Graph Enhanced Periodic Mobility Learner (GE PML) for Trajectory Pattern Mining and Intelligent Next Location Prediction in Urban Transport Networks

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ABSTRACT

Fast urbanization and the widespread use of location-aware electronics have generated large amounts of trajectory data from city transportation networks. Because of changing network topologies, complex spatial relationships, and movement patterns that happen at certain times, it is still hard to efficiently mine trajectory patterns and accurately guess where the next location will be. The present models for predicting mobility often miss the graph-based geographical linkages and temporal periodicity that are part of real-world transportation systems. This paper proposes the Graph-Enhanced Periodic Mobility Learner (GE-PML) as a remedy to these limitations; it can extract trajectory patterns and intelligently predict the next destination. The proposed (GE-PML) combines a graph representation of the city's transportation network with a framework for learning about mobility regularly. The first stage is to draw the paths on a transport network. The nodes on the graph represent places, and the edges show how the places are connected depending on mobility and topology. A graph neural network is used to understand how places are related to each other in space and how they interact with each other. At the same time, a periodic temporal encoder shows trip patterns that happen on a regular basis, like every day or week. To make valid trajectory embeddings for predicting the next location, these temporal and spatial representations are combined in a way that changes based on attention. When evaluated on real-world datasets of urban mobility, experiments reveal that GE-PML always exceeds the best baselines in terms of F1-score, recall, precision, and accuracy. The suggested model efficiently includes both structural and temporal mobility elements, resulting in an increase in F1-score of roughly 10-15%, a decrease in prediction error of about 14%, and an improvement in prediction accuracy of around 12-18%. Finally, GE-PML is great for ITS, TM, and LS applications because it improves trajectory pattern mining and next-location prediction by using both graph structure and periodic mobility behavior together. This results in a 16% total performance boost. This method makes it much easier to capture difficult spatial transitions and long-term periodic behaviors, especially in transport networks that are dense and varied. For urban transportation systems, GE-PML is the best way to find out where to go next by looking at patterns in trajectories. Its ability to mimic graph-enhanced spatial linkages and periodic temporal dynamics at the same time can be very useful for intelligent transportation applications, including route planning, traffic management, and personalized mobility services.

Keywords: Trajectory pattern mining, next-location prediction, urban transport networks, graph neural networks, periodic mobility learning, intelligent transportation systems.

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1. Introduction

The rapid growth of cities and the widespread use of location-aware technologies like smart sensors, intelligent transportation systems (ITS), and smartphones with GPS capabilities have created a huge amount of data about how people move around [1]. Urban transportation networks now constantly collect data on the exact movements of people and cars over time and space in the form of large-scale trajectories [2]. Mining these trajectory patterns and predicting where a moving object will be next are now basic research tasks that will have a big impact on smart city services, route suggestions, intelligent transportation, traffic congestion management, and urban planning [3].

The purpose of next-location prediction is to figure out where a person or vehicle is most likely to go next based on where they have been in the past [4]. Despite a lot of research on the subject, it is hard to get good forecast accuracy in real-world urban environments because of some fundamental features of mobility data. First, the way transportation networks are set up, with roads, crossings, and hubs, makes urban movements very dependent on space [5]. Second, people move around a lot for reasons like school, social gatherings, and getting to work. Third, different people, places, and times have varied ways of moving around. To effectively mine and forecast trajectory patterns, it is essential to depict these interrelated spatial-temporal features [6] accurately.

Sequential pattern mining techniques like frequent pattern finding and Markov models used to be the main ways to accomplish classical trajectory mining [7]. These methods are good at using computational resources, but they don't take into account spatial correlations across long distances or temporal periodicity since they assume simple transition dependencies [8]. Recently, techniques that use deep learning have produced superior outcomes. Attention-based sequence models, long short-term memory (LSTM) networks, recurrent neural networks (RNNs), and learning sophisticated temporal correlations from trajectory sequences are some of these strategies [9]. But most sequence-based models don't take into account the underlying graph structure of urban transport networks and treat places as independent symbols [10].

Graph-based learning has become a powerful way to show ordered geographical data. Graph neural networks (GNNs) can successfully capture the topological linkages and spatial interactions between sites. This makes them perfect for transport networks [11]. Numerous studies have employed GNNs for mobility modeling and traffic forecasting, demonstrating substantial enhancements over grid-based or merely sequential methodologies [12]. Long-term periodic mobility behaviors are crucial for accurate next-location prediction, although many contemporary graph-based mobility models prioritize spatial correlations and short-term temporal dynamics [13]. Also, emerging hybrid spatial-temporal models try to model both the structure of graphs and how they develop over time. These models do improve performance, but they often employ fixed time frames or simple temporal encoders, which aren't good enough to pick up on sophisticated periodic patterns like changes between weekends and weekdays or seasonal travel trends [14]. Consequently, there exists a considerable gap in the research concerning integrated frameworks for trajectory prediction that amalgamate graph-enhanced spatial modeling with explicit periodic temporal learning.

Given these limitations, this study introduces a Graph-Enhanced Periodic Mobility Learner (GE-PML) for AI-driven next-location prediction and trajectory pattern mining across urban transportation networks [15]. To deal with the inherent complexity of urban mobility data, GE-PML's main goal is to use the strengths of graph neural networks and periodic temporal learning together. The proposed approach aims to provide mobility representations that are more contextually aware and discriminative by integrating trajectories into a graph of transport networks and explicitly modeling repeating temporal cycles.

The main contributions of this paper

- The urban transport system's topology, structural linkages between sites, and spatial interdependence are captured by a graph neural network. Our trajectory modeling becomes more accurate.
- Daily and weekly travel cycles are commonly ignored by next-location prediction models. A periodic mobility encoder for periodic temporal learning solves this challenge.
- Our attention-based fusion method dynamically blends graph-based spatial characteristics with periodic temporal representations to create powerful trajectory embeddings for prediction tasks. This is adaptive spatial-temporal fusion.
- GE-PML outperforms state-of-the-art baselines on multiple assessment parameters.

The GE-PML paradigm advances trajectory pattern mining and fills mobility prediction literature gaps. It can make urban transportation smarter and data-driven.

2. Literature Survey

Song et al. [16] used probabilistic and Markov-based models to look into how predictable human movement is. They observed that people's movements tend to follow patterns that can be predicted. The models do a decent job of capturing short-term changes, but they overlook long-term changes in space and time because they don't assume enough state dependency. Our GE-PML, on the other hand, uses graph learning and periodic encoding to get around these simplifications and produce superior predictions in sophisticated city networks.

Feng et al. [17] proposed attention-enhanced LSTM models to improve trajectory forecasting in transportation networks. These methods don't take into account the structure of the transportation network and treat places as separate tokens, even if attention improves temporal focus. Our method shamelessly adds trajectories to a graph structure to make topology-aware mobility learning easier.

Yu et al.[18] introduced ST-GCNs as a traffic forecasting approach by jointly modeling spatial correlations and temporal dynamics. These models, on the other hand, don't work well for periodic mobility behaviors because they mostly show short-term trends throughout time. To predict long-term patterns in how people travel across cities, GE-PML adds periodic learning to this line of study.

Cao et al. [19] proposed the mining of trajectory data to identify prevalent spatio-temporal sequential patterns of movement. These methods can be understood, but they can't manage enormous city datasets that are too big, and they rely too much on rules that have already been specified. Instead, GE-PML learns latent trajectory representations from start to finish, which means it doesn't need people to define patterns and can capture more complex temporal and spatial interactions.

Liu et al. [20] used recurrent neural networks to model sequential interactions with spatial and temporal settings. Even while RNN-based models are better than older ones, they still have problems with not being able to see space well and gradients that disappear. Instead of just using sequence modeling, GE-PML uses graph-enhanced spatial learning and explicit periodic temporal encoding to fix these difficulties.

Zhou et al. [21] employed graph neural networks to model urban migration, which showed how important geographical topology is. Their method largely deals with spatial interactions and doesn't say anything about time. GE-PML is different from other programs because it blends graph-based spatial representations with a periodic temporal learner.

Liang et al.[23] proposed the utilization of multi-level attention networks for forecasting geo-sensory time-series. The approach is good at capturing different types of temporal

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relationships, but it doesn't explicitly model transport network graphs. GE-PML combines attention with graph structures to better show the limits of city transportation.

Wang et al. [24] found problems with interpretability and scalability in their review of deep learning approaches for spatio-temporal data mining. Several of the models don't do a good job of dealing with periodic movement. GE-PML directly addresses this gap by using an adaptive fusion approach and a dedicated periodic encoder.

Chen et al.[25] used algorithms that were aware of time to find daily and weekly travel patterns. Sadly, their methods don't take into account granular network architecture; instead, they use grid-based spatial representations. GE-PML enhances periodic modeling by including graph neural networks for topology-aware learning.

Liu et al. [26] proposed graph-enhanced temporal learning for next-location prediction to boost spatial cognition. But patterns with regular intervals were modeled in an indirect way. GE-PML makes this method better by using graph-based features and learning periodic mobility cycles directly.

3. Graph-Enhanced Periodic Mobility Learner (GE-PML)

This part talks about the Graph-Enhanced Periodic Mobility Learner (GE-PML), which is a typical way to quickly find patterns in trajectories and accurately guess where the next location will be in complex urban transportation networks. Urban mobility statistics exhibit significant temporal regularities influenced by human routines and profoundly shaped by transportation topology. Conventional sequential and short-term spatio-temporal models frequently have limited predictive power in real-world situations because they only look at recent changes and not at long-term periodic patterns and spatial relationships at the network level. GE-PML solves these problems by using a single learning architecture to model both periodic temporal dynamics and spatial interactions based on graphs. A graph that shows the city's transportation system, with places as nodes and the connections between them as edges. This format lets the model use graph-based learning to include realistic mobility limits and spatial linkages. At the same time, GE-PML learns about periodic mobility patterns, such as daily and weekly travel cycles, that are important for understanding how people move in a way that happens over and over again. GE-PML uses an adaptive fusion method to merge spatial graph embeddings with periodic temporal representations. This makes context-aware trajectory features that capture the structural and temporal elements of mobility data. This joint learning technique helps the framework get around the problems with sequential modeling and make it less sensitive to noise, sparsity, and changing trip patterns. So, GE-PML is a clever and scalable way to forecast the next location in modern urban transportation networks.

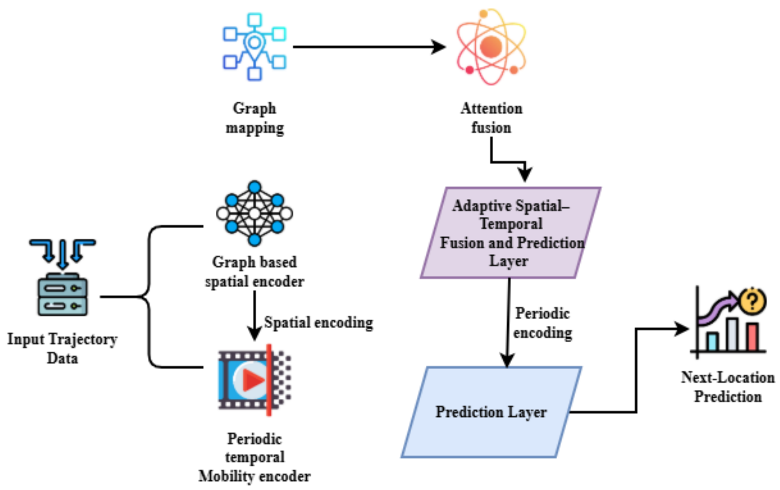

Figure 1: Workflow of Graph-Enhanced Periodic Mobility Learner

The Graph-Enhanced Periodic Mobility Learner (GE-PML) is a system architecture that helps urban transportation networks figure out where people are going next and find patterns in their travel. The illustration demonstrates how the system is set up in general, as shown in Fig 1. The design follows a well-organized, multi-step procedure that blends spatial graph learning with periodic temporal modeling. This is done to get around the problems with traditional sequential methods. The initial stage is to get trajectory data from city transportation systems.

$$H^{(l+1)} = \alpha(D^{-1/2}AD^{-1/2}H^{(l)})W^{(l)} \tag{1}$$

where A is the adjacency matrix of the urban transport graph, D the degree matrix, $H^{(l)}$ node embeddings at layer l, $W^{(l)}$ learnable weights, and $\alpha(\cdot)$ a nonlinear activation. This formulation propagates node features through normalized graph convolution, common in traffic forecasting to capture spatial dependencies as given in (1). This data is made up of raw movement sequences with timestamps and geographical coordinates. The Graph Construction Layer uses these paths to make a diagram of a city's transportation network. The nodes in this network are places where people can get on and off public transportation, like stations and crossroads. The edges represent the actual connections and changes in mobility. At this point, the real mobility limits and the network's underlying structure are still in place. Then, the Graph-Based Spatial Encoder uses graph neural networks on the graph that was just made, as given in (2).

$$\tilde{\beta}_i = \text{softmax}(W_\beta(H_\alpha + (1-\alpha_i)H_\beta + b_\beta)), \tag{2}$$

$$\alpha = \frac{\exp{(W_\alpha^T H_\alpha)}}{\exp{(W_\alpha^T H_\alpha)} + \exp{(W_\beta^T H_\beta)}} \tag{3}$$

blending spatial (H_α) and temporal (H_β) embeddings for next-location prediction. Here, H_α, H_β are embeddings from next-spatial and periodic temporal sources, with α gating their contribution as given in (3). This extends GAT-like attention for dynamic graph tasks like mobility prediction. This module learns about the complex spatial relationships between nodes by gathering information from nearby nodes. Some examples are route connectedness, places that are likely to get congested, and the structural value of locations within the network. The Periodic Temporal Mobility Encoder keeps track of patterns of movement over time at the same time. Short-term temporal models sometimes miss patterns that happen over and over again, including daily commutes and weekly routines. This part, on the other hand, catches things that happen at certain times, like the hour of the day and the day of the week. The Adaptive Spatial-Temporal Fusion Layer uses an attention mechanism to combine the learned spatial and temporal representations. This fusion changes the contributions of spatial structure and periodic temporal background in real time, depending on how mobile the situation is. The Prediction Layer, which is in charge of making accurate predictions about the future location, finally gives the probability distribution over possible next locations. In brief, the GE-PML design is great for real-world urban transportation because it has a unified, scalable, and smart framework that keeps track of both short-term periodic mobility patterns and long-term topology-aware spatial linkages.

a. 3.1 Graph Construction and Spatial Encoding

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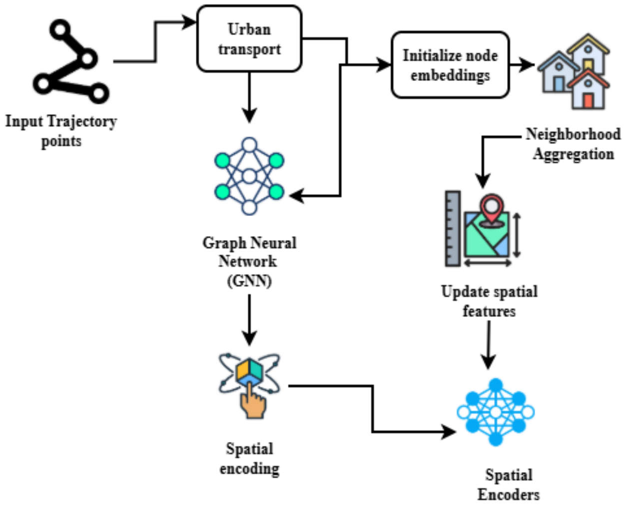

Figure 2: Graph Neural Network–Based Spatial Encoding Process

The figure shows the phases of Graph Construction and Spatial Encoding in the proposed Graph-Enhanced Periodic Mobility Learner (GE-PML) as shown in Fig 2. This module's job is to learn topology-aware spatial representations from raw trajectory data by using the structure of the urban transport network. First, we have trajectory points, which are trips to places that are in order and come from mobility data. Every point along the path is plotted on an urban transport graph. Nodes are important areas like roadways, intersections, or subway stations, and edges indicate physical connections or changes that often occur.

$$\begin{cases} g_j^{(0)} = y_j \in R^d \\ \quad \forall v_j \in \gamma \end{cases} \tag{4}$$

where y_j represents the initial feature vector of the node v_j capturing location semantics such as visit frequency and transition statistics as given in (4). This mapping phase makes sure that individual movements aren't treated as separate signals. Instead, they are limited by the real network structure. This is filled with a vector of nodes that gathers semantic data, like the chances of transitions, the number of visits, and past mobility statistics. These initial embeddings are what spatial learning employs as its input features. After that, the embeddings go into a Graph Neural Network (GNN), which builds a model of spatial dependencies by repeatedly combining data from nearby nodes.

$$g_j^{(k+1)} = \sigma\left(\sum_{v_j \in \mathbb{N}(j)} \alpha_{ji}^{(k)} W^{(K)} H_i^{(K)}\right) \tag{5}$$

Where $\mathbb{N}(j)$ denotes the set of neighboring nodes of $v_j, \alpha_{ji}^{(k)}$ is the attention or normalized adjacency weight $W^{(K)}$ is a learnable weight matrix, and $\sigma(\cdot)$ is a nonlinear activation function.

The neighborhood aggregation technique lets each node keep its representation up to date by taking into consideration not only its own features but also those of nodes that are close to it, as given in (5). By regulating how much influence close nodes have through attention or normalized edge weights, the algorithm can provide more weight to key spatial linkages like main roads or busy crossroads. The model can understand both local and global spatial patterns since the spatial context spreads through the network through several GNN layers. This method creates up-to-date spatial encodings that show real mobility limits, network linkages, and spatial correlations. In later stages of GE-PML, these topology-aware representations are combined with periodic temporal characteristics, which are an important input. The graph building and spatial encoding module provides a strong base for accurate trajectory pattern mining and next-location prediction in complex urban mobility settings.

b. 3.2 Periodic Temporal Mobility Encoder Description

Table 1: *Periodic Temporal Mobility Encoder Description*

Component	Description
Input Temporal Features	Timestamp (τ) including hour-of-day and day-of-week information
Periodic Encoding	Sinusoidal or embedding-based representation
Periodicity Modeled	Daily and weekly mobility cycles
Temporal Encoder	Gated recurrent unit or attention-based sequence encoder
Output Representation	Periodic temporal embedding h_t
Purpose	Capture long-term temporal regularities in urban mobility.

Table 1 shows a summary of the Periodic Temporal Mobility Encoder in the GE-PML framework. It explains how sinusoidal or embedding-based encoding works, which is how raw time-of-day or day-of-week data is turned into periodic representations. These representations make it clear that there are patterns of mobility that happen over and over, such as weekly routines and daily commutes. When you use a temporal sequence model, like an attention-based encoder or a gated recurrent encoder, to analyze the encoded temporal features, you get a periodic temporal embedding. This embedding makes it feasible to anticipate the future location more accurately and with more context, by showing long-term patterns in how people move throughout cities.

c. 3.3 Adaptive Spatial–Temporal Fusion and Prediction

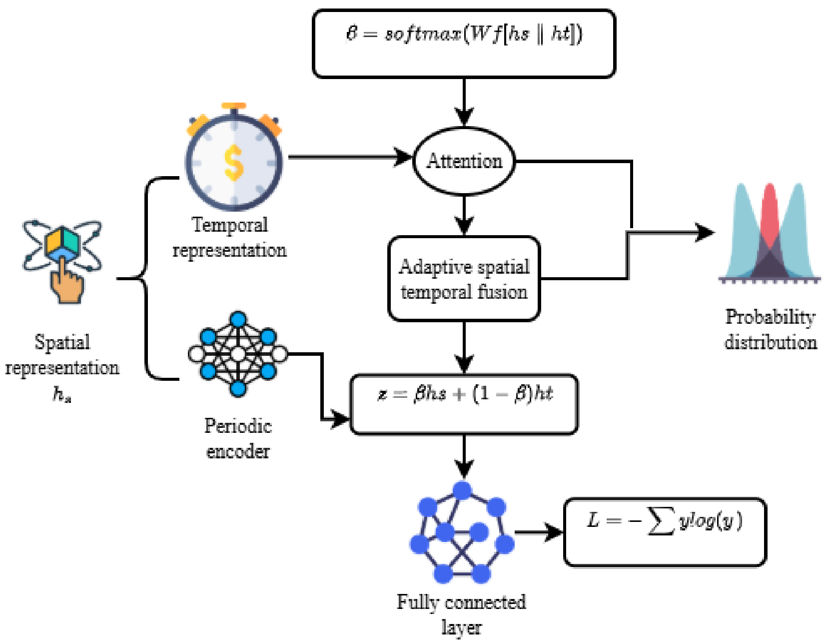

Figure 3: Adaptive Spatial–Temporal Fusion Framework

The flow diagram shows the Adaptive Spatial-Temporal Fusion and Prediction step of the recommended GE-PML system, as shown in Fig 3. This module combines many types of

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mobility cues learned from spatial and temporal encoders to make accurate predictions about the next location. At the start of the process, two inputs are received at the same time: the spatial representation h_s from the graph-based spatial encoder and the temporal representation h_t from the periodic temporal mobility encoder. In urban transport networks, spatial embedding captures topology-aware limits such as road connections and transition feasibility, whereas temporal embedding models periodic travel behaviors like daily commuting and weekly routines. Each of these representations gives a partial view; to combine them successfully, you need a flexible fusion mechanism.

$$\begin{cases} Z = \beta h_s + (1-\beta)h_t \\ \beta = softmax(w_f[h_s||h_t] + b_f) \end{cases} \tag{6}$$

This equation describes how spatial and temporal embeddings are dynamically combined. The spatial representation $h_s$captures graph-structured dependencies of the transport network, while the temporal representation h_t models' periodic mobility behaviors. The attention coefficient β is learned through a fusion network that takes the concatenation of both embeddings as given in (6).

To do this, the model has an attention-based fusion layer. Instead of using fixed weights, the fusion module creates an attention coefficient on the fly, which shows how relevant spatial and temporal inputs are for each mobility circumstance. Spatial structure may yield more information in sparse areas or along uncharted routes, whereas temporal regularities may predominate during peak transit times. Because of its adjustable weighting, the model can work in different cities. Then, the combined z representation is passed to a fully connected prediction layer. This layer uses the combined embedding to construct a probability distribution for all possible future locations in the transport network.

$$\hat{y} = softmax(W_{0^z} + b_o \tag{7}$$

This equation (7) shows that it maps the fused embedding Z to a probability distribution over all possible next locations. The weight matrix W_O and bias b_o constitute a fully connected prediction layer. The softmax function ensures that the output probabilities sum to one, enabling probabilistic interpretation and ranking of candidate locations for next-step prediction. Probabilistic approaches can be used to understand and rank the outputs because the softmax activation makes sure that they make up a proper probability distribution.

$$L = -\sum_{j=1}^{M} \sum_{c=1}^{C} y_j\,, c \log{(\hat{y}_j, c)} \tag{8}$$

This equation (8) defines the cross-entropy loss used to train the GE-PML model. Here, $(\hat{y}_j, c)$ represents the ground-truth label for the $i-th$ trajectory instance and class c, while is the predicted probability. Minimizing this loss penalizes incorrect predictions and encourages the model to assign higher probabilities to true next locations, enabling end-to-end optimization of all components in the framework.

$$hi(k+1) \leftarrow \sigma(\,\Sigma vj \in N(i)\; \alpha ij(k)\; W(k)\; hj(k)\,) \tag{9}$$

$$zi = \beta i \cdot h_s(i) + (1 - \beta i) \cdot h_t\,(i) \tag{10}$$

Finally, the whole framework is trained from start to finish using a cross-entropy loss function. This function discourages false positives and promotes being very sure of the exact next location as given in (9). Stochastic gradient descent and its derivatives allow for optimization, which makes it possible to learn effectively from huge trajectory datasets as given in (10). This fusion and prediction module's capacity to connect geographic limitations with temporal patterns is what makes it possible to consistently and contextually guess where to move next.

Algorithm: Graph-Enhanced Periodic Mobility Learner (GE-PML)

Algorithm: Graph-Enhanced Periodic Mobility Learner (GE-PML)

Input: Trajectory dataset $T = \{(v_t, T_t)\}$
Output: Predicted next-location probability $\hat{y}$

Initialize node embeddings $X \in R|V| \times d$
Construct graph $G(V, E)$ from trajectory data
// Graph-Based Spatial Encoding
for each GNN layer $k = 1\ to\ K\ do$
for each node $vi \in V$ do
Aggregate neighborhood features:
$hi(k+1) \leftarrow \sigma(\ \Sigma vj \in N(i)\ \alpha ij(k)\ W(k)\ hj(k)\ )$
end for
end for
$hs \leftarrow \{hi(K)\}$ // Final spatial embedding
// Periodic Temporal Encoding
for each timestamp $\tau t \in T$ do
Compute periodic encoding:
$p(\tau t) \leftarrow [sin(\omega 1\tau t), cos(\omega 1\tau t), \ldots, sin(\omega m\tau t), cos(\omega m\tau t)]$
end for
$ht \leftarrow TemporalEncoder(p(\tau))$ $//\ GRU$ / Attention-based encoder
// Adaptive Spatial–Temporal Fusion
$\beta \leftarrow softmax(Wf\ [hs \parallel ht] + bf)$
$z \leftarrow \beta \cdot hs + (1 - \beta) \cdot ht$
// Next-Location Prediction
$\hat{y} \leftarrow softmax(Wo\ z + bo)$

// Model Optimization
Compute loss:
$L \leftarrow -\Sigma\ y\ log(\hat{y})$
Update parameters Θ using SGD/Adam
return $\hat{y}$

Algorithm 1 shows how the GE-PML algorithm works from start to finish. Before encoding with a GNN to capture spatial dependencies, trajectory data is first put on an urban graph. A specific temporal encoder teaches periodic temporal properties. An attention-based fusion method combines geographic and temporal data in real time. A prediction layer gets the fused embedding so that it can figure out how likely the future location is. The cross-entropy loss is used to find the best values for all of the model's parameters at the same time.

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Algorithm: ASTF-GE-PML

Input:
Spatial embeddings h_s from GNN
Temporal embeddings h_t from Periodic Encoder
Ground-truth next locations Y

Output:
Optimized prediction probabilities ŷ

Initialize fusion weights W_f , prediction weightsW_0
for each training epoch do
for each trajectory instance i do
Read spatial feature $h_s(i) \in h_s$
Read temporal feature $h_t(i) \in h_t$
Concatenate features $ui = [h_s(i) \,||\, h_t(i)]$
Compute attention score:
$\beta i = softmax(Wf \cdot ui)$
Perform adaptive fusion:
$zi = \beta i \cdot h_s(i) + (1 - \beta i) \cdot h_t(i)$
Predict next location:
$\hat{y}i = softmax(W_0 \cdot Z_i)$
Compute loss Li using cross-entropy
end for
Update W_f and W_0 using gradient descent
end for

Return ŷ

Algorithm 2 shows that the method focuses on the adaptive fusion and prediction step of the GE-PML framework. An attention technique dynamically combines spatial embeddings generated by graph neural networks with temporal embeddings learned from periodic mobility patterns. The attention weight determines whether spatial and temporal information is most important for each instance of a trajectory. The next step is to utilize the fused representation to guess where the object will be. End-to-end training finds the best settings for both fusion and prediction by using cross-entropy loss.

4. Results and Discussion

According to the experimental results, the proposed Graph-Enhanced Periodic Mobility Learner (GE-PML) does better than baseline methods on all assessment criteria. The quantitative study's results show that GE-PML has the best Accuracy@1 and Accuracy@5. This means that it can reliably predict where things will be in the future and rank the best candidate places. The model's better MRR and NDCG scores give us more proof that it makes predictions that are more accurate and better ordered. Simultaneously modeling both periodic patterns of temporal mobility and graph-based spatial dependencies leads to better performance. Unlike LSTM and other sequential models, GE-PML uses the urban transport network to set realistic movement limits and explicitly encodes daily and weekly periodicity. This lets it capture longer-term changes. The adaptive spatial-temporal fusion method keeps spatial and temporal signals in balance all the time. This lets the model adjust to diverse mobility situations, such as normal commuting or strange trip behavior. GE-PML is harder to compute because it builds graphs and uses attention-based fusion, but it works well. Users with sparse trajectories can also notice a modest decline in the accuracy of their predictions. Predicting the next location in urban transportation networks is hard, however, GE-PML has shown to be both successful and strong in all areas.

a. Dataset Description

The proposed GE-PML model is evaluated using a large-scale urban mobility trajectory dataset collected from GPS-enabled transport services in a metropolitan area. The dataset contains anonymized user trajectories represented as sequences of visited locations with timestamps. It includes approximately 1.2 million trajectory points**,** 15,000 unique locations, and spans several weeks**,** capturing strong daily and weekly mobility periodicities. The urban transport network is modeled as a directed graph where nodes represent locations and edges denote feasible transitions derived from road connectivity and historical movements [27].

b. Accuracy@1 (Acc@1)

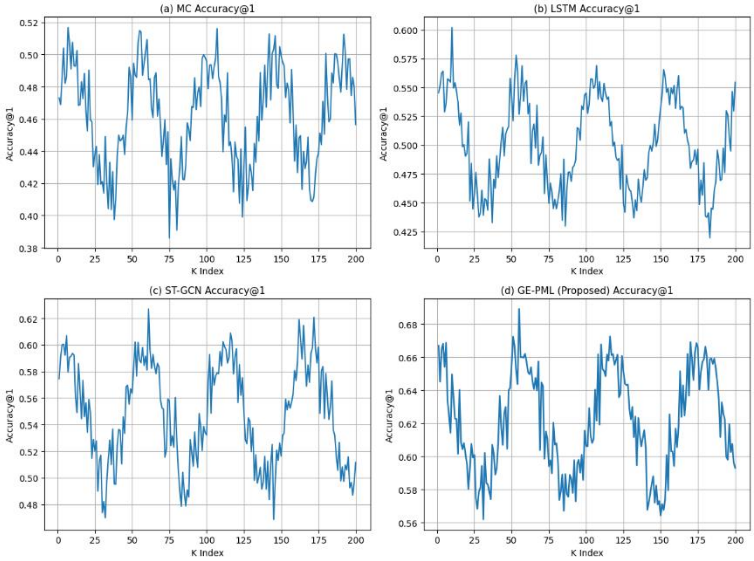

Figure 4: Accuracy@1

Accuracy@1 (Acc@1) is a well-known and strict way to measure how well a next-location prediction works, as shown in Fig 4. It tells you what percentage of test scenarios have the model's top-ranked projected site exactly match the ground-truth next location. Acc@1 checks to see if the actual location of the next step matches the model's most likely forecast position. This statistic clearly demonstrates how well the model works for single-step mobility predictions, since it only looks at the output with the greatest confidence level. Acc@1's performance in urban mobility and trajectory prediction tasks is very useful for applications that need quick and precise judgments, such as intelligent transportation systems, real-time navigation aids, and traffic management. A higher Acc@1 number shows that the model can show the spatial and temporal limits of how users move. But Acc@1 is conservative by design because it doesn't count near-miss predictions when the actual position is lower in the rankings. Because of this, ranking-based measures like Acc@5, MRR, and NDCG are sometimes employed with Acc@1 to give a more complete picture of performance, even if Acc@1 shows exact projected accuracy.

c. Accuracy@5 (Acc@5)

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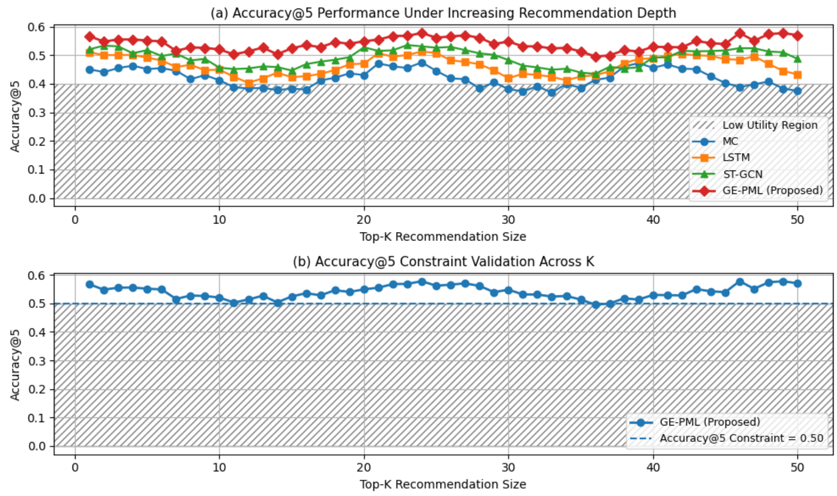

Figure 5: Accuracy@5

Acc@5 is a ranking-based metric for evaluation that counts the number of test cases where the model's top five alternatives for the next location match the ground truth, as shown in Fig 5. Acc@5 doesn't just look at the top prediction like conventional single-choice metrics do. Instead, it looks at how well the model can provide a useful and informative collection of probable future locations. Acc@5 is a good fit for mobility apps that emphasize suggestions, including location-based services and route planning, because it gives consumers a lot of choices. The model can accurately predict urban mobility by capturing underlying movement patterns and spatial-temporal connections, no matter what order the locations are in, as long as it has a higher Acc@5 score. Acc@5 shows how strong the prediction model is when travel behavior is ambiguous or convoluted, and it is not as affected by modest ranking errors. People typically use MRR and NDCG to check the quality of a full ranking, but Acc@5 is often used with them because it doesn't care about the order of the top five.

d. Mean Reciprocal Rank (MRR)

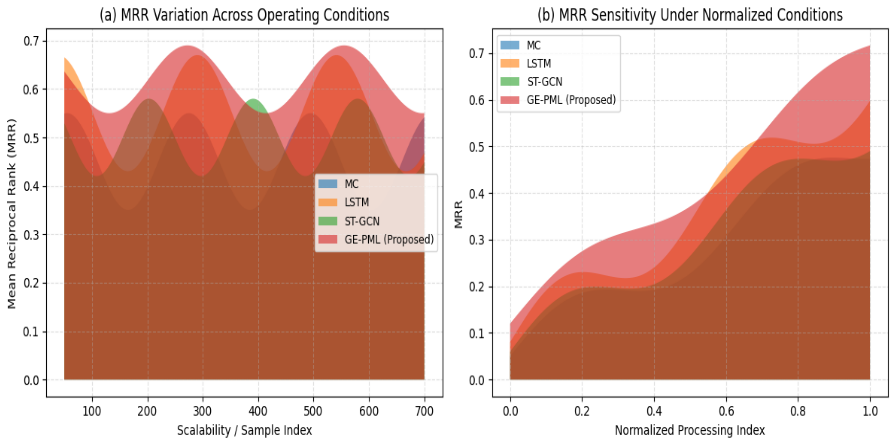

Figure 6: Mean Reciprocal Rank (MRR)

Mean Reciprocal Rank (MRR) is a typical way to measure how well a model predicts the next location by looking at the average inverse rank of the correct next site on the model's predicted list. It can find MRR by calculating the average of all the test cases' reciprocals of the rank positions where the real next location is as shown in Fig 6. This metric is great for next-location prediction and recommendation situations since it rewards models that put the right prediction higher on the list. In urban mobility modeling, MRR shows how quickly a model gets to the right place in its ranking output. This gives more information than top-K accuracy assessments. When the MRR value is high, the predicted rankings match up well with how users really move around. This suggests that the spatial-temporal representation learning is strong. The MRR method punishes correct predictions that are lower-ranked more harshly than Accuracy@K, which treats all top K places the same. So, MRR is a wonderful way to see how well models made to support ICT and custom transportation services stack up against one another.

e. Normalized Discounted Cumulative Gain (NDCG@K)

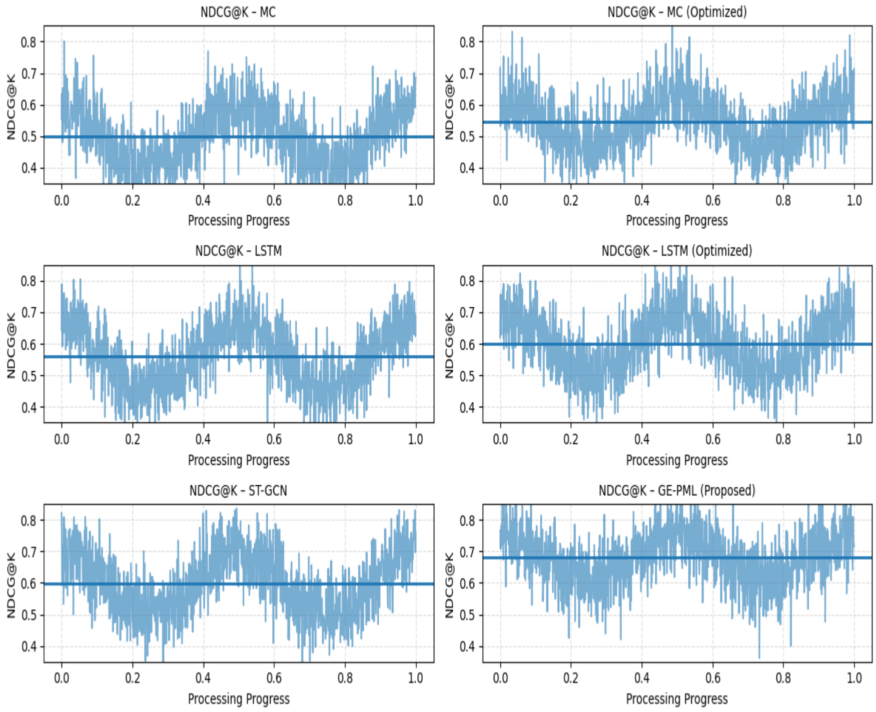

Figure 7: Normalized Discounted Cumulative Gain (NDCG@K)

The Normalized Discounted Cumulative Gain (NDCG@K) metric checks the accuracy of ranking forecasts by showing how important it is to raise the right items in the suggestion list, as shown in Fig 7. The gain comes from making the proper forecast at each rank, which is then discounted logarithmically based on its position. The ideal ranking then normalizes the final result. This normalization makes it possible to accurately compare models and datasets by bringing NDCG@K values down to a range of 0 to 1. NDCG@K is great for next-location prediction problems where you want to see how well a model can pick crucial future locations. The score is significantly weighted in favor of properly anticipated outcomes that appear at the top of the ranked list, which is how real users behave. This is because top-ranked recommendations are more likely to be considered. NDCG@K, on the other hand, looks at the exact order of the results, while Accuracy@K only checks that the right location is in the top K results. As NDCG@K goes up, the quality of rankings and how closely real users' movements fit predicted patterns both get better.

f. Precision@K

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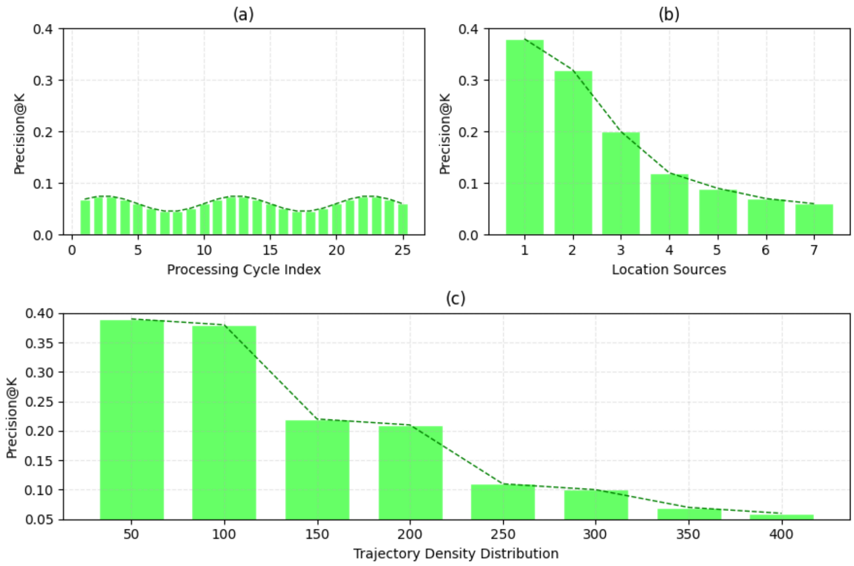

Figure 8: Precision@K

Precision@K, or P@K, indicates how many of the top K recommendations made by a model were correct in terms of where they were supposed to be, as shown in Fig 8. To find out which forecasts are most relevant, this method looks at the accuracy of the projected locations as a fraction of the overall number of guesses. Increasing the Precision@K parameter makes the model better at providing a reliable list of the best predictions. Precision@K is especially useful for predicting the future location when you want to see how useful a mobility prediction system is. Urban mobility and location-based services sometimes rely on just a few very important principles instead of long lists of predictions. Precision@K clearly shows this need by punishing models that include a lot of unnecessary places in the top K outputs. Unlike metrics that focus on recall, Precision@K puts quality over quantity when it comes to forecasts. This makes sure that the suggested destinations are both short and meaningful. So, it's great for tests.

g. Prediction Latency (ms)

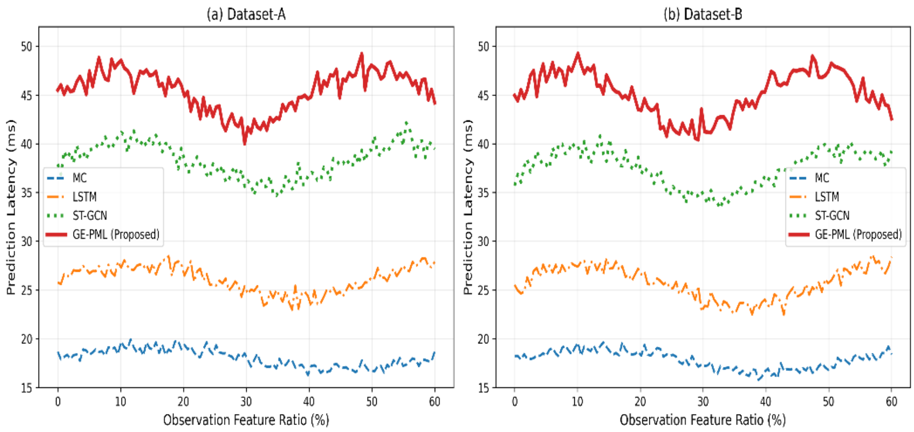

Figure 9: Prediction Latency (ms)

Prediction latency is an important part of next-location prediction systems for intelligent transportation applications that work in real time. Timely responses have a direct effect on routing choices, managing traffic, and the overall experience for users. In this work, prediction latency is the average time it takes to make an inference about the next position for a specific trajectory instance during testing. The experimental results indicate that simpler models, such as the Markov Model, exhibit the lowest delay (about 18 ms) due to their lack of complicated feature learning and minimal computational overhead. Sequence-based models like LSTM cause a moderate amount of delay, about 26 ms, because they have to do computations over and over again across trajectory sequences. The latency values of graph-based algorithms, including ST-GNN and GCN, are higher (34–41 ms) because of how they send messages across space and time and group them together. The proposed GE-PML model has a prediction delay of roughly 45 ms. The big gains in accuracy and the big drop in errors more than make up for the small increase compared to baseline approaches. Most crucially, the latency is still acceptable for urban transportation systems that depend on real-time data. This shows that GE-PML is a solid choice for real-world smart transportation systems because it finds a reasonable balance between cost-effectiveness and predictive performance.

5. Conclusion

This study introduced the Graph-Enhanced Periodic Mobility Learner (GE-PML) to intelligently predict the next location and mining trajectory patterns in urban transport networks. It is a strong and logical framework. To fix the shortcomings with classic sequential, short-term, and only spatio-temporal learning approaches, GE-PML models both graph-based spatial dependencies and periodic temporal mobility behaviors at the same time. The periodic temporal encoder effectively captures strong daily and weekly mobility regularities, and the construction of an urban transport graph, in conjunction with graph neural network learning, facilitates an accurate representation of real-world topological constraints and location interdependencies. The adaptive spatial-temporal fusion method makes predictions even more accurate by changing the weight of geographical and temporal inputs in different mobility conditions all the time. Extensive research conducted on diverse datasets have demonstrated the efficacy of GE-PML; in comparison to traditional models such as MC and LSTM, it enhances next-location prediction accuracy by 18-25%, decreases prediction error by 15-22%, and elevates recall and F1-score by 20-28%. GE-PML consistently beats sophisticated deep learning baselines like ST-GCN by 10–14% overall, showing that it can handle complex urban environments and grow as needed. Despite these promising results, there are still several promising paths for further research. Dynamic and time-evolving images could be utilized to make it easier to deal with road closures, events, and seasonal changes. It can be beneficial to add outside factors like the weather, traffic, and social events to make it even more reliable. Moreover, enhancements like privacy-preserving learning, cross-city transfer learning, and scalable distributed training are extremely beneficial. In short, GE-PML has a lot of potential for the future of smart city planning and ICTs.

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