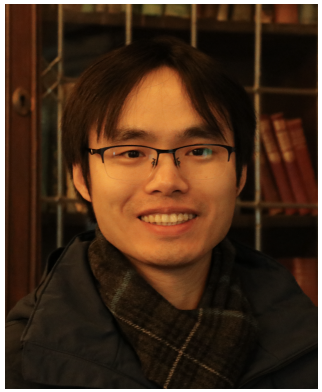


Xinyu Chen

Postdoc, MIT (now)
Advisor: Prof. Jinhua Zhao

PhD, University of Montreal ('23)
Transportation Engineering

Interests

- Advanced computing for engineering
- Urban system & human mobility
- Data-driven traffic flow modeling
- Climate system monitoring
- Machine learning & data science
- Optimization & math programming

Collaboration w/ CEE, EECS, Stat, Math

Interdisciplinary Research

Science-Informed Artificial Intelligence in ISE

PhD (ML for Transportation)

- **Traffic imputation** w/ tensor decomposition
  Chen et al.'19; Chen et al.'21 in Transportation Research Part C (cited 300+)
  Chen et al.'22 in IEEE Transactions Intelligent Transportation Systems (cited 100+)
  Chen et al.'24 in IEEE Transactions on Knowledge and Data Engineering (TKDE)
- **Mobility prediction** w/ nonconvex optimization
  Chen & Sun'22 in IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI) (cited 250+)
  Chen et al.'24 in INFORMS Journal on Computing (IJOC)
  Chen et al.'25, accepted in Transportation Science
- **Dynamic climate pattern discovery**
  Chen et al.'24 in TKDE

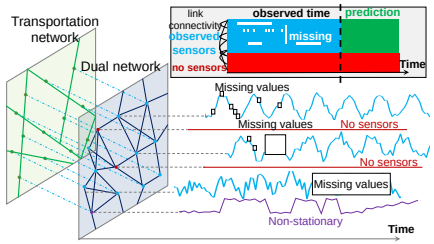
Postdoc (ML + Optimization for Spatiotemporal Data)

- **Tensor decomposition for ML**
  Chen et al.'25, major revision in TPAMI
- **Causal inference from climate systems**
  Chen et al.'25, 2nd-round review in TKDE
- **Mobility periodicity quantification**
  Ready for submission to IJOC

Research Contributions

- Formulating challenging engineering problems (w/ practical contributions)

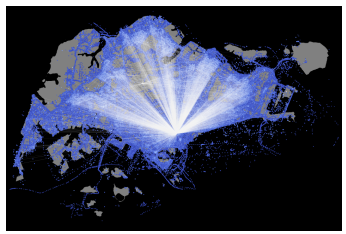
Traffic Imputation



Missing data in transport

Matrix/tensor decomposition
Temporal dynamics

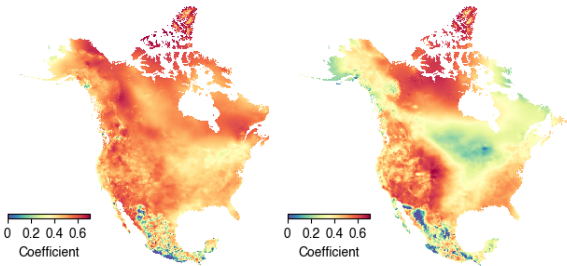
Mobility Pattern Discovery



Singapore movement

Dynamical system modeling
Tensor decomposition

Climate Seasonality Qualification

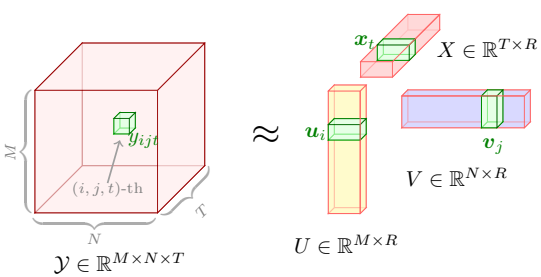


2000s 2010s

Interpretable ML
Mixed-integer programming

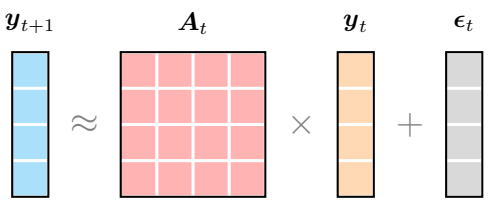
- Advancing AI & ML development (w/ methodological contributions)

Tensor decomposition



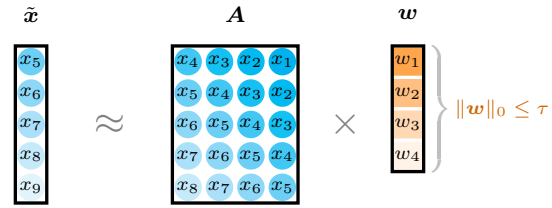
Integrate traffic flow patterns

Dynamic mode decomposition



Formulate dynamic patterns

Sparse autoregression

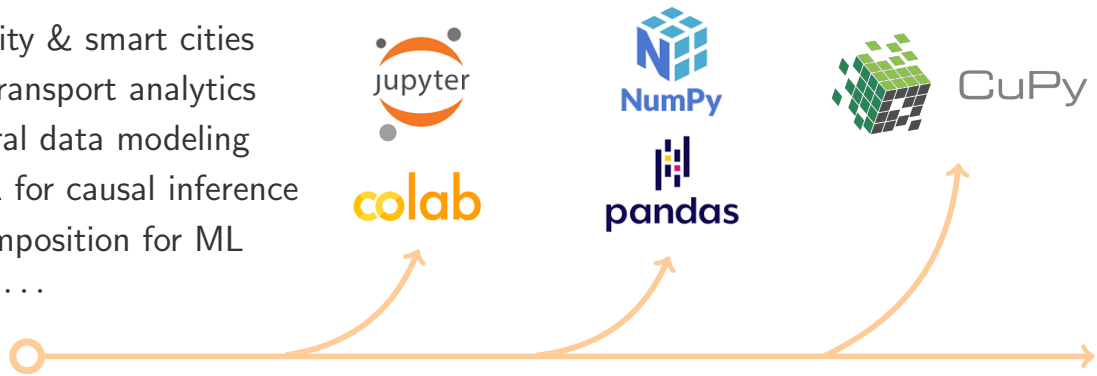


Find sparse autocorrelations

Reproducible Research for Engineering

- The last mile of AI for computational engineering

Human mobility & smart cities
Data-driven transport analytics
Spatiotemporal data modeling
Interpretable ML for causal inference
Tensor decomposition for ML
...



Directions & Topics → **Reproducible Research**

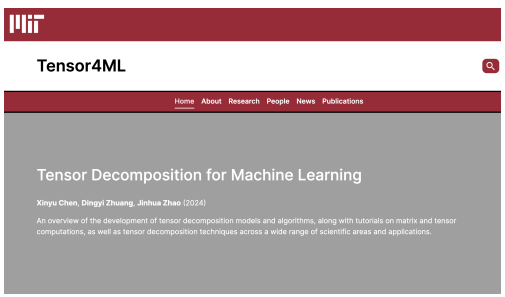
- Advancing ML development with open-source research

transdim

(1,200+ GitHub stars)

ML for Transport Data Imputation

https://github.com/xinychen/transdim



Tensor Decomposition for ML

(ML initiative)

Math & ML Tutorials

https://sites.mit.edu/tensor4ml

Spatiotemporal Data Modeling

(Data valorization initiative)

Model Development of ML & Data Science

https://spatiotemporal-data.github.io

Building Research Impact at UTK

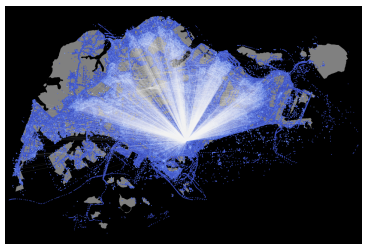
- Contributing to ISE, Science-Informed Artificial Intelligence Cluster

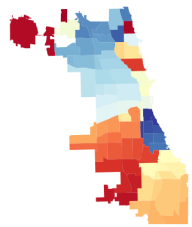
Physical systems — Spatiotemporal data

Data Availability — Collecting data, Releasing data

Data Valorization — Processing data, Improving data quality, Formulating problems

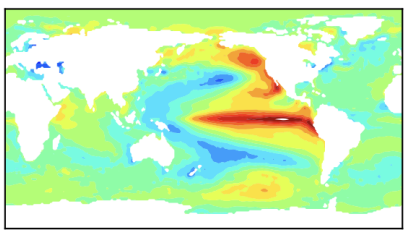
Computational Engineering — Machine learning, Deep learning, Matrix computations, Nonconvex optimization, Mathematical programming



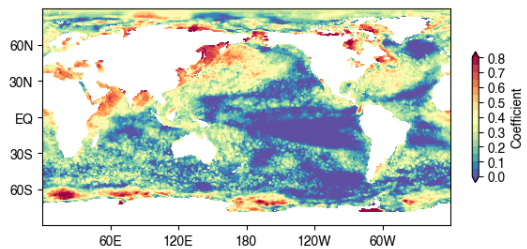


Vision: Connecting engineering with data, mathematics, and AI.

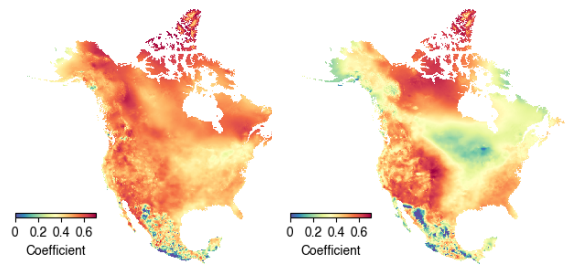
- Contributing to Institute for a Secure & Sustainable Environment, partnership w/ Climate Change Science Institute at Oak Ridge National Lab



El Niño patterns



Sea surface temperature seasonality



Climate seasonality (2000s vs. 2010s)

- Research group: Developing ML and optimization for spatiotemporal data modeling; Developing innovative AI tools for computational engineering.

Teaching & Grant

- **Teaching Interests & Plan at UTK**
  - Formats: Tutorial, data example, LaTeX graphic, Python code, GitHub repository, and course website

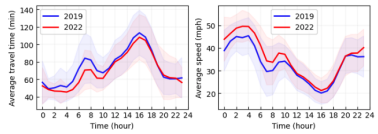
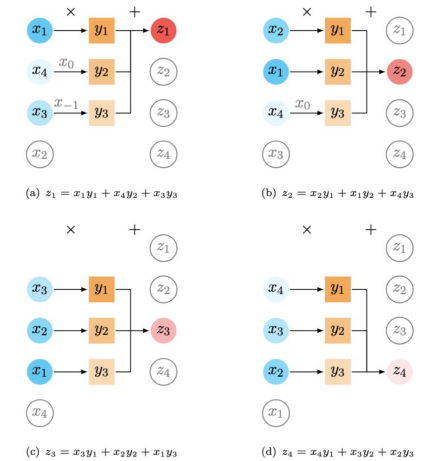


Figure 6. Average travel time and speed from area 32 (i.e., Downtown) to area 76 (i.e., Airport) in both 2019 and 2022.

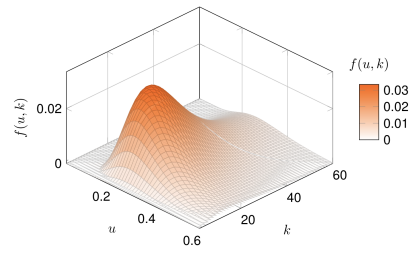
```python
import numpy as np
import matplotlib.pyplot as plt

fig = plt.figure(figsize = (8, 2.5))
ax = fig.add_subplot(1, 2, 1)
# Average travel time in 2019
m1 = df1.groupby(['hour'])['Trip Seconds'].mean().values / 30
s1 = df1.groupby(['hour'])['Trip Seconds'].std().values / 30
plt.plot(m1, color = 'blue', linewidth = 1.8, label = '2019')
upper = m1 + s1
lower = m1 - s1
x_bound = np.append(np.append(np.append(np.arange(0, 24),
                    np.array([24 - 1, 24 - 1])), np.arange(24 - 1, -1,
y_bound = np.append(np.append(np.append(upper[0], lower[0]]), lower),
                    np.array([lower[-1], upper[-1]])), np.flip(upper))
plt.fill(x_bound, y_bound, color = 'blue', alpha = 0.05)

# Average travel time in 2022
m1 = df2.groupby(['hour'])['Trip Seconds'].mean().values / 30
s1 = df2.groupby(['hour'])['Trip Seconds'].std().values / 30
plt.plot(m1, color = 'red', linewidth = 1.8, label = '2022')
upper = m1 + s1
lower = m1 - s1
```

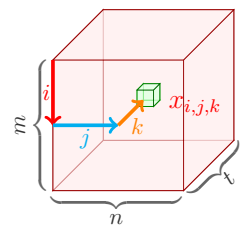


(a) $z_1 = x_1y_1 + x_4y_2 + x_3y_3$ (b) $z_2 = x_2y_1 + x_1y_2 + x_4y_3$

(c) $z_3 = x_3y_1 + x_2y_2 + x_1y_3$ (d) $z_4 = x_4y_1 + x_3y_2 + x_2y_3$

Figure 2. Illustration of the circular convolution between $\boldsymbol{x} = (x_1, x_2, x_3, x_4)^\top$ and $\boldsymbol{y} = (y_1, y_2, y_3)^\top$. (a) Computing z_1 involves $x_0 = x_4$ and $x_{-1} = x_3$. (b) Computing z_2 involves $x_0 = x_4$. The figure inspired by Prince (2023).



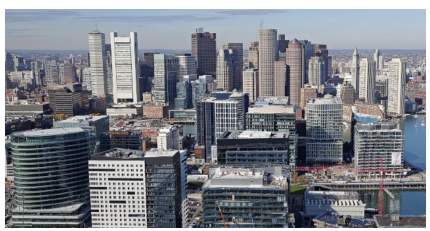


Data-Driven Analytics

Computing Fundamentals in ISE

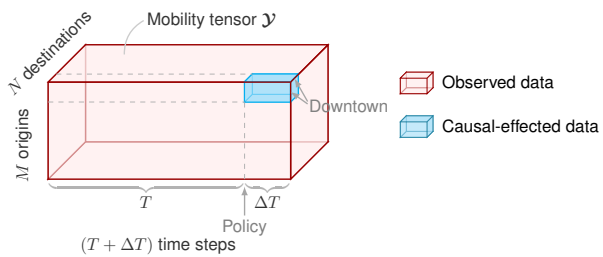
Spatiotemporal Modeling in ISE

- **Grant & Funding**



Transit-Centric Smart Mobility System with ML (DOE)

(PI: Jinhua Zhao. **Role**: Senior Researcher)



Causal inference for congestion pricing (NSF, submitted)

(PI: Jinhua Zhao; Co-PI: Ankur Moitra. **Role**: Senior Researcher)