Traffic Flow Forcasting and Visualization

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Abstract—**Traffic flow forecasting plays a critical role in modern urban management, helping to mitigate congestion, optimize traffic routing, and ensure smooth transportation. In this paper, we propose a unified framework for Traffic Flow Forecasting and Visualization. Our approach integrates a Spatio-Temporal Unitized Model (STUM) that captures both spatial and temporal dependencies for more accurate forecasting. STUM leverages low-rank matrices to efficiently handle complex spatio-temporal interactions, minimizing computational overhead while maintaining high predictive accuracy. Furthermore, we develop a comprehensive visualization platform that presents traffic flow predictions through intuitive visual tools such as heatmaps, time-series plots, and interactive dashboards. This visualization aids stakeholders, including city planners and traffic managers, in understanding traffic dynamics and making informed decisions. Our model is extensively validated on real-world traffic datasets, demonstrating significant improvements in both prediction accuracy and usability through visualization.**

Index Terms—**Traffic Prediction, Deep Learning, Spatio-Temporal Data Mining.**

I. Introduction

TRAFFIC flow forecasting is a critical task in modern urban management, playing a significant role in mitigating congestion, optimizing traffic routes, and ensuring smoother transportation. As cities continue to grow rapidly, the increasing number of vehicles has led to widespread traffic congestion and parking difficulties. To address these challenges, many countries are investing heavily in the development of *Intelligent Transportation Systems (ITS)*, which leverage data collection and mobile computing technologies [1], [2]. Spatio-temporal data modeling and analysis have become essential in a variety of predictive scenarios, particularly in traffic flow forecasting, which has received sustained research attention over the past few decades [3], [4]. As a core component of ITS, traffic flow prediction is critical for improving traffic management efficiency, enhancing road safety, and alleviating severe traffic conditions [5].

Initial research primarily focused on statistical models for traffic prediction, such as the *Historical Average (HA)* [6] method and the *Auto-Regressive Integrated Moving Average (ARIMA)* [7], [8]. Machine learning models, including *Vector Auto-Regression (VAR)* [9], [10] and *Artificial Neural Networks (ANN)* [11], were also explored. However, these methods often struggled to capture the complex and nonlinear relationships in large-scale traffic networks, particularly for spatio-temporal prediction tasks.

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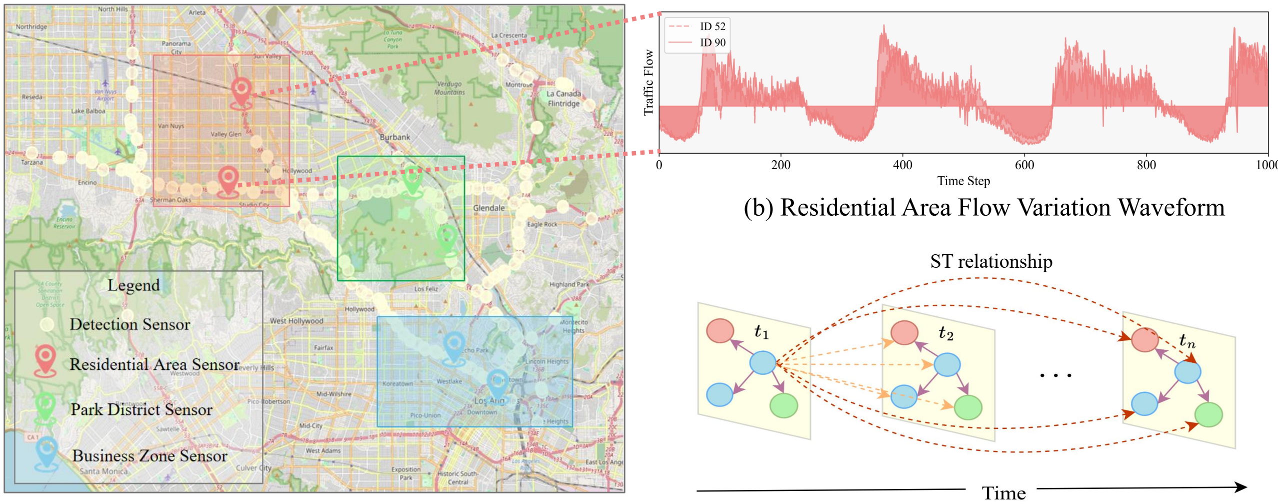
With the advent of big data, recent research has shifted towards deep learning models, which better capture the inherent spatio-temporal dependencies in traffic systems [12]. For example, *Convolutional Neural Networks (CNNs)* [13] have been used to capture spatial dependencies, while *Recurrent Neural Networks (RNNs)* [14] and their variants, such as *Long Short-Term Memory (LSTM)* networks [15] and *Gated Recurrent Units (GRUs)* [16], have been employed to model temporal dependencies, achieving better performance [17].

Recently, traffic prediction methods have increasingly combined sophisticated temporal models with *Graph Neural Networks (GNNs)* to capture both global temporal dependencies and regional spatial patterns. *Spatio-Temporal Graph Neural Networks (STGNNs)* [18], [19] have gained attention due to their ability to learn robust spatio-temporal representations by aggregating local information [5]. Researchers have developed a variety of innovative models, including advanced graph convolutional methods [20], [21], [22], [23], [24], [25], [26], [27], [28], [3], [29], [30], [31], dynamic graph structures [4], [32], [33], [34], [35], and efficient attention mechanisms [36], [37], [38], [39], [40]. Despite these advancements, improvements in predictive performance have plateaued due to several key challenges:

- *Heterogeneity:* Spatio-temporal data exhibit different patterns across various spatial and temporal scales. For instance, as shown in Figure 1(a), the traffic flow can vary significantly between different regions. Figure 1(b) illustrates that even within the same region, traffic dynamics fluctuate at different times of the day.
- *Separation of Spatial and Temporal Modules:* Many approaches separate the computation of spatial and temporal dependencies, limiting the efficiency and effectiveness of spatio-temporal representation learning. Figure 1(c) shows how spatio-temporal relationships affect prediction results across time. Models that compute spatial and temporal dependencies separately often fail to propagate important regional relationships effectively over time.
- *Low Combination Efficiency:* Integrating the latest advancements in temporal and graph-based prediction techniques can increase computational complexity and memory requirements, making it difficult to achieve significant performance improvements without sacrificing efficiency.

To address these challenges, we propose a unified framework for *Traffic Flow Forecasting and Visualization*, which incorporates both the prediction of traffic flows and their intuitive presentation through visual tools. At the core of this framework is the *Spatio-Temporal Unitized Model (STUM)*, which addresses the heterogeneity of spatio-temporal data by jointly processing spatial and temporal information. This model is built using *Adaptive Spatio-Temporal Unitized Cells*



(a) Sensor Distribution Map

(b) Residential Area Flow Variation Waveform

(c) Spatiotemporal Dependencies

Fig. 1. Motivation for our proposed method. (a) shows the sensor distribution of the PEMS04 dataset. (b) presents the traffic flow variation in two residential areas over a random period. (c) highlights spatio-temporal dependencies in traffic flow prediction tasks.

(ASTUCs), which leverage low-rank matrix factorization to efficiently capture complex non-linear spatio-temporal dependencies.

Our approach departs from traditional methods that separate spatial and temporal modules by computing, updating, and storing all spatio-temporal information in a unified matrix. We use trainable adaptive matrices at each node to capture dynamic traffic patterns at each time step. Additionally, we implement multi-layer fusion residual blocks to reduce over-parameterization and avoid redundant computations. Finally, all adaptive spatio-temporal unitized cells contribute to the prediction process, resulting in more accurate traffic flow forecasts.

II. Related Work

A. Spatio-temporal Forecasting

Spatio-temporal forecasting has been a subject of extensive study for decades, with the primary goal of predicting future states by analyzing historical data. Traditional spatio-temporal prediction methods are rooted in statistics and time series analysis, achieving success to a certain extent but facing limitations in handling complex spatial structures and spatio-temporal relationships [23]. To overcome these issues, researchers have turned to deep learning frameworks, which excel in uncovering potential feature representations such as non-linear spatial and temporal correlations from historical data [12]. Among these frameworks, Spatio-Temporal Graph Neural Networks (STGNNs) have emerged as a powerful tool for prediction tasks. These models integrate Graph Neural Networks (GNNs) [41] with temporal models [14], enabling better capture of spatio-temporal dynamics. Over the past few years, several notable STGNN models have been proposed, including Graph WaveNet [32], STGCN [19], DCRNN [18], and AGCRN [42], all of which have achieved remarkable results in spatio-temporal prediction tasks. Additionally, the attention mechanism [43] has gained popularity due to its effectiveness in modeling the dynamic dependencies present in spatio-temporal data. Despite the diversity of STGNN architectures, their performance improvements have plateaued [44], prompting a shift in research focus toward integrating Self-Supervised Learning (SSL) [44] and Large Language Models (LLMs) [45].

B. Optimization Through Low-Rank Matrix Factorization

Low-rank matrix factorization aims to decompose high-dimensional matrices into the product of multiple low-rank matrices, thereby reducing computational complexity while minimizing information loss. This approach has wide applications in data compression, dimensionality reduction, missing data recovery, and more [46].The deep structure of deep learning models results in numerous training parameters and low training efficiency. Motivated by the idea of data compression, researchers have tried to utilize low-rank matrix factorization to compress deep neural network models to make a trade-off between precision and computational efficiency [47]. There are mainly two kinds of such compression methods. The first kind compresses the whole deep learning architectures through constructing the corresponding tensor network representation, which has been successfully applied to convolutional architectures [48]. The second kind leverages low-rank matrix factorization on the single layers of the network. For instance, [49] introduced the Tucker tensor layer as an alternative to the dense weight matrices of neural networks. Recently, the use of low-rank matrix factorization methods in processing graph data has emerged as a lively research field. Low-rank matrix factorization can reveal the hidden information or main components of spatio-temporal data. Graph neural networks (GNNs) perform end-to-end calculations on graph data which contain a vast amount of potential information. To improve the performances of GNNs, researchers have adopted low-rank matrix factorization to mine the hidden information in graph data. For example, [31] and [50] utilized low-rank matrix factorization to capture spatial and temporal dependencies in traffic data forecasting, thus reducing the computational burden.

III. Current Progress

Currently, we have implemented the Spatio-Temporal Unitized Model (STUM) and tested it on several real-world traffic flow datasets, including PEMS04. Preliminary results show that STUM outperforms traditional methods such as STGCN and Graph WaveNet in terms of prediction accuracy, while also reducing computational overhead. The low-rank matrix factorization used in ASTUC has proven effective in capturing complex spatio-temporal interactions without significantly increasing model parameters.

In addition to the forecasting model, we are developing an interactive visualization platform to present the predicted traffic data. This platform allows users to explore traffic flow patterns across different regions and time periods, providing a valuable tool for traffic management and planning. The visualization is built using Python libraries such as Plotly and Dash, enabling dynamic and responsive visual representations of the data.

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