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Context-Aware Deep Learning Model for Predicting Non-Mandatory Activity Locations

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by

Chenchen Kuai

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ABSTRACT OF THE THESIS

Context-Aware Deep Learning Model for Predicting
Non-Mandatory Activity Locations

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University of California, Los Angeles, 2024
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The explosion of mobile internet usage has generated vast amounts of data on users' spatiotemporal activities. This data is crucial for studying human movement, enhancing traffic management, and understanding epidemic spread dynamics. Our study aims to tackle the challenge of predicting locations for non-mandatory activities using mobile location data.

The thesis introduces the SageGRU model, which combines GraphSage with Attentional Gated Recurrent Units, to predict the next visiting Point of Interest (POI) for non-mandatory activities. SageGRU leverages historical visitation data, categorizes activity types, and considers temporal dimensions and global movement trends using POI-to-POI transition graphs. Validated with the Veraset dataset, SageGRU achieves 10.2% accuracy at predicting the top location, 20.8% for the top two locations, and 27.4% for the top three, significantly outperforming existing models.

This highlights the importance of comprehensive spatio-temporal context in predicting non-mandatory activity locations. SageGRU's capability to reconstruct real-life trajectories and aggregate travel patterns underscores its potential to advance urban mobility and public health planning by offering deeper insights into human movement.

The thesis of Chenchen Kuai is approved.

Regan Patterson

Tierra Suzan Bills

Jiaqi Ma, Committee Chair

University of California, Los Angeles

2024

To my parents . . .

who—among so many other things—

taught me how to see and feel the world

with the gentlest encouragement

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CHAPTER 1

Introduction

Human movement studies are fundamental to our society and an essential component of understanding societal challenges (Smolak et al., 2021), such as urbanization, urban activity, and epidemic spread (Pardo-Araujo et al., 2023). At the heart of the study on human mobility is predicting daily visited locations (Song, 2023). Predicting an individual's future location helps with a lot of downstream applications including traffic flow prediction (Shi et al., 2019), personalized recommendation systems (Sánchez and Bellogín, 2022), and network resource optimization (Li et al., 2021).

Despite its importance, next-location prediction is challenging and yet not fully tackled. Next location prediction requires capturing spatial and temporal patterns that characterize human habits (Barbosa et al., 2018). Also, accurate prediction requires combining heterogeneous data sources to model multiple factors influencing human displacements, including weather, travel modes, the presence of points of interest, and even the influence of friendships based on social networks (Cho et al., 2011). Focusing on the individual level, the theoretical predictability of mobility suggests that specific sections of location visits are difficult to predict based on mobility entropy measurements (Song et al., 2010).

1.1 Background of Next Location Prediction Problem

Activity-based models (ABMs) in urban planning delineate between mandatory (e.g., work) and non-mandatory (e.g., leisure) activities to predict travel patterns. These models prioritize activities, scheduling mandatory ones first due to their priority in people's daily planning (Guo et al., 2024). Mandatory activities typically have stable, predictable locations (Alexander et al., 2015). Non-mandatory activities, however, are characterized by their flexibility and randomness, posing a greater challenge for prediction (Benita, 2023). The decision mechanisms behind choosing locations for these two types of activities differ significantly. While the spatial dynamics of mandatory activities, such as the home-work relationship, have been extensively examined (Alexander et al., 2015; Wu and Hong, 2022), specific models for predicting non-mandatory activity locations remain underexplored.

Traditionally, pattern-based models have been applied to predict people's visiting locations and to capture the exploration and preferential return visit patterns and power law distribution of travel distance patterns. Despite the pattern-based approaches making good use of domain knowledge in the prediction, such models have limitations in making use of all informative features (Luca et al., 2023). The development of powerful Artificial Intelligence (AI) techniques and the availability of big mobility data offered unprecedented opportunities for researchers to use Deep Learning approaches to solve mobility-related challenges (Chen et al., 2020). Features of historical spatial and temporal context (Liu et al., 2016), representation of user networks and human social interactions (Kothari et al., 2022), and so on could be mined and incorporated in next location predictions to improve the performance.

The Mobile device location data has been used in recent human mobility studies recently (Fan et al., 2021), but has not been applied in next-location prediction yet. The fine-grained mobile phone data has a vast amount of dwelling points for anonymized devices, but not poi tagged, only with coordinates and timestamps.

The integration of activity-based models into urban and transportation planning (Jiang et al., 2018; Yu et al., 2020) represents a pivotal shift in understanding human mobility. These models suggest that human movements are intricately linked to the pursuit of specific activities at key locations, rather than being mere random traversals. By leveraging large-scale datasets, like mobile phone records, within the framework of activity-based modeling, researchers are able to reveal complex spatial patterns of human mobility that are invaluable for enhancing urban and transportation systems. Researchers (Yu et al., 2020) advanced this paradigm by embedding the semantic importance of locations—defined by their associated activities—into predictive models of location forecasting. This acknowledges the fundamental role of activity motivation in travel, a factor previously underappreciated in mobility models. Such a focus on the motivational underpinnings of travel, recognizing activities as the primary catalysts for movement, promises to refine prediction models and inform urban planning processes in profound ways. Nonetheless, the critical role of activities as a foundational element of human mobility has often been overlooked in research, despite its evident influence on the reasons behind travel behaviors.

This study aims to bridge the gap by the following steps:

1. Emphasizing activity types as predictors, acknowledging that the motivations behind movements are pivotal in understanding human travel patterns.
2. Utilizing a novel dataset replete with extensive human movement records, providing a granular view of mobility at a scale previously untapped.
3. Integrating historical information with a global transition graph of POIs into our

model framework, a strategy validated for its effectiveness in enhancing predictive accuracy.

4. Conducting thorough experiments that not only underscore the precision of our location predictions but also the adeptness of our model in mirroring actual travel patterns, culminating in the open-sourcing of our framework to foster further research and application in the domain of location prediction.

1.2 Related Work of Human Movement Models

Human mobility patterns are fundamentally regular in their spatial and temporal dimensions, often describable by statistical distributions. Research(González et al., 2008) have highlighted the predictability of aggregated human movements, suggesting a deep-rooted regularity in how people traverse spaces. This regularity stems partly from daily activities, which not only dictate the locations people visit but also the purposes behind these visits(Tian et al., 2023).

Traditional models, like the gravity model (Voorhees, 1956), offer insights into the movement flow between areas, though they tend to operate at an aggregated level, such as traffic flow between Traffic Analysis Zones (TAZs). These models, while foundational, often overlook the nuanced spatiotemporal dynamics at the individual level. Recent advancements have sought to address these limitations by incorporating concepts of activity space. Researchers (Zhang and Li, 2024) have introduce an innovative Activity Space-based Gravity (ASG) model that uses urban region attractiveness as a proxy, allowing for a more detailed analysis of mobility patterns. Similarly, a Spatiotemporal Flow Force Model (FFM) inspired by fluid mechanics principles has been proposed(Fang et al., 2024), specifically the Navier-Stokes equations, to describe human mobility flows within cities with greater precision.

At the individual level, the TimeGeo framework (Jiang et al., 2018) represents a significant leap forward. It leverages passive and sparse digital traces to model individual mobility with high spatio-temporal resolution, capturing the heterogeneous nature of travel choices through interpretable mechanisms and parameters. These developments signify a shift towards more granular, individual-focused models that accommodate the complex interplay of factors influencing human mobility. By bridging the gap between traditional aggregated models and the nuanced reality of individual movements, these innovative approaches offer a comprehensive understanding of human mobility patterns.

1.3 Related Work of Next Location Prediction Models

In recent years, the field of next location prediction has seen the emergence of diverse models leveraging deep learning techniques, utilizing datasets like Gowalla and Foursquare. Studies employing LSTM or RNN (Kong and Wu, 2018; Sun and Kim, 2021), focus on capturing sequential dependencies in human mobility. Attention mechanisms, highlighted in research (Hong et al., 2023), aim to identify critical features for prediction accuracy. Others (Tsanakas et al., 2024) also explore the use of knowledge distillation to create specialized prediction models. Additionally, graph methods are increasingly applied and researchers (Liu et al., 2023; Rao et al., 2022) proposing models that understand the complex interactions within POI-POI graphs or User-POI knowledge graphs, underscoring the evolving landscape of location prediction methodologies.

CHAPTER 2

Problem Formulation

Mobility data, typically collected through mobile devices, are processed to derive activity chains that inform next-location predictions. This section introduces key terms and notions fundamental to our discussion and formalizes the problem of predicting a user's next location.

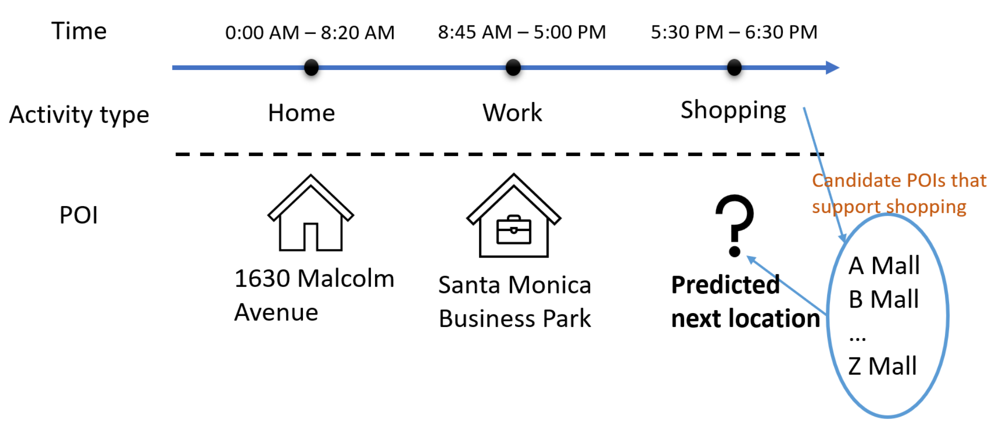

Figure 2.1: Overview of the process of next location prediction with prior knowledge of activity type and time.

2.1 Next Location Prediction Problem for Non-Mandatory Activities

Definition 1 (Activity Chain). For a user u within the set U of all users, an activity chain, $\mathcal{A}_u$, is a chronologically ordered sequence of N_u activities, represented as $\mathcal{A}_u = \{A_{1,u}, A_{2,u}, \ldots, A_{N_u,u}\}$. Here, $A_{n,u}$ denotes the n-th activity undertaken by user u.

Definition 2 (Activity). An activity, $A_{n,u}$, part of user u's activity chain $\mathcal{A}_u$, is characterized by a tuple $[p_{n,u}, t_{n,u}, s_{n,u}, e_{n,u}]$, where $p_{n,u}$ specifies the activity's location as a POI, $t_{n,u}$ its type, and $s_{n,u}$ and $e_{n,u}$ the start and end times, respectively.

Definition 3 (POI). The set of POIs, denoted as $\mathcal{P}$, is given by $\mathcal{P} = \{p_1, p_2, \ldots, p_N\}$, where each POI, p_j, is detailed by a tuple $[\mathrm{lon}_j, \mathrm{lat}_j, \mathrm{t}_j]$. This tuple includes the POI's longitude (lon_j) and latitude (lat_j), alongside the types of activities (t_j) it accommodates. The subset of POIs supporting a specific activity type t is denoted as $\mathcal{P}_t$.

Given these definitions, we now articulate the next location prediction problem.

Problem Statement (Next Location Prediction). The objective is to construct a predictive model, M, capable of forecasting the next activity's POI, $p_{n+1,u}$, for an individual u, based on their historical activity chain $\mathcal{A}_u$ and temporal context $[t_{n+1,u}, s_{n+1,u}, e_{n+1,u}]$ of the forthcoming activity. The model endeavors to identify the most likely POI, $p_{n+1,u}$, from $\mathcal{P}_{t_{n+1,u}}$, the set of POIs compatible with the anticipated activity type, $t_{n+1,u}$.

CHAPTER 3

GraphSage with Attentional Gated Recurrent Units (SageGRU) Model

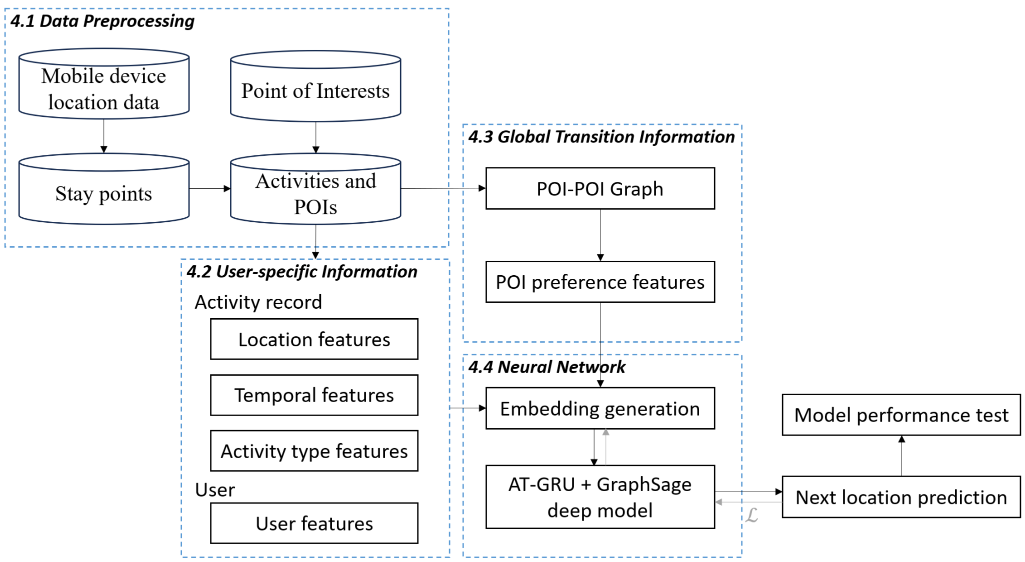

Figure 3.1: Overview of the proposed framework for location prediction. The framework outlines the process from data collection, preprocessing, feature extraction, and model development, to the evaluation of the model's performance.

The study proposes a neural network architecture that leverages contextual information to enhance the prediction of future locations. The architecture's pipeline is depicted in Figure 1. Initially, data preprocessing is conducted through stay point detection, activity type inference, and POI matching algorithms, as detailed in Section 4.1. The study then extracts historical visit patterns and user-specific features, as outlined in Section 4.2, and arranges these into sequential vectors. Additionally, we incorporate global transition information in Section 4.3 to construct a POI-POI graph, which aids in creating preference features for the current POI. The study employs an AT-GRU combined with GraphSage to effectively learn dependencies from historical sequences, user characteristics, and global transition patterns, thereby enhancing the prediction accuracy for the subsequent visit location, as elaborated in Section 4.4. A comprehensive description of each component of the model is provided in the subsequent sections.

3.1 Data Preprocessing

Our study utilizes the Veraset dataset, a compendium of mobile device data that includes location information in the form of longitude, latitude, and timestamps. This dataset is renowned for its granularity and accuracy, making it ideal for mobility studies. In conjunction with the PlantSense POI data, it forms the foundation of our preprocessing workflow.

The preprocessing begins with the extraction of mobile device records from the Veraset dataset. The records are points in space and time, marked by longitude, latitude, and timestamps. The initial phase involves applying a stay point identification algorithm to discern locations indicative of user immobility for a considerable duration. This process results in stay points characterized by their geographical coordinates and the associated start and end times.

The POI matching process leverages spatial and temporal data to correlate activities with specific locales. Rule-based algorithms(Alexander et al., 2015), deduce mandatory activities for stays, such as home, work, and school locations.

Home and Work Activities: These locations are identified based on the frequency of visits. Home locations are recognized during evenings and weekends, while work locations are determined by the maximum cumulative distance from the home during standard work hours on weekdays.

School Activities: A school location is pinpointed from a stay point that satisfies both the maximal distance criterion, similar to work locations and the presence of an 'education' POI within a 250-meter radius.

For other types of activities, POI matching algorithms are typically designed to select the nearest POIs. Our method involves the following steps:

1. *POI Local Candidate Pool Construction:* Identification of the three nearest POIs to create a candidate pool.

2. *Calculate POI Match Score:* Computation of a score incorporating the probability of an activity type based on its start time, the proportion of the type, and a spatial distance calculated using a Gaussian kernel.

3. *Final POI Match:* The POI with the highest score is selected, assigning the corresponding activity type to the stay point.

The score for a POI match is calculated using the following formula:

$$Score = P(t_i|T) \times \alpha \times e^{-\frac{(d-\mu)^2}{2\sigma^2}} \tag{3.1}$$

where:

Table 3.1: Activity types and their corresponding descriptions

Category	Description
1	Home activities (sleep, chores, etc) or Work from home
2	Work-related activity or Volunteer
3	Attend school
4	Attend child or adult care
5	Buy goods (groceries, clothes, gas)
6	Buy services (dry cleaners, banking, service a car)
7	Buy meals (go out for a meal, food, carry-out)
8	General errands (post office, library)
9	Recreational activities (visit parks, movies, bars)
10	Exercise (jog/walk, walk the dog, gym, etc)
11	Visit friends or relatives
12	Health care visit (medical, dental, therapy)
13	Religious or community activities
14	Something else
15	Drop off/pick up someone

- $P(t_i|T)$ is the conditional probability of activity type t_i given the start time T,
- α represents the proportion of the activity type t_i within the set of all activities,
- e is the base of the natural logarithm,
- d is the distance from the stay point to the POI,
- μ is the mean distance for the activity type t_i,

- σ is the standard deviation of the distance for the activity type t_i.

The non-mandatory activities and POIs are selected as the ones with the highest scores.

3.2 Integration of User-Specific Information

Each user profile is augmented with a history of site visitations alongside data on users' habitual locations, such as places of residence and employment. The model is designed to retain the most recent twenty entries of this visitation log; if a user's history is insufficiently expansive, reaching fewer than twenty records, the remaining entries are filled with a designated placeholder or 'mask'. The historical data are represented as a concatenation of spatial vectors V and temporal vectors T.

The spatial component V encapsulates longitudinal and latitudinal coordinates, along with the corresponding longitudinal and latitudinal displacements, signifying the distance traversed. Conversely, the temporal component T encompasses the commencement and conclusion times of the activity, the classification of the day (e.g., whether it is a workday), and the type of the activity. Temporal attributes related to the timing of activities are encoded via a Trigonometric Time Encoding scheme, which effectively captures the cyclical nature of daily and weekly patterns. This method transforms hours into a sinusoidal form, facilitating the model's interpretation of temporal continuity and periodicity.

Furthermore, users' fixed locations—namely their homes, workplaces, and educational institutions—are incorporated as persistent features within their profile, reflecting the long-term stability of these sites. Before integration into the model, all features undergo a normalization process to ensure homogeneity of scale across the dataset.

3.3 Integration of Global Transition Information

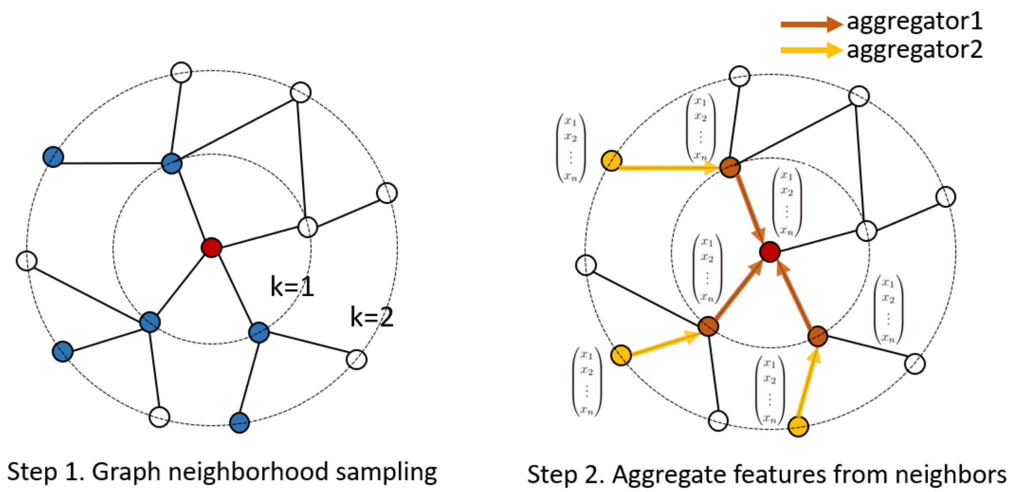

Figure 3.2: GraphSage sampling and aggregating approach illustration

The POI-POI transition graph is constructed to understand the movement patterns among various POIs. For each POI, the graph captures the preferences of next POIs by all visitors. The GraphSAGE algorithm is utilized to predict the next POI by generating embeddings through graph convolution. This method efficiently reduces computational expenses by sampling neighboring POIs and aggregating their information to provide an embedding for each centered POI.

The key steps, illustrated in Fig. 3, involve the centered POI aggregating information from its immediate neighbors and their neighbors in turn, which helps in generating a comprehensive embedding of the centered POI. These embeddings serve as crucial inputs for predicting movements between POIs.

The process of information aggregation within the GraphSAGE framework is formalized for a node i as follows:

$$x'_i = W_1 x_i + W_2 \sum_{j \in N(i)} e_{j,i} x_j$$

where $e_{j,i}$ denotes the edge weight from source node j to target node i, representing the historical transitions between POIs.

In a vectorized form, especially when considering a graph convolutional layer, this aggregation can be expressed as:

$$X' = \hat{A} X \Theta$$

Here, $\hat{A} = A + I$ is the augmented adjacency matrix that includes self-loops, allowing the inclusion of a node's own features in the aggregation process.

The graph under consideration includes nodes and edges where each node represents a POI, with features including longitude, latitude, visited frequency, median visited time, median leaving time, and activity type. Meanwhile, edges signify historical transitions between POIs, encapsulating the movement patterns among them. This structured approach facilitates an understanding of POI dynamics and assists in predicting future movements with enhanced accuracy.

3.4 Neural Network

The GraphSage and Attential Gated Recurrent Units (SageGRU) model (Fig. 4) combines the Attential Gated Recurrent Units for users historical visit information extraction and the GraphSage module for global transition information extraction

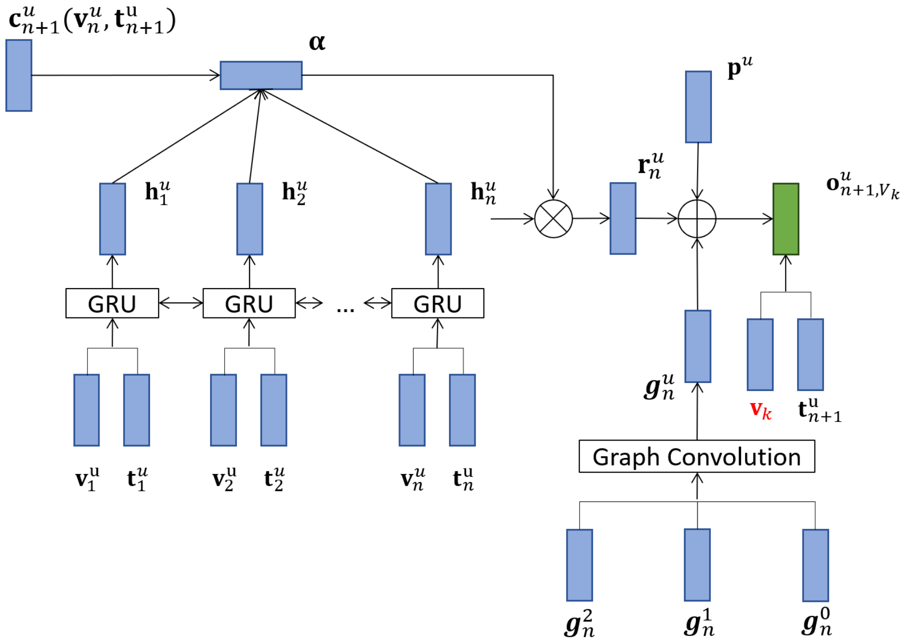

Figure 3.3: Neural network structure illustration

and from features.

Attential Gated Recurrent Units The model's Spatio-temporal feature extraction from historical user activity is a critical step in predicting future locations. The vectors obtained from these features carry essential information about the user's mobility patterns. To effectively utilize this information, it is necessary to understand the sequential dependencies present within the data. Our approach involves the use of an attention module, which is specifically designed to discern the most relevant features for location prediction.

The attention mechanism employed in our module relies on the dot-product attention function, which calculates the compatibility of each historical data point with

Table 3.2: Explanation of symbols in neural networks

Symbol	**Description**
v_i^u	Embedded POI visited by user u at time point i
t_i^u	Embedded temporal information by user u at time point i
v_k	Embedded POI of kth sample
h_i^u	The hidden vector of GRU unit
c_{n+1}^u	Embedded picking context by user u at time point $n+1$
p^u	Latent representation of user information u
g_n^u	Embedding of the global graph information on the current location
o_{n+1,V_k}^u	The probability of picking the kth POI sample at time point $n+1$ for user u

the context of future location choices. Formally, the attention function for the historical hidden vector h_i^u and the context vector for the subsequent location c_{n+1}^u is defined as follows:

$$f(h_i^u, c_{n+1}^u) = \frac{(h_i^u)^{\mathrm{T}} c_{n+1}^u}{\sqrt{d}}$$

The weight α_i corresponding to each hidden vector h_i^u is then calculated to measure how well the ith historical stay point matches with the context of the next stay point. This is expressed by:

$$\alpha_i = \frac{\exp(f(h_i^u, c_{n+1}^u))}{\sum_{j=1}^{n} \exp(f(h_j^u, c_{n+1}^u))}$$

Then, the output of the attention module is a weighted sum of the hidden vectors, yielding a composite hidden representation r_n^u of the user's historical visits. This is mathematically represented as:

$$r_n^u = \sum_{i=1}^{n} \alpha_i h_i^u$$

The weighted hidden representation r_n^u effectively captures the essence of the user's historical location patterns, which is then used to forecast future locations with higher precision. The attention module serves as a cornerstone in our predictive model, enabling it to discern and leverage the most significant factors that influence the user's location choices.

GraphSage Convolution The communal movement dynamics inherent to a POI is extracted by examining the connectivity patterns among neighboring nodes and their extensions. Graph convolution is employed to amalgamate contextually pertinent data, thereby delineating the typical movement routes and visitor behaviors at a particular POI. In the GraphSage schema, such an information synthesis for a convolutional stratum is mathematically represented as:

$$g_n^u = \hat{A} G_n^u \Theta$$

where G_n^u signifies the node features sourced from the graph with the context POI at its nucleus, and Θ denotes the trainable weight matrix of the deep learning graph framework. Consequently, the derived context vector g_n^u proficiently portrays the generalized movement patterns associated with the POI.

Score and Loss Function The predicted score for user u's visit to POI v_k at time point $n+1$ is calculated by the operation:

$$s^u_{(n+1,V_k)} = (W_N r^u_n + W_p p^u + W_g g^u_n)^{\mathrm{T}} \left(W_v v_k + W_t t^u_{(n+1)}\right)$$

Negative Sampling is employed in the model, distinguishing the visited POI (positive sample) from the non-visited ones (negative samples). The probability $p^u_{(n+1,V_k)}$ is obtained by applying a softmax function to the scores, where N_n is the size of negative samples and N_{n+1} is the total size of positive and negative samples:

$$p^u_{(n+1,V_k)} = \frac{e^{s^u_{(n+1,V_k)}}}{\sum_{j=1}^{N_{n+1}} e^{s^u_{(n+1,V_j)}}}$$

Given the predicted probabilities, the loss function L integrates cross-entropy loss, distance loss, and L2 regularization:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\log(p_{i1}) + \frac{\alpha}{N}\sum_{i=1}^{N}\sum_{j=1}^{n}[(D_{ij} - D_{i1})p_{ij}] + \frac{\lambda}{2}||\mathrm{param}||^2$$

Here, p_{i1} represents the probability assigned to the positive sample in the ith prediction, D_{ij} denotes the distance from the current location to the jth POI in the ith prediction, and D_{i1} indicates the distance to the positive sample POI.

Next POI prediction After incorporating negative samples into the training process, the model assigns a probability $p^u_{(n+1,V_k)}$ to each POI, indicating the likelihood that it will be the next location visited by a user. To incorporate the compatibility of the POI's activity type with user preferences, the model refines this probability by applying a type filtering mechanism. The final probability $P^u_{(n+1,V_k)}$ of a POI being the next destination is calculated as follows:

$$P^u_{(n+1,V_k)} = p^u_{(n+1,V_k)} \cdot T_S \cdot (T_P^T)$$

Here, T_S is a binary vector representing the POI's support for each activity type, with dimensions $[1, \text{all\_types}]$, where each element is either 0 (not supported) or 1 (supported), akin to a one-hot encoding scheme. T_P is a binary vector indicating the presence (1) or absence (0) of the specified next activity type for the user, also with dimensions $[1, \text{all\_types}]$.

The resulting probability $P^u_{(n+1,V_k)}$ provides a refined likelihood of each POI being the next visit, based on both the initial model prediction and the compatibility of activity types. POIs are then ranked by this final probability in descending order, with the top-ranked POI predicted as the user's next destination.

CHAPTER 4

Experiment Settings

4.1 Description of Veraset Mobile Location Dataset

The research utilizes the PlanetSense POI dataset in LA County, a comprehensive compendium of geographical locations following an extensive cleansing process. This dataset, now refined to contain 340,087 distinct POIs, serves as an instrumental component in our analytical undertakings, particularly in the domains of POI matching and location prediction.

This study utilizes a comprehensive dataset provided by Veraset, encompassing a complete record of mobile device locations within Los Angeles County for the period of February 1st to February 28th, 2019. The data captures the intricacies of user movement by employing sophisticated algorithms to identify stay points, consistent with the methodology delineated in Section 4.1. A key stipulation for inclusion in the analysis was that each user must exhibit a minimum of 15 recorded activities within the month-long timeframe, ensuring robustness in behavioral patterns captured.

The resultant dataset comprises 221,217 unique users and a total of 11,392,455 activity instances. Of these, 4,912,292 activities are classified as non-mandatory, reflecting a variety of discretionary movements. The aggregation and subsequent analysis of these activities have facilitated a comparison with the National Household

Travel Survey (NHTS) data for the Los Angeles area. Krishna2018

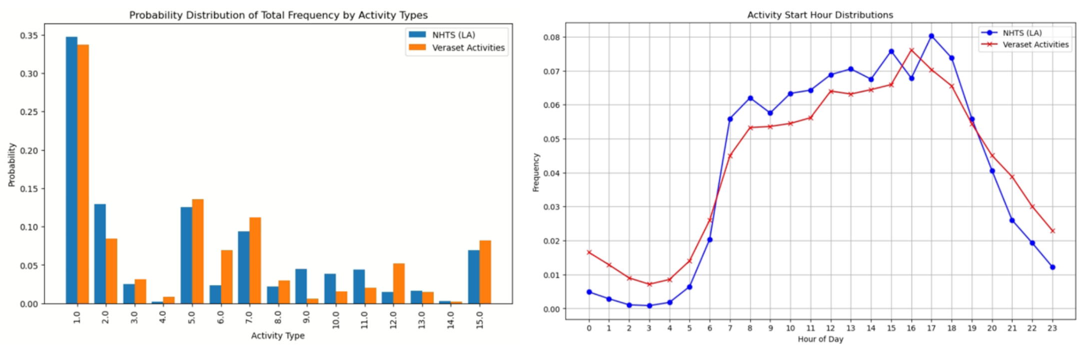

Figure 4.1: Comparative data description with the National Household Travel Survey illustrating LA's activity patterns.

A salient finding from the dataset analysis is the increase in activity frequency during night hours. This nighttime activity surge, as indicated by our data, can be correlated with the prevalent mobile device usage during these hours, such as eating out and home activities. The comparison illuminates the efficacy of our algorithm and confirms the general mobility patterns observed within the region. Moreover, the findings provide valuable insights into urban dynamics and user behavior, underscoring the potential of mobile device data to inform transportation planning and policy-making.

4.2 Model Evaluation Measurements and Benchmark Models

After training with negative samples, we finally apply the model to the scenario of all possible POIs and rank the scores. The following evaluation matrices help define the model's performance in the prediction.

Accuracy. It measures the correctness of the predicted location compared to the ground truth of the next visited location. Practically, we rank the location probability vector $\hat{P}(l_{n+1})$, obtained from Eq. (5), in descending order and check whether the ground truth location appears within the top-k predictions. Acc@k measures the proportion of times this is true in the test dataset. In location prediction literature, this metric is also referred to as Recall@k or Hit Ratio@k. We report Acc@1, Acc@5, and Acc@10 to allow comparisons with other work.

JSD of the distance distribution For the predicted POIs, the measurement measures the distance distribution from the last POI to the observed POI and the distance distribution from the last POI to the predicted next POI. The measurement is able to check the prediction is able to provide good general human mobility travel distance patterns.

<d km Rate The rate measures the probability that the distance from the predicted next POI to the observed next POI is smaller than d km, which could indicate how close the prediction is to the observed.

We evaluate the efficacy of our proposed model by benchmarking against deep learning-based models reported in contemporary literature that address this problem:

- LSTM. A classical deep learning architecture for sequence modeling, LSTMs are extensively employed and recognized as one of the foremost models for predicting subsequent locations, as evidenced by studies from (Krishna et al., 2018; Solomon et al., 2021; Xu et al., 2021). They maintain a continuous hidden state and sequentially process the input data, which enables them to capture temporal dependencies effectively.

- Attention-Based Spatiotemporal LSTM Network (ATST-LSTM). The ATST-LSTM (Huang et al., 2021) employs an attention mechanism that selectively concentrates on pertinent historical check-in data within a sequence by leveraging spatiotemporal context.

- AT-GRU. While AT-GRU forms the fundamental structure of the SageGRU that we have implemented, it is used as a comparison benchmark in the absence of graph information knowledge.

4.3 Training Configurations

In our research, activity chain data was divided into training, validation, and test sets with ratios of 60%, 20%, and 20% respectively, ensuring a comprehensive evaluation framework. A specific focus was placed on predicting non-human activities within the dataset. One activity chain is set with multiple predictions. Model training utilized an NVIDIA V100 GPU, optimizing the balance between computational efficiency and learning effectiveness.

The configuration for model training included a batch size of 15, facilitating an optimal balance between memory usage and model update granularity. A learning rate of 0.0002 was chosen to ensure a steady approach towards optimal loss minimization. To prevent overfitting and promote generalization, a dropout rate of 0.6 and a regularization parameter of 0.002 were applied. Additionally, the model employed a k-nearest neighbors algorithm with $k = 100$ and a sampled subgraph technique with `num_neighbors` set to [3,3]. A negative sampling strategy incorporating 500 filtered-type negative samples, evenly split between difficult and easy samples, was implemented to enhance the model's discrimination capability.

4.4 Activity Chain Reconstruction with SageGRU Model

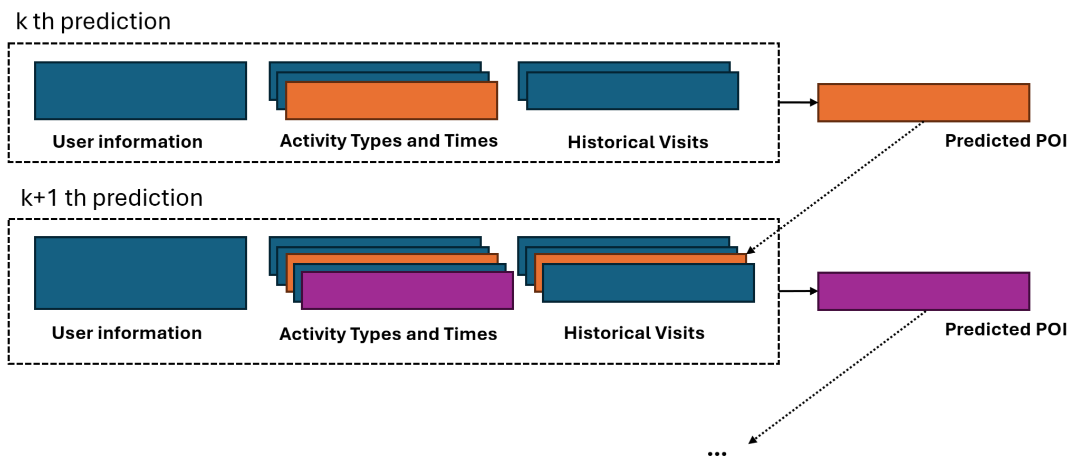

Figure 4.2: Illustration of sequential prediction with next location prediction model

In this study, we also implemented a sequential prediction framework that extends the capabilities of the next location prediction model. Our approach leverages an autoregressive model that uses past location data and user-specific information to forecast a series of future POIs. The sequential prediction model generates forecasts for non-mandatory activities by incorporating each user's predicted previous POI as an additional contextual feature for subsequent predictions.

The autoregressive nature of the sequential prediction facilitates the reconstruction of individual activity chains, providing detailed insights into human mobility and location preferences. Through iterative predictions and the integration of user-specific data, the model aims to capture the complex interdependencies of locations within an individual's daily routine. The efficacy of our sequential prediction approach is evaluated on its ability to replicate realistic activity chains, thereby contributing to our understanding of spatial travel behavior.

CHAPTER 5

Results

5.1 Performance Results

We first present the prediction performance for all considered methods in Table 2. For each learning-based model, we train the model and record the best performance of the model structure after testing parameters.

Table 5.1: Performance comparison of models on next location prediction.

Model	Acc@1	Acc@5	Acc@10	Distance JSD	<0.1km Rate	<1km Rate
LSTM	5.4%	14.3%	19.5%	0.336	9.3%	44.0%
ATST-LSTM	6.0%	14.8%	20.2%	0.315	10.0%	47.5%
AT-GRU	6.3%	14.4%	19.6%	0.322	10.2%	47.2%
SageGRU	**10.2%**	**20.8%**	**27.4%**	**0.257**	**14.8%**	**49.3%**

Compared with other deep learning baselines, the SageGRU model outperforms in all metrics, suggesting a significant advancement in predictive accuracy. Specifically, SageGRU achieves the highest accuracy rates at 10.2% for Acc@1, 20.8% for Acc@5, and 27.4% for Acc@10. These improvements indicate that SageGRU is notably better at predicting the exact next location as the first choice and within the top 5 and 10 predictions compared to the LSTM and attention-based models. Also, the improvement in the prediction between SageGRU and AT-GRU indicates the effectiveness of Global transition information in such predictions.

Furthermore, the Jensen-Shannon Divergence (JSD) for SageGRU is the lowest at 0.257, implying that the probability distribution of SageGRU's predictions closely aligns with that of the true distribution of the observed data. This metric, particularly relevant in the context of location data, reflects the model's ability to understand and recreate the natural variance in human mobility patterns.

The rates of predicting a location within a 0.1km and 1km radius are significantly better as well. With a 1km rate of 49.3%, the SageGRU demonstrates a high level of accuracy in terms of Transportation Analysis Zone (TAZ) level prediction. This is indicative of the model's utility in practical applications, such as urban planning and location-based services, where TAZ-level accuracy is often sufficient.

The distance distribution, as visualized in the figure, further corroborates the model's proficiency. The majority of predictions fall within a 5km distance from the observed points of interest, with a steep decline in frequency as the distance increases. This distribution suggests that the SageGRU model is proficient at capturing the common patterns in the data, such as the tendency for subsequent locations to be within a certain proximity of previous points of interest. Such a characteristic is particularly useful for predicting human movement within urban areas, where most activities are likely to occur within a relatively condensed geographical space.

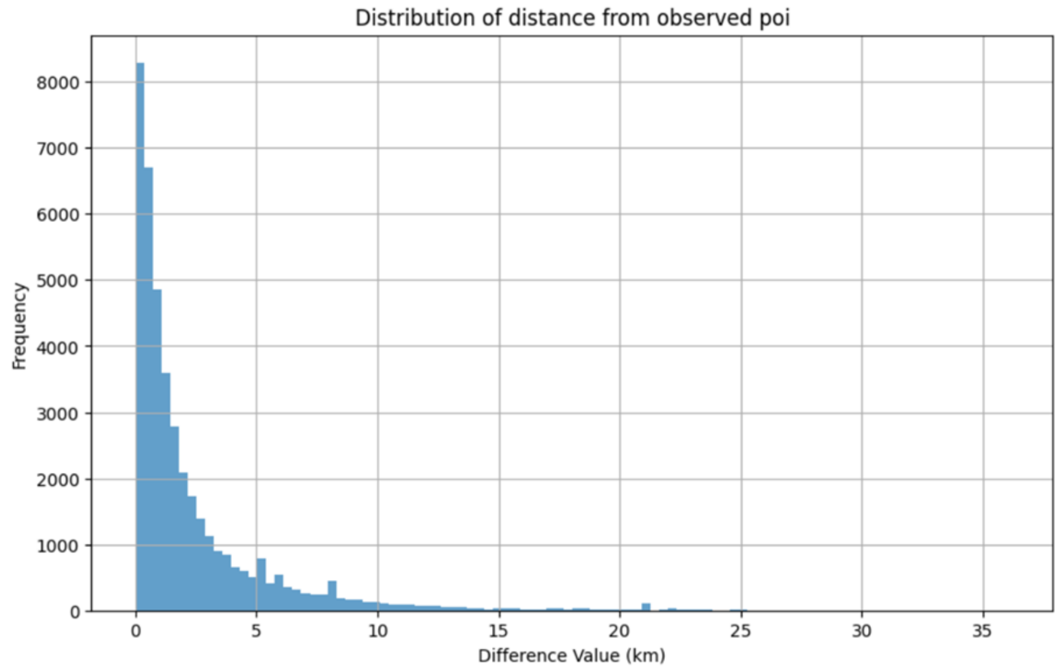

Figure 5.1: Distance distribution from the predicted next poi to the observed next POI

5.2 Impact of Negative Sampling Methods

Negative sampling plays a pivotal role in training our model by enabling it to differentiate the observed next POI from a pool of potential negative samples. In our study, we carefully curate these samples based on their probability of being the next POI, with a specific focus on ensuring they support the type of activity predicted to occur next.

We categorize the negative samples into two groups: 'Difficult' and 'Simple'. Difficult samples consist of POIs within a 20km radius from the last location, presenting a higher challenge for the model to distinguish due to their proximity. On the other hand, simple samples are those beyond this 20km threshold, which aids in enhancing the model's general performance by covering a broader range of less likely locations.

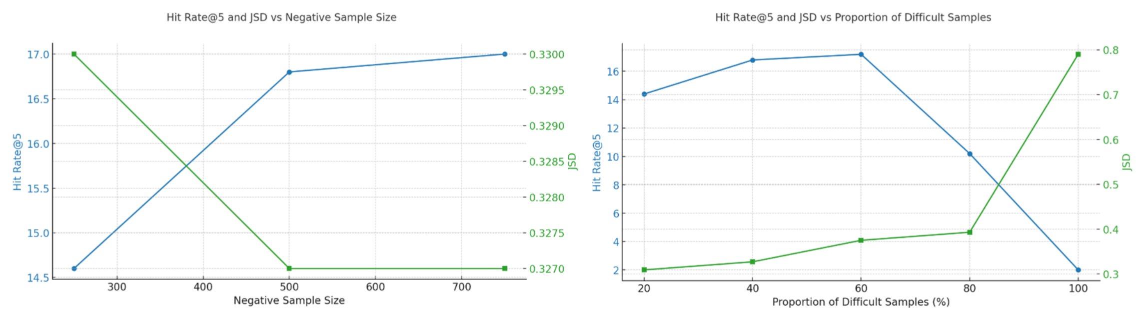

Figure 5.2: Test of different negative sampling parameters: left: Sample size Right: Proportion of difficult samples

Literature suggests that having a balanced mix of difficult and simple samples is imperative for a model's ability to discern effectively while maintaining overall performance. The proportion of these samples can be fine-tuned for optimal results. Specifically, a greater proportion of difficult samples tends to increase the hit rate, whereas the best performance for the Jensen-Shannon Divergence (JSD) of travel distance is observed with a lower proportion of difficult samples.

Experimentally, we determine that the inclusion of more negative samples can lead to improved prediction outcomes. Our evaluations show that sample sizes of 500 and 750 yield comparable performances, indicating a plateau beyond which additional samples may not contribute to significant gains.

Consequently, we adopt a configuration of 40% difficult samples within a total of 500 negative samples for training our model. This setting has been chosen to balance the trade-offs between accuracy and the ability to capture distributional characteristics of travel distances.

5.3 Activity Chain Reconstruction Performances

The application of the sequential prediction methodology leverages the SageGRU model to reconstruct activity chains for non-mandatory activities, providing insight into its predictive capacity on a macroscopic scale. The focus on aggregated data allows for an evaluation of the model's competence in capturing overarching trends rather than granular, individualized predictions.

As evidenced in Fig. 9, the spatial distribution of predicted POIs exhibits a high degree of correlation with the actual data observed, particularly within the densely populated southern region and West Los Angeles. These areas demonstrate a pronounced pattern of visitation frequency, underscoring the model's effectiveness in identifying areas of high activity engagement.

Further, Fig. 10 presents the Origin-Destination (OD) pairs as forecasted by the model, with a clear demarcation of the central activity hubs. This visual representation confirms the SageGRU model's adeptness at discerning spatio-level predictions, substantiating its utility in urban planning and mobility studies. The model's predictive ability aligns with the actual spatial dynamics, thus affirming its applicability in the context of non-mandatory activity flows.

The findings underscore the potential of the SageGRU model as a tool for understanding urban mobility patterns, with implications for the planning of transport systems and the allocation of resources within urban environments. The congruence between predicted and observed data sets serves as a testament to the model's ro-

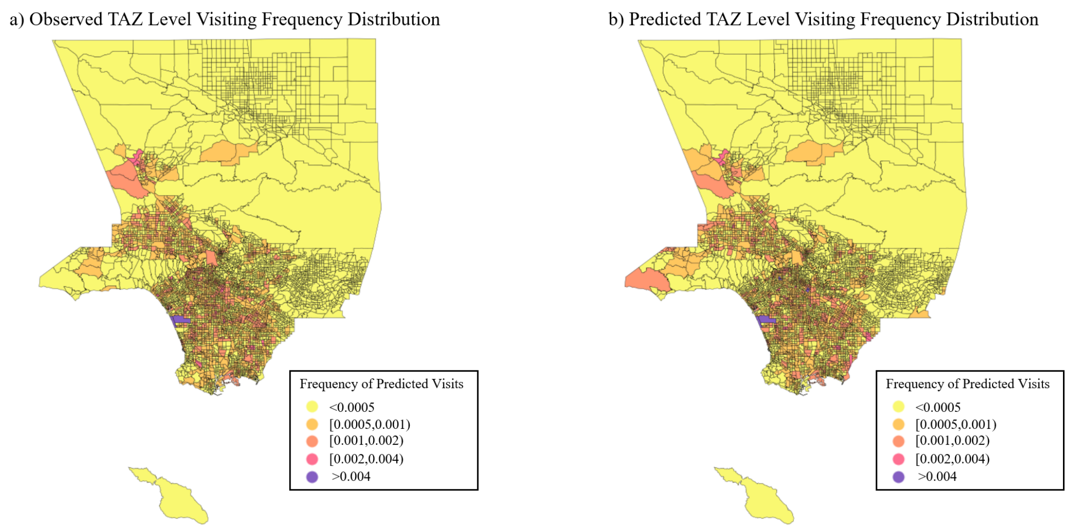

Figure 5.3: TAZ level visiting frequency comparison between observed visits in the dataset and predicted visits with sequential prediction

bustness, setting a precedent for further research into the refinement of predictive algorithms within the domain of urban analytics.

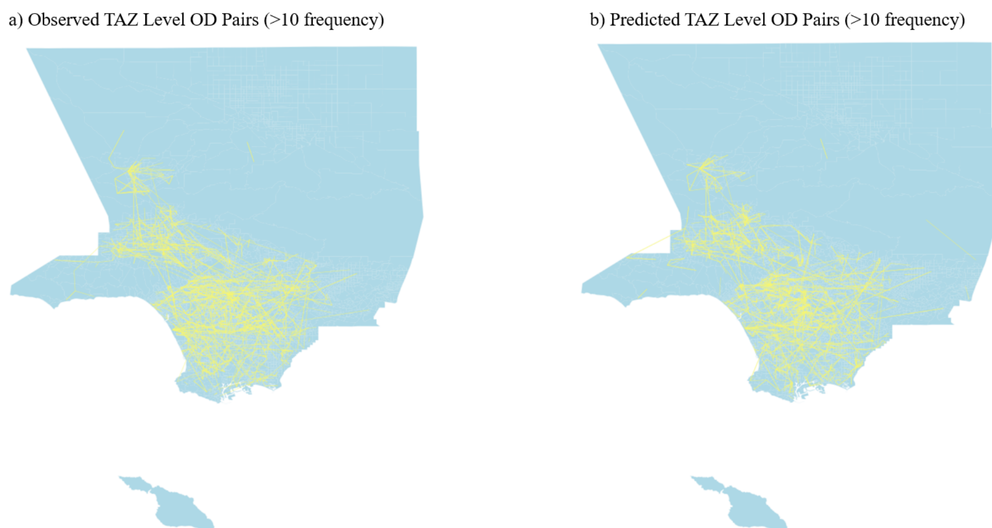

Figure 5.4: TAZ level OD pairs distribution comparing between observed visits in the dataset and predicted visits with sequential prediction

CHAPTER 6

Discussion and Conclusion

Our study introduces a novel predictive model that leverages the advanced structural capabilities of GraphSage and Attential Gated Recurrent Units (SageGRU). This model has been specifically designed to incorporate the richness of temporal context and user activity patterns in making precise location predictions. The distinctive characteristic of our approach lies in the construction of activity chains, which are essential in understanding individual mobility patterns and are central to our predictive model. By focusing on reconstructing activity chains, our model goes beyond mere location prediction to capture the sequence of locations a user is likely to visit.

In comparison to traditional models such as LSTM and ATST-LSTM, our SageGRU model showcases superior performance in single-point predictions. This is evident from its higher accuracy in pinpointing the exact next location. The model operates under the premise that a robust understanding of temporal dynamics is crucial for accurate location prediction, and as such, the predictions are made with prior knowledge of temporal context, which is unique in the landscape of location prediction studies.

The efficacy of the SageGRU model is not limited to individual predictions; it also exhibits commendable performance on an aggregated level. The model adeptly captures general human mobility and travel distance patterns, which is substantiated by our experimental results showing the distribution of distances from predicted to observed POIs aligning closely with real-world data.

The accomplishments of this study are manifold. By utilizing a sophisticated neural network architecture, we have addressed the unique challenge of next-location prediction, a task that is integral to understanding human mobility. Our model, with its state-of-the-art approach to processing spatiotemporal data, has set new benchmarks for accuracy in both individual predictions and aggregated travel patterns.

However, the current research is based on some assumptions of human movement patterns: everyone has only one home and one work/school location. This may limit the study, as it does not account for individuals who do not have a fixed work location or those who are shift workers. These cases should be studied and discussed to improve the current model.

In conclusion, the proposed SageGRU model stands as a testament to the power of deep learning in the realm of predictive analytics. Its ability to reconstruct activity chains and predict future locations with high precision marks a significant stride forward in our understanding of human mobility. As we continue to explore the vast potential of AI in this domain, the foundational work presented in this study paves the way for even more sophisticated and impactful research in the future.

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