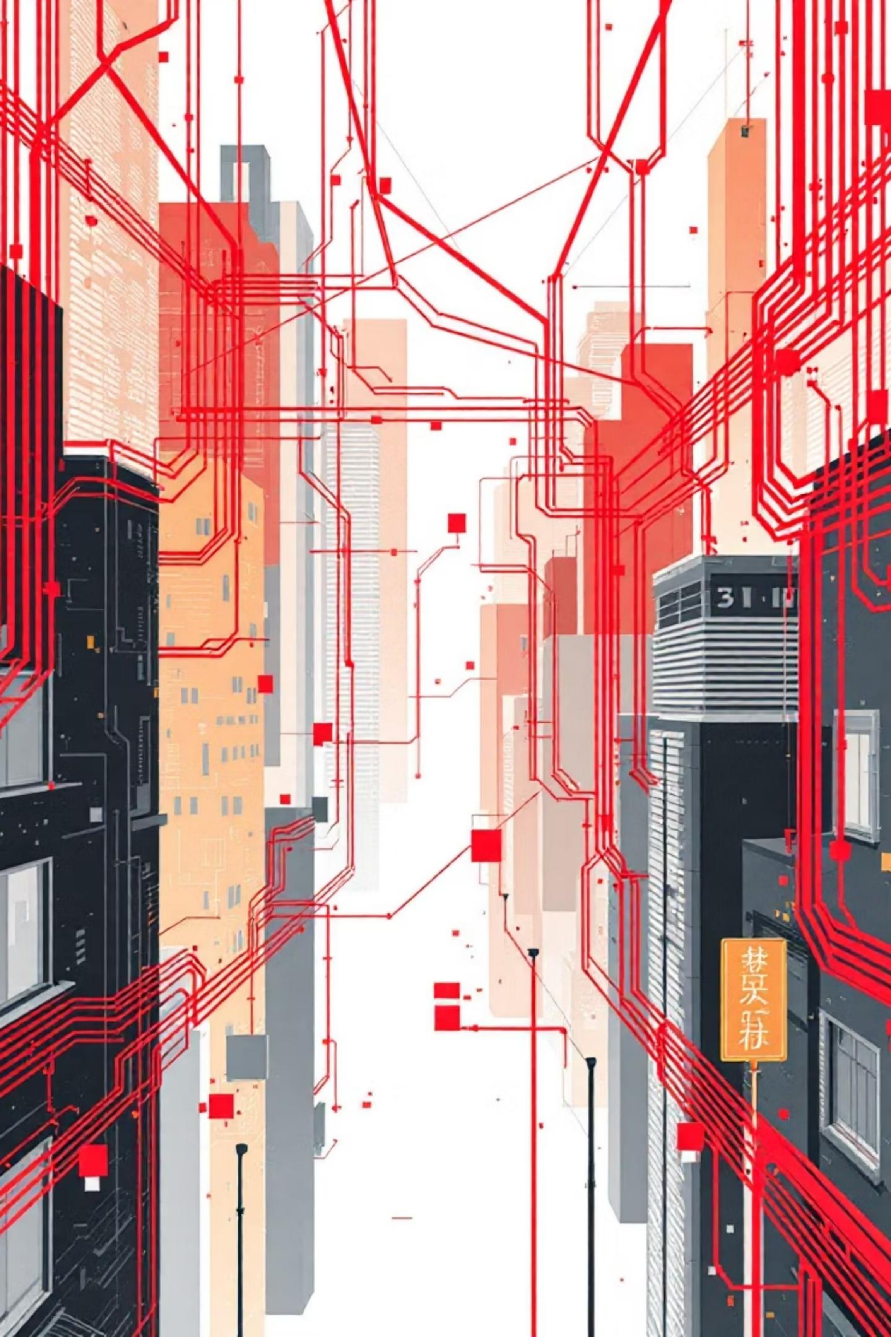
CoSSA: Cross-City Urban Forecasting

Correlation-Structure Shift Adapter for robust model transfer.

Presenter: Md Muntaqim Meherab
Daffodil International University
Dhaka, Bangladesh

Made with GAMMA



The Cross-City Challenge

Sensor Mismatch

Urban sensor IDs, layouts, and metadata rarely align across cities.

Ontology Brittleness

Traditional ontology mapping is fragile and doesn't scale for complex urban data.

Model Limitations

Existing spatiotemporal models assume fixed graphs and aligned nodes, failing in cross-city scenarios.

Made with GAMMA

Introducing CoSSA

A lightweight, ontology-free adapter for seamless urban model transfer.

Aligns Latent Structure

Transfers models by matching latent correlation structure, not identities.

Unsupervised SSM Loss

Matches pairwise correlation geometry using unlabeled target data.

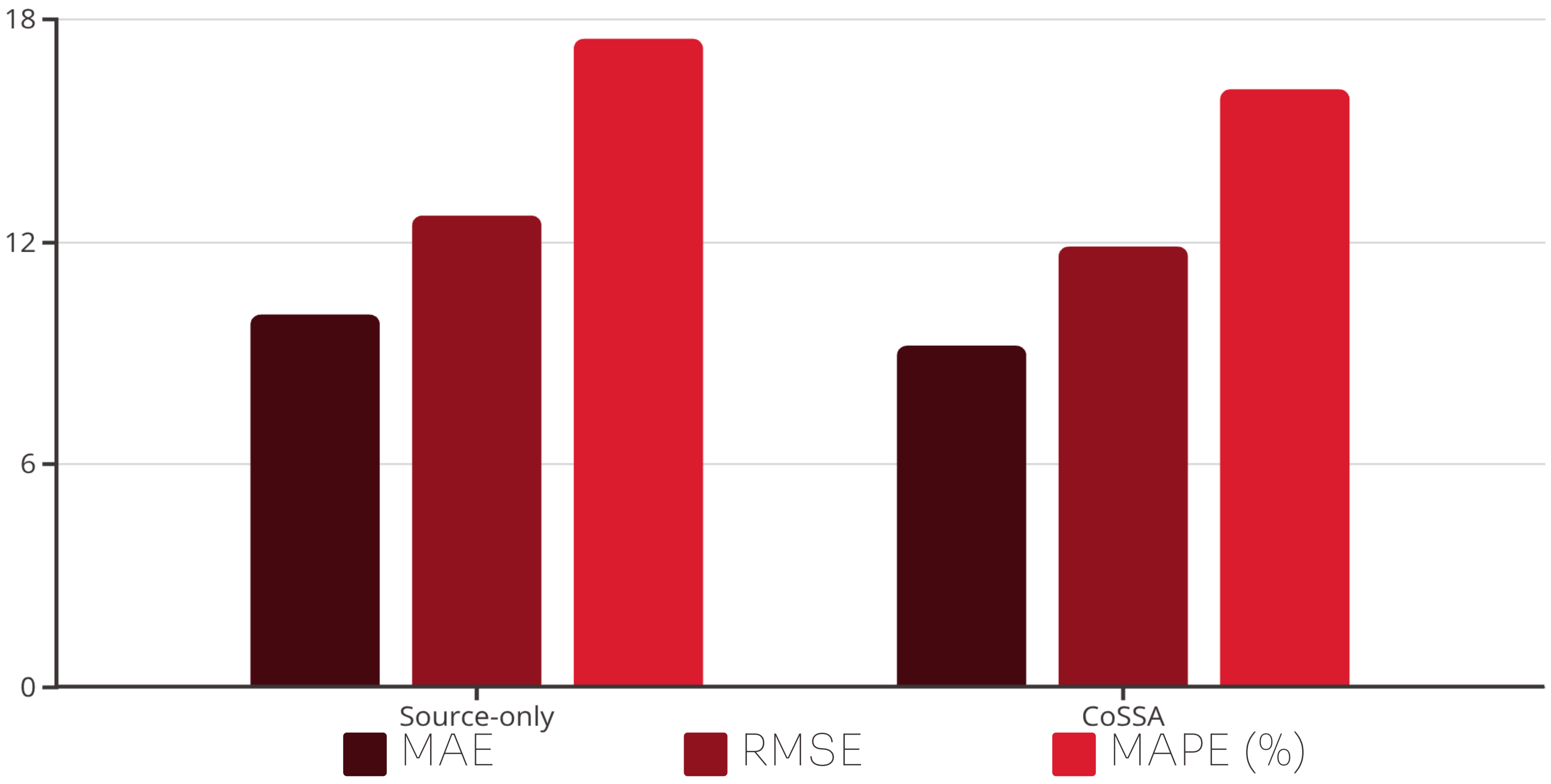
Simple & Scalable

Uses a Temporal CNN with a dynamic similarity graph, efficient for large datasets.

Made with GAMMA

CoSSA's Impact

Significant improvements in cross-city urban forecasting.



8.2%

MAE Improvement

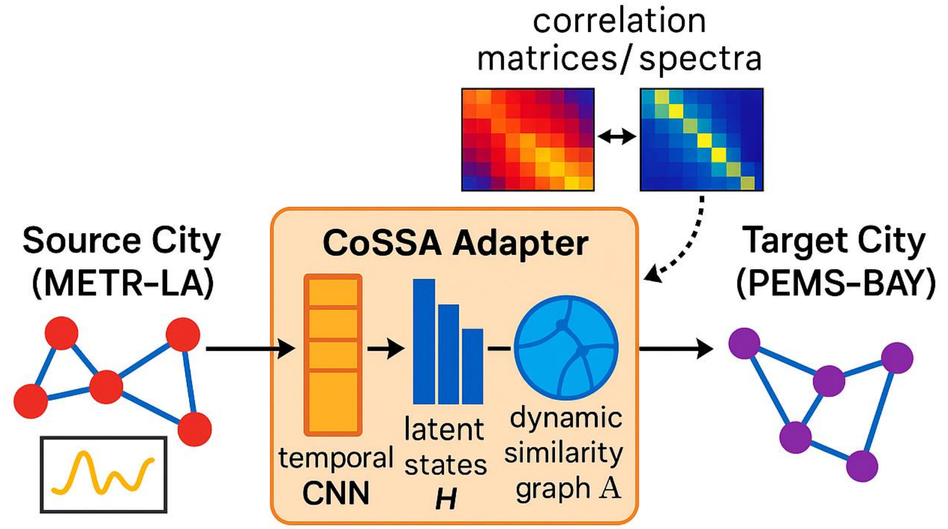
Over source-only baseline.

6.5%

RMSE Improvement

On held-out target tests.

Made with GAMMA



High-level idea of CoSSA. A temporal CNN and dynamic similarity graph produce latent sensor states whose correlation structure is aligned between source and target cities, without requiring node-level correspondence.

Methodology: The CoSSA Core

01

Temporal CNN Backbone

Processes multivariate observations to generate multi-horizon predictions and latent states.

02

Dynamic Similarity Graph

Formed from latent states, mixing node states before readout.

03

Correlation Structure

Per-sample correlation captures relational geometry among sensors.

04

SSM Loss

Minimizes the difference in correlation geometry between source and target latents.

Made with GAMMA

Training Objective & Complexity

Training Objective

CoSSA combines source forecasting loss with target correlation alignment.

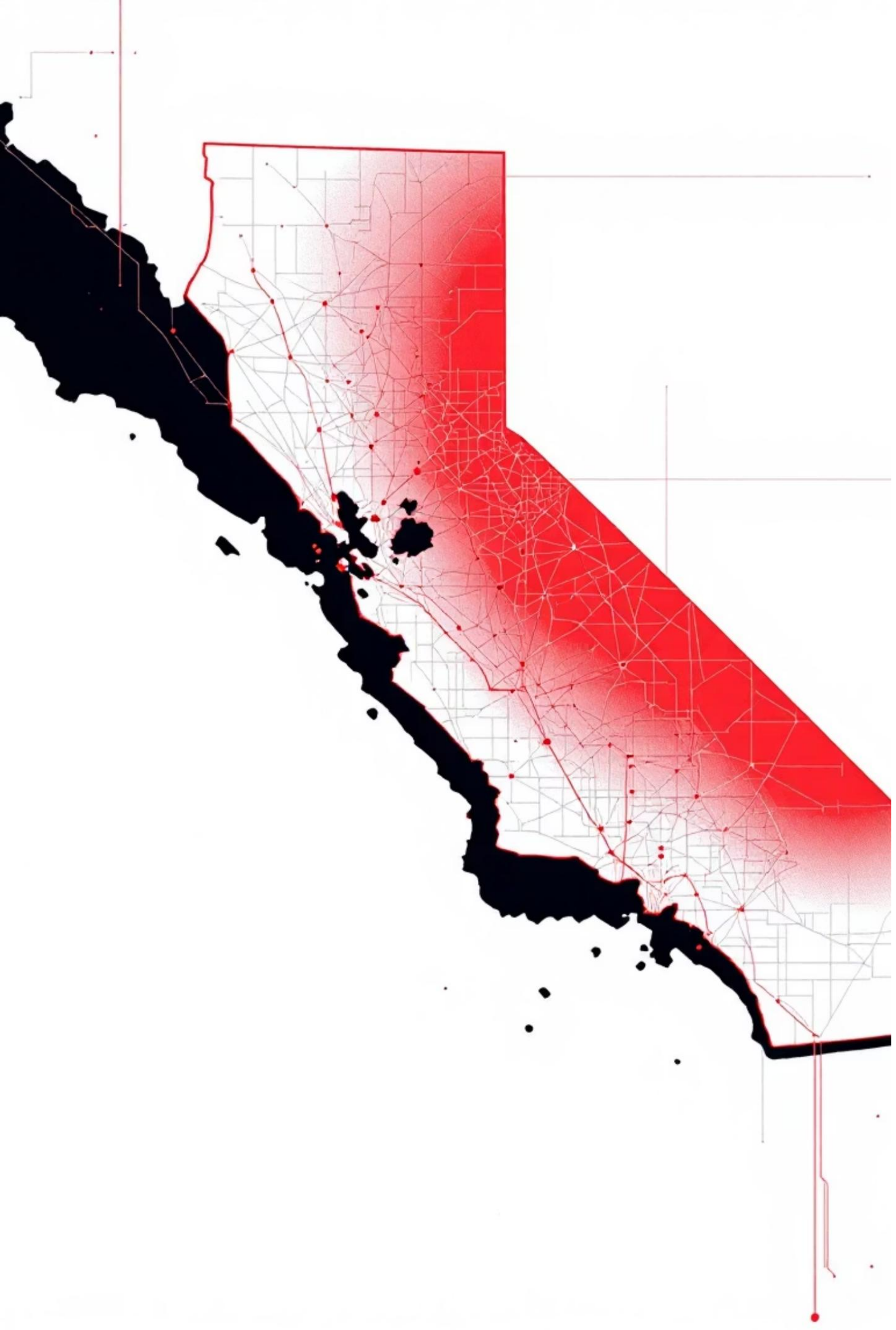
$\mathcal{L} = \|\hat{y}_s - y_s\|_1 + \lambda (\mathcal{L}_{\text{SSM}} \text{ or } \mathcal{L}_{\text{SSM-spec}})$

Alternates source/target mini-batches; no target labels needed. Ontology-free, using only raw target sequences.

Complexity

Computing correlation is $\mathcal{O}(N^2)$ per batch.

- Sub-sample nodes
- Sparsify via k-NN
- Downweight long-range pairs



Experimental Setup

1

Transfer Scenario

METR-LA (Los Angeles, N=207) to PEMS-BAY (Bay Area, N=325).

2

Sampling & Metrics

5-min sampling. Metrics: MAE, RMSE, MAPE. Horizons: 15/30/60 minutes.

3

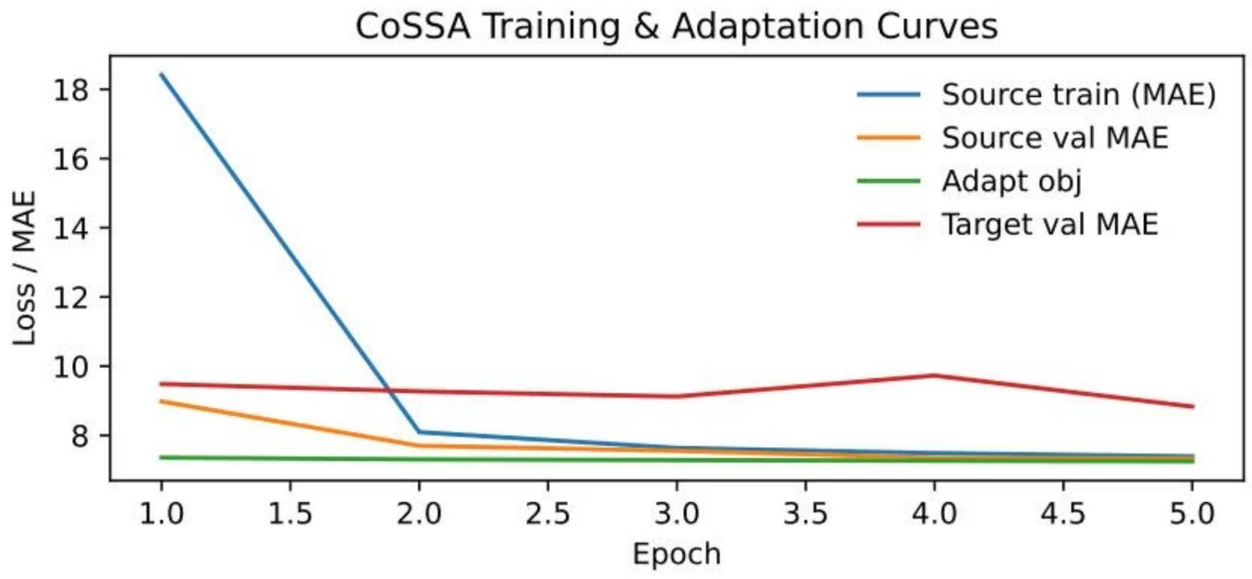
Baselines

Source-only (pretrain on METR-LA, test on PEMS-BAY) and Few-shot fine-tuning.

Made with GAMMA

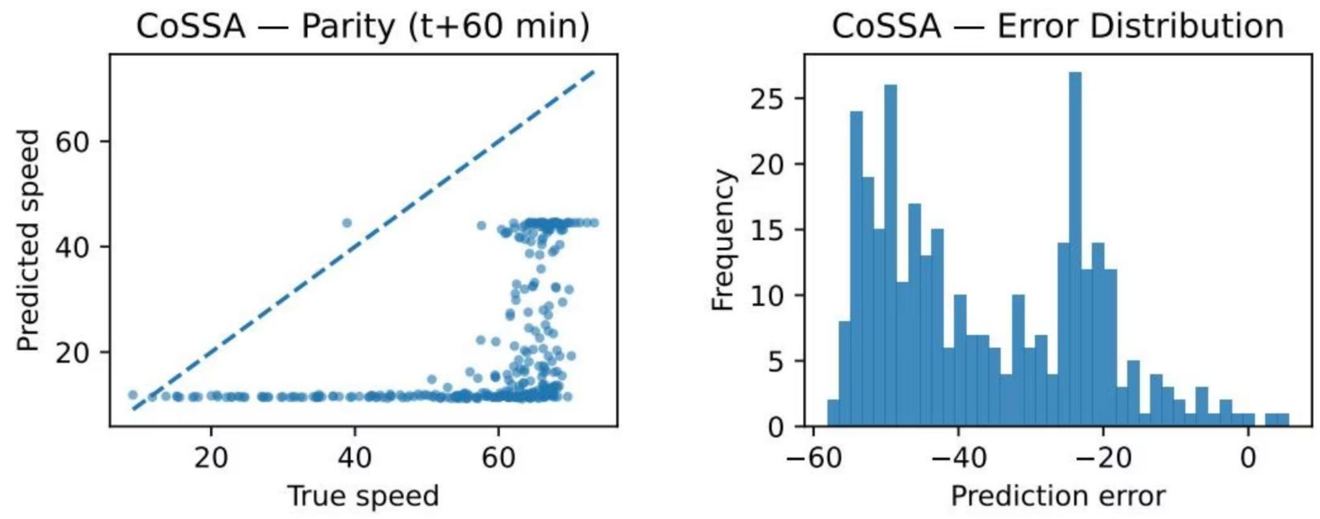
Learning Dynamics & Error Structure

Learning Dynamics



CoSSA steadily reduces target validation error, with source supervision stabilizing training.

Error Structure



(a) Parity at t+60.

(b) Error histogram.

CoSSA tightens parity at t+60 and shrinks long-tail errors, improving prediction accuracy.

Made with GAMMA

Why Correlation Structure?

Relational Urban Signals

Urban dynamics like congestion propagate relationally along corridors.

Aligning correlation geometry preserves this inductive bias across differing sensor sets more faithfully than feature matching alone.

Robustness & Limits

CoSSA tolerates missing metadata and partial coverage.

Limits include *\\mathcal{O}(N^2)* cost for very large N (mitigated by sparsification) and residual domain gaps from sharp covariate shifts.

Conclusion & Future Work

1

CoSSA's Achievement

Ontology-free correlation-structure adapter for cross-city urban forecasting, delivering consistent gains.

2

Future Directions

Multi-source adaptation, scalable dynamic sparsification, and broader urban tasks beyond traffic.

Made with GAMMA