Map-Matching is No Longer Needed: An End-to-End GPS-based Traffic Speed Prediction

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1 INTRODUCTION

Traffic speed prediction is a highly relevant research area that is crucial both for government agencies and for research (Tedjopurnomo *et al.*, 2020). Existing methods primarily involve spatial-temporal analysis to make future predictions relying on historical traffic dynamics. Recently, efforts have been made to capture traffic variance with the incorporation of trajectories that demonstrate drivers' preferred routes (Yang *et al.*, 2022, Li *et al.*, 2021). Vehicle trajectories are typically composed of GPS sequences with latitude and longitude coordinates, which are analyzed to be collected deviating from roads with low sampling rates. This will pose a threat to imprecise trajectories from map-matching techniques, which inevitably degrade the accuracy of traffic speed prediction when considering the state transition based on vehicles' driving patterns.

To eliminate the errors caused by wrongly matched trajectories, we aim to predict traffic speed directly from raw GPS data. Our approach addressed two primary challenges: (1) **Data Uncertainty brought by severe GPS drift.** With GPS points potentially being recorded far from their actual position, GPS data exhibit significant drifting patterns. The lack of ground truth map-matching labels poses a challenge in aligning these points with the correct roads or paths on a map. (2) **Data Sparsity caused by low GPS sampling rates.** Those collected GPS points between long-gapped time intervals can not capture the true path taken by vehicles, especially in complex road networks. It is non-trivial to identify dependent traffic behaviors apparent on roads along.

To address those technical challenges, we propose an end-to-end GPS-based Traffic prediction Network, named GT-Net, which is optimized by next-step traffic speed to eliminate the errors from map-matching techniques. The contributions of our work are summarized as follows: (1) To our knowledge, it is the first work that integrates raw GPS-based trajectories into traffic speed prediction, liberating the necessity of map-matching. (2) We develop a GPS-to-Road attention network that dynamically models the likelihood of a GPS point aligning with surrounding roads. This module relies on the attention mechanism regarding the geographical closeness between the vehicle's location and road candidates. (3) We create a time-aware attention-based trajectory

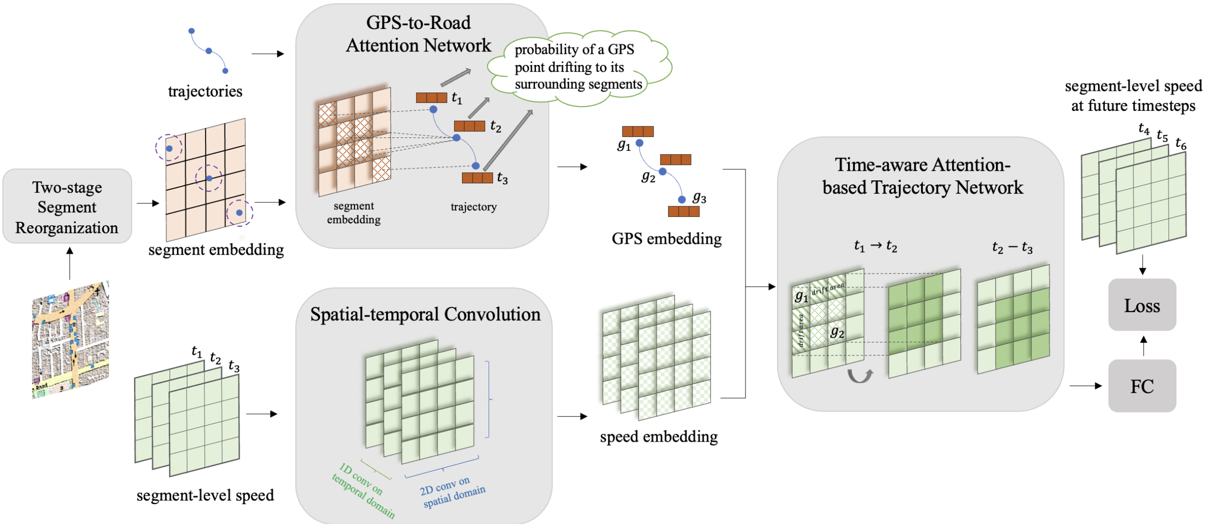

Figure 1 – *The overall framework of the GT-Net.*

network that effectively enhances the variety of the influence of paths between two locations on traffic state transitions. (4) Our research involves experiments based on a city-scale real-world dataset. The preliminary results demonstrate the superiority of our model over traffic prediction models as well as those incorporating trajectories.

2 METHODOLOGY

2.1 Problem Definition

The formal definition of GPS-based traffic speed prediction is: Given grid-based road segments V, drivers' trajectories $\mathcal{T}$, and historical traffic speed $\mathcal{X}^T$, the objective is to predict the traffic speed at next T' time steps $\mathcal{X}^{T'} = \left(X^{t+1}, X^{t+2}, \ldots, X^{t+T'}\right) \in R^{N\times T'}$.

2.2 Our model

The overall framework of GT-NET is presented in Figure 1, which consists of three modules: spatial-temporal convolution, GPS-to-Road attention network, and time-aware attention-based trajectory network. The model is trained to minimize the Root Mean Square Error (RMSE) loss to reduce the gap between ground truths and predicted traffic speed.

Spatial-temporal convolution. To model spatial dependencies among neighboring roads and temporal dependencies along time-series patterns, the grid-based segment-level historical speed data is fed into a two-dimensional (2D) convolution following a 1D convolution block to generate high-dimensional embeddings for segment-level speed dynamics.

GPS-to-Road attention network. In light of the challenge caused by aligning a GPS point with a single road through map-matching preprocessing, we aim to estimate the likelihood that a location drifts away from a set of road candidates. To achieve this, a GPS sample derived from a trajectory is embedded as

$$g = softmax\left(\frac{PointsPosition\left(RoadsPosition \odot M\right)^T}{\sqrt{d}}\right) RoadsEmbeddings \in R^d, \quad (1)$$

based on the similarity calculated between the sample and road candidates based on geographical distances with M denoting the drifting range. The embedding serves as the prerequisite for modeling a complete trajectory's impact on traffic state transitions.

Table 1 – *Traffic speed prediction with different forecasting time periods in 1-month data.*

Models	15min		30min		45min		60min	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
STResNet	4.000	5.875	4.014	5.930	4.176	6.217	4.455	6.651
STGCN	2.961	5.076	3.424	5.985	3.776	6.590	4.073	7.100
GraphWaveNet	2.987	5.054	3.536	6.106	4.000	6.937	4.404	7.599
AGCRN	2.908	4.898	3.294	5.523	3.587	6.045	3.846	6.478
STGODE	3.026	5.041	3.364	5.773	3.633	6.311	3.888	6.743
TrajNet	3.093	4.880	3.562	5.709	3.838	6.171	4.045	6.521
GT-Net	**2.832**	**4.627**	**2.935**	4.873	**3.076**	**5.067**	**3.222**	**5.314**
GT-Net(mmGPS)	2.909	4.723	2.996	**4.781**	3.196	5.542	3.337	5.511

Time-aware attention-based trajectory network For the variety and scarcity characteristics shared by road mapping, it becomes difficult to generate a decided path vehicles traveled along. To better get the advantages of flexibility shared by deep neural network learning, we also develop a learnable message propagation mechanism to mimic traffic state transitions potentially influenced by traversed paths. Specifically, a grid-to-grid attention matrix A^t is involved with each element $A^t_{i,j}$ refers to the message propagation degree from grid i to grid j from time step t to the next within the trajectory range covered by two GPS samples.Then, the segment-level speed features S are updated with learnable parameters W as:

$$S^{t_2}_{(i,j)} = A_{(i,j)} \cdot W \cdot S^{t_1}_{(i,j)} + S^{t_1}_{(i,j)}. \tag{2}$$

3 RESULTS

3.1 Dataset and experimental settings

We collect city-scale trajectory data in Hong Kong, consisting of GPS location sequences covered by 36450 taxis over 5 months. Traffic speed data of 938 road segments are obtained from the open data platform of the Transportation Department[1]. Based on statistics, approximately 38% of trajectories have fewer than 1000 GPS points along the complete 8640 sequence while 78 % contain fewer than 2000. We aggregate the road-segment-level traffic speed data and the trajectory data at 5-minute intervals. The traffic speed for the past hour is used to predict the next hour. The dataset is divided into training, validation and test sets in a 6:2:2 ratio.

3.2 Preliminary results

We adopt Mean Average Error (MAE) and Root Mean Square Error (RMSE) as evaluation metrics. Several traffic prediction baselines are involved for comparisons. STResNet (Zhang *et al.*, 2017) employs convolutional neural networks (CNN) with residuals to capture dynamics in traffic flows. STGCN (Yu *et al.*, 2018), Graph WaveNet (Wu *et al.*, 2019), AGCRN (Bai *et al.*, 2020), and STGODE (Fang *et al.*, 2021) utilized stacked graph neural networks (GNN) and recurrent neural networks (RNN) based on historical traffic speed. Besides, TrajNet (Hui *et al.*, 2021) incorporates vehicle trajectories into traffic speed prediction. We implement map-matching to preprocess raw GPS point sequences.

The experimental results using the first 1-month dataset with predictions made at 15-minute, 30-minute, 45-minute, and 60-minute forecasting time intervals are presented in Table 1. We

[1]`https://data.gov.hk/sc/`

observe that GT-Net outperforms all other baselines across different predicted time intervals. The superiority can be attributed to its effectiveness for GPS-based trajectory incorporation. It is shown that TrajNet, though also involving trajectories, performs even worse than those that solely rely on historical traffic speed data. This is largely possibly related to errors generated during the map-matching preprocessing on which incorrect traffic state transitions depend.

To get rid of the chance of the model's improvement only caused by the incorporation of vehicles' trajectories, we invite another model GT-NET(mmGPS) where "mm" is the short of map-matching. The model involves map-matching to align GPS points with road segments and recurrently updates the traffic state of the two corresponding segments (the same as our framework). GT-Net achieves an improvement of 2.6%, 2.0%, 3.8%, and 3.4% in MAE for predictions over the 15, 30, 45, and 60 minutes, and of 2.0%, 8.6%, and 3.6% in RMSE over the 15, 45, and 60 minutes, which demonstrates our designed model's ability to handle drifting GPSs.

4 Discussion

In this work, we present a novel model for traffic speed prediction using raw GPS-based trajectories, trying to eliminate the errors caused by map-matching. Based on the preliminary results obtained from a city-scale real-world dataset, our model outperforms other traffic speed prediction ones as well as those incorporating trajectories, and has the ability to deal with GPS drift. Due to the page limit of the extended abstract, we do not include many technical details of our framework. Also, the experiment part will be extended with more traffic speed prediction baselines included, especially with the trail of different map-matching techniques applied to baselines with vehicles' trajectories involved. Furthermore, we will provide a case study related to parameter learning visualization in Hong Kong to see how our work can handle GPS drift and GPS low sampling rate that may be beneficial to real-world scenarios.

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