Mobility Forum May 5
AI Applications in Public Transit (DOE, CTA, WMATA) Annotation by Jinhua Zhao

Shoichi Ishida

Part I Related Research

Alexandre, T., Bernardini, F., Viterbo, J., & Pantoja, C. E. (2023). Machine Learning Applied to Public Transportation by Bus: A Systematic Literature Review. *Transportation Research Record: Journal of the Transportation Research Board*. https://doi.org/10.1177/03611981231155189

Chandra, V., Gill, P., Kohli, S., Venkataraman, K., & Yoshimura, J. (2022, April 29). *The Next Horizon for Grocery e-commerce: Beyond the Pandemic Bump*. McKinsey & Company. https://www.mckinsey.com/industries/retail/our-insights/the-next-horizon-for-grocery-ecommerce-beyond-the-pandemic-bump

Kuberkar, S. & Singhal, T.K. (2020). Adoption Intention of AI Powered Chatbot for Public Transport Services within a Smart Factors Influencing City. *International Journal on Emerging Technologies, 11(3),* 948-958.

Sankari, S., Varshini, S. S., & Shifana, S. M. A. (2022). COVID-19: Machine learning for safe transportation. *Concurrency and Computation, 34(19)*. https://doi.org/10.1002/cpe.7041

Solihati, K. D. & Indriyani, D. (2021). Managing Artificial Intelligence on Public Transportation (Case Study Jakarta City, Indonesia). *IOP Conference Series Earth and Environmental Science, 717*. https://doi.org/10.1088/1755-1315/717/1/012021

Transportation Research Board. (2007, January). https://onlinepubs.trb.org/onlinepubs/circulars/ec113.pdf

Ushakov, D., Dudukalov, E., Shmatko, L., & Khodor, S. (2022). Artificial Intelligence as a factor of public transportations system development. *Transportation Research Procedia, 63*, 2401-2408. https://doi.org/10.1016/j.trpro.2022.06.276

Yin, M., Li, K., & Cheng, X. (2022). A review on artificial intelligence in high-speed rail. *Transportation Safety and Environment, 2(4),* 247-259. https://doi.org/10.1093/tse/tdaa022

Part II News Article

Cole, A. (2021, October 25). *Utilizing AI to Improve Mass Transit*. Venture Beat. https://venturebeat.com/ai/utilizing-ai-to-improve-mass-transit/

Intelligent Transport. (2023, March 6). *STM and Transit Test New AI-Based Tool to Monitor Bus Detours*. https://www.intelligenttransport.com/transport-news/144330/stm-and-transit-test-new-ai-based-tool-for-bus-detours/

Martin, J. (2022, January 10). *Artificial Intelligence in Public Transport*. Intelligent Transport. https://www.intelligenttransport.com/transport-articles/131855/artificial-intelligence-public-transport/

Security. (2023, February 24). *Philadelphia Adds Gun-Detection Software to Public Transit*. https://www.securitymagazine.com/articles/98990-philadelphia-adds-gun-detection-software-to-public-transit

UITP/ International Association of Public Transport. (2018, December). *Artificial Intelligence in Mass Public Transport.* https://cms.uitp.org/wp/wp-content/uploads/2020/08/UITP-AP-CTE-AI-in-PT-Executive-Summary-Dec-2018_0.pdf

Part III Summary of Audience QA

Q1.

[John Moavenzadeh]

Can AI enable predictive analytics such as demand prediction? Do we really see our future where AI will be incorporated into the reality?

[Jinhua Zhao]

There are two types of arguments. One is density argument, where public transport is the only way to achieve high-speed mode of transportation. The other is equity argument, where public transport is a lifeline for people. In any type, AI can contribute to improvement on prediction or customer experience, however, it should come with other factors such as political, financial, and operational support from the government etc.

[Shenhao Wang]

There are three tensions in the public transport AI research. One is between computer science and other research domains. Like "backward feedback", applying computer science to many other domains and considering how to create synergy are important. The second one is a gap between the state of the art and the real-world practice, implementation may require changes in the technology used, like simplification. The last tension is between public and private sectors. Private sectors usually think simply, with a single objective such as maximizing profit or increasing accuracy of the prediction. For public organizations, there are multiple objectives like equity, basic accessibility and so on.

[Anson Stewart] There is an especially interesting application of AI to public transit. It is mitigation of sever workforce shortage. As Jinhua pointed out, AI is not going to solve the fundamental problem itself, however, it is possible for AI to mitigate it. For example, AI can help dispatchers scheduling trains, instead of training employees for two years, although it may produce unintended consequences or unnecessary complexity.

Q2.
[Bhuvan Atluri]
How did introduction of electric buses affect the prediction models with AI?
[Awad Adbelhalim]
I think it will become more important to provide the passengers with precise arrival time based on real-time information with electric buses, considering battery charges.
[Bhuvan Atluri]
Is there any research that mentioned efficiency of electric buses (e.g., minimizing turnaround time) using AI, including the timing of battery charge, the battery status, and so on?
[Jinhua Zhao]
Thank you. Better control of the system is another reason for AI. Since electric buses generally cannot travel as long as diesel buses, many agencies have to prioritize turnaround time. Therefore, scheduling process and charging process can't be separated anymore, which creates a new integrated field of AI to handle.

Q3.
[Bhuvan Atluri]
How does your model incorporate contexts, for example, sarcasm, different by countries and cultures?
[Michael Leong]
There are some universal expressions with specific contexts. However, local-specific expressions like sarcasm or irony should be chosen based on local areas, which our model does not do at this moment.

Q4.
[Bhuvan Atluri]
Another question is about AI and route optimization with new modes of transportation such as autonomous driving cars. Can we see AI as a larger role in ensuring better transit and optimizing route where public transport exists such as Chicago and Boston?
[Jinhua Zhao]
AI does not guarantee a value judgement. There is a gap between implementation capacity and technological capacity, which MIT has an important role in filling.
Also, regarding autonomous cars, they can change the definition of the "bus driver". Now bus drivers "navigate the bus", but in the future, this role may change into "instruct passengers". In this way, jobs may need to be redefined in the future.

Q5.
[Bhuvan Atluri]
How can large-scale AI be implemented in the near term? Even a simple implementation of rule-based policy is not being in place right now. For example, T Greenline was extremely crowded after a Redsox game and takes double time, but no additional cars didn't come.
[Joseph Rodriguez]
Decisions are currently being made by different people with different strategies. The potential of AI is to get together different information and make it more coordinated.
[Jinhua Zhao]
I was talking with one certain company. There was a dilemma. If the company does not use AI and a competitor does, it can lead to more competitiveness of the competitor. But if the company decides to engage in AI, how can it protect its own intellectual property? This problem is what many companies are facing now.

Q6.
[John Moavenzadeh]
I would also like to know more about behavioral aspect of AI, not only technological things. Do you see behavioral trends nudging people toward public transportation such as ID cards with free access to transit systems for MIT staffs?
[Jinhua Zhao]
Our lab focuses on two aspects. One is computational and technological, and the other is behavioral. Two are not separable, for example, while companies can hire the best scientists of AI to urge people to use social media more, being addicted to it is a huge behavioral problem. The lab is very closely working with other labs and schools, too, to cover this complex topic and benefit from each other.

Part IV Summary of Reflection Memos

- (Jason Luo) The delivery format of this week's forum was standing out in a good way, introducing a variety of different research projects at the same time. It was remarkable that Zhao categorized research with two dimensions: long-term v.s. short-term and structured v.s. unstructured. Also, it is interesting that the students in the lab are all using different tools to get more impact.
- (Yen-Chu Wu) The research on deep learning and urban imagery for demand analysis was outstanding, having much potential to improve efficiency. Also, natural language processing was interesting in the point that researchers can gain insights from it would lead to clearer understanding of customer behaviors and better customer satisfaction. I'm looking forward to seeing a lot more applications of AI in the future.

- (Yuhan Zheng) The presenter of the issue of algorithmic fairness in travel behavior modeling and explored methods for mitigating modeling bias.
- (McKenzie Humann) There are some points to mention about the webinar. 1.opening the information of how the customers' feedbacks are used and tracked to themselves is useful, 2. I wonder whether the TNC companies care about the AI bias, 3. Our "lived experience" can be a missing component to express cities, 4. Shenhao's point, tensions between multiple industries really make sense.
- (Spencer McDonald) There are some points to be addressed about use of AI. They are ethical implications of implementation of AI, balancing respecting the privacy and leveraging data, and transparency in AI, which leads to a problem of "who is responsible for AI's results?"
- (Ao Qu) Jinhua successfully introduced a variety of research of different categories. Since urban system is complex, it is difficult but necessary to obtain frameworks to deal with a large number of data. The growth in AI will have a high impact on the urban logistics.
- (Nineveh O'Connel) JTL Transit Lab was interesting, especially customer feedback mining. However, eliminating bias from AI is difficult and important.
- (Samuel Chin) Recently, multiple fields, such as computer vision and NLP, are being combined. However, lack of large data available like traditional CS can be a problem. LLMs is a powerful tool, but we need to be careful about the bias.
- (Myself) One thing that surprised me in a good way was Jinhua's idea on the future perspective of his research. He suggested including multiple elements such as images, text information, geographical information, and others into one single model to make it more sophisticated. This is to me an intriguing opinion, because I have not seen many research incorporating this idea, and most of them are solely based on one single aspect such as images. I'm confident that this will leverage precision of machine learning. However, I personally think there are two major problems about current machine learning applications for public transport. One is that there are few opportunities to test out their machine learning models in reality. Even though one of their research topics on public buses successfully obtained a chance to try out their prototype in Chicago, in partnership with Chicago Transport Department, it is generally not easy to get this kind of chance, considering data privacy, lack of benefit for public and private organizations, cost and time burdens. But for machine learning, it is necessary to gather information enough to train and test models. Therefore, starting more collaborative projects between research institutes such as universities and public or private sectors in the industry will be more significant. The other problem is sometimes research lacks further actions after the use of machine learning. For example, machine learning might be able to tell how late the bus will be, but just feeding back the information to the passengers may not create a big motivation for companies or customers to invest more. It may be

necessary to aim at creating more additional values such as preparing additional "shuttle busses" or commendations for other transports with free transit tickets.

Part V Other Resources

A variety of transport or public transport labs from different universities.

-MIT

https://mobility.mit.edu/machine-learning

-Northeastern

https://web.northeastern.edu/hnkoutsopoulos/

-Imperial College London

https://www.imperial.ac.uk/transport-studies/transport-and-environment/

A.I. and Public Transit

Prof. Jinhua Zhao

With Shenhao Wang, Haris N. Koutsopoulos, Nigel Wilson, Joseph Rodriguez, Qingyi Wang, Dingyi Zhuang, Baichuan Mo, Awad Abdelhalim, Michael Leong, Yunhan Zheng, and Anson Stewart

MIT Mobility Forum

May 5, 2023

JTL

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What is not covered in this talk

Sparks of Artificial General Intelligence (AGI)

- Impact on jobs
- Impact on education
- Disinformation and fate of democracy
- Existential threats to human species

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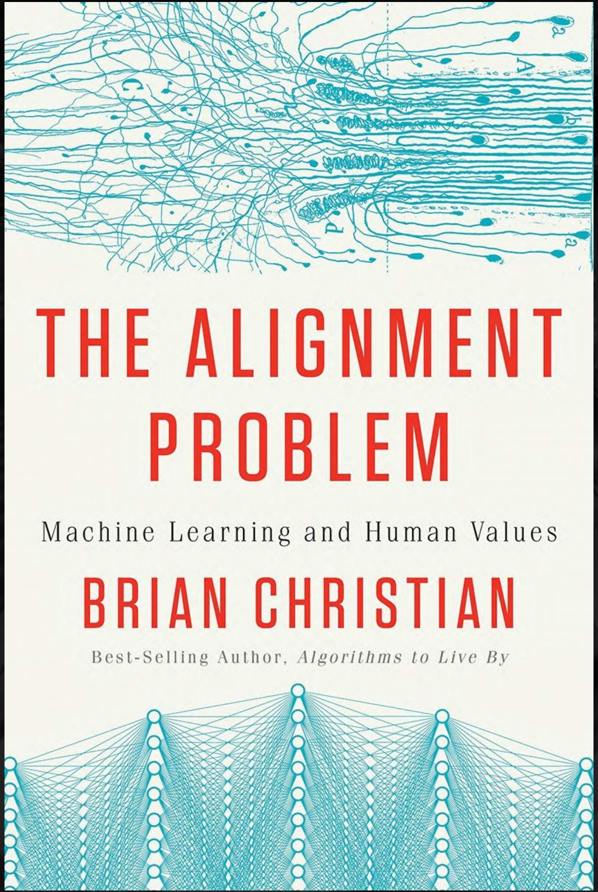
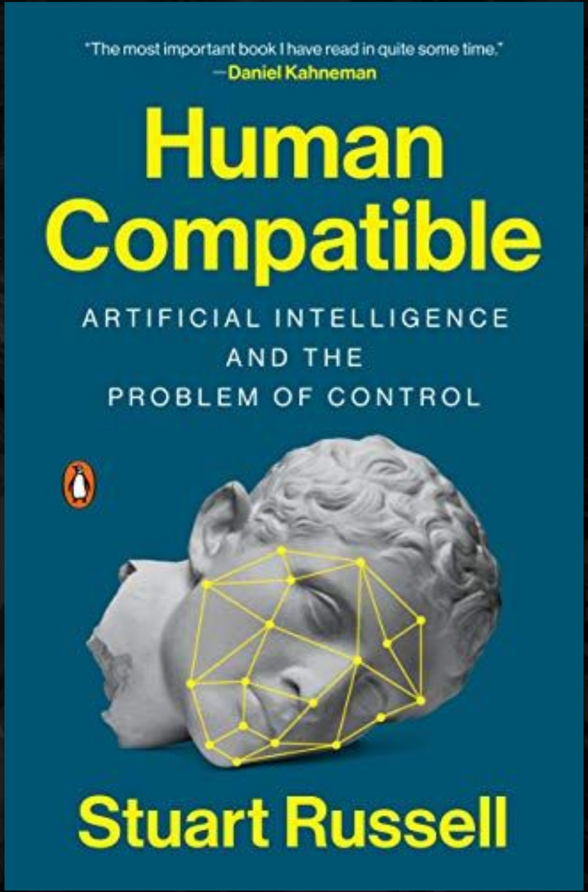
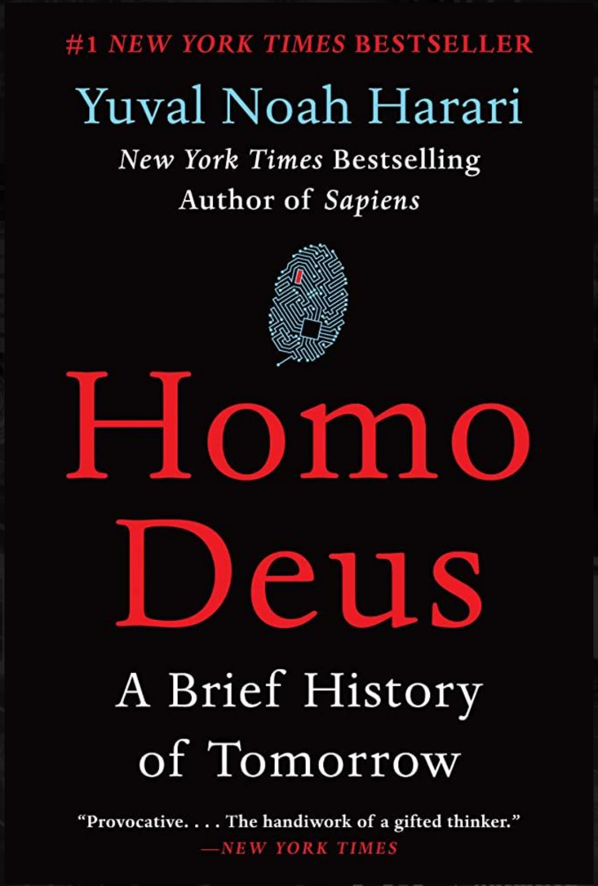
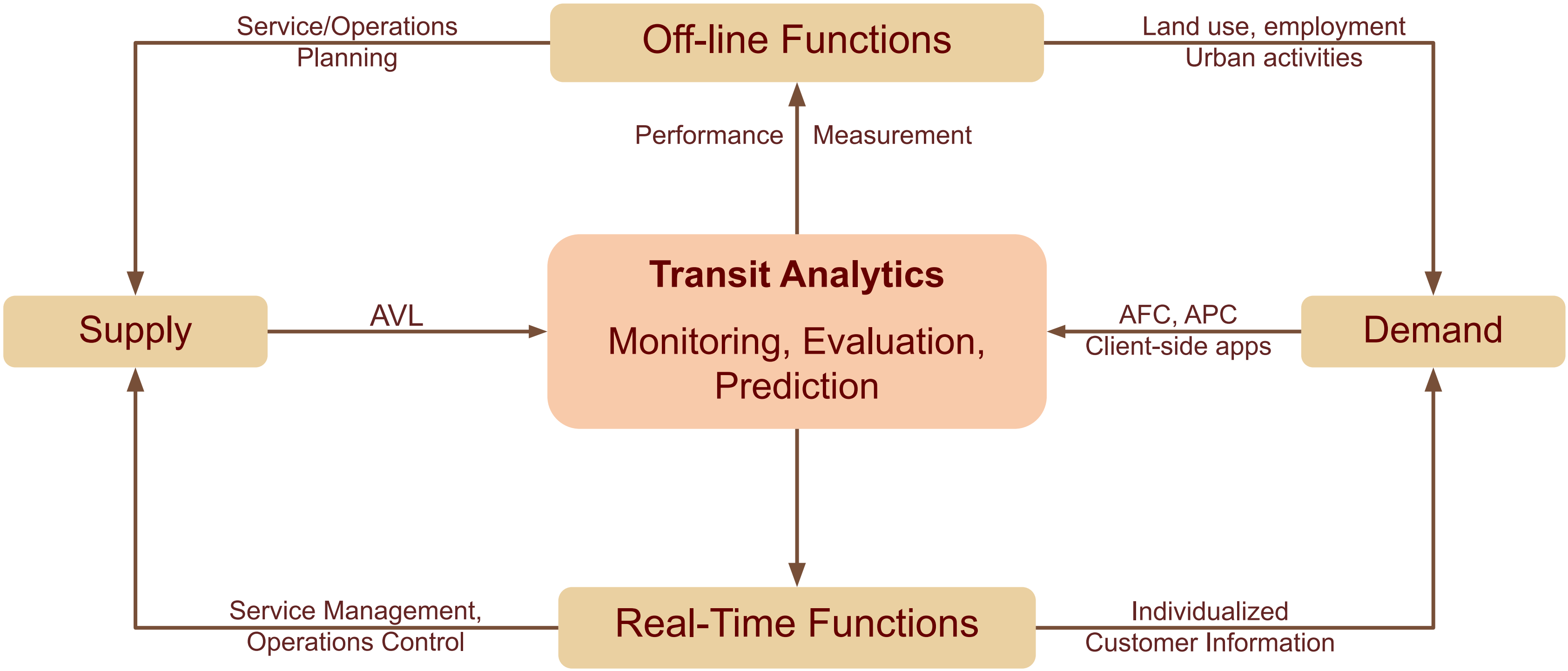
If interested,



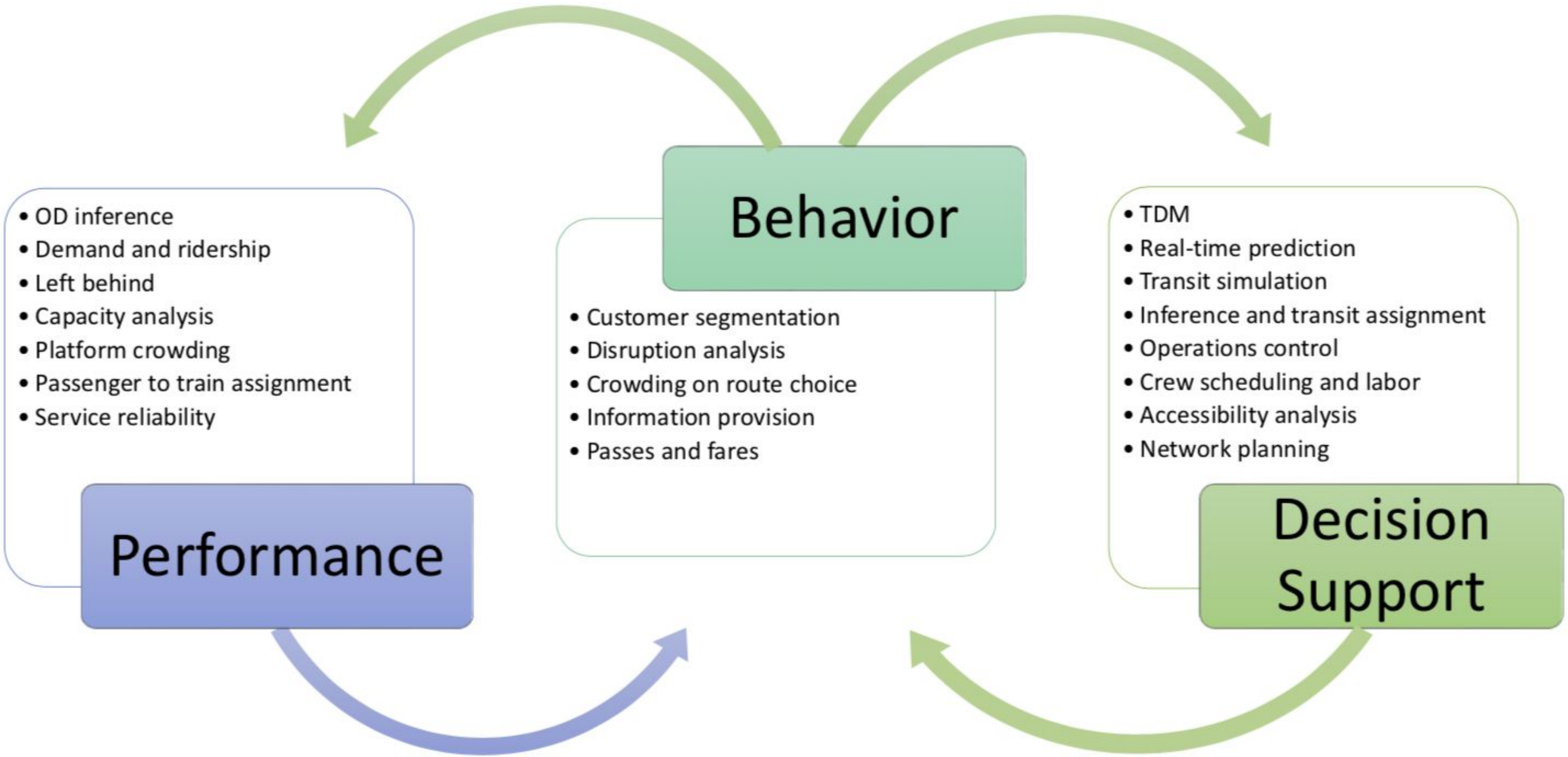




Public Transit Analytic Functions



MIT Transit Lab Research Areas



MIT Transit Lab Research Applications

Operational

- Operational control
- Disruption Recovery
- Crew scheduling and labor
- Service Planning and Scheduling

Tactical

- Behavior / choice
- Passes and Fare Policy
- OD inference
- Demand and ridership
- Travel Demand Management

Strategic

- Long-term planning
- Funding and financing
- Network planning
- Accessibility and Wider Benefit Assessment

Public transit in the US has much bigger issues than what AI can address.

A.I. Applications in Public Transport

Clustering (Un-supervised learning)

Descriptive and Exploratory (Gabriel Goulet)

Demand prediction (Supervised Learning)

1. Aggregate Demand Prediction

Origin only and OD pair prediction (Peyman Noursalehi)

2. Individual Demand Prediction

Language model (n-gram) (Zhan Zhao)
Input Output Hidden Markov Model (Baichuan Mo)

3. Synergy between Discrete choice model + Deep Neural Network(Shenhao Wang)

Operations Control (Reinforcement learning)

1. Bus holding, stop skipping; Travel time uncertainty; Driver compliance uncertainty (Joseph Rodriguez)
2. Train dispatching during service disruptions

Text Mining (Customer Experience)

1. TfL Incidences Log Analysis (Peyman)
2. WMATA Sentiment Analysis (Michael Leong)

Computer Vision

1. Estimate traffic state using camera data
2. Right of way blockage on bus lanes
3. Left behind passengers
   (Awad Abdelhalim)

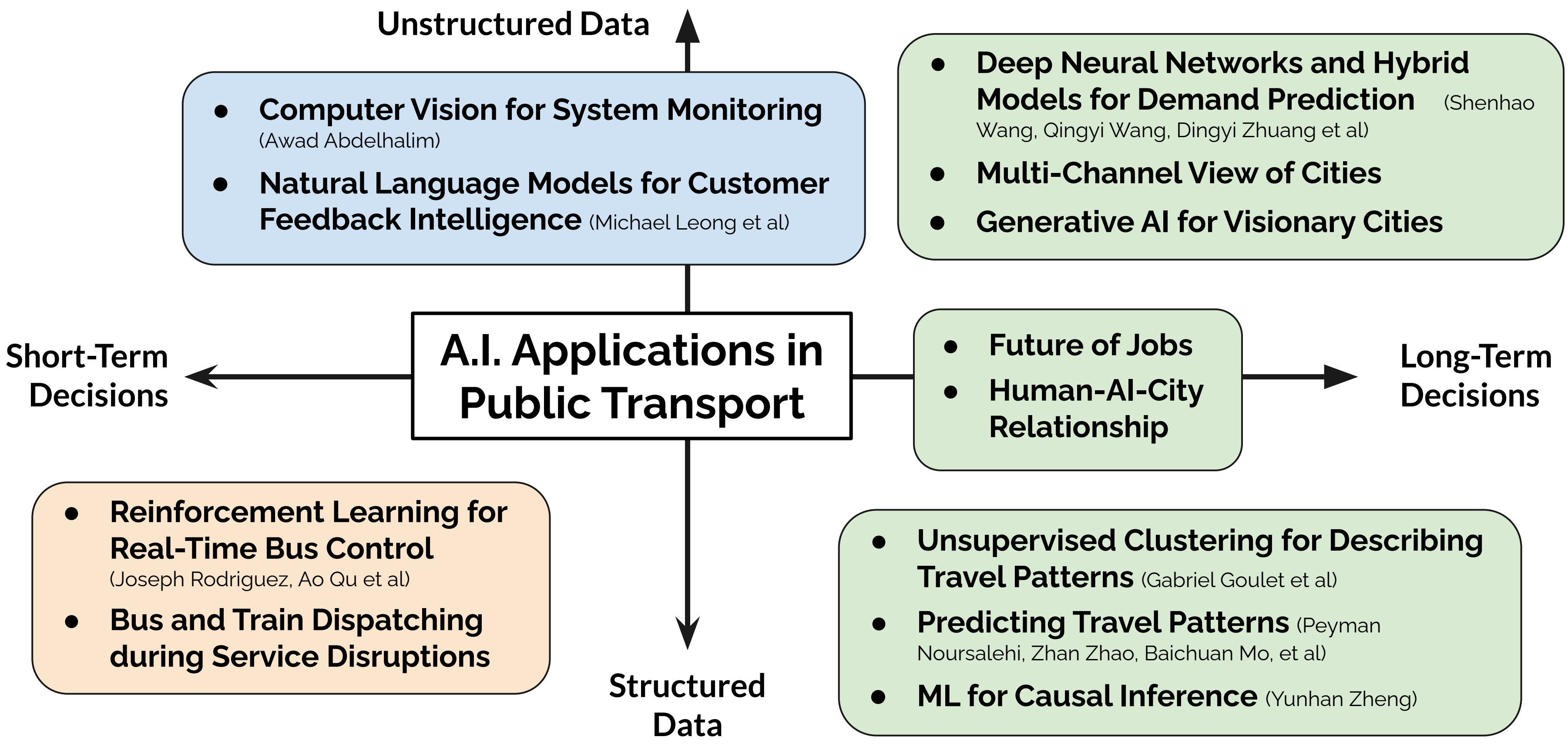
Causal Inference with ML

1. Impacts of Green Line Extension (Yunhan Zheng)

Generative AI

1. “styles” of cities with generative models (Qingyi Wang)

Control Monitoring Demand & Policy



AI and Public Transit

Introduction	Introduction	 Jinhua Zhao
ZONE 1 Demand	Deep Hybrid Model: Urban Imagery for Demand Analysis	 Qingyi Wang
	Deep Hybrid Model: Graph Embedded Urban Road Network	 Dingyi Zhuang
ZONE 2 Monitoring	Computer Vision for Transit Travel Time Prediction	 Awad Abdelhalim
	Natural Language Models for Transit Customer Feedback Intelligence	 Michael Leong
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Future	Future Projects	 Jinhua Zhao

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Demand

Deep Hybrid Models: Urban Imagery for Demand Analysis

Qingyi Wang

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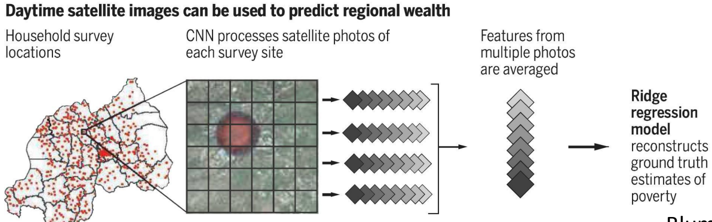
Research gap: the lack of **unstructured data** in demand analysis

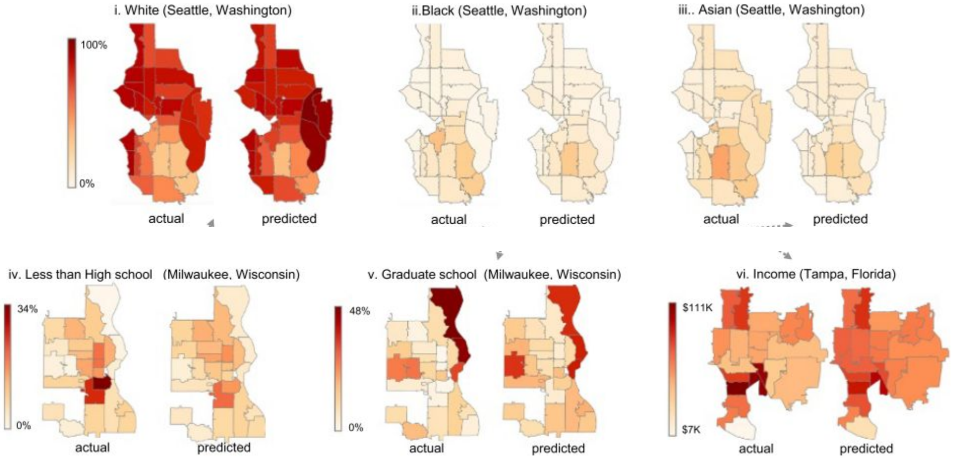
Uniqueness of deep learning lies in its ability to digest unstructured data.

DALL·E 2 | Midjourney | GPT-4

Studies have shown that imagery is predictive of socio-demographic indicators.



Blumenstock, 2016



Gebru et al. 2017

Research gap: the lack of **unstructured data** in demand analysis

Current

Goal

Numeric

Uniqueness of deep learning lies in its ability to digest unstructured data.

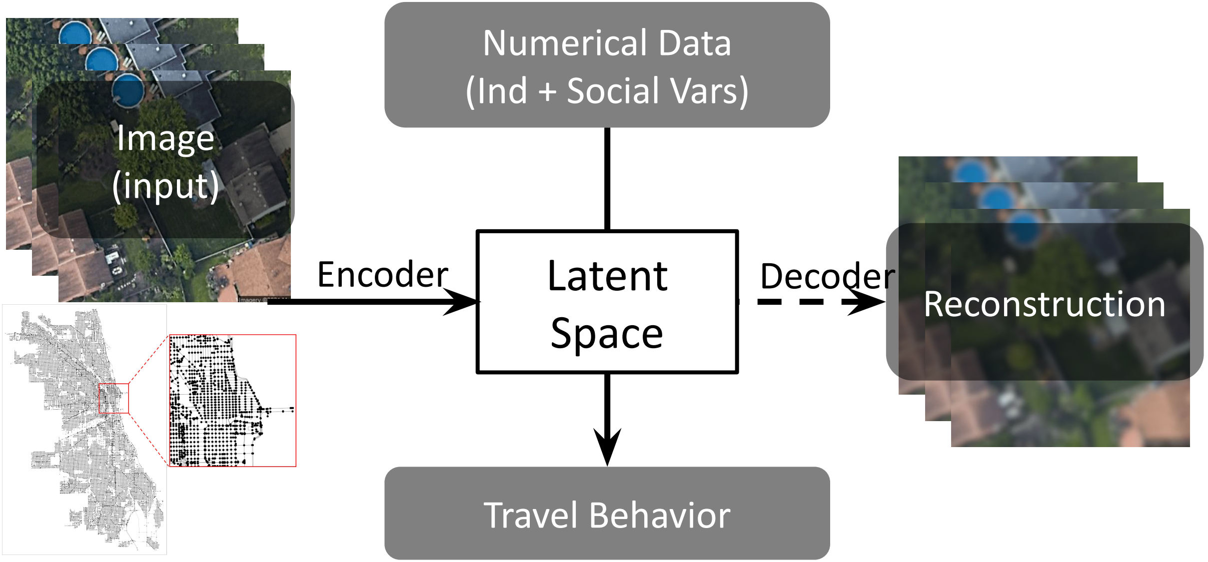
DALL·E 2

Midjourney

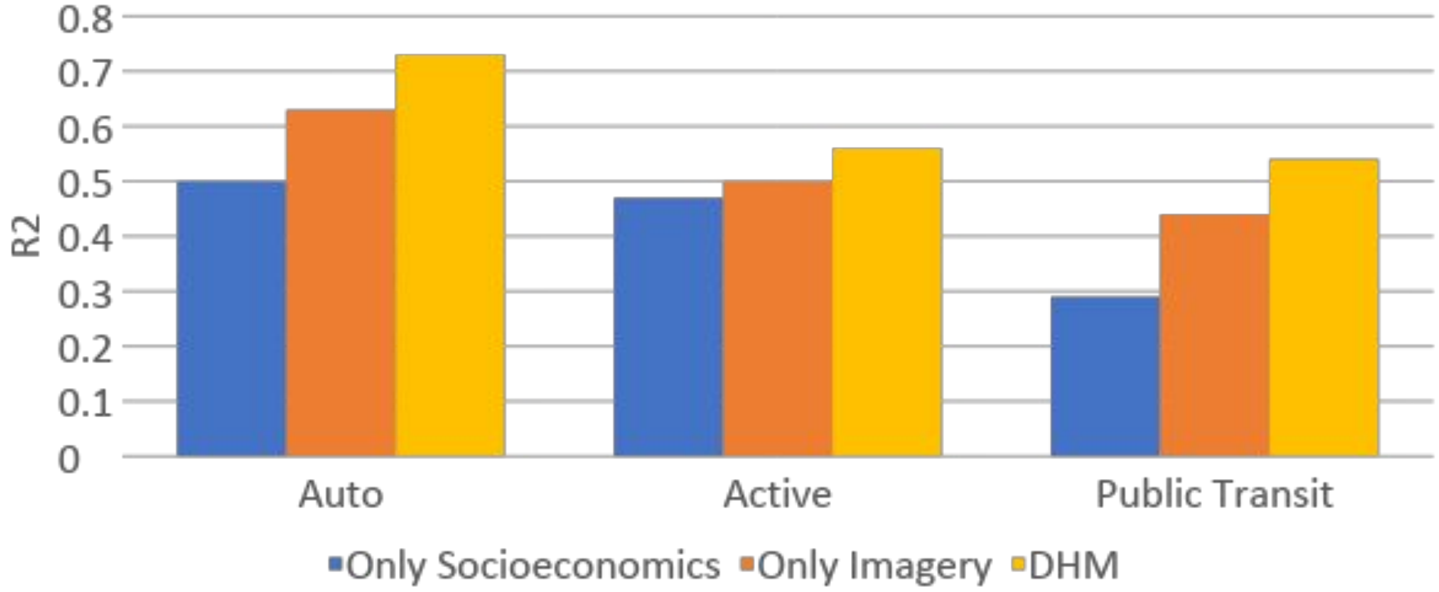
GPT-4

Studies have shown that imagery is predictive of socio-demographic indicators.

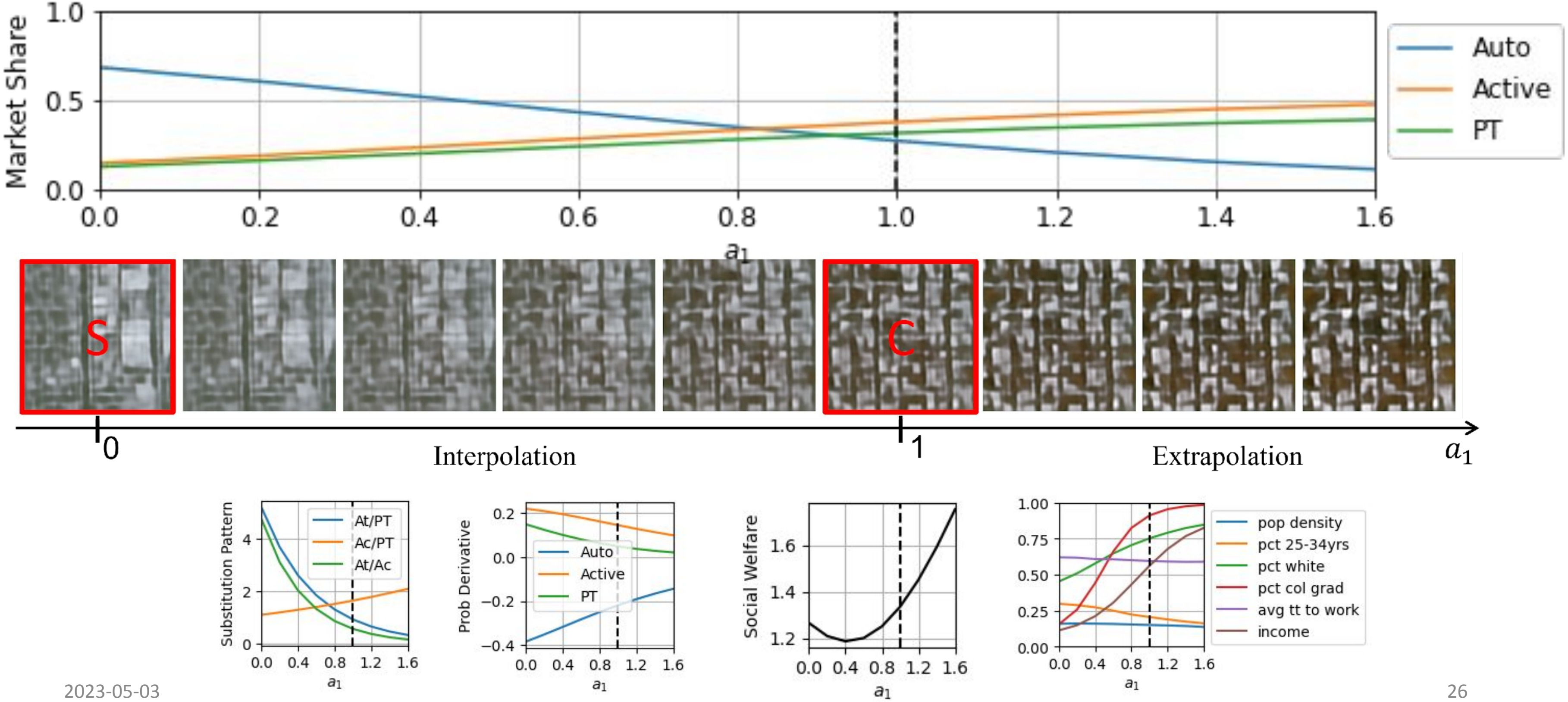
Deep Hybrid Models:
Combining unstructured data with numerical data

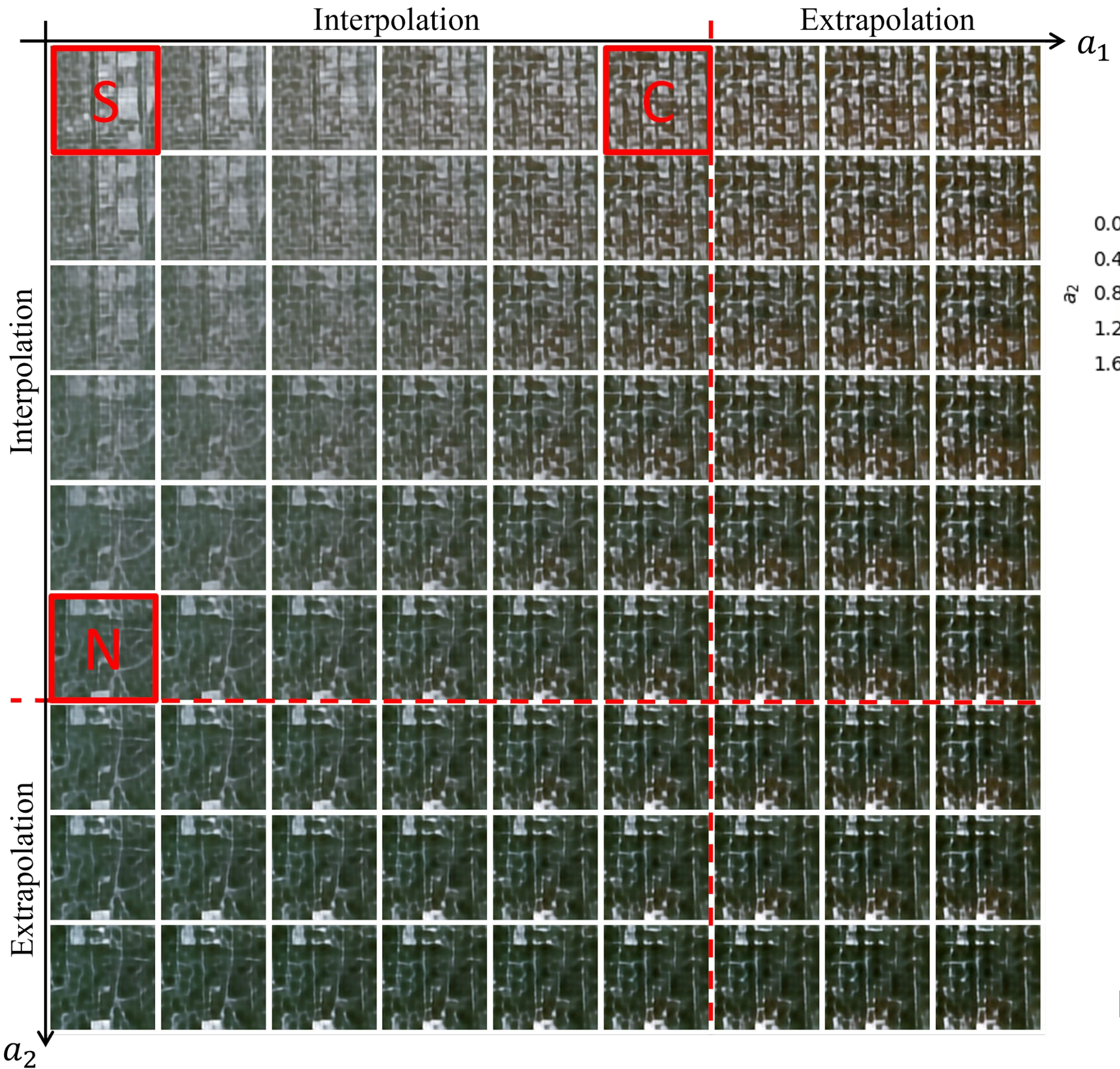


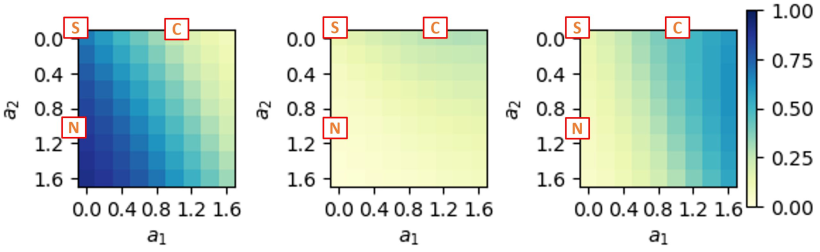
Images and socio-demographics contain **complementary** information.



Economic interpretation of existing and generated images



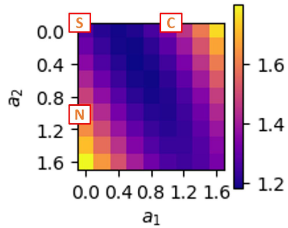




Auto

Active

Public Transit



Social welfare

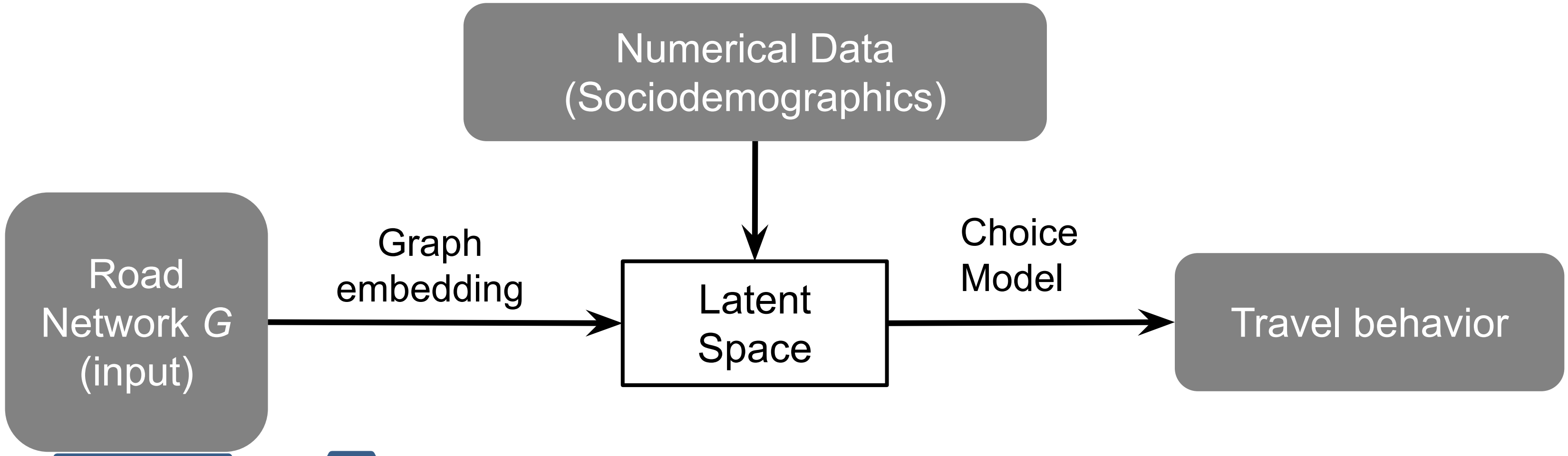
https://arxiv.org/abs/2303.04204

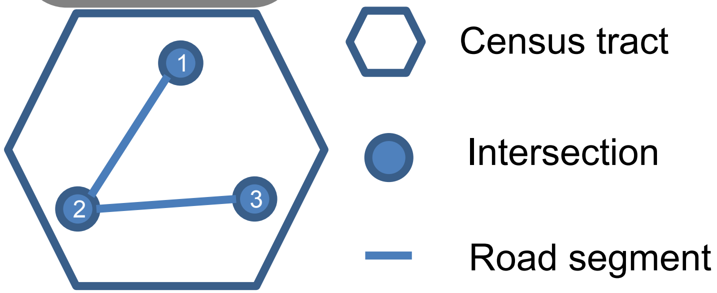
Demand

Deep Hybrid Models: Graph Embedded Urban Road Network

Dingyi Zhuang

Methodology: Deep hybrid models with Urban Road Networks





- Graph Embedding (GE) learns the representation of the road networks in a low-dimensional Euclidean space
- Free from feature engineering and prior knowledge/assumptions on the networks

Case study

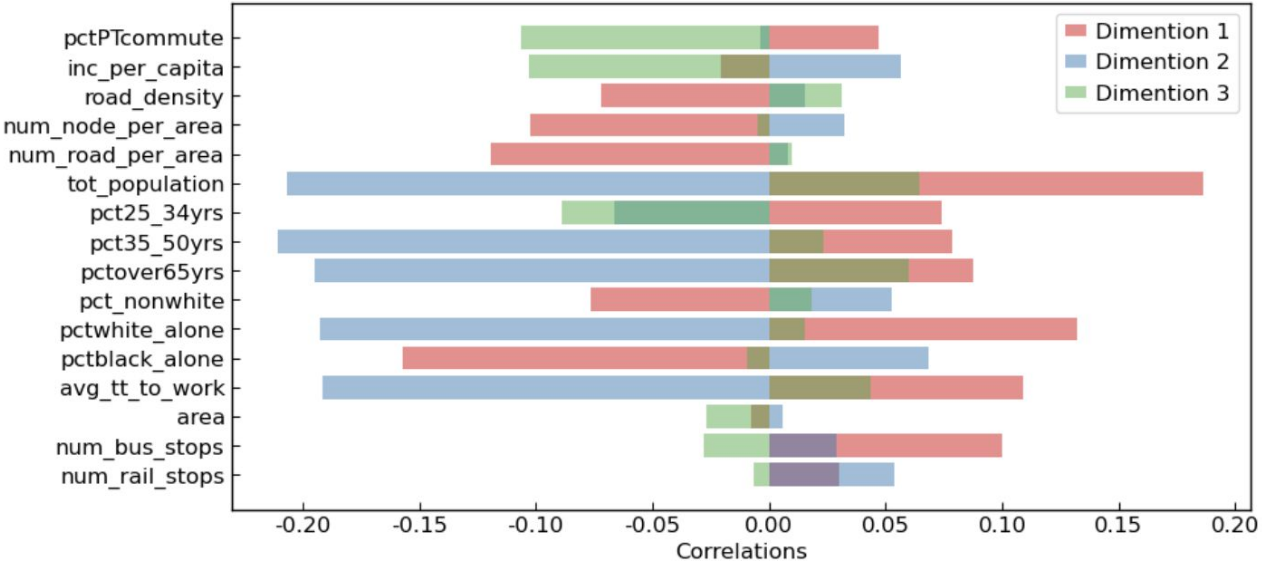
Input data:

- Urban road network in Chicago, including **road topology** and **road travel distance**
- 2017-2018 Chicago sociodemographic information

Task:

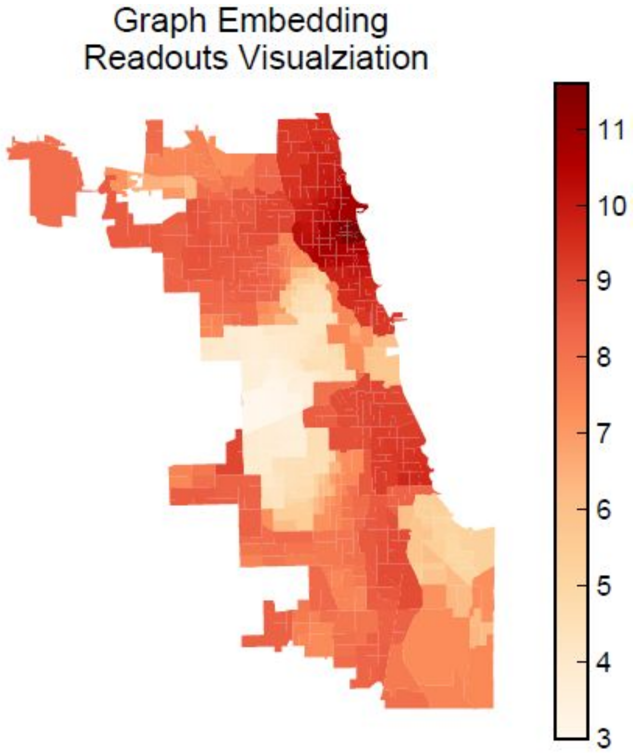
- Regress public transit mode share and income per capita using road networks

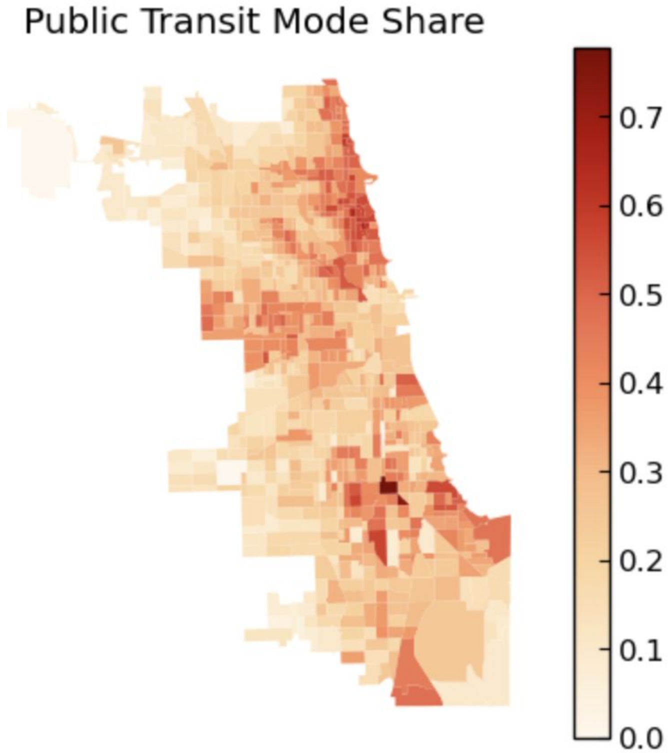
Latent space learns different perspectives of sociodemographics



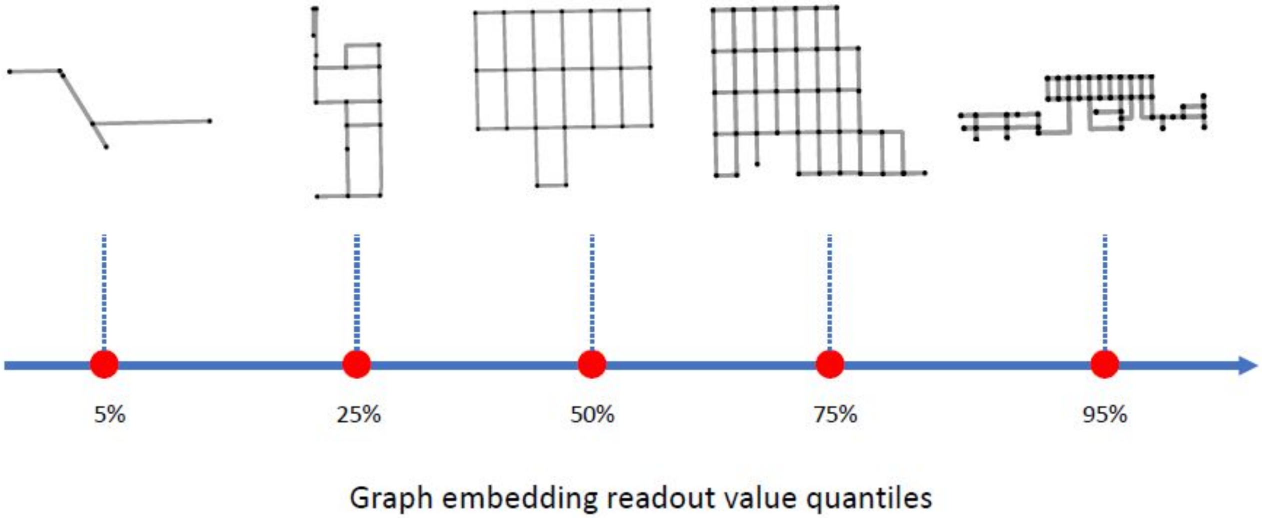
- The first 3 of 128 dimensions of latent space
- Each dimension presents a very different perspective of socio-demographic correlations

Latent space provides spatial insights on public transit mode choice





Quantiles of latent space aggregated values



From the small quantiles to a larger one, the represented road network structure transitions from sparse, irregular, and non-rectangular shapes into a dense, organized, and gridded counterpart.

Regression performance

- **70%** census tract as training and the rest **30%** as testing

- Baseline model:
  - linear regression
  - **Inputs:** feature engineered inputs

- Graph embedded model:
  - linear regression
  - **Inputs:** graph embedding vectors

Dependent variable	Metrics R^2	Baseline model	Graph embedded model	Improvement
Public transit mode share	In-sample	0.387	0.690	78%
	Out-of-sample	0.450	0.561	24%
Income per capita	In-sample	0.504	0.843	67%
	Out-of-sample	0.532	0.794	49%

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Monitoring

Computer Vision for Transit Travel Time Prediction

Awad Abdelhalim

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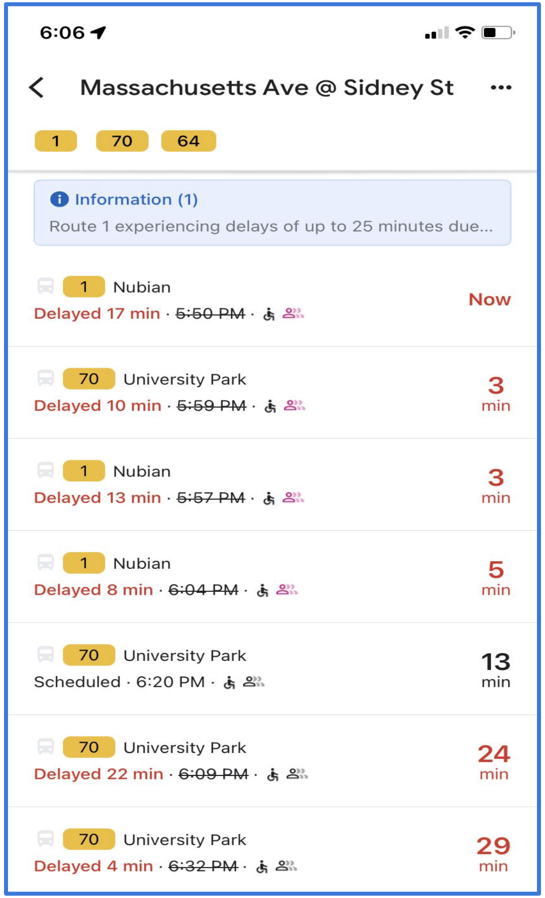
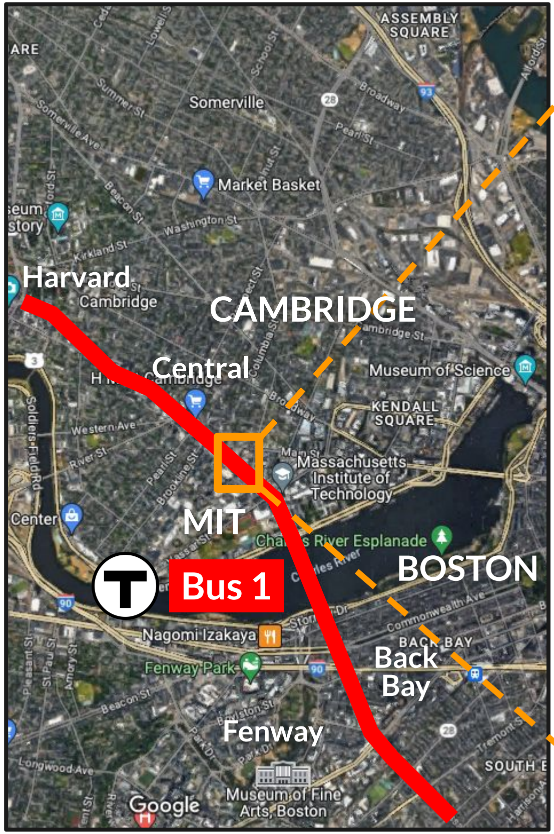
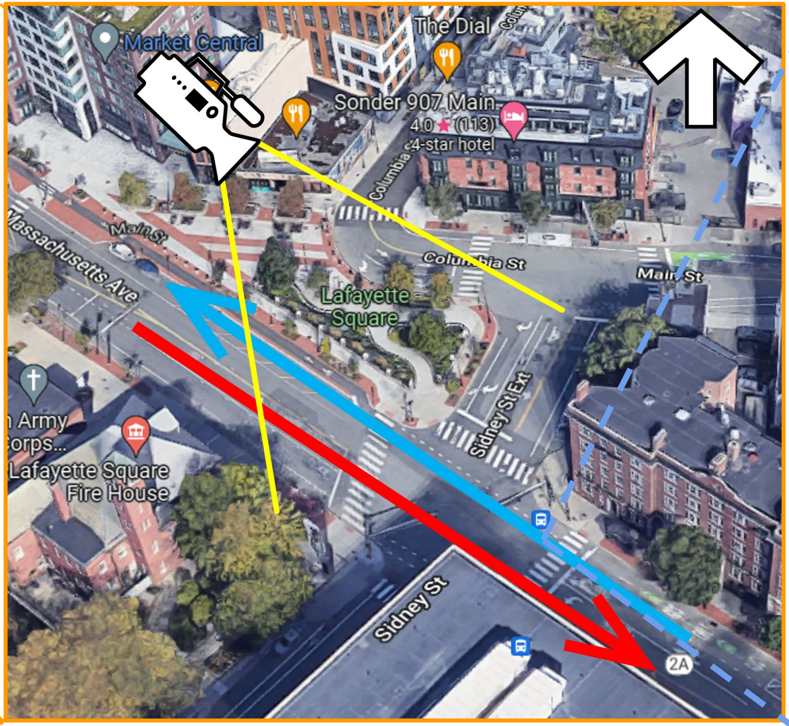
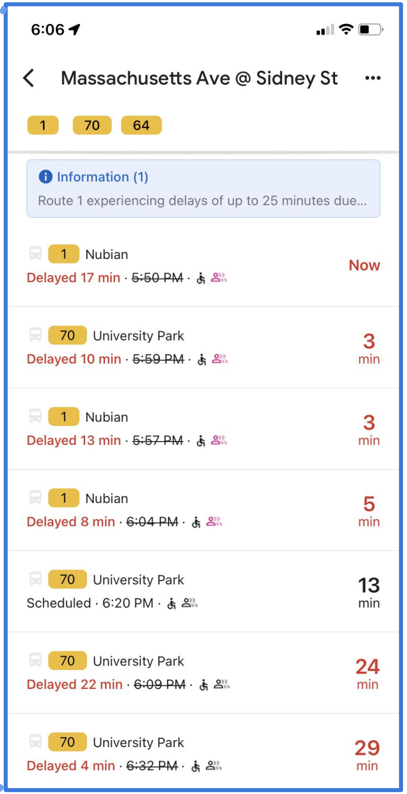
Reliable Arrival Time Prediction is Challenging



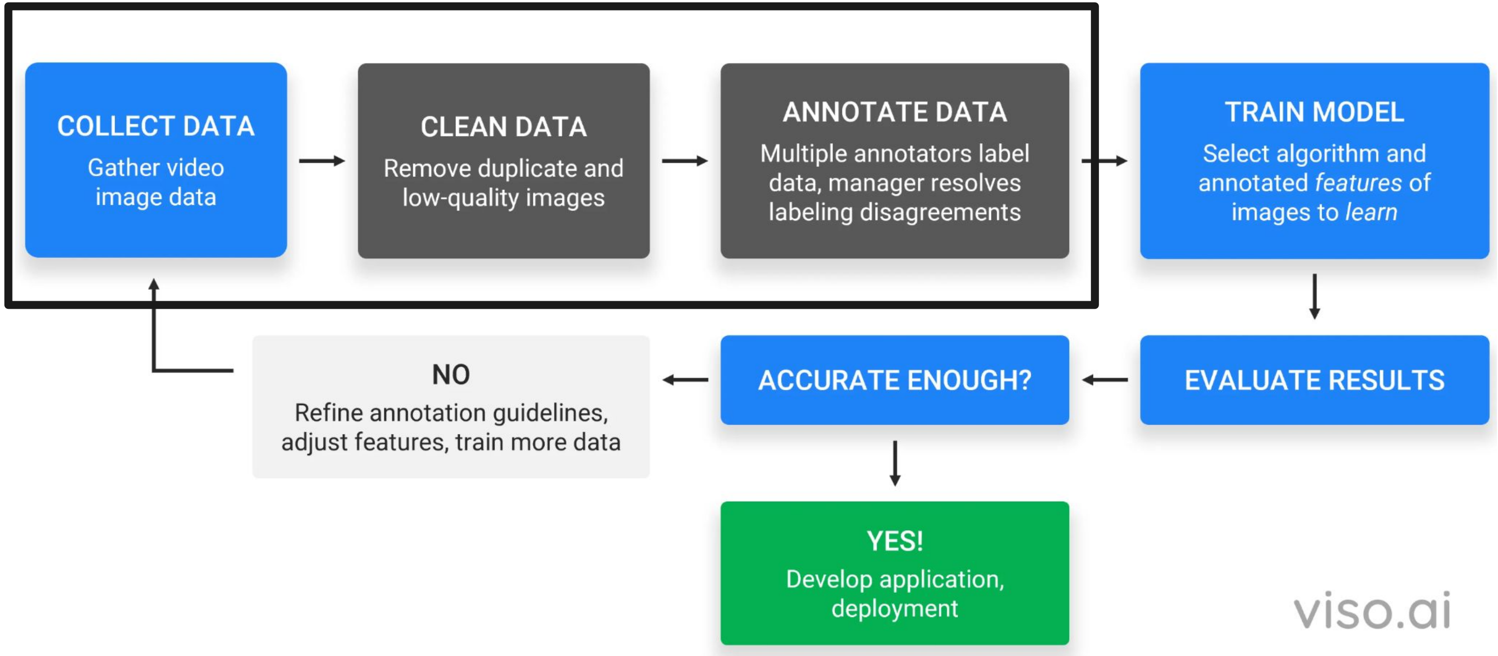
Mass Ave, Route 1, Central Square

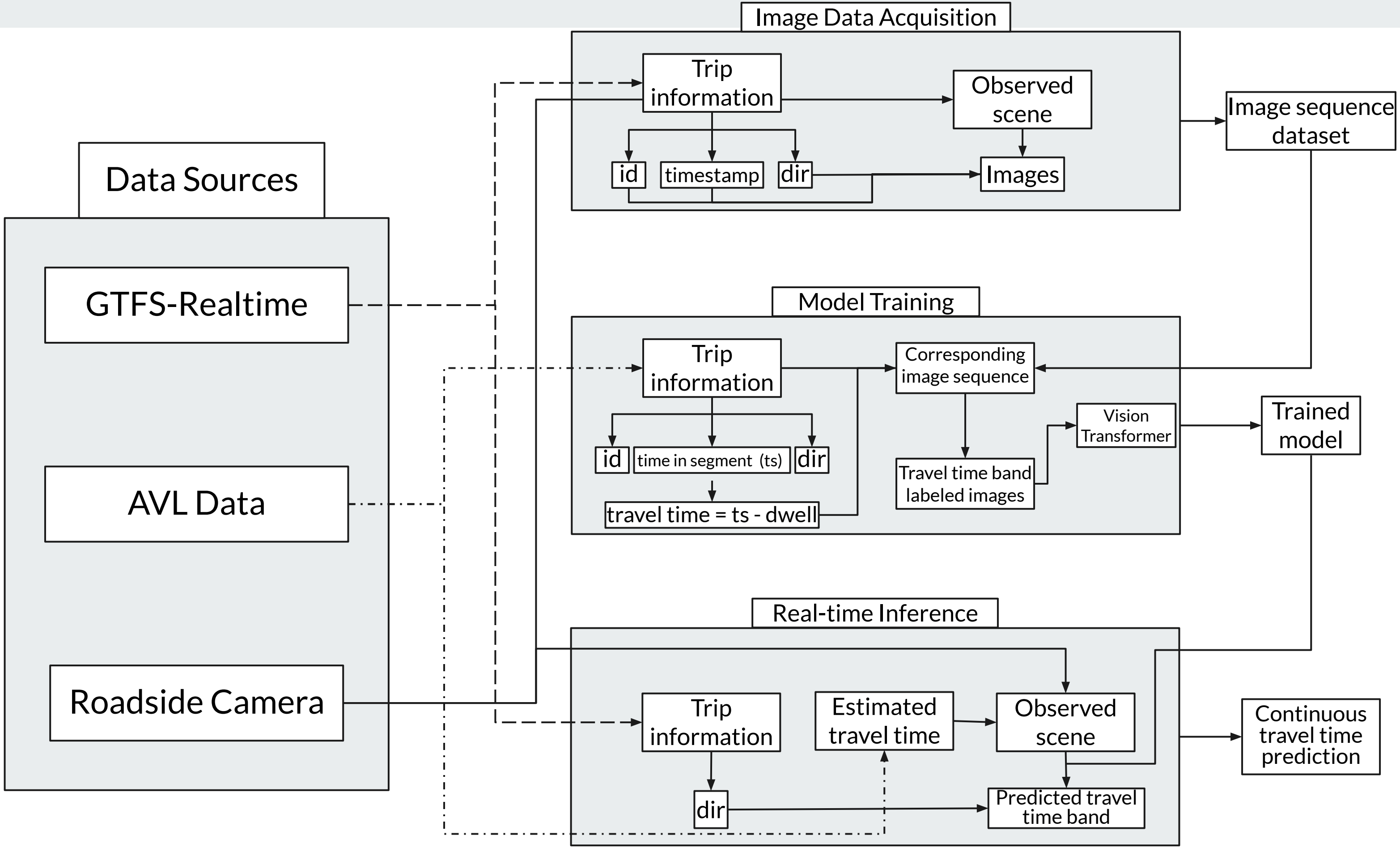






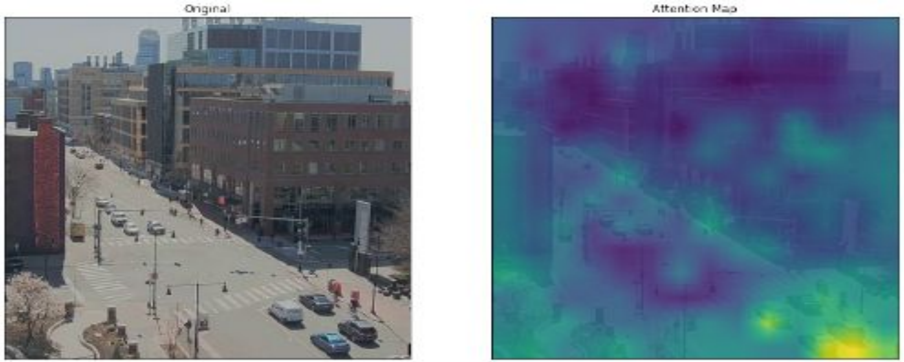
Transit Advantage: Comprehensive data sources
Gap: Functional integration for vision applications



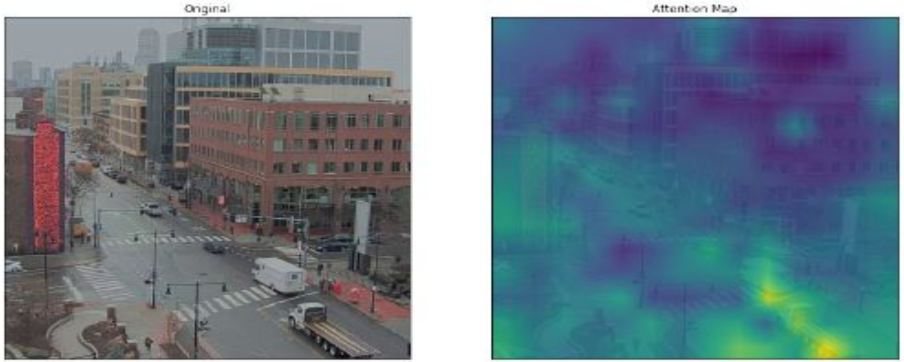


Data Sources
GTFS-Realtime
AVL Data
Roadside Camera
Image Data Acquisition
Trip information
Observed scene
id
timestamp
dir
Images
Image sequence dataset
Model Training
Trip information
Corresponding image sequence
id
time in segment (ts)
dir
travel time = ts - dwell
Travel time band labeled images
Vision Transformer
Trained model
Real-time Inference
Trip information
Estimated travel time
Observed scene
dir
Predicted travel time band
Continuous travel time prediction

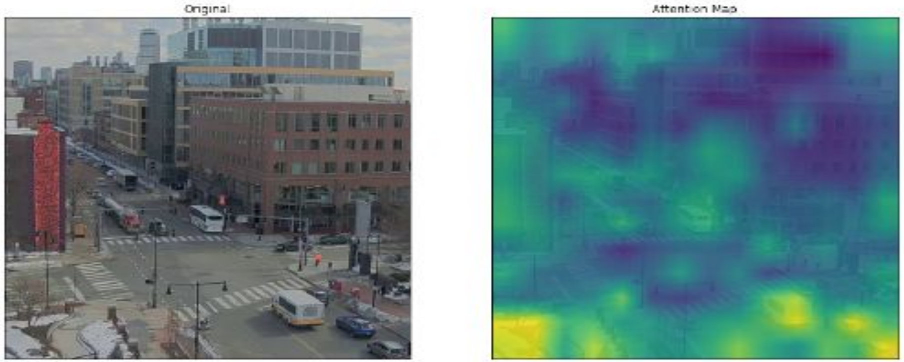
Learning to “See” Potential Causes of Delay



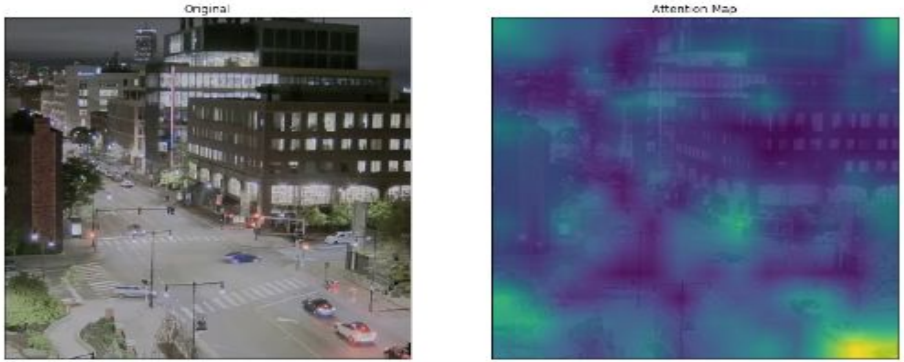
(a) Normal.



(b) Rain.



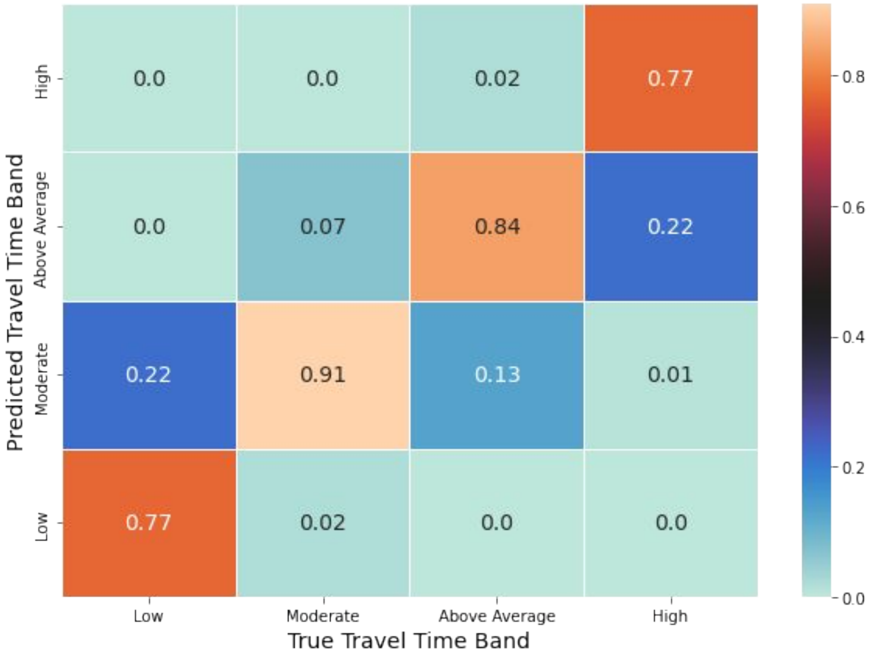
(c) Snow.



(d) Night.

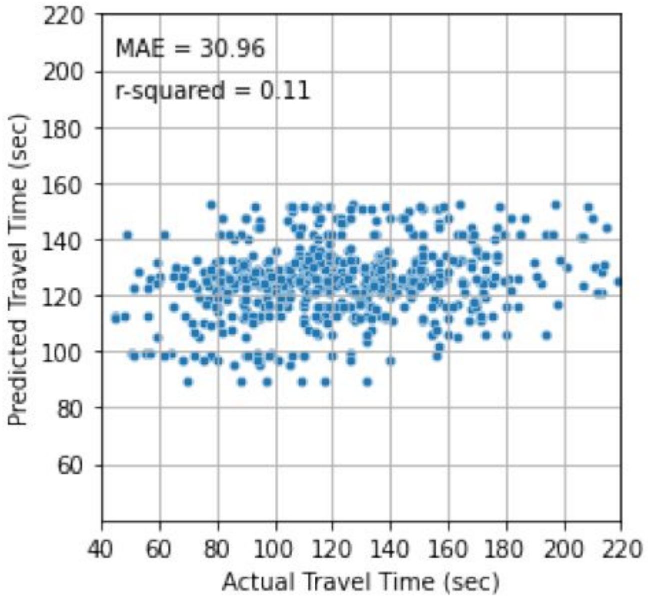
Learning to “See” Potential Causes of Delay

Class	Inbound				Outbound			
	Prc	Recall	F-1	Support	Prc	Recall	F-1	Support
Low	0.93	0.77	0.84	201	0.94	0.76	0.84	213
Moderate	0.83	0.91	0.87	539	0.83	0.89	0.86	557
Above Average	0.81	0.84	0.82	396	0.78	0.87	0.82	433
High	0.94	0.77	0.85	193	0.95	0.73	0.83	199
Accuracy	**0.85**				**0.84**			



Preprint available at: https://arxiv.org/abs/2211.12322

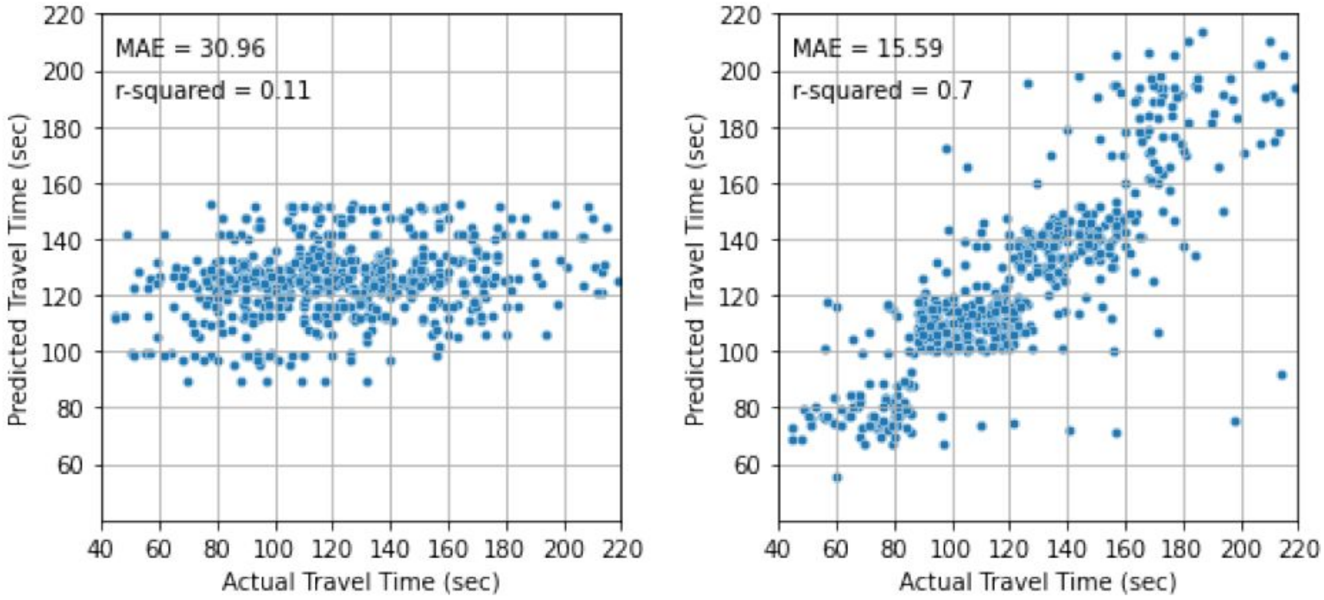
Learning to “See” Potential Causes of Delay



(a) AVL-based linear regression.

Preprint available at: https://arxiv.org/abs/2211.12322

Learning to “See” Potential Causes of Delay



(a) AVL-based linear regression.

(b) With image-based state prediction.

Preprint available at: https://arxiv.org/abs/2211.12322

Other Potential Use Cases

Monitoring

Natural Language Models for Customer Feedback Intelligence

Michael Leong

JTL URBAN MOBILITY LAB AT MIT

Transit Lab

MIT Mobility Initiative

What happens when customers give feedback to transit agencies?

Current Case

- Unstructured Data (text)
- Manually processed, treated as individual tasks
- Difficult to discern areas of concern or trends over time

Aspirational Case

- Quantifiable data (statistics)
- Automatically identify & interpret anomalies and trends
- Proactive system monitoring and customer intelligence

How can we quantify, interpret, and monitor customer feedback?

Tony @_tonymm · Apr 12

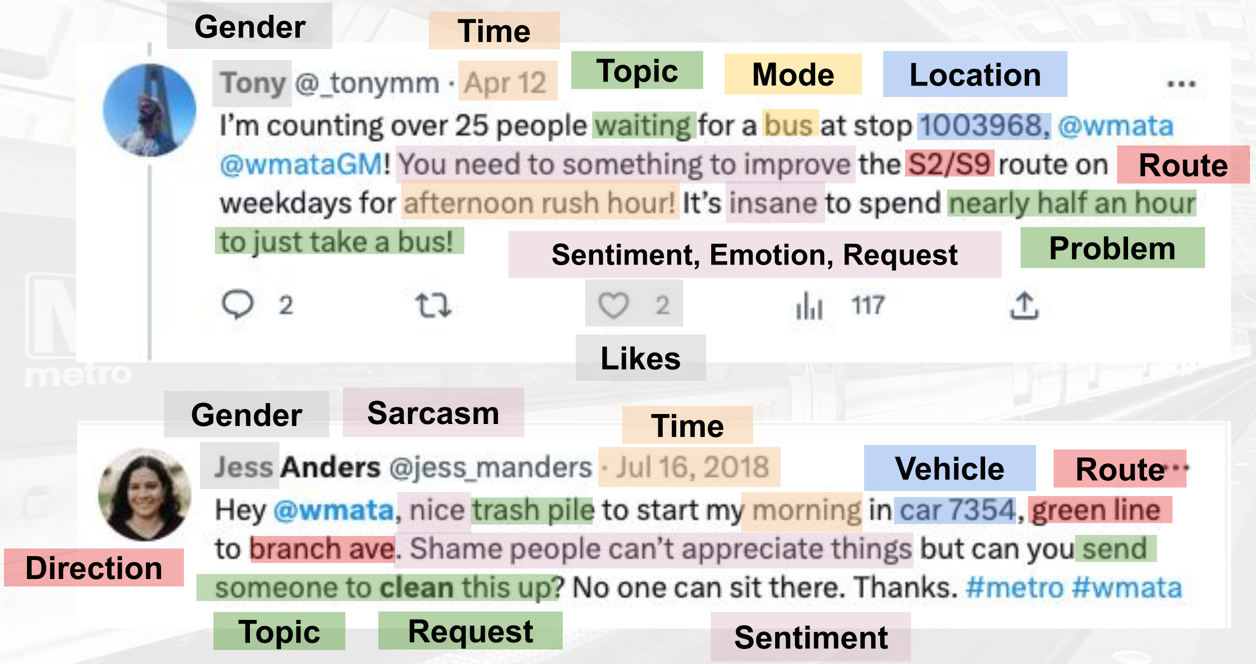
I'm counting over 25 people waiting for a bus at stop 1003968, @wmata @wmataGM! You need to something to improve the S2/S9 route on weekdays for afternoon rush hour! It's insane to spend nearly half an hour to just take a bus!

2 · 2 · 117

Jess Anders @jess_manders · Jul 16, 2018

Hey @wmata, nice trash pile to start my morning in car 7354, green line to branch ave. Shame people can't appreciate things but can you send someone to **clean** this up? No one can sit there. Thanks. #metro #wmata

How can we quantify, interpret, and monitor customer feedback?



Mode: Bus
Route: S2, S9
Location: Stop 1003968
Time: 4/12/2023 6:48pm
Topic: Operations, Delays
Sentiment: Negative
Emotion: Angry
Gender: Male

Mode: Train
Route: Green Line (Branch Ave)
Vehicle: Car 7354
Time: 7/16/2018 8:03am
Topic: Cleanliness, Maintenance
Sarcasm: Present
Sentiment: Negative
Gender: Female

How can we quantify, interpret, and monitor customer feedback?

Customer Relationship Management (CRM)

Twitter & Social Media

Classification

my | train | ride | was | smooth!

Identifying Features: Unigram / N-Gram Models

- **Mode** Bus, Train, Paratransit, Parking
- **Location**
- **Vehicles/Assets**
- **Route**
- **Gender** Similarity Match from Database of 84,000+ Names

my train ride was smooth!

Uncovering Meaning: Masked Language Models

- **Sentiment** +, 0, -
- **Sarcasm**
- **Topic** *In-House BERT Model to Classify:* Operations/Delays, Customer Service, Cleanliness/Maintenance, Information Provision, Crime/Safety, Suggestions, General, Crowding, Cards/Fares

How can we quantify, interpret, and monitor customer feedback?

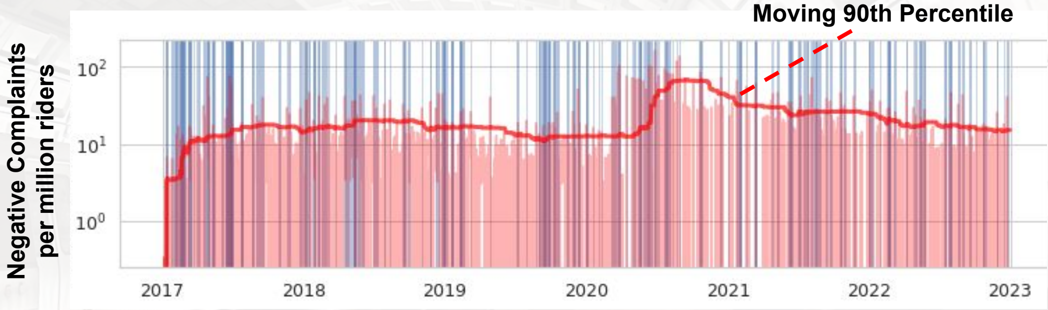
Customer Relationship Management (CRM)

Twitter & Social Media

Classification

Routing to Departments

Analysis



Proactive Monitoring

When should we sound the alarm on issues detected on live feedback trends?

Trends & Policy Analysis

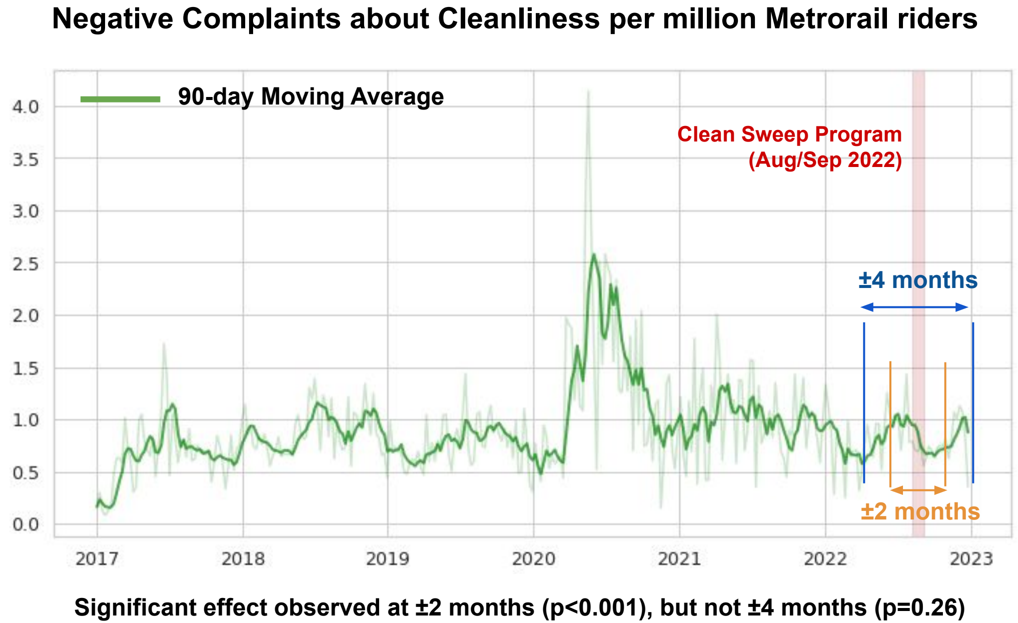
Did specific initiatives lead to changes in feedback and sentiment? How are specific routes performing on a quarterly basis?

Did a Deep Cleaning Initiative lead to less complaints about cleanliness?

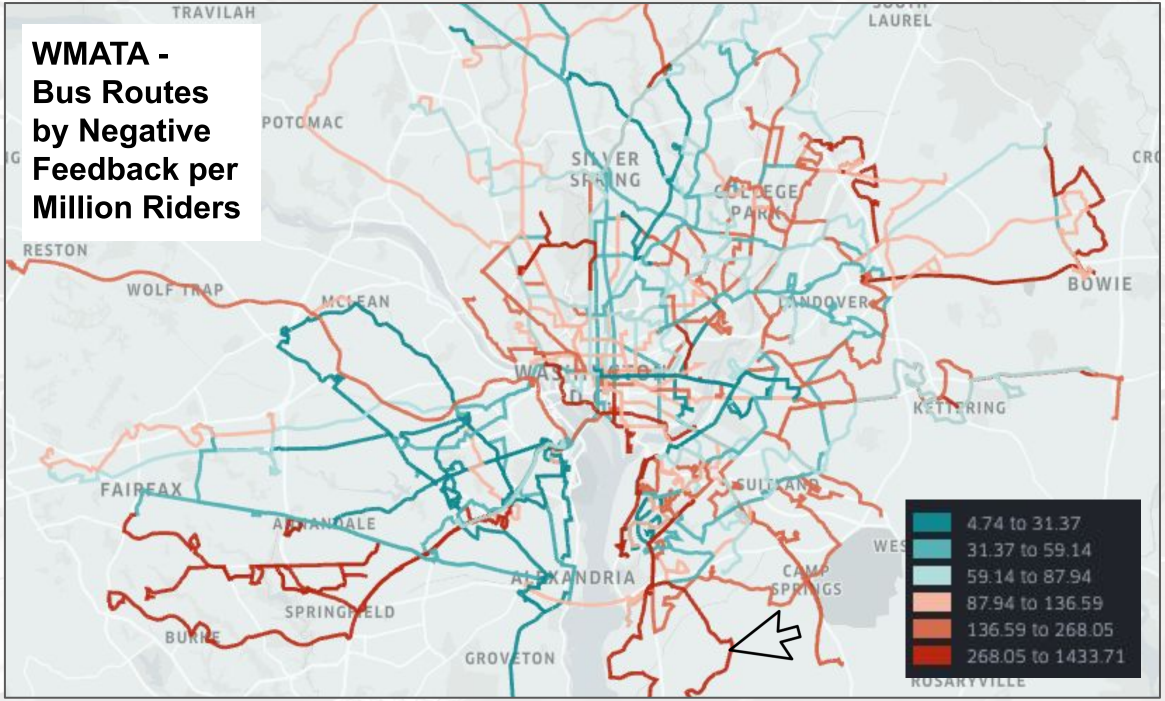
Metro Forward
@wmata

We've recently kicked off Metro's Clean Sweep 🧹. Teams are heading to every Metrorail station to deep clean, repaint, and update light fixtures, so you can enjoy a safer and more comfortable experience. Share a pic when your station gets spruced up! #wmata #yourmetro

5:59 PM · Sep 7, 2022



Which bus routes have the highest amounts of negative feedback per rider?



Bus W14: 362 Complaints / Million Riders

What are the main causes of complaints?

- Buses have been late or did not show up altogether, leading to unreliable service
- Bus drivers turn around midway, do not serve the correct stop, leave passengers behind, or do not follow the scheduled route

What are the impacts to customers?

- Challenges with planning day-to-day activities, including getting to work on time
- Loss of pay due to questionable punctuality
- Need to use expensive ride-hailing services when the bus does not arrive
- Lack of weekend service forces customers to look for alternative transportation

What did customers suggest WMATA do?

- Improve scheduling and service reliability
- Improve communication regarding delays and route changes

How can we use unstructured data to improve transit operations?

Many other data sources, such as **surveys**, **logs**, and **incident reports**, exist in unstructured form

---

Existing Measures

- Frequency/LOS, Accessibility, On-Time Performance, Completed Trips, Speed, etc.
- Absolute and Numerical
- Limited Understanding of Customer Experience in a statistically significant way

↔

…Future Measures?

- Capture abstract (perceptual, emotional) side of travel
- Quantify soft metrics beyond numbers and distances
- Towards more responsive transit operations & planning

AI and Public Transit

Zone	Topic	Presenter
Introduction	Introduction	Jinhua Zhao
ZONE 1 Demand	Deep Hybrid Model: Urban Imagery for Demand Analysis	Qingyi Wang
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Future	Future Projects	Jinhua Zhao

U.S. DEPARTMENT OF ENERGY

Massachusetts Institute of Technology

Transit-Centric Smart Mobility System: Improving Energy Efficiency through Machine Learning

JTL URBAN MOBILITY LAB AT MIT

Transit Lab

MIT Mobility Initiative

Transit-Centric Smart Mobility System: Improving Energy Efficiency through Machine Learning

1. Designing a Transit-Centric Smart Mobility System (TSMS) that is adaptive to changing demand patterns, resilient to system disruptions, and responsive to real-time conditions.
2. Building the Integrated TSMS with the state-of-the-art technology, including robust optimization (RO), reinforcement learning (RL), and deep learning (DL)
3. Deploying operations control and demand predictions in real-world experiments (Chicago and Boston) and large-scale simulations.

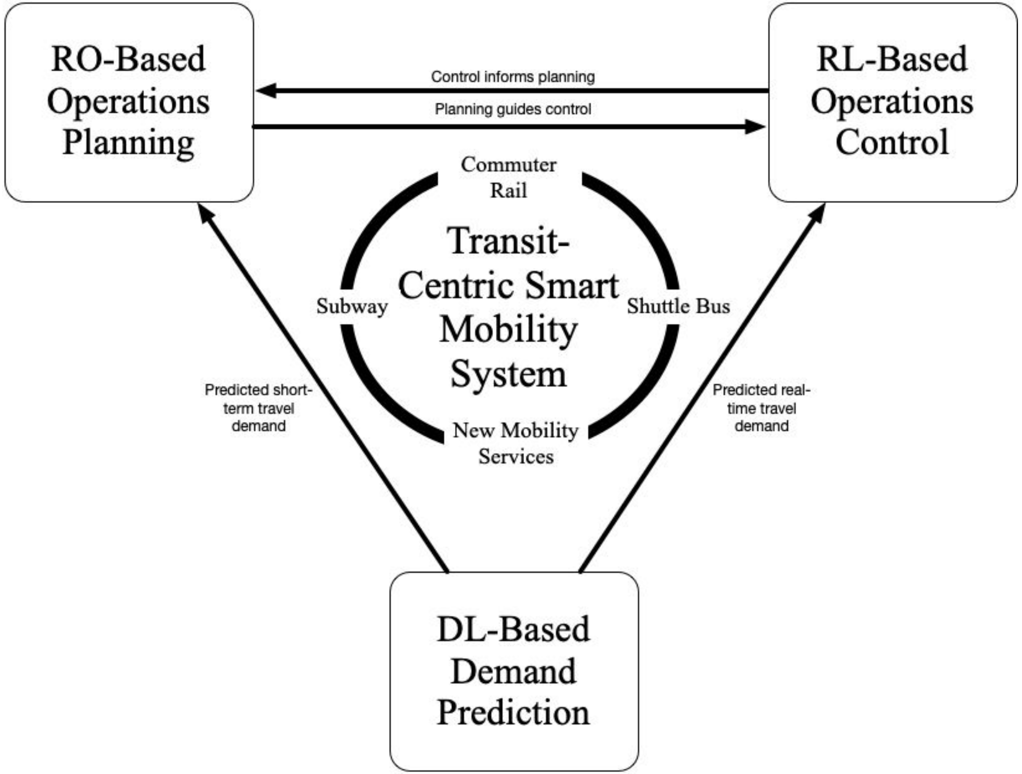


Figure 1. Diagram of the project framework

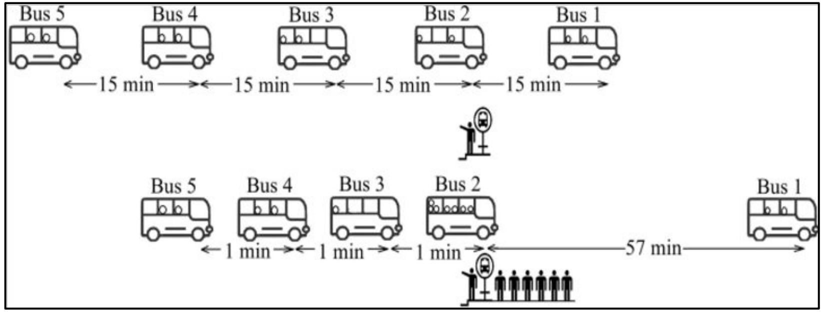
Control

Cooperative Stop-Holding: A Deep Reinforcement Learning Framework

Joseph Rodriguez

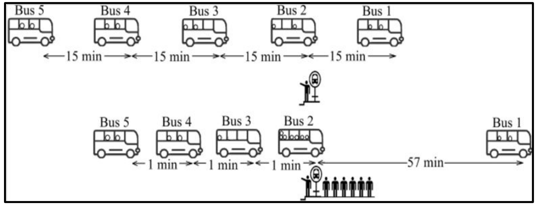
JTL URBAN MOBILITY LAB AT MIT
Transit Lab
MIT Mobility Initiative

Motivation: Bus bunching



Motivation

Problem → **Strategies** → **Bus Control Criteria**



Bus service prone to bunching is:
- ➔ Unreliable
- ➔ Delayed
- ➔ Overcrowded
- ➔ Requires over-budgeted time

Corrective actions for even spacing include:
- ➔ Holding
- ➔ Skipping

Bus Control Criteria:

Decision Rules
: Ignores uncertainties

Optimization
: Trade-offs between prediction horizon and computational complexity

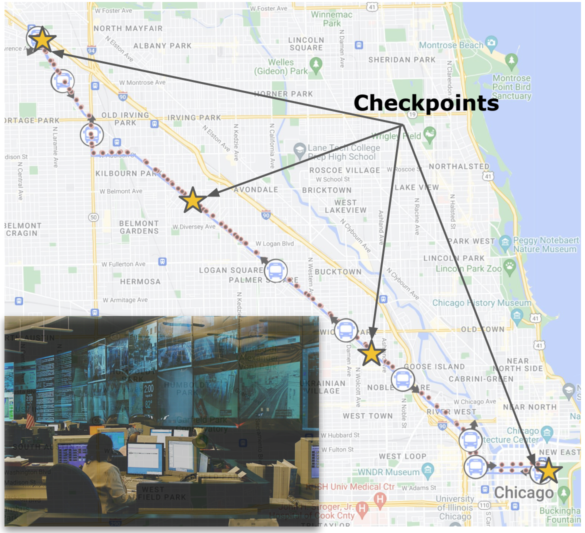
Reinforcement Learning
: Predicted best actions based on simulated experience

“Best actions” maximize long-term expected reward

(Under review) Rodriguez, J and Koutsopoulos, H.N. and Wang, S. and Zhao, J., Cooperative Bus Holding and Stop-Skipping: A Deep Reinforcement Learning Framework.

Motivation

Control of Fixed-route Bus Ops



Properties:

- Event-triggered control (e.g., stop arrival)
- Sparse interventions
- Delayed rewards

Multiagent Reinforcement Learning

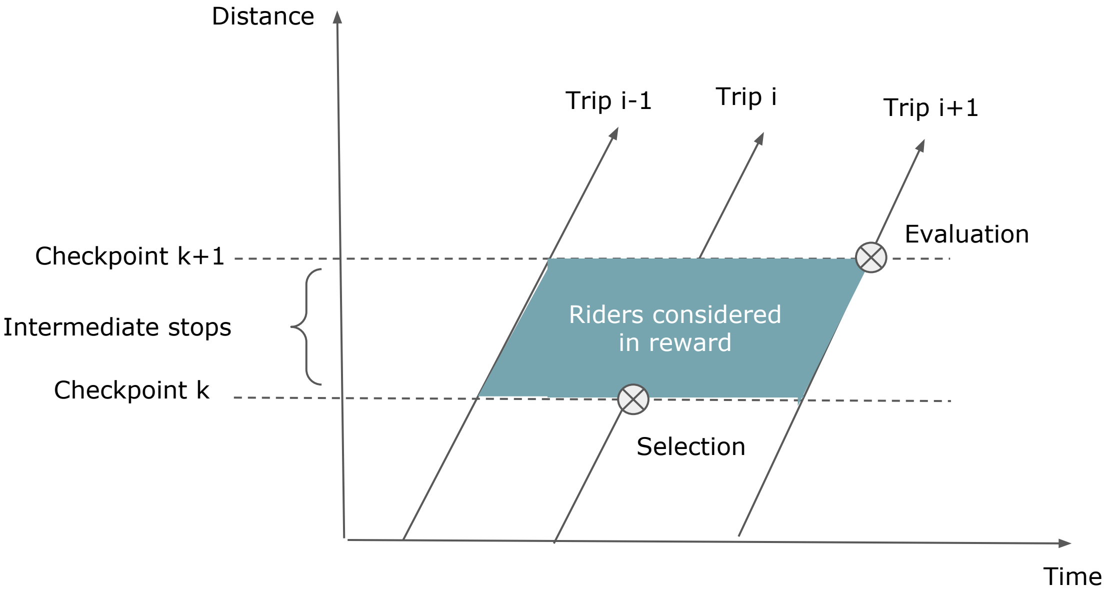
Execution	Centralized	Decentralized	
Training	Centralized	Centralized	Decentralized
Limitations	• Infeasible for event-driven process	• Computational complexity • Equal contribution from each agent	• Individually selfish policies • Noise in global reward signals

Proposed approach: Information sharing with neighbor agents

Methodology

Contributions:

- ★ Maintain **decentralization with shared information** between neighbor agents
- ★ Include **global information** for decision-making: prior N headways, current ridership levels
- ★ **Rider-centric reward**: waiting and riding time
- ★ Supports **hybrid** hold/skip strategies



Observation
(Location, headways, demand)

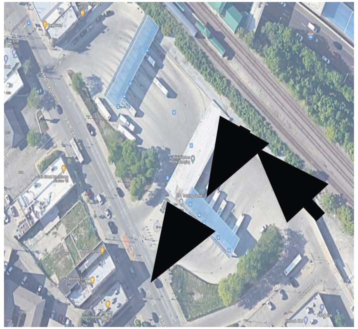
Actions
(Hold 0.5min-2min, Skipping, None)

Reward
Waiting time + Riding time

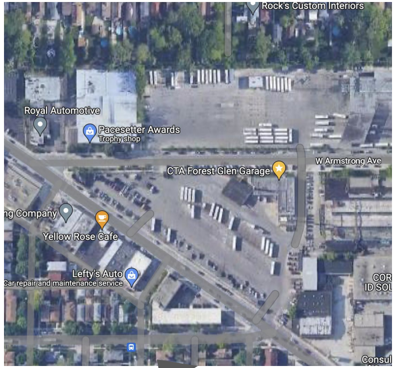
Learning
Independent DDQN with shared policy

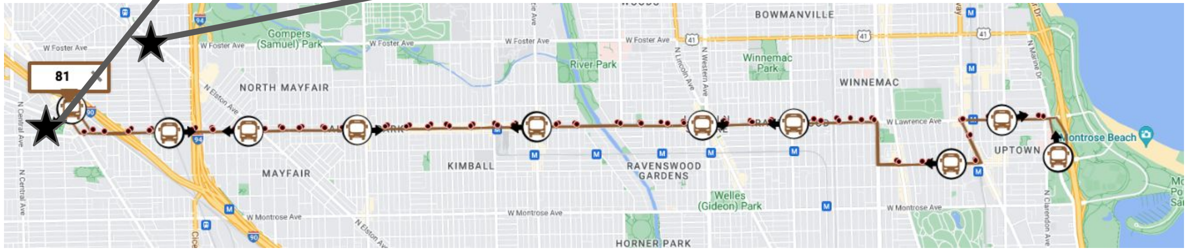
Field implementation: Route 81 (Chicago)

Terminal: Jefferson Park, serves 10 routes



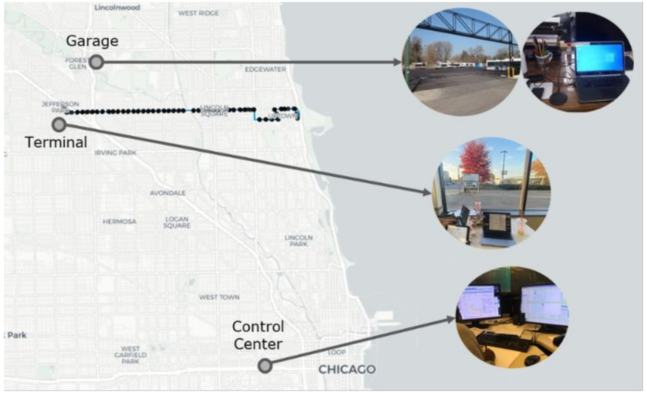
Garage: Forest Glen, North Chicago routes





Implementation details

- ➔ One week: October 17-21, 2022
- ➔ AM and PM peak periods
- ➔ Researchers+staff at 3 key locations



Field trial: Effectiveness

Stakeholder				Metric	Improvement
Riders	Drivers	Agencies	City		
✓				Average excess wait time	37%*
✓	✓			90th percentile loads	Up to 20%
✓				90th percentile headways	Up to 40%
	✓	✓		90th percentile cycle times	2.4%
			✓	MEP score	6%

***Wait time reduction by 37% is equivalent to adding two bus trips**

AI and Public Transit

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Ethics

Algorithmic Fairness in Travel Behavior Prediction

Yunhan Zheng

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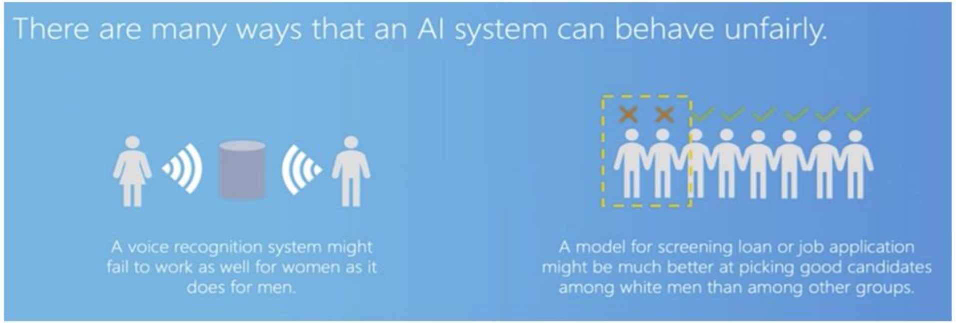
Background: fairness in machine learning

Minority homebuyers face widespread statistical lending discrimination, study finds

NOVEMBER 13, 2018 | BY LAURA COUNTS

Both online and face-to-face mortgage lenders charge higher interest rates to black and Latino borrowers, costing those homebuyers up to half a billion dollars more in interest every year than white borrowers with comparable credit scores, researchers at UC Berkeley have found.



MACHINE BIAS

Facebook Ads Can Still Discriminate Against Women and Older Workers, Despite a Civil Rights Settlement

The company used Facebook's new special ads portal, which doesn't allow targeting by gender, age, race or ethnicity. That was fine with Dolese. While its drivers tend to be men, the company has no gender preference. "The gals we have in our group are fabulous," Frank said. "We'd take any and all of them we could ever get."

By the time the ad stopped running ten days later, more than 20,000 people had seen it. Eighty-seven percent of them were men.

Sources:
https://www.propublica.org/article/facebook-ads-can-still-discriminate-against-women-and-older-workers-despite-a-civil-rights-settlement
https://newsroom.haas.berkeley.edu/minority-homebuyers-face-widespread-statistical-lending-discrimination-study-finds/

Fairness Metric: Equality of Opportunity in ML

- "Equality of opportunity" in machine learning (ML):
  - The predicted outcome (e.g. travel behavior) needs to be conditionally independent of the sensitive attributes given that the actual outcome is positive
- Two groups should have comparable false negative rates:

$$\boxed{False\ Negative\ Rate\ (FNR)\ Gap = \frac{FN_{z=0}}{TP_{z=0} + FN_{z=0}} - \frac{FN_{z=1}}{TP_{z=1} + FN_{z=1}}}$$

Note:

- $z = 0$ represents the disadvantaged group
- For the FNR gap, a lower absolute value is preferred

Prediction Disparities in Travel Behavior Modeling (using NHTS data)

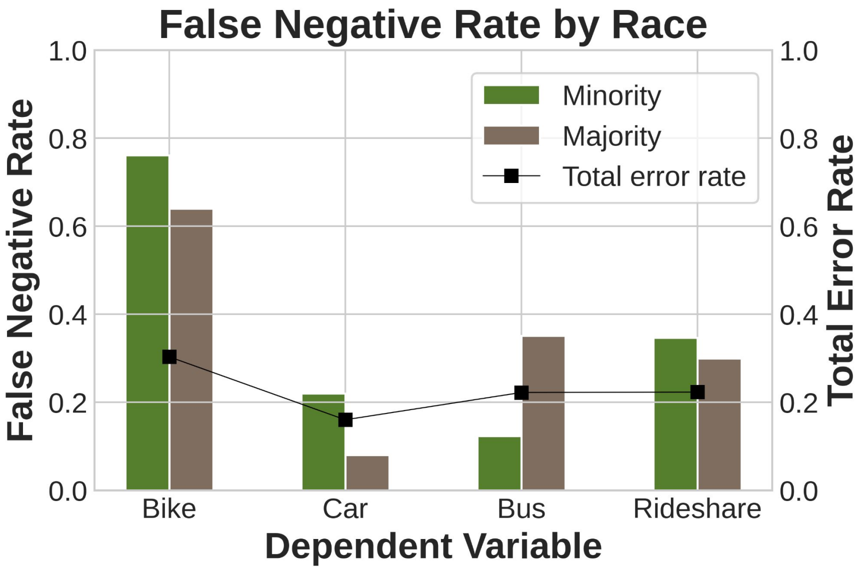


Figure (a). Racial disparity in prediction using binary logistic regression (BLR)

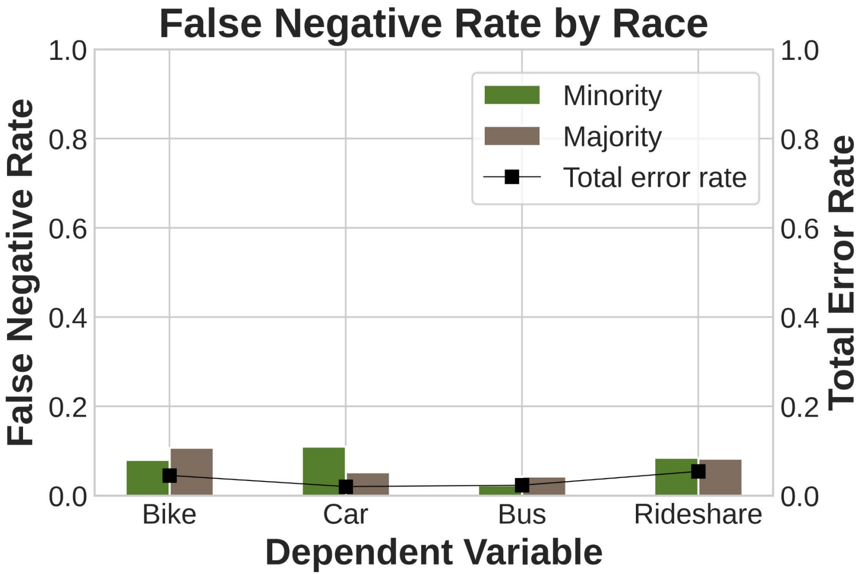


Figure (b). Racial disparity in prediction using deep neural network (DNN)

- DNN generally outperforms BLR in terms of both accuracy and fairness.
- However, even with DNN, the prediction disparities still exist.

Bias Mitigation Method

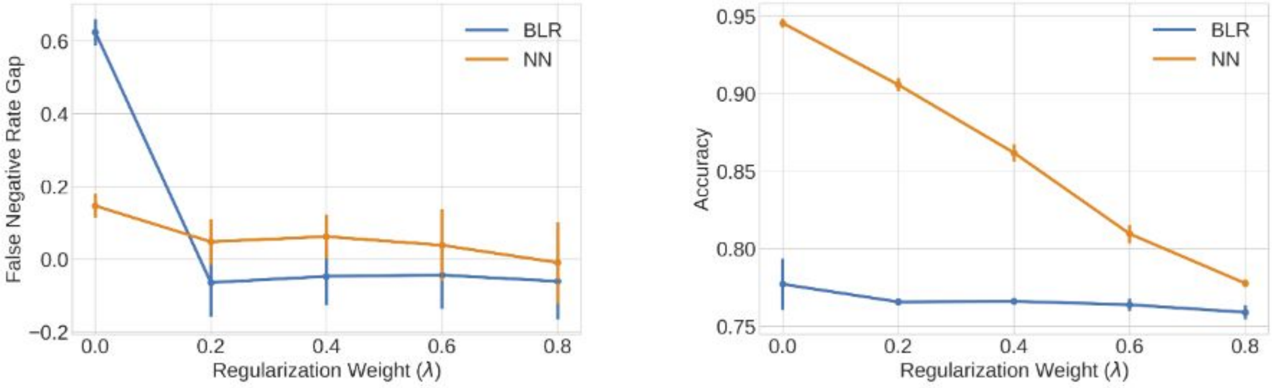
The absolute correlation regularization method

Loss function:

$$\min_{p} \underbrace{\boxed{(1-\lambda)L_{primary}}}_{\text{Accuracy loss}} + \underbrace{\boxed{\lambda|Corr(p(\boldsymbol{x}), z|y=1)|}}_{\text{Fairness loss}}$$

- *p(x)*: predicted probability
- *λ*: the bias mitigation weight
- Correlation loss is used to reduce the FNR gap

Results: Bias Mitigation Results (using NHTS data)



(a) FNR gap vs. Regularization Weight

(b) Accuracy vs. Regularization Weight

Figure 10: Fairness and accuracy by bias mitigation weight (λ): regional bias in the prediction of frequent rideshare usage

- Left figure: FNR declines as the regularization weight increases
- Right figure: accuracy declines as the regularization weight increases
- Implication: There is an accuracy-fairness trade-off when mitigating the bias

Paper available: Zheng, Y., Wang, S., & Zhao, J. (2021). Equality of opportunity in travel behavior prediction with deep neural networks and discrete choice models. *Transportation Research Part C: Emerging Technologies*, *132*, 103410.

AI and Public Transit

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Future/On-going Projects

- Causal analysis with ML
- Generative AI in urban images
- Future of jobs in public transit
- Multi-channel view of cities

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Multi-channel view of cities

Shenhao Wang, Qingyi Wang, Jinhua Zhao

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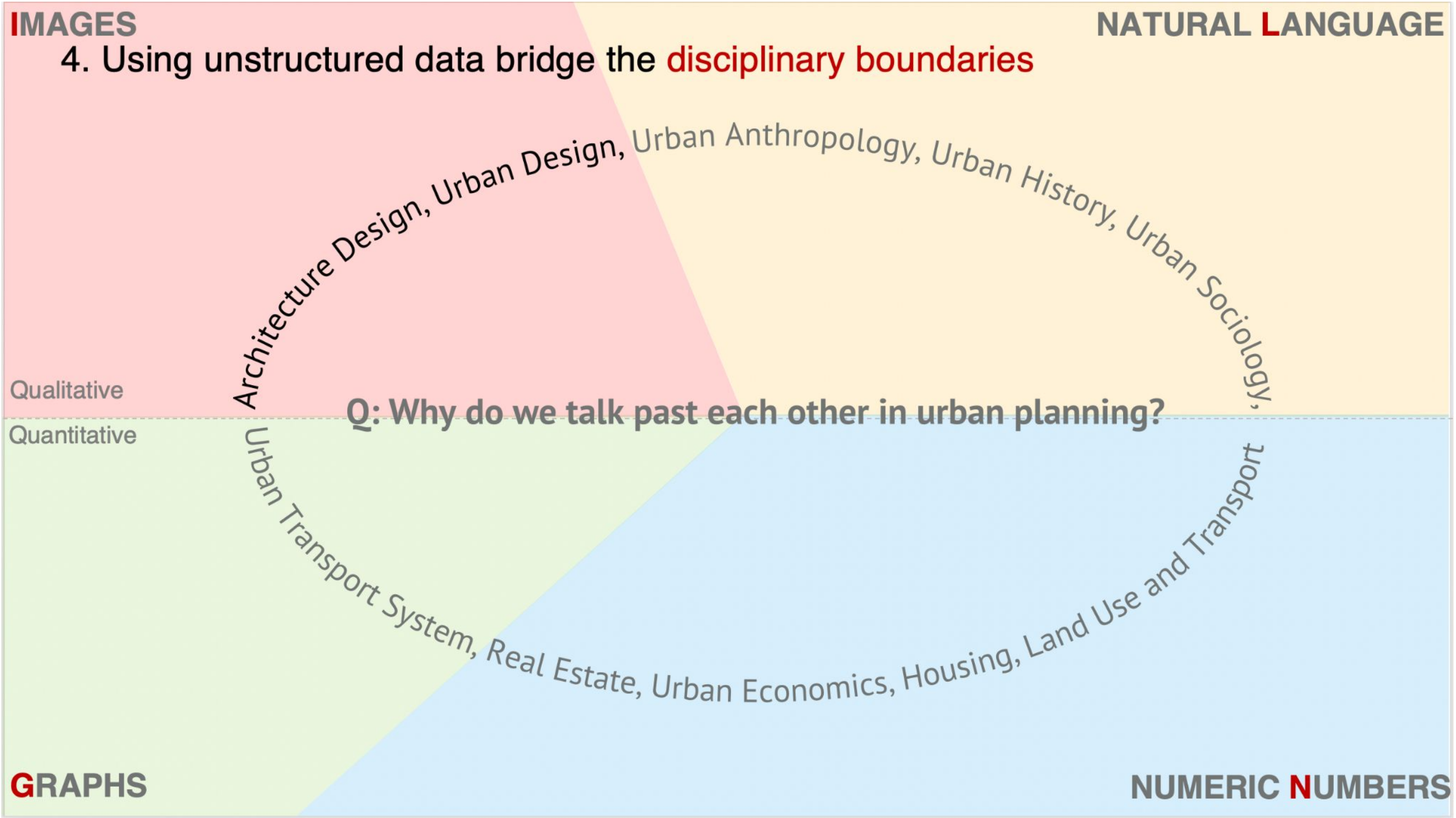
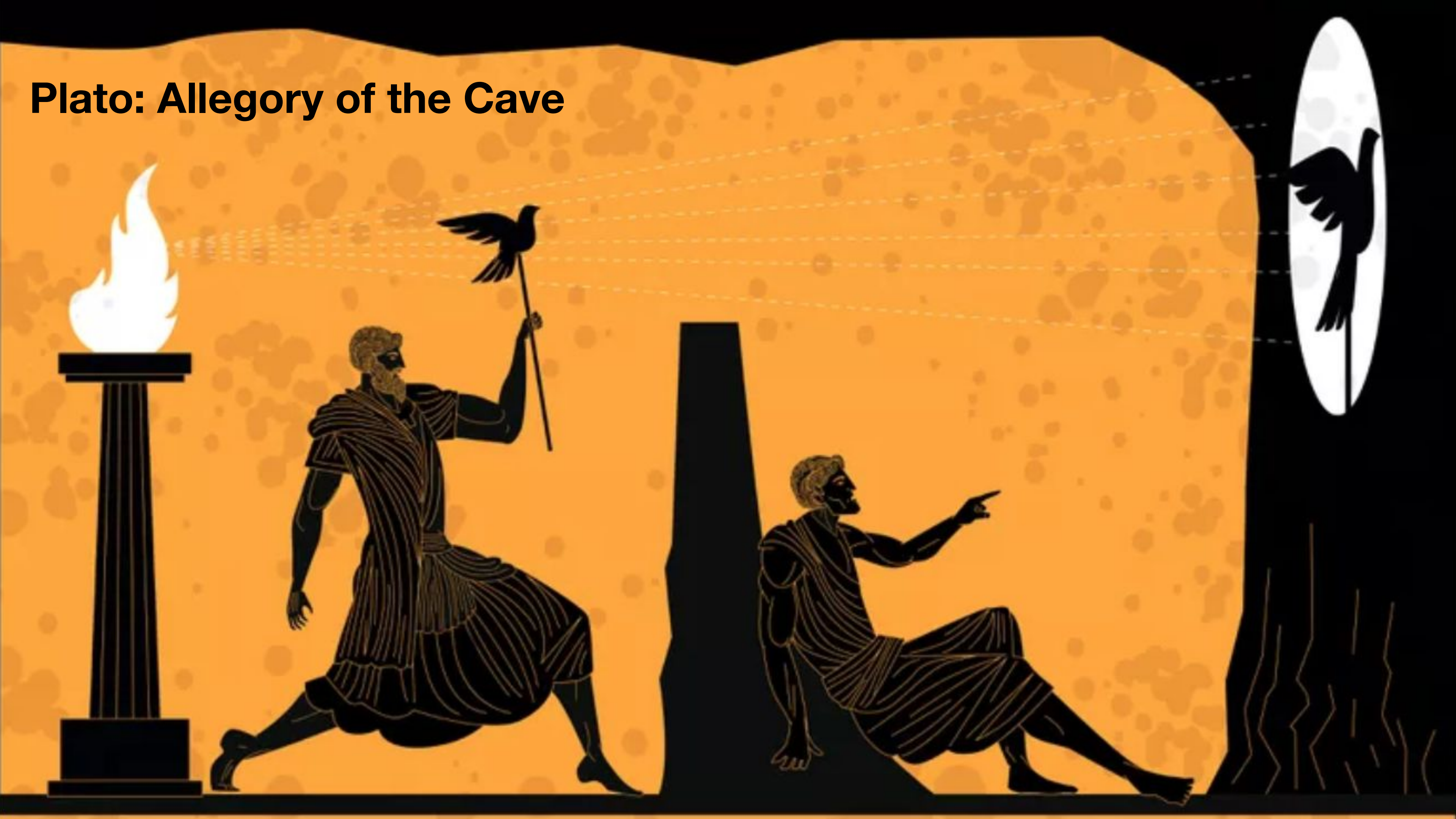
How do we describe cities?

4. Using unstructured data bridge the disciplinary boundaries



Plato: Allegory of the Cave



A multi-channel view city (e.g. Chicago)

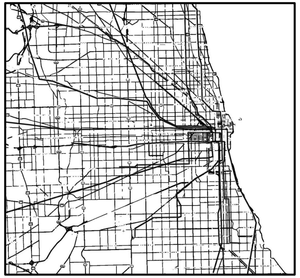
Numeric values

Population : 2,693,976

Auto ownership per HH: 1.12/HH

…

Graphs (Transit and Road)



Images (Aerial or Street-view)

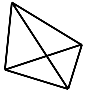
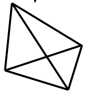
Natural **Languages** (From Wikipedia)

Chicago, officially the City of Chicago, is the most populous city in the U.S. state of Illinois, and the third-most-populous city in the United States. With an estimated population of 2,693,976 in 2019, it is also the most populous city in the Midwestern United States. Chicago is the county seat of Cook County, the second-most-populous county in the US, with a small portion of the northwest side of the city extending into DuPage County near O'Hare …

DNN: a unified framework for Graphs, Language, Images and Numbers

$$P(y_i|x_i) = f(x_i)$$

Images Graph

$P(y_i|x_i,$ , We love Chicago ,  $) = f(x_i,$ , We love Chicago ,  $)$ **[GLIN]**

Numbers Language

DNN provides a unified framework to process GLIN.

Allegory of the Cities

cities projected to **graph**

cities projected to **image**

cities projected to natural **language**

cities projected to **numbers**

IMAGES | **NATURAL LANGUAGE**

4. Using unstructured data bridge the disciplinary boundaries

Architecture Design, Urban Design, Urban Anthropology, Urban History, Urban Sociology,

Qualitative

Q: Why do we talk past each other in urban planning?

Quantitative

Urban Transport System, Real Estate, Urban Economics, Housing, Land Use and Transport

GRAPHS | **NUMERIC NUMBERS**

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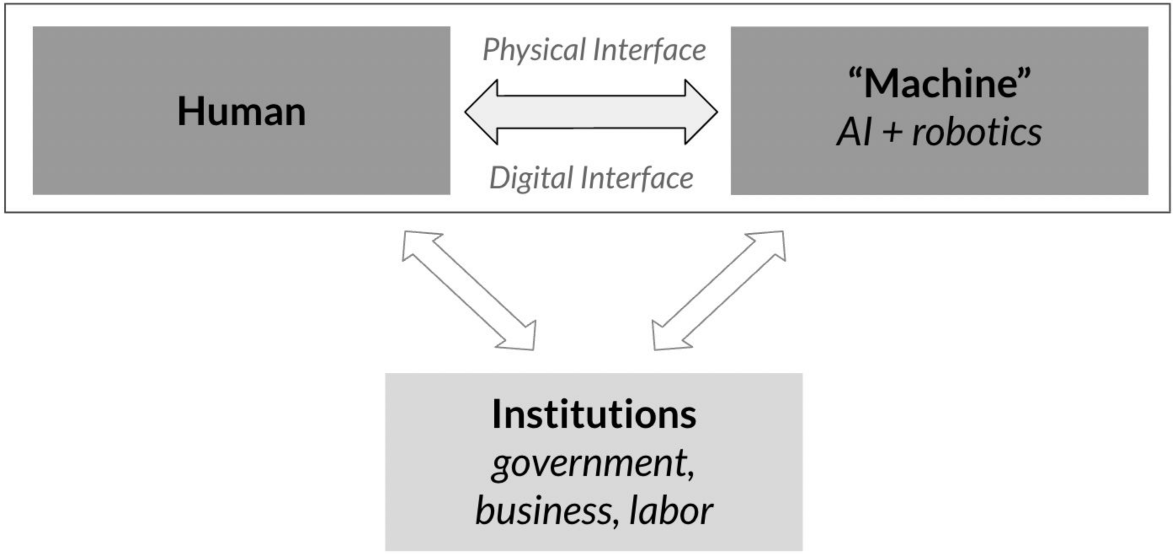
Mens, Manus and Machina:
How AI Empowers People, Institutions and the City in Singapore

Image credit: Forbes

Mens, Manus and Machina: How AI Empowers People, Institutions and the City



A.I. and Public Transit

Prof. Jinhua Zhao

With Shenhao Wang, Haris N. Koutsopoulos, Nigel Wilson, Joseph Rodriguez, Qingyi Wang, Dingyi Zhuang, Baichuan Mo, Awad Abdelhalim, Michael Leong, Yunhan Zheng, and Anson Stewart

MIT Mobility Forum

May 5, 2023

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