Heterogeneity-Guided Tensor Decomposition for Traffic Flow Imputation

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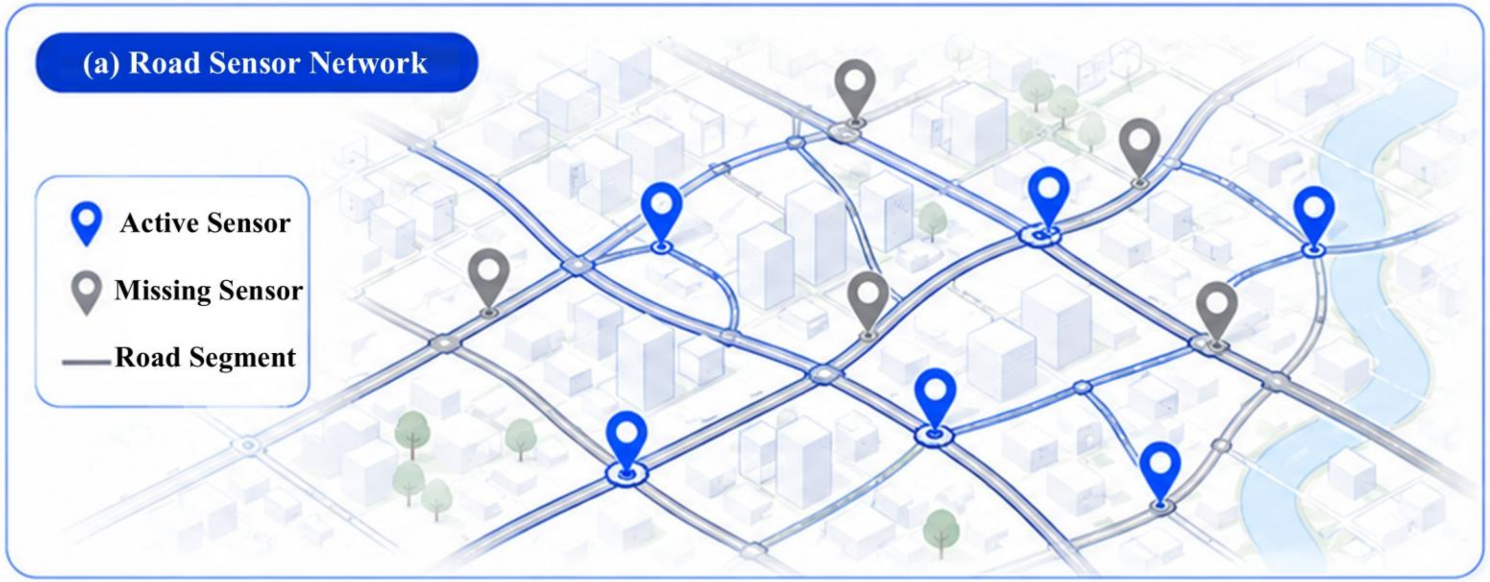
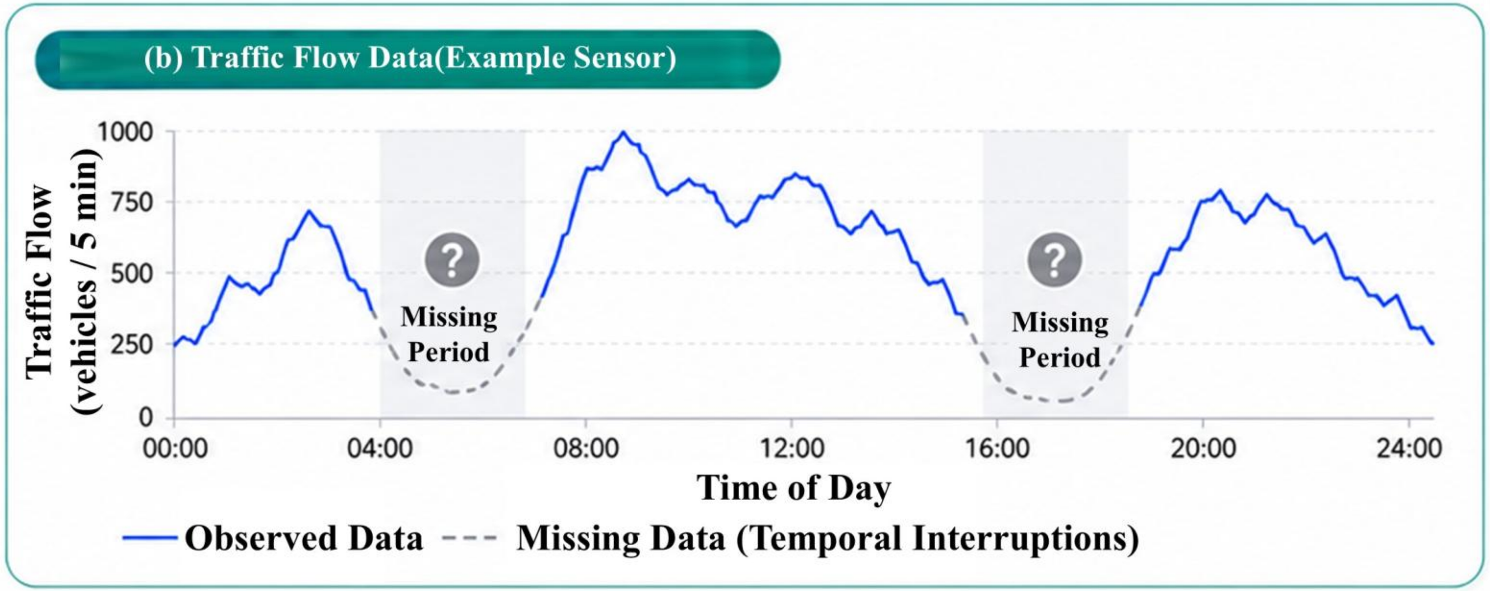
Background

- Traffic flow data support urban mobility analysis and intelligent transportation systems.
- However, fixed sensors often suffer from uneven spatial coverage and temporal interruptions.
- Traffic flow imputation is an important task for GeoAI and intelligent transportation systems.





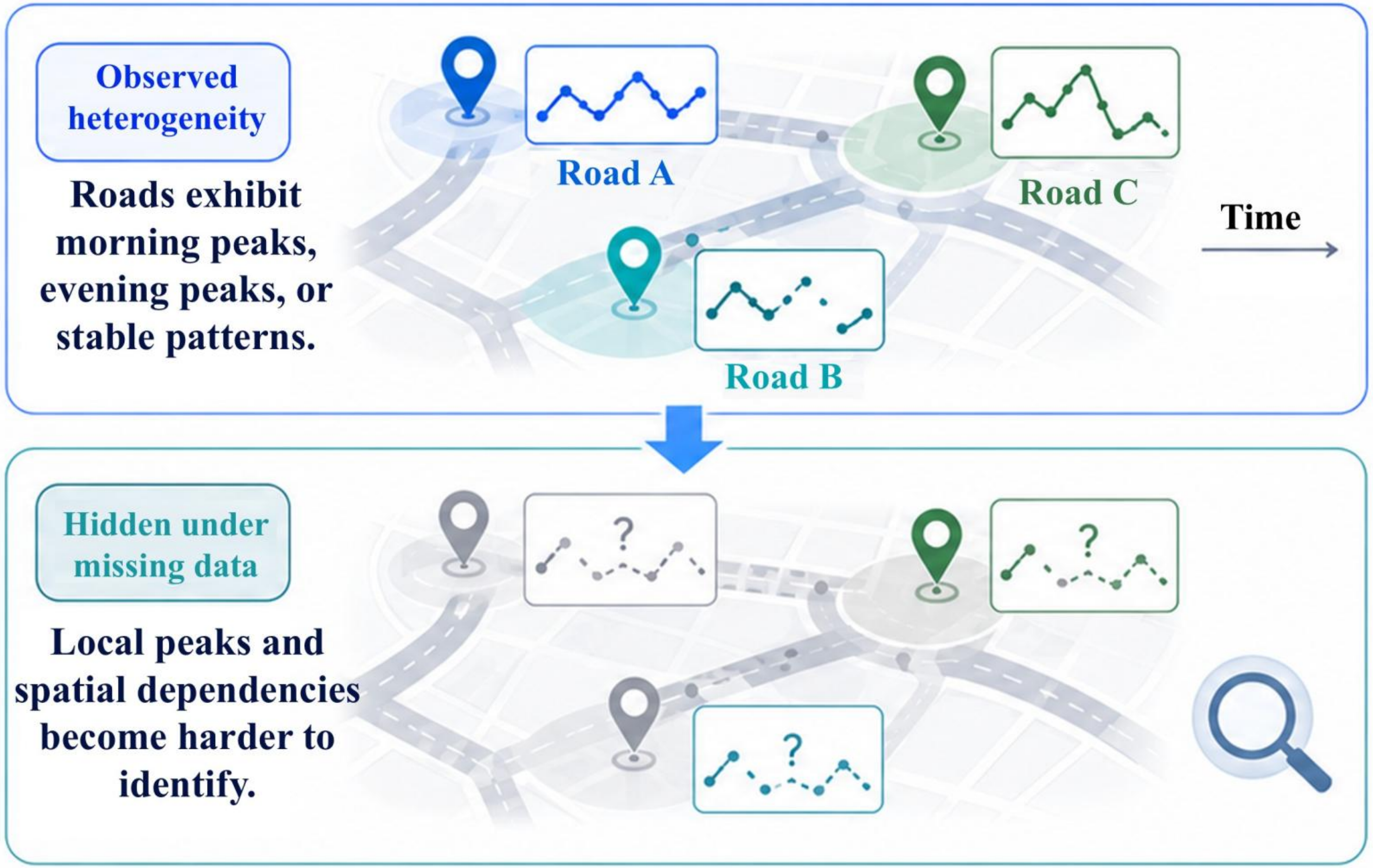
Core Challenge

Traffic flow patterns vary across different locations and time periods.

Even geographically similar regions can exhibit different traffic patterns.

Missing data obscure local temporal peaks and spatial dependencies.

Therefore, imputation is not only a reconstruction problem, but also a heterogeneity representation problem.

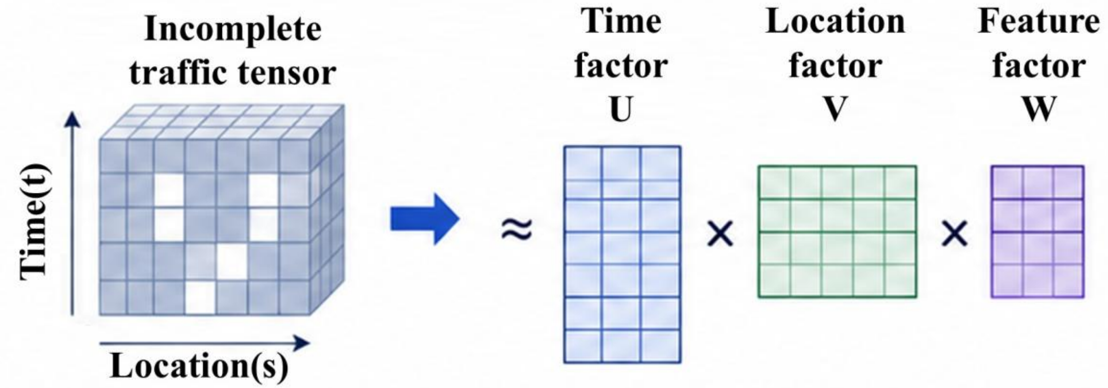


Missing values make heterogeneity harder to identify, while poor heterogeneity modeling further weakens imputation

Limitation of Existing Methods

Existing tensor decomposition

1. Captures low-rank spatiotemporal structures
2. Efficient and interpretable
3. Often uses spatial similarity constraints



Limitations

1. Static similarity assumptions
2. Limited ability to represent missing-location heterogeneity
3. Lack of feedback from imputation results to representation learning

This creates a gap between heterogeneity representation and missing data imputation

Research Question

This study asks a central research question:

How can we **learn spatiotemporal heterogeneity** from incomplete traffic data and use it to **guide tensor decomposition**?

To answer this question, we need three abilities:

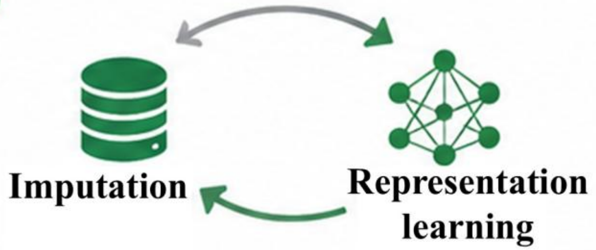
1

First, the model should **capture traffic patterns** under missing data.

2

Second, it should **represent spatial and temporal heterogeneity** explicitly.

3



Third, it should allow **imputation and representation learning** to improve each other.

Our answer is a **heterogeneity-guided tensor decomposition** framework, named **Hg-TD**

Overview of Hg-TD

1. Incomplete traffic tensor
2. Decoupled masking and encoding
3. Heterogeneity representation learning
4. Heterogeneity-guided tensor decomposition
5. Imputed traffic tensor

The key idea is to make heterogeneity representation and imputation mutually reinforced

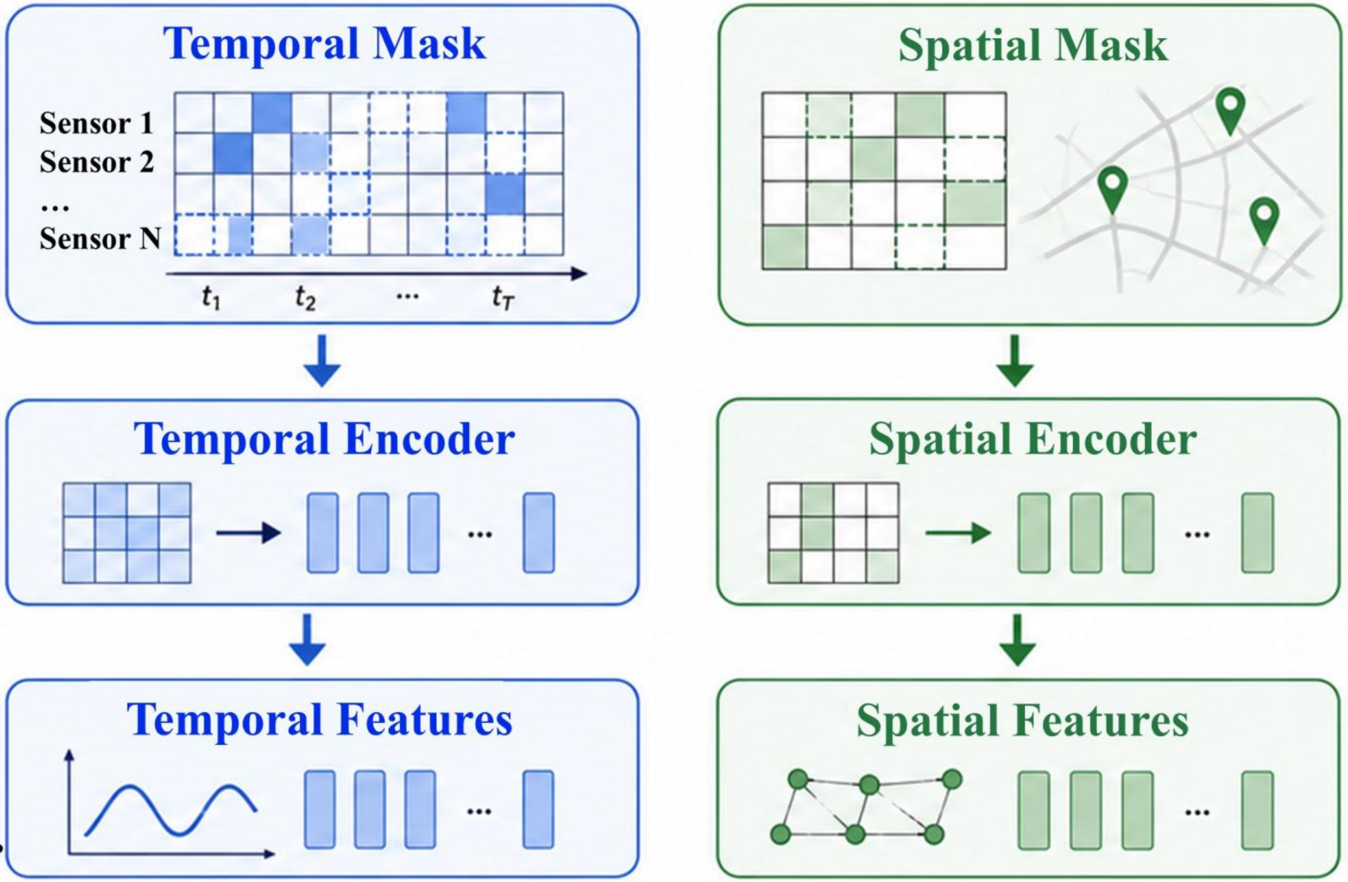
Component 1: Decoupled Masking and Encoding

Temporal and spatial missingness influence traffic patterns in different ways.

Therefore, Hg-TD does not use a **single unified** masking strategy.

Hg-TD **separately masks and encodes** the temporal and spatial dimensions.

This design helps the model learn **temporal periodicity and spatial locality** more clearly.



Decoupled masking provides a cleaner input for learning heterogeneous traffic patterns

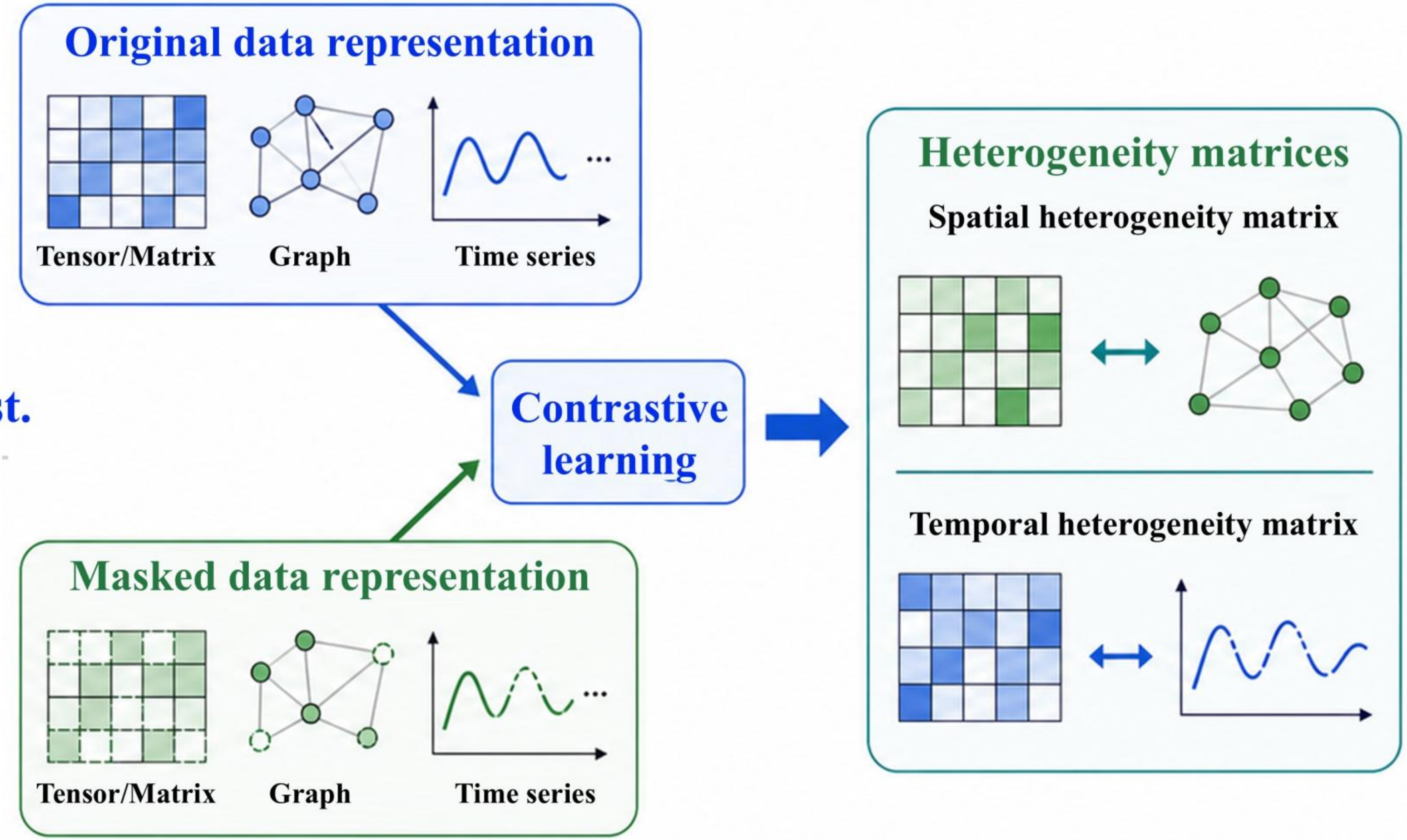
Component 2: Learning Heterogeneity Under Missing Data

Hg-TD **learns heterogeneity** by comparing representations from original data and masked data.

The model can recover similar heterogeneity structures from masked inputs, then **the learned representation becomes more robust.**

Masked contrastive learning provides a **self-supervised signal** for missing locations.

The output is a set of **spatial and temporal heterogeneity matrices.**



These matrices describe how traffic relationships vary across sensors and time periods

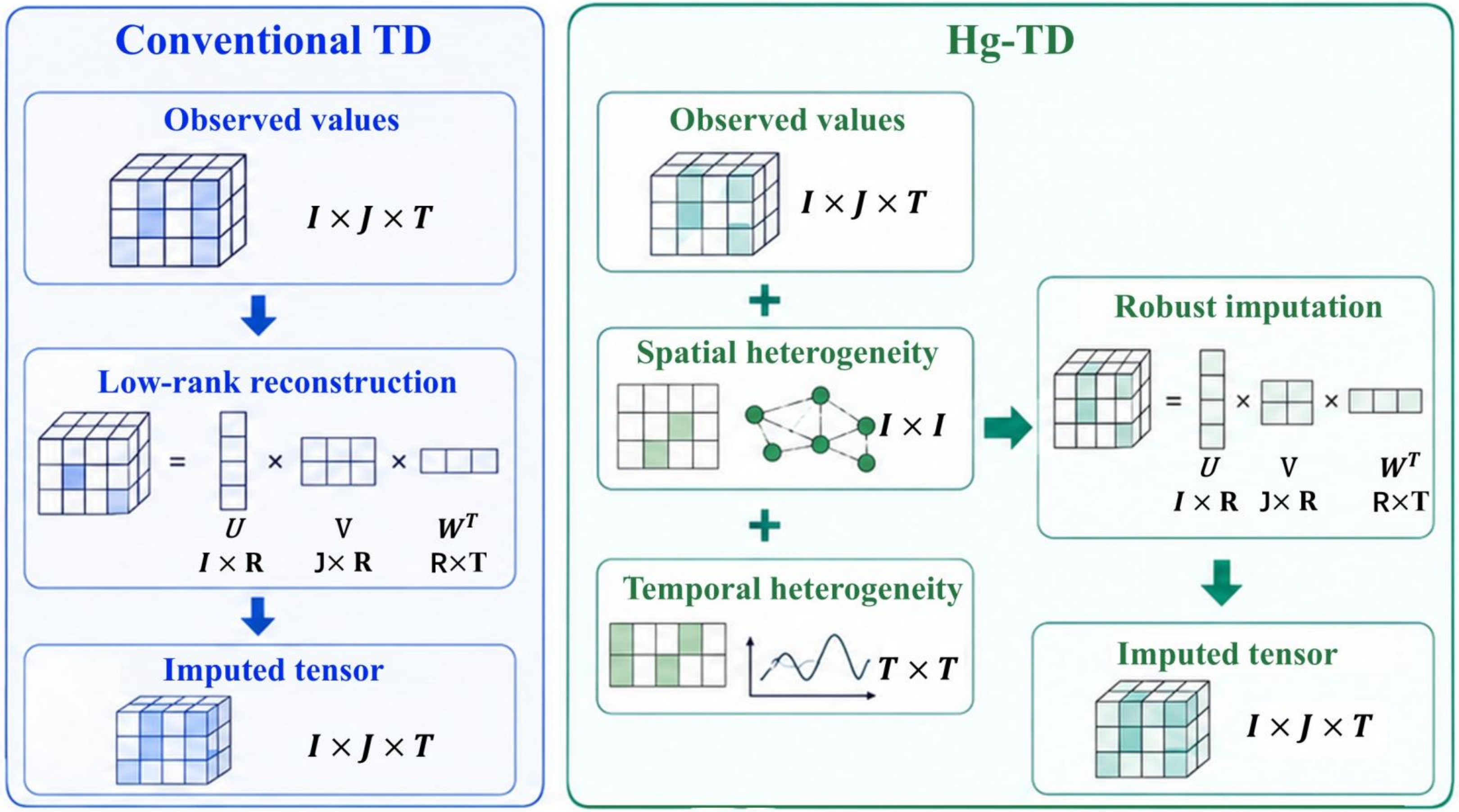
Component 3: Heterogeneity-Guided Tensor Decomposition

In conventional TD, factor matrices are optimized to fit the observed traffic values.

In Hg-TD, the factor matrices are constrained by the learned heterogeneity matrices.

The spatial heterogeneity matrix guides the model to capture relationships among road sensors.

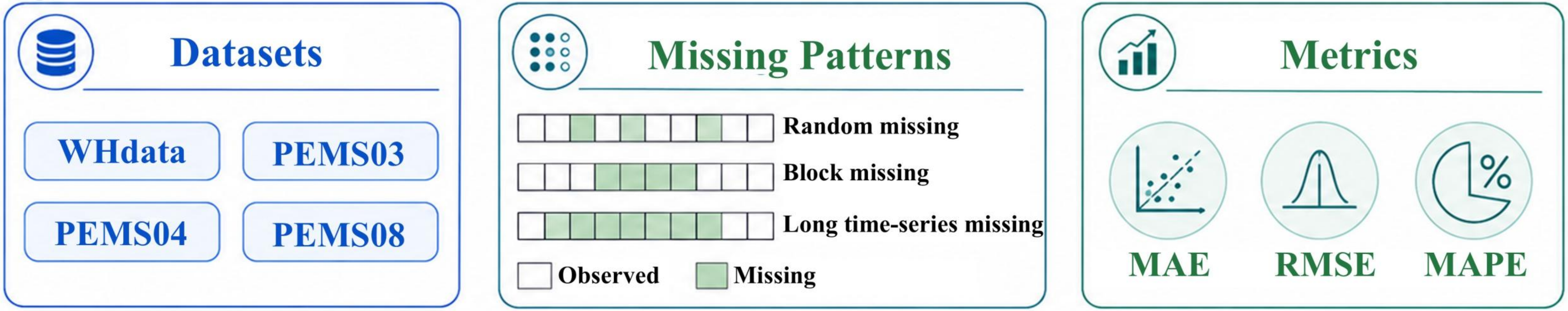
The temporal heterogeneity representation helps the model adapt to traffic changes over time.



Tensor decomposition becomes heterogeneity-aware rather than only correlation-based

Experimental Setup

- We evaluated Hg-TD on four real-world traffic flow datasets: WHdata, PEMS03, PEMS04, and PEMS08.
- Three missing patterns were considered: random missing, block missing, and long time-series missing.
- The model was compared with statistical methods, deep learning models, and tensor decomposition baselines.
- We used MAE, RMSE, and MAPE as evaluation metrics.



Baselines: statistical methods, deep learning models, and tensor decomposition methods.

This setup tests both accuracy and robustness under diverse missing scenarios

Baseline Model Comparison

Method	RM	BM	TM
	Friedman's test		
	$\chi^2 = 62.5804$	$\chi^2 = 148.3649$	$\chi^2 = 152.6141$
	p (Cohen's d)		
HA	0.00019***(-2.363)	0.00019*** (-2.363)	0.00016***(-2.183)
SES	0.00033***(-2.320)	0.00033***(-2.320)	0.00026***(-2.196)
KNN	0.00039***(-1.033)	0.00039***(-1.033)	0.00002***(-0.642)
BRITS	0.03103*(-1.252)	0.03103*(-1.252)	0.02879*(-1.262)
USGAN	0.03103*(-1.240)	0.03103*(-1.240)	0.00864**(-1.587)
BGCP	0.01038*(-0.048)	0.01038*(-0.048)	0.00864**(-0.123)
BTTF	0.00203**(-0.156)	0.00203**(-0.156)	0.02879*(-0.206)
BATF	0.00638**(-0.056)	0.00638**(-0.056)	0.00864**(-0.131)
BTMF	0.00073***(-0.349)	0.00073***(-0.349)	0.00736**(-0.113)
LAMC-TNN	0.03103*(-0.605)	0.03103*(-0.605)	0.02879*(-0.381)
LRTC-TNN	0.00514**(-0.065)	0.00514**(-0.065)	0.02879*(-0.963)
Meta-TD	0.03103*(-0.034)	0.03103*(-0.034)	0.02879*(-0.060)

Statistical Significance Test

We compare Hg-TD with statistical, deep learning, and tensor decomposition baselines.

Hg-TD achieves the best overall performance across four real-world datasets.

The improvement becomes larger when the missing rate increases.

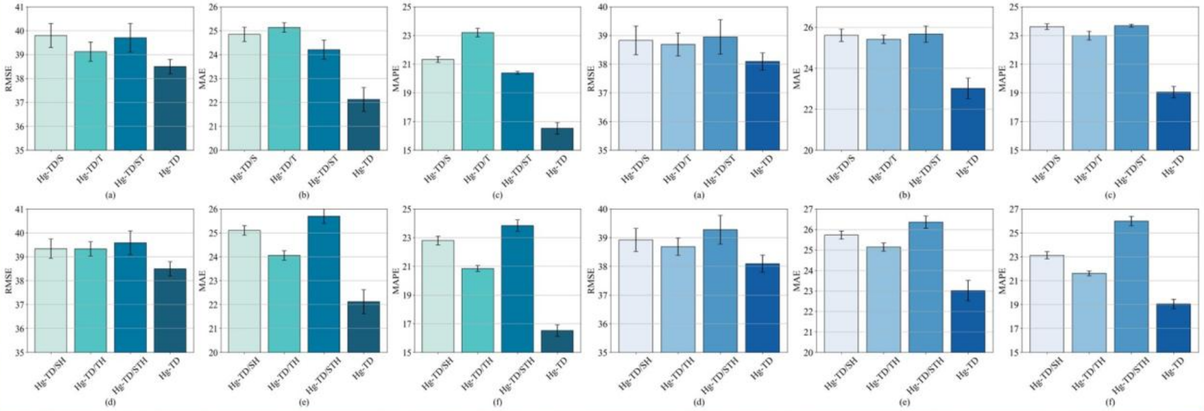
This shows the value of heterogeneity modeling under severe missingness.

Hg-TD consistently improves imputation accuracy, especially under high missing rates

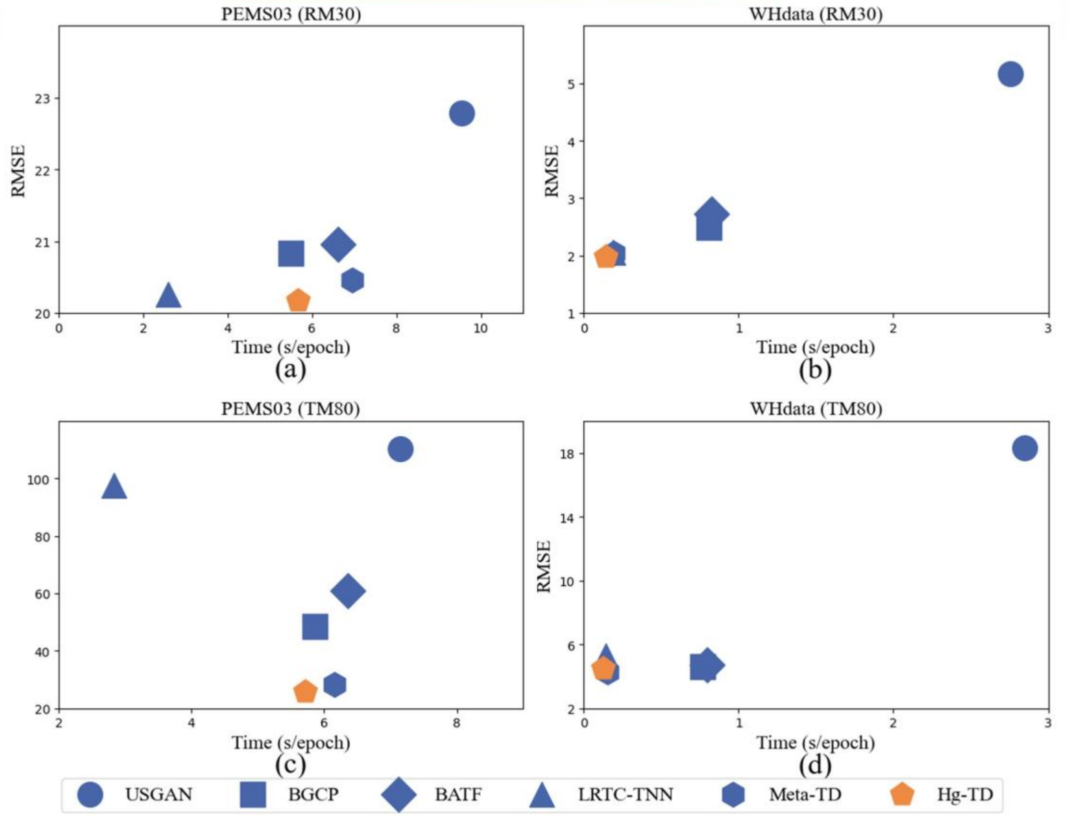
Ablation Study and Computational Complexity

Ablation Study

- **Each component contributes to the final performance.**
- **Without decoupled masking, the model becomes less effective in separating temporal and spatial patterns.**
- **Without contrastive learning, the learned representation becomes less robust under missing data.**
- **Without heterogeneity constraints, tensor decomposition loses important guidance from traffic dynamics.**



Complexity Analysis

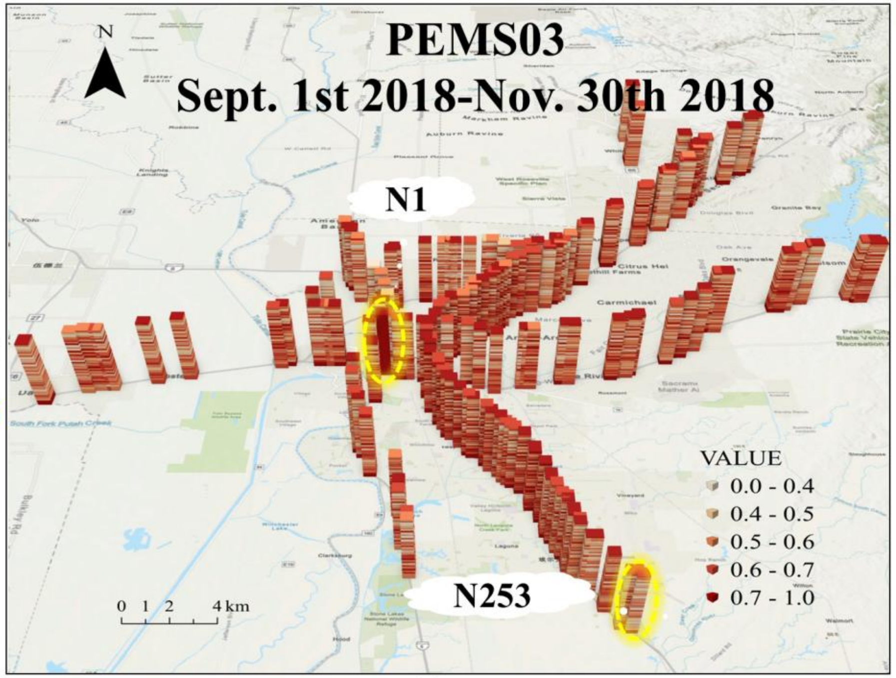


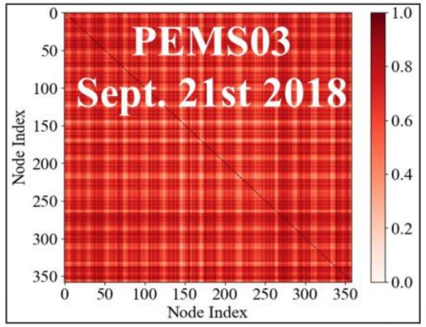
Hg-TD balances imputation accuracy and computational cost.

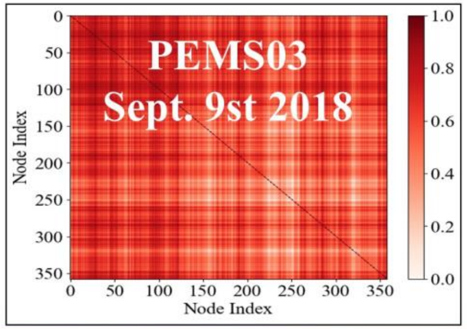
The full Hg-TD framework is both effective and computationally practical

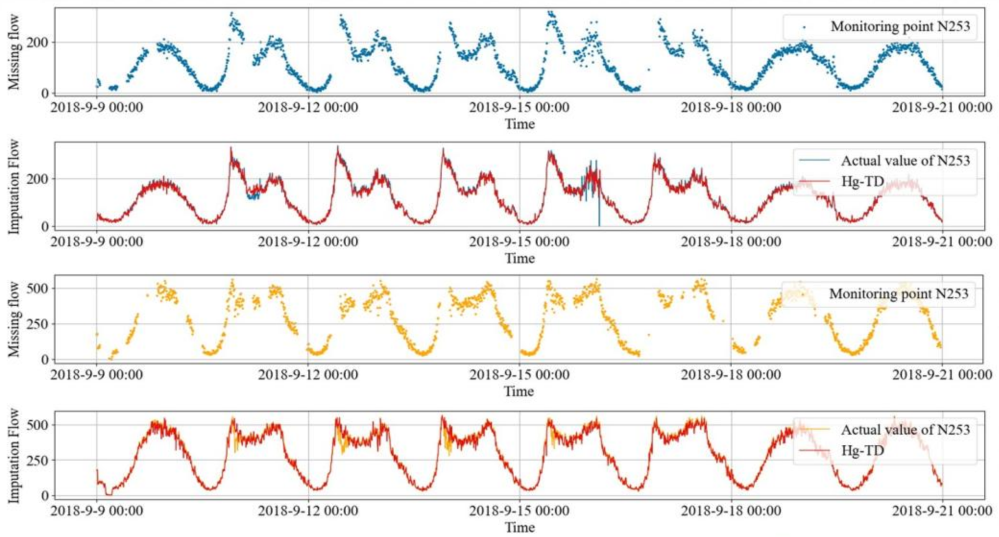
Effectiveness of Representation Learning

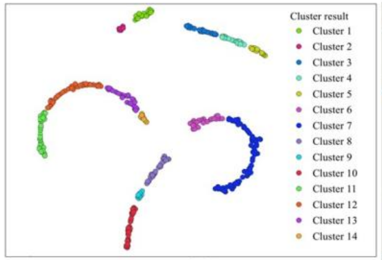
- We examine whether Hg-TD learns **meaningful heterogeneity representations.**
- The spatial matrix reveals **non-uniform relationships** among traffic sensors.
- The temporal representation captures changes between **peak and off-peak** periods.
- These representations provide **useful guidance** for tensor decomposition.











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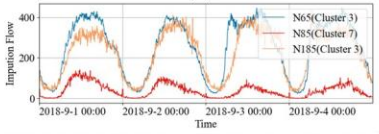
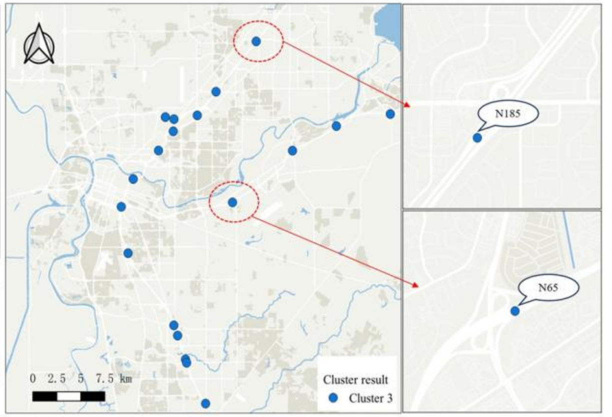
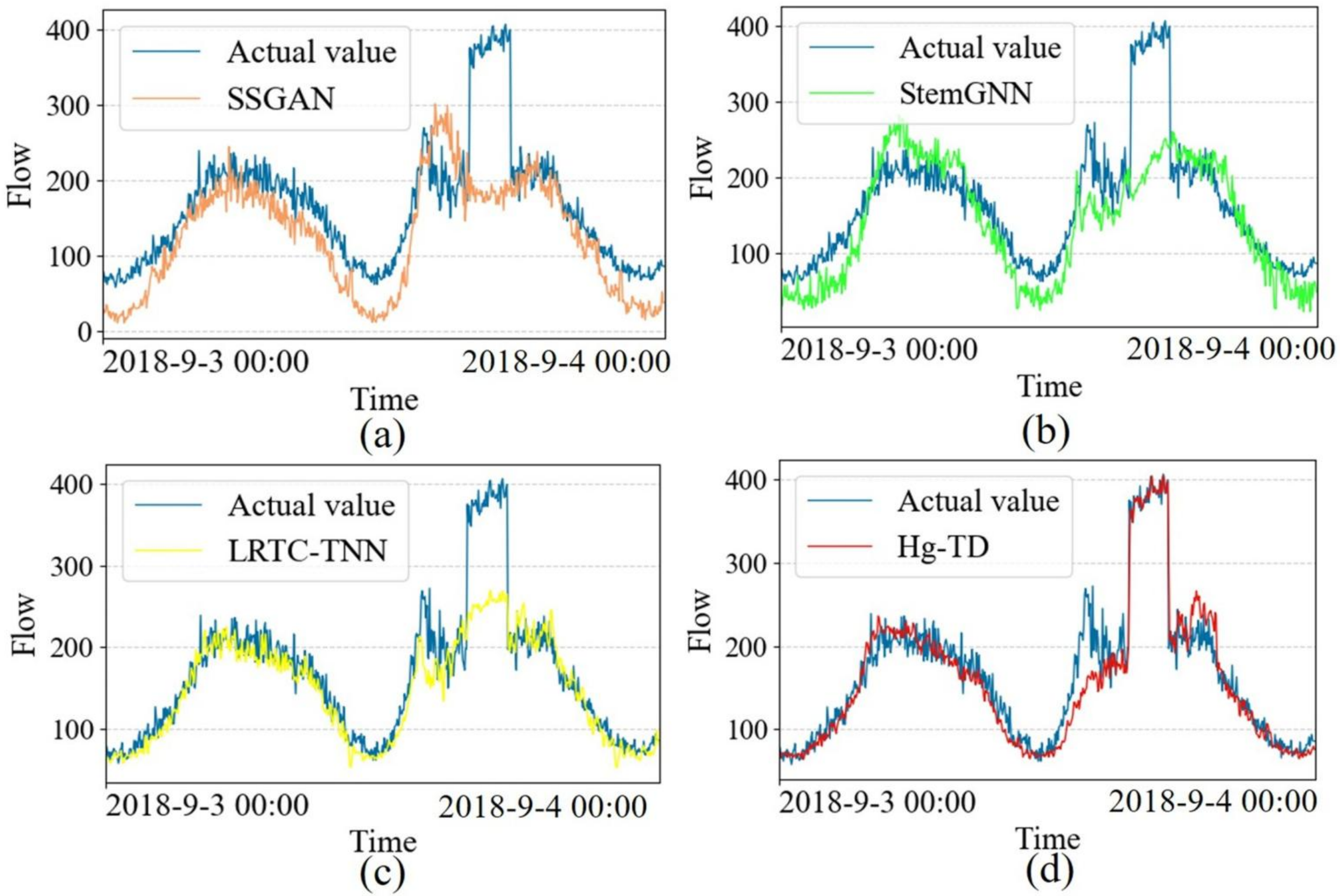




Hg-TD learns interpretable spatiotemporal heterogeneity for traffic imputation

Case Study

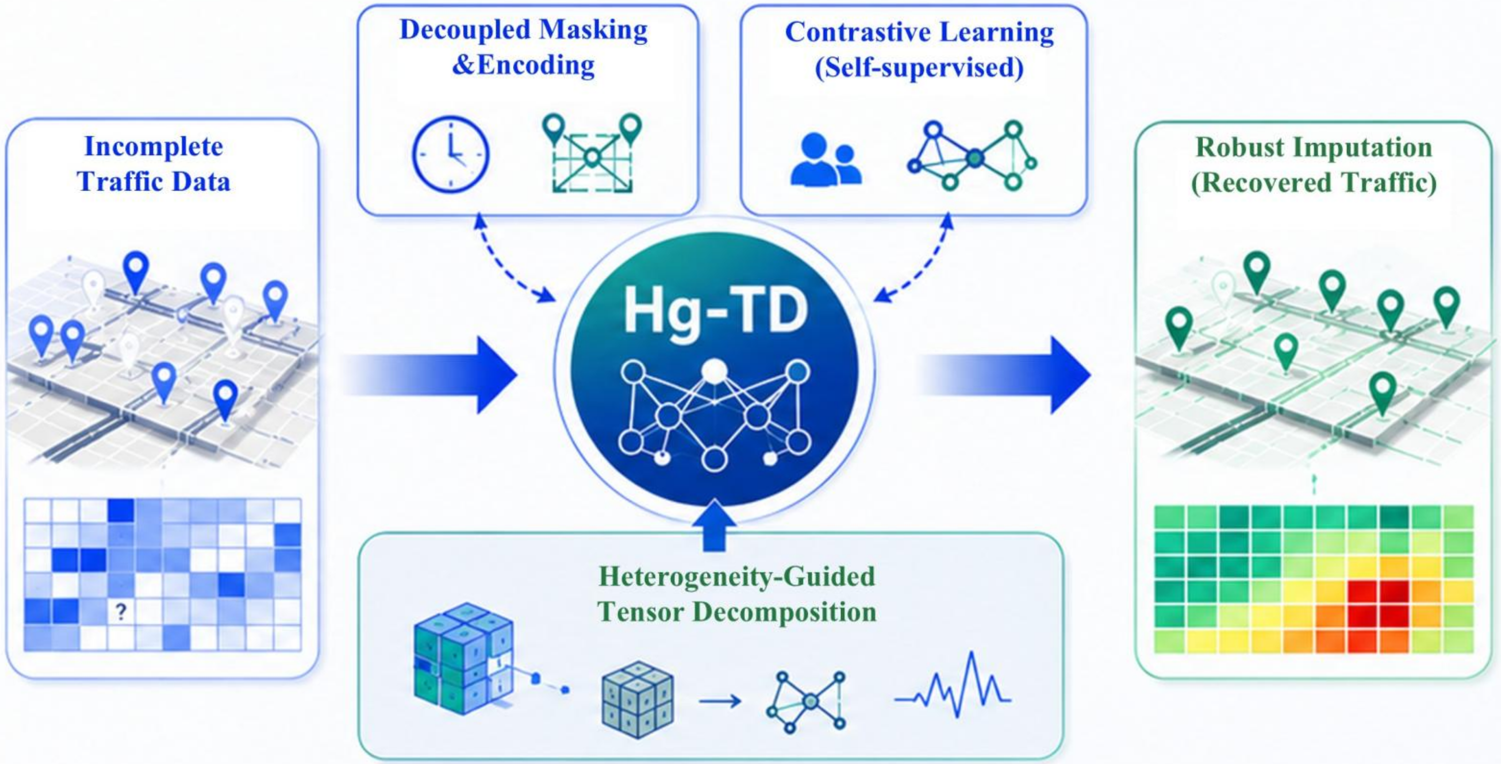
- We use a representative case to visualize the imputation results.
- Baseline methods tend to smooth local traffic variations.
- Hg-TD better reconstructs peak-hour changes and local fluctuations.
- This produces more realistic traffic flow patterns.



Hg-TD better preserves local traffic dynamics in heterogeneous missing-data scenarios

Conclusion

- This study reformulates traffic flow imputation as a heterogeneity-aware spatiotemporal inference problem.
- We propose Hg-TD, which learns spatial and temporal heterogeneity from incomplete traffic data.
- The learned heterogeneity representations are embedded into tensor decomposition as adaptive constraints.
- Experiments on four real-world datasets demonstrate improved accuracy and robustness under diverse missing patterns.



01 Problem
Missing data with heterogeneity

02 Method
Self-supervised heterogeneity-guided tensor decomposition

03 Result
Robust imputation under diverse missing patterns

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Thank you!

Q&A