Spatiotemporal Implicit Neural Representation as a Generalized Traffic Data Learner

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0 Learning Traffic Dynamics with Implicit Neural Representations

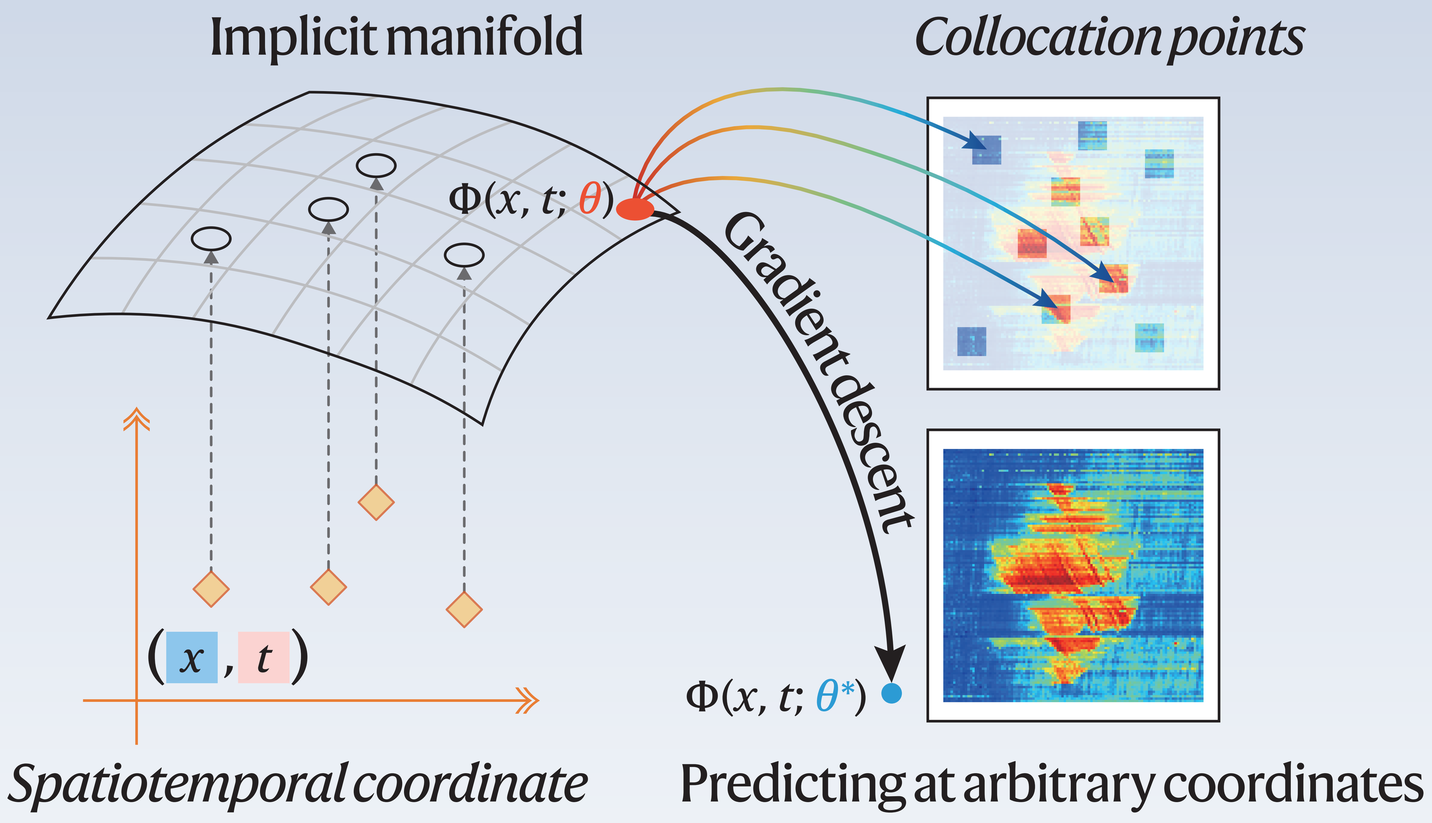
TL/DR; We present a novel paradigm to address the STTD learning problem by parameterizing STTD as an implicit neural representation (continuous, learnable, expressive).

CHALLENGES OF EXISTING LOW-RANK MODELS

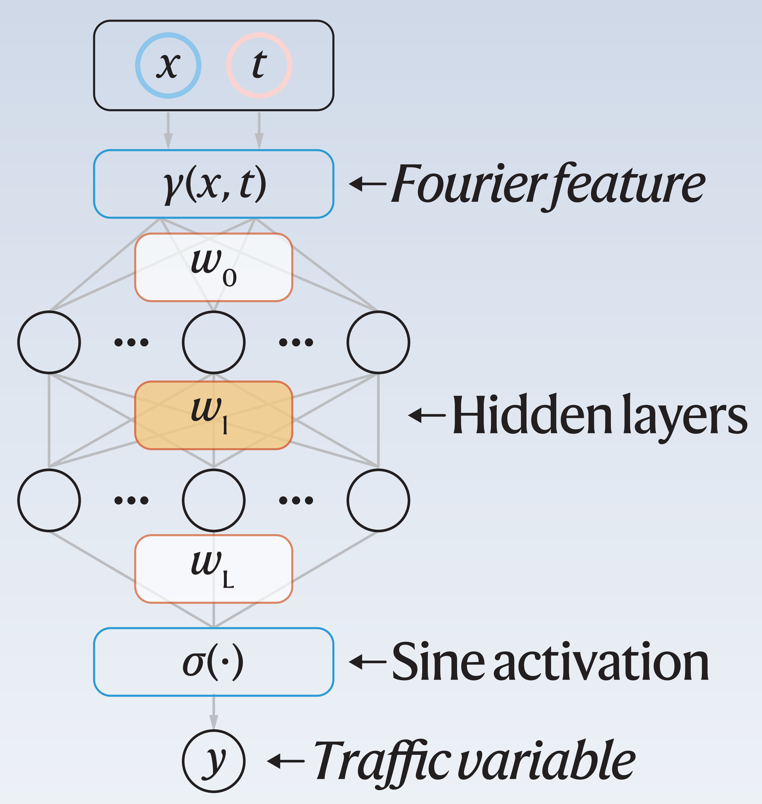
- Discrete Methods
- Predefined Patterns
- Explicit Regularization
- Instance-dependent

1 Addressing Spectral Bias in Neural Networks

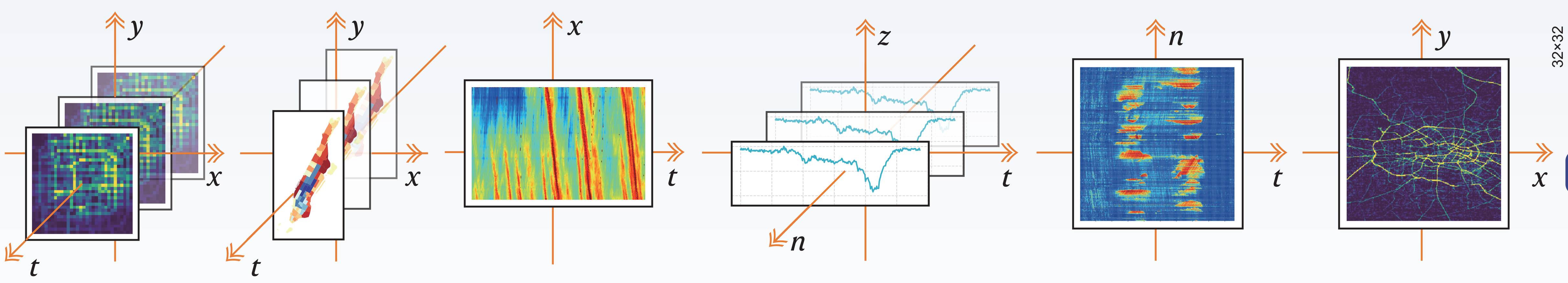
a. Representing traffic data as continuous functions



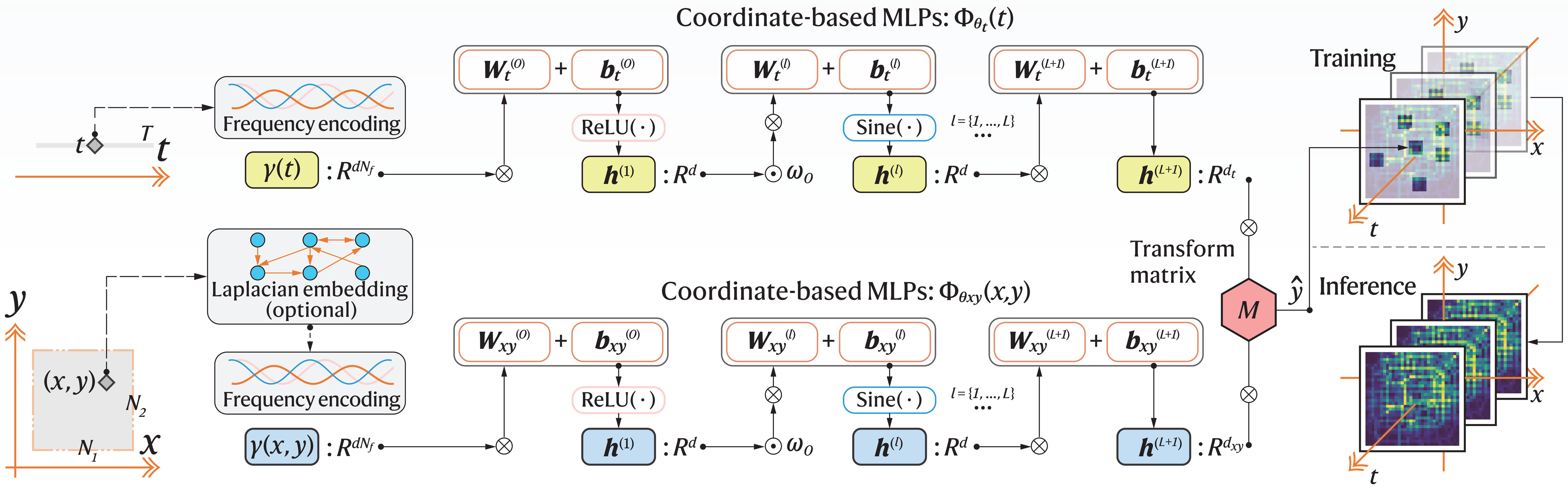
b. Coordinate-based MLPs



c. Multiscale spatiotemporal traffic data



Overall Architecture of ST-INR



Learning Traffic Dynamics with Continuous Neural Parameterizations

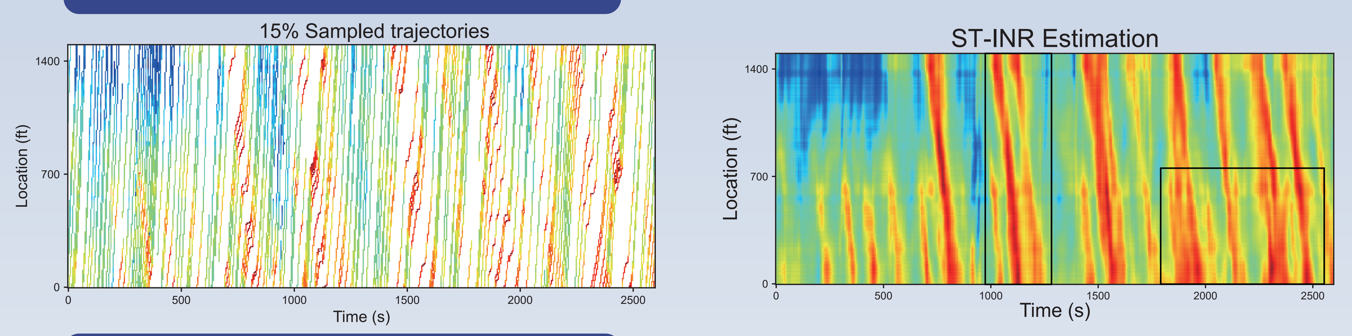
$$\min_{\theta} \mathcal{L} = \int_{\mathcal{D}} \|\mathcal{F}(f(\mathbf{x}), \Phi_\theta, \nabla_{\mathbf{x}}\Phi_\theta, \nabla^2_{\mathbf{x}}\Phi_\theta, \ldots)\| d\mathbf{x},$$
$$\Phi_\theta(x,t) : (x,t) \mapsto \mathcal{F}_\theta(x,t) \in \mathbb{R}^{D_{\text{out}}},$$
$$\mathcal{F}_\theta(x,t) = \mathbf{W}^{(L+1)}(\phi^{(L)} \circ \phi^{(L-1)} \circ \cdots \circ \phi^{(0)})([x,t]) + \mathbf{b}^{(L+1)},$$
$$\mathbf{x}^{(\ell+1)} = \phi^{(\ell)}(\mathbf{x}^{(\ell)}) = \sigma(\mathbf{W}^{(\ell)}\mathbf{x}^{(\ell)} + \mathbf{b}^{(\ell)}),$$

High-frequency Encodings for Complex Patterns

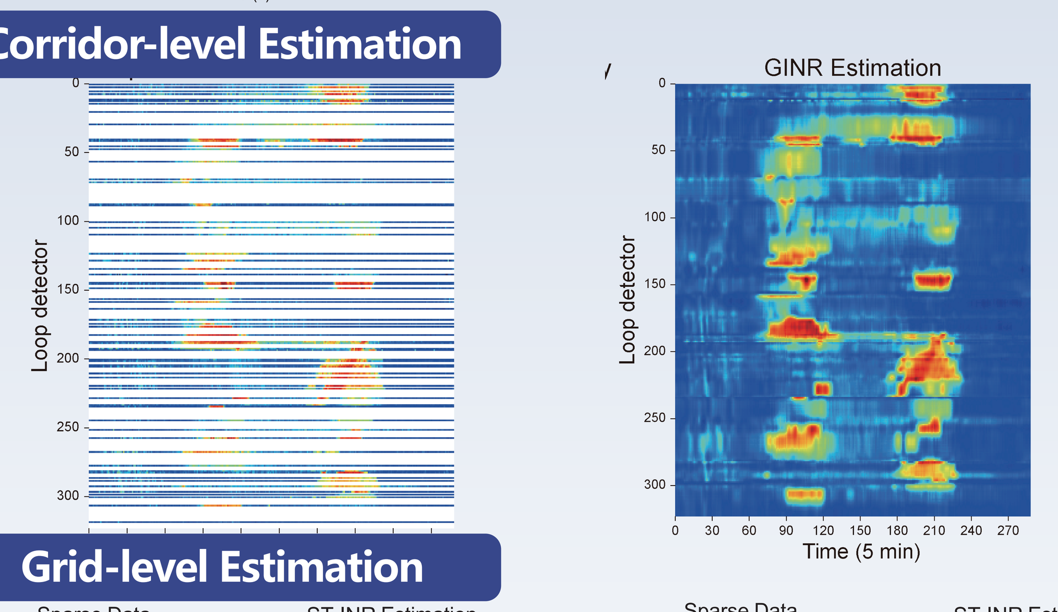
$$\phi_s^{(\ell)}(\mathbf{v}^{(\ell)}) = \sin(\omega_0 \cdot \mathbf{W}^{(\ell)}\mathbf{v}^{(\ell)} + \mathbf{b}^{(\ell)}),\ \ell = \{1,\ldots,L\},$$
$$\gamma(\mathbf{v}) = [\sin(2\pi\mathbf{B}_1\mathbf{v}), \cos(2\pi\mathbf{B}_1\mathbf{v}), \ldots, \sin(2\pi\mathbf{B}_{N_f}\mathbf{v}), \cos(2\pi\mathbf{B}_{N_f}\mathbf{v})]^\top \in \mathbb{R}^{dN_f},$$
$$\mathbf{h}^{(1)} = \mathtt{ReLU}(\mathbf{W}^{(0)}\gamma(\mathbf{v}) + \mathbf{b}^{(0)}),$$
$$\mathbf{h}^{(\ell+1)} = \phi_s^{(\ell)}(\mathbf{h}^{(\ell)}) = \sin(\omega_0 \cdot \mathbf{W}^{(\ell)}\mathbf{h}^{(\ell)} + \mathbf{b}^{(\ell)}),\ \ell = \{1,\ldots,L\},$$
$$\hat{\mathbf{y}} = \mathbf{W}^{(L+1)}\mathbf{h}^{(L+1)} + \mathbf{b}^{(L+1)},$$

2 Multiscale Traffic Data Learning

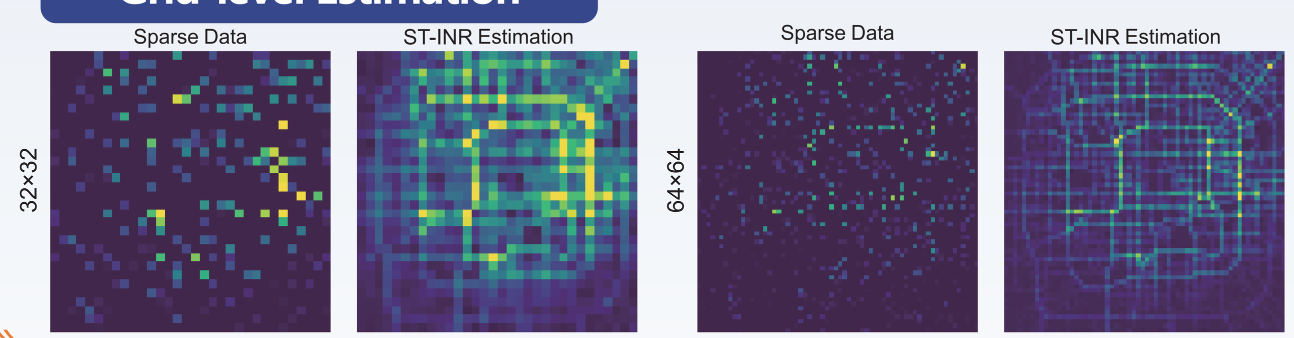
Lane-level State Estimation



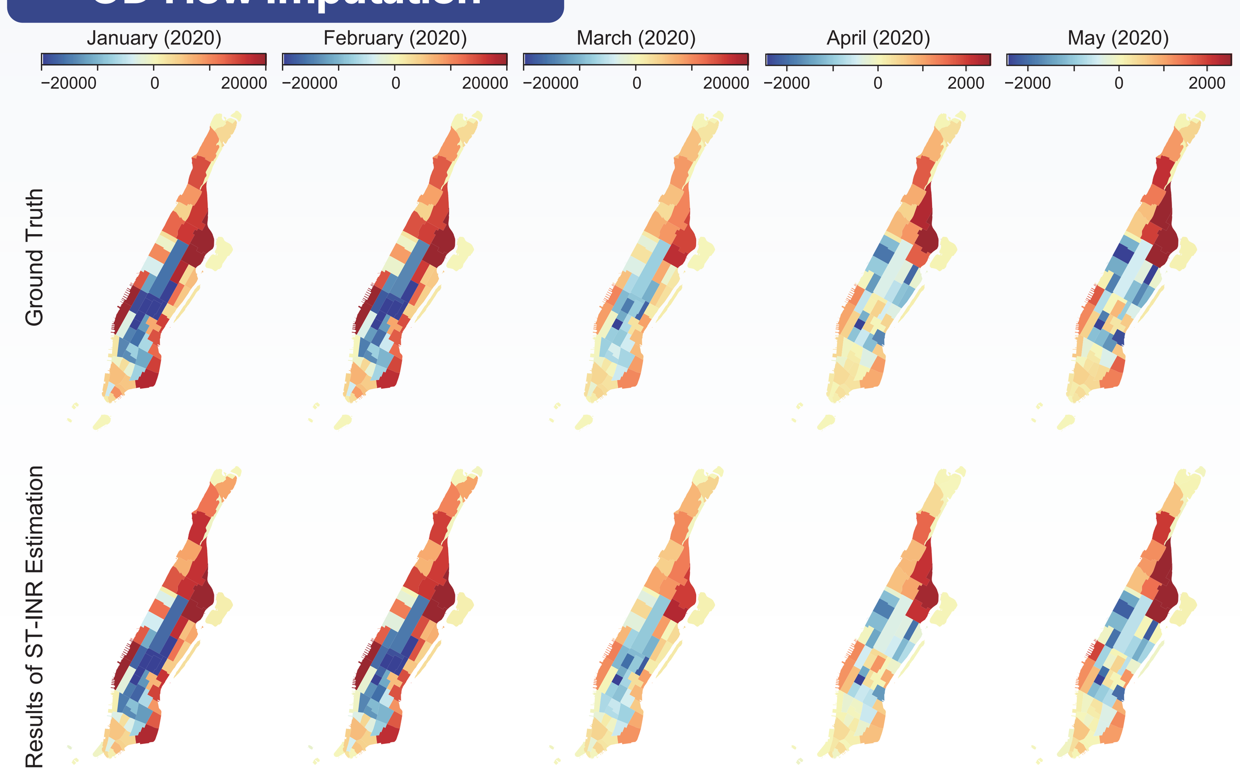
Corridor-level Estimation



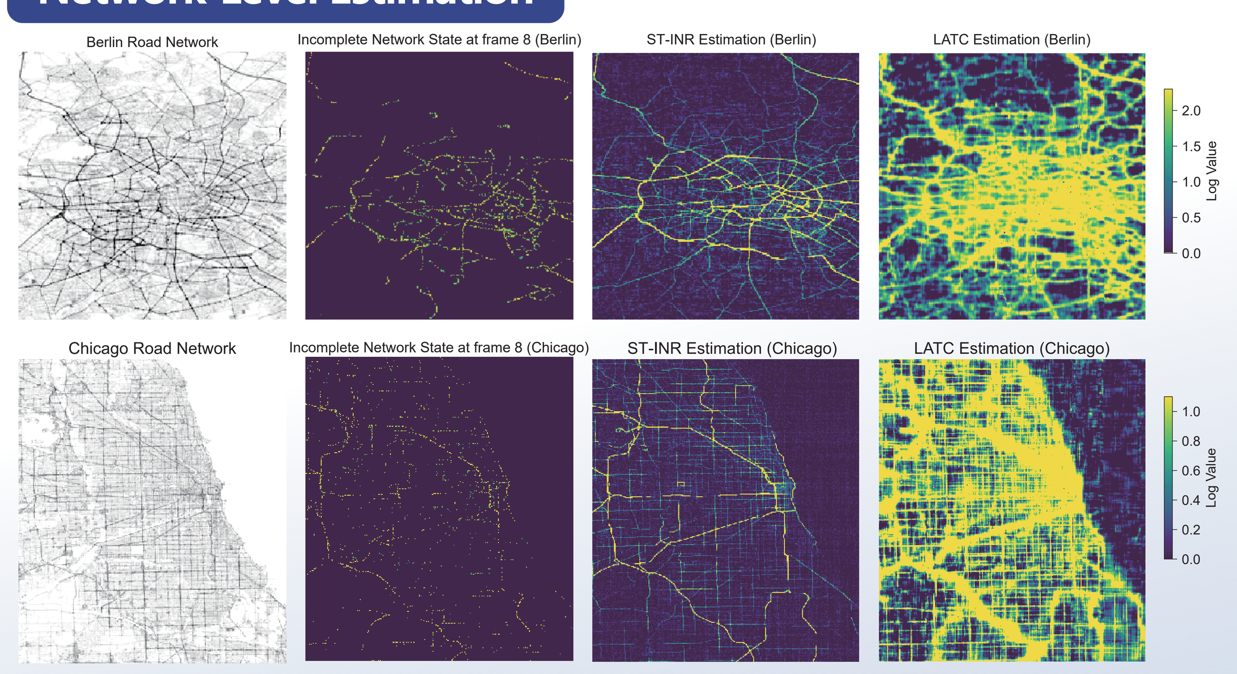
Grid-level Estimation



OD Flow Imputation



Network-Level Estimation



HIGHLIGHTS

- A new paradigm for STTD learning using INRs
- An integration of the unique characteristics of STTD
- Salient analytical properties are revealed as a regularization

OUR FINDINGS

- ST-INR can learn adaptive low-rank priors and smooth regularization from partially observed data
- High-frequency structures are signigicant for capturing complex details of data

POTENTIAL DIRECTIONS

- Physics-informed learning
- Integration with LLMs
- Scalability in large-scale data

TOPS Mobility AI Lab

WE ARE INTERESTED IN:

- Spatiotemporal Data
- Smart Transportation
- Urban Science
- Large Language Models

SCAN TO VIEW MORE OF OUR WORK

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