Open Research Day

9 April 2025

“

09:15-09:55

Parallel Sessions- *lightning talks followed by breakout session*

A108: Robots and People

Chair: Associate Professor Jana Tumova, KTH

A123: Smart Mobility

Chair: Professor Jonas Mårtensson, KTH

A123: Smart Mobility

- Lightning talk: Session chair: Professor Jonas Mårtensson, KTH

1. cAIMBER: Causal Artificial Intelligence for Human Mobility Behavior Analysis Using Trajectory Data (RP)
2. MicroVRide: Virtual Reality Micromobilty Simulator (Demo)
3. GPARSE: Guaranteeing Pro-Active and Reactive Safety in intersections through resource management at the Edge (RP)
4. CAVeaT – Connected Automated Vehicles Trialling and Trustworthiness (Demo)
5. CIML4MOB-Causally informed machine learning for individual mobility dynamics (RP)
6. Smart Transportation in Cities Facilitated by Integrated Sensing and Communication Networks – Stacey (II)

cAIMBER: Causal Artificial Intelligence for Human Mobility Behavior Analysis Using Trajectory Data (RP)

Yuanyuan Wu

PostDoc, Transport Planning, ABE, KTH

Zhenliang Ma (PI), Liam Solus (Co-PI)

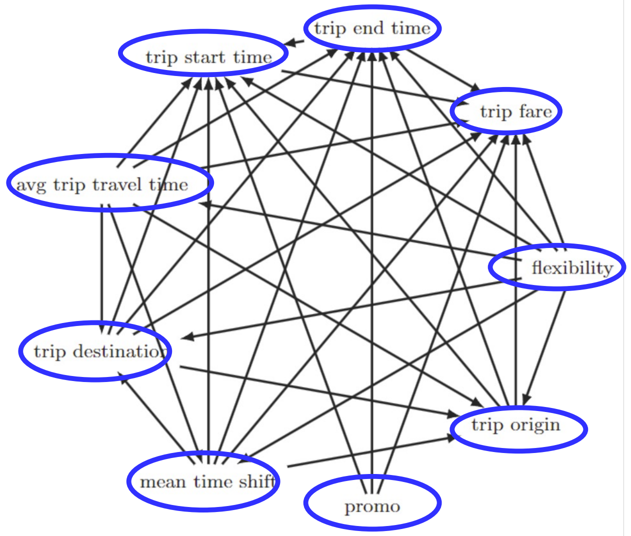
Project activities

- Behavior learning from trajectory data for transport policy making
- Planning: Causal effect of incentive on behavior changes in public transport
- Operational: Process modeling of individual behavior changes under incentives
- Case study: Hong Kong incentive program, smart card data, 2014 - 2018

Data-Driven Causal Inference

- Incentive program in public transportation (off-peak travel, 25% discount)
- Smartcard data over several years
- Methods: causal discovery and casual inference
- **Results:**
    - Introduced causal discovery to transportation
    - A causal model giving easy access to conditional treatment effects
    - The average effect of incentive is 0.7%
        - 2.5% in conventional statistical analysis

- (Static) causal graph — purely data-driven with **no prior** expert knowledge)

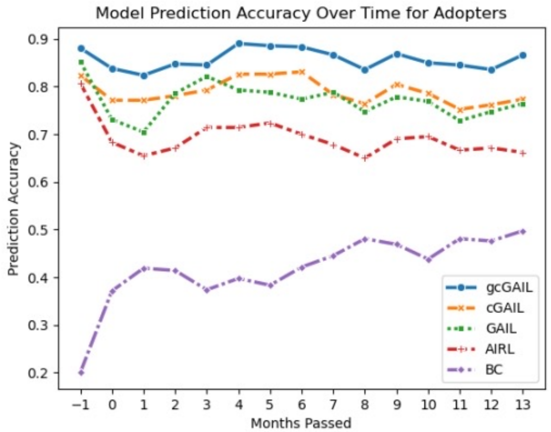


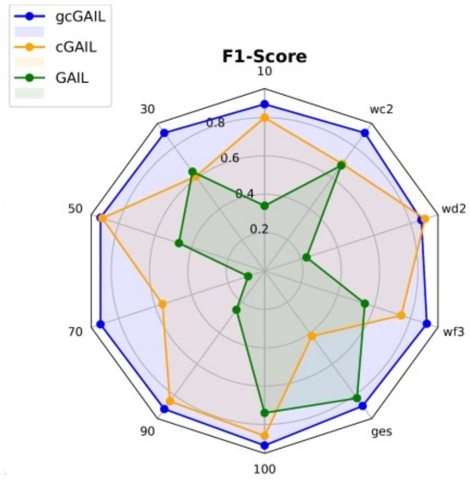
Wu, Y., Markham, A., Wang, L., Solus, L., Ma, Z., 2025. Data-driven causal behaviour modelling from trajectory data: A case for fare incentives in public transport. Journal of Public Transportation 27, 100114.

Individual travel behavior learning

- Goal: prediction modeling of individual behavior changes over time
- Problem: sequential Markov decision-making process $< S_t, A_t, f, R, \gamma >$
- Solution (inverse reinforcement learning, IRL):
  - Trajectories $\{(s_0, a_0), (s_1, a_1), \cdots, (s_t, a_t)\}$
  - Reward $R(s_t,\ a_t)$/Policies $\pi(a_t|s_t)$

$$\pi^* = \arg\max_{\pi} \mathbb{E}_{\pi}\left[\sum_t \gamma^t R(s_t, a_t)\right]$$





- Group effect enhanced generative adversarial imitation learning (*gcGAIL, blue line*)
- Data quality, data diversity, behavior diversity
- Benchmarks:
  - Behavior cloning (BC) ; Adversarial IRL (AIRL) ; Conditional GAIL (cGAIL) ; GAIL (*baseline, green line*)

Wu, Y., Qin, Z., Wang, L., Ma, Z., 2025. Group effect enhanced generative adversarial imitation learning for individual mobility dynamics under Incentives.


Thank you

MicroVRide: Virtual Reality Micromobilty Simulator

Xiaoyan Zhou
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Team

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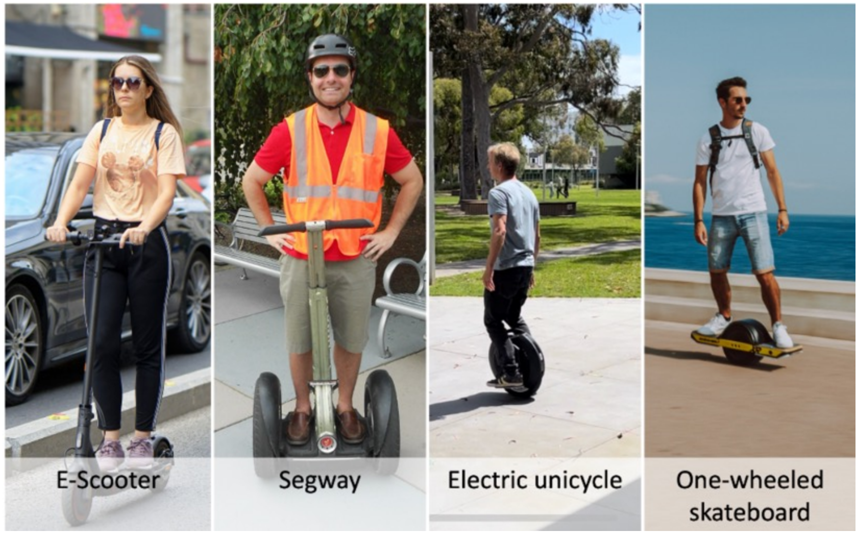
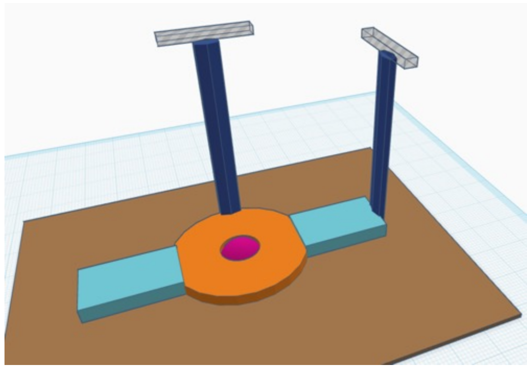
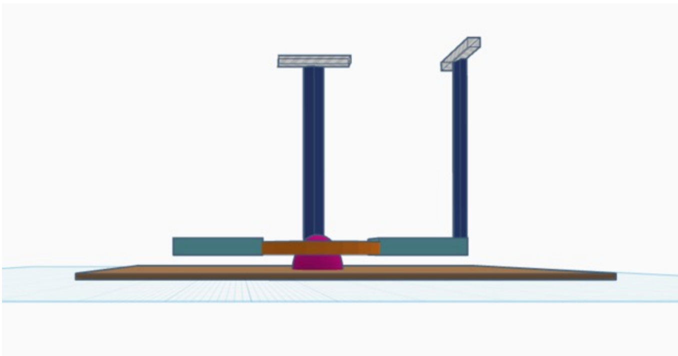
Motivation & Objective

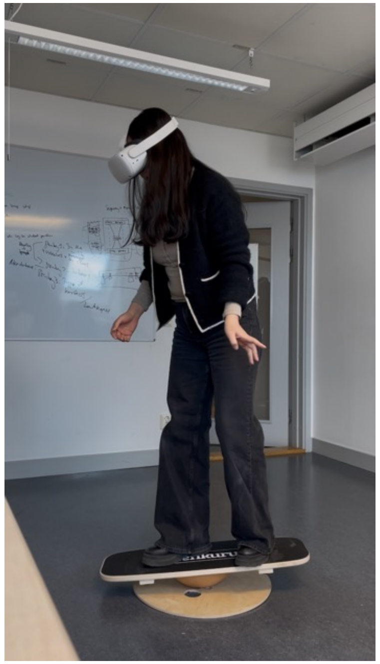
- How a VR micromobilty simulator can be designed to accommodate the current and future micromobility vehicle innovations?
- What are the implications for research and innovation in the domain of VR simulators?
- Design and construction of a fixed hardware platform for simulating micromobility experiences in Virtual Reality.
- Implementation of Virtual Reality simulations to replicate real world experiences.
- Evaluation of experiences with users of different levels of riding proficiency in MicroVRide.

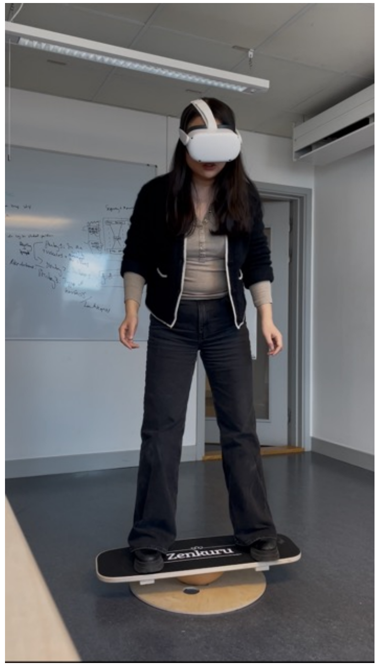


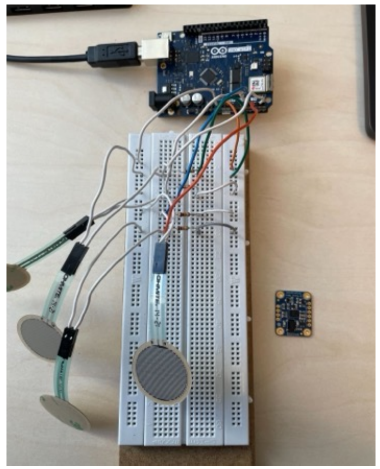
Prototype











Two-stage Study

- Stage 1 – Field Study with Real Micromobility Vehicles
  - Use Force-Sensitive Resistors (FSRs) on foot platforms to capture pressure distribution
  - Understand natural interaction patterns, balance strategies, and lean-based control
- Stage 2 – VR Micromobility Simulator Development
  - Use field study data to implement FSRs and IMU for creating realistic user experience
  - Simulate all four vehicles with VR HMD

Thank you

Guaranteeing Pro-Active and Reactive Safety in intersections through resource management at the Edge (GPARSE)

Fredrik Asplund, KTH/ITM

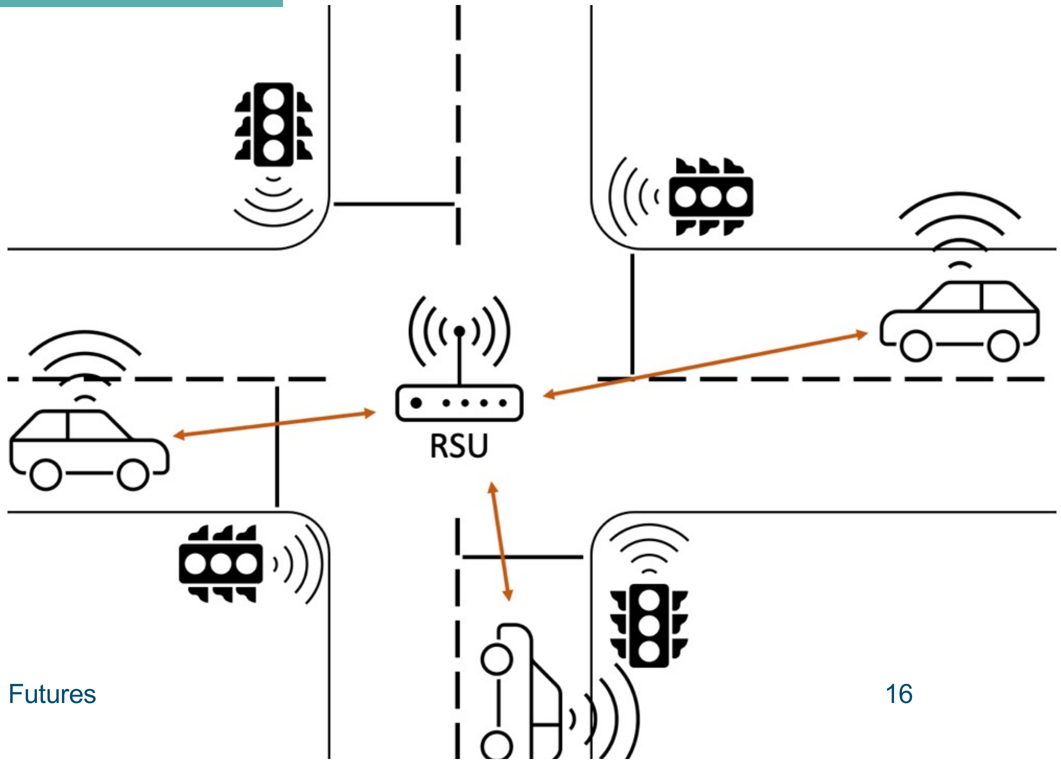
Matthias Becker, KTH/EECS

Project Overview

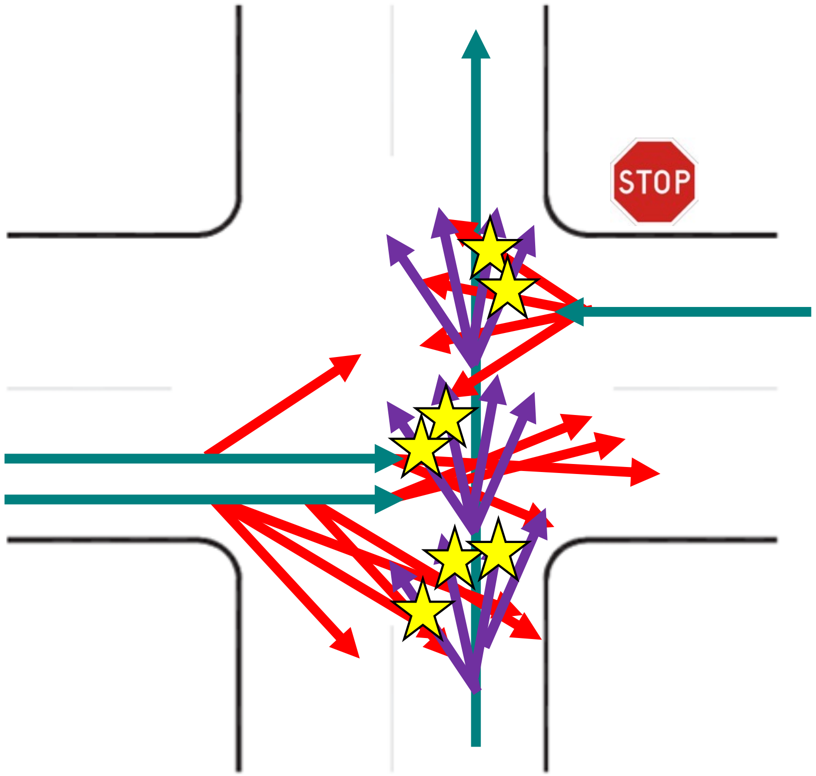
Mitigate harm of collision at road intersections

Pro-active
Orchestrate the arrival of traffic at the intersection
- Establish safety zones
- Avoid congestion

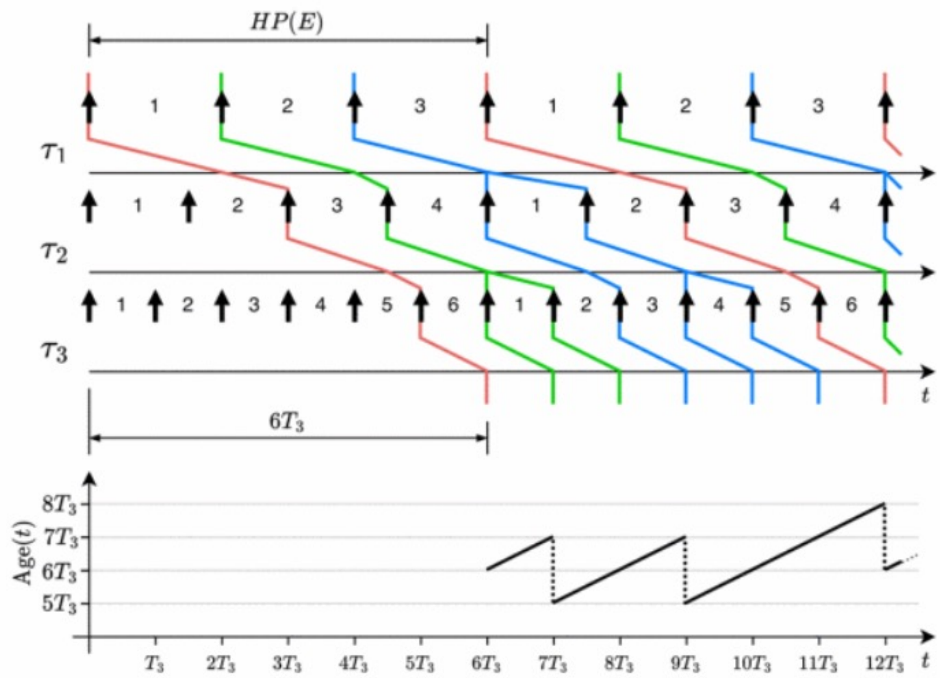
Reactive
Enable RSU resources for vehicles during likely collision
- Contingency path planning
- Sensors for a complete view



Remote Safety Indicator

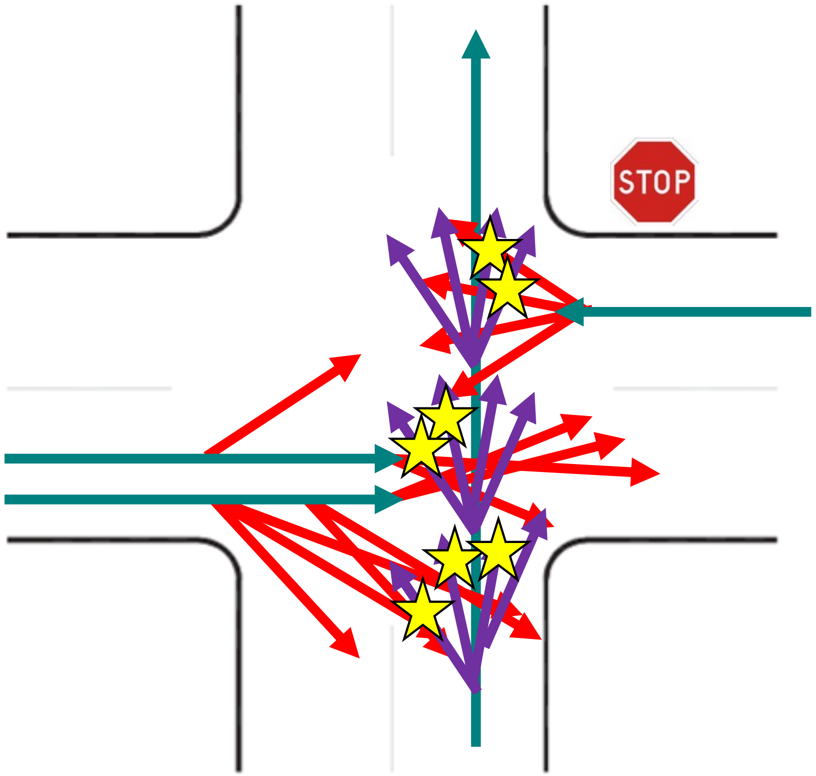


Data Age

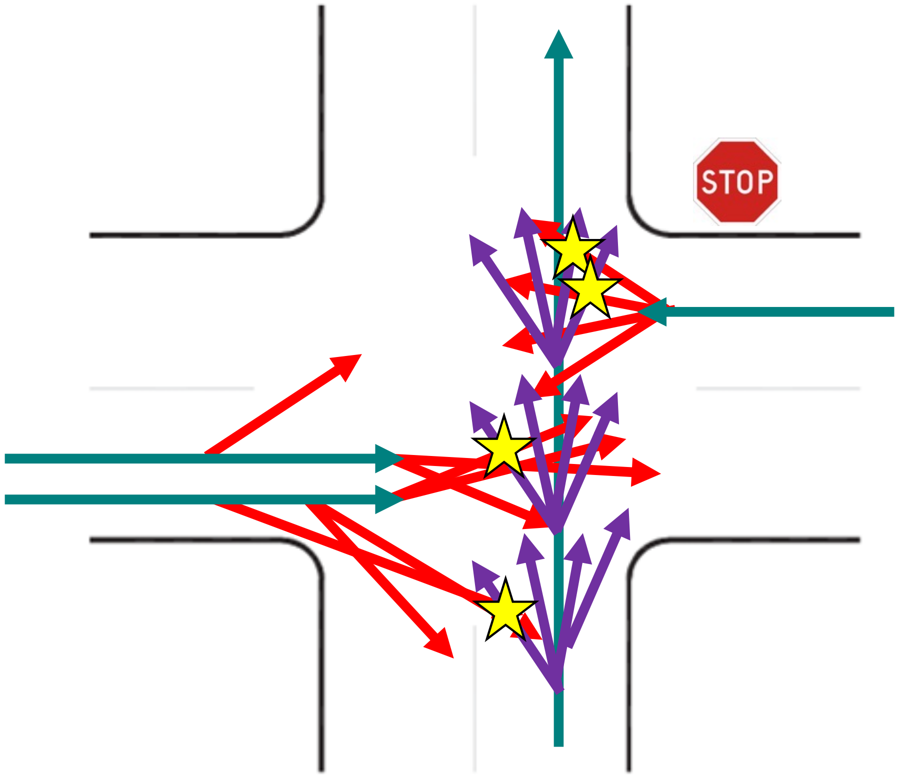


$HP(E)$
τ_1
τ_2
τ_3
$6T_3$
Age(t)
$8T_3$
$7T_3$
$6T_3$
$5T_3$
T_3 $2T_3$ $3T_3$ $4T_3$ $5T_3$ $6T_3$ $7T_3$ $8T_3$ $9T_3$ $10T_3$ $11T_3$ $12T_3$ t

Remote Safety Indicator



Remote Safety Indicator & Data Age




Thank you

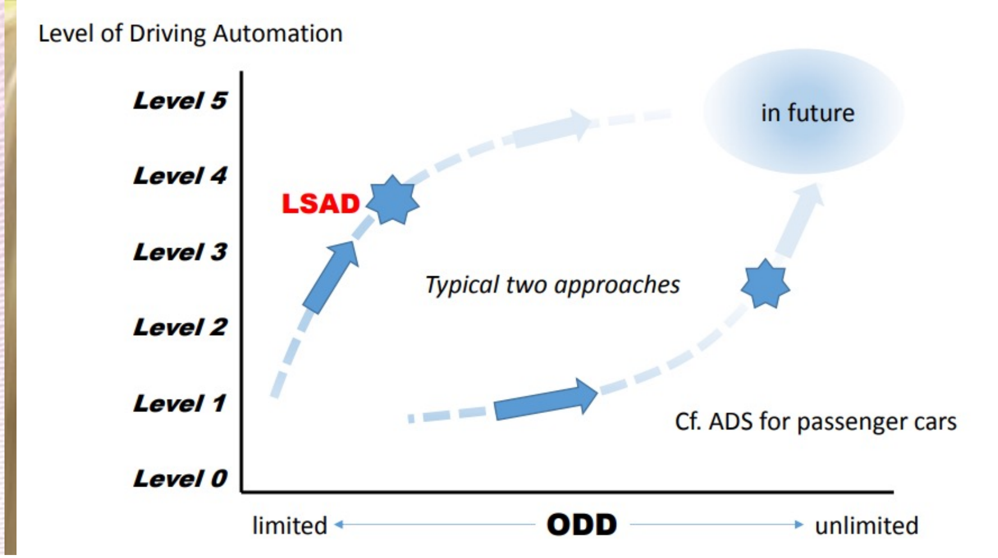
CAVeaT
Connected Automated Vehicles trialling and Trustworthiness

Martin Törngren
ITM

György Dán
EECS/NSE

~100 B US dollar investments

10 Million Self-Driving Cars Will Hit The Road By 2020 -- Here's How To Profit



Human intelligence as a reference for automated CPS? Breaking new grounds

ADI – Autonomous Driving Intelligence

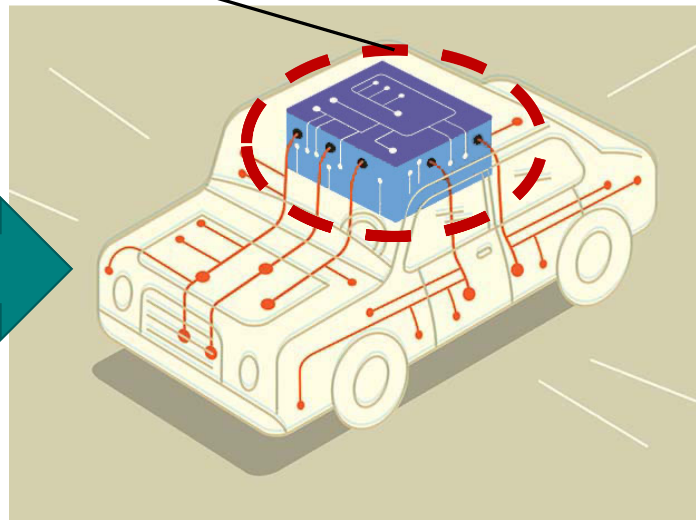
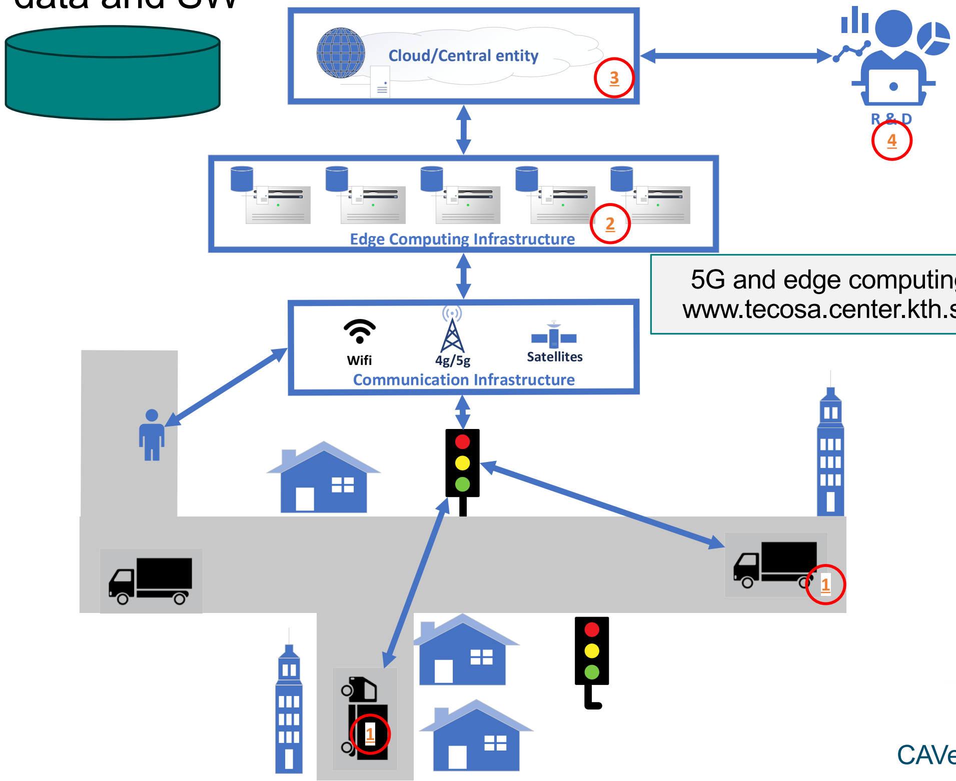


Illustration: Harry Campbell, IEEE Spectrum
http://spectrum.ieee.org/cars-that-think/transportation/self-driving/nxps-bluebox-bids-to-be-the-brains-of-your-car

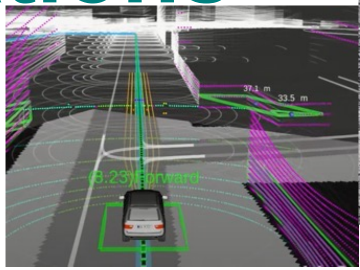
CAVeaT demonstrations and outputs

Open and closed source data and SW



AD-EYE (www.adeye.se) and security toolchains

5G and edge computing
www.tecosa.center.kth.se

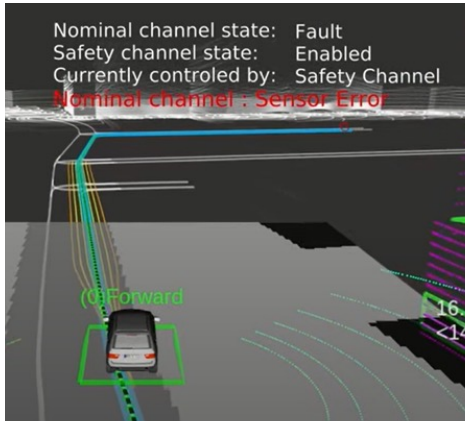


Demonstration scenarios

(I) **Automated Driving trials** at low speeds on selected campus roads with in-vehicle safety operator

(II) **Cooperative situational awareness**, combining information from the automated vehicle and from road-side sensors

(III) **Trustworthy operation**, demonstrating handling of SW & HW failures, cyber-physical attacks on perception, and capability of performing minimal risk maneuvers



Thank you

CIML4MOB: Causally Informed ML for individual MOBility dynamics

Dr. Zhenliang Ma, Associate Professor in Transport Science, ABE, KTH

Dr. Liam Solus, WASP Assistant Professor in Mathematics, SCI, KTH

Changing mobility behavior

- Challenges
  - Behavior: Elusive and interconnected
  - Data: Large-scale trajectory data
- Scientific gaps
  - Static, survey, correlation-based model (e.g., DCM)
  - Lack of knowledge of individual behavior dynamics
    - Data-driven causal inference
    - Behavior change evolution process

New method and behavior dynamics model from trajectory data

cAIMBER: Static, Data-Driven Causal Learning

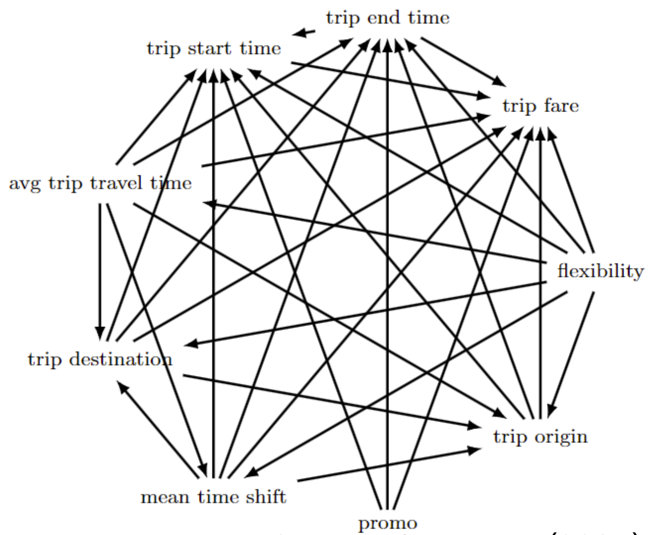
Use case

- Incentive program in public transport (to incentivize off-peak travel)
- Smart card data over several years

Highlights

- Introduced causal discovery to transportation
- A causal model giving easy access to conditional treatment effects
- The average effect of incentive is 0.7% (2.5% in conventional analysis)

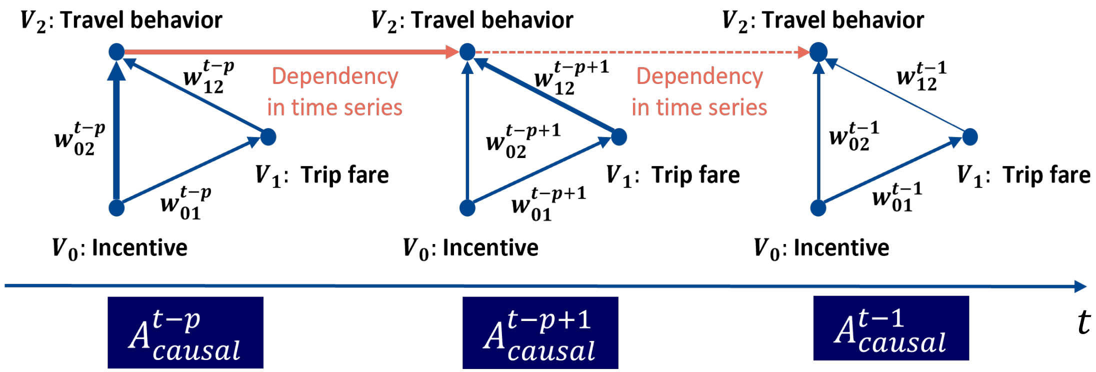
- Causal graph — purely data-driven with **no prior** expert knowledge)



Wu, Y., Ma, Z., Markham, A., Solus, L., & Wang, L. (2024). Data-Driven Causal Behaviour Modelling from Trajectory Data: A Case for Fare Incentives in Public Transport. In TransitData 2024, London and Journal of Public Transportation.

CIML4MOB: Behavior change process modeling

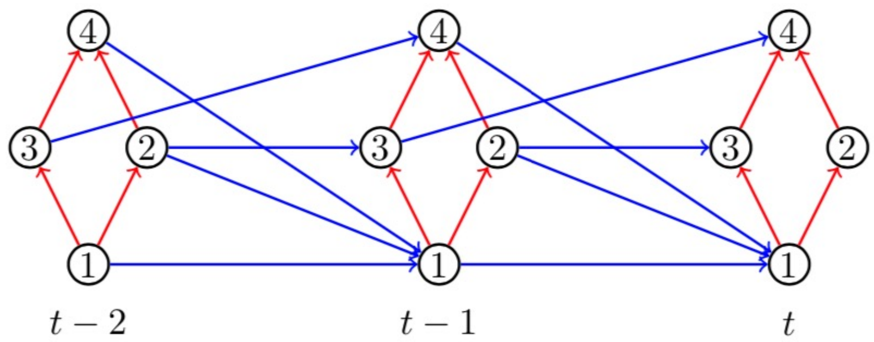
- **Goal:** Extend from static to dynamic models to predict individual adoption and attrition behavior over time
- **Model:** Construct a time series of causal graphs to understand the evolving behaviors of individuals under incentives



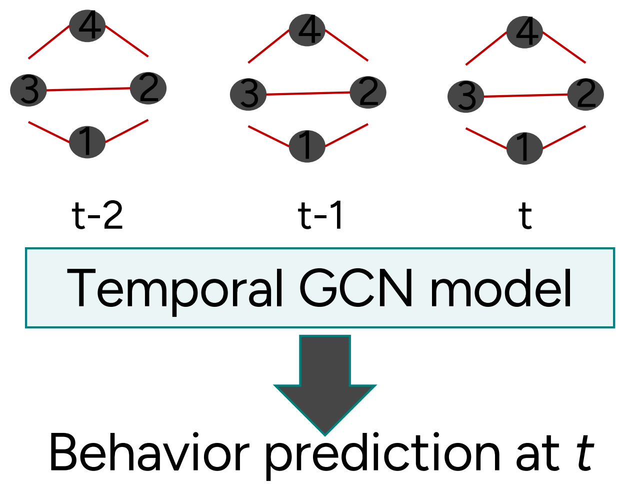
- **Application:** Market strategy for adoption and program loyalty

Methodology

- Approaches (several methods will be developed/compared):
  - Granger causality methods for structural equation modeling
  - Differentiable structure learning of time-dependent graphs
  - Diffusion-based Graph Neural Network approaches



$$\mathbf{X}^{(t)} = W\mathbf{X}^{(t)} + \mathbf{A}_{t-1}\mathbf{X}^{(t-1)} + \mathbf{A}_{t-2}\mathbf{X}^{(t-2)} + \mathbf{N}$$



Data

- Smart card data
  - August 2014 – October 2016
  - Tap-in and tap-out transactions
  - Avg. 5 million trips per day
- Train movement data
- Network performance model data[1]
- Choice estimation model data[2]

Category	Data information
Individual	Anonymized ID
	Individual attributes
Trip information	Date
	Activity
Travel behavior	Frequency
	Departure time
	Origin
	Destination
	Route
Service	Station crowding
	Train load
	Left behind
	In-vehicle travel time
	Transfer times
	Fare cost

1. B. Mo, Z. Ma*, H. N. Koutsopoulos, and J. Zhao (2020). Capacity-Constrained Network Performance Model for Urban Rail Systems. *Transportation Research Record*, 2674(5):59-69.
2. B. Mo, Z. Ma*, H. N. Koutsopoulos, and J. Zhao (2023). Ex-Post Path Choice Estimation for Urban Rail Systems Using Smart Card Data: An Aggregated Time-Space Hypernetwork Approach. *Transportation Science*, 57(2), 313-335.

Contributions

- cAIMBER results gave improved estimates of the treatment effect of incentive program by learning a static causal graph model
- CIML4MOB aims to extend these benefits to behavior models over time
  - Introduce causal learning method to dynamic behavior in transportation
  - New applications to the underexplored behavior evolution process
- Contribute to DF research matrix on 'smart society' and 'learn'
- Core research expertise in transportation data analytics and causal inference


Thank you

digital futures

STACEY – Smart Transportation Facilitated by Integrated Sensing and Communication Networks

KTH EECS and Ericsson

digital futures

Project Team

digital futures

Cellular Networks Facilitate Smart Transportation

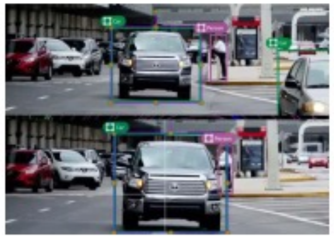
Situational awareness

Situational awareness requires sensing and communications

Cellular integrated sensing and communication network (ISAC)

- Detecting and classifying objects with the ubiquitous cellular infrastructure

- Creating regularly refreshed digital inventories of objects on roads
- Detecting, localizing, classifying and tracking large unconnected objects



S. Daei, A. Zamani, S. Chatterjee, M. Skoglund, G. Fodor, "Near-Field ISAC in 6G: Addressing Phase Nonlinearity via Lifted Super-Resolution, *IEEE ICASSP*, April 2025.
S. Daei, G. Fodor, M. Skoglund, M. Telek, "Towards Optimal Pilot Spacing and Power Control in Multi-Antenna Systems Operating Over Non-Stationary Rician Aging Channels", *IEEE TCOM*, Early Access, 2025.

Thank you

digital futures

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