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# **Matrix and Tensor Models for Spatiotemporal Traffic Data Imputation and Forecasting**

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December 28, 2023

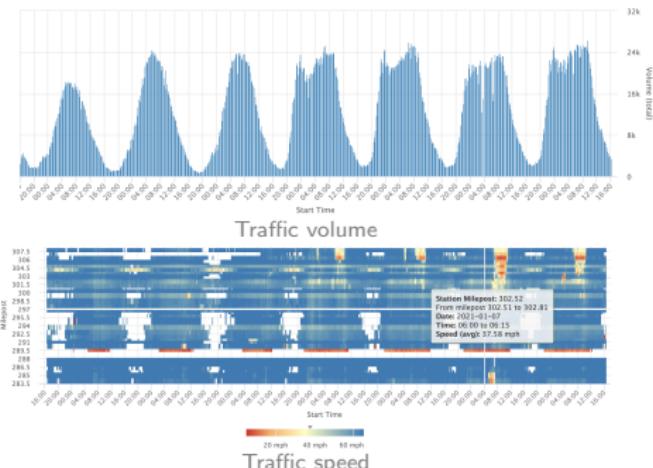
# **Outline**

- 1. Background**
- 2. Literature Review**
- 3. Nonstationary Temporal Matrix Factorization (NoTMF)**
- 4. Laplacian Convolutional Representation (LCR)**
- 5. Hankel Tensor Factorization (HTF)**
- 6. Conclusion**

# Spatiotemporal Traffic Data

Many spatiotemporal traffic time series data are in the form of **matrix**.

- Portland highway traffic data<sup>1</sup>



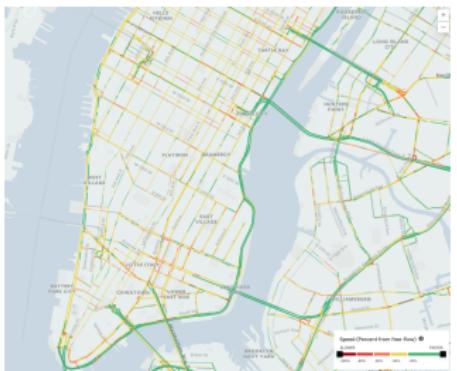
- $X \in \mathbb{R}^{N \times T}$  with  $N$  spatial locations  $\times$   $T$  time steps
- Traffic volume/speed shows strong spatial/temporal dependencies

<sup>1</sup><https://portal.its.pdx.edu/home>

# Urban Movement Data

## High-dimensional & sparse

- Uber (hourly) movement speed data



NYC movement



Seattle movement

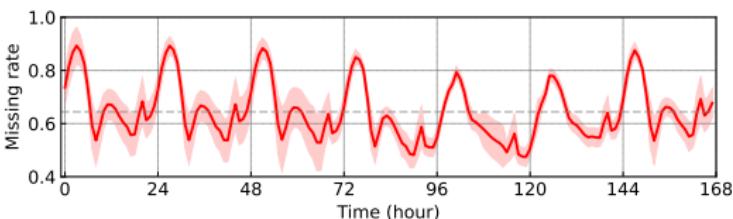
- {road segment, time slot (hour), average speed}
- Computing hourly speed: Road segments have 5+ unique trips.

**Issue:** Insufficient sampling of ridesharing vehicles on the road network!

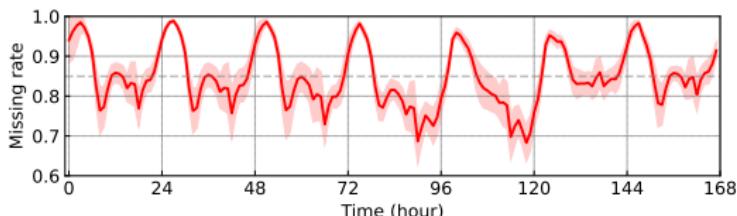
# Urban Movement Data

## High-dimensional & sparse

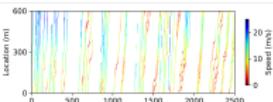
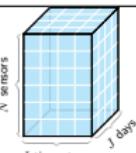
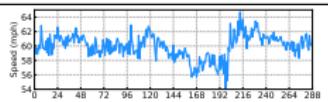
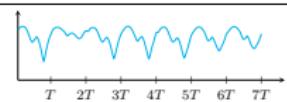
- **NYC** movement speed data (2019)
  - **98,210** road segments & 8,760 time steps (hours)
  - Overall missing rate: **64.43%**



- **Seattle** movement speed data (2019)
  - **63,490** road segments & 8,760 time steps (hours)
  - Overall missing rate: **84.95%**



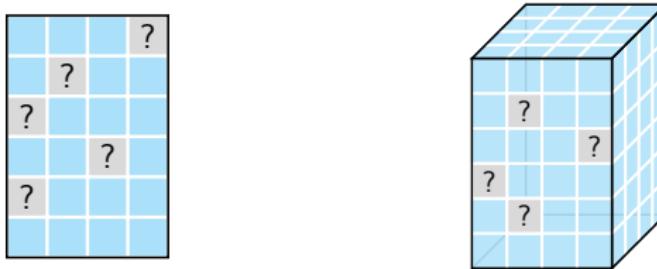
# Spatiotemporal Traffic Data

Sparse	
High-dimensional	
Multidimensional	
Noises & outliers	
Nonstationary	

Traffic data show complicated spatiotemporal patterns and correlations.

## Problem Formulation

**Objective A:** Impute missing values in the data matrix  $\mathbf{Y} \in \mathbb{R}^{N \times T}$  (or tensor  $\mathcal{Y} \in \mathbb{R}^{M \times N \times T}$ ).



- Matrix completion (Observed index set  $\Omega$ )

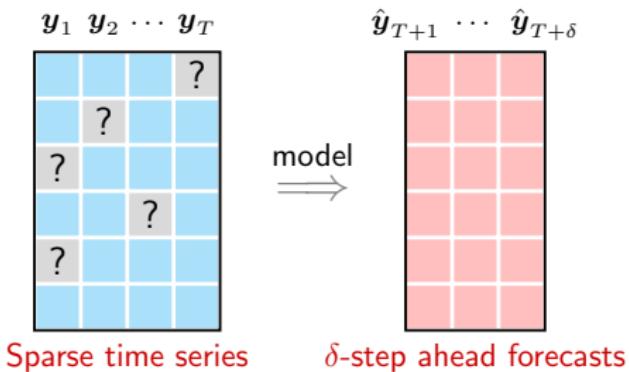
$$\underbrace{\mathcal{P}_\Omega(\mathbf{Y})}_{\text{Partially observed}} \xrightarrow{\text{Estimate}} \underbrace{\mathcal{P}_\Omega^\perp(\mathbf{Y})}_{\text{Unobserved}}$$

Modeling process:

- How to make use of spatiotemporal traffic patterns?
- How to make use of traffic time series dynamics?

## Problem Formulation

**Objective B:** Given a partially observed data  $\mathbf{Y} \in \mathbb{R}^{N \times T}$  consisting of time series  $\mathbf{y}_1, \dots, \mathbf{y}_T \in \mathbb{R}^N$ , forecast data points  $\hat{\mathbf{y}}_{T+\delta}, \delta \in \mathbb{N}^+$ .

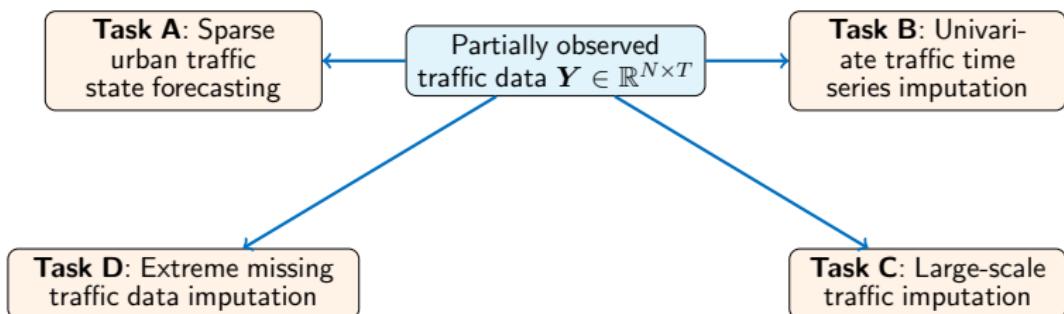


Modeling process:

- How to characterize time series dynamics in high-dimensional and sparse traffic data?

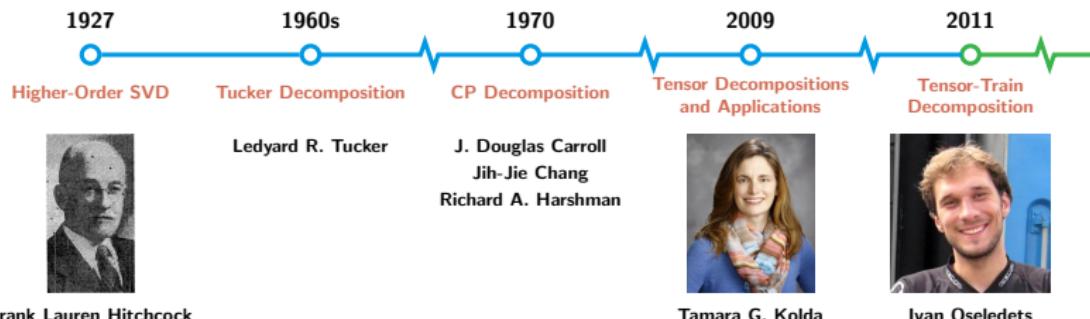
# Tasks

We are working on **spatiotemporal traffic data imputation and forecasting**.



# Tensor Factorization

- Revisit tensor factorization



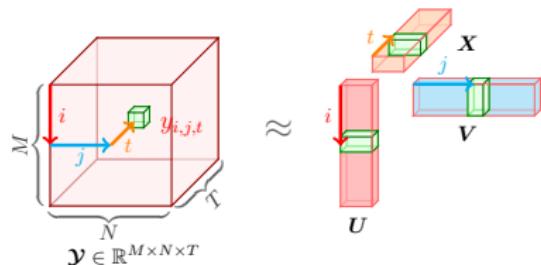
Frank Lauren Hitchcock

J. Douglas Carroll  
Jih-Jie Chang  
Richard A. Harshman

Tamara G. Kolda

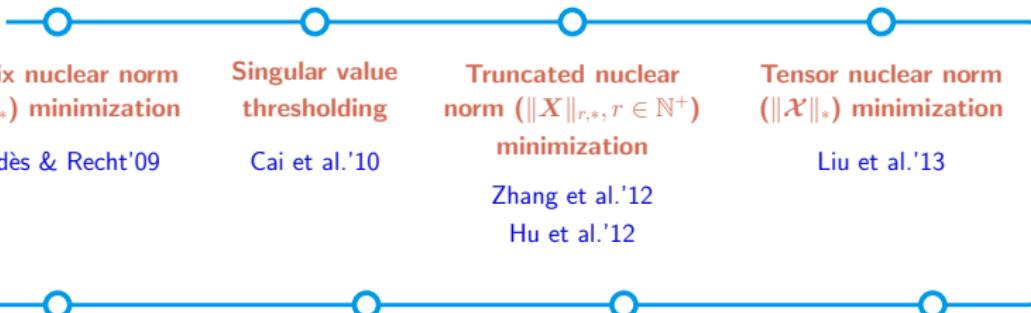
Ivan Oseledets

- CP tensor factorization:** Factorize  $\mathcal{Y}$  into the combination of three rank- $R$  factor matrices (i.e., low-dimensional latent factors).



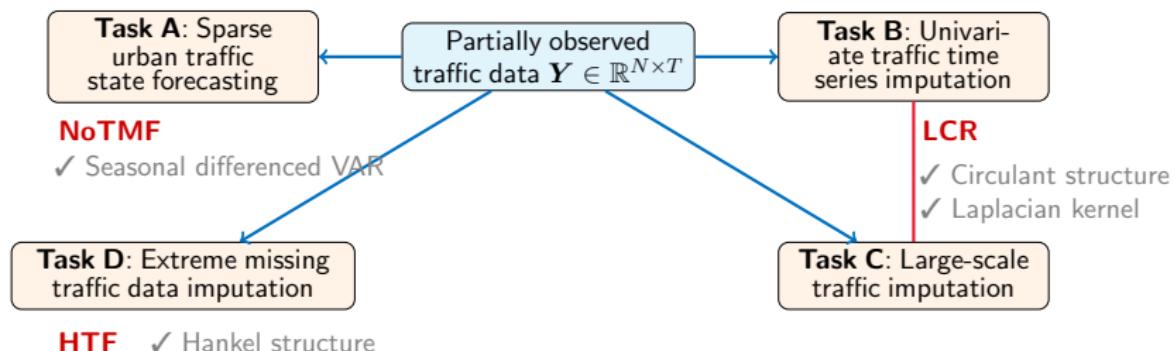
$$\left\{ \begin{array}{l} y_{i,j,t} \approx \sum_{r=1}^R u_{i,r} v_{j,r} x_{t,r} \\ \mathcal{Y} \approx \sum_{r=1}^R \mathbf{u}_r \otimes \mathbf{v}_r \otimes \mathbf{x}_r \end{array} \right.$$

# Matrix/Tensor Completion



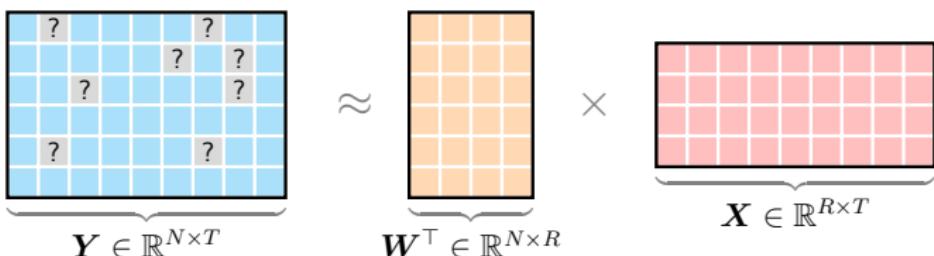
# Overview

Matrix/Tensor methods + temporal modeling (e.g., smoothing & autoregression)



# Matrix Factorization

A simple approach to reconstruct missing values.



## MF (Koren et al.'09)

Estimating low-dimensional  $\mathbf{W}, \mathbf{X}$ :

$$\min_{\mathbf{W}, \mathbf{X}} \frac{1}{2} \|\mathcal{P}_\Omega(\mathbf{Y} - \mathbf{W}^\top \mathbf{X})\|_F^2$$

on data  $\mathbf{Y}$  w/ observed index set  $\Omega$ .

- ✓ Learn from sparse data
- ✓ Spatial factor matrix  $\mathbf{W}$
- ✓ Temporal factor matrix  $\mathbf{X}$

How to build temporal correlations on MF?

# Temporal Matrix Factorization

Vector autoregression (VAR) on the temporal factor matrix.

$$\begin{matrix} \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \end{matrix} \underbrace{\quad}_{\mathbf{Y} \in \mathbb{R}^{N \times T}} \approx \begin{matrix} \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \end{matrix} \underbrace{\quad}_{\mathbf{W}^\top \in \mathbb{R}^{N \times R}} \times \begin{matrix} \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \end{matrix} \underbrace{\quad}_{\mathbf{X} \in \mathbb{R}^{R \times T}}$$

$$\begin{matrix} \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \end{matrix} \underbrace{\quad}_{\mathbf{Y} \in \mathbb{R}^{N \times T}} \approx \begin{matrix} \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \\ \text{?} & \text{?} \end{matrix} \underbrace{\quad}_{\mathbf{W}^\top \in \mathbb{R}^{N \times R}} \times \begin{matrix} \mathbf{x}_{t-2} & \mathbf{x}_{t-1} & \mathbf{x}_t & \mathbf{x}_{t+1} & \mathbf{x}_{t+2} \\ \dots & & & & \dots \end{matrix} \left. \right\} R$$

time step

$\Downarrow$   **$\mathbf{X}$  is time series?**

**Why?** Temporal factor matrix  $\mathbf{X} \in \mathbb{R}^{R \times T}$  is the low-dimensional representation of time series dynamics of  $\mathbf{Y} \in \mathbb{R}^{N \times T}$ .

# Temporal Matrix Factorization

Vector autoregression (VAR) on the temporal factor matrix.

## MF (Koren et al.'09)

Estimating low-dimensional  $\mathbf{W}, \mathbf{X}$ :

$$\min_{\mathbf{W}, \mathbf{X}} \frac{1}{2} \|\mathcal{P}_\Omega(\mathbf{Y} - \mathbf{W}^\top \mathbf{X})\|_F^2$$

on data  $\mathbf{Y}$  w/ observed index set  $\Omega$ .

## dth-order VAR

$$\mathbf{x}_t = \sum_{k=1}^d \mathbf{A}_k \mathbf{x}_{t-k} + \underbrace{\boldsymbol{\epsilon}_t}_{\mathcal{N}(\mathbf{0}, \mathbf{I})}$$

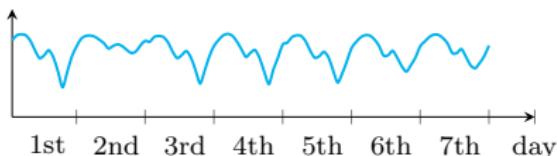
w/ coefficients  $\{\mathbf{A}_k\}$ .

↓ Yu et al.'16  
Chen & Sun'21

$$\min_{\mathbf{W}, \mathbf{X}, \{\mathbf{A}_k\}_{k=1}^d} \frac{1}{2} \underbrace{\|\mathcal{P}_\Omega(\mathbf{Y} - \mathbf{W}^\top \mathbf{X})\|_F^2}_{\text{MF on data } \mathbf{Y}} + \frac{\gamma}{2} \underbrace{\sum_{t=d+1}^T \left\| \mathbf{x}_t - \sum_{k=1}^d \mathbf{A}_k \mathbf{x}_{t-k} \right\|_2^2}_{\text{VAR on temporal factors } \mathbf{X}}$$

# Nonstationary Temporal Matrix Factorization

Traffic data are nonstationary due to daily patterns of traffic flow.



- Season- $m$  differencing ( $m \in \mathbb{N}^+$ , e.g., daily/weekly):

$$\mathbf{x}_t \approx \sum_{k=1}^d \mathbf{A}_k \mathbf{x}_{t-k} \quad \Rightarrow \quad \mathbf{x}_t - \mathbf{x}_{t-m} \approx \sum_{k=1}^d \mathbf{A}_k (\mathbf{x}_{t-k} - \mathbf{x}_{t-m-k})$$

- (Ours) Optimization problem:

$$\begin{aligned} \min_{\mathbf{W}, \mathbf{X}, \{\mathbf{A}_k\}_{k=1}^d} & \frac{1}{2} \underbrace{\|\mathcal{P}_\Omega(\mathbf{Y} - \mathbf{W}^\top \mathbf{X})\|_F^2}_{\text{MF on data } \mathbf{Y}} + \frac{\rho}{2} \underbrace{(\|\mathbf{W}\|_F^2 + \|\mathbf{X}\|_F^2)}_{\text{Regularization}} \\ & + \frac{\gamma}{2} \underbrace{\sum_{t=d+m+1}^T \left\| (\mathbf{x}_t - \mathbf{x}_{t-m}) - \sum_{k=1}^d \mathbf{A}_k (\mathbf{x}_{t-k} - \mathbf{x}_{t-m-k}) \right\|_2^2}_{\text{VAR on seasonal differenced temporal factors}} \end{aligned}$$

# Nonstationary Temporal Matrix Factorization

## Rewrite NoTMF

- Optimization problem:<sup>2</sup>

$$\min_{\mathbf{W}, \mathbf{X}, \mathbf{A}} \frac{1}{2} \underbrace{\|\mathcal{P}_\Omega(\mathbf{Y} - \mathbf{W}^\top \mathbf{X})\|_F^2}_{\text{MF on data } \mathbf{Y}} + \frac{\rho}{2} \underbrace{(\|\mathbf{W}\|_F^2 + \|\mathbf{X}\|_F^2)}_{\text{Regularization}} + \frac{\gamma}{2} \underbrace{\|\mathbf{X} \Psi_0^\top - \mathbf{A} (\mathbf{I}_d \otimes \mathbf{X}) \Psi^\top\|_F^2}_{\text{VAR on } \mathbf{X}}$$

where  $\Psi_0 \in \mathbb{R}^{(T-d-m) \times T}$ ,  $\Psi \in \mathbb{R}^{(T-d-m) \times (dT)}$  are temporal operators.

- Alternating minimization (let  $f$  be the obj.):

$$\left\{ \begin{array}{ll} \text{Spatial factors} & \mathbf{W} := \{\mathbf{W} \mid \frac{\partial f}{\partial \mathbf{W}} = \mathbf{0}\} \quad (\text{least squares}) \\ \text{Temporal factors} & \mathbf{X} := \{\mathbf{X} \mid \frac{\partial f}{\partial \mathbf{X}} = \mathbf{0}\} \quad (\text{conjugate gradient}) \\ \text{VAR coefficients} & \mathbf{A} := \{\mathbf{A} \mid \frac{\partial f}{\partial \mathbf{A}} = \mathbf{0}\} \quad (\text{least squares}) \end{array} \right.$$

---

<sup>2</sup>  $\mathbf{A} \triangleq [\mathbf{A}_1 \quad \cdots \quad \mathbf{A}_d] \in \mathbb{R}^{R \times (dR)}$  (coefficient matrix).

# Nonstationary Temporal Matrix Factorization

NoTMF forecasting?

## Implementation

- Estimate  $\mathbf{W}, \mathbf{X}, \mathbf{A}$
- Forecast  $\hat{\mathbf{x}}_{t+1}$  with VAR
- Return  $\hat{\mathbf{y}}_{t+1} = \mathbf{W}^\top \hat{\mathbf{x}}_{t+1}$

- ✓ Sparse input  $\mathbf{Y}_t$
- ✓ Forecast in latent spaces

$$\underbrace{\mathbf{Y}_t}_{\in \mathbb{R}^{N \times t}} \quad \text{A matrix with } N \text{ rows and } t \text{ columns. Some entries are marked with question marks.}$$

$$R \left\{ \begin{array}{c} \mathbf{x}_{t-3} \quad \mathbf{x}_{t-2} \quad \mathbf{x}_{t-1} \quad \mathbf{x}_t \quad \mathbf{x}_{t+1} \\ | \qquad | \qquad | \qquad | \qquad | \\ t-3 \quad t-2 \quad t-1 \quad t \quad t+1 \end{array} \right. \quad \hat{\mathbf{x}}_{t+1} = \mathbf{x}_{t+1-m} + \text{VAR}(d, m)$$

The diagram shows a set of vectors  $\mathbf{x}_{t-3}, \mathbf{x}_{t-2}, \mathbf{x}_{t-1}, \mathbf{x}_t, \mathbf{x}_{t+1}$  arranged vertically. Below them, time steps are labeled:  $t-3, t-2, t-1, t, t+1$ . An arrow labeled "time step" points to the right, indicating the progression of time from left to right.

# Nonstationary Temporal Matrix Factorization

NoTMF forecasting on streaming data?

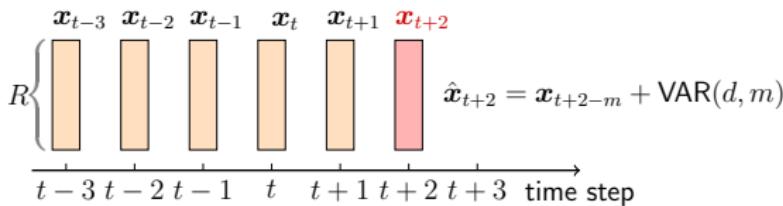
- Online forecasting (Gultekin & Paisley'18):
  - Fix the spatial factor matrix  $\mathbf{W}$
  - Use input data  $\mathbf{Y}_{t+1}$  to update the temporal factor matrix  $\mathbf{X}$  and the coefficient matrix  $\mathbf{A}$

## Implementation

- Estimate  $\mathbf{X}, \mathbf{A}$
- Forecast  $\hat{\mathbf{x}}_{t+2}$  with VAR
- Return  $\hat{\mathbf{y}}_{t+2} = \mathbf{W}^\top \hat{\mathbf{x}}_{t+2}$

- ✓ Sparse input  $\mathbf{Y}_{t+1}$
- ✓ Forecast in latent spaces

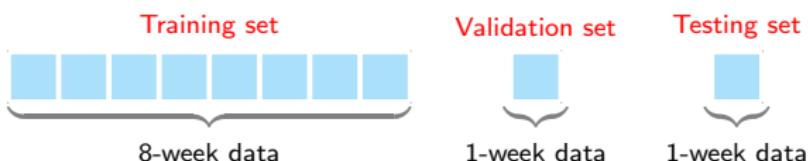
$$\mathbf{Y}_{t+1} \in \mathbb{R}^{N \times (t+1)}$$



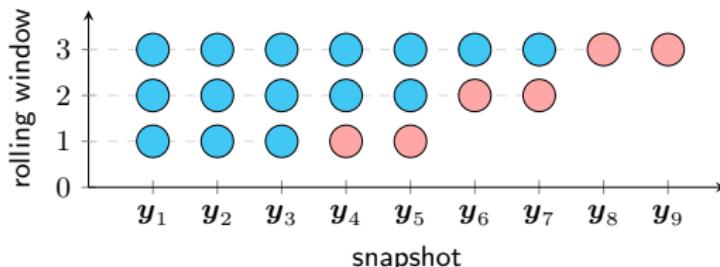
# Sparse Urban Traffic State Forecasting

## NoTMF forecasting

- NYC Uber movement speed dataset:
  - 10-week data of size  $98210 \times 1680$ ; **66.56%** missing values
- Rolling forecasting setup (Time horizon  $\delta = 1, 2, 3, 6$ ):



- Weight parameter  $\gamma \in \{10^{-2}, 10^{-1}, 10^0, 10^1, 10^2\}$
- Weight parameter  $\rho = \{10^{-1}\gamma, 5 \times 10^{-1}\gamma, \gamma, 5\gamma, 10\gamma\}$
- Rolling forecasting illustration ( $\delta = 2$ ):



# Sparse Urban Traffic State Forecasting

## NoTMF vs. baseline (in MAPE/RMSE)

- On the NYC Uber movement speed dataset

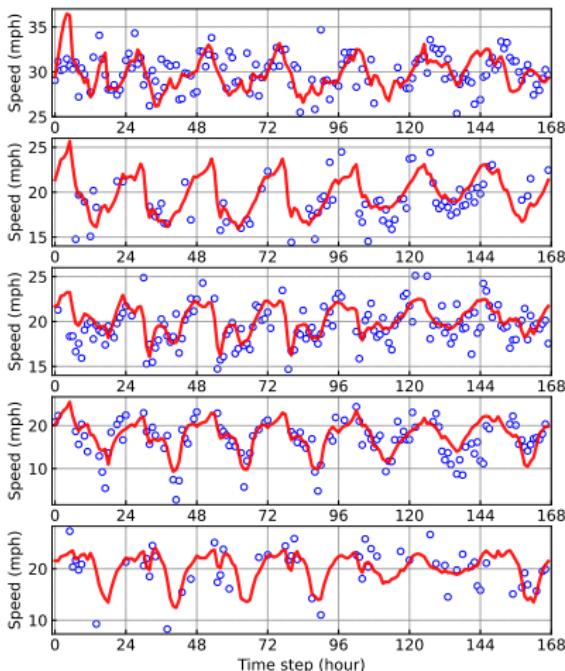
$\delta$	$d$	NoTMF ( $m = 24$ )	NoTMF ( $m = 168$ )	NoTMF-1st ( $m = 168$ )	TRMF	BTMF	BTRMF
1	1	13.63/2.88	13.53/2.86	<b>13.45/2.85</b>	14.50/3.12	14.94/3.13	15.93/3.33
	2	<b>13.47/2.84</b>	<b>13.41/2.84</b>	<b>13.42/2.84</b>	14.14/3.05	15.70/3.41	15.90/3.35
	3	13.46/2.84	<b>13.39/2.83</b>	13.43/2.84	13.87/2.96	15.80/3.34	16.08/3.43
	6	<b>13.41/2.83</b>	<b>13.39/2.83</b>	<b>13.41/2.83</b>	14.00/2.98	15.45/3.27	16.26/3.48
2	1	13.91/2.96	13.76/2.94	<b>13.70/2.92</b>	15.85/3.43	15.33/3.21	16.85/3.56
	2	13.77/2.92	<b>13.63/2.89</b>	13.72/2.92	15.04/3.31	15.87/3.32	17.27/3.71
	3	13.72/2.91	<b>13.61/2.89</b>	13.73/2.92	15.25/3.36	15.69/3.33	17.24/3.74
	6	<b>13.59/2.87</b>	<b>13.57/2.88</b>	13.68/2.91	14.92/3.24	15.91/3.39	18.18/3.97
3	1	14.30/3.05	14.06/3.02	<b>14.02/3.00</b>	17.52/3.83	15.86/3.32	18.61/3.91
	2	14.01/2.98	<b>13.84/2.94</b>	13.96/2.98	17.32/4.00	16.30/3.40	18.90/4.10
	3	13.95/2.97	<b>13.79/2.93</b>	13.98/2.98	16.91/3.71	16.56/3.49	18.68/4.05
	6	<b>13.78/2.92</b>	<b>13.73/2.92</b>	13.91/2.96	16.72/3.65	15.49/3.27	20.45/4.66
6	1	<b>14.61/3.11</b>	14.67/3.20	14.98/3.32	21.20/4.70	15.99/3.32	22.40/4.69
	2	<b>14.30/3.03</b>	14.33/3.09	14.90/3.28	20.87/5.01	16.04/3.33	23.56/5.63
	3	<b>14.26/3.03</b>	14.28/3.09	14.86/3.26	20.08/4.65	15.67/3.28	24.27/5.72
	6	<b>14.06/2.97</b>	14.16/3.06	14.80/3.23	20.40/4.35	16.38/3.50	26.34/6.60

NoTMF performs better than other TMF models (e.g., TRMF, BTMF & BTRMF).

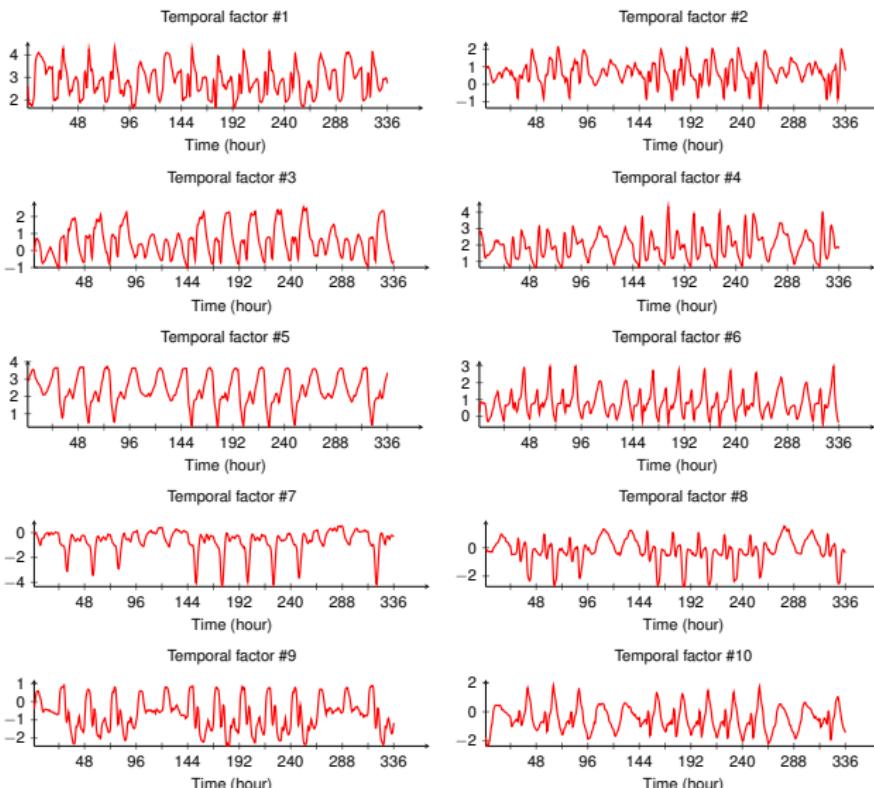
# Sparse Urban Traffic State Forecasting

## NoTMF forecasting ( $\delta = 6$ )

- On the NYC Uber movement speed dataset



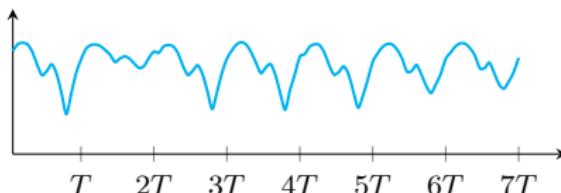
# Sparse Urban Traffic State Forecasting



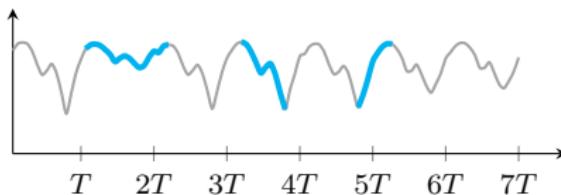
# Laplacian Convolutional Representation

## Motivation: Time series imputation

- Global trends (e.g., long-term quasi-seasonality & daily/weekly rhythm):



- Local trends (e.g., short-term time series trends):

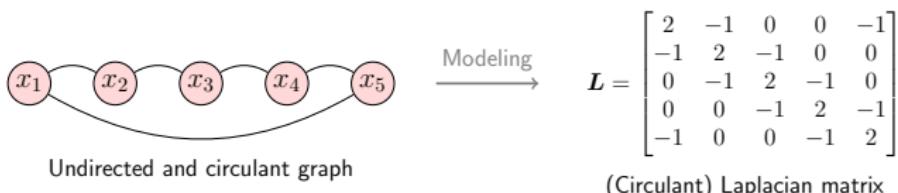


How to characterize both global and local trends in sparse time series?

# Laplacian Convolutional Representation

## Local trend modeling

- Intuition of (circulant) Laplacian matrix



- Define Laplacian kernel:

$$\boldsymbol{\ell} \triangleq (2, -1, 0, 0, -1)^\top$$

↓

$$\boldsymbol{\ell} \triangleq (\underbrace{2\tau}_{\text{degree}}, \underbrace{-1, \dots, -1}_{\tau}, 0, \dots, 0, \underbrace{-1, \dots, -1}_{\tau})^\top \in \mathbb{R}^T$$

for any time series  $\mathbf{x} = (x_1, \dots, x_T)^\top \in \mathbb{R}^T$ .

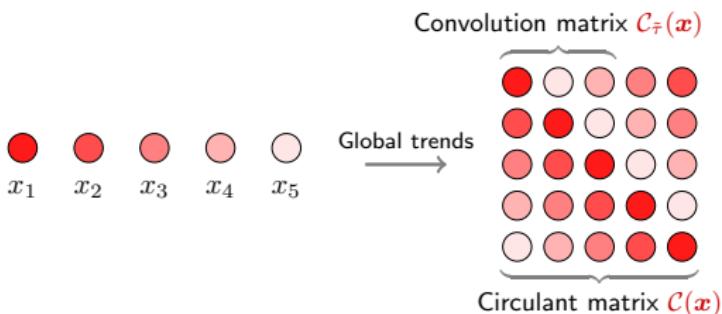
- (Laplacian) Temporal regularization:

$$\mathcal{R}_\tau(\mathbf{x}) = \frac{1}{2} \|\mathbf{L}\mathbf{x}\|_2^2 = \frac{1}{2} \|\boldsymbol{\ell} * \mathbf{x}\|_2^2$$

Reformulate temporal regularization with circular convolution.

# Laplacian Convolutional Representation

**Global trend modeling:** Circulant matrix  $\mathcal{C}(\mathbf{x})$  vs. convolution matrix  $\mathcal{C}_{\tilde{\tau}}(\mathbf{x})$



- Circulant/Convolution nuclear norm minimization
  - A balance between global and local trends modeling?

## CircNNM (Liu'22, Liu & Zhang'23)

Estimating  $\mathbf{x}$ :

$$\begin{aligned} \min_{\mathbf{x}} \quad & \|\mathcal{C}(\mathbf{x})\|_* \\ \text{s.t. } & \|\mathcal{P}_\Omega(\mathbf{x} - \mathbf{y})\|_2 \leq \epsilon \end{aligned}$$

on data  $\mathbf{y}$  w/ observed index set  $\Omega$ .

## ConvNNM (Liu'22, Liu & Zhang'23)

Estimating  $\mathbf{x}$ :

$$\begin{aligned} \min_{\mathbf{x}} \quad & \|\mathcal{C}_{\tilde{\tau}}(\mathbf{x})\|_* \\ \text{s.t. } & \|\mathcal{P}_\Omega(\mathbf{x} - \mathbf{y})\|_2 \leq \epsilon \end{aligned}$$

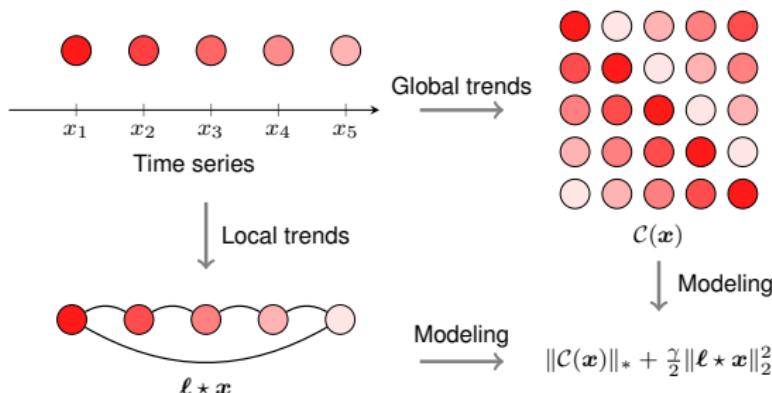
on data  $\mathbf{y}$  w/ observed index set  $\Omega$ .

# Laplacian Convolutional Representation

## Laplacian Convolutional Representation (LCR)

For any partially observed time series  $\mathbf{y} \in \mathbb{R}^T$  with observed index set  $\Omega$ , LCR utilizes **circulant matrix** and **Laplacian kernel** to characterize global and local trends in time series, respectively, i.e.,

$$\begin{aligned} \min_{\mathbf{x}} \quad & \underbrace{\|\mathcal{C}(\mathbf{x})\|_*}_{\text{global}} + \frac{\gamma}{2} \underbrace{\|\ell * \mathbf{x}\|_2^2}_{\text{local}} \\ \text{s.t. } & \|\mathcal{P}_\Omega(\mathbf{x} - \mathbf{y})\|_2 \leq \epsilon \end{aligned}$$



## Laplacian Convolutional Representation

- Augmented Lagrangian function:<sup>3</sup>

$$\mathcal{L}(\mathbf{x}, \mathbf{z}, \mathbf{w}) = \|\mathcal{C}(\mathbf{x})\|_* + \frac{\gamma}{2} \|\boldsymbol{\ell} * \mathbf{x}\|_2^2 + \frac{\lambda}{2} \|\mathbf{x} - \mathbf{z}\|_2^2 + \langle \mathbf{w}, \mathbf{x} - \mathbf{z} \rangle + \frac{\eta}{2} \|\mathcal{P}_\Omega(\mathbf{z} - \mathbf{y})\|_2^2$$

- The ADMM scheme:

$$\begin{cases} \mathbf{x} := \arg \min_{\mathbf{x}} \mathcal{L}(\mathbf{x}, \mathbf{z}, \mathbf{w}) & \text{(Nuclear norm minimization)} \\ \mathbf{z} := \arg \min_{\mathbf{z}} \mathcal{L}(\mathbf{x}, \mathbf{z}, \mathbf{w}) & \text{(Closed-form solution)} \\ \mathbf{w} := \mathbf{w} + \lambda(\mathbf{x} - \mathbf{z}) & \text{(Standard update)} \end{cases}$$

- Optimize  $\mathbf{x}$ ?

$$\|\mathcal{C}(\mathbf{x})\|_* = \|\mathcal{F}(\mathbf{x})\|_1 \quad \& \quad \frac{1}{2} \|\boldsymbol{\ell} * \mathbf{x}\|_2^2 = \frac{1}{2T} \|\mathcal{F}(\boldsymbol{\ell}) \circ \mathcal{F}(\mathbf{x})\|_2^2$$

Nuclear norm minimization  $\Rightarrow$   **$\ell_1$ -norm minimization with FFT** in  $\mathcal{O}(T \log T)$  time.

---

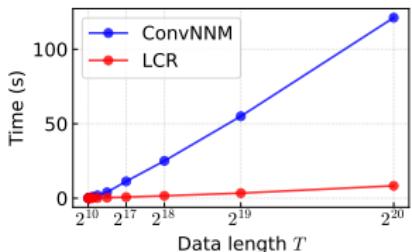
<sup>3</sup> $\mathbf{w} \in \mathbb{R}^T$  (Lagrange multiplier);  $\langle \cdot, \cdot \rangle$  (inner product).

# Laplacian Convolutional Representation

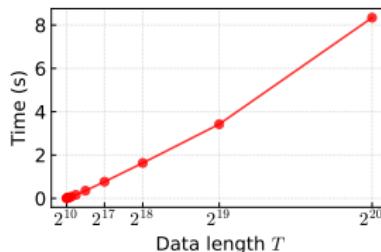
## Empirical time complexity

On the synthetic data  $\mathbf{y} \in \mathbb{R}^T$  with  $T \in \{2^{10}, 2^{11}, \dots, 2^{20}\}$

- Ours: **LCR**
  - An FFT implementation in  $\mathcal{O}(T \log T)$
  - The logarithmic factor  $\log T$  makes the FFT highly efficient
- Baseline: **ConvNNM**<sup>4</sup> ([Liu'22](#), [Liu & Zhang'23](#))
  - Convolution matrix  $C_{\tilde{\tau}}(\mathbf{y}) \in \mathbb{R}^{T \times \tilde{\tau}}$  with kernel size  $\tilde{\tau} = 2^4$
  - Singular value thresholding in  $\mathcal{O}(\tilde{\tau}^2 T)$



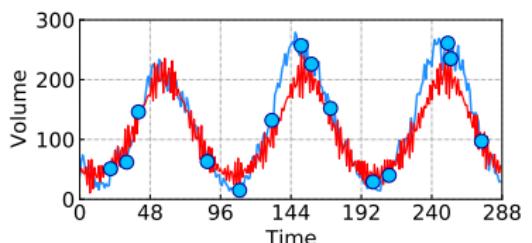
ConvNNM vs. LCR



LCR

<sup>4</sup>Convolution nuclear norm minimization.

# Univariate Traffic Time Series Imputation

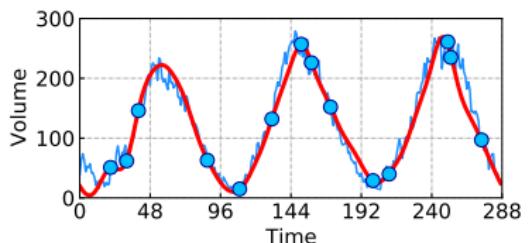


CircNNM:

$$\min_{\mathbf{x}} \underbrace{\|\mathcal{C}(\mathbf{x})\|_*}_{\text{global}}$$

$$\text{s. t. } \|\mathcal{P}_\Omega(\mathbf{x} - \mathbf{y})\|_2 \leq \epsilon$$

↓ Plus temporal regularization

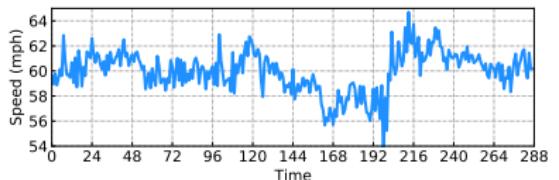


LCR:

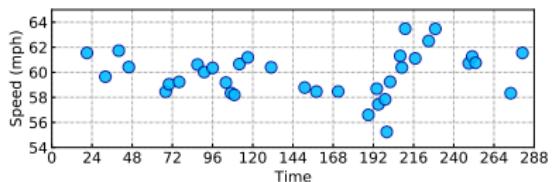
$$\min_{\mathbf{x}} \underbrace{\|\mathcal{C}(\mathbf{x})\|_*}_{\text{global}} + \frac{\gamma}{2} \underbrace{\|\ell * \mathbf{x}\|_2^2}_{\text{local}}$$

$$\text{s. t. } \|\mathcal{P}_\Omega(\mathbf{x} - \mathbf{y})\|_2 \leq \epsilon$$

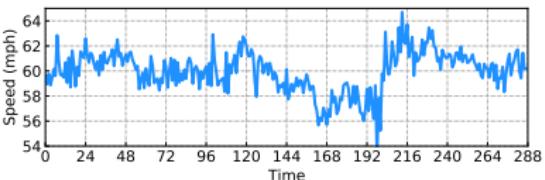
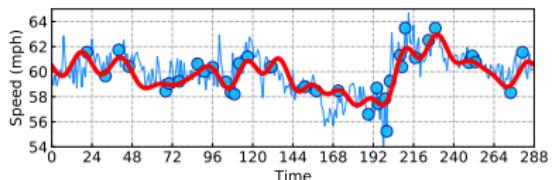
# Univariate Traffic Time Series Imputation



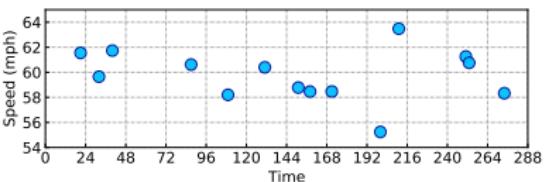
↓ Mask 90% observations



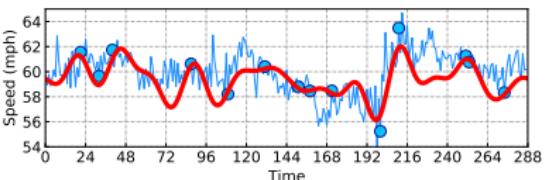
↓ Reconstruct time series



↓ Mask 95% observations



↓ Reconstruct time series



LCR can reconstruct traffic time series from very sparse data.

# Large-Scale Traffic Data Imputation

## LCR vs. baseline (in MAPE/RMSE)

- PeMS-4W: California freeway traffic speed dataset ( $Y \in \mathbb{R}^{11160 \times 8064}$ )

Model	Missing rate			
	30%	50%	70%	90%
LCR-2D	<b>1.50/1.49</b>	<b>1.76/1.69</b>	<b>2.07/2.06</b>	<b>3.19/3.05</b>
LCR <sub>N</sub>	<b>1.48/1.50</b>	<b>1.73/1.73</b>	<b>2.07/2.12</b>	3.24/3.22
LCR	<b>1.50/1.49</b>	<b>1.76/1.69</b>	2.08/2.07	3.21/3.06
CTNNM	2.26/1.84	2.67/2.14	3.40/2.66	5.22/3.90
CircNNM	2.26/1.84	2.69/2.15	3.43/2.67	5.34/3.96
LRMC	2.04/1.80	2.43/2.12	3.08/2.66	6.05/4.43
HaLRTC	1.98/1.73	2.22/1.98	2.84/2.49	4.39/3.66
LRTC-TNN	1.68/1.55	1.93/1.77	2.33/2.14	3.40/3.10
NoTMF	2.95/2.65	3.05/2.73	3.33/2.97	5.22/4.71

## Results

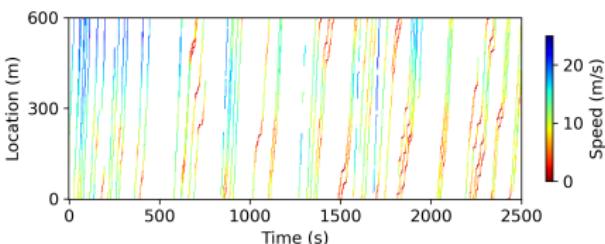
- LCR-2D > CTNNM: The importance of temporal regularization.
- CTNNM  $\geq$  CircNNM: Cyclic tensor is superior to circulant matrix.
- LCR > LRMC/LRTC: The importance of global/local modeling.

$\mathcal{O}(NT \log(NT))$  (FFT) vs.  $\mathcal{O}(\min\{N^2T, NT^2\})$  (SVD)

# Hankel Tensor Factorization

## Motivation: Spatiotemporal data reconstruction

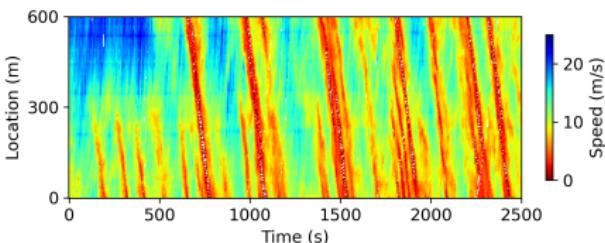
- Sparse speed field reconstruction problem in vehicular traffic flow.



200-by-500 matrix  
(NGSIM)



Reconstruct speed field from  
5% sparse trajectories?



How to characterize both spatial and temporal dependencies?

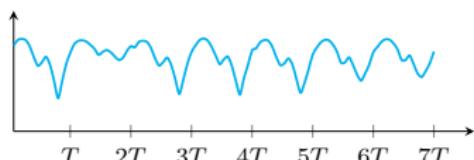
# Hankel Tensor Factorization

- Hankel matrix

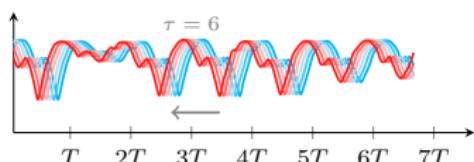
- Given  $\mathbf{x} = (1, 2, 3, 4, 5)^\top$  and window length  $\tau = 2$ , we have

$$\mathcal{H}_\tau(\mathbf{x}) = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 3 & 4 \\ 4 & 5 \end{bmatrix} \in \mathbb{R}^{4 \times 2}$$

- Automatic temporal modeling



Traffic time series



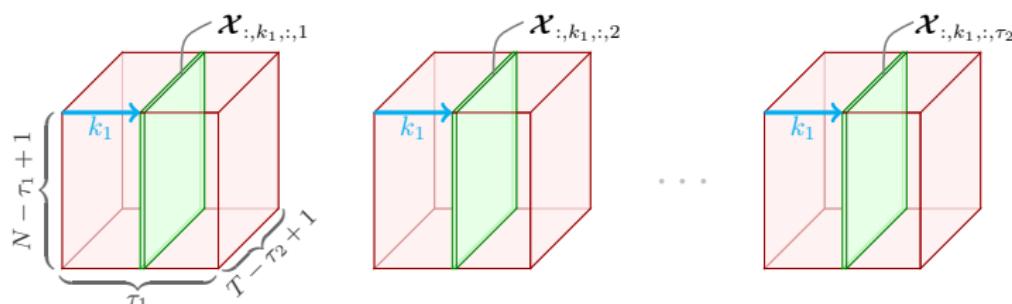
Hankel matrix

# Hankel Tensor Factorization

- Hankel tensor: Given any matrix  $\mathbf{X} \in \mathbb{R}^{N \times T}$ , we have

$$\mathcal{X} \triangleq \mathcal{H}_{\tau_1, \tau_2}(\mathbf{X})$$

- Window lengths:  $\tau_1, \tau_2 \in \mathbb{N}^+$ ;
- Tensor size:  $(N - \tau_1 + 1) \times \tau_1 \times (T - \tau_2 + 1) \times \tau_2$ ;



(Figure) 4th-order Hankel tensor: A sequence of third-order tensors.

- Slice:  $\mathcal{X}_{:,k_1,:,:k_2}$ ,  $\forall k_1, k_2$ ;
- Slice size:  $(N - \tau_1 + 1) \times (T - \tau_2 + 1)$ .

# Hankel Tensor Factorization

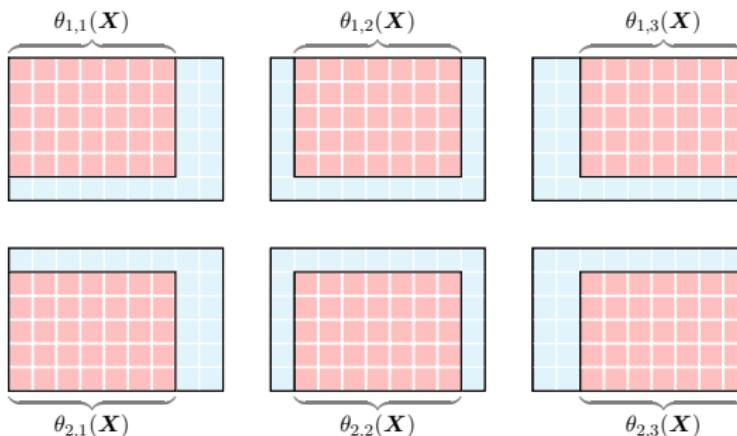
## Hankel indexing

- Sampling function for the Hankel tensor:

$$\theta_{k_1, k_2}(\mathbf{X}) \triangleq [\mathcal{H}_{\tau_1, \tau_2}(\mathbf{X})]_{:, k_1, :, k_2},$$

referring to as the tensor slice with  $k_1 \in \{1, \dots, \tau_1\}$ ,  $k_2 \in \{1, \dots, \tau_2\}$ .

- [Importance] Developing memory-efficient algorithms



- Tensor slices  $\theta_{k_1, k_2}(\mathbf{X})$  vs. data matrix  $\mathbf{X}$

# Hankel Tensor Factorization

## Ours:

- Convolutional tensor decomposition (circular convolution  $\star_{\text{row}}$ ):

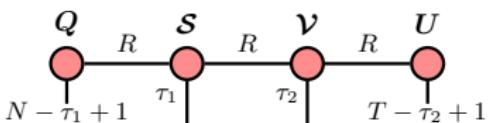
$$\theta_{k_1, k_2}(\mathbf{Y}) \approx (\mathbf{Q} \star_{\text{row}} \mathbf{s}_{k_1}^{\top})(\mathbf{U} \star_{\text{row}} \mathbf{v}_{k_2}^{\top})^{\top}$$

## Baselines:

- Tensor-train decomposition:

$$\theta_{k_1, k_2}(\mathbf{Y}) \approx (\mathbf{Q} \mathbf{S}_{k_1})(\mathbf{U} \mathbf{V}_{k_2})^{\top}$$

- $\{\mathbf{S}_{k_1}, \mathbf{V}_{k_2}\}$  are **circulant matrices**  $\Rightarrow$  convolutional decomposition
- $\{\mathbf{S}_{k_1}, \mathbf{V}_{k_2}\}$  are **diagonal matrices**  $\Rightarrow$  CP decomposition



- CP tensor decomposition (Khatri-Rao product  $\odot$ ):

$$\theta_{k_1, k_2}(\mathbf{Y}) \approx (\mathbf{Q} \odot \mathbf{s}_{k_1}^{\top})(\mathbf{U} \odot \mathbf{v}_{k_2}^{\top})^{\top}$$

# Hankel Tensor Factorization

## HTF (convolutional decomposition)

- Optimization problem:

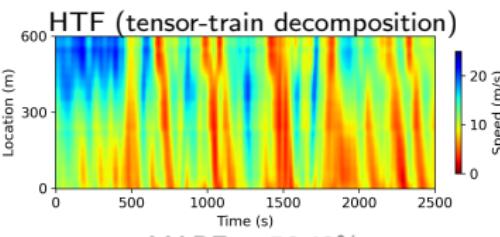
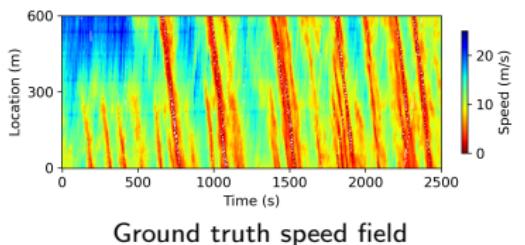
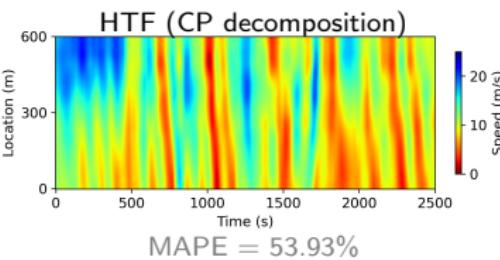
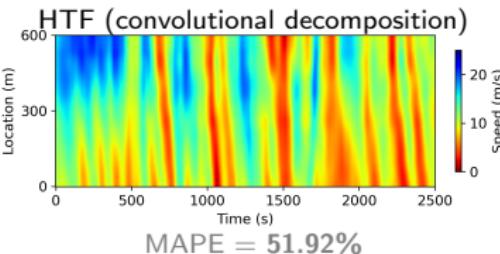
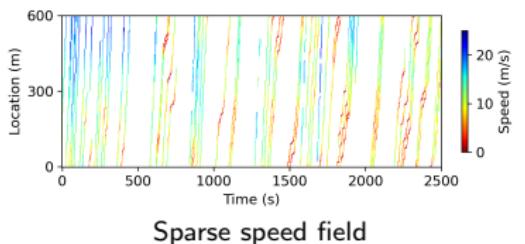
$$\min_{Q, S, U, V} \frac{1}{2} \underbrace{\sum_{k_1, k_2} \left\| \mathcal{P}_{\Omega_{k_1, k_2}} (\theta_{k_1, k_2}(\mathbf{Y}) - (Q \star_{\text{row}} s_{k_1}^{\top})(U \star_{\text{row}} v_{k_2}^{\top})^{\top}) \right\|_F^2}_{\text{Tensor decomposition on Hankel tensor slices}} + \frac{\rho}{2} (\|Q\|_F^2 + \|S\|_F^2 + \|U\|_F^2 + \|V\|_F^2)$$

- Alternating minimization (let  $f$  be the obj.):

$$\begin{cases} Q := \{Q \mid \frac{\partial f}{\partial Q} = \mathbf{0}\} & \text{(conjugate gradient)} \\ s_{k_1} := \{s_{k_1} \mid \frac{\partial f}{\partial s_{k_1}} = \mathbf{0}\}, \forall k_1 & \text{(conjugate gradient)} \\ U := \{U \mid \frac{\partial f}{\partial U} = \mathbf{0}\} & \text{(conjugate gradient)} \\ v_{k_2} := \{v_{k_2} \mid \frac{\partial f}{\partial v_{k_2}} = \mathbf{0}\}, \forall k_2 & \text{(conjugate gradient)} \end{cases}$$

- Memory-efficient but still computationally costly!

# Extreme Missing Traffic Data Imputation



# Extreme Missing Traffic Data Imputation

## HTF vs. baseline (in MAPE/RMSE)

- On the Seattle freeway traffic speed dataset ( $Y \in \mathbb{R}^{323 \times 8064}$ )

Model	Random missing rate			
	80%	85%	90%	95%
HTF (convolution)	<b>6.21/3.88</b>	<b>6.51/4.06</b>	<b>6.98/4.30</b>	<b>8.02/4.84</b>
HTF (tensor-train)	8.75/5.16	9.86/5.76	9.24/5.36	9.89/5.70
HTF (CP)	7.25/4.33	7.93/4.66	8.61/4.96	9.25/5.20
LATC	6.50/4.00	6.90/4.21	7.47/4.51	8.75/5.05
LRTC-TNN	6.97/4.24	7.43/4.43	8.19/4.81	9.60/5.55
LCR-2D	6.75/4.15	7.31/4.38	7.96/4.71	9.78/5.39
BTMF	6.85/4.17	7.36/4.42	8.13/4.79	9.63/5.48

### Results

- Convolutional tensor decomposition outperforms both tensor-train and CP tensor decomposition.
- Our HTF model performs better than state-of-the-art baseline models.

# Conclusion

Sparse	
High-dimensional	
Multidimensional	
Noises & outliers	
Nonstationary	

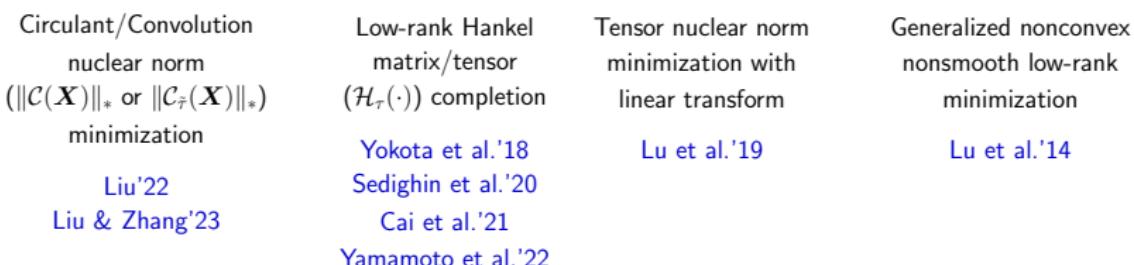
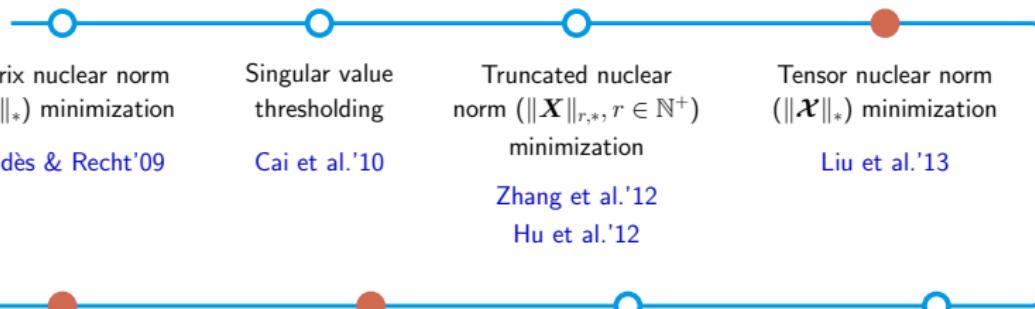
## Low-rank framework:

- NoTMF: matrix factorization
- LCR: circulant matrix nuclear norm minimization
- HTF: tensor factorization

## ⇒ Temporal modeling:

- NoTMF: seasonal differenced vector autoregression
- LCR: temporal smoothing
- HTF: automatic temporal modeling with Hankel tensor

## Highlights & Contributions



(Ours) LCR:

- ✓ Local trend modeling
- ✓ An FFT implementation

(Ours) HTF:

- ✓ Memory-efficient
- ✓ Conv. para.

# References

A short list:

- ([Candès & Recht'09](#)) "Exact matrix completion via convex optimization." *Foundations of Computational Mathematics*. 2009, 9(6): 717-772.
- ([Cai et al.'10](#)) "A singular value thresholding algorithm for matrix completion." *SIAM Journal on optimization*. 2010, 20(4): 1956-1982.
- ([Zhang et al.'12](#)) "Matrix completion by truncated nuclear norm regularization." *IEEE Conference on computer vision and pattern recognition*. 2012.
- ([Hu et al.'12](#)) "Fast and accurate matrix completion via truncated nuclear norm regularization." *IEEE transactions on pattern analysis and machine intelligence*. 2012, 35(9): 2117-2130.
- ([Lu et al.'14](#)) "Generalized nonconvex nonsmooth low-rank minimization." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2014.
- ([Gultekin & Paisley'18](#)) "Online forecasting matrix factorization." *IEEE Transactions on Signal Processing*. 2018, 67(5): 1223-1236.
- ([Yokota et al.'18](#)) "Missing slice recovery for tensors using a low-rank model in embedded space." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.
- ([Lu et al.'19](#)) "Tensor robust principal component analysis with a new tensor nuclear norm." *IEEE transactions on pattern analysis and machine intelligence*. 2019, 42(4): 925-938.
- ([Cai et al.'21](#)) "Accelerated structured alternating projections for robust spectrally sparse signal recovery." *IEEE Transactions on Signal Processing*. 2021, 69: 809-821.
- ([Chen & Sun'22](#)) "Bayesian temporal factorization for multidimensional time series prediction." *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2022, 44(9): 4659-4673.
- ([Liu'22](#)) "Time series forecasting via learning convolutionally low-rank models." *IEEE Transactions on Information Theory*. 2022, 68(5): 3362-3380.
- ([Liu & Zhang'23](#)) "Recovery of future data via convolution nuclear norm minimization." *IEEE Transactions on Information Theory*. 2023, 69(1): 650-665.



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# Thanks for your attention!

Any Questions?

Slides: <https://xinychen.github.io/slides/sustech23.pdf>

## About me:

- Homepage: <https://xinychen.github.io>
- How to reach me: [chenxy346@gmail.com](mailto:chenxy346@gmail.com)

# Research Interests

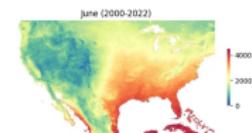
- Machine learning & spatiotemporal data modeling



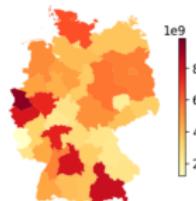
Transportation



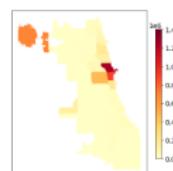
Mobile service



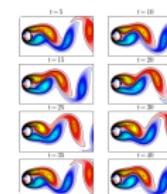
Climate



Energy



Mobility



Dynamical system

- Urban science
- Intelligent transportation systems

## Past Works

### Spatiotemporal traffic data imputation:

1. Xinyu Chen, Zhaocheng He, Jiawei Wang (2018). Spatial-temporal traffic speed patterns discovery and incomplete data recovery via SVD-combined tensor decomposition. *Transportation Research Part C: Emerging Technologies*. 86: 59-77. (100+ citations)
2. Xinyu Chen, Zhaocheng He, Lijun Sun (2019). A Bayesian tensor decomposition approach for spatiotemporal traffic data imputation. *Transportation Research Part C: Emerging Technologies*. 98: 73-84. (200+ citations, ESI highly cited paper)
3. Xinyu Chen, Zhaocheng He, Yixian Chen, Yuhuan Lu, Jiawei Wang (2019). Missing traffic data imputation and pattern discovery with a Bayesian augmented tensor factorization model. *Transportation Research Part C: Emerging Technologies*. 104: 66-77. (100+ citations)
4. Xinyu Chen, Jinming Yang, Lijun Sun (2020). A nonconvex low-rank tensor completion model for spatiotemporal traffic data imputation. *Transportation Research Part C: Emerging Technologies*. 117: 102673. (100+ citations)
5. Xinyu Chen, Yixian Chen, Nicolas Saunier, Lijun Sun (2021). Scalable low-rank tensor learning for spatiotemporal traffic data imputation. *Transportation Research Part C: Emerging Technologies*. 129: 103226.

## Past Works

### Spatiotemporal traffic data imputation:

6. Xinyu Chen, Mengying Lei, Nicolas Saunier, Lijun Sun (2022). Low-rank autoregressive tensor completion for spatiotemporal traffic data imputation. *IEEE Transactions on Intelligent Transportation Systems*. 23 (8): 12301-12310. (50+ citations, ESI hot paper)

### Spatiotemporal time series forecasting:

7. Xinyu Chen, Lijun Sun (2022). Bayesian temporal factorization for multidimensional time series prediction. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 44 (9): 4659-4673. (150+ citations, ESI hot paper & ESI highly cited paper)

### Spatiotemporal pattern discovery:

8. Xinyu Chen, Chengyuan Zhang, Xiaoxu Chen, Nicolas Saunier, Lijun Sun (2023). Discovering dynamic patterns from spatiotemporal data with time-varying low-rank autoregression. *IEEE Transactions on Knowledge and Data Engineering*. Early access.

## Past Works

A strong advocate of open-source and reproducible research:

Algorithms: e.g., **transdim** (1.1k stars)

- Machine learning for transportation data imputation and prediction.
- <https://github.com/xinychen/transdim>

Tools: e.g., **awesome-latex-drawing** (1.2k stars)

- Drawing Bayesian networks, graphical models, technical frameworks, and illustrations in LaTeX.
- <https://github.com/xinychen/awesome-latex-drawing>

Tutorials: e.g., **latex-cookbook** (1.1k stars)

- Academic writing with LaTeX.
- <https://github.com/xinychen/latex-cookbook>
- Published in Tsinghua University Press.

## Future Plan

### Research directions:

- Urban science
- Human mobility modeling
- Geospatial data analysis
- Intelligent & sustainable urban systems
- Optimization & decision making

**Goals:** Solving many scientific, mathematical, and engineering problems with AI algorithms.

**Website:** <https://spatiotemporal-data.github.io>