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Matrix and Tensor Models for Spatiotemporal Traffic Data Imputation and Forecasting

Ph.D. Defense

Xinyu Chen

Polytechnique Montréal, Canada

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President
Prof. Francesco Ciari
Polytechnique Montréal



Supervisor
Prof. Nicolas Saunier
Polytechnique Montréal



Co-supervisor
Prof. Lijun Sun
McGill University



Member
Prof. James Goulet
Polytechnique Montréal



External member
Prof. Guillaume Rabusseau
Université de Montréal

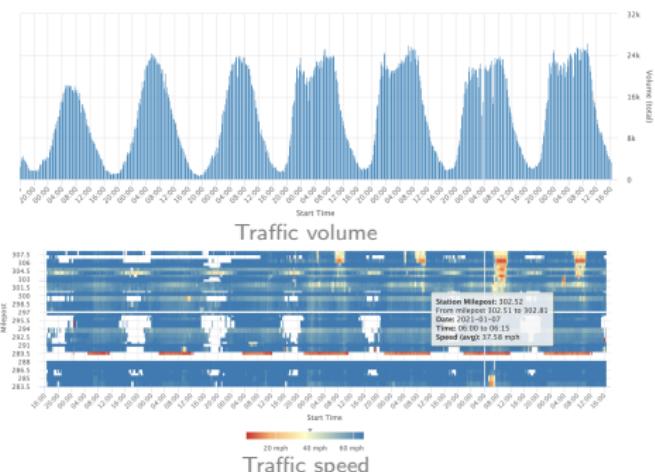
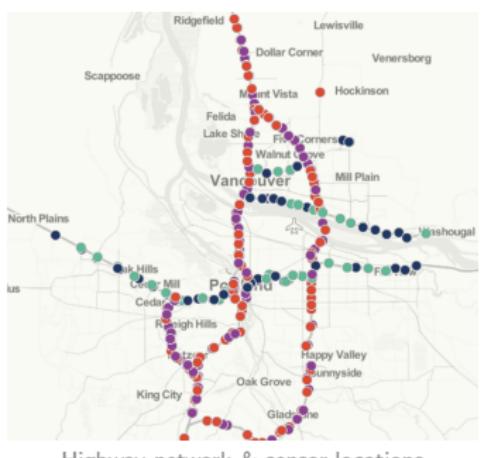
Outline

1. Background
2. Literature Review
3. Nonstationary Temporal Matrix Factorization (NoTMF)
4. Low-Rank Autoregressive Tensor Completion (LATC)
5. Laplacian Convolutional Representation (LCR)
6. Hankel Tensor Factorization (HTF)
7. Experiments
8. Conclusion

Traffic Flow Data

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

- Portland highway traffic data¹



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

¹<https://portal.its.pdx.edu/home>

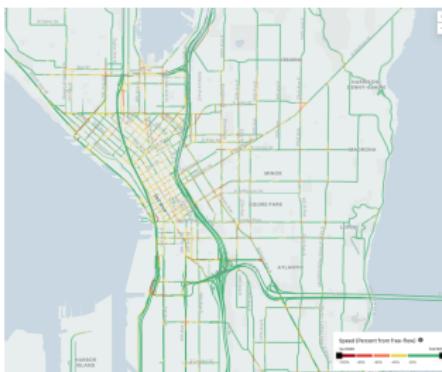
Urban Movement Data

High-dimensional & sparse

- Uber (hourly) movement speed data



NYC movement

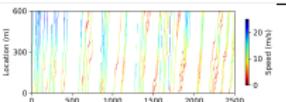
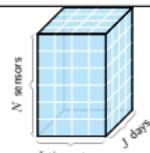
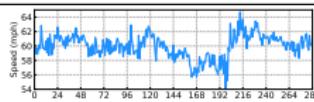
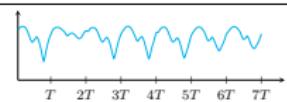


Seattle movement

- {(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!

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 Ω)

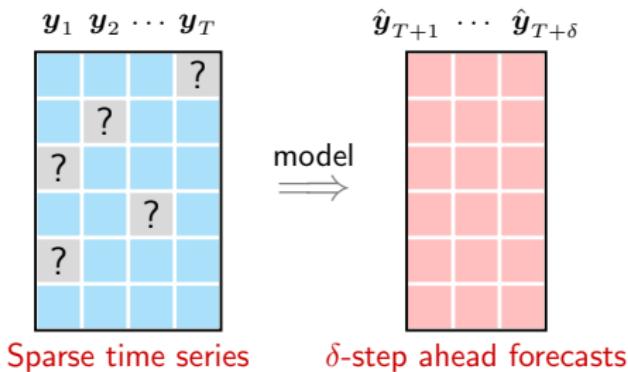
$$\underbrace{\mathcal{P}_{\Omega}(\mathbf{Y})}_{\text{Partially observed}} \xrightarrow{\text{Estimate}} \underbrace{\mathcal{P}_{\Omega}^{\perp}(\mathbf{Y})}_{\text{Unobserved}}$$

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 $\mathbf{y}_{T+\delta}, \delta \in \mathbb{N}^+$.

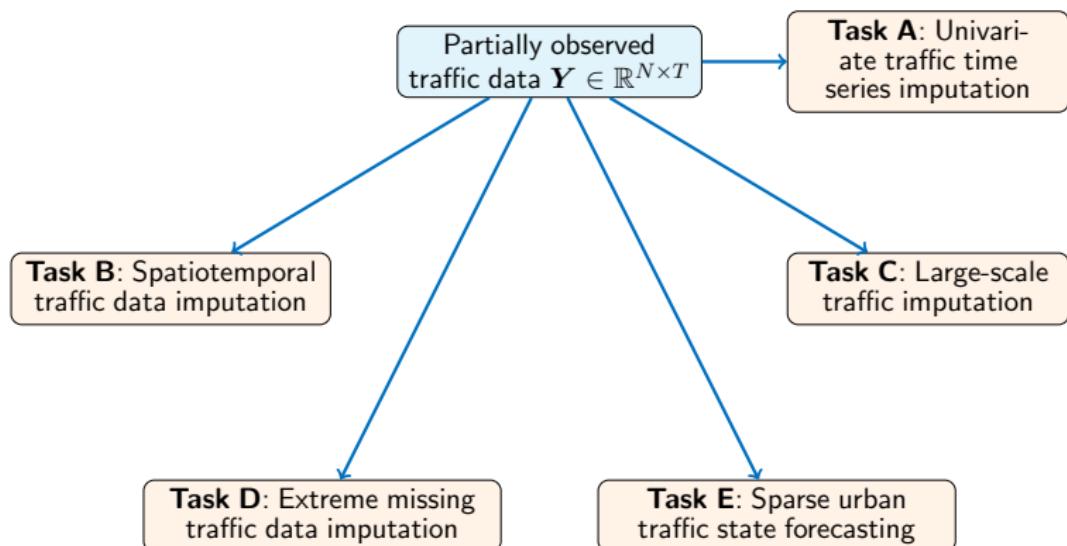


Modeling process:

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

Tasks

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



Imputation & Forecasting

Traffic data imputation

- Time series autoregression
(Schafer'97, Chen & Shao'00)
- Principal component analysis
(Qu et al.'09, Li et al.'13)
- Matrix factorization
(Asif et al.'13, Asif et al.'16)
- Tensor factorization
(Tan et al.'13, Chen et al.'19)
- Low-rank tensor completion
(Ran et al.'16, Chen et al.'20)
- Temporal matrix/tensor factorization
(Chen & Sun'22)

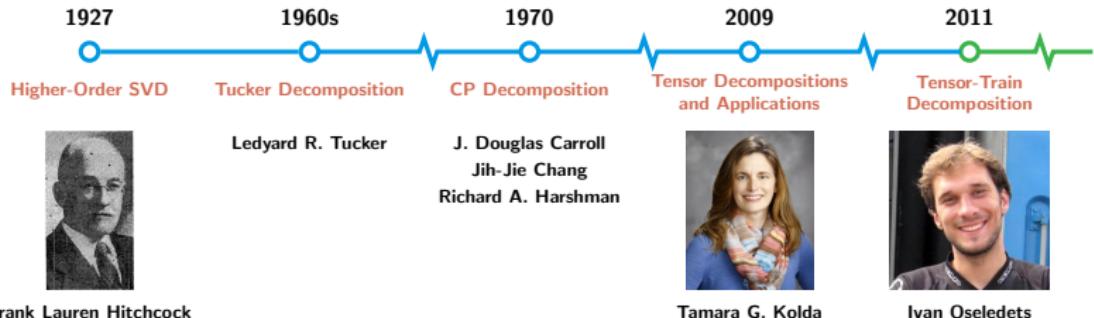
Time series forecasting on sparse data

- Autoregression predictor
(Anava et al.'15)
- Prediction on the imputed data
(e.g., Che et al.'18)
- Dynamic tensor completion
(Tan et al.'16)
- Temporal matrix factorization
(Yu et al.'16, Chen & Sun'22)
- Online matrix factorization
(Gultekin & Paisley'18)

Autoregression, matrix/tensor factorization/completion, ...

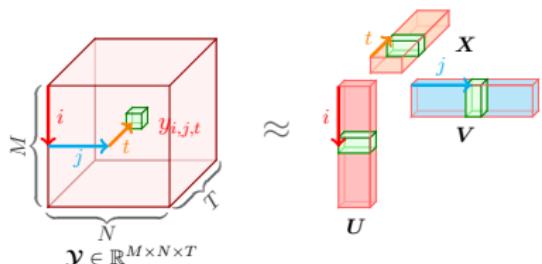
Tensor Factorization

- Revisit tensor factorization



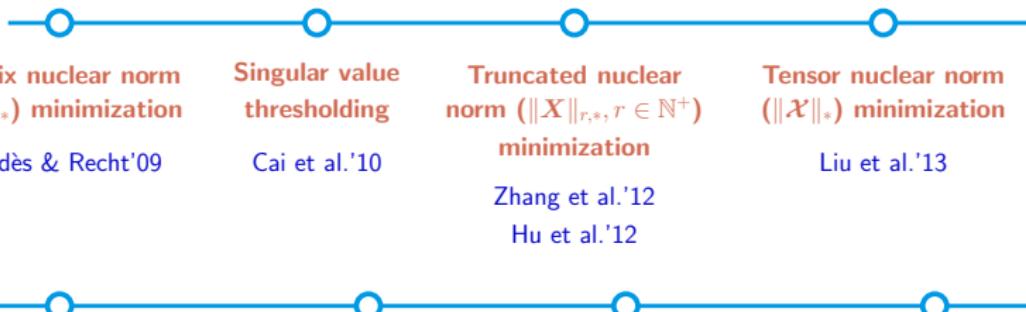
Frank Lauren Hitchcock

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



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

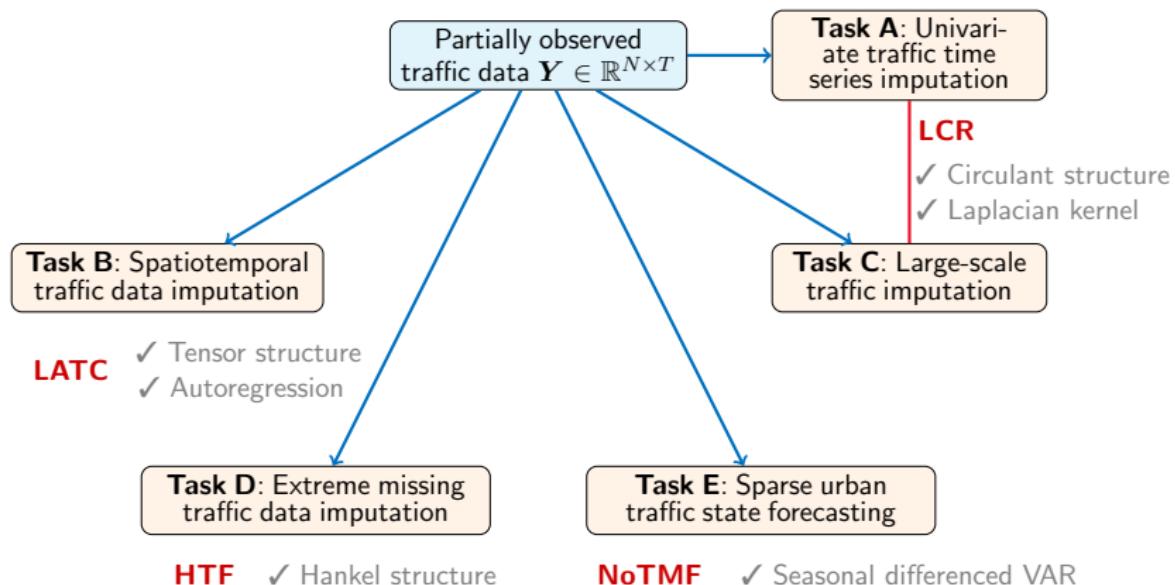
Matrix/Tensor Completion



| | | | |
|--|---|--|---|
| Circulant/Convolution nuclear norm ($\ \mathcal{C}(X)\ _*$ or $\ \mathcal{C}_{\tilde{T}}(X)\ _*$) minimization | Low-rank Hankel matrix/tensor ($\mathcal{H}_T(\cdot)$) completion | Tensor nuclear norm minimization with linear transform | Generalized nonconvex nonsmooth low-rank minimization |
| Liu'22 Liu & Zhang'23 | Yokota et al.'18 Sedighin et al.'20 Cai et al.'21 Yamamoto et al.'22 | Lu et al.'19 | Lu et al.'14 |

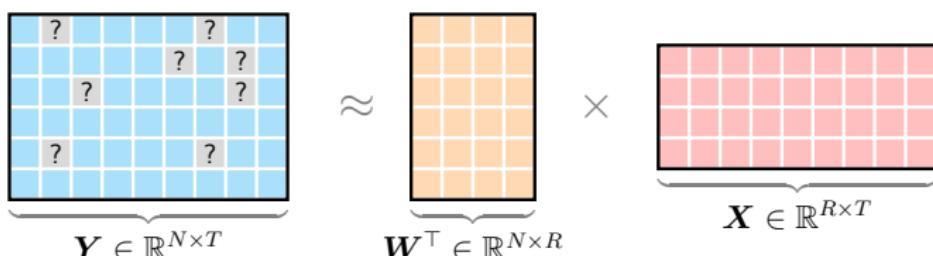
Overview

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 Ω .

- ✓ 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.

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

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

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 Ω .

dth-order VAR

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

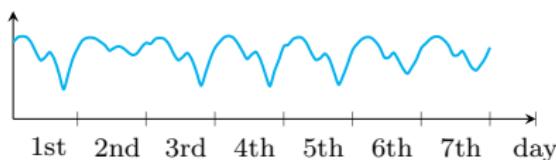
w/ coefficients $\{\mathbf{A}_k\}$.

↓ 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:

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

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

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

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

Nonstationary Temporal Matrix Factorization

NoTMF forecasting?

Implementation

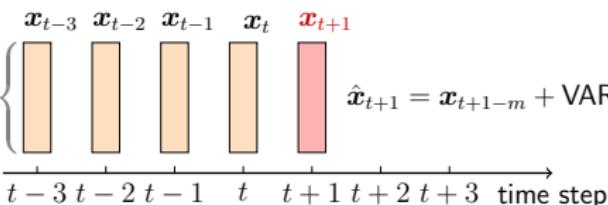
- Estimate $\mathbf{W}, \mathbf{X}, \mathbf{A}$
- Forecast $\hat{\mathbf{x}}_{t+1}$ with VAR
- Return $\hat{\mathbf{y}}_{t+1} = \mathbf{W}^\top \hat{\mathbf{x}}_{t+1}$

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

$$\underbrace{\mathbf{Y}_t \in \mathbb{R}^{N \times t}}_{\text{Matrix } \mathbf{Y}_t \text{ with } N \text{ rows and } t \text{ columns}} \quad \begin{matrix} ? & & & ? & ? \\ & ? & & & ? \\ ? & & & ? & ? \end{matrix}$$

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

time step



Nonstationary Temporal Matrix Factorization

NoTMF forecasting on streaming data?

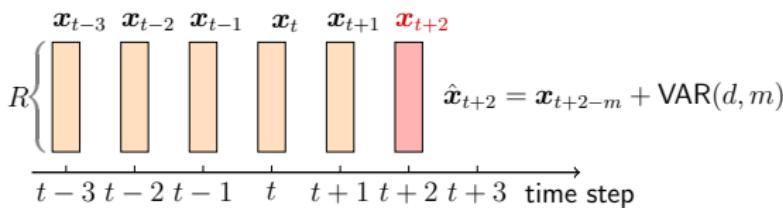
- Online forecasting (Gultekin & Paisley'18):
 - Fix the spatial factor matrix \mathbf{W}
 - Use input data \mathbf{Y}_{t+1} to update the temporal factor matrix \mathbf{X} and the coefficient matrix \mathbf{A}

Implementation

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

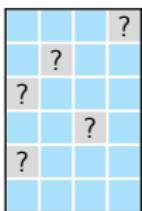
- ✓ Sparse input \mathbf{Y}_{t+1}
- ✓ Forecast in latent spaces

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

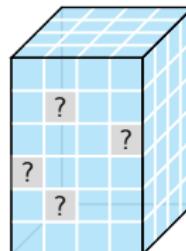


Matrix/Tensor Completion

Problem? Impute missing values in matrices/tensors.



$$\mathcal{P}_\Omega(\mathbf{Y}) \in \mathbb{R}^{N \times T}$$



$$\mathcal{P}_\Omega(\mathbf{Y}) \in \mathbb{R}^{N \times I \times J}$$

Cornerstone: Nuclear norm minimization

LRMC (Candès & Recht'09)

Estimating the matrix \mathbf{X} :

$$\min_{\mathbf{X}} \|\mathbf{X}\|_*$$

$$\text{s.t. } \mathcal{P}_\Omega(\mathbf{X}) = \mathcal{P}_\Omega(\mathbf{Y})$$

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

vs.

LRTC (Liu et al.'13)

Estimating the tensor \mathcal{X} :

$$\min_{\mathcal{X}} \|\mathcal{X}\|_*$$

$$\text{s.t. } \mathcal{P}_\Omega(\mathcal{X}) = \mathcal{P}_\Omega(\mathbf{Y})$$

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

Limitation: Nuclear norm minimization only covers global consistency.

Low-Rank Autoregressive Tensor Completion

- Introduce traffic tensors with day dimension² (Tan et al.'13, Chen et al.'19, ...).



- Build temporal correlations with univariate autoregression.

On the time series $\mathbf{Y} \in \mathbb{R}^{N \times T}$:

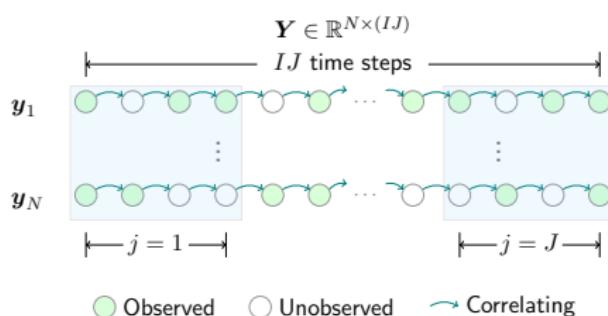
$$\|\mathbf{Y}\|_{\mathbf{A}, \mathcal{H}} \triangleq \sum_{n,t} \left(y_{n,t} - \sum_k \mathbf{a}_{n,k} y_{n,t-h_k} \right)^2$$

w/ the time lag set $\mathcal{H} = \{h_1, \dots, h_d\}$ and the coefficient matrix $\mathbf{A} \in \mathbb{R}^{N \times d}$.

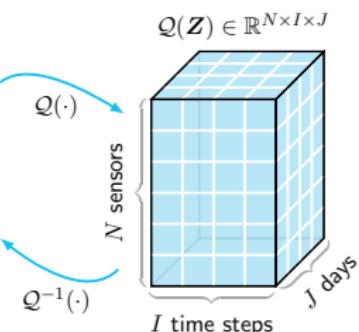
²There are $T = IJ$ time steps in total.

Low-Rank Autoregressive Tensor Completion

Local consistency w/ autoregression



Global consistency w/ tensor structure



LATC

Optimization problem:

$$\min_{\mathbf{Z}, \mathbf{A}} \underbrace{\|Q(\mathbf{Z})\|_{r,*}}_{\text{global}} + \frac{\gamma}{2} \underbrace{\|\mathbf{Z}\|_{\mathbf{A}, \mathcal{H}}}_{\text{local}}$$

s.t. $\mathcal{P}_\Omega(\mathbf{Z}) = \mathcal{P}_\Omega(\mathbf{Y})$

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

Two subproblems

$$\Rightarrow \begin{cases} \mathbf{Z} := \underset{\mathcal{P}_\Omega(\mathbf{Z}) = \mathcal{P}_\Omega(\mathbf{Y})}{\arg \min} \|Q(\mathbf{Z})\|_{r,*} + \frac{\gamma}{2} \|\mathbf{Z}\|_{\mathbf{A}, \mathcal{H}} \\ \mathbf{A} := \frac{1}{2} \|\mathbf{Z}\|_{\mathbf{A}, \mathcal{H}} \end{cases} \quad (\text{Least squares})$$

Low-Rank Autoregressive Tensor Completion

Z -subproblem:

$$Z := \arg \min_{\mathcal{P}_\Omega(Z) = \mathcal{P}_\Omega(Y)} \|Q(Z)\|_{r,*} + \frac{\gamma}{2} \|Z\|_{A,\mathcal{H}}$$

- Augmented Lagrangian function:³

$$\mathcal{L}(X, Z, W) = \|X\|_{r,*} + \frac{\gamma}{2} \|Z\|_{A,\mathcal{H}} + \frac{\lambda}{2} \|X - Q(Z)\|_F^2 + \langle W, X - Q(Z) \rangle + \pi(Z)$$

Implementation

Repeat

- Compute Z
- Compute A



Implementation

Repeat

- Repeat
 - # Alternating Direction Method of Multipliers (ADMM)
 - Compute X
 - Compute Z
 - Compute W
- Compute A

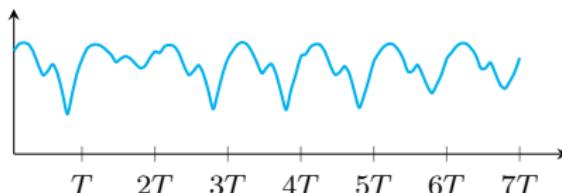
³ $W \in \mathbb{R}^{N \times I \times J}$ (Lagrange multiplier); $\langle \cdot, \cdot \rangle$ (inner product). The indicator function:

$$\pi(Z) = \begin{cases} 0, & \text{if } \mathcal{P}_\Omega(Z) = \mathcal{P}_\Omega(Y), \\ +\infty, & \text{otherwise.} \end{cases}$$

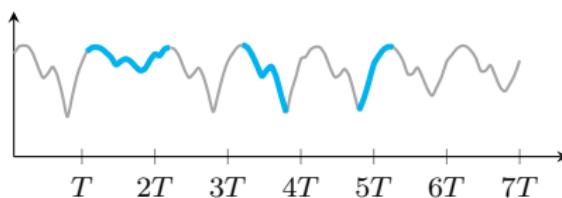
Laplacian Convolutional Representation

Motivation: Time series imputation

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



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

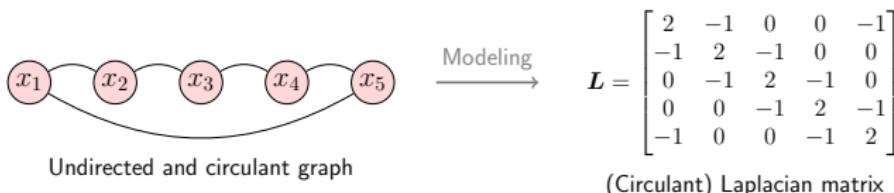


How to characterize both global and local trends in sparse time series?

Laplacian Convolutional Representation

Local trend modeling

- Intuition of (circulant) Laplacian matrix



- Define Laplacian kernel:

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

\Downarrow

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

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

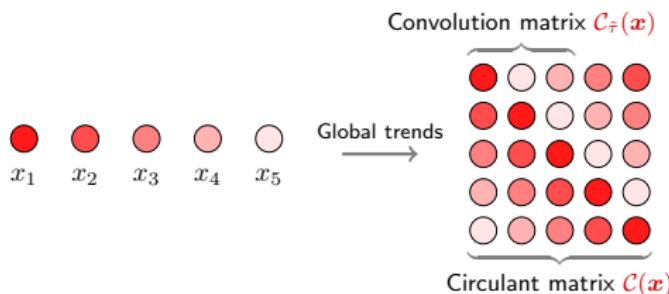
- (Laplacian) Temporal regularization:

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

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 Ω .

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 Ω .

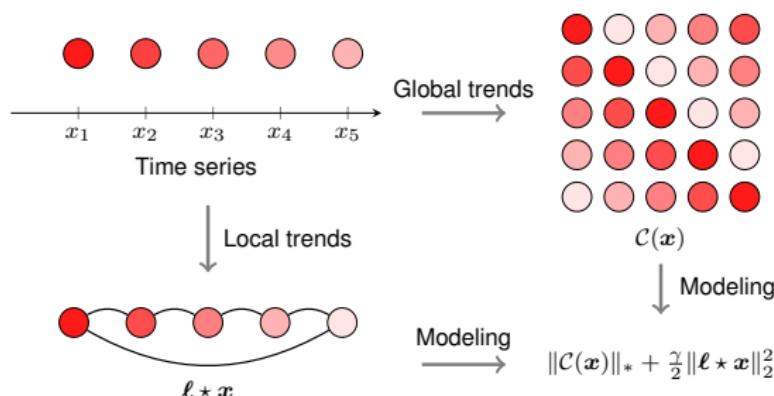
Laplacian Convolutional Representation

Laplacian Convolutional Representation (LCR)

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

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

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



Laplacian Convolutional Representation

- Augmented Lagrangian function:⁴

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

- 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 **ℓ_1 -norm minimization with FFT** in $\mathcal{O}(T \log T)$ time.

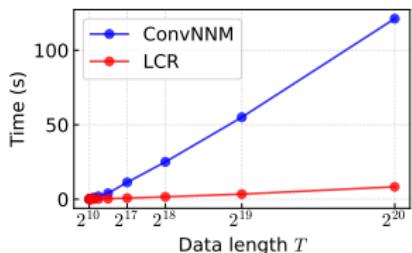
⁴ $\mathbf{w} \in \mathbb{R}^T$ (Lagrange multiplier); $\langle \cdot, \cdot \rangle$ (inner product).

Laplacian Convolutional Representation

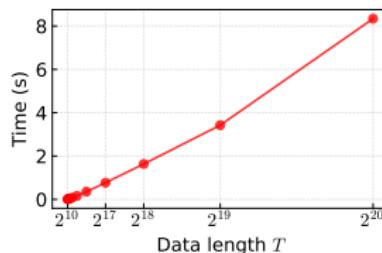
Empirical time complexity

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**⁵ ([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



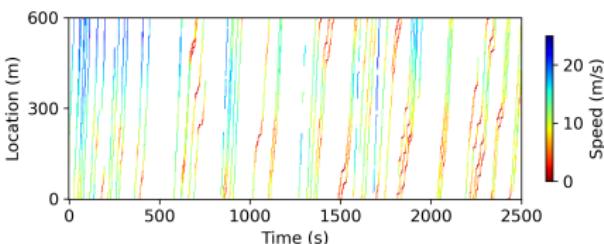
LCR

⁵Convolution nuclear norm minimization.

Hankel Tensor Factorization

Motivation: Spatiotemporal data reconstruction

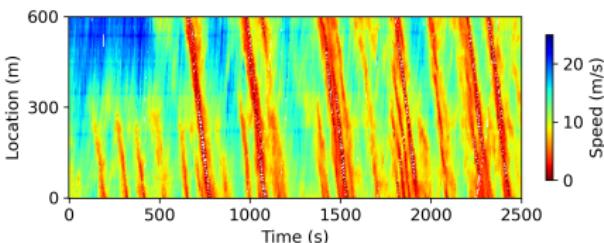
- Sparse speed field reconstruction problem in vehicular traffic flow.



200-by-500 matrix
(NGSIM)



Reconstruct speed field from
5% sparse trajectories?



How to characterize both spatial and temporal dependencies?

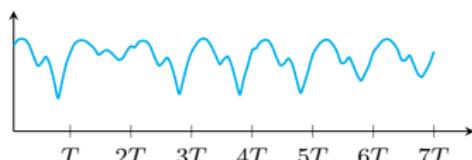
Hankel Tensor Factorization

- Hankel matrix

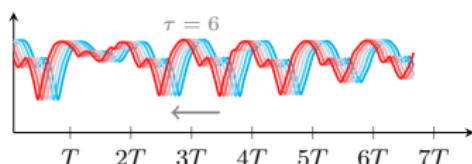
- Given $\mathbf{x} = (1, 2, 3, 4, 5)^\top$ and window length $\tau = 2$, we have

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

- Automatic temporal modeling



Traffic time series



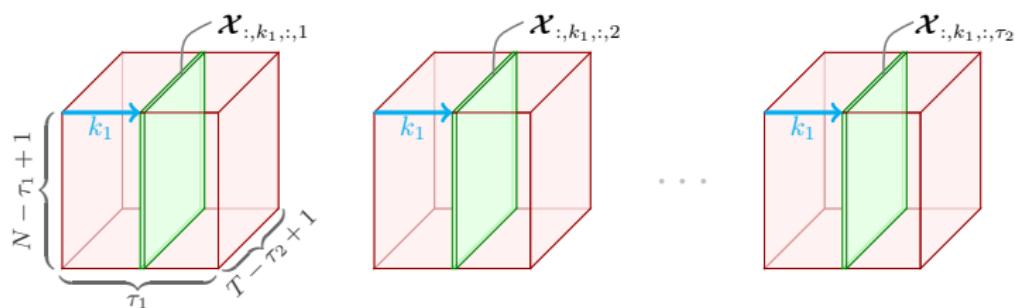
Hankel matrix

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

Hankel Tensor Factorization

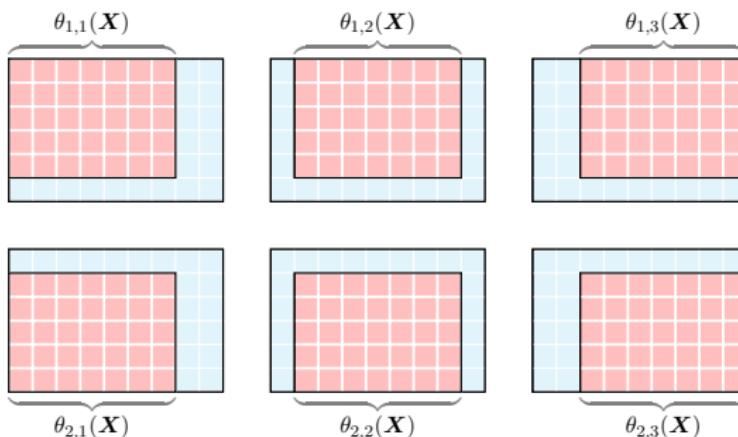
Hankel indexing

- 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_{row}):

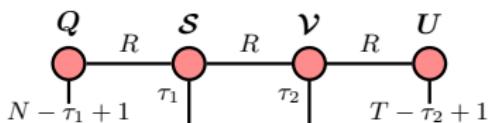
$$\theta_{k_1, k_2}(\mathbf{Y}) \approx (\mathbf{Q} \star_{\text{row}} \mathbf{s}_{k_1}^{\top})(\mathbf{U} \star_{\text{row}} \mathbf{v}_{k_2}^{\top})^{\top}$$

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:

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

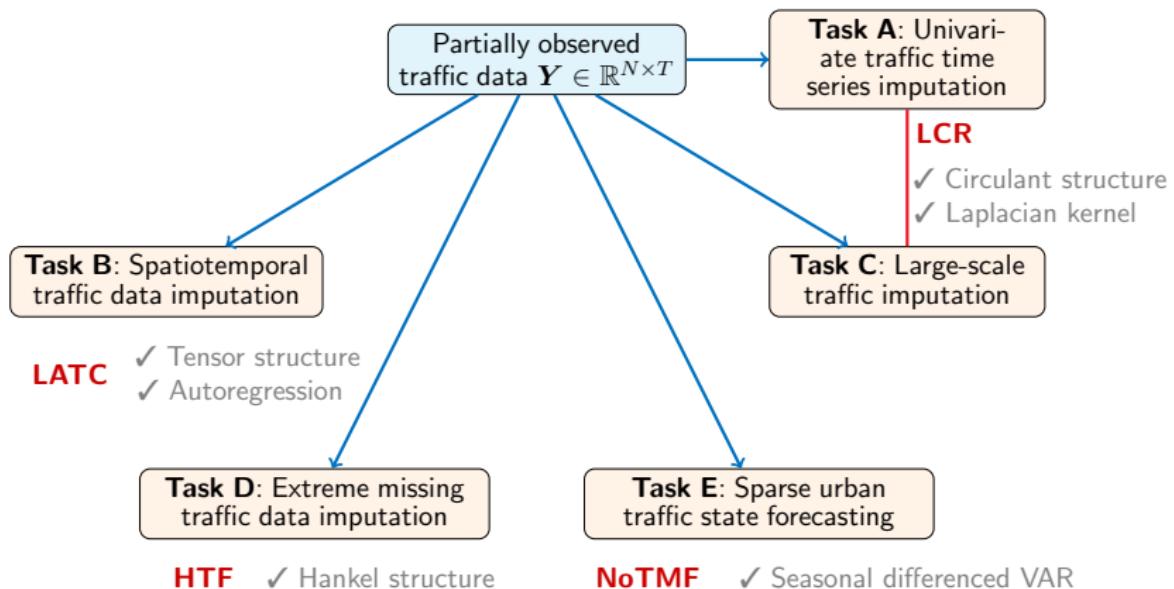
- Alternating minimization (let f be the obj.):

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

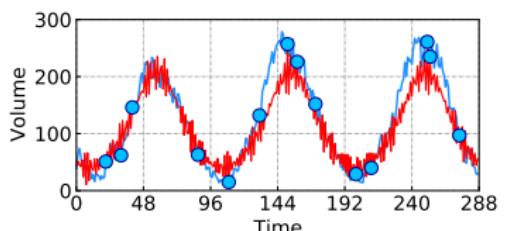
- Memory-efficient but still computationally costly!

Overview

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



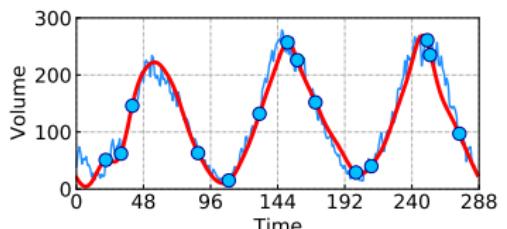
Task A: Univariate Traffic Time Series Imputation



CircNNM:

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

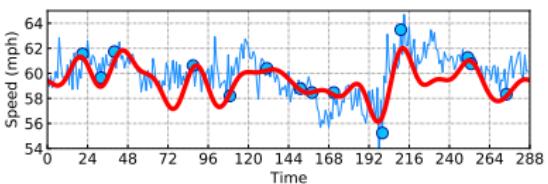
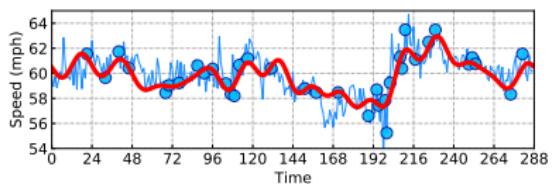
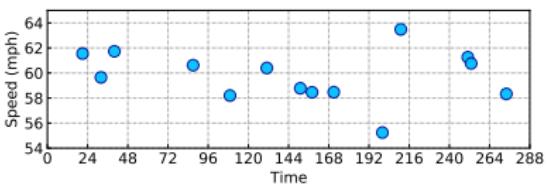
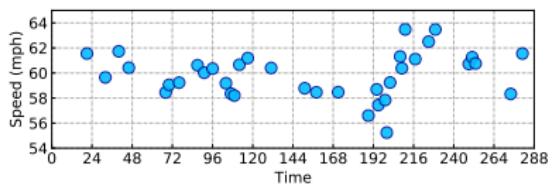
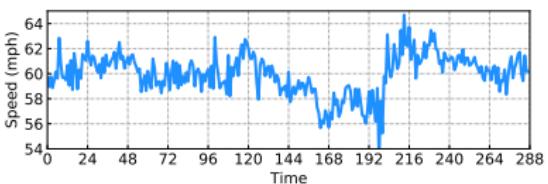
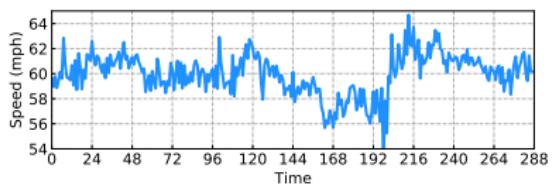
↓ Plus temporal regularization



LCR:

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

Task A: Univariate Traffic Time Series Imputation



Task B: Spatiotemporal Traffic Data Imputation

LATC vs. baseline models (in MAPE/RMSE)

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

| Missing rate | LATC | LAMC | LRTC-TNN | BTMF | SPC |
|------------------------|------------------|-------------|------------------|-------------|------------|
| 30%, Random Missing | 4.90/3.16 | 5.98/3.73 | 4.99/3.20 | 5.91/3.72 | 5.92/3.62 |
| 70%, Random Missing | 5.96/3.71 | 8.02/4.70 | 6.10/3.77 | 6.47/3.98 | 7.38/4.30 |
| 90%, Random Missing | 7.46/4.50 | 10.56/5.91 | 8.08/4.80 | 8.17/4.81 | 9.75/5.31 |
| 30%, Nonrandom Missing | 7.10/4.33 | 6.99/4.25 | 6.85/4.21 | 9.26/5.36 | 8.87/4.99 |
| 70%, Nonrandom Missing | 9.40/5.40 | 9.75/5.60 | 9.23/5.35 | 10.47/6.15 | 11.32/5.92 |
| 30%, Block-out Missing | 9.43/5.36 | 27.05/13.66 | 9.52/5.41 | 14.33/13.60 | 11.30/5.84 |

- On the Portland highway traffic volume dataset ($\mathbf{Y} \in \mathbb{R}^{1156 \times 2976}$)

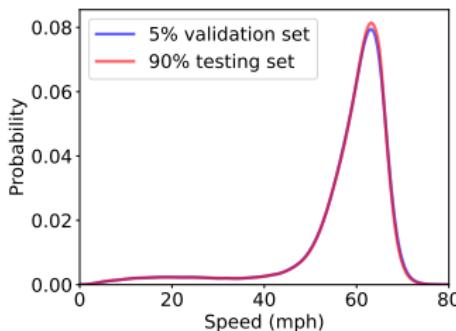
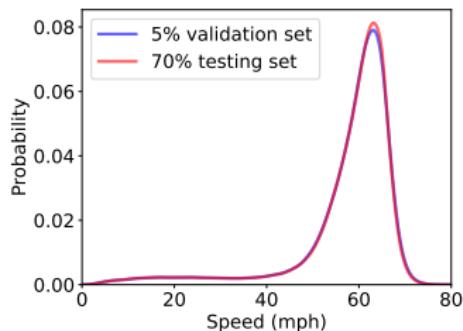
| Missing rate | LATC | LAMC | LRTC-TNN | BTMF | SPC |
|------------------------|--------------------|-------------|---------------------|--------------------|-------------|
| 30%, Random Missing | 16.95/15.99 | 17.93/16.03 | 17.27/16.08 | 18.22/19.14 | 21.29/56.73 |
| 70%, Random Missing | 19.59/18.70 | 21.26/19.37 | 19.99/18.73 | 19.96/22.21 | 24.35/43.32 |
| 90%, Random Missing | 23.15/22.83 | 25.64/23.75 | 22.90/22.68 | 23.90/25.71 | 28.45/39.65 |
| 30%, Nonrandom Missing | 19.48/19.14 | 19.93/19.69 | 19.59/ 18.91 | 19.55/20.38 | 26.96/60.33 |
| 70%, Nonrandom Missing | 27.67/45.03 | 25.75/28.25 | 30.26/60.85 | 23.86/26.74 | 33.42/47.34 |
| 30%, Block-out Missing | 24.01/23.50 | 29.21/27.60 | 31.74/74.42 | 27.85/25.68 | 31.01/60.33 |

- LATC vs. LAMC: The significance of tensor representation
- LATC vs. LRTC-TNN: The significance of temporal autoregression

Task B: Spatiotemporal Traffic Data Imputation

Parameter tuning process: Training set, validation set, and testing set?

- Random missing on the Seattle freeway traffic speed dataset



- Imputation performance (e.g., 70% missing rate)

On the validation set (5% data)

| γ/λ | Truncation parameter | | | | |
|------------------|----------------------|-----------|-----------|-----------|------------------|
| | $r = 5$ | $r = 10$ | $r = 15$ | $r = 20$ | $r = 25$ |
| 1/10 | 7.84/4.52 | 7.20/4.25 | 6.82/4.08 | 6.60/3.98 | 6.41/3.92 |
| 1/5 | 7.84/4.52 | 7.20/4.25 | 6.82/4.08 | 6.59/3.97 | 6.41/3.92 |
| 1 | 7.81/4.51 | 7.18/4.24 | 6.80/4.07 | 6.58/3.97 | 6.39/3.91 |
| 5 | 7.70/4.45 | 7.09/4.20 | 6.72/4.04 | 6.49/3.93 | 6.29/3.87 |
| 10 | 7.59/4.39 | 7.00/4.16 | 6.64/4.00 | 6.41/3.89 | 6.22/3.83 |

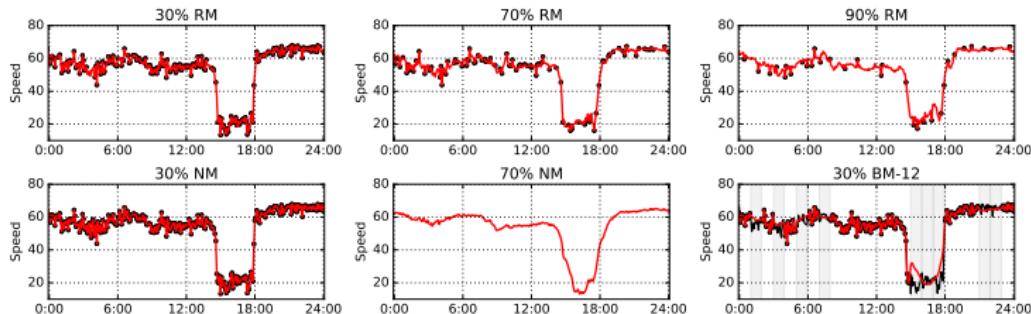
On the testing set (70% data)

| γ/λ | Truncation parameter | | | | |
|------------------|----------------------|-----------|-----------|-----------|------------------|
| | $r = 5$ | $r = 10$ | $r = 15$ | $r = 20$ | $r = 25$ |
| 1/10 | 7.83/4.53 | 7.18/4.27 | 6.80/4.09 | 6.58/3.99 | 6.41/3.92 |
| 1/5 | 7.83/4.53 | 7.18/4.26 | 6.80/4.09 | 6.57/3.98 | 6.40/3.92 |
| 1 | 7.80/4.52 | 7.16/4.25 | 6.78/4.08 | 6.55/3.98 | 6.40/3.92 |
| 5 | 7.70/4.47 | 7.08/4.21 | 6.70/4.04 | 6.46/3.94 | 6.29/3.87 |
| 10 | 7.58/4.41 | 6.99/4.17 | 6.62/4.01 | 6.39/3.90 | 6.21/3.84 |

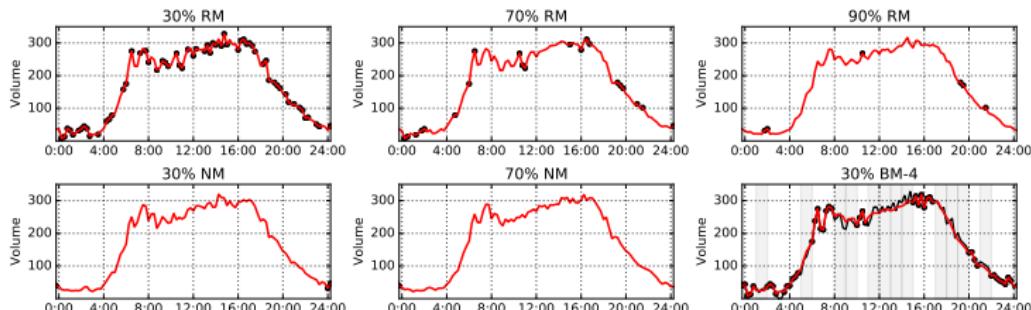
Task B: Spatiotemporal Traffic Data Imputation

LATC imputation

- Seattle freeway traffic speed data



- Portland highway traffic volume data



Task C: Large-Scale Traffic Data Imputation

LCR vs. baseline models (in MAPE/RMSE)

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

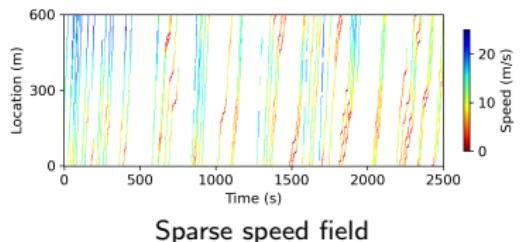
| Model | Missing rate | | | |
|----------|------------------|------------------|------------------|------------------|
| | 30% | 50% | 70% | 90% |
| LCR-2D | 1.50/1.49 | 1.76/1.69 | 2.07/2.06 | 3.19/3.05 |
| LCR_N | 1.48/1.50 | 1.73/1.73 | 2.07/2.12 | 3.24/3.22 |
| LCR | 1.50/1.49 | 1.76/1.69 | 2.08/2.07 | 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

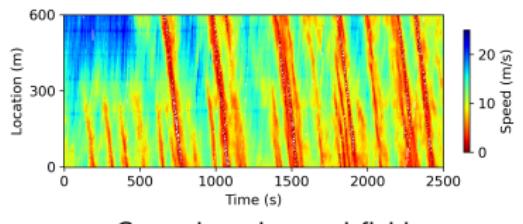
- LCR-2D > CTNNM: The importance of temporal regularization.
- CTNNM \geq CircNNM: Cyclic tensor is superior to circulant matrix.
- LCR > LRMC/LRTC: The importance of global/local modeling.

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

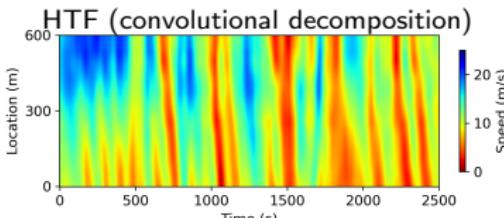
Task D: Extreme Missing Traffic Data Imputation



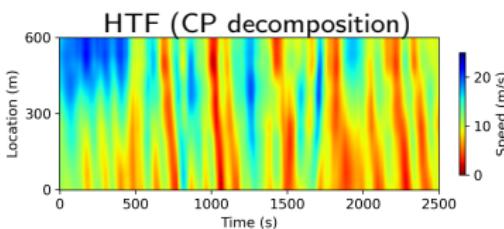
Sparse speed field



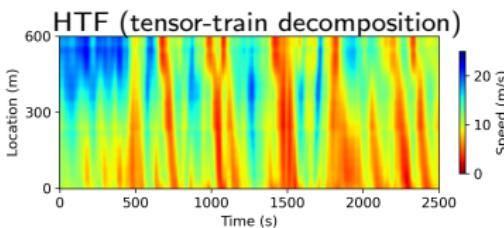
Ground truth speed field



MAPE = 51.92%



MAPE = 53.93%



MAPE = 56.48%

Task D: Extreme Missing Traffic Data Imputation

HTF vs. baseline models (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) | 6.21/3.88 | 6.51/4.06 | 6.98/4.30 | 8.02/4.84 |
| 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 | 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 |

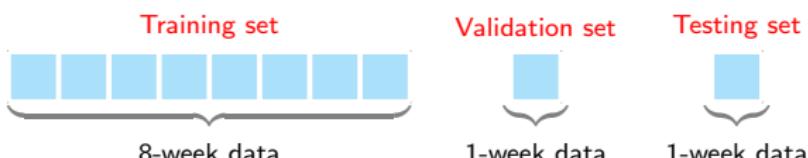
Results

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

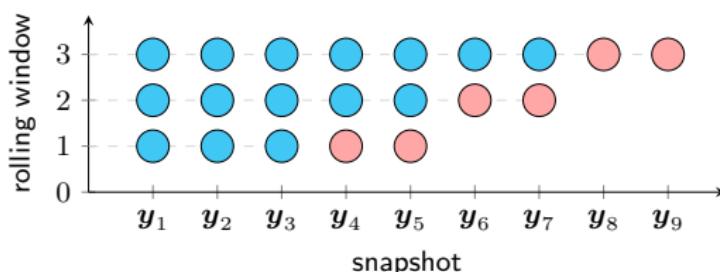
Task E: Sparse Urban Traffic State Forecasting

NoTMF forecasting

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



- Rolling forecasting illustration ($\delta = 2$):



Task E: Sparse Urban Traffic State Forecasting

NoTMF vs. baseline models (in MAPE/RMSE)

- On the NYC Uber movement speed dataset

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

Task E: Sparse Urban Traffic State Forecasting

NoTMF vs. baseline models (in MAPE/RMSE)

- On the Seattle Uber movement speed dataset

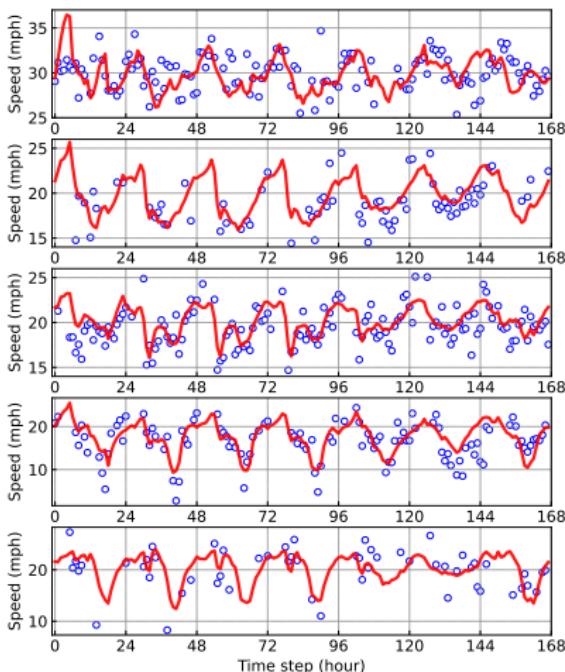
| δ | d | NoTMF ($m = 24$) | NoTMF ($m = 168$) | NoTMF-1st ($m = 168$) | TRMF | BTMF | BTRMF |
|----------|-----|-----------------------|----------------------------|----------------------------|------------|------------|------------|
| 1 | 1 | 10.45/3.32 | 10.26 /3.22 | 10.26 / 3.21 | 11.58/3.79 | 12.23/3.89 | 12.52/4.01 |
| | 2 | 10.53/3.34 | 10.29/3.23 | 10.23 / 3.21 | 10.92/3.51 | 12.95/4.18 | 13.16/4.31 |
| | 3 | 10.42/3.30 | 10.30/3.22 | 10.25 / 3.21 | 10.86/3.47 | 12.96/4.22 | 13.89/4.64 |
| | 6 | 10.50/3.32 | 10.21 / 3.21 | 10.27/3.22 | 10.99/3.51 | 12.91/4.18 | 13.90/4.67 |
| 2 | 1 | 10.90/3.55 | 10.32/3.25 | 10.25 / 3.23 | 12.07/4.02 | 12.74/4.06 | 13.31/4.32 |
| | 2 | 10.90/3.52 | 10.31/3.24 | 10.25 / 3.23 | 12.59/4.24 | 13.68/4.45 | 13.44/4.43 |
| | 3 | 10.81/3.49 | 10.31/3.24 | 10.27 / 3.23 | 12.01/3.96 | 13.55/4.46 | 13.66/4.56 |
| | 6 | 10.57/3.38 | 10.25 / 3.23 | 10.27/ 3.23 | 12.18/3.98 | 13.56/4.42 | 14.67/4.92 |
| 3 | 1 | 11.27/3.71 | 10.41 / 3.29 | 10.41 / 3.29 | 13.47/4.62 | 13.16/4.15 | 14.01/4.52 |
| | 2 | 11.26/3.71 | 10.30 / 3.27 | 10.34/ 3.27 | 14.48/5.19 | 13.63/4.37 | 14.39/4.76 |
| | 3 | 11.11/3.62 | 10.35 / 3.28 | 10.38/ 3.28 | 14.04/4.83 | 13.76/4.42 | 14.67/4.84 |
| | 6 | 10.96/3.55 | 10.30 / 3.26 | 10.30 / 3.26 | 13.32/4.51 | 13.28/4.29 | 15.64/5.31 |
| 6 | 1 | 11.88/3.97 | 10.63/3.43 | 10.60 / 3.42 | 15.59/5.32 | 13.63/4.30 | 16.39/5.28 |
| | 2 | 11.58/3.83 | 10.55 / 3.40 | 10.56/ 3.40 | 18.66/7.20 | 13.27/4.19 | 16.77/5.58 |
| | 3 | 11.54/3.81 | 10.57/3.39 | 10.53 / 3.38 | 17.94/6.32 | 13.88/4.36 | 17.35/5.70 |
| | 6 | 11.27/3.70 | 10.53/ 3.35 | 10.50 / 3.35 | 15.12/5.24 | 13.30/4.24 | 16.63/5.62 |

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

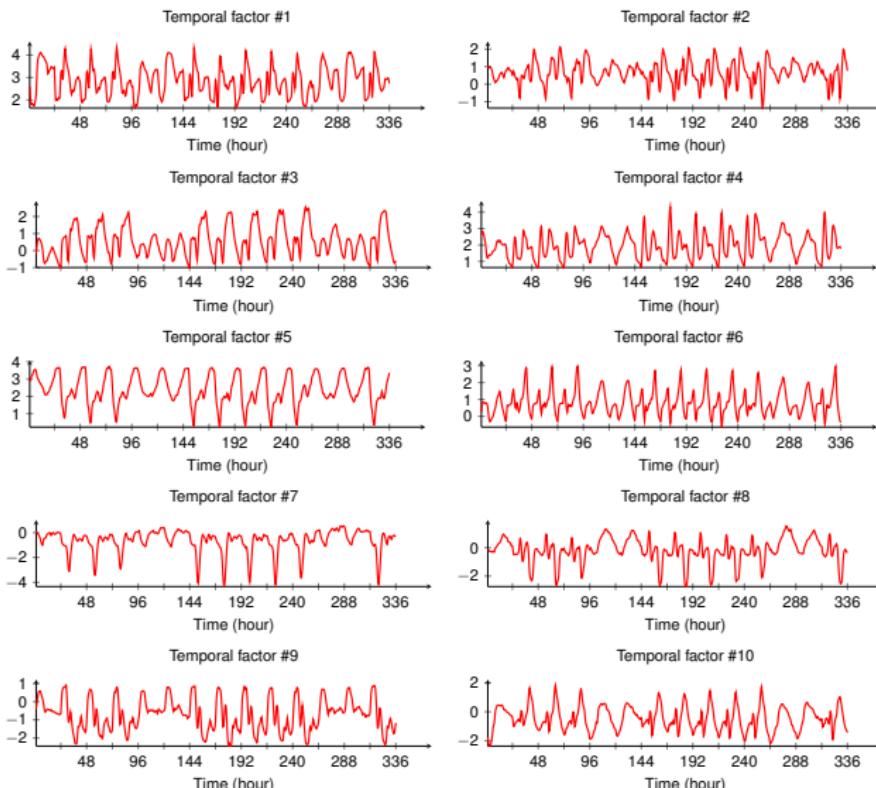
Task E: Sparse Urban Traffic State Forecasting

NoTMF forecasting ($\delta = 6$)

- On the NYC Uber movement speed dataset



Task E: Sparse Urban Traffic State Forecasting



Conclusion

| | |
|-------------------|--|
| Sparse | |
| High-dimensional | |
| Multidimensional | |
| Noises & outliers | |
| Nonstationary | |

Low-rank framework:

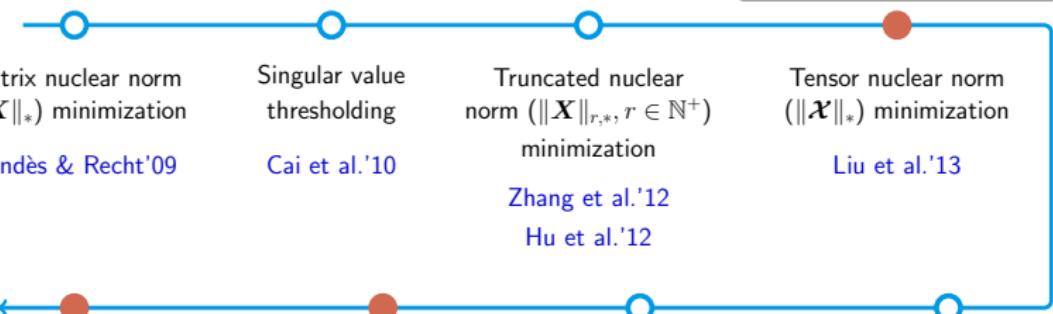
- NoTMF: matrix factorization
- LATC: low-rank tensor completion
- LCR: circulant matrix nuclear norm minimization
- HTF: tensor factorization

⇒ Temporal modeling:

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

Highlights & Contributions

(Ours) LATC:
 ✓ Temporal autoregression



(Ours) LCR:
 ✓ Local trend modeling
 ✓ An FFT implementation

(Ours) HTF:
 ✓ Memory-efficient
 ✓ Conv. para.

Collaborators



Dr. HanQin Cai



Xiaoxu Chen



Dr. Zhanhong Cheng



Chengyuan Zhang



Dr. Xi-Le Zhao

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.



POLYTECHNIQUE
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Thanks for your attention!

Any Questions?

<https://xinychen.github.io/papers/thesis.pdf>

About me:

- Homepage: <https://xinychen.github.io>
- How to reach me: chenxy346@gmail.com

Supplementary Material

- Another way to tune models' hyperparameters in the imputation task:
https://xinychen.github.io/papers/model_settings_v1.pdf
- NoTMF slides: <https://xinychen.github.io/slides/notmf.pdf>
- LCR slides: <https://xinychen.github.io/slides/LCR.pdf>
- MF & TF slides: https://xinychen.github.io/slides/MF_TF_SFR.pdf
- transdim project: <https://github.com/xinychen/transdim>

Flipping Operation in LCR

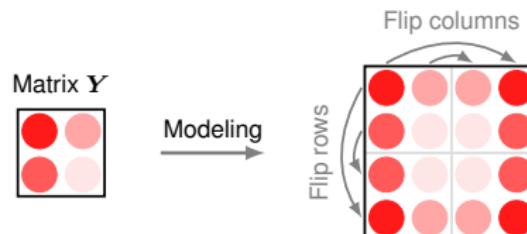
Circulant operation: Start and end data points are connected!

- On $\mathbf{y} \in \mathbb{R}^T$, we have

$$\mathbf{y}_{\text{new}} = \begin{bmatrix} \mathbf{x} \\ \mathbf{J}_T \mathbf{x} \end{bmatrix} = (y_1, \dots, y_T, y_T, \dots, y_1)^\top \in \mathbb{R}^{2T}$$

w/ exchange matrix $\mathbf{J}_T \in \mathbb{R}^{T \times T}$.

- On $\mathbf{Y} \in \mathbb{R}^{N \times T}$, we have



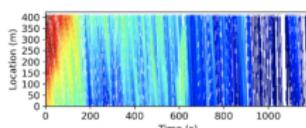
flipping \mathbf{Y} along rows and columns.

[Significance] Preventing LCR-2D from misleading values on the border rows and columns.

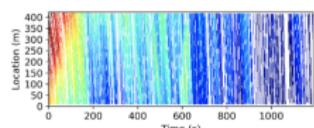
Flipping Operation in LCR

Speed field reconstruction:

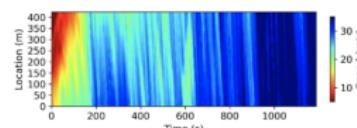
- LCR-2D on 70%-masked trajectories of the HighD dataset.
- Length: 426 meters; time duration: 1,190 seconds.



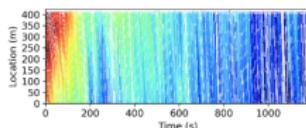
(a) Original speed field (lane #1).



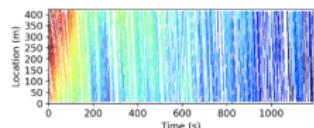
(b) Incomplete speed field (lane #1).



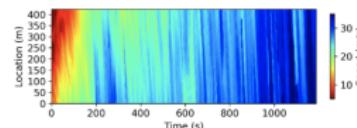
(c) Reconstructed speed field (lane #1).



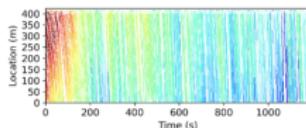
(d) Original speed field (lane #2).



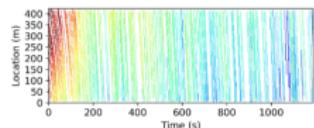
(e) Incomplete speed field (lane #2).



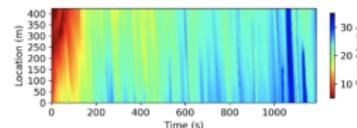
(f) Reconstructed speed field (lane #2).



(g) Original speed field (lane #3).



(h) Incomplete speed field (lane #3).



(i) Reconstructed speed field (lane #3).