

A Unified Spatio-Temporal and Coupled Multi-View Tensor Framework

Simultaneous Traffic Data Reconstruction and Event Detection

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Outline

- ① Motivation
- ② USCMT Model
- ③ Optimization of USCMT
- ④ Experiments
 - Data reconstruction
 - Event detection
 - Joint reconstruction and detection

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- 2 USCMT Model
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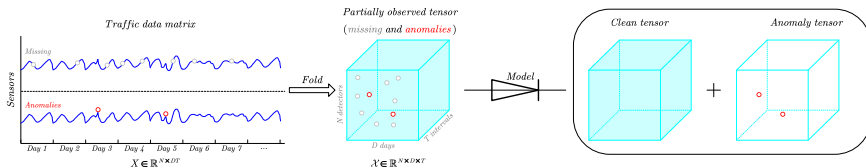
Traffic sensing involves two coupled challenges

Data quality challenges

- **Missing observations:** sensor failures, communication loss....
- **Anomalous events:** crashes, abnormal congestion...

Why joint modeling is needed

- Events can distort the estimation of normal traffic states.
- Poor reconstruction can weaken event signatures.



White dots denote missing entries; red dots denote potential anomalies.

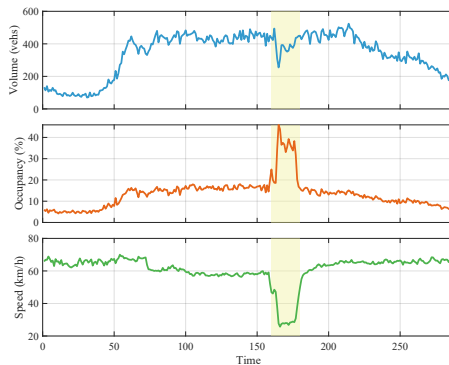
Why multi-view coupling is needed

Key observation

Volume, occupancy, and speed characterize the same traffic state from complementary perspectives.

Cross-view consistency

- ▶ Normal traffic states exhibit shared latent structure across views.
- ▶ Traffic incidents induce synchronized deviations across views.



Research gap

Line of work	Model	Main limitation
Robust recovery	$\begin{aligned} \min_{\mathcal{X}, \mathcal{E}} \quad & \sum_{i=1}^N \ X_{(i)}\ _* + \lambda \ E_{(1)}\ _{2,1} \\ \text{s.t.} \quad & \mathcal{B}_\Omega = (\mathcal{X} + \mathcal{E})_\Omega \end{aligned}$	Handles sparse corruptions, but does not fully couple shared backgrounds across views.
Multi-view recovery	$\begin{aligned} \arg \min_{X^\nu, Z^\nu, E^\nu} \quad & R_1(Z^1, \dots, Z^V) + \gamma \sum_{\nu=1}^V R_2(E^\nu) \\ \text{s.t.} \quad & X^\nu = X^\nu Z^\nu + E^\nu, \mathcal{P}_{\Omega^\nu}(X^\nu) = \mathcal{P}_{\Omega^\nu}(M^\nu). \end{aligned}$	Exploits cross-view consistency, but the fusion mechanism is often coarse or matrix-based.

Outline

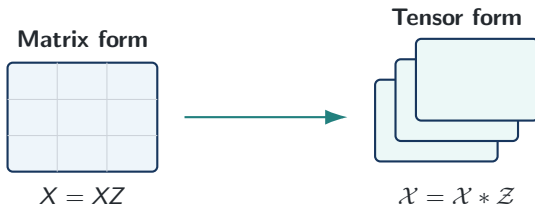
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Overall USCMT formulation

$$\begin{aligned}
 & \min_{\mathcal{X}^v, \mathcal{Z}^v, \mathcal{E}^v} \underbrace{\|\mathcal{Z}\|_\phi}_{\text{shared background structure}} + \gamma \underbrace{\|\mathcal{E}\|_{F,\psi}}_{\text{coupled event deviations}} + \underbrace{\frac{\lambda}{2} \sum_{v=1}^V \sum_{u=1}^3 \|\mathcal{X}^v \times_u D_u\|_F^2}_{\text{traffic regularity}} + \sum_{v=1}^V \delta_{\mathbb{S}^v}(\mathcal{X}^v) \\
 & \text{s.t.} \quad \mathcal{X}^v = \mathcal{X}^v * \mathcal{Z}^v + \mathcal{E}^v, \quad v = 1, \dots, V.
 \end{aligned}$$

$$\delta_{\mathbb{S}^v}(\mathcal{X}^v) = \begin{cases} 0, & \mathcal{X}^v \in \mathbb{S}^v, \\ +\infty, & \mathcal{X}^v \notin \mathbb{S}^v, \end{cases} \quad \mathbb{S}^v = \{\mathcal{X}^v \mid \mathcal{P}_{\Omega^v}(\mathcal{X}^v) = \mathcal{P}_{\Omega^v}(\mathcal{O}^v)\}.$$

Innovation 1: tensor self-representation



定理

Suppose $X \in \mathbb{R}^{n_1 n_3 \times n_2}$ and $Z \in \mathbb{R}^{n_2 \times n_2}$ satisfy $X = XZ$. Then there exist two third-order tensors $\mathcal{X} \in \mathbb{R}^{n_1 \times n_2 \times n_3}$ and $\mathcal{Z} \in \mathbb{R}^{n_2 \times n_2 \times n_3}$ such that $\mathcal{X} = \mathcal{X} * \mathcal{Z}$, where $\mathcal{X}$ can be constructed from X by setting $\mathcal{X} = \text{fold}_2(X^T)$ and $\mathcal{Z}$ can be computed as $\mathcal{Z}(:, t, :) = \text{ifft}(\bar{\mathcal{Z}}(:, t, :), [], 3)$ in which $\bar{\mathcal{Z}}(:, t, j) = Z(:, t)$ for $t \in [n_2]$ and $j \in [n_3]$. The converse, however, does not hold in general.

Innovation 2: two-level cross-view coupling

Level 1: coupled traffic backgrounds

- ▶ Each view learns its own representation tensor $\mathcal{Z}^v$.
- ▶ Concatenate them into a shared tensor $\mathcal{Z}$ with $\mathcal{Z}(:, :, v) = \mathcal{Z}_{(3)}^v$.
- ▶ Enforce common structural patterns through the low-rank penalty

$$\mathcal{R}_1(\mathcal{Z}) = \text{rank}_t(\mathcal{Z}) \approx \|\mathcal{Z}\|_\phi.$$

This captures consistent background traffic structure without forcing all views to be identical.

Level 2: coupled anomalous events

- ▶ Stack residuals into $\mathcal{E} \in \mathbb{R}^{N \times D \times T \times V}$ with $\mathcal{E}(:, :, :, v) = \mathcal{E}^v$.
- ▶ Couple the same space–day–time location across views through

$$\mathcal{R}_2(\mathcal{E}) = \|\mathcal{E}\|_{F, \psi} = \sum_{i,j,k} \psi(\|\mathcal{E}(i, j, k, :)\|_F).$$

This suppresses idiosyncratic noise while preserving synchronized cross-view anomalies.

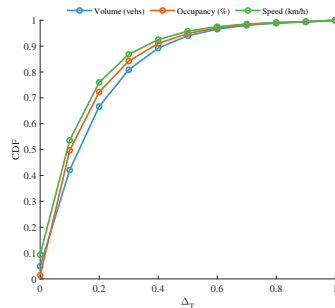
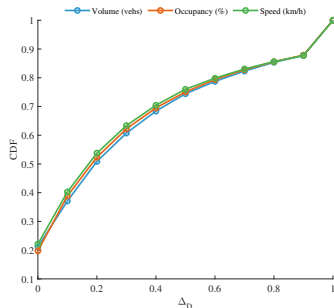
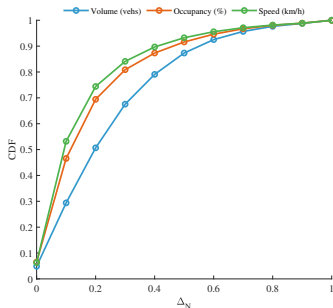
Takeaway. USCMT performs *double coupling*: the traffic background is coupled through $\mathcal{Z}$, and anomalous event patterns are coupled through $\mathcal{E}$.

Innovation 3: traffic-aware spatio-temporal regularity

Regularization term

$$\frac{\lambda}{2} \sum_{v=1}^V \sum_{u=1}^3 \|\mathcal{X}^v \times_u D_u\|_F^2.$$

- D_1 : neighboring road segments;
- D_2 : weekly periodicity;
- D_3 : short-term temporal continuity.



Overall USCMT formulation

$$\begin{aligned}
 \min_{\mathcal{X}^v, \mathcal{Z}^v, \mathcal{E}^v} \quad & \underbrace{\|\mathcal{Z}\|_\phi}_{\text{shared background structure}} + \gamma \underbrace{\|\mathcal{E}\|_{F,\psi}}_{\text{coupled event deviations}} + \underbrace{\frac{\lambda}{2} \sum_{v=1}^V \sum_{u=1}^3 \|\mathcal{X}^v \times_u D_u\|_F^2}_{\text{traffic regularity}} + \sum_{v=1}^V \delta_{\mathbb{S}^v}(\mathcal{X}^v) \\
 \text{s.t.} \quad & \mathcal{X}^v = \mathcal{X}^v * \mathcal{Z}^v + \mathcal{E}^v, \quad v = 1, \dots, V.
 \end{aligned} \tag{1}$$

$$\delta_{\mathbb{S}^v}(\mathcal{X}^v) = \begin{cases} 0, & \mathcal{X}^v \in \mathbb{S}^v, \\ +\infty, & \mathcal{X}^v \notin \mathbb{S}^v, \end{cases} \quad \mathbb{S}^v = \{\mathcal{X}^v \mid \mathcal{P}_{\Omega^v}(\mathcal{X}^v) = \mathcal{P}_{\Omega^v}(\mathcal{O}^v)\}.$$

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The augmented Lagrangian function of (1) is

$$\begin{aligned}
 \mathcal{L}_{\rho_i}(\mathcal{X}, \mathcal{Z}, \mathcal{E}, \mathcal{G}, \mathcal{Y}, \mathcal{K}; \mathcal{P}, \mathcal{Q}, \mathcal{R}, \mathcal{J}) = & \|\mathcal{G}\|_{\phi} + \gamma \|\mathcal{E}\|_{F, \psi} + \frac{\lambda}{2} \sum_{v=1}^V \sum_{u=1}^3 \|\mathcal{K}^v \times_u D_u\|^2 + \\
 & \sum_{v=1}^V \delta_{\mathbb{S}^v}(\mathcal{X}^v) + \sum_{v=1}^V \left(\langle \mathcal{P}^v, \mathcal{X}^v - \mathcal{Y}^v * \mathcal{Z}^v - \mathcal{E}^v \rangle + \frac{\rho_1}{2} \|\mathcal{X}^v - \mathcal{Y}^v * \mathcal{Z}^v - \mathcal{E}^v\|^2 \right) \\
 & + \langle \mathcal{Q}, \mathcal{G} - \mathcal{Z} \rangle + \frac{\rho_2}{2} \|\mathcal{G} - \mathcal{Z}\|^2 + \langle \mathcal{R}, \mathcal{Y} - \mathcal{X} \rangle + \frac{\rho_3}{2} \|\mathcal{Y} - \mathcal{X}\|^2 \\
 & + \langle \mathcal{J}, \mathcal{K} - \mathcal{X} \rangle + \frac{\rho_4}{2} \|\mathcal{K} - \mathcal{X}\|^2.
 \end{aligned}$$

Within the framework of the ADMM algorithm, we alternatively update each variable:

$$\left\{ \begin{array}{l} \mathcal{X}^{l+1} \in \operatorname{argmin}_{\mathcal{X}} \mathcal{L}_{\rho_i^l}(\mathcal{X}, \mathcal{Z}^l, \mathcal{E}^l, \mathcal{G}^l, \mathcal{Y}^l, \mathcal{K}^l; \mathcal{P}^l, \mathcal{Q}^l, \mathcal{R}^l, \mathcal{J}^l); \\ \mathcal{Z}^{l+1} \in \operatorname{argmin}_{\mathcal{Z}} \mathcal{L}_{\rho_i^l}(\mathcal{X}^{l+1}, \mathcal{Z}, \mathcal{E}^l, \mathcal{G}^l, \mathcal{Y}^l, \mathcal{K}^l; \mathcal{P}^l, \mathcal{Q}^l, \mathcal{R}^l, \mathcal{J}^l); \\ \mathcal{E}^{l+1} \in \operatorname{argmin}_{\mathcal{E}} \mathcal{L}_{\rho_i^l}(\mathcal{X}^{l+1}, \mathcal{Z}^{l+1}, \mathcal{E}, \mathcal{G}^l, \mathcal{Y}^l, \mathcal{K}^l; \mathcal{P}^l, \mathcal{Q}^l, \mathcal{R}^l, \mathcal{J}^l); \\ \mathcal{G}^{l+1} \in \operatorname{argmin}_{\mathcal{G}} \mathcal{L}_{\rho_i^l}(\mathcal{X}^{l+1}, \mathcal{Z}^{l+1}, \mathcal{E}^{l+1}, \mathcal{G}, \mathcal{Y}^l, \mathcal{K}^l; \mathcal{P}^l, \mathcal{Q}^l, \mathcal{R}^l, \mathcal{J}^l); \\ \mathcal{Y}^{l+1} \in \operatorname{argmin}_{\mathcal{Y}} \mathcal{L}_{\rho_i^l}(\mathcal{X}^{l+1}, \mathcal{Z}^{l+1}, \mathcal{E}^{l+1}, \mathcal{G}^{l+1}, \mathcal{Y}, \mathcal{K}^l; \mathcal{P}^l, \mathcal{Q}^l, \mathcal{R}^l, \mathcal{J}^l); \\ \mathcal{K}^{l+1} \in \operatorname{argmin}_{\mathcal{K}} \mathcal{L}_{\rho_i^l}(\mathcal{X}^{l+1}, \mathcal{Z}^{l+1}, \mathcal{E}^{l+1}, \mathcal{G}^{l+1}, \mathcal{Y}^{l+1}, \mathcal{K}; \mathcal{P}^l, \mathcal{Q}^l, \mathcal{R}^l, \mathcal{J}^l), \end{array} \right.$$

and

$$\left\{ \begin{array}{l} \mathcal{P}^{v,l+1} = \mathcal{P}^{v,l} + \rho_1^l (\mathcal{X}^{v,l+1} - \mathcal{Y}^{v,l+1} * \mathcal{Z}^{v,l+1} - \mathcal{E}^{v,l+1}); \\ \mathcal{Q}^{l+1} = \mathcal{Q}^l + \rho_2^l (\mathcal{G}^{l+1} - \mathcal{Z}^{l+1}); \\ \mathcal{R}^{l+1} = \mathcal{R}^l + \rho_3^l (\mathcal{Y}^{l+1} - \mathcal{X}^{l+1}); \\ \mathcal{J}^{l+1} = \mathcal{J}^l + \rho_4^l (\mathcal{K}^{l+1} - \mathcal{X}^{l+1}); \\ \rho_i^{l+1} = \beta_i \rho_i^l. \end{array} \right.$$

Algorithm

Algorithm 1: The ADMM-based solver for the proposed USCMT model.

Input: Incomplete multi-source traffic dataset $\mathcal{P}_{\Omega}(\mathcal{M}^v)$, regularization parameters γ and λ .

Output: Multi-source traffic tensor $\mathcal{X} = [\mathcal{X}^1, \dots, \mathcal{X}^V]$ and event detection tensor $\mathcal{E} = [\mathcal{E}^1, \dots, \mathcal{E}^V]$.

```
1  $t \leftarrow 0$ ;  
2 while not converged do  
3   | Update  $\mathcal{X}^{l+1}$ ,  $\mathcal{Z}^{l+1}$ ,  $\mathcal{E}^{l+1}$ ,  $\mathcal{G}^{l+1}$ ,  $\mathcal{Y}^{l+1}$ ,  $\mathcal{K}^{l+1}$  respectively;  
4   | Update Lagrangian multipliers and the penalty parameter;  
5   |  $l \leftarrow l + 1$ .  
6 end
```

Convergence analysis

定理

Let $\{\mathcal{W}^l\}_{l=1}^{\infty}$ be the sequence generated by Algorithm 1. If the sequences $\{\mathcal{P}^l, \mathcal{Q}^l, \mathcal{R}^l, \mathcal{J}^l\}_{l=1}^{\infty}$ and $\{\mathcal{X}^l\}_{l=1}^{\infty}$ are bounded, then every accumulation point of $\{\mathcal{W}^l\}_{l=1}^{\infty}$ satisfies the Karush–Kuhn–Tucker (KKT) conditions of problem (1).

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Random Missing (RM)

表 1: Performance comparison for data reconstruction on RM scenarios. MAPE / RMSE

Dataset	Scenario	View / Metric	BGCP	BATF	LRTC-TNN	LATC	IGNNK	MVLR	USCMT
PeMS-D8	RM-40%	Volume	11.05 / 25.97	12.14 / 26.36	8.86 / 21.90	8.62 / 20.87	14.26/28.83	8.74 / 21.57	8.58 / 20.94
		Occupancy	15.43 / 1.71	16.51 / 1.55	10.76 / 1.21	10.63 / 1.14	20.69/1.54	10.83 / 1.18	9.64 / 1.07
		Speed	2.93 / 2.94	3.01 / 2.97	1.79 / 1.86	1.61 / 1.67	2.56/2.43	1.71 / 1.80	1.28 / 1.41
		Time (s)	257.45	215.63	96.19	247.96	74.12	69.83	16.27
	RM-80%	Volume	11.31 / 27.60	13.53 / 28.57	10.37 / 26.89	9.91 / 24.30	25.65/40.41	10.65 / 26.51	9.38 / 23.60
		Occupancy	17.82 / 2.64	18.34 / 2.46	12.87 / 1.53	13.45 / 1.51	32.94/2.05	16.71 / 2.40	10.86 / 1.37
		Speed	3.34 / 3.63	3.33 / 3.43	2.72 / 2.87	2.55 / 2.67	4.85/4.13	2.82 / 2.91	2.02 / 2.27
		Time (s)	164.77	165.07	75.70	192.28	62.46	57.08	24.71
PeMS-D4	RM-40%	Volume	16.33 / 32.18	17.32 / 32.96	12.90 / 26.54	12.68 / 25.88	19.06/36.14	12.89 / 26.43	12.10 / 25.79
		Occupancy	27.20 / 1.71	27.31 / 1.72	16.61 / 1.35	16.33 / 1.29	29.74/1.58	17.00 / 1.32	14.79 / 1.19
		Speed	3.47 / 3.18	3.56 / 3.23	2.16 / 2.01	2.01 / 1.87	3.22/2.92	2.04 / 1.92	1.55 / 1.50
		Time (s)	302.49	328.24	92.01	268.83	123.79	125.52	27.86
	RM-80%	Volume	17.03 / 32.95	18.74 / 34.65	14.67 / 30.63	14.31 / 28.69	27.36/43.99	15.18 / 30.09	13.46 / 28.10
		Occupancy	30.26 / 2.21	30.33 / 2.13	20.12 / 1.71	20.34 / 1.67	47.37/2.19	24.15 / 2.26	17.89 / 1.54
		Speed	3.68 / 3.37	3.73 / 3.40	3.19 / 2.98	3.00 / 2.83	5.67/4.55	3.17 / 2.96	2.42 / 2.41
		Time (s)	297.09	309.72	97.57	320.67	119.91	105.58	37.35

Best results are highlighted in bold fonts.

Cross Detector Missing (CDM)

表 2: Performance comparison for data reconstruction on CDM scenarios. MAPE / RMSE

Dataset	Scenario	View / Metric	BGCP	BATF	LRTC-TNN	LATC	IGNNK	MVLR	USCMT
PeMS-D8	CDM-40%	Volume	11.60 / 27.86	13.31 / 27.48	10.19 / 24.06	9.39 / 22.26	22.48/47.95	14.27 / 34.34	8.50 / 20.84
		Occupancy	15.79 / 1.59	16.89 / 1.49	12.40 / 1.24	11.64 / 1.14	31.72/1.91	16.10 / 1.47	9.74 / 1.04
		Speed	3.24 / 3.15	3.08 / 3.03	2.08 / 2.10	1.76 / 1.79	4.64/3.90	2.37 / 2.38	1.33 / 1.46
		Time (s)	213.18	120.98	47.59	156.18	73.76	76.77	12.83
	CDM-80%	Volume	31.96 / 85.41	20.31 / 42.94	21.17 / 71.11	11.20 / 26.01	43.65/70.66	27.23 / 80.21	9.42 / 23.45
		Occupancy	21.89 / 2.00	24.29 / 2.05	22.53 / 2.40	15.79 / 1.55	48.72/2.57	33.58 / 3.15	11.14 / 1.40
		Speed	14.41 / 11.50	3.78 / 3.83	5.75 / 10.00	2.85 / 2.85	7.81/6.08	8.46 / 14.05	2.01 / 2.27
		Time (s)	166.61	229.37	59.41	187.42	62.46	113.35	23.14
PeMS-D4	CDM-40%	Volume	17.41 / 33.48	18.00 / 33.65	14.35 / 28.89	13.46 / 27.19	27.21/45.56	22.16 / 42.45	12.03 / 25.91
		Occupancy	29.45 / 1.75	25.57 / 1.69	18.05 / 1.38	17.35 / 1.28	40.97/1.65	24.07 / 1.75	14.88 / 1.15
		Speed	3.65 / 3.27	3.61 / 3.28	2.47 / 2.24	2.13 / 1.97	5.03/4.19	3.04 / 2.70	1.51 / 1.48
		Time (s)	400.15	274.82	96.38	282.79	124.06	174.67	26.69
	CDM-80%	Volume	38.93 / 56.12	35.83 / 50.33	26.98 / 66.54	20.15 / 52.16	42.30 / 70.12	39.30 / 97.22	13.54 / 28.16
		Occupancy	44.14 / 2.30	42.91 / 2.19	31.12 / 2.43	25.48 / 1.75	60.37 / 2.40	46.15 / 3.32	18.30 / 1.54
		Speed	12.70 / 10.24	4.37 / 3.93	6.91 / 10.28	3.60 / 3.26	7.95 / 6.19	9.50 / 12.99	2.43 / 2.42
		Time (s)	428.73	726.77	197.53	537.08	108.80	223.39	64.96

Best results are highlighted in bold fonts.

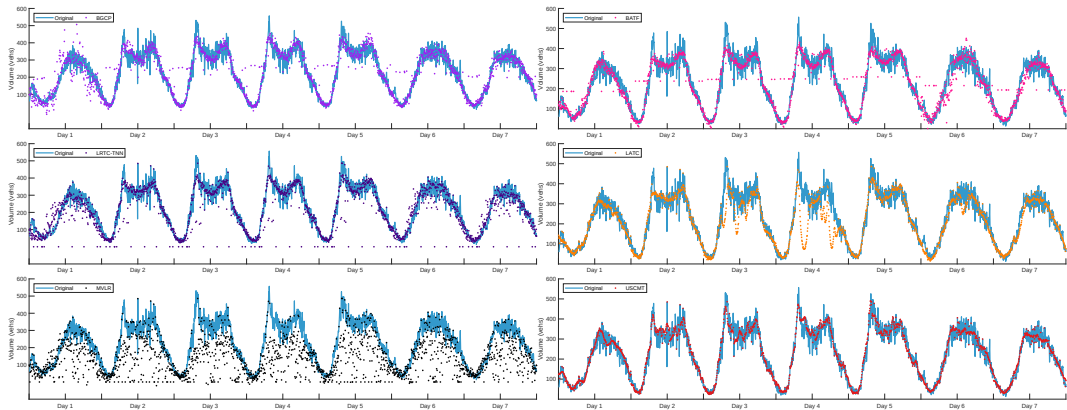
Continuous Temporal Missing (CTM)

表 3: Performance comparison for data reconstruction on CTM scenarios. MAPE / RMSE

Dataset	Scenario	View / Metric	BGCP	BATF	LRTC-TNN	LATC	IGNNK	MVLR	USCMT
PeMS-D8	CTM (2h, 40%)	Volume	11.25 / 27.57	12.87 / 28.39	9.87 / 27.08	9.79 / 25.99	133.38 / 258.82	12.83 / 33.76	9.13 / 25.64
		Occupancy	16.85 / 3.95	16.95 / 3.08	12.72 / 1.64	13.10 / 1.70	70.13 / 3.69	15.94 / 1.83	10.84 / 1.60
		Speed	3.30 / 3.44	3.55 / 3.60	2.74 / 3.04	2.98 / 3.39	24.56 / 18.62	3.88 / 3.76	2.63 / 3.00
		Time (s)	127.95	110.70	28.35	98.53	60.40	51.89	19.36
PeMS-D4	CTM (2h, 40%)	Volume	16.42 / 30.23	17.43 / 31.23	14.41 / 28.66	14.48 / 28.62	88.96 / 165.37	18.81 / 36.48	13.91 / 28.61
		Occupancy	33.66 / 5.96	29.36 / 2.62	20.69 / 1.79	20.99 / 1.90	117.88 / 3.59	27.32 / 1.99	17.40 / 1.77
		Speed	4.23 / 3.83	4.42 / 3.99	3.65 / 3.37	3.64 / 3.42	25.59 / 19.34	4.67 / 4.12	3.39 / 3.22
		Time (s)	224.14	218.14	52.86	183.76	108.23	104.91	33.75

Best results are highlighted in bold fonts.

Qualitative reconstruction comparison



Scenario: PeMS-D4, CDM-80%, volume reconstruction.

Event detection

表 4: AUC comparison for event detection.

View	iForest	MLP	RTC	MVLR	USCMT
Volume	0.5469	0.6941	0.5883	0.5124	0.7270
Occupancy	0.7077	0.6294	0.7095	0.6590	0.7270
Speed	0.5632	0.7084	0.5976	0.6925	0.7270

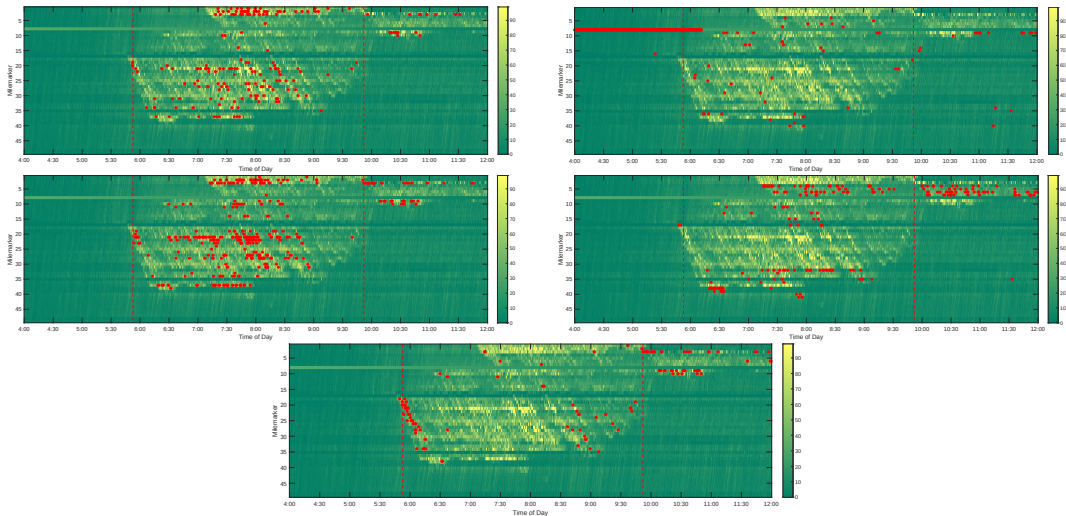
Best results are highlighted in bold fonts.

表 5: Effect of the FPR on detection delay (mean $\pm$ standard deviation) and miss percentage, where missed crashes are defined as crashes not detected within 15 minutes after the official report time.

FPR (%)	iForest		MLP		RTC		MVLr		USCMT	
	Delay (min)	Miss (%)	Delay (min)	Miss (%)	Delay (min)	Miss (%)	Delay (min)	Miss (%)	Delay (min)	Miss (%)
Volume										
1	-2.17 $\pm$ 5.98	61.36	-1.66 $\pm$ 6.26	52.27	-2.09 $\pm$ 5.85	61.36	-0.40 $\pm$ 5.07	72.73	-1.80 $\pm$ 5.44	52.27
2.5	-5.17 $\pm$ 6.72	31.82	-4.14 $\pm$ 7.86	27.27	-5.08 $\pm$ 6.62	31.82	-1.44 $\pm$ 6.00	59.09	-4.70 $\pm$ 7.09	36.36
5	-7.05 $\pm$ 7.38	18.18	-5.86 $\pm$ 8.16	20.45	-7.02 $\pm$ 7.36	18.18	-3.10 $\pm$ 7.66	27.27	-6.97 $\pm$ 6.38	25.00
Occupancy										
1	-1.61 $\pm$ 6.66	43.18	-0.03 $\pm$ 4.92	81.82	0.00 $\pm$ 0.00	100.00	-1.82 $\pm$ 6.61	50.00	-1.80 $\pm$ 5.44	52.27
2.5	-3.68 $\pm$ 6.64	36.36	-0.61 $\pm$ 5.61	63.64	0.00 $\pm$ 0.00	100.00	-3.95 $\pm$ 7.03	27.27	-4.70 $\pm$ 7.09	36.36
5	-6.86 $\pm$ 6.90	29.55	-5.01 $\pm$ 7.05	15.91	-7.39 $\pm$ 7.25	27.27	-6.13 $\pm$ 7.33	15.91	-6.97 $\pm$ 6.38	25.00
Speed										
1	-0.28 $\pm$ 4.17	86.36	-0.14 $\pm$ 6.31	63.64	0.42 $\pm$ 2.94	81.82	-1.31 $\pm$ 4.92	72.73	-1.80 $\pm$ 5.44	52.27
2.5	-0.77 $\pm$ 6.65	59.09	-3.31 $\pm$ 7.64	43.18	-1.59 $\pm$ 6.20	38.64	-1.41 $\pm$ 6.20	47.73	-4.70 $\pm$ 7.09	36.36
5	-2.50 $\pm$ 7.61	50.00	-5.33 $\pm$ 8.00	34.09	-5.14 $\pm$ 7.02	18.18	-3.45 $\pm$ 6.65	34.09	-6.97 $\pm$ 6.38	25.00

Best results are highlighted in bold fonts.

Event detection visualization



Crash detection at 5% FPR for iForest, MLP, RTC, MVLR, and USCMT.

Joint reconstruction and detection

表 6: Comprehensive performance comparison for the joint task of data reconstruction and anomaly detection.

Scenario	View / Metric	RTC			MVLR			USCMT		
		MAPE	RMSE	AUC	MAPE	RMSE	AUC	MAPE	RMSE	AUC
RM-40%	Volume	44.29	3.01	0.5075	43.10	2.63	0.6010	38.52	2.35	0.6854
	Occupancy	61.06	8.31	0.5115	66.96	8.08	0.5947	51.77	7.07	0.6854
	Speed	3.04	2.40	0.5008	3.12	1.88	0.6166	1.99	1.40	0.6854
	Time (s)	99.04			319.79			54.89		
CDM-40%	Volume	40.71	2.57	0.5348	43.96	2.69	0.5807	38.60	2.41	0.6113
	Occupancy	58.77	8.64	0.5770	68.74	8.37	0.5995	50.09	7.27	0.6113
	Speed	8.61	4.97	0.5959	6.94	4.16	0.6228	2.56	1.68	0.6113
	Time (s)	95.82			394.85			62.26		

Best results are highlighted in bold fonts.

Pattern Analysis

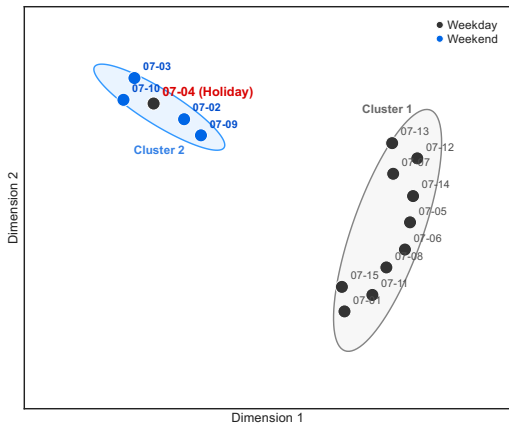


图 1: Visualization of the global affinity structure among daily traffic patterns in the Volume view via spectral t-SNE.

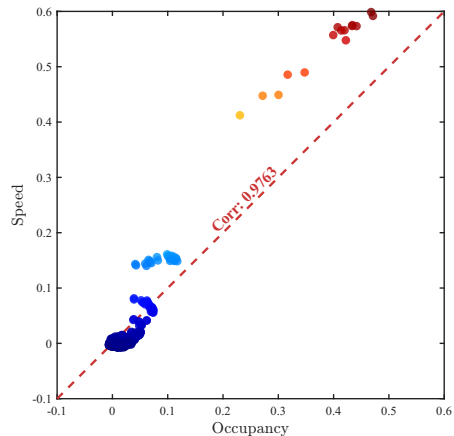


图 2: Visualization of cross-view structural consistency between Speed and Occupancy views.

Effectiveness of the unified multi-view multi-task framework

Does the unified multi-view multi-task formulation matter?

Method	Volume			Occupancy			Speed		
	MAPE	RMSE	AUC	MAPE	RMSE	AUC	MAPE	RMSE	AUC
SS	40.30	2.52	0.5031	61.79	7.20	0.5815	2.88	1.99	0.5018
US	40.30	2.52	0.5017	60.69	7.11	0.6366	2.28	1.60	0.5020
SM	39.84	2.50	0.5569	59.65	7.07	0.5569	2.75	1.93	0.5569
UM	39.82	2.50	0.5968	58.78	7.00	0.5968	2.27	1.60	0.5968

Thank you

Questions and discussion