Enhancing Sustainable Urban Mobility Prediction with Telecom Data: A Spatio-Temporal Framework Approach

ChungYi Lin1,2, Shen-Lung Tung1, Hung-Ting Su2 and Winston H. Hsu2,3

1Internet of Things Laboratory, Chunghwa Telecom Laboratories
2National Taiwan University
3Mobile Drive Technology

Abstract

Traditional traffic prediction, limited by the scope of sensor data, falls short in comprehensive traffic management. Mobile networks offer a promising alternative using network activity counts, but these lack crucial directionality. Thus, we present the TeltoMob dataset, featuring undirected telecom counts and corresponding directional flows, to predict directional mobility flows on roadways. To address this, we propose a two-stage spatio-temporal graph neural network (STGNN) framework. The first stage uses a pre-trained STGNN to process telecom data, while the second stage integrates directional and geographic insights for accurate prediction. Our experiments demonstrate the framework’s compatibility with various STGNN models and confirm its effectiveness. We also show how to incorporate the framework into real-world transportation systems, enhancing sustainable urban mobility.

1 Introduction

Effective traffic management is crucial for intelligent transportation systems [Xie et al., 2020; Lv et al., 2021]. Traditional methods rely on costly detectors with limited coverage [Sen et al., 2012; Li et al., 2018; Guo et al., 2019]. With over 71% of the global population connected to mobile networks [Cisco, 2021], cellular traffic activities [Jiang, 2022] offer valuable insights. The count of cellular traffic (i.e., cellular traffic flow) can proxy traffic conditions [Lin et al., 2021a]. However, the lack of directionality in cellular traffic flows from road areas limits understanding commuting patterns and easing congestion, thus reducing their utility.

To extract directionality for traffic management, we present a task utilizing cellular traffic flows from selected road areas to predict user mobility counts (i.e., mobility flows) along routes (as Figure 1). This enhances the utility of undirected telecom data by providing directional insights, reducing costs and environmental impact associated with sensor deployment, and aligning with the Sustainable Development Goals (SDG)1 for urban sustainability. To support this task, we propose the Tel-to-Mob dataset, including undirected telecom-based flows from 34 roads and directed mobility flows for 84 routes, with analysis to exhibit its relevance to road structure.

We identified two main challenges: Magnitude Disparity, where cellular traffic flows capture all users in an area, unlike mobility flows that reflect specific directional movements; and Amount Disparity, where a single road area being part of multiple routes leads to misalignments, hindering direct mapping from cellular traffic to mobility flows, a gap not addressed by current models (e.g., [Li et al., 2023; Lin et al., 2024]). To tackle these, we propose a Spatio-Temporal Graph Neural Network (STGNN) Framework with two stages. Stage 1 employs a pre-trained STGNN to extract features from cellular traffic flows. Stage 2 transforms these features to integrate directionality and enhances them with geographical insights, using another STGNN to capture spatio-temporal dynamics and predict future mobility flows.

Overall, our main contributions:
- What Addressed: We use telecom-based flows to forecast directional mobility flows, overcoming traffic sensor limitations and advancing sustainable urban living.
- Who Involved: We use anonymous data from extensive mobile users provided by a cooperating telecom operator.
- How Evaluated: Our framework’s effectiveness is evaluated based on prediction accuracy. All related data and code are accessible at: https://github.com/cy07gn/TeltoMob.

1https://sdgs.un.org/goals/goal11
2 TeltoMob Dataset

Related Tasks. As cellular traffic is collected from mobile users moving across adjacent areas [Zhang et al., 2018], it exhibits spatial correlations [Wang et al., 2018; Wang et al., 2022]. However, the primary goal usually focuses on enhancing network resource allocation in specific areas [Yao et al., 2021; Zhao et al., 2021] or at base stations [Wang et al., 2018], as well as inducing energy savings [Lin et al., 2021b] and improving resource scheduling [He et al., 2020].

However, as we aim to utilize cellular traffic for transportation evaluation, the lack of directionality reduces its practicality for traffic management. Thus, we introduce the TeltoMob dataset, which contains undirected telecom-based flow and directed mobility flow among road sections.

2.1 Definitions

- **Geographical Cellular Traffic (GCT)**. A cellular traffic record with its originating GPS coordinates, as Table 1A.
- **Road Segment**. A 20m x 20m road area, based on the average road size in the Proof-of-Concept area, as Figure 2(a).
- **Route**. A directional pathway from start road segment $i$ to end segment $j$, denoted as $ij$.
- **GCT Flow**. The count of GCT records on a road segment, accumulated over a fixed time interval, as Figure 2(b).
- **GCT Pairing**. An entry by associating two GCT records from consecutive segments of the same user, as Table 1B.
- **Mobility Flow**. The count of GCT pairings along routes, recorded over fixed time intervals (see Figure 2(c)), offers an alternative to physical detectors, aligning with SDG aims.

```
A. Examples of GCT Records

<table>
<thead>
<tr>
<th>IMEI</th>
<th>Date</th>
<th>Latitude</th>
<th>Longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td>2022-09-06</td>
<td>24.801066</td>
<td>120.987103</td>
</tr>
<tr>
<td>524edbbd5122</td>
<td>2022-09-06</td>
<td>24.801219</td>
<td>120.987091</td>
</tr>
<tr>
<td>a63cc2cc752e</td>
<td>2022-09-06</td>
<td>24.801246</td>
<td>120.987090</td>
</tr>
<tr>
<td>...</td>
<td>2022-09-06</td>
<td>24.801066</td>
<td>120.987103</td>
</tr>
</tbody>
</table>

B. Examples of GCT Pairings

<table>
<thead>
<tr>
<th>Pairing</th>
<th>Start Time</th>
<th>End Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td>2022/09/06 18:02:17</td>
<td>2022/09/06 18:04:02</td>
</tr>
<tr>
<td>524edbbd5122</td>
<td>2022/09/06</td>
<td>2022/09/06 18:11:52</td>
</tr>
<tr>
<td>a63cc2cc752e</td>
<td>2022/09/06</td>
<td>2022/09/06 18:11:51</td>
</tr>
<tr>
<td>...</td>
<td>2022/09/06 18:02:17</td>
<td>2022/09/06 18:04:02</td>
</tr>
</tbody>
</table>
```

Table 1: Examples of GCT Records and GCT Pairings.

2.2 Data Collection and Processing

**Location Selection.** In collaboration with City Authorities, we selected 34 road segments based on criteria like daily commutes, and congestion-prone areas. The segments are near areas with distinct environments, including universities, shopping centers, and science parks.

After identifying road segments, we determined 84 directional routes based on the road network structure, facilitating GCT record pairing to capture mobility. Each route connects a start and end road segment.

**GCT Records Sourcing.** All GCT records are stored in the telecom company’s Geographical Cellular Traffic Database. We extracted GCTs from 34 road segments, focusing on essential data fields—IMEI, recording time, and coordinates—for time efficiency, as shown in Table 1A.

**GCT Pairings.** We match two GCT records with the same IMEI number (i.e., the same user) across adjacent road segments, originating from the start and end road segments, respectively. The time difference between these records is kept within a 15-minute window to exclude pedestrian or non-vehicular traffic, thus focusing on vehicle movements. Table 1 displays the pairing results for route 3071.

**Processing.** GCT and mobility flows denote the cumulative counts of GCT records and GCT pairings at 15-minute intervals, respectively, revealing unique temporal patterns for each road segment and route over time.

![Figure 2: Overview of data collected from 34 road segments, including 84 directional routes in Hsinchu City.](image)

**2.3 Data Privacy Protection**

Data privacy is paramount in telecom data. Here’s how we protect user anonymity and privacy for our task:

**Location Constraints.** We restrict data collection to road segments, avoiding sensitive areas like commercial or residential districts. We focus on GCTs from these segments, preventing tracking of journeys or user pattern identification.

**Data Aggregation.** GCT flow is the cumulative count of GCT records that masks individual identities, securing user information for telecom data use.

**International Standards.** Our partner telecom company follows ISO 27001 standards, ensuring sensitive data management and access are rigorously controlled.
2.4 Data Analysis

Descriptive Statistics. Table 2 summarizes the descriptive statistics of our dataset from 2022/08/28 to 2022/09/27 with 2,976 samples from 34 road segments and 84 routes. Notably, segment 31 near a hospital has the highest GCT flow with 400.58 entries per 15 minutes, and Route 30/31, linking downtown to the freeway, records the highest mobility flow with 57.82 movements per 15 minutes.

<table>
<thead>
<tr>
<th>Type</th>
<th>#Samples</th>
<th>#Amount</th>
<th>Interval</th>
<th>Avg.</th>
<th>STD</th>
<th>Max Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GCT</td>
<td>2976</td>
<td>34</td>
<td>15-min.</td>
<td>159.9</td>
<td>116.59</td>
<td>400.5</td>
</tr>
<tr>
<td>Mobility</td>
<td>2976</td>
<td>84</td>
<td>15-min.</td>
<td>12.9</td>
<td>11.03</td>
<td>57.8</td>
</tr>
</tbody>
</table>

Table 2: Descriptive Statistics of the Dataset.

Magnitude Discrepancy. Table 2 shows that the average GCT flow markedly exceeds that of the mobility flow. This difference is due to the GCT flow including all users—stationary and pedestrians—without considering direction, while mobility flow counts directional movements between segments, typically vehicular. Thus, GCT flow reflects broader user activity, and mobility flow precisely indicates directional vehicular traffic.

Flow Distribution Analysis. Figure 3 shows the distribution of average GCT and mobility flows for road segments and routes. The right skew indicates low traffic in most locations, with few experiencing high volumes. This reflects the typical urban network structure [Peng et al., 2016; Babu and Manoj, 2020] where arterials carry main traffic, while local streets have less flow. The dataset accurately reflects real-world traffic trends, proving valuable for urban planning.

Interactions Between Route’s Neighbors. Acknowledging that the mobility flow of a route is influenced by upstream movements as users transition from upstream to downstream areas, we analyzed its correlation with upstream neighbors. Focusing on route 54 and its upstream routes on 2022/09/05 as an example, we employed Pearson correlation coefficients [Cohen et al., 2009] to assess daily patterns. Figure 5 reveals strong correlations (above 0.8) with direct upstream routes (85 and 305), signifying their significant impact. Conversely, 2-hop upstream routes exhibit weaker correlations (0.3 to 0.6), suggesting a reduced impact with increased distance. This chart highlights the critical role of the nearest upstream routes in ensuring traffic flow continuity, which informs the geographical insights incorporated in our framework.
3 Methodology

3.1 Task Definition

Using undirected \( N \) GCT flows from past steps (\( T_{in} \)) to forecast directional \( M \) mobility flows for future steps (\( T_{out} \)).

3.2 Framework Overview

As Figure 6, our framework functions in two stages to address the magnitude disparity among GCT and mobility flows, and the amount disparity among 32 segments and 84 routes:

- **Stage 1.** We pre-train the first STGNN on GCT flows for feature extraction, separate from the framework’s training. This enables the model to focus on the attributes of GCT flows, thus mitigating the impact of magnitude disparity.
- **Stage 2.** We transform the features extracted in Stage 1 to align with the amount of mobility flows, addressing the amount disparity. The secondary STGNN is then used to process them and predict the mobility flows.

3.3 Stage 1 of the Framework

**Motivations.** The first STGNN model on GCT flows, separately from the framework, enhances focus on capturing spatial-temporal patterns, thus yielding enriched features. This distinct training approach simplifies the learning process and reduces the risk of overfitting [Lin et al., 2023b].

**Notations.** The following are the notations for this stage:

- \( X \): GCT flows of size \([N, D]\), regarded as \( N \) road segment with \( D \) observations.
- \( g_{get} \): The graph structure representing connections among road segments collecting GCT flows.
- \( h_i \): Multi-channel feature of GCT flow \( i \), sized \([C, D]\), representing \( D \) dimensions across \( C \) channels.
- \( H \): The set of all \( h_i \), denoted \( H = \{h_i\}_i \), sized \([N, C, D]\).
- \( STGNN^{1st} \): The pre-trained STGNN in Stage 1, used for feature extraction.

**Implementation.** The following are the details for this stage:

**Training.** We utilize existing STGNNs (e.g., [Li et al., 2023; Lin et al., 2024]) trained for feature extraction. Following the traffic prediction [Wu et al., 2019], we train the STGNN to predict \( N \) GCT flows in the future \( D' \) steps, based on \( X \) (sized \([N, D]\)). Details on the data setup are available\(^3\).

**Extracted Feature.** STGNN models often encode the input \( X \) into multi-channel features \( H \) (sized \([N, C, D]\)) to enrich the representation, with each channel encapsulating distinct spatial-temporal dynamics. Once trained, we regard the output of the STGNN as the extracted feature, denoted as:

\[
H = STGNN^{1st}(X, g_{get}), \tag{1}
\]

where \( STGNN^{1st} \) is the pre-trained STGNN in Stage 1, and \( H = \{h_1, h_2, \ldots, h_N\} \in \mathbb{R}^{N \times C \times D} \), with each \( h_i \) representing the multi-channel feature of GCT flow of segment \( i \).

3.4 Stage 2 of the Framework

Stage 2 uses the extracted feature \( H \) from Stage 1 to generate mobility flow predictions, comprising three steps as follows:

**Transformation Step**

**Motivations.** Due to the misalignment between the amounts of GCT and mobility flows, the extracted feature \( H \) cannot be directly mapped to individual mobility flows. Thus, we transform \( H \) into representations that align with the amounts of mobility flows, integrating directionality within each route.

**Notations.** The following are the notations for this step:

- \( h_{ij} \): The representation for the mobility flow of route \( ij \).
- \( H \): The set of all \( h_{ij} \), as \( H = \{h_{ij}\}_{ij} \), sized \([M, C, D]\).

**Implementation.** To incorporate directionality, we denote \( ij \) as the result of subtracting the extracted feature \( h_i \) of the starting segment \( i \) from \( h_j \) of the ending segment \( j \), as:

\[
h_{ij} = \sigma(h_j - h_i), \tag{2}
\]

where \( \sigma(\cdot) \) is a nonlinear function. After process for all \( M \) routes, we obtain the initial representation set:

\[
\overline{H} = \{h_{ij}\}, \tag{3}
\]

where \( \overline{ij} \in \mathbb{R}^M \) and \( \overline{H} \in \mathbb{R}^{M \times C \times D} \).

**Enhancement Step**

**Motivations.** While the derived \( h_{ij} \) corresponds to the mobility flow \( \overline{ij} \), it may not capture correlations with neighboring routes, potentially overlooking factors such as congestion propagation from upstream routes [Saberi et al., 2020; Yidan et al., 2021]. Thus, we enrich these representations by integrating interactions among a route’s upstream neighbors.

**Notations.** The following are the notations for this step:

- \( \overline{k_i} \): The 1-hop upstream neighbor of route \( \overline{ij} \), where segment \( k \) leads directly into the start segment \( i \) of route \( \overline{ij} \).
- \( \{h_{ij}^k\} \): The set of representations for all 1-hop upstream neighbors of route \( \overline{ij} \).
- \( \overline{H}^i \): The set of representations comprised of route \( \overline{ij} \) and its upstream neighbors \( \{\overline{k_i}\} \).
- \( h_{ij}^a \): \( a \)-th channel representation of the mobility flow \( \overline{ij} \).
- \( h_{ij}^z \): The enhanced representation of route \( \overline{ij} \) after fusion.
- \( H \): The set of all \( h_{ij}^z \) denoted \( H = \{h_{ij}^z\} \).

**Implementation.** The following are the details for this step:

**Preliminary.** While Graph Attention Networks (GAT) [Veličković et al., 2018] are adept at exploring interactions among features and adaptively adjusting weights [Zhao et al., 2020], current GATs fall short in exploring correlations between multi-channel features as they apply uniform weights across all channels. This process may potentially overlook channels that are critical for prediction [Brody et al., 2022].

**Solution.** We employ the concept of Multi-Channel GAT (MGAT) [Lin et al., 2023a], which is simple but effectively handles multi-channel representations. Below, we briefly outline how we applied MGAT in the fusion process:

1. We concatenate each \( h_{ij}^z \) with its upstream neighbors \( \{h_{ij}^k\} \), as \( \overline{H}^i \) with size \([Z, C, D]\), \( Z = 1 + |\{h_{ij}^k\}| \).
2. We explore the interactions among entities in \( \overline{H}^i \). To determine channel-specific weights, MGAT employs \( C \) independent GATs, each focusing on the \( c \)-th channel representation \( \overline{H}^i \in \mathbb{R}^{Z \times D} \).
4 Experiments

4.1 Experimental Setup

Data Sets. We collected data at 15-minute intervals from 2022/8/28 to 2022/9/27, yielding 2,976 samples of GCT and mobility flows across 34 road segments and 84 routes. Sequences for the Train/Test/Valid were formed from these samples, each comprising 12 steps: the initial 8 steps ($T_{in}$) as historical GCT flows and the next 4 steps ($T_{out}$) as future mobility flows. Following [Li et al., 2021], we divided these sequences into Train/Test/Valid sets in a 70%-20%-10% ratio. Each experiment runs for 180 epochs with early stopping.

Baselines. We chosen representative STGNN baselines integrated into our framework for this new task: DMGCN [Han et al., 2021]: Leverages time-specific spatial dependencies with a multi-faceted fusion. ESG [Ye et al., 2022]: Employs evolutionary and multi-scale graph structures. DGCRN [Li et al., 2023]: Models the dynamic graph with a seq2seq architecture. MFGM [Lin et al., 2024]: Captures multivariate, temporal, and spatial dynamics with a GNN-based approach.

Following $STGNN_{2^{nd}}$, an MLP is employed to transform $\hat{H}$ into the prediction output format:

$$Y = MLP(\hat{H}).$$

Here, the MLP achieves nonlinear transformations to map the high-level features of $STGNN_{2^{nd}}$ to the desired output.

Framework Training

We fix the hyperparameters of the pre-trained $STGNN_{1^{st}}$ in Stage 1 to ensure consistency. The feature extracted in Stage 1 is fed forward through Stage 2 to generate mobility flow predictions. We adopt the Mean Absolute Error (MAE) as our loss function, evaluating the accuracy of predictions against the ground truth in our dataset. The MAE is minimized by tuning the hyperparameters of the transformation, enhancement, and prediction steps to achieve optimal accuracy. Details are provided at: https://github.com/cy07gn/TeltoMob/tree/main/Model
Metrics. We use Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) to assess our predictions against ground truth mobility flows from 15 (1 step) to 60 minutes (4 steps).

4.2 Prediction Performance

Performance Improvement with Framework. We evaluated the integration of various STGNN models with our framework, focusing on prediction intervals ranging from 15 to 60 minutes. Each model was examined under two settings: without the framework integration (w/o) and with our framework integration (w). For the w/o setting, we used the STGNN, inputting the GCT flow from each route’s starting segment, to output the predicted mobility flows.

Table 3 presents the performance of all models in both settings, with each reported result representing the average of 10 individual runs. We use the Improvement Ratio (IR) to measure the enhancement achieved by integrating STGNN models into our framework. The results reveal that this integration boosts performance, with overall average IRs of 8.9%, 13.2%, and 8.6% for MAE, RMSE, and MAPE, respectively, and up to a 17.5% RMSE improvement for long-term predictions. This underlines the compatibility of our framework across different STGNN models and its effectiveness.

Notably, as the prediction interval lengthens, performance typically declines due to the increased complexity of long-term dependencies. However, models enhanced with our framework consistently improve in prediction accuracy, achieving progressively larger IRs as the forecast duration extends. Specifically, the average IR for MAE, RMSE, and MAPE grew from 7.8%, 10.4%, and 7.2% at 15 minutes to 10.2%, 16.0%, and 10.1% at 60 minutes, respectively. These findings underscore our framework’s capability for more complex, long-term predictions, which is practical for real-world applications [Tian and Chan, 2021].

Computational Efficiency Table 4 presents the computational efficiency of various STGNN models within our framework on a Nvidia Tesla T4 GPU, with each value representing the average of 10 runs. DMGCN and MFGM show promising inference times (0.73 and 0.79 seconds respectively), suitable for near real-time applications, while ESG and DGCRN are slightly slower. Regarding training times, MFGM is most efficient at 13.53 seconds, suggesting an advantage in environments requiring rapid model updates, whereas DMGCN and ESG were slower, which might impact their adaptability in environments with rapidly changing data. This assessment indicates that our framework is capable of providing efficient inference, supporting its potential for integration within real-time transportation systems, as depicted in Section 4.4.

4.3 Ablation Study of Our Framework

We assessed the contributions of framework’s components by comparing the framework with four ablated settings: without the Pre-trained STGNN (w/o STGNN), without the Transformation step (w/o Trans.), without the Enhancement step (w/o Enhan.), and without Stage 2’s STGNN (w/o STGNN). Table 5 shows the average results for prediction length 15 min to 60 min, ordered by performance impact:

Impact of w/o STGNN. This setting omits the pre-trained STGNN from Stage 1, using raw GCT flows instead of the extracted features that capture spatio-temporal dynamics. Without these extracted implicit features within the GCT flow, this configuration demonstrates the worst performance.
metrics across all intervals, indicating a significant decrease in accuracy. This suggests that the pre-trained STGNN to capture the underlying patterns in GCT flows is very crucial.

**Impact of w/o Enh.** This setting excludes the Enhancement step, thereby omitting the incorporation of correlations between each route and its upstream neighbors. This omission leads to the second-largest performance decrease. We argue that, given the spatial dependencies among routes as shown in our dataset (see Figure 5), overlooking these correlations might miss crucial insights, such as congestion propagation from upstream, thus decreasing the performance.

**Impact of w/o STGNN**. This setting omits STGNN in the Prediction step, opting for MLPs to generate the predictions. Although this removal is not as severe as omitting the STGNN, it still consistently increases prediction errors across all intervals. This validates that capturing implicit dynamics with STGNN contributes to the outcomes.

**Impact of w/o Trans.** This setting omits the Transformation step, directly using the extracted GCT flow feature as a representation of mobility flow, without integrating the directionality among routes. Although excluding the transformation step leads to slightly worse metrics, it still leads to increased errors across the 15 to 60 minutes, confirming that incorporating directionality can enhance mobility flow prediction.

Figure 7 presents the predictive performance as measured by MAE across time intervals. As the interval lengthsen, the error for all settings increases. However, it is observed that the full framework consistently outperforms the other ablated settings at all prediction lengths, with the MAE gap widening over time. This not only demonstrates the superior performance of the full framework but also highlights its stability for complex, long-term tasks.

### 4.4 Applications and Impact on Transportation

As our framework achieves promising inference times from GCT flow to mobility flow predictions (as Table 4), we integrate this framework into the transportation system, as illustrated in Figure 8:

- **Traffic Monitoring**: Predicted mobility flows offer insights for authorities to monitor potential congestion.
- **Traffic Indicator**: The system employs these forecasts in a threshold-based alert mechanism, serving as a new indicator of traffic conditions. When pre-set thresholds are exceeded, it triggers various strategies: sending notifications to authorities, suggesting alternative routes through Changeable Message Signs (CMS) to redirect commuters, and dynamically adjusting traffic signal plans to optimize flow.

Beyond the above, our work can contribute further impact:

- **Reconstruction of Road Networks**: Our framework’s predictions provide city authorities with better insights into congestion points, leading to the expansion or reconstruction of road networks to better accommodate traffic demands.

- **Public Transport Improvement**: By understanding mobility flows, public transport routes can be optimized to match demand, potentially increasing the use of multi-passenger transport options.

### 5 Conclusion

We leverage undirected telecom data to forecast directional mobility flows along routes, enhancing the utility of telecom data in transportation and reducing the deployment and maintenance costs of detectors, thus advancing sustainable cities (SDG 11). To tackle the challenge, we propose a two-stage STGNN framework, facilitated by our TeltoMob dataset, to assess its effectiveness. Our experiments confirm the framework’s compatibility with various STGNN models and its effectiveness in enhancing their performance, with up to a 17.5% improvement in long-term prediction. We also demonstrate the integration of the framework into the transportation system as a traffic indicator. This work underscores the potential of telecom data in transportation and contributes to the enhancement of sustainable urban mobility.
Acknowledgments

This work was supported in part by National Science and Technology Council, Taiwan, under Grant NSTC 111-2634-F-002-022 and by Qualcomm through a Taiwan University Research Collaboration Project.

References


[Li et al., 2023] Fuxian Li, Jie Feng, Huan Yan, Guanyin Jin, Fan Yang, Funing Sun, Depeng Jin, and Yong Li. Dynamic graph convolutional recurrent network for traffic prediction: Benchmark and solution. *ACM Transactions on Knowledge Discovery from Data*, 17(1):1–21, 2023.


