Part I Related Research


Part II News Article

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 Abdelhalim]
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
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
If interested,
Public Transit Analytic Functions

Supply
- AVL
- Service Management, Operations Control

Real-Time Functions
- Individualized Customer Information

Off-line Functions
- Performance Measurement
- Service/Operations Planning
- Land use, employment Urban activities

Transit Analytics
- Monitoring, Evaluation, Prediction

Demand
- AFC, APC Client-side apps
MIT Transit Lab Research Areas

Performance
- OD inference
- Demand and ridership
- Left behind
- Capacity analysis
- Platform crowding
- Passenger to train assignment
- Service reliability

Behavior
- Customer segmentation
- Disruption analysis
- Crowding on route choice
- Information provision
- Passes and fares

Decision Support
- TDM
- Real-time prediction
- Transit simulation
- Inference and transit assignment
- Operations control
- Crew scheduling and labor
- Accessibility analysis
- Network planning
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)
A.I. Applications in Public Transport

Short-Term Decisions
- Reinforcement Learning for Real-Time Bus Control (Joseph Rodriguez, Ao Qu et al)
- Bus and Train Dispatching during Service Disruptions

Structured Data
- Unsupervised Clustering for Describing Travel Patterns (Gabriel Goulet et al)
- Predicting Travel Patterns (Peyman Noursalehi, Zhan Zhao, Baichuan Mo et al)
- ML for Causal Inference (Yunhan Zheng)

Unstructured Data
- Computer Vision for System Monitoring (Awad Abdelhalim)
- Natural Language Models for Customer Feedback Intelligence (Michael Leong et al)

Long-Term Decisions
- Future of Jobs
- Human-AI-City Relationship

Demand & Policy
- Deep Neural Networks and Hybrid Models for Demand Prediction (Shenhao Wang, Qingyi Wang, Dingyi Zhuang et al)
- Multi-Channel View of Cities
- Generative AI for Visionary Cities

Monitoring
- Control
Deep Hybrid Model: Urban Imagery for Demand Analysis

Deep Hybrid Model: Graph Embedded Urban Road Network

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Future Projects
Deep Hybrid Models:
Urban Imagery for Demand Analysis

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

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

Uniqueness of deep learning lies in its ability to digest unstructured data.
Research gap: the lack of **unstructured data** in demand analysis

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

Studies have shown that imagery is predictive of socio-demographic indicators.
Deep Hybrid Models: Combining unstructured data with numerical data

Image (input) → Encoder → Latent Space → Decoder → Travel Behavior

Numerical Data (Ind + Social Vars) → Reconstruction
Images and socio-demographics contain complementary information.
Economic interpretation of existing and generated images
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

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Metrics R^2</th>
<th>Baseline model</th>
<th>Graph embedded model</th>
<th>Improvement</th>
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<tbody>
<tr>
<td>Public transit mode share</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>In-sample</td>
<td>0.387</td>
<td>0.690</td>
<td></td>
<td>78%</td>
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<tr>
<td>Out-of-sample</td>
<td>0.450</td>
<td>0.561</td>
<td></td>
<td>24%</td>
</tr>
<tr>
<td>Income per capita</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>In-sample</td>
<td>0.504</td>
<td>0.843</td>
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<td>67%</td>
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<tr>
<td>Out-of-sample</td>
<td>0.532</td>
<td>0.794</td>
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<td>49%</td>
</tr>
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</table>
Deep Hybrid Model: Urban Imagery for Demand Analysis

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Future Projects
Computer Vision for Transit Travel Time Prediction

Awad Abdelhalim
Reliable Arrival Time Prediction is Challenging

<table>
<thead>
<tr>
<th>Route</th>
<th>Next Stop</th>
<th>Delayed</th>
<th>Time</th>
<th>Status</th>
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<tbody>
<tr>
<td>1</td>
<td>Nubian</td>
<td>17 min</td>
<td>6:50 PM</td>
<td>Delayed</td>
</tr>
<tr>
<td>70</td>
<td>University Park</td>
<td>10 min</td>
<td>6:59 PM</td>
<td>Delayed</td>
</tr>
<tr>
<td>1</td>
<td>Nubian</td>
<td>13 min</td>
<td>6:57 PM</td>
<td>Delayed</td>
</tr>
<tr>
<td>1</td>
<td>Nubian</td>
<td>8 min</td>
<td>6:04 PM</td>
<td>Delayed</td>
</tr>
<tr>
<td>70</td>
<td>University Park</td>
<td>-</td>
<td>6:20 PM</td>
<td>Scheduled</td>
</tr>
<tr>
<td>70</td>
<td>University Park</td>
<td>22 min</td>
<td>6:09 PM</td>
<td>Delayed</td>
</tr>
<tr>
<td>70</td>
<td>University Park</td>
<td>4 min</td>
<td>6:32 PM</td>
<td>Delayed</td>
</tr>
</tbody>
</table>
Mass Ave, Route 1, Central Square
Transit Advantage: Comprehensive data sources
Gap: Functional integration for vision applications

- **COLLECT DATA**
  - Gather video image data

- **CLEAN DATA**
  - Remove duplicate and low-quality images

- **ANNOTATE DATA**
  - Multiple annotators label data, manager resolves labeling disagreements

- **TRAIN MODEL**
  - Select algorithm and annotated features of images to learn

- **ACCURATE ENOUGH?**
  - Refine annotation guidelines, adjust features, train more data
  - YES!
    - Develop application, deployment
  - NO
    - Refine annotation guidelines, adjust features, train more data

- **EVALUATE RESULTS**
GTFS-Realtime

Roadside Camera

Data Sources

AVL Data

Image Data Acquisition

Trip information

Observed scene

Images

Image sequence dataset

Model Training

Trip information

Corresponding image sequence

Trained model

Vision Transformer

Travel time band labeled images

Real-time Inference

Trip information

Estimated travel time

Observed scene

Predicted travel time band

Continuous travel time prediction

id
timestamp
dir

id
time in segment (ts)
dir

travel time = ts - dwell
Learning to “See” Potential Causes of Delay

(a) Normal.

(b) Rain.

(c) Snow.

(d) Night.
Learning to “See” Potential Causes of Delay

<table>
<thead>
<tr>
<th>Class</th>
<th>Inbound</th>
<th></th>
<th>Outbound</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pr, Recall, F-1</td>
<td>Support</td>
<td>Pr, Recall, F-1</td>
<td>Support</td>
</tr>
<tr>
<td>Low</td>
<td>0.93 0.77 0.84</td>
<td>201</td>
<td>0.94 0.76 0.84</td>
<td>213</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.83 0.91 0.87</td>
<td>539</td>
<td>0.83 0.89 0.86</td>
<td>557</td>
</tr>
<tr>
<td>Above Average</td>
<td>0.81 0.84 0.82</td>
<td>396</td>
<td>0.78 0.87 0.82</td>
<td>433</td>
</tr>
<tr>
<td>High</td>
<td>0.94 0.77 0.85</td>
<td>193</td>
<td>0.95 0.73 0.83</td>
<td>199</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.85</td>
<td></td>
<td>0.84</td>
<td></td>
</tr>
</tbody>
</table>

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
Natural Language Models for Customer Feedback Intelligence
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 @tonymmm · 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!

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?

**Classification**

**Identifying Features:**
- **Unigram / N-Gram Models**
  - **Mode** Bus, Train, Paratransit, Parking
  - **Location** Vehicles/Assets
  - **Route** Gender Similarity Match from Database of 84,000+ Names

**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

Moving 90th Percentile

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?

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

Negative Complaints about Cleanliness per million Metrorail riders

Significant effect observed at ±2 months (p<0.001), but not ±4 months (p=0.26)
Which bus routes have the highest amounts of negative feedback per rider?

WMATA - Bus Routes by Negative Feedback per Million Riders

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
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Future Projects
Transit-Centric Smart Mobility System: Improving Energy Efficiency through Machine Learning
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
Cooperative Stop-Holding: A Deep Reinforcement Learning Framework

Joseph Rodriguez
Motivation: Bus bunching
Motivation

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

Corrective actions for even spacing include:
➔ Holding
➔ Skipping

Problem

Strategies

Corrections

Bus Control Criteria

Decision Rules

Optimization

Reinforcement Learning

predicted best actions based on simulated experience

Ignores uncertainties

Trade-offs between prediction horizon and computational complexity

"Best actions" maximize long-term expected reward

**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

---

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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**

---

**Diagram Description**

- **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

<table>
<thead>
<tr>
<th>Stakeholder</th>
<th>Metric</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Riders ✓</td>
<td>Average excess wait time</td>
<td>37%*</td>
</tr>
<tr>
<td>✓</td>
<td>90th percentile loads</td>
<td>Up to 20%</td>
</tr>
<tr>
<td>✓</td>
<td>90th percentile headways</td>
<td>Up to 40%</td>
</tr>
<tr>
<td>✓</td>
<td>90th percentile cycle times</td>
<td>2.4%</td>
</tr>
<tr>
<td>✓</td>
<td>MEP score</td>
<td>6%</td>
</tr>
</tbody>
</table>

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

Demand

Monitoring

Control

Ethics

Future

Future Projects

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Algorithmic Fairness in Travel Behavior Prediction

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Background: fairness in machine learning

Minority homebuyers face widespread statistical lending discrimination, study finds

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.

Sources:
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:

\[
\text{False Negative Rate (FNR) Gap} = \frac{FN_{z=0}}{TP_{z=0} + FN_{z=0}} - \frac{FN_{z=1}}{TP_{z=1} + FN_{z=1}}
\]

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)

- **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:

\[
\min_p \quad (1 - \lambda) L_{primary} + \lambda |Corr(p(x), z | y = 1)|
\]

- \(p(x)\): predicted probability
- \(\lambda\): the bias mitigation weight
- Correlation loss is used to reduce the FNR gap
**Results:** Bias Mitigation Results (using NHTS data)

- **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

**Figure 10:** Fairness and accuracy by bias mitigation weight ($\lambda$): 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

Future/On-going Projects

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

Shenhao Wang, Qingyi Wang, Jinhua Zhao
How do we describe cities?
4. Using unstructured data bridge the disciplinary boundaries

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

\[ P(y_i|x_i) = f(x_i) \]

\[ P(y_i|x_i, \text{Images}, \text{Language}, \text{Graph}, \text{Numbers}) = f(x_i, \text{Images}, \text{Language}, \text{Graph}, \text{Numbers}) \]

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
4. Using unstructured data bridge the disciplinary boundaries

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

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

- Human
  - Physical Interface
  - Digital Interface
- “Machine”
  - AI + robotics
- Institutions
  - government,
  - business, labor
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

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