



Quantifying Time Series Periodicity with Interpretable Machine Learning

Climate Systems & Urban Human Mobility

Xinyu Chen

Postdoctoral Associate, MIT

October 28, 2025

Atlanta, USA

Spatiotemporal Time Series Data

- Transport & mobility & climate application scenarios



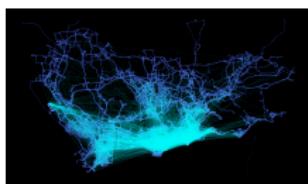
Highway (Portland)



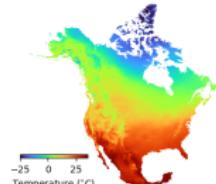
Uber movement (NYC)



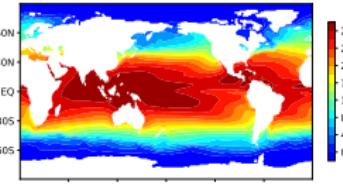
Uber movement (Seattle)



Taxi trajectory (Shenzhen)



Temperature (NA)

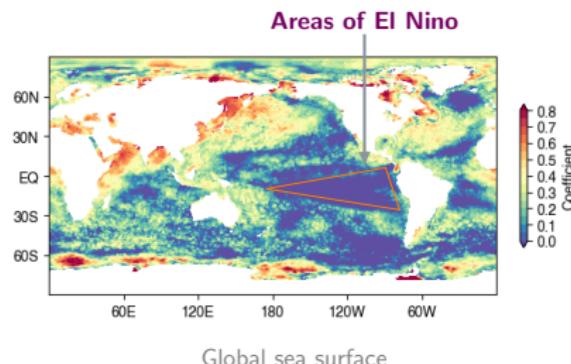
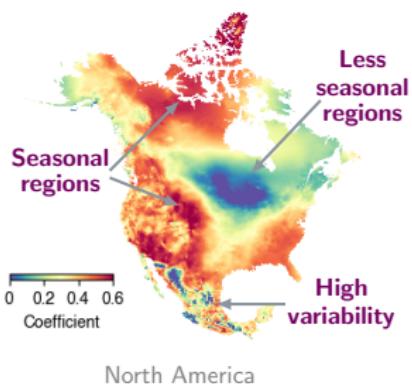


Temperature (sea surface)

- Challenges: Sparsity, high-dimensionality, multi-dimensionality, heavy tails, irregular sampling, and time-varying systems

Motivation

Yearly temperature seasonality patterns in 2010s

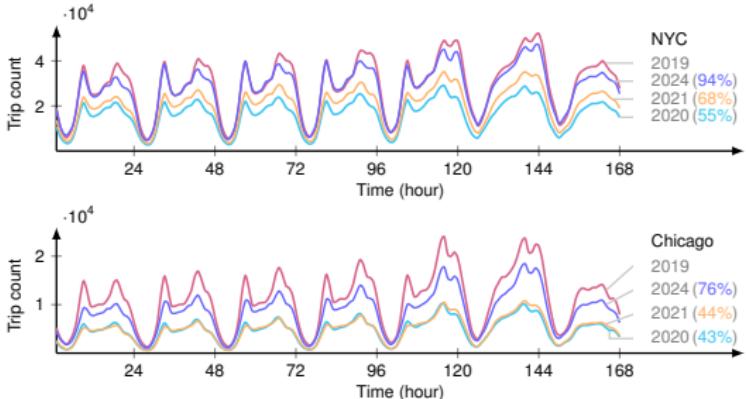
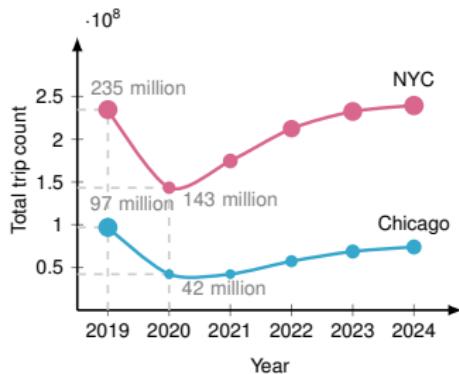


What motivates us most about periodicity?

- ① **Monitoring climate systems:** Empirically measure the periodicity of climate variables (e.g., temperature, precipitation).
- ② **Discovering spatiotemporal patterns:** Identify periodicity pattern shift and special climate events.

Motivation

Ridesharing trip data



What motivate us most about periodicity?

- ① Resilience and stability of systems:** Empirically measure the periodicity and predictability of urban systems.
- ② Optimization of transport systems:** Optimize resources (e.g., public transit, taxi, ridesharing, micromobility) to meet transport demand efficiently.
- ③ Design of sustainable transport & infrastructure:** Implement energy-efficient solutions (e.g., congestion pricing) tailored to peak hours.



Interpretable Time Series Autoregression



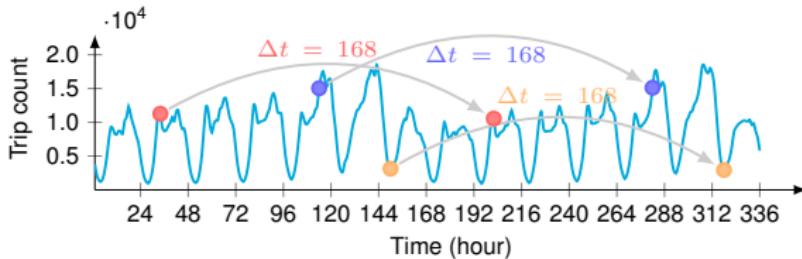
<https://github.com/xinychen/integers>

- Interpretable ML
- ℓ_0 -norm optimization
- Climate system seasonality
- Sparse autoregression
- Mixed-integer programming
- Human mobility regularity

Valorizing Autoregression

- Time series autoregression on $\mathbf{x} \in \mathbb{R}^T$ with order $d \in \mathbb{Z}^+$

$$\mathbf{w} := \arg \min_{\mathbf{w}} \sum_{t=d+1}^T \left(\mathbf{x}_t - \sum_{k=1}^d w_k \mathbf{x}_{t-k} \right)^2$$



Periodicity of hourly rideshare trip time series

- Sparse** coefficient vector \mapsto **Interpretability?**

$$\underbrace{\mathbf{w}}_{\text{sparsity } \|\mathbf{w}\|_0 \triangleq 3} = (\underbrace{0.33}_{k=1}, 0, \dots, 0, \underbrace{0.20}_{k=167}, \underbrace{0.46}_{k=168})^\top \in \mathbb{R}^{168}$$

Sparse Autoregression

- Identify the dominant auto-correlations
 - $\tau \in \mathbb{Z}^+$: Upper bound of the number of nonzero entries in $w \in \mathbb{R}^d$

$$\tilde{x} \approx A \begin{pmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{pmatrix} \quad \left\{ \begin{array}{l} w := \arg \min_{\|w\|_0 \leq \tau} \sum_{t=d+1}^T \left(x_t - \sum_{k=1}^d w_k x_{t-k} \right)^2 \\ = \arg \min_{\|w\|_0 \leq \tau} \|\tilde{x} - Aw\|_2^2 \end{array} \right.$$

- ℓ_0 -norm optimization is NP-hard
- Formulate it as a mixed-integer programming
 - Introduce binary decision variables $\beta \in \{0, 1\}^d$

$$\begin{aligned} \min_w \|\tilde{x} - Aw\|_2^2 & \iff \min_{w, \beta} \|\tilde{x} - Aw\|_2^2 \\ \text{s.t. } \underbrace{\|w\|_0 \leq \tau}_{\clubsuit \text{ sparsity of } w} & \iff \text{s.t. } \underbrace{-\beta \leq w \leq \beta}_{\text{bounds being either 0 or } \pm 1}, \underbrace{\|\beta\|_1 \leq \tau}_{\clubsuit \text{ sparsity of } \beta} \end{aligned}$$

ℓ_0 -Norm Optimization

Sparse Autoregression Done Right

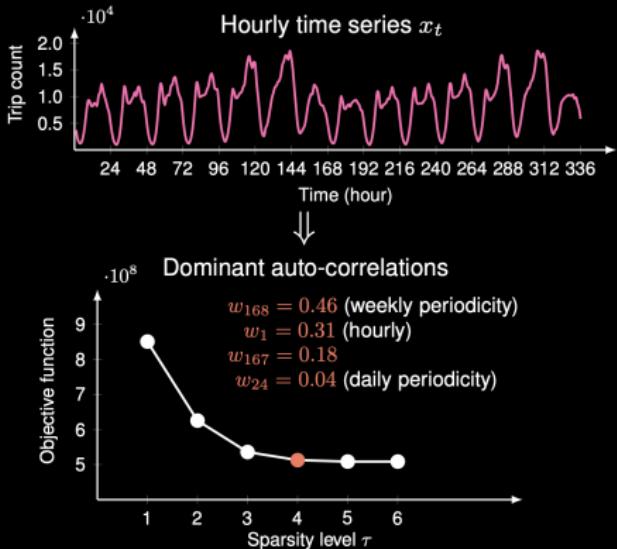
$$\min_{\mathbf{w}, \boldsymbol{\beta}} \underbrace{\sum_{t=d+1}^T \left(x_t - \sum_{k=1}^d w_k x_{t-k} \right)^2}_{\text{Time series autoregression}} \quad \text{s.t. } \underbrace{-\beta_k \leq w_k \leq \beta_k}_{\text{Lower and upper bounds}}, \quad \underbrace{\sum_{k=1}^d \beta_k \leq \tau}_{\clubsuit \text{ Sparsity}} , \quad \underbrace{\beta_k \in \{0, 1\}}_{\text{Binary variable}}$$

- $\mathbf{w} \in \mathbb{R}^d$: Auto-correlations
- $\boldsymbol{\beta} \in \{0, 1\}^d$: Sparsity pattern
- $d = 168$: Autoregression order

```

1 import numpy as np
2 from docplex.mp.model import Model
3
4 def sparse_ar(x, d, tau):
5     model = Model('Sparse Autoregression')
6     T = x.shape[0]
7     w = [model.continuous_var(name = f'w_{k}') for k in range(d)]
8     beta = [model.binary_var(name = f'beta_{k}') for k in range(d)]
9     model.minimize(model.sum((x[t] - model.sum(w[k] * x[t - k - 1]
10                                for k in range(d))) ** 2
11                                for t in range(d, T)))
12     model.add_constraint(model.sum(beta[k] for k in range(d)) <= tau)
13     for k in range(d):
14         model.add_constraint(w[k] <= beta[k])
15         model.add_constraint(w[k] >= -beta[k])
16     solution = model.solve()
17     return np.array(solution.get_values(w))

```



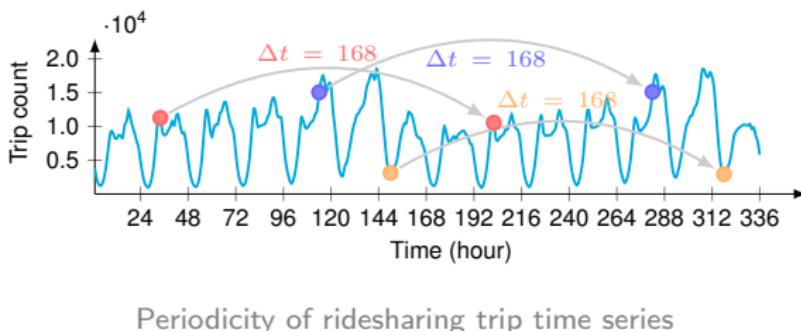
<https://github.com/xinychen/integers>

Solution Quality → Better Interpretability?

- Sparse autoregression

$$\min_{\mathbf{w} \geq 0} \|\tilde{\mathbf{x}} - \mathbf{A}\mathbf{w}\|_2^2 \quad \text{s.t. } \|\mathbf{w}\|_0 \leq \tau$$

- Subspace pursuit (SP) sometimes fails

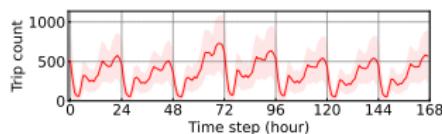
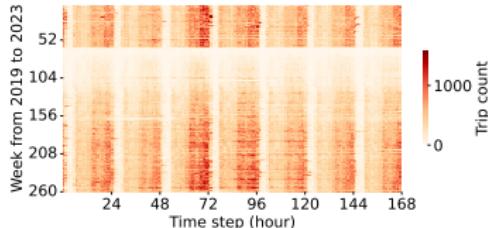


- Exact solution w/ mixed-integer programming (MIP)
- An intuitive example (sparsity $\tau = 2$):

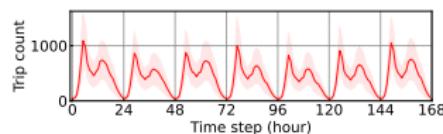
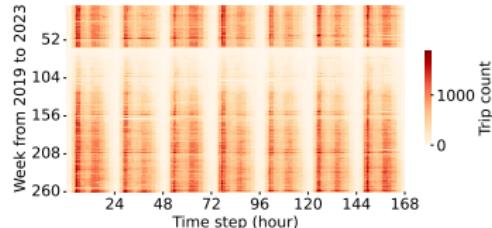
$$\underbrace{\mathbf{w} = (\dots, \underbrace{0.02}_{k=53}, \dots, \underbrace{0.96}_{k=168})^\top}_{\text{obj. } = 8.32 \times 10^7 \text{ (SP)}} \quad \text{vs.} \quad \underbrace{\mathbf{w} = (\underbrace{0.22}_{k=1}, \dots, \underbrace{0.77}_{k=168})^\top}_{\clubsuit \text{ obj. } = 6.25 \times 10^7 \text{ (MIP)}}$$

John F. Kennedy International Airport

- Daily & weekly periodicity: **dropoff > pickup** trips at JFK airport
 - Pickup trips are relevant to flight delay, baggage claim, and other factors.
 - Dropoff trips to airport are highly related to flight schedules.



Pickup trips from airport



Dropoff trips to airport

- Sparse coefficient vectors (**sparsity $\tau = 3$**):

$$\mathbf{w} = (\underbrace{0.31}_{k=1}, \dots, \underbrace{0.28}_{k=24}, \dots, \underbrace{0.41}_{k=168})^\top \quad \text{vs.} \quad \mathbf{w} = (\underbrace{0.18}_{k=1}, \dots, \underbrace{0.35}_{k=24}, \dots, \underbrace{0.47}_{k=168})^\top$$

High-Dimensional Sparse Autoregression

- On high-dimensional time series with a large N :

$$\begin{aligned} & \underbrace{\min_{\{\mathbf{w}_n\}_{n=1}^N, \boldsymbol{\beta}}}_{(N+1)d \text{ decision var.}} \quad \underbrace{\sum_{n=1}^N \|\tilde{\mathbf{x}}_n - \mathbf{A}_n \mathbf{w}_n\|_2^2}_{\text{multivariate time series}} \\ \text{s.t.} \quad & \underbrace{0 \leq \mathbf{w}_n \leq \boldsymbol{\beta},}_{\text{bounds being either 0 or 1}} \quad \underbrace{\|\boldsymbol{\beta}\|_1 \leq \tau,}_{\text{sparsity of } \boldsymbol{\beta}} \quad \boldsymbol{\beta} \in \{0, 1\}^d \end{aligned}$$

- How to handle millions of time series (e.g., $N \geq 10^6$)?

High-Dimensional Sparse Autoregression

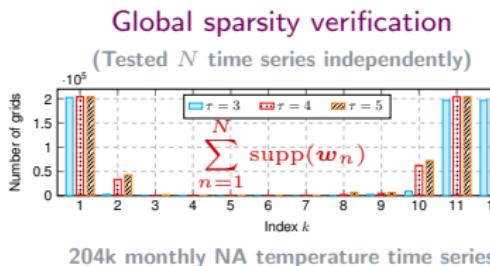
- On high-dimensional time series with a large N :

$$\begin{aligned}
 & \underbrace{\min_{\{\mathbf{w}_n\}_{n=1}^N, \boldsymbol{\beta}}}_{(N+1)d \text{ decision var.}} \quad \underbrace{\sum_{n=1}^N \|\tilde{\mathbf{x}}_n - \mathbf{A}_n \mathbf{w}_n\|_2^2}_{\text{multivariate time series}} \\
 \text{s.t.} \quad & \underbrace{0 \leq \mathbf{w}_n \leq \boldsymbol{\beta},}_{\text{bounds being either 0 or 1}} \quad \underbrace{\|\boldsymbol{\beta}\|_1 \leq \tau,}_{\text{sparsity of } \boldsymbol{\beta}} \quad \boldsymbol{\beta} \in \{0, 1\}^d
 \end{aligned}$$

- How to handle millions of time series (e.g., $N \geq 10^6$)?
- Two-stage optimization (♣):

① Learn sparsity patterns in $\boldsymbol{\beta} \in \{0, 1\}^d$

$$\begin{aligned}
 & \min_{\mathbf{w}, \boldsymbol{\beta}} \underbrace{\text{tr}(\mathbf{w} \mathbf{w}^\top \mathbf{P})}_{\text{quadratic}} - \underbrace{2 \mathbf{w}^\top \mathbf{q}}_{\text{linear}} \\
 \text{s.t.} \quad & 0 \leq \mathbf{w} \leq \boldsymbol{\beta}, \quad \|\boldsymbol{\beta}\|_1 \leq \tau
 \end{aligned}$$



② Quadratic programming with index set $\Omega = \text{supp}(\boldsymbol{\beta})$

$$\mathbf{w}_n := \arg \min_{\mathbf{w} \geq 0} \|\tilde{\mathbf{x}}_n - \mathbf{A}_n \mathbf{w}\|_2^2 \quad \text{s.t. } w_k = 0, \forall k \notin \Omega$$

Climate Seasonality Patterns

(arXiv:2506.22895)

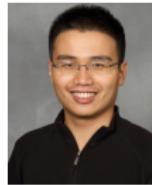
- North America temperature
- Climate variable seasonality
- Sea surface temperature
- Spatiotemporal patterns



Xinyu Chen
MIT



Vassilis Digalakis Jr.
BU



Lijun Ding
UCSD



Dingyi Zhuang
MIT



Jinhua Zhao
MIT

Understanding Climate Systems

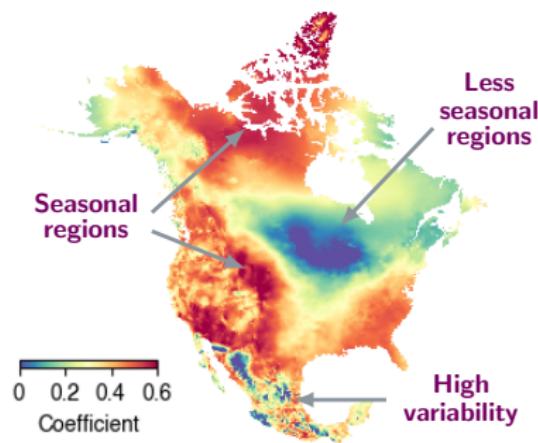
Quantify yearly seasonality by $\{w_{m,n,\gamma,k}\}$ at index $k = 12$

$$\min_{\{\mathbf{w}_{m,n,\gamma}\}, \boldsymbol{\beta}} \sum_{m=1}^M \sum_{n=1}^N \sum_{\gamma=1}^{\delta} \|\tilde{\mathbf{x}}_{m,n,\gamma} - \mathbf{A}_{m,n,\gamma} \mathbf{w}_{m,n,\gamma}\|_2^2$$

longitude
latitude | decade monthly
 ↓ ↓ ↓ temperature

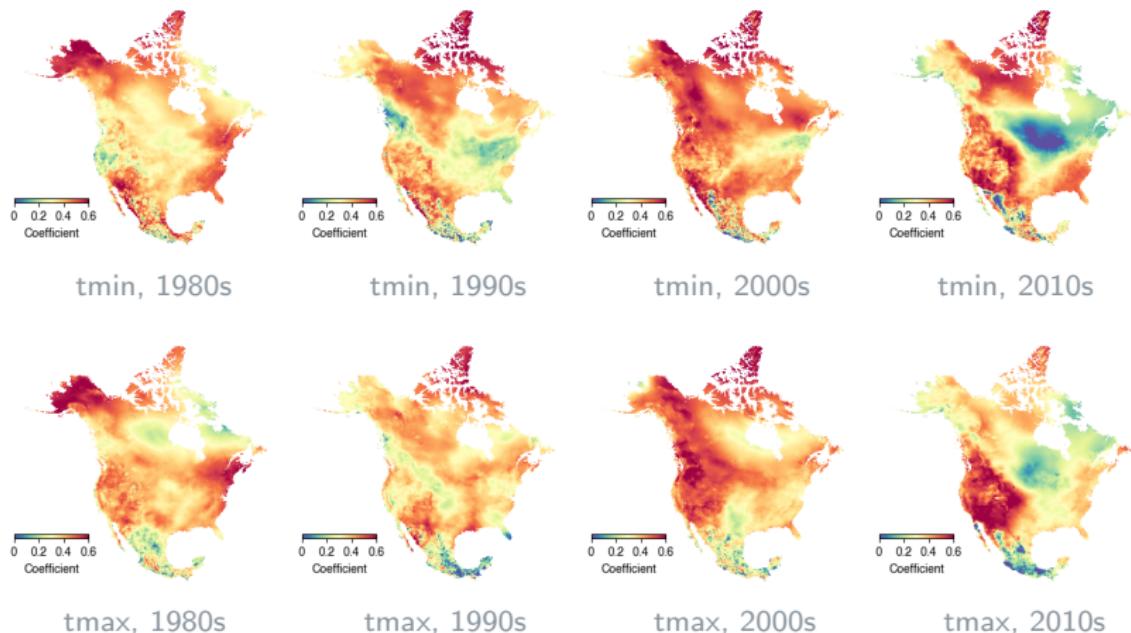
s.t. $0 \leq \mathbf{w}_{m,n,\gamma} \leq \boldsymbol{\beta}$ sparsity constraint
 $\|\boldsymbol{\beta}\|_1 \leq \tau$
 $\boldsymbol{\beta} \in \{0, 1\}^d$ binary decision var.

North America Temperature



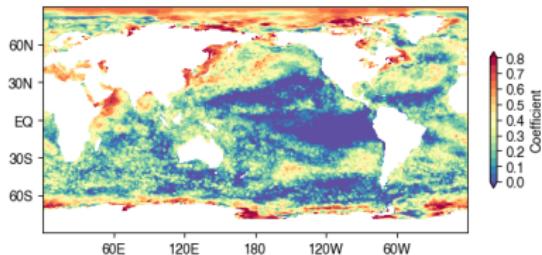
Yearly temperature **seasonality** pattern in 2010s

North America Temperature

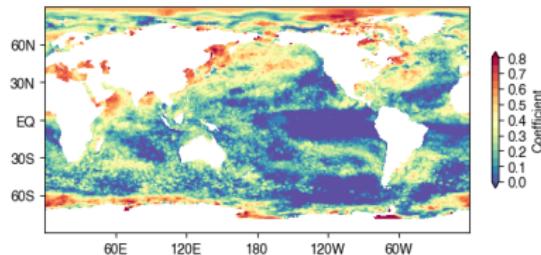


- Identify yearly periodicity at $k = 12$ from temperature data ($\tau = 3$)
 - ❶ Stronger yearly seasonality in high-latitude areas
 - ❷ Less seasonal temperature in south areas (e.g., Mexico)
 - ❸ Seasonality patterns in 2000s & 2010s are different from 1980s & 1990s

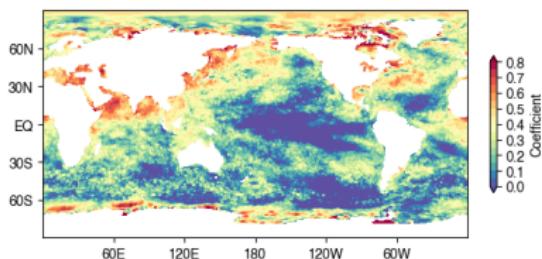
Sea Surface Temperature



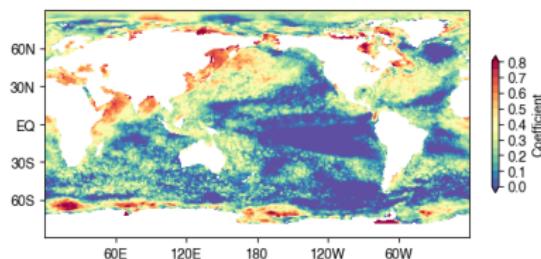
1980s



1990s



2000s



2010s

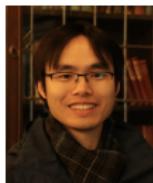
- Identify yearly periodicity at $k = 12$ from SST data ($\tau = 3$)
 - ➊ The areas of El Niño events are less seasonal/predictable
 - ➋ Arctic becomes less seasonal/predictable in the past 20 years

Human Mobility Regularity

Applications and Case Studies

(arXiv:2508.03747)

- Daily & weekly periodicity
- NYC & Chicago ridesharing
- Multi-modal mobility
- Network resilience
- Post-pandemic recovery
- Metro passenger flow



Xinyu Chen
MIT



Qi Wang
NEU



Yunhan Zheng
MIT → PKU



Nina Cao
MIT



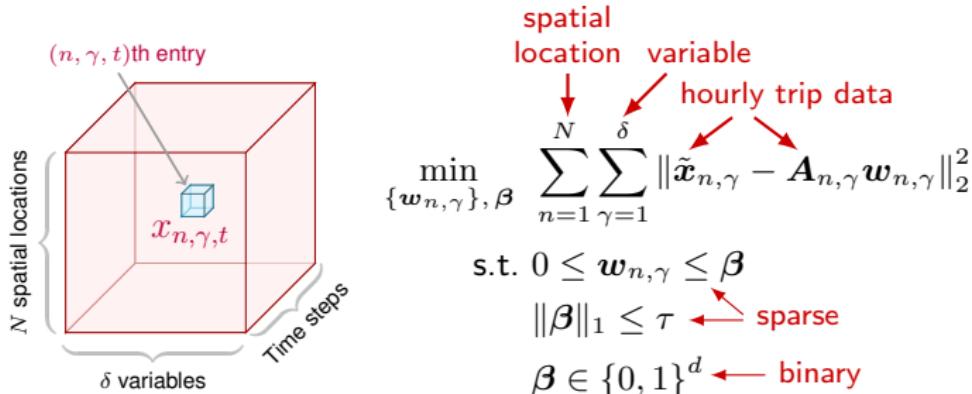
HanQin Cai
UCF



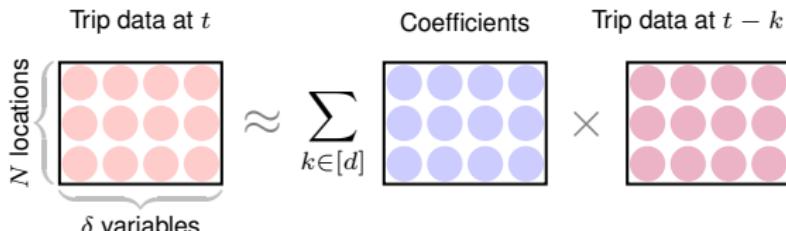
Jinhua Zhao
MIT

Envisioning Human Mobility

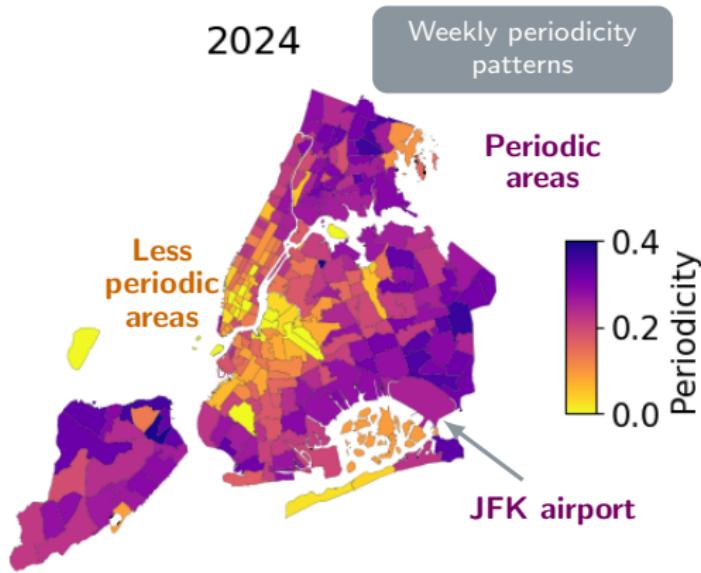
- Human mobility data



- Quantify **weekly periodicity** by $\{\mathbf{w}_{n,\gamma,k}\}$ at index $k = 168$



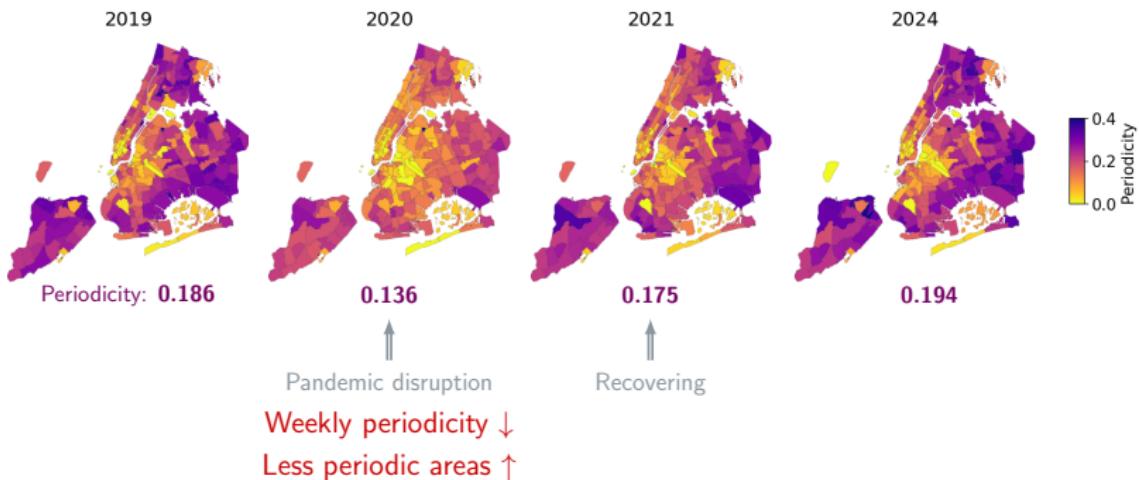
NYC Ridesharing



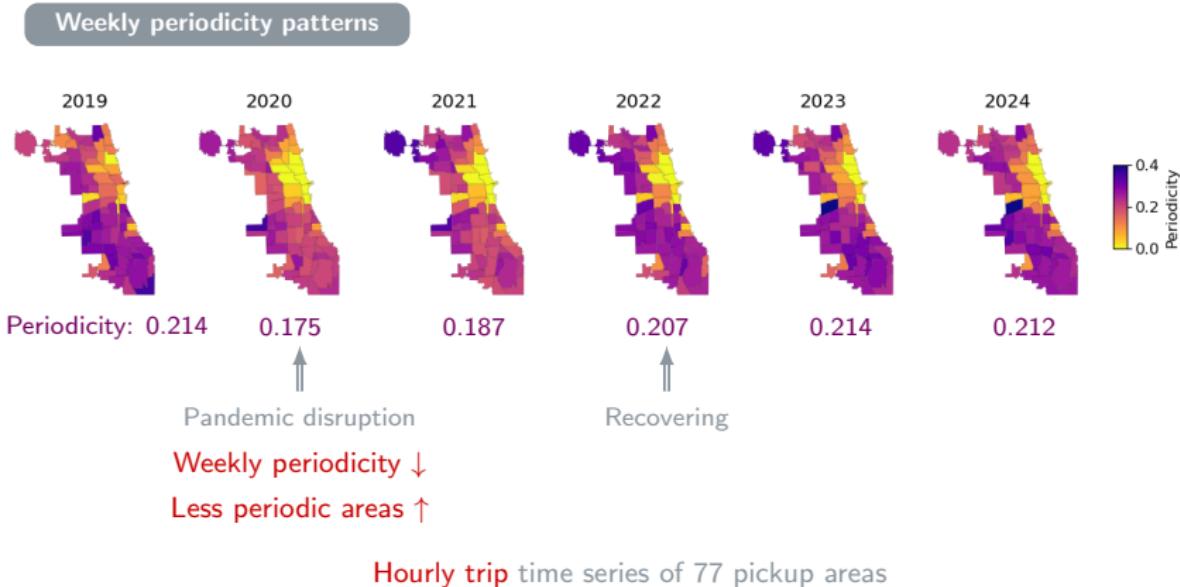
Hourly trip time series of 265 pickup areas

NYC Ridesharing

Weekly periodicity patterns

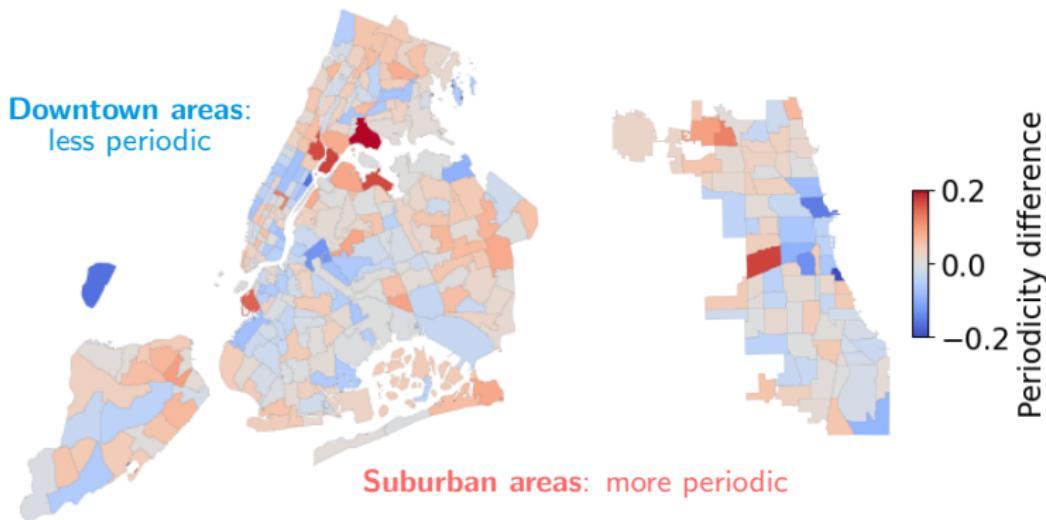


Chicago Ridesharing



Post-Pandemic Recovery

2024's periodicity minus 2019's periodicity



Weekly Periodicity of Manhattan Mobility

Mobility data of 2024

North areas:

Ridesharing > yellow taxi

Overall:

Subway > others

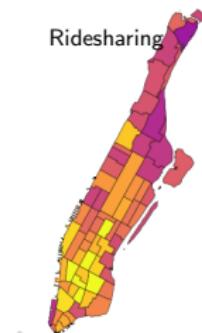
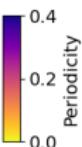
Ridesharing

Yellow taxi

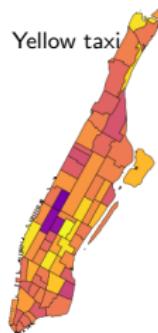
Subway

Bikesharing
(member)

Bikesharing
(all)



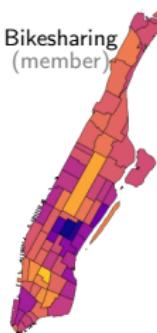
Periodicity: 0.122



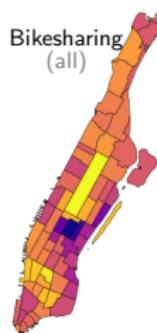
0.120



0.363



0.191



0.151

South areas:
Yellow taxi > Ridesharing

Remarkable weekly periodicity difference
between membership and all travels

Daily Periodicity of Manhattan Mobility (Weekdays)

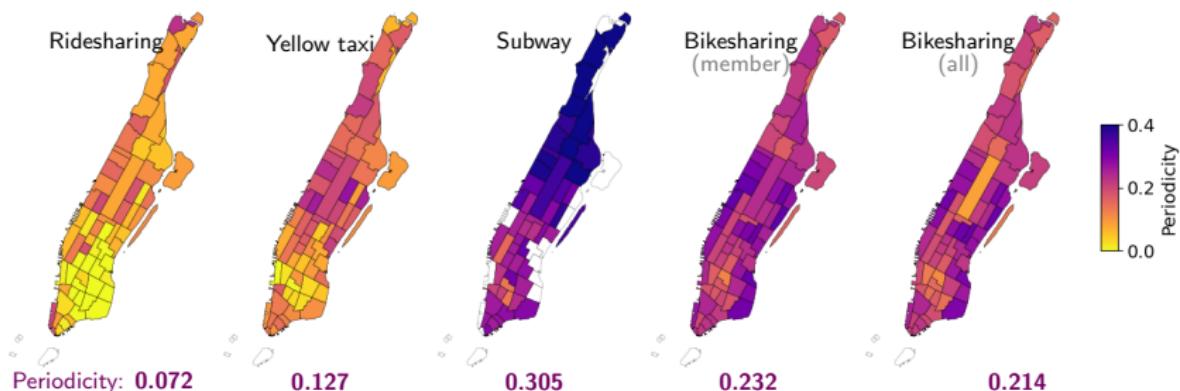
Mobility data of 2024

Overall:

Yellow taxi > ridesharing

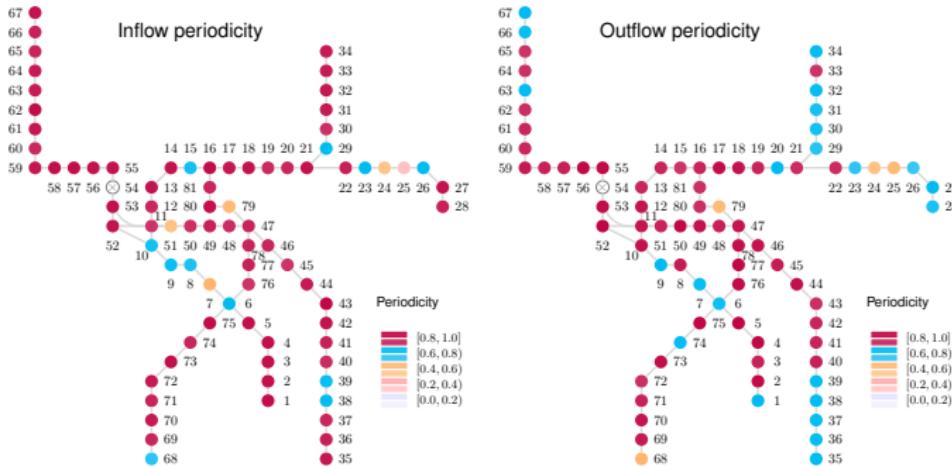
Subway:

North areas > south areas

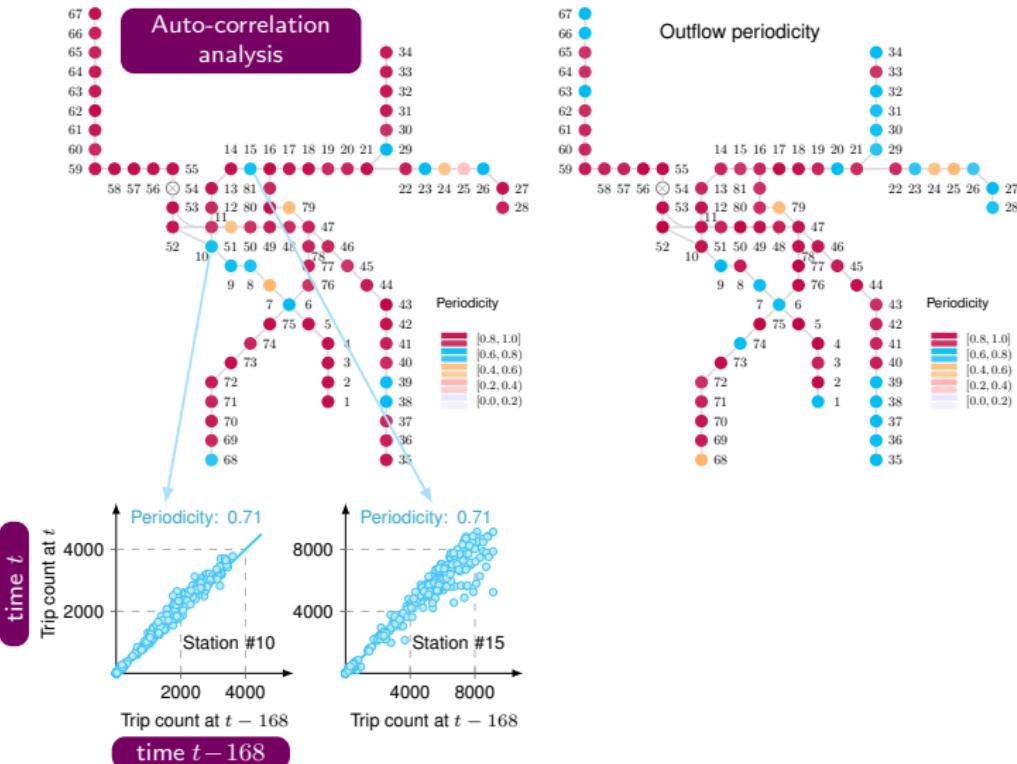


Marginal daily periodicity difference
between membership and all travels

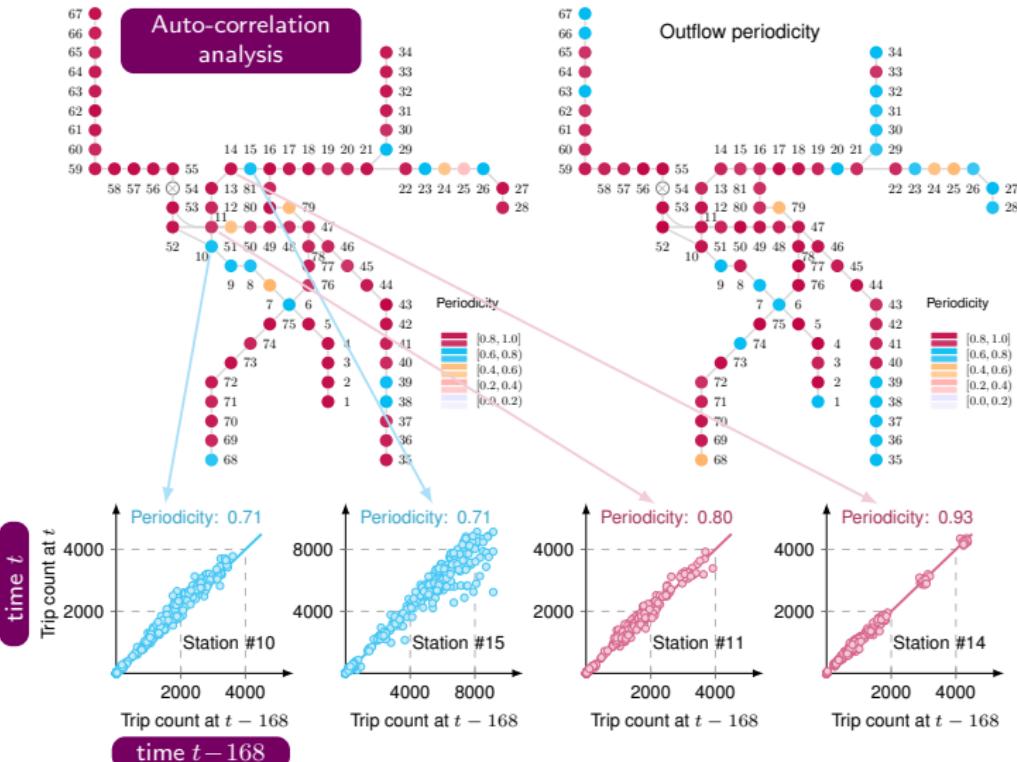
Hangzhou Metro Passenger Flow



Hangzhou Metro Passenger Flow



Hangzhou Metro Passenger Flow



"Closeness" to the anti-diagonal curve $y = x$



Thanks for your attention!

Any Questions?

Slides: <https://xinychen.github.io/slides/informs25.pdf>

About me:

- 🏠 Homepage: <https://xinychen.github.io>
- /github/ GitHub: <https://github.com/xinychen>
- ✉️ How to reach me: xinychen@mit.edu