

BIGCity: A Universal Spatiotemporal Model for Unified Trajectory and Traffic State Data Analysis

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Abstract—Spatiotemporal (ST) data analysis is a critical area of research in data engineering. Typical dynamic ST data includes trajectory data (representing individual-level mobility) and traffic state data (representing population-level mobility). Traditional studies often treat trajectory and traffic state data as distinct, independent modalities, each tailored to specific tasks within a single modality. However, real-world applications, such as navigation apps, require joint analysis of trajectory and traffic state data. Treating these data types as two separate domains can lead to suboptimal model performance. Although recent advances in ST data pre-training and ST foundation models aim to develop universal models for ST data analysis, most existing models are “multi-task, solo-data modality” (MTSM), meaning they can handle multiple tasks within either trajectory data or traffic state data, but not both simultaneously.

To address this gap, this paper introduces BIGCity, a pioneer multi-task, multi-data modality (MTMD) model for ST data analysis. The model targets two key challenges in designing an MTMD ST model: (1) unifying the representations of different ST data modalities, and (2) unifying heterogeneous ST analysis tasks. To overcome the first challenge, BIGCity introduces a novel ST-unit that represents both trajectories and traffic states in a unified format. Additionally, for the second challenge, BIGCity adopts a tunable large model with ST task-oriented prompt, enabling it to perform a range of heterogeneous tasks without the need for fine-tuning. Extensive experiments on real-world datasets demonstrate that BIGCity achieves state-of-the-art performance across 8 tasks, outperforming 17 baselines. Our code are available at <https://github.com/bigscity/BIGCity>.

Index Terms—Spatiotemporal data, Universal Model, Trajectory, Traffic State

I. INTRODUCTION

Spatiotemporal (ST) data analysis has been a cornerstone of research in data engineering, with models such as trajectory analysis and traffic state prediction playing critical roles in various domains. These models are integral to the development of intelligent transportation systems (ITS) [1], [2], smart cities [3]–[8], and location-based service (LBS) applications [9], enabling advanced solutions for urban mobility, infrastructure planning, and personalized services.

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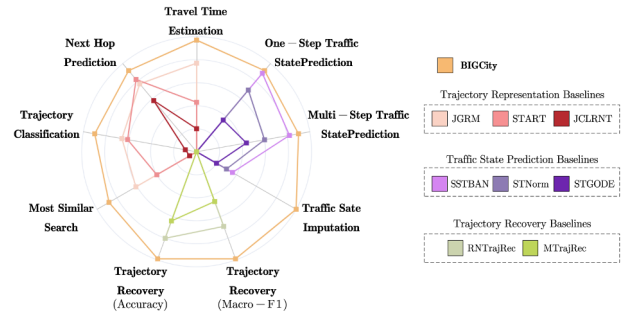


Fig. 1: Performance Radarchart of BIGCity on Various Tasks.

From a data perspective, ST data analysis models are categorized into two types based on the targeted data: individual-level models for trajectory data and population-level models for traffic state data. Individual-level trajectory models, such as next-hop prediction [10]–[13], trajectory-user linkage [14], [15], and trajectory traffic pattern classification [16], process mobility trajectories of individuals on road networks or among POIs to uncover patterns in individual human mobility. Population-level traffic state models, including traffic state prediction [17], [18], traffic state imputation [19], [20] and *etc*, analyze time series data on traffic metrics like speed, density, and flow volumes. These models aim to capture spatiotemporal correlations at a population level, reflecting crowd behaviors in transportation systems, such as urban road networks.

In the literature, current ST data analysis methods are often narrowly tailored to specific types of data, focusing either on trajectories or traffic states. Most studies treat trajectories and traffic states as entirely distinct data modalities, designing task-specific models for one modality (*sole task in sole data modality (STSD)*). A model designed for trajectory next-hop prediction cannot be applied to tasks like trajectory-user linkage, let alone traffic state prediction. While some ST data pre-training models, such as trajectory or time-series representation learning models, can generate universal representation

vectors for multiple downstream tasks [16], [21], they remain limited to handling a single data modality, either trajectories or traffic states (**multiple tasks in sole data modality (MTSD)**)).

However, individual-level mobility behaviors and population-level traffic states are intrinsically interconnected. Macro-level traffic states are aggregated from micro-level individual trajectories, while population traffic states influence individual mobility patterns. Many ITS and LBS applications require analyzing trajectory and traffic state data jointly. For example, car-hailing platforms need to predict the location of a taxi while considering traffic speed predictions. Treating trajectories and traffic states as separate domains in such scenarios can lead to suboptimal model performance.

In recent years, there has been growing attention to developing a unified spatiotemporal model capable of simultaneously processing both macro-level and micro-level data, supporting various spatiotemporal tasks (**multiple tasks in multiple data modalities (MTMD)**). Models such as UniST [22], UrbanGPT [23], and OpenCity [24] provided unified frameworks solely for macro-level data analysis, while UniTraj [25] and TrajCogn [26] provided a unified framework for micro-level tasks. Above models are successful in supporting multiple tasks [25], cross-dataset knowledge transfer [22], and few-/zero-shot data analysis [24] within a single data modality. But these models remain limited to *MTSD*. A truly *MTMD* model is still lacking.

Outside the field of ST data analysis, versatile and universal foundation models capable of processing heterogeneous data with a single framework have become widespread in domains such as text processing and image processing [27]. Notable examples include the success of large language models (LLMs) like [28], [29] in natural language processing and visual-language multimodal data analysis [30]. Despite the achievements of versatile models in these fields, developing a MTMD model for ST data remains constrained by several unique challenges, as outlined below.

(1) Challenges in unified representations of ST data: In NLP, all text data can be uniformly represented as sequences of characters (unified units), and in CV, images are uniformly represented as matrices or tensors of pixels (unified units). However, in ST data analysis, trajectories are modeled as sequences of geographical units (*e.g.*, road segments or POIs), while traffic states are represented as graphs with dynamic signals (*e.g.*, traffic speed over road networks). The differing basic units make developing a unified representation framework for the two data modalities a significant challenge.

(2) Challenges in unifying heterogeneous ST analysis tasks: In NLP, diverse tasks can be unified as next-word generation, enabling a single model to handle various tasks efficiently. However, in ST data analysis, tasks are highly heterogeneous, with even identical inputs requiring different outputs. For instance, given the same trajectory inputs, travel time estimation outputs continuous timestamps, while user-trajectory linkage outputs discrete user IDs. Unifying such heterogeneous tasks within a single data processing and model training framework remains a significant challenge.

To address these challenges, we propose a Bi-modality unified General model for ST data analysis in road network-based City scenarios (BIGCity). BIGCity focuses on road networks as the foundational scenario for ST data analysis. To tackle the challenge of unified data representation, BIGCity introduces *ST-units* (see Sec. IV-A), enabling the expression of ST data from both trajectories and traffic state series in a unified format, *i.e.*, a sequence of ST-units. These ST-units are further embedded into token sequences via a neural network-based *Spatiotemporal Tokenizer* (see Sec. IV-B). To address the challenge of task heterogeneity, we propose a *Universal ST Model with Task-oriented Prompt (VMTP)* (see Sec. V), which employs novel *Task-oriented Prompts* to guide an *LLM-based Tunable Model* for executing diverse ST analysis tasks. Additionally, we design a two-stage *training strategy* (see Sec. VI), combining self-supervised masked reconstruction and task-oriented prompt tuning, to train the model on heterogeneous ST data for multiple tasks. Extensive experiments on three real-world datasets involving both trajectory and traffic state data demonstrate that BIGCity outperforms 18 baselines across 8 tasks, highlighting its superior performance and versatility.

II. RELATED WORKS

A. Spatiotemporal Representation learning (MTSD Models)

Self-supervised pre-training representation learning is crucial for ST data analysis, such as traffic state prediction [31]–[36], trajectory prediction [37]–[40], trajectory classification [41], [42], and ST recommendation [43], [44]. Existing trajectory models [3], [15], [45]–[52] employ sequential models with self-supervised tasks, while traffic state models [17], [31], [53]–[60] leverage graph neural networks (GNNs) [17], [57], [61]–[64] to capture spatiotemporal dependencies for predicting future traffic states. Recent models have focused on integrating more comprehensive ST features. For example, START [15] accounts for temporal periodicity. Beyond the above models, physics-guided deep learning approaches have recently emerged, providing deeper theoretical insights into spatiotemporal data analysis (STSD) [5], [62], [65]–[67].

Comparison: Existing MTSD models address various tasks within a single architecture but require fine-tuning for each specific task, thus failing to qualify as true multi-task models. Moreover, their task types are limited, typically focusing on basic tasks such as classification and regression, and lacking the capability to handle more complex tasks like generation. In contrast, BIGCity accommodates a broader range of spatiotemporal tasks, including classification, regression, and generation.

B. Universal Spatiotemporal Models (ST Foundation Models)

Universal foundation models aim to build a unified framework for ST data analysis, similar to LLMs for NLP. There are two main research directions: 1) *Cross-Dataset Universal Models*: These models aim to generalize across different datasets (*e.g.*, datasets from various cities), enabling rapid adaptation to new datasets through few-shot or zero-shot learning [22]–[24], [68]–[74] for traffic states or trajectory analysis.

TABLE I: Direct Comparisons Between BIGCity and Recent Models. TR is trajectory, TS is traffic state, ST FM is Spatiotemporal Foundation Model, Gene. is generation tasks, Pred. is prediction tasks

Type	Methods	Trajectory		Traffic State		Others	
		Gene.	Pred.	Gene.	Pred.	Data	Cost
MTSD	ST-Norm	✗	✗	✓	✓	TS	Low
	START	✓	✓	✗	✗	TR	Low
	RNTrajRec	✓	✗	✗	✗	TR	Low
ST FM	UrbanGPT	✗	✗	✓	✓	TS	Low
	UniTraj	✓	✓	✗	✗	TR	High
	BIGCity	✓	✓	✓	✓	TS&TR	Medium

For example, approaches [75], [76] treat LLMs as spatio-temporal encoders, training them for traffic prediction over cross-datasets. UniST [22] introduced spatiotemporal prompt learning, using statistical features of the dataset as prompts for the prediction of cross-dataset traffic. 2) *Universal Models for Heterogeneous Tasks*: These models focus on multi-task capabilities; a direct strategy is to train from scratch on large datasets [77]–[79]. Recent works [26], [80]–[82] exploit LLMs’ multi-task capabilities by converting trajectory data into textual format. What’s more, some studies aim to build general models only based on LLM’s architectures instead of their parameters. UniTraj [79] collected a huge trajectory dataset, and trained the model on this dataset from scratch. Such methods are simple in design but highly expensive in computational costs. Besides, VecCity [83] proposed a comprehensive ST model library, where each map entity is represented as a vector.

Comparison: Current ST foundation models struggle to balance strong generalization and multi-task capabilities. Models like UniST [22] and UrbanGPT [23] prioritize generalization, enabling few-shot transfer across datasets, but they typically handle only a single task. In contrast, UniTraj [79] and TrajFM [78] focus on multi-task learning, supporting diverse tasks within a single data modality. However, they cannot simultaneously process macro-level traffic states and micro-level trajectories. BIGCity, by comparison, integrates multi-modality and multi-task capabilities, offering a distinct direction. A direct comparison is in Tab. I.

III. PRELIMINARIES

Our model is designed for road network-based urban traffic scenarios, where the city is represented as a road network and ST data are generated from individuals’ movements. These scenarios are common in many widely used ST datasets. This section outlines the *basic spatial and temporal components* of such scenarios, defining the two types of *dynamic spatiotemporal data*: trajectories and traffic states.

A. Basic Spatial and Temporal Elements

The basic spatial elements in the scenario are road segments.

Definition 1 (Road Segment). Consider a city map with I road segments, denoted as r_i for the i -th segment. The set of segments is $\mathcal{R} = \{r_1, \dots, r_i, \dots, r_I\}$. Each segment r_i is

associated with a static feature vector $e_i^{(s)} \in \mathbb{R}^{D_r}$, describing attributes such as road type, length, lane count, in-degree, out-degree, and speed limit. Therefore, each road segment can be initially represented as a fixed-length feature with 6 dimension.

All road segments collectively form a road network.

Definition 2 (Road Network). A road network is a directed graph denoted as $\mathcal{G} = \{\mathcal{R}, \mathcal{A}, \mathbf{E}^{(s)}\}$, where $\mathcal{R}$ is the set of vertices corresponding to road segments. $\mathcal{A} \in \mathbb{R}^{|\mathcal{R}| \times |\mathcal{R}|}$ is the binary adjacency matrix indicating connectivity between road segments. $\mathbf{E}^{(s)} = (e_1^{(s)}, \dots, e_n^{(s)}, \dots, e_N^{(s)})$ represents the static feature vectors for all road segments.

The basic temporal elements are conceptualized in two forms: discrete time slice and continuous timestamp.

Definition 3 (Time Slice). A time slice is a fixed-length interval partitioning the timeline, indexed as $\{1, \dots, t, \dots, T\}$. For the t -th time slice, a feature vector $\iota_t \in \mathbb{R}^{D_t}$ is defined to describe its attributes, such as the slice’s start time, its index within a day, the day index within a week, and so on.

Definition 4 (Timestamp). A timestamp represents an instantaneous UTC time, denoted as τ . For a given timestamp τ , a feature vector $\iota_\tau \in \mathbb{R}^{D_\tau}$ describes its attributes, including its absolute time and the features of the time slice it belongs to.

In BIGCity, both discrete and continuous temporal elements coexist. For a time slice t , its start time is represented by the timestamp τ_t , and for a timestamp τ , the corresponding time slice is denoted as t_τ . Additionally, We define complex spatiotemporal data as combinations of above basic elements.

B. Dynamic Spatiotemporal Data

Dynamic ST data can be categorized into two types: individual-level trajectories and population-level traffic states. Trajectories capture individual mobility behaviors, defined as follows:

Definition 5 (Trajectory). A trajectory is a time-ordered sequence of road segments with associated timestamps, defined as $tr = ((r_{tr_1}, \tau_{tr_1}), \dots, (r_{tr_l}, \tau_{tr_l}), \dots, (r_{tr_L}, \tau_{tr_L}))$, where (r_{tr_l}, τ_{tr_l}) is the l -th sample in the trajectory. Here, $r_{tr_l} \in \mathcal{R}$ is the road segment, and τ_{tr_l} is the corresponding timestamp. The trajectory can also be expressed as $tr = ((e_{tr_1}^{(s)}, \tau_{tr_1}), \dots, (e_{tr_l}^{(s)}, \tau_{tr_l}), \dots, (e_{tr_L}^{(s)}, \tau_{tr_L}))$, where $e_{tr_l}^{(s)}$ denotes the static feature of road segment r_{tr_l} .

Definition 6 (Traffic State). For a given time slice t , the traffic state of the road segment r_i is represented as a vector $e_{i,t}^{(d)} \in \mathbb{R}^{D_d}$, contains the dynamic characteristics of r_i , such as average speed, traffic entry and exit. D_d is the number of traffic state channels. The traffic state series for r_i is $ts_i = (e_{i,1}^{(d)}, \dots, e_{i,t}^{(d)}, \dots, e_{i,T}^{(d)})$. Using the start time of each time slice as its timestamp, we have $ts_i = ((e_{i,1}^{(d)}, \tau_1), \dots, (e_{i,t}^{(d)}, \tau_t), \dots, (e_{i,T}^{(d)}, \tau_T))$, where τ_t is the timestamp of time slice t .

According to Def. 5 and 6, both trajectories and traffic states are sequences of the basic spatial and temporal elements. Both

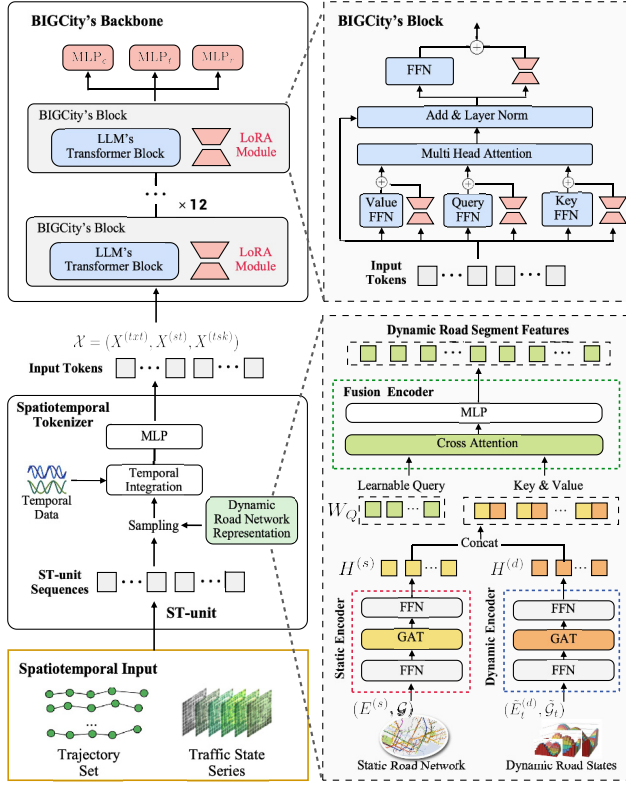


Fig. 2: The model architecture of BIGCity.

trajectory and traffic states can be divided into basic elements, which are combinations of specific fundamental spatiotemporal attributes. As mentioned above, all fundamental attributes are predefined with a fixed feature dimension. Therefore, the initial feature vector for a given type of spatiotemporal data can always maintain a fixed length.

C. Motivation of BIGCity

Trajectories and traffic states represent human mobility patterns at different levels: individual-level and population-level, respectively. Although typically treated as distinct, heterogeneous data modalities, these two types of data are inherently interconnected. According to Def. 5 and Def. 6, both trajectories and traffic states share similar structural formats.

- For a trajectory, a sample corresponds to the road segment where an individual is located at a given sampling time, and the location is associated with a corresponding traffic state.
- For a traffic state series, a sample represents the dynamic traffic state of a road segment at a given sampling time.

Thus, the triple (segment, traffic state, sampling time), i.e., “a road segment with its traffic state sampled at a specific time”, can be seen as the basic unit of ST data, analogous to words in NLP or pixels in image data. This insight suggests a viable opportunity to develop a versatile *MTMD* model that simultaneously handles both trajectories and traffic states.

Based on this idea, we propose BIGCity as to achieve *MTMD* ST modeling. Figure 2 illustrates the framework, which consists of two core components: *i*) a *Unified ST Tokenizer* to address heterogeneous data representation (Sec. IV), and *ii*) a *Versatile ST Model with Task-oriented Prompt* to handle distinct ST tasks (Sec. V).

IV. UNIFIED REPRESENTATIONS FOR ST DATA

In this section, we address *Challenge 1*: the unification of spatiotemporal data representations for MTMD model design. We first define *spatiotemporal units* (ST-units) as a unified representation format for both micro-level trajectory and macro-level traffic state data. Then, we introduce the *Spatiotemporal Tokenizer* to encode these ST-units into input tokens (ST tokens) for BIGCity.

A. Basic Spatiotemporal Units

Based on the motivation in Sec. III-C, we define the basic spatiotemporal unit (ST-unit), a unified data format for both trajectory and traffic state data. Specifically, it is a triple that contains all fundamental spatiotemporal properties: (location, traffic state, timestamp), where location is equal to a specific road segment ID. Formally, for a road segment r_i and a timestamp τ , an ST-unit is expressed as:

$$U_{i,\tau} = (e_i^{(s)}, e_{i,\tau}^{(d)}, \iota_\tau), \quad (1)$$

where $e_i^{(s)}$ represents the static features of segment r_i , ι_τ is the timestamp feature for τ , and $e_{i,\tau}^{(d)}$ represents the dynamic traffic state of segment r_i at the time slice containing τ .

Using the ST-unit in Eq. (1), we redefine traffic states and trajectories in a unified format as sequences of ST-units.

Definition 7 (ST-unit-based Traffic State). *For a road segment r_i , its traffic state series is redefined as:*

$$U_i = (U_{i,\tau_1}, \dots, U_{i,\tau_t}, \dots, U_{i,\tau_T}), \quad (2)$$

where $U_{i,\tau_t} = (e_i^{(s)}, e_{i,\tau_t}^{(d)}, \iota_{\tau_t})$. Here, ι_{τ_t} represents the features of the timestamp τ_t , and τ_t is the start time of time slice t .

Definition 8 (ST-unit-based Trajectory). *Given a trajectory tr of length L , its ST-unit-based representation is defined as:*

$$U_{tr} = (U_{tr_1}, \dots, U_{tr_l}, \dots, U_{tr_L}), \quad (3)$$

where $U_{tr_l} = (e_{tr_l}^{(s)}, e_{tr_l,t_{tr_l}}^{(d)}, \iota_{\tau_{tr_l}})$ denotes the ST-unit for the l -th sample. Here, $e_{tr_l}^{(s)}$ represents the static features of road segment tr_l , $e_{tr_l,t_{tr_l}}^{(d)}$ the dynamic features at time slice t_{tr_l} , and $\iota_{\tau_{tr_l}}$ the timestamp feature of τ_{tr_l} .

In certain datasets, road segments may lack dynamic features. In such cases, we set $e_{tr_l,\tau_{tr_l}}^{(d)} = \text{NULL}$.

Remark: In Eq. (3) and Eq. (2), both individual-level trajectories and population-level traffic states, despite their heterogeneous modalities, are represented in a unified format – sequences of ST-units. This unification resolves the challenge of heterogeneous data representation, enabling the design of a model capable of analyzing multiple ST data modalities.

B. Spatiotemporal Tokenizer

This subsection presents the spatiotemporal (ST) tokenizer, which converts ST-units into token vectors (ST-tokens). Specifically, it first generates dynamic road network representations as ST feature library, and then samples specific features for input data according to ST-units. The tokenizer comprises four modules: a static feature encoder, a dynamic feature encoder, a fusion encoder, and a temporal integration module.

Static Feature Encoder. This module encodes the static features $e_i^{(s)}$ of an ST-unit into a representation vector. To capture the spatial and topological relationships among road segments, the encoder employs a graph attention network (GAT) [84], generating segment representations based on the road network $\mathcal{G} = \{\mathcal{R}, \mathcal{A}, \mathbf{E}^{(s)}\}$ defined in Def. 2. Specifically, for the static feature matrix $\mathbf{E}^{(s)} = (e_1^{(s)}, \dots, e_N^{(s)})$, the encoder outputs a representation matrix $\mathbf{H}^{(s)}$ as follows:

$$\mathbf{H}^{(s)} = \text{FFN} \left(\text{GAT}_s(\mathbf{E}^{(s)}, \mathcal{G}) \right), \quad (4)$$

where $\text{GAT}_s(\cdot, \cdot)$ is the GAT model and $\text{FFN}(\cdot)$ a feed-forward network for dimensional transformation. The result is $\mathbf{H}^{(s)} = (\mathbf{h}_1^{(s)}, \dots, \mathbf{h}_I^{(s)})$, with $\mathbf{h}_i^{(s)} \in \mathbb{R}^{D_h}$ as the *static representation* for road segment r_i .

Dynamic Feature Encoder. This module encodes the dynamic features $e_{i,\tau}^{(d)}$ of an ST-unit into a representation vector. To capture temporal dependencies, historical features are incorporated from a time window of length T' . For time slice t , the window is defined as $W = (t - T', \dots, t - 1, t)$, and the concatenated historical features for segment r_i are $\tilde{e}_{i,t}^{(d)} = (e_{i,t-T'}^{(d)} \parallel \dots \parallel e_{i,t}^{(d)})$, where $\parallel$ denotes concatenation. The integrated historical dynamic feature matrix is $\tilde{\mathbf{E}}_t^{(d)} = (\tilde{e}_{1,t}^{(d)}, \dots, \tilde{e}_{I,t}^{(d)})$. By replacing the static feature matrix in the road network with $\tilde{\mathbf{E}}_t^{(d)}$, a dynamic road network $\tilde{\mathcal{G}}_t = \{\mathcal{R}, \mathcal{A}, \tilde{\mathbf{E}}_t^{(d)}\}$ is constructed. The dynamic feature encoder uses a GAT to encode $\tilde{\mathcal{G}}_t$ as:

$$\mathbf{H}_t^{(d)} = \text{FFN} \left(\text{GAT}_d(\tilde{\mathbf{E}}_t^{(d)}, \tilde{\mathcal{G}}_t) \right), \quad (5)$$

where the result $\mathbf{H}_t^{(d)} = (\mathbf{h}_{1,t}^{(d)}, \dots, \mathbf{h}_{I,t}^{(d)})$ represents the *dynamic representation* of segment r_i at time slice t .

Fusion Encoder. This module has two purposes: (1) integrate dynamic and static features; (2) capture long-distance dependencies in road network. First, the dynamic and static feature of a road segment r_i at time slice t is integrated by concatenation, denoted as $\mathbf{h}_{i,t} = (\mathbf{h}_i^{(s)} \parallel \mathbf{h}_{i,t}^{(d)})$. Feature concatenation can expand the feature dimensions and mitigates information loss.

Then, a cross-attention layer is employed for capturing long-distance dependencies. Specifically, for segments r_i and r_j , their relationship is computed as:

$$\alpha_{ij} = (\mathbf{q}_i^\top \mathbf{h}_{j,t}) / \sqrt{2D_h}, \quad (6)$$

where $\mathbf{W}_Q \in \mathbb{R}^{I \times D_h}$ is a learnable query matrix, and q_i is the i -th vector. The fused *spatial representation* for r_i at time slice t is then:

$$\mathbf{s}_{i,t} = \sum_{j=1}^I \text{ATT}_{ij} \cdot \mathbf{h}_{j,t}, \quad \text{where} \quad \text{ATT}_{ij} = \alpha_{ij} / \sum_{j=1}^I \alpha_{ij}. \quad (7)$$

GATs in the static and dynamic encoders only capture correlations between directly connected segments, but a trajectory. However, a spatiotemporal trajectory often connects dozens of road segments, extending well beyond the range of directly connected neighbors. Therefore, we employ cross-attention to facilitate global feature exchange. Learnable queries in cross-attention are employed for better adaptation to the given dataset.

Temporal Integration & ST Tokens. This module integrates the timestamp and its features with the spatial representation to generate an ST token. Specifically, for a ST-unit $U_{i,\tau} = (e_i^{(s)}, e_{i,\tau}^{(d)}, \mathbf{t}_\tau)$, the static and dynamic features $e_i^{(s)}$ and $e_{i,\tau}^{(d)}$ are encoded into a spatial representation $\mathbf{s}_{i,t_\tau}$. An MLP then combines $\mathbf{s}_{i,t_\tau}$ with the timestamp feature $\mathbf{t}_\tau$ and the time interval δ_τ between adjacent ST-units to generate the ST token:

$$\mathbf{x}_{i,\tau} = \text{MLP} \left(\mathbf{s}_{i,t_\tau} \parallel \mathbf{t}_\tau \parallel \delta_\tau \right), \quad (8)$$

where δ_τ is the time interval between consecutive ST-units in a sequence. For a sequence of ST-units $(U_1, \dots, U_l, \dots, U_L)$ corresponding to a trajectory or traffic state series, the interval is $\delta_{\tau_l} = \tau_l - \tau_{l-1}$. Including δ_{τ_l} helps the model handle non-uniformly spaced ST-unit sequences, which is crucial for real-world trajectory data with irregular sampling intervals. The resulting vector $\mathbf{x}_{i,\tau}$ is the *ST Token* for ST-unit $U_{i,\tau}$.

Remark: The ST tokenizer converts a sequence of ST-units, representing either a trajectory or a traffic state series, into an ST-token sequence. Specifically, it transforms the trajectory $\mathcal{U}_{tr}$ (Eq. (3)) into $\mathbf{X}_{tr} = (\mathbf{x}_{tr_1}, \dots, \mathbf{x}_{tr_L})$, and the traffic state series $\mathcal{U}_i$ (Eq. (2)) into $\mathbf{X}_i = (\mathbf{x}_{i,\tau_1}, \dots, \mathbf{x}_{i,\tau_T})$. These ST-token sequences serve as unified inputs for the BIGCity model, allowing it to process heterogeneous ST data across modalities. Thus, both individual-level trajectories and population-level traffic states are represented in a unified form, enabling seamless processing by a single model.

V. VERSATILE MODEL WITH TASK ORIENTED PROMPT

This section introduces a method to address the challenge of adapting to diverse ST analysis tasks (*Challenge 2*) for designing an *MTMD* model. A key difficulty for this challenge lies in informing the model about the specific task it should perform. Even with identical data inputs, different tasks require distinct types of outputs. For instance, given the same trajectory inputs, the travel time estimation task outputs continuous arrival time predictions, while the user-trajectory linkage task outputs discrete user ID.

Drawing inspiration from the prompt mechanism in LLMs, we propose a *Versatile Model with Task-oriented Prompts (VMTP)* to address this difficulty. VMTP employs textual instructions as prompts to guide the model on the desired task

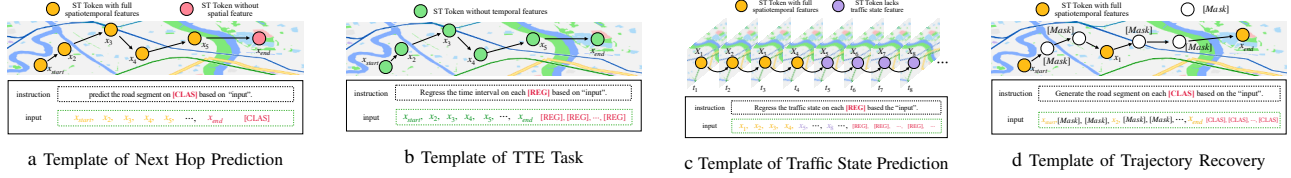


Fig. 3: The templates for Task-oriented Prompts with different tasks.

and utilizes a tunable LLM with ST tokens as inputs to perform specific ST data analysis tasks. The model consists of three modules: *Task-oriented Prompts* (input module), *LLM-based Backbone Model* (data-processing module), and *General-task Heads* (output module).

A. Task-oriented Prompts

The input to our model is a task-oriented prompt that combines the ST token sequences generated by the ST tokenizer in Sec. IV-B with textual instructions specifying the type of task to be performed.

Prompt Contents. The task-oriented prompt consists of three components:

- *Textual Instructions.* This part of the prompt is a textual description of the data analysis task to be executed. For example, the instruction “Where is the next hop position of the input trajectory?” informs the model to perform a next hop prediction task. We use the tokenizer of the backbone LLM (see Sec. V-B) to convert the instructions into a sequence of *Text Tokens*, denoted as $\mathbf{X}^{(\text{txt})}$.
- *Input Data.* This part of the prompt provides the spatiotemporal data to be analyzed, such as a traffic state series or a trajectory, formatted as ST-unit sequences according to Eq. (2) or Eq. (3). The ST tokenizer, as described in Sec. IV-B, converts these sequences into a series of *ST Tokens*, denoted as $\mathbf{X}^{(\text{st})}$.
- *Task Placeholders.* This part of the prompt provides a format guide for the task outputs. Two types of placeholders are used: the classification placeholder, denoted as [CLAS], and the regression placeholder, denoted as [REG]. These placeholders represent the expected output structure of the ST data analysis task. We use two learnable token vectors, $\mathbf{x}^{(\text{clas})}$ and $\mathbf{x}^{(\text{reg})}$, to corresponding to the two types of placeholders. The sequence of learnable token vectors is named as *Task Tokens* and denoted as $\mathbf{X}^{(\text{tsk})}$.

The complete inputs to the VMTP model is a combined sequence consisting of the text tokens $\mathbf{X}^{(\text{txt})}$, the ST tokens $\mathbf{X}^{(\text{st})}$, and the task tokens $\mathbf{X}^{(\text{tsk})}$, named as *input prompt tokens*, represented as:

$$\mathcal{X} = (\mathbf{X}^{(\text{txt})}, \mathbf{X}^{(\text{st})}, \mathbf{X}^{(\text{tsk})}). \quad (9)$$

Formula 9 is the format of task prompts, and $\mathbf{X}^{(\text{st})}$ is stands for $\mathcal{X}$. Specifically, $\mathcal{X}$ can be transformed into $\mathbf{X} = (\mathbf{X}^{(\text{txt})}, \mathbf{X}^{(\text{st})}, \mathbf{X}^{(\text{tsk})})$ by replacing $\mathbf{X}^{(\text{st})}$ as $\mathcal{X}$. Task prompts offer specific identifiers that help the model

identify the current task type automatically. This reduces task-switching costs and improves model’s multitasking abilities.

Prompt Templates. As illustrated in the examples in Fig. 3, we use a template to organize the *instructions*, *input data*, and *task placeholders* of task-oriented prompts into a unified structure for various tasks.

The first part of the template is the instruction. For each task, we start by using a language model, specifically ChatGPT, to understand the task’s function. Then, the language model generates a set of candidate instructions describing the task. For example, for the travel time estimation task, candidate instructions might include: “Give me the estimated time of arrival for the input trajectory” or “When will I walk to the ending position in this trajectory?”. Finally, we evaluate these candidates and select the most effective instruction based on testing. This selected instruction is then used as a fixed component in the prompt template.

The second and third parts of the template are the input data and task placeholders. These components vary slightly depending on the type of task:

- *For classification tasks*, such as trajectory next hop prediction and user-trajectory linkage, the input data consists of a sequence of ST tokens corresponding to a trajectory to be classified. The task placeholder is a classification placeholder [CLAS] (see Fig. 3a).
- *For regression tasks*, such as trajectory travel time estimation (TTE) and traffic state prediction, the input data is a sequence of ST tokens corresponding to a trajectory or traffic state series. The task placeholder is a sequence of regression placeholder [REG] (see Fig. 3b and Fig. 3c).
- *For generation tasks*, such as trajectory recovery, the input consists of a sequence of ST tokens with [MASK] inserted at the positions to be generated. In recovery, [MASK] are placed between adjacent samples in a low-rate trajectory. The task placeholders are sequences of classification pairs, denoted as ([CLAS], ..., [CLAS], ..., [CLAS]) (see Fig. 3d). The number of pairs matches the number of inserted [MASK] tokens, with each pair corresponding to a specific [MASK]. The *General Task Head* decodes these task placeholders into the ID of segments for the generated ST-units at the positions of [MASK] (see Sec. V-C).

The task-oriented prompts structured by this template serve as the final inputs to the backbone model in BIGCity.

B. LLM-based Backbone Model

We employ a tunable LLM as the backbone model for our framework. In the implementation, the backbone LLM is GPT-2 [29], but it can be replaced with other models based on user requirements. To enable efficient fine-tuning, we incorporate Low-Rank Adaptation (LoRA) modules into the backbone model. LoRA is a lightweight method for fine-tuning LLMs [85]. It extends the backbone model parameters by attaching low-rank matrices externally. During fine-tuning, LoRA keeps the original model weights frozen and updates the model using low-rank matrix decomposition. This approach significantly reduces storage and computational costs while maintaining flexibility for task-specific adaptations.

In our model, LoRA modules are integrated into the *query*, *key*, and *value* matrices, as well as the FFN layers of each transformer block in GPT-2. During training, only the parameters of the LoRA modules are updated, while the original parameters of GPT-2 remain frozen. This approach allows us to transfer GPT-2's general sequence modeling capabilities to ST-unit sequence analysis tasks efficiently. For each input prompt $\mathcal{X}$, the backbone processes the input as follows:

$$\{\mathbf{Z}, \mathbf{V}\} = \text{LLM}(\mathcal{X}, \Phi_{\text{LoRA}}), \quad (10)$$

where Φ_{LoRA} is the tuneable parameters of the LoRA modules.

In Eq. (10), the output sequence is divided into two parts: *i)* $\mathbf{Z}$, which is named as *output tokens* corresponding to the inputs task tokens $\mathbf{X}^{(\text{task})}$; and *ii)* $\mathbf{V}$, which corresponds to the remaining parts of the inputs prompt tokens. The output module (*i.e.*, *General Task Heads*) processes only the output tokens $\mathbf{Z}$, where the k -th token z_k in $\mathbf{Z}$ directly corresponds to the k -th [CLAS] or [REG] in the task placeholders.

C. General-task Heads

Unlike many ST representation learning methods that employ different task-specific output heads for various tasks [15], [86], our model utilizes unified general-task heads to decode the output tokens $\mathbf{Z}$ into results for different types of tasks. Similar to task tokens, the result tokens $z_k \in \mathbf{Z}$ are classified into two types: $z_k^{(\text{clas})}$ corresponding to [CLAS], and $z_k^{(\text{reg})}$ corresponding to [REG]. We use multilayer perceptrons (MLPs) as decoders to map the result tokens to classification or regression outputs, as follows:

$$\begin{aligned} \hat{\mathbf{y}}_k^{(\text{clas})} &= \text{MLP}_c(z_k^{(\text{clas})}), \\ \hat{\mathbf{y}}_k^{(\text{tim})} &= \text{MLP}_t(z_k^{(\text{reg})}), \quad \hat{\mathbf{y}}_k^{(\text{reg})} = \text{MLP}_r(z_k^{(\text{reg})}), \end{aligned} \quad (11)$$

Here, $\text{MLP}_c(\cdot)$ generates results for classification tasks, $\text{MLP}_t(\cdot)$ handles timestamp regression (used in tasks such as TTE and timestamp generation for trajectory recovery), and $\text{MLP}_r(\cdot)$ is responsible for regressing other types of outputs. The predicted classification, timestamp, and general regression results are denoted by $\hat{\mathbf{y}}_k^{(\text{clas})}$ (in one-hot encoding), $\hat{y}_k^{(\text{tim})}$, and $\hat{\mathbf{y}}_k^{(\text{reg})}$, respectively. Given the significant differences between temporal and spatial features, a specialized MLP decoder, $\text{MLP}_t(\cdot)$, is used exclusively for timestamp regression.

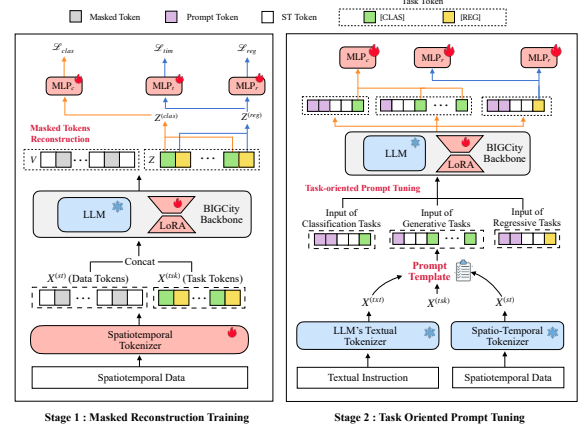


Fig. 4: The hierarchical training strategy of BIGCity.

Remark: Guided by the textual instructions in task-oriented prompts, our model is equipped with the knowledge of which task to execute. By adapting to different instructions, the backbone model and general-task heads generate task-specific outputs for various types of tasks, effectively addressing the challenge of adapting to diverse spatiotemporal analysis tasks (Challenge 2). Furthermore, we leverage a LLM as the backbone, offering two key advantages: First, the LLM's powerful text processing capabilities enable our model to accurately interpret instructions and adapt the data processing accordingly. Second, the LLM's strong general sequence modeling abilities can be seamlessly transferred to ST sequence data analysis tasks, enhancing the model's performance and versatility.

VI. MODEL TRAINING

As shown in Fig. 4, BIGCity adopts a two-stage training strategy comprising *Masked Reconstruction Training* and *Multi-Task Prompt Tuning*. In the first stage, masked reconstruction training, a self-supervised approach is employed to enable the model to learn general spatiotemporal dependencies from ST sequence data. In the second stage, multi-task prompt tuning, a multi-task co-training method is utilized to allow the model to handle a variety of tasks within a unified framework, eliminating the need for task-specific fine-tuning.

A. Masked Reconstruction Training

In this stage, we employ a masked reconstruction task to enable the model to capture general features of ST sequences without being tailored to specific data analysis tasks. Masked reconstruction is a widely used approach in LLM pre-training, where certain samples from the input sequence are randomly masked, and the model predicts the masked samples. This task allows the model to learn intrinsic correlations within the input sequence data without requiring labeled data. The specific process of masked reconstruction training in our model is described as follows.

Inputs. Given an ST-unit sequence corresponding to a trajectory or traffic state series, *i.e.*, $\mathcal{U} = (\mathcal{U}_1, \dots, \mathcal{U}_L)$, the

ST tokenizer encodes it into an ST token sequence $\mathbf{X}^{(\text{st})} = (\mathbf{x}_1, \dots, \mathbf{x}_L)$. We randomly mask K tokens in $\mathbf{X}^{(\text{st})}$, replacing them with the mask token [MASK], resulting in $\tilde{\mathbf{X}}^{(\text{st})} = (\mathbf{x}_1, \dots, [\text{MASK}]_1, \dots, \mathbf{x}_L, \dots, [\text{MASK}]_K, \dots, \mathbf{x}_L)$. For each $[\text{MASK}]_k$, we assign a task placeholder pair $([\text{CLAS}]_k, [\text{REG}]_k)$, producing a task token sequence:

$$\mathbf{X}^{(\text{tsk})} = ((\mathbf{x}_1^{(\text{clas})}, \mathbf{x}_1^{(\text{reg})}), \dots, (\mathbf{x}_K^{(\text{clas})}, \mathbf{x}_K^{(\text{reg})})). \quad (12)$$

Finally, the token sequence $\mathcal{X} = (\tilde{\mathbf{X}}^{(\text{st})}, \mathbf{X}^{(\text{tsk})})$ is fed into the backbone LLM model for masked reconstruction training.

Outputs. Given $\mathcal{X}$ as input to the backbone model, the output is a result token sequence $\mathbf{Z}$, where each element corresponds one-to-one with elements in $\mathbf{X}^{(\text{tsk})}$, as follows:

$$\mathbf{Z} = ((\mathbf{z}_1^{(\text{clas})}, \mathbf{z}_1^{(\text{reg})}), \dots, (\mathbf{z}_K^{(\text{clas})}, \mathbf{z}_K^{(\text{reg})})). \quad (13)$$

For the k -th output token $(\mathbf{z}_k^{(\text{clas})}, \mathbf{z}_k^{(\text{reg})})$, the general-task head (Eq. (11)) decodes it into an predicted ST-unit:

$$\hat{\mathcal{U}}_k = (\hat{\mathbf{y}}_k^{(\text{clas})}, \hat{\mathbf{y}}_k^{(\text{reg})}, \hat{\mathbf{y}}_k^{(\text{tim})}), \quad (14)$$

which represents the reconstructed sample for the ST-unit masked by $[\text{MASK}]_k$. In Eq. (14), $\hat{\mathbf{y}}_k^{(\text{clas})}$ is the predicted road segment ID, $\hat{\mathbf{y}}_k^{(\text{reg})}$ is the predicted dynamic feature of the road segment, and $\hat{\mathbf{y}}_k^{(\text{tim})}$ is the predicted timestamp.

Loss Function. We employ the Cross-Entropy loss for classification and the Mean Squared Error (MSE) loss for regression. For each masked ST-unit, there are three losses:

$$\begin{aligned} \mathcal{L}_{\text{clas}} &= \sum_{k=1}^K \phi(r_k) \log(\hat{\mathbf{y}}_k^{(\text{clas})}), \\ \mathcal{L}_{\text{reg}} &= \sum_{k=1}^K \|e_k^{(d)} - \hat{\mathbf{y}}_k^{(\text{reg})}\|_F^2, \quad \mathcal{L}_{\text{tim}} = \sum_{k=1}^K (\tau_k - \hat{\mathbf{y}}_k^{(\text{tim})})^2, \end{aligned} \quad (15)$$

where $\phi(r_k)$, $e_k^{(d)}$, and τ_k are the ground truths for $\hat{\mathcal{U}}_k$. The final loss function for masked reconstruction training is:

$$\mathcal{L}_{\text{MRT}} = \frac{1}{K \times N} \sum_{n=1}^N (\mathcal{L}_{\text{clas}}^{(n)} + \lambda_1 \mathcal{L}_{\text{reg}}^{(n)} + \lambda_2 \mathcal{L}_{\text{tim}}^{(n)}), \quad (16)$$

where λ_1 and λ_2 are predefined parameters, the superscript (n) indicates the index of a training sample, and N is the total number of training samples.

During Masked Reconstruction Training, the ST tokenizer and the LoRA module in the backbone are jointly trained by minimizing the loss function $\mathcal{L}_{\text{MRT}}$.

B. Task-oriented Prompt Tuning

This stage trains our model to perform various ST data analysis tasks using task-oriented prompts.

Inputs. In this stage, the inputs are task-oriented prompts for diverse tasks. Datasets for all task types are combined into a unified training dataset, referred to as the *full training set*. For each sample in the full training set, a corresponding prompt is generated as $\mathcal{X} = (\mathbf{X}^{(\text{txt})}, \mathbf{X}^{(\text{st})}, \mathbf{X}^{(\text{tsk})})$, which serves as the input to the backbone model of BIGCity.

In the implementation, we incorporate three types of tasks for prompt tuning: *classification*, *regression*, and *generation*. The textual instruction tokens $\mathbf{X}^{(\text{txt})}$ in $\mathcal{X}$ follow fixed templates as shown in Fig. 3. The data tokens $\mathbf{X}^{(\text{st})}$ and task tokens $\mathbf{X}^{(\text{tsk})}$ for these tasks are described as follows:

- **Classification Tasks** include next hop prediction and trajectory classification. Trajectory classification tasks further comprise trajectory traffic pattern classification and user-trajectory linkage. The data tokens $\mathbf{X}^{(\text{st})}$ in $\mathcal{X}$ represent a sequence of ST-units corresponding to a trajectory. The task tokens $\mathbf{X}^{(\text{tsk})}$ consist of a single [CLAS], corresponding to the class label to be predicted.
- **Regression Tasks** include travel time estimation and traffic state prediction. *i)* For the travel time estimation task, the data tokens $\mathbf{X}^{(\text{st})}$ are a trajectory ST-unit sequence, where timestamps at locations with unknown travel times are replaced by [MASK]. The task tokens are a sequence of [REG], each corresponding to an unknown timestamp. *ii)* For traffic state prediction, the data tokens represent the first half of a traffic state sequence, and the task tokens are a sequence of [REG], each corresponding to the rest traffic state steps to be predicted.
- **Generation Task** includes trajectory recovery. The data tokens consist of a low-sampling-rate trajectory where locations to be recovered are inserted with [MASK]. The task tokens are a sequence of [CLAS] with the same number of elements as the [MASK] tokens. Each [CLAS] corresponds to a sample to be recovered in the low-sampling-rate trajectory.

Outputs. For classification tasks, the general-task heads decode the output token corresponding to [CLAS] into the predicted class label. For regression tasks, the output token corresponding to [REG] is decoded into predicted timestamps or traffic states. For generation tasks, the output tokens corresponding to [CLAS] are decoded into the road segment IDs of the recovered samples.

Loss Function. In task-oriented prompt tuning, we use samples from all tasks, *i.e.*, the full training set, to co-train the model. The overall loss function is defined as:

$$\mathcal{L}_{\text{PT}} = \mathcal{L}_{\text{CLAS}} + \lambda_2 \mathcal{L}_{\text{REG}} + \lambda_3 \mathcal{L}_{\text{GEN}}, \quad (17)$$

where $\mathcal{L}_{\text{CLAS}}$, $\mathcal{L}_{\text{REG}}$, and $\mathcal{L}_{\text{GEN}}$ represent the loss functions for classification, regression, and generation tasks, respectively. Cross-entropy loss is applied for classification tasks, while mean squared error (MSE) loss is used for regression tasks.

In task-oriented prompt tuning, only the parameters in the LoRA modules of the backbone model are updated using the loss function $\mathcal{L}_{\text{PT}}$, while the parameters of the ST tokenizer remain frozen. After completing both the masked reconstruction training and task-oriented prompt tuning, the ST tokenizer and the VMTP are assembled to form the complete BIGCity model, capable of ST data analysis across multiple tasks in multiple data modalities (*MTMD*).

TABLE II: Types of ST Data Analysis Tasks

Task Type	Trajectory Based	Traffic State Based
Classification	Next Hop Prediction	\
	Trajectory Classification	
Regression	Travel Time Estimation	One-Step Prediction
		Multi-Step Prediction
Comparison	Most Similar Search	\
Generation	Trajectory Recovery	Traffic State Imputation

VII. EXPERIMENTS

A. Experimental Setting

Spatiotemporal (ST) Tasks. As a multi-task model, BIGCity is co-trained on four types of ST tasks and simultaneously tackles eight specific tasks, as listed in Tab. II.

Implementation Details. We evaluated BIGCity on three real-world datasets: Beijing (BJ), Xi'an (XA), and Chengdu (CD). Details about datasets please refer to our code link.

Baselines. BIGCity is evaluated by comparing with 18 task-specific baselines of each particular task. For classification, regression and comparison tasks of trajectory input, we select the seven current state-of-art (SOTA) trajectory representation models: Trajectory2vec (Tr2v) [10], T2vec (T2v) [87], TremBR (TBR) [14], Toast (Toa) [11], JCLRNT (JCL) [12], START (STA) [15], and JGRM (JRM) [13]. For traffic state input, BIGCity is compared with six current SOTA traffic state prediction models: DCRNN [56], GWNEN [57], MTGNN [17], TrGNN [18], STGODE [88], ST-Norm [19], and SSTBAN [20]. Table V. For generation tasks, BIGCity is compared with four recovery models: Linear+HMM [1], DTHR+HMM [1], MTrajRec [89], and RNTrajRec [90].

Evaluation Metrics. For trajectory Travel Time Estimation: we adopt three metrics, including mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE); For next hop prediction: Following the settings in [16], we used three metrics: Accuracy (ACC), mean reciprocal rank at 5 (MRR@5) and Normalized Discounted Cumulative Gain at 5 (NDCG@5); For trajectory classification: We use Accuracy (ACC), F1-score (F1), and Area Under ROC (AUC) to evaluate binary classification on BJ dataset. Using Micro-F1, Macro-F1 and Macro-Recall on XA and CD datasets; For most similar trajectory search: we evaluated the model using Top-1 Hit Rate (HR@1), Top-5 Hit Rate (HR@5), and Top-10 Hit Rate (HR@10), where Top-k Hit rate indicates the probability that the ground truth is in the top-k most similar samples ranked by the model; Metrics used in traffic state tasks are: MAE, MAPE, RMSE; For trajectory Recovery: We evaluated our model on three types of mask ratios: 85%, 90%, 95%. The evaluation metric is the recovery accuracy and Macro-F1 on masked road segments.

B. Performance Comparison

We conducted extensive experiments on all 3 datasets across 8 ST tasks. As current baselines handle trajectories and traffic states separately, we compared BIGCity to trajectory and traffic state baselines individually. All comparison experiments are repeated ten times, we list the mean values in this paper and provide standard deviation in the code link.

Trajectory Tasks. Firstly, we conclude *trajectory next-hop prediction (Next)*, *travel time estimation (TTE)*, *trajectory classification (CLAS)*, and *similar trajectory search (Simi)* as trajectory-based non-generative tasks as these four tasks share similar pipelines. Following the settings in [13], *Next* task prediction the next token of an input, In *TTE*, we mask off all timestamps, and the ground truth for each segment is the time interval between its former one segment. *Simi* takes a certain input samples as queries and search the most similar samples from the whole dataset, and more details please refer to [13]. *CLAS* in BJ is a binary classification. In XA and CD, *CLAS* is a user-trajectory link classification and we only retained users with more than 50 trajectories. The comparison results are given in Tab. III. BIGCity consistently and significantly outperforms the baselines across all scenarios.

Trajectory Recovery (Reco) task usually employs task-specific models. For each input trajectory, we down-sample it using a predefined mask window to mask a specific ratios of the data, generating a sparse trajectory. Then, we use the original trajectory as the ground truth, and train models to reconstruct the original trajectories from sparse trajectories. We evaluate model's performance under different mask ratios. The comparison results are given in Tab. IV.

Traffic State Tasks. We evaluate BIGCity on three traffic state tasks, *i.e.*, *one-step prediction (O-Step)*, *multi-step prediction (M-Step)*, and *traffic state imputation (TSI)*. Specifically, one-step prediction generates the traffic state in the next time slice, and multi-step prediction generates traffic states in the next 6 time slice. In traffic state imputation, we masked 25% input data and trained models to recovery the masked data. Here, we only conducted experiments on XA and CD, as the trajectories in BJ are too sparse to get reliable traffic states. As shown in Tab. V, our model largely outperforms the other baselines for both one-step and multi-step predictions on the two datasets. The average performance advantage is **2.83%**, with the largest reaching **7%**. As for traffic state imputation, the average and largest improvement are **7.8%|12.3%**.

In above experiments, BIGCity outperforms 18 baselines (8 representation models and 10 task-specific models) across all tasks, datasets, and metrics, indicating its universality and robust multi-task ability.

C. Generalization Ability

We evaluate BIGCity's generalization ability in across datasets scenario. Specifically, we first trained the whole BIGCity on BJ dataset. Then, we transfer BIG-BJ's backbone model to XA and CD dataset. Specifically, we combined the spatiotemporal tokenizer of XA and CD with the backbone

TABLE III: Performance on the trajectory-based non-generative tasks, *i.e.*, Travel Time Estimation, Trajectory Classification, Trajectory Next Hop Prediction, Most Similar Trajectory Search. Particularly, MAPE here are percentage numbers.

Task		Travel Time Estimation			Trajectory Classification			Next Hop Prediction			Most Similar Search		
Data	Model	MAE↓	RMSE↓	MAPE↓	ACC↑	F1↑	AUC↑	ACC↑	MRR@5↑	NDC@5↑	HR@1↑	HR@5↑	HR@10↑
BJ	Tr2v	10.13	56.83	37.95	0.811	0.852	0.837	0.633	0.746	0.784	0.607	0.766	0.867
	T2v	10.03	56.65	36.42	0.814	0.863	0.879	0.623	0.731	0.769	0.788	0.885	0.932
	TBR	9.981	36.97	34.25	0.818	0.876	0.871	0.537	0.625	0.659	0.596	0.699	0.878
	Toa	10.79	57.41	35.37	0.821	0.861	0.862	0.714	0.841	0.878	0.326	0.399	0.767
	JCL	10.23	46.49	41.22	0.808	0.859	0.873	0.714	0.841	0.881	0.531	0.699	0.936
	STA	9.156	35.41	32.01	0.853	0.885	0.905	0.734	0.836	0.882	0.776	0.878	0.934
	JRM	10.18	41.88	39.51	0.849	0.879	0.897	0.746	0.843	0.896	0.681	0.852	0.906
	Ours	8.869	33.21	30.34	0.872	0.891	0.909	0.751	0.855	0.902	0.801	0.895	0.952
Data	Model	MAE↓	RMSE↓	MAPE↓	Mi-F1↑	Ma-F1↑	Ma-Re↑	ACC↑	MRR@5↑	NDC@5↑	HR@1↑	HR@5↑	HR@10↑
XA	Tr2v	2.051	3.147	35.14	0.086	0.085	0.093	0.679	0.759	0.788	0.673	0.854	0.889
	T2v	2.035	3.132	33.73	0.086	0.082	0.089	0.672	0.747	0.774	0.733	0.821	0.877
	TBR	2.016	3.121	32.13	0.091	0.088	0.081	0.568	0.633	0.657	0.538	0.67	0.725
	Toa	2.152	3.266	33.93	0.099	0.095	0.092	0.778	0.887	0.913	0.283	0.393	0.442
	JCL	2.173	3.257	33.12	0.093	0.091	0.095	0.793	0.889	0.919	0.335	0.551	0.634
	STA	1.833	2.982	30.57	0.101	0.098	0.102	0.825	0.903	0.928	0.741	0.883	0.893
	JRM	1.915	3.152	31.88	0.097	0.094	0.097	0.829	0.906	0.934	0.703	0.826	0.863
	Ours	1.723	2.614	29.76	0.112	0.104	0.113	0.837	0.923	0.942	0.791	0.887	0.909
Data	Model	MAE↓	RMSE↓	MAPE↓	Mi-F1↑	Ma-F1↑	Ma-Re↑	ACC↑	MRR@5↑	NDC@5↑	HR@1↑	HR@5↑	HR@10↑
CD	Tr2v	1.635	2.432	34.74	0.142	0.152	0.156	0.726	0.809	0.837	0.607	0.748	0.794
	T2v	1.632	2.433	34.45	0.149	0.151	0.158	0.711	0.791	0.819	0.543	0.715	0.753
	TBR	1.620	2.405	34.15	0.142	0.156	0.155	0.608	0.682	0.708	0.409	0.532	0.576
	Toa	1.708	2.493	37.23	0.143	0.152	0.153	0.789	0.872	0.911	0.225	0.322	0.357
	JCL	1.657	2.481	36.42	0.148	0.164	0.157	0.792	0.881	0.904	0.348	0.552	0.642
	STA	1.433	2.394	32.12	0.151	0.163	0.159	0.795	0.885	0.919	0.607	0.757	0.776
	JRM	1.372	2.253	30.79	0.143	0.152	0.151	0.798	0.888	0.927	0.631	0.774	0.815
	Ours	1.287	2.181	28.59	0.153	0.169	0.162	0.821	0.912	0.938	0.646	0.787	0.821

* The bold results are the best, and the underlined results are the second best. The metric with "↑" ("↓") means that a larger (smaller) result is better.

TABLE IV: Performance on trajectory based generative tasks, *i.e.*, Trajectory Recovery. 85%, 90%, and 95% are masked ratios.

Metric		Accuracy ↑									Macro-F1 ↑								
Models	Data	BJ			XA			CD			BJ			XA			CD		
		85%	90%	95%	85%	90%	95%	85%	90%	95%	85%	90%	95%	85%	90%	95%	85%	90%	95%
Linear+HMM		0.219	0.205	0.196	0.275	0.239	0.207	0.289	0.268	0.233	0.098	0.095	0.089	0.125	0.101	0.094	0.131	0.117	0.099
DTHR+HMM		0.236	0.227	0.208	0.269	0.218	0.201	0.296	0.264	0.224	0.118	0.097	0.091	0.135	0.121	0.105	0.141	0.119	0.106
MTrajRec		0.456	0.418	0.323	0.495	0.443	0.338	0.512	0.459	0.347	0.201	0.177	0.136	0.221	0.199	0.145	0.244	0.240	0.164
RNTrajRec		0.475	0.439	0.338	0.503	0.456	0.359	0.523	0.478	0.369	0.205	0.181	0.152	0.267	0.226	0.173	0.292	0.257	0.185
Ours		0.518	0.471	0.368	0.562	0.489	0.381	0.585	0.513	0.405	0.259	0.217	0.177	0.309	0.258	0.194	0.321	0.269	0.212

trained on BJ, and only fine-tuned the last MLP layer of tokenizers on XA and CD datasets. The experimental results are given in Tab. VI. In both XA and CD, BIGCity-BJ denotes the transferred model with its backbone trained on BJ, and BIGCity is the model completely trained on XA or CD. The generalization ability is evaluated by the performance loss between BIGCity and BIG-BJ. As shown in the table, the average performance degradation for BIGCity-BJ compared with original BIGCity model is within 7%. In comparison with the results in Tab. III, BIGCity-BJ still outperforms all of baselines in most cases, demonstrating our BIGCity's superior cross-city generalization capability as well as the robustness. The experimental results indicate that our model has potential to be applied in a valuable scenario: pre-training the backbone model on a large city with ample data and then transferring it to smaller cities with limited data.

D. Ablation Studies

We first conducted ablations on the static encoder, dynamic encoder of the spatiotemporal tokenizer, thereby evaluating the contribution of general representation. Subsequently, we conduct ablations on task-oriented prompts. Specifically, 1) *w/o-Dyn* removes the dynamic encoder, resulting in the loss of dynamic traffic state information. 2) *w/o-Sta* removes the static encoder, resulting in the loss of static topology information. 3) *w/o-Fus* removes the fusion encoder, resulting in the loss of long-range ST features integration. 4) *w/o-Pro* removes prompts from the input, and we trained a specific task MLP for each individual task. As shown in Tab. VII, the fusion encoder benefits all ST tasks, especially in tasks prefer long-range ST dependencies, *i.e.*, travel time estimation. Results in *w/o-Sta* and *w/o-Dyn* indicate that the general representation indeed enhances BIGCity's performance. Dynamic features enhance

TABLE V: The Performance in Traffic State Tasks

Data	XA								
Task	One-Step			Multi-Step			Imputation		
Metric	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE
DCR	1.092	11.77	2.312	1.293	16.38	2.492	0.585	7.493	1.403
GWN	1.113	11.44	2.264	1.304	15.59	2.331	0.847	10.63	1.833
MTG	1.072	10.56	1.903	1.223	14.91	2.163	0.906	11.12	1.790
TrG	1.103	11.46	2.042	1.263	15.90	2.423	0.944	11.79	1.815
STG	1.122	12.59	2.272	1.392	17.34	2.304	0.989	12.40	1.709
STN	0.974	10.27	1.973	1.268	15.64	2.281	0.940	11.64	1.789
SST	0.802	9.972	1.873	1.183	14.21	2.292	0.883	11.23	1.736
Ours	0.791	9.732	1.743	1.162	14.01	2.143	0.536	6.671	1.335
Data	CD								
Task	One-Step			Multi-Step			Imputation		
Metric	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE
DCR	1.232	13.02	2.324	1.552	18.22	2.862	0.731	8.601	1.704
GWN	1.342	12.71	2.414	1.612	18.14	2.713	1.024	11.80	2.121
MTG	1.183	11.93	2.132	1.413	16.76	2.506	1.109	12.71	2.055
TrG	1.234	12.39	2.312	1.562	17.69	2.761	1.165	13.14	2.082
STG	1.352	12.91	2.413	1.633	18.77	2.603	1.235	14.37	2.046
STN	1.203	11.99	2.201	1.491	17.02	2.594	1.152	12.88	2.061
SST	1.163	11.77	2.191	1.452	17.01	2.954	1.027	11.84	2.005
Ours	1.122	11.16	2.103	1.412	15.98	2.471	0.665	8.192	1.617

TABLE VI: Generalization experiments on three tasks, *i.e.*, travel time estimation, next hop prediction (Next), trajectory classification (CLAS)

Data	Tasks	TTE		Next		CLAS	
		MAE↓	RMSE↓	ACC↑	MRR@5↑	Mi-F1↑	Ma-F1↑
XA	BIGCity	1.72	2.61	0.837	0.923	0.110	0.104
	BIG-BJ	1.82	2.78	0.806	0.912	0.103	0.097
	Loss	5.89%	5.98%	3.81%	1.20%	6.46%	6.94%
CD	BIGCity	1.29	2.18	0.821	0.910	0.153	0.169
	BIG-BJ	1.37	2.31	0.792	0.878	0.144	0.159
	Loss	5.63%	5.72%	3.62%	1.12%	6.22%	6.15%

trajectory tasks by improving representational distinctiveness, while static features benefit traffic state tasks by incorporating long-range topology information through input trajectories. As for task-oriented prompts, they have the most significant influence on performance of all tasks. The experimental results demonstrate their importance in BIGCity's multi-task ability, as they provide task-specific guidance.

VIII. MODEL ANALYSIS

A. Time Complexity

BIGCity consists of three components: a graph-based ST tokenizer, a transformer-based backbone, and MLP-based general task heads. Suppose the number of edges in the road network is E , the feature dimension of the ST-tokenizer is d_{st} ; Input sample's length to the backbone is L_{seq} , and feature dimension of the backbone is d_{ba} ; The input and output feature dimension of task specific heads is M_{in} , M_{out} . Therefore,

TABLE VII: Ablation Studies on Model Designs

Task	TTE MAE↓	CLAS Ma-F1↑	Next Acc↑	Simi. HR10↑	Reco. Acc.↑	TSI MAPE↓	M-Step MAPE↓	AveGAP
w/o-Dyn+Fus	1.96	0.102	0.803	0.801	0.537	-	-	-
GAP	13.9%	2.2%	4.1%	11.8%	4.4%	-	-	7.28
w/o-Dyn	1.87	0.102	0.815	0.805	0.550	-	-	-
GAP	11.7%	2.2%	2.7%	11.4%	2.2%	-	-	6.9%
w/o-Sta+Fus	-	-	-	-	-	7.18	14.83	-
GAP	-	-	-	-	-	6.8%	4.9%	5.8%
w/o-Sta	-	-	-	-	-	7.02	14.48	-
GAP	-	-	-	-	-	5.3%	3.4%	4.4%
w/o-Pro	2.03	0.096	0.759	0.892	0.513	7.672	15.51	-
GAP	18.0%	11.5%	9.3%	1.8%	8.7%	15.0%	9.6%	10.5%
BIGCity	1.72	0.104	0.837	0.909	0.562	6.671	14.01	-

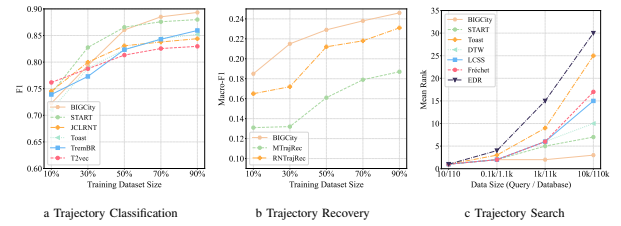


Fig. 5: (a) All models perform similarly. (b) BIGCity consistently gained from increased data scale. (c) Mean Rank: Average rank of ground truth in similarity-based ranking; lower is better.

the time complexity of the ST-tokenizer is $O(|E| \times d_{st})$, that of the backbone is $O(L_{seq} \times d_{ba}^2 + L_{seq}^2 \times d_{ba})$, and that of task heads are $O(L_{seq} \times d_{ba}^2 + L_{seq}^2 \times d_{ba})$. The only variable is L_{seq} . In practice, $d_{ba} \gg L_{seq}$, where $d_{ba} = 768$ but $L_{seq} < 128$. Thus, the time complexity of BIGCity is actually linearly scaling with L_{seq} , which can be validated in the following experiments.

B. Scalability

We double the scale of BJ dataset by doubling the time span of data collection. The extended dataset contains more than 2.3 million trajectories. We divide the dataset into subsets of 10%, 30%, 50%, 70%, and 90% to evaluate the model's performance across multiple downstream tasks. We select three representative tasks: trajectory classification, trajectory search, and trajectory recovery. Among these, trajectory recovery is the most challenging and best demonstrates the benefits of increased data volume. Trajectory search is the most sensitive to the scale of the inference data. As shown in Fig.5a and Fig.5b, BIGCity consistently benefits from larger data scales, with its advantage over the baselines becoming more pronounced as task difficulty increases. This suggests that BIGCity effectively leverages large-scale data. In Fig.5c, we employ certain non-deep learning models, including DTW [91], LCSS [92], Fréchet Distance [93], and EDR [94] for more comprehensive comparison. To increase task difficulty, We gradually expand the inference space by increasing the number of queries from 10 to 10k and keeping the search space

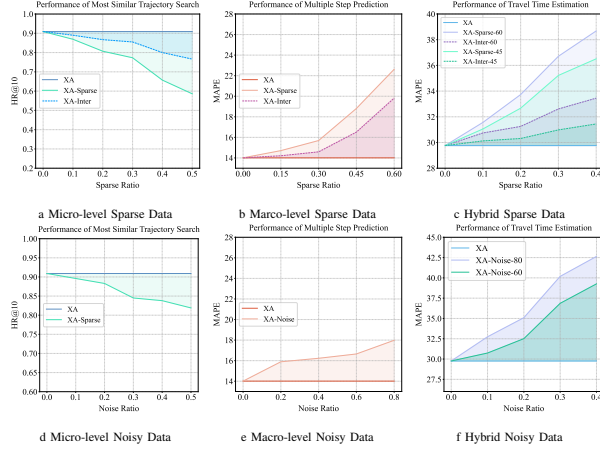


Fig. 6: Edges Cases in Sparse Data and Noisy Data; “XA-inter” denotes the results tested on interpolated dataset; In (c), “XA-Sparse-60” means macro-level sparsity is 60%, and the x-axis is micro-level sparsity; In (f) “XA-Noise-80” means macro-level noise is 0.8, and the x-axis is micro-level noise.

fixed at ten times the query size. As shown in Fig. 5c, BIGCity maintains stable performance with tiny degradation under increasing inference complexity, demonstrating its robustness to large-scale data.

C. Edge Cases

We conducted experiments on edge cases involving sparse and noisy data. Since our model can process both micro-level and macro-level data, we evaluated these edge cases separately under three scenarios: purely micro-level, purely macro-level, and hybrid-level data. Specifically, the hybrid-level scenario represents an extreme case where both macro-level and micro-level data are sparse or noisy. For evaluation, we selected three representative tasks: trajectory search, which is sensitive to micro-level data; multi-step prediction, which primarily depends on macro-level data; and travel time estimation, which is influenced by both micro-level and macro-level data.

Taking XA as an example, Fig. 6a, Fig. 6b, and Fig. 6c illustrate the impact of data sparsity. We simulate sparse datasets through down-sampling and explore interpolation as a potential mitigation strategy. Fig. 6a, Fig. 6b, and Fig. 6c show that: (1) BIGCity remains robust to micro-level sparsity but is more sensitive to macro-level sparsity, with performance degradation reaching nearly 40% in extreme cases; (2) Interpolation effectively mitigates the impact of data sparsity but has limited effectiveness in addressing macro-level sparsity.

Fig. 6d, Fig. 6e, and Fig. 6f illustrate the impact of noisy data. We first calculate the standard deviation of our dataset and then introduce Gaussian noise based on certain proportions of this standard deviation. Fig. 6d, Fig. 6e, and Fig. 6f reveal that: (1) Noise in micro-level data affects the model more significantly, while noise in macro-level data has a negligible impact; (2) Compared to data sparsity, BIGCity is more robust to noise. In most cases, BIGCity still outperforms



Fig. 7: Interfaces of the Prototype System

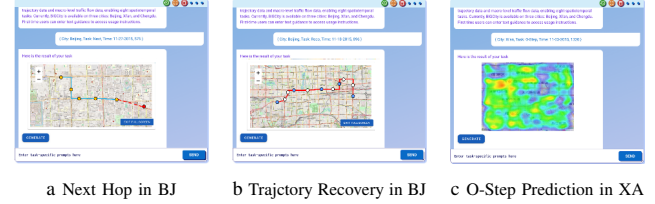


Fig. 8: Several Tasks Examples in the Prototype System

many baselines, with significant performance degradation only occurring in extremely noisy scenarios.

IX. THE PROTOTYPE SYSTEM

The Prototype System. We aim to integrate BIGCity into Huawei Maps to enhance their intelligence and functionality. Therefore, we developed a prototype system, which is a user-friendly Chatbot. The initial interface is presented in Fig. 7a, where it provides a standardized input format. As shown in Fig. 7b and Fig. 7c, our prototype system collects spatiotemporal data through an interactive map and gathers user task instructions via a chat window. Users can mark a continuous trajectory segment on the interactive map or select a specific region. This design eliminates the need to manually input road segment IDs, latitude, and longitude, thereby enhancing the usability of this system. Several tasks examples are illustrated in the Fig. 8.

X. CONCLUSIONS

This study introduced BIGCity, a versatile model for spatiotemporal analysis. By employing unified ST representations and task-oriented prompts, BIGCity unified the processing of diverse spatiotemporal data and tasks within a single framework. Extensive experiments demonstrated BIGCity’s versatility and robustness. In addition, although BIGCity has a large volume of parameters, it still demonstrates reasonable efficiency and impressive scalability. *Future work:* The current BIGCity model focused solely on road segments, excluding other spatial elements such as POIs and grids. We consider incorporating these elements is a promising direction for future research.

XI. ACKNOWLEDGMENTS

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