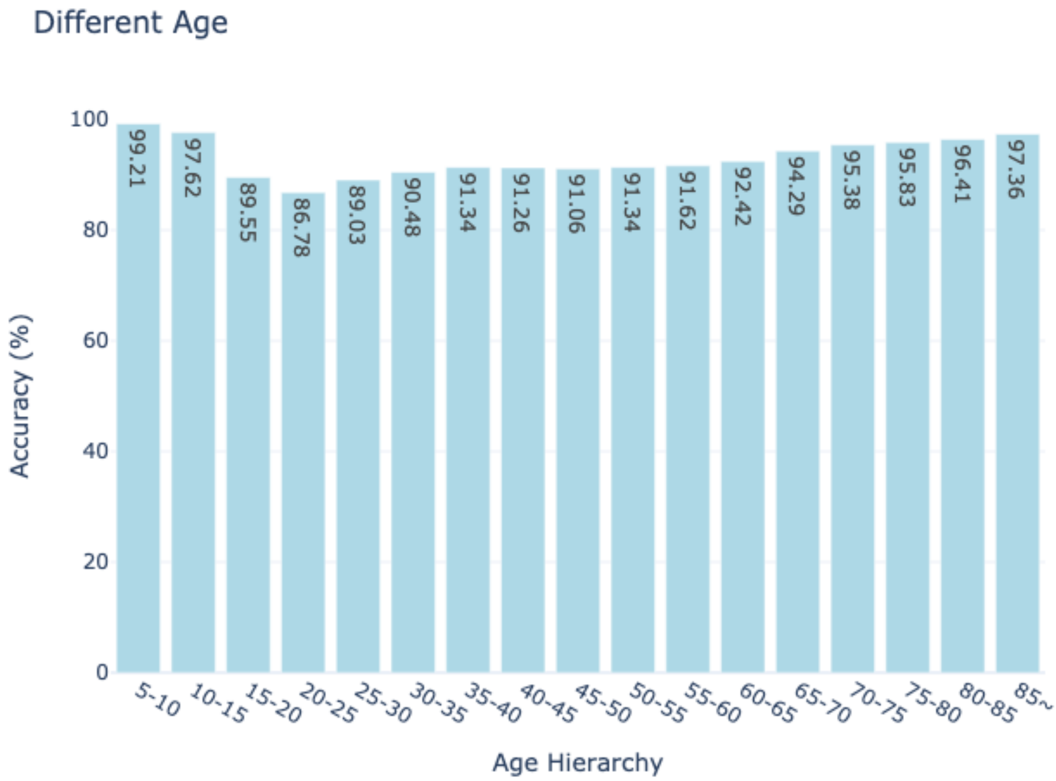

Figure 10: Adjacent accuracy of each age group

involves taxis, ferries, railways, or subways. Since these modes often cover long distances and extend over prolonged periods, and our model primarily focuses on the initial point of the trip, predicting the final destination becomes relatively challenging. This finding underscores the considerable impact that different transportation types have on the accuracy of the model's predictions regarding mobility patterns.

In the trip purpose adjacent accuracy analysis chart below, we observed a significant trend: the model's prediction accuracy is higher when the final trip purpose in the time series is short-distance movements such as drop-offs, medical visits, or agricultural activities, or when the destination is a fixed shopping area. Conversely, for complex or non-routine trip purposes such as tourism, sales, courier delivery, procurement, meetings, or collections, the model's prediction accuracy significantly decreases. Douglas do Couto Teixeira, 2021 suggested that predicting irregular and novel mobility patterns based on past data is challenging. This result reflects the spatial regularity of trip purposes, making fixed and routine mobility patterns easier for the model to capture. In contrast, non-fixed routes or highly variable mobility behaviors pose greater challenges for the model.

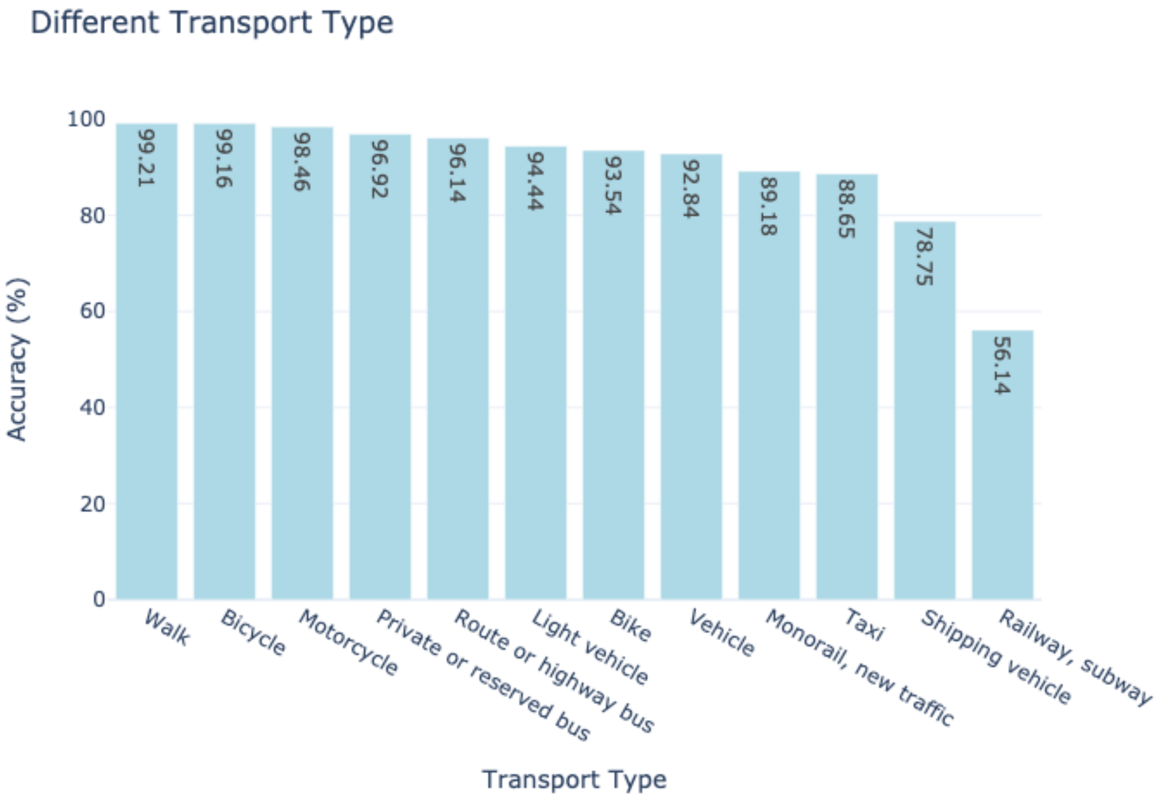

Figure 11: Adjacent accuracy of different transportation

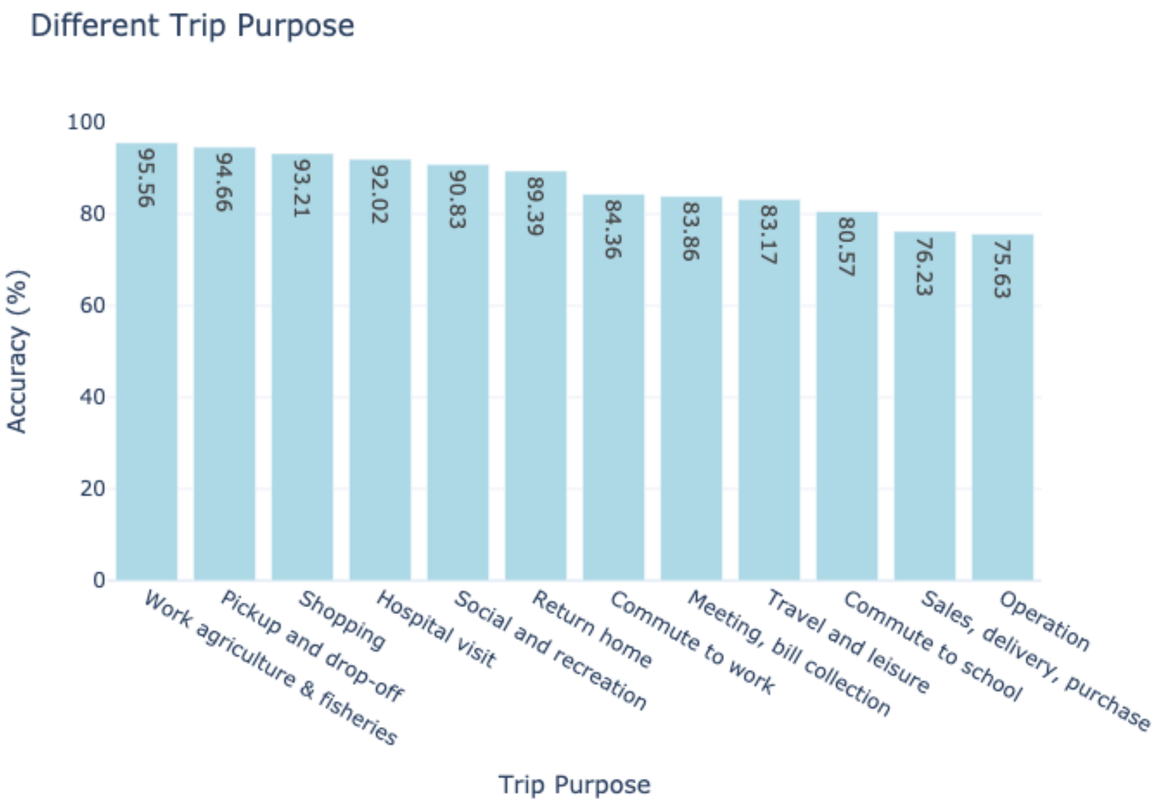

Figure 12: Adjacent accuracy of different trip purpose

7.2 Extendibility and value across regions

7.2.1 Universality and value of the methodology

The core of our research methodology involves using individual GPS and PHS tracking technologies combined with remote sensing image analysis to identify land use categories, thereby organizing data for AI model training to predict human mobility behaviors. The primary advantage of this methodology lies in its universal applicability and lack of restriction to specific geographic areas, allowing adjustments based on large mobility datasets and general algorithms for human behavior analysis and prediction worldwide.

By integrating Geographic Information System (GIS) technology to process target area pedestrian data and remote sensing images, our method is not only suitable for accurately analyzing and predicting human mobility behaviors within specific areas but also provides a flexible and adaptive framework for applications in urban planning, traffic management, and environmental monitoring.

In summary, this research not only deepens the understanding of human mobility patterns in Tokyo but also offers a viable methodology for related analyses and predictions in other regions, demonstrating great potential and broad value for cross-regional application.

7.2.2 Universality of mobility patterns from a phenomenological perspective

Noulas et al., 2012 explored the universal laws of human mobility from a phenomenological perspective, finding that differences in human flow between cities are mainly due to variations in location distribution. While physical distance influences the mobility patterns of each city, a universal behavior pattern emerges when considering the land use of locations and their interactions. This indicates the commonality of human mobility across different urban backgrounds, regardless of cultural and geographical differences. Thus, our proposed research method emphasizes this universality and points out its extendibility and value for other major metropolitan study areas.

7.3 Limitations of the study

Our research faces some implementation limitations. In terms of data collection, relying on current geospatial remote sensing and GIS technologies makes it difficult to accurately capture people’s trip purposes and transportation type at different times. Without cooperation with official institutions, the purchase cost of most required datasets is extremely high. Moreover, the gradual update and transformation of urban facilities may change people’s mobility patterns over time, causing biases in behavioral predictions for different periods. Finally, the datasets relied upon in this study all come from the same day, failing to reflect the impact of seasonal changes on humans’ mobility behaviors. Including additional features might effectively help predict mobility patterns at different times.

8 Conclusion

This study proposes improvements in the methodology for predicting human mobility's next location by emphasizing the role of trip purposes in time series to capture changes in mobility behavior patterns. It also considers individual static background information to enable the model to successfully differentiate between different mobility behavior patterns among groups. In terms of data processing and model design, besides incorporating geographic land use features to represent individuals' spatial characteristics, separating static and dynamic features allows the model to focus more on the dynamic changes in the series while retaining individual background information to reveal mobility behaviors.

Practically, the human mobility prediction framework developed in this study has demonstrated its broad adaptability and can be widely applied to different geographical areas. Characterized by low complexity and flexibility, this framework allows for effective data selection and preprocessing methods that accurately reflect human mobility patterns, further highlighting the importance and feasibility of this data processing strategy in successfully predicting human mobility behaviors. The core contribution of this research lies in its methodology, which can achieve high-accuracy prediction results even with a low-complexity model architecture, thus validating the decisive role of this methodology in the task of predicting next location in human mobility patterns.

For future research, by collecting human mobility data for specific areas and applying the methodology proposed in this study to these new data sets for retraining and adjustment, the prediction results will provide strong support for urban planning and business strategy formulation in various regions. This not only offers new perspectives for urban planning and business decisions but also promotes deeper exploration of business value, providing a solid scientific foundation and innovative direction for the development of urban economies.

9 References

Douglas do Couto Teixeira, A. C. V., Jussara M. Almeida. (2021). On estimating the predictability of human mobility: The role of routine. *EPJ Data Science*, 10(1), 49. https://doi.org/10.1140/epjds/s13688-021-00304-8

Gidófalvi, G., & Dong, F. (2012). When and where next: Individual mobility prediction. *Proceedings of the First ACM SIGSPATIAL International Workshop on Mobile Geographic Information Systems*, 57–64. https://doi.org/10.1145/2442810.2442821

Jamal, S., & Newbold, K. B. (2020). Factors associated with travel behavior of millennials and older adults: A scoping review. *Sustainability*, 12(19). https://doi.org/10.3390/su12198236

Ke, S., Xie, M., Zhu, H., et al. (2022). Group-based recurrent neural network for human mobility prediction. *Neural Computing and Applications*, 34, 9863–9883. https://doi.org/10.1007/s00521-022-06971-6

Lenormand, M., Arias, J. M., San Miguel, M., & Ramasco, J. J. (2020). On the importance of trip destination for modelling individual human mobility patterns. *J. R. Soc. Interface*, 17(2020), 20200673. https://doi.org/10.1098/rsif.2020.0673

Luca, M., Barlacchi, G., Lepri, B., & Pappalardo, L. (2021). A survey on deep learning for human mobility. *ACM Comput. Surv.*, 55(1). https://doi.org/10.1145/3485125

Montero, L., Mejia-Dorantes, L., & Barcelo, J. (2023). The role of life course and gender in mobility patterns: A spatiotemporal sequence analysis in barcelona. *European Transport Research Review*, 15. https://doi.org/10.1186/s12544-023-00621-1

Noulas, A., Scellato, S., Lathia, N., & Mascolo, C. (2012). Mining user mobility features for next place prediction in location-based services. *2012 IEEE 12th International Conference on Data Mining*, 1038–1043. https://doi.org/10.1109/ICDM.2012.113

Shi, S., Wang, L., Xu, S., & Wang, X. (2022). Prediction of intra-urban human mobility by integrating regional functions and trip intentions. *IEEE Transactions on Knowledge and Data Engineering*, 34(10), 4972–4981. https://doi.org/10.1109/TKDE.2020.3047406

Smolak, Kamil, Rohm, Witold, & Sila-Nowicka, Katarzyna. (2022). Explaining human mobility predictions through a pattern matching algorithm. *EPJ Data Sci.*, 11(1), 45. https://doi.org/10.1140/epjds/s13688-022-00356-4

Wang, P., Fu, Y., Liu, G., Hu, W., & Aggarwal, C. (2017). Human mobility synchronization and trip purpose detection with mixture of hawkes processes. *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 495–503. https://doi.org/10.1145/3097983.3098067

Wang, Z., Chen, X., & Chen, X. ((2019). Ridesplitting is shaping young people ' s travel behavior: Evidence from comparative survey via ride-sourcing platform. *Transportation Research Part D: Transport and Environment*, 75, 57–71. https://doi.org/https://doi.org/10.1016/j.trd.2019.08.017

Wilinski, A. (2019). Time series modeling and forecasting based on a markov chain with changing transition matrices. *Expert Systems with Applications*, 133, 163–172. https://doi.org/https://doi.org/10.1016/j.eswa.2019.04.067

Xie, P., Li, T., Liu, J., Du, S., Yang, X., & Zhang, J. (2020). Urban flow prediction from spatiotemporal data using machine learning: A survey. *Information Fusion*, 59, 1–12. https://doi.org/https://doi.org/10.1016/j.inffus.2020.01.002

Zheng, X., Han, J., & Sun, A. (2018). A survey of location prediction on twitter. *IEEE Transactions on Knowledge and Data Engineering*, 30(9), 1652–1671. https://doi.org/10.1109/TKDE.2018.2807840

Zhu, Z., Blanke, U., & Tröster, G. (2014). Inferring travel purpose from crowd-augmented human mobility data. *Proceedings of the First International Conference on IoT in Urban Space*, 44–49. https://doi.org/10.4108/icst.urb-iot.2014.257173

10 Appendix

I Original Dataset

Column	Column name	Format	Note
x_1	UserID	Integer	Sample ID
x_2	Trip No	Integer	Indicates single Origin-Destination movement
x_3	Sub trip No	Integer	Indicates single transport during trip
x_4	Timestamp	Datetime	Once per minute
x_5	Longitude	Decimal	WGS84
x_6	Latitude	Decimal	WGS84
x_7	Gender	Integer	1: Male, 2: Female, 9: Unknown
x_8	Age	Integer	Divided into five-year intervals. See Appendix II
x_9	Address Code	Integer	Indicates spatial area, (some areas confidential)
x_{10}	Work	Integer	For occupational coding, see Appendix III
x_{11}	Trip	Integer	For trip coding, see Appendix IV
x_{12}	Transport	Integer	For transportation mode coding, see Appendix V

II Age Group

Value	Age Range	Value	Age Range	Value	Age Range
0	0-5 years	6	30-35 years	12	60-65 years
1	5-10 years	7	35-40 years	13	65-70 years
2	10-15 years	8	40-45 years	14	70-75 years
3	15-20 years	9	45-50 years	15	75-80 years
4	20-25 years	10	50-55 years	16	80-85 years
5	25-30 years	11	55-60 years	17	Over 85 years

III Occupation

Value	Value Label
1	Agriculture, Forestry, and Fisheries
2	Product Processing and Labor Services
3	Sales
4	Service Industry
5	Transportation and Communication Services
6	Security Services
7	Clerical Work
8	Professional and Technical Work
9	Management
10	Other Professions
11	Kindergarten child, elementary school student, and middle school student
12	High school student
13	University student and vocational school student
14	Housewives and Househusbands
15	Unemployed
16	Others
99	Unknown

IV Trip

Value	Value Label	Value	Value Label
1	Commuting to work	9	Picking up / Dropping off
2	Commuting to school	10	Sales, delivery, purchasing
3	Going Home	11	Meetings, collecting payments
4	Shopping	12	Operational activities
5	Socializing and entertainment	13	Work of agriculture, forestry, fisheries
6	Travel and leisure	14	Other works
7	Hospital visits	99	Other
8	Other personal matters		

V Transportation

Value	Value Label	Value	Value Label
1	Walking	10	Bus or Express Bus
2	Bicycle	11	Monorail, New Transit
3	Motorcycle	12	Railway, Subway
4	Electric Bike	13	Boat
5	Taxi	14	Airplane
6	Private Car	15	Other
7	Light Vehicle	97	Stay
8	Transport Vehicle	99	Unknown
9	Private or Charter Bus		

VI Landuse type

Value	Value Label	Value	Value Label	Value	Value Label
0	Forest	3	Agricultural Land	6	Water Body
1	Grassland	4	Industrial Area	7	Other
2	Paddy Field	5	Urban Area	8	Ocean