Future Studies with A Focus on AI for Urban Science

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Outline

- Land Transport Authority (LTA) proposals[1]
- M3S projects (e.g., spatiotemporal mobility networks)
  - Process urban datasets in Singapore
  - Formulate the problem with machine learning
- DOE projects (TBD)
- Spatiotemporal data modeling[2]
- Current work: Dynamic autoregressive tensor factorization for pattern discovery of spatiotemporal systems (Finished 50%+)
  - Advance the prior art (e.g., dynamic mode decomposition, time-varying autoregression)
  - Use the orthogonal Procrustes rotation to find orthogonal patterns
  - Well-suited to multidimensional dynamical systems (e.g., mobility with dimensions {origin, destination, time})
- Future work: Deep sequence models (TBD)
- Assist other people in the lab and their research
- Present results at INFORMS/TRB meetings

[1] https://www.dropbox.com/home/SMART_T4_T5_HQ

[2] https://spatiotemporal-data.github.io

LTA Proposals

A quick look...

- By Yunhan:
  1. Understanding the usage of electric vehicle charging stations and estimating their impacts on local economic vitality
  2. Learning dynamic activity and travel decisions in the post-pandemic era
- By Xinyu:
  3. Identifying travel modes and commuter behavior patterns with machine learning
  4. Anomaly detection and vehicular monitoring on trajectories of autonomous vehicles in future human mobility
- Dingyi:
  5. Analyzing pedestrian jaywalking and vehicle interactions in the age of autonomous vehicles
  6. Uncertainty quantification in spatiotemporal prediction of walk-cycle rides demand

M3S Project

Main tasks:

- Pre-process the urban datasets (e.g., Veraset) in Singapore[3]
- Define the scientific questions in the project
- Formulate the problems with machine learning
- Analyze the results and their impacts

Current ideas: Discovering dynamics of urban human activity with dynamic autoregressive tensor factorization

- (On 2D activity data) Uncover spatial modes/patterns (e.g., POI patterns)
- (On 3D mobility data) Uncover temporal modes/patterns (e.g., long-term changing behavior impacted by special events and policy)

[3] https://spatiotemporal-data.github.io/trajectory/veraset/

Spatiotemporal Data Modeling

Goals:

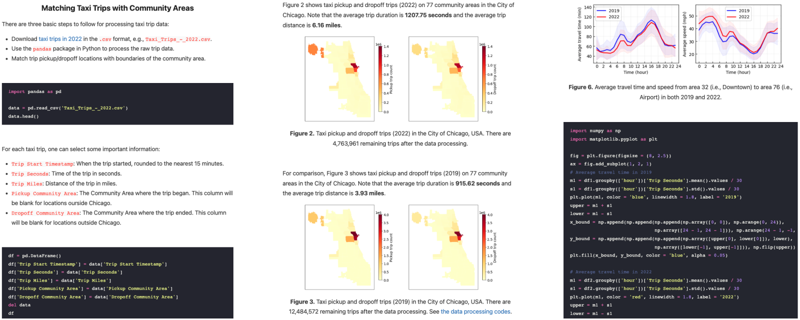
- Supporting research for all aspects of spatiotemporal data modeling with machine learning
- Solving many scientific, mathematical, industrial, and engineering problems in:
  - Urban Science
  - Human Mobility Modeling
  - Geospatial Data Analysis
  - Intelligent & Sustainable Urban Systems
  - Optimization & Decision Making

Website: https://spatiotemporal-data.github.io

Spatiotemporal Data Modeling

Plan?

- Coding and computing with data
- Posting scientific questions
- Supporting open-source and reproducible research



Source: https://spatiotemporal-data.github.io/Chicago-mobility/taxi-data

Current Work

Check out the Overleaf project

Past posts:

- Time-varying autoregression:
  https://spatiotemporal-data.github.io/posts/time_varying_model/
- Orthogonal time-varying autoregression:
  https://spatiotemporal-data.github.io/probs/orth-var/

Past work:

- X. Chen, C. Zhang, X. Chen, N. Saunier, L. Sun (2024). Discovering dynamic patterns from spatiotemporal data with time-varying low-rank autoregression. IEEE Transactions on Knowledge and Data Engineering. 36 (2): 504-517.

Future Work

State-Space Model (SSM)

- **State transition equation:**

$$\underbrace{\boldsymbol{x}_{t+1}}_{\text{state}} = \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{B}\underbrace{\boldsymbol{u}_t}_{\text{input}} + \underbrace{\boldsymbol{w}_t}_{\mathcal{N}(\boldsymbol{0},\boldsymbol{I})}$$

- **Observation equation:**

$$\underbrace{\boldsymbol{y}_t}_{\text{output}} = \boldsymbol{C}\boldsymbol{x}_t + \boldsymbol{D}\underbrace{\boldsymbol{u}_t}_{\text{input}} + \underbrace{\boldsymbol{v}_t}_{\mathcal{N}(\boldsymbol{0},\boldsymbol{I})}$$

vs.

Recurrent Neural Network (RNN)

- **Hidden state update:**

$$\boldsymbol{h}_t = \text{activation}(\boldsymbol{W}_{hh}\boldsymbol{h}_{t-1} + \boldsymbol{W}_{hx}\boldsymbol{x}_t + \underbrace{\boldsymbol{b}_h}_{\text{bias}})$$

- **Output:**

$$\underbrace{\boldsymbol{y}_t}_{\text{output}} = \text{activation}(\boldsymbol{W}_{yh}\underbrace{\boldsymbol{h}_t}_{\text{state}} + \underbrace{\boldsymbol{b}_y}_{\text{bias}})$$

- Long-range spatiotemporal modeling, e.g.,
  - State-space layers (Smith et al.'22)
  - Convolutional SSM (Smith et al.'23)
- Linear-time sequence modeling (e.g., selective SSM, Gu & Dao'23)

References

A short list:

- [Cai et al.'14] J.-F. Cai, H. Ji, Z. Shen, and G.-B. Ye, "Data-driven tight frame construction and image denoising," Applied and Computational Harmonic Analysis, vol. 37, no. 1, pp. 89–105, 2014.
- [Calamai & More'87] P. H. Calamai and J. J. More, "Projected gradient methods for linearly constrained problems," Mathematical programming, vol. 39, no. 1, pp. 93–116, 1987.
- [Golub & Van Loan'13] G. H. Golub and C. F. Van Loan, Matrix computations. JHU press, 2013.
- [Gu & Dao'23] A. Gu and T. Dao, "Mamba: Linear-time sequence modeling with selective state spaces." arXiv preprint arXiv:2312.00752.
- [Smith et al.'22] J. T. H. Smith, A. Warrington, and S. W. Linderman, "Simplified state space layers for sequence modeling." arXiv preprint arXiv:2208.04933. (ICLR'23)
- [Smith et al.'23] J. T. H. Smith, S. De Mello, J. Kautz, S. W. Linderman, and W. Byeon, "Convolutional state space models for long-range spatiotemporal modeling." arXiv preprint arXiv:2310.19694.

Thanks for your attention!

Any Questions?

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