Data-friendly Mesoscopic Modeling for Large-scale Networks: Learning, Prediction and Decision Making

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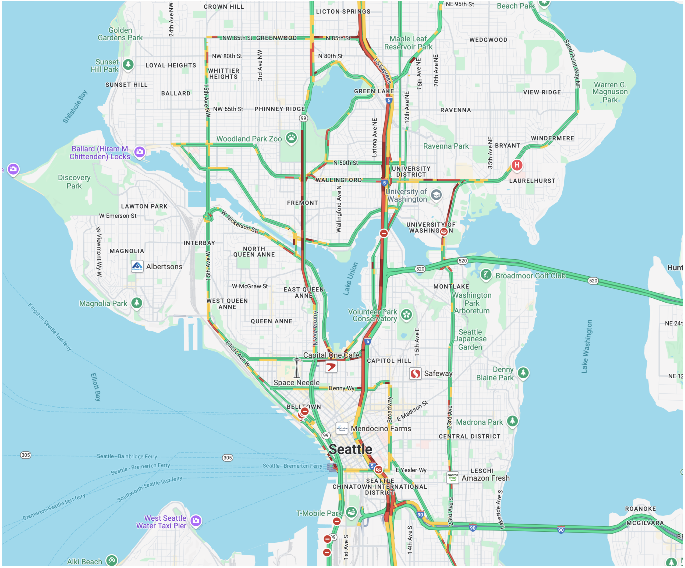
Carnegie Mellon University
UW workshop, May 30, 2025

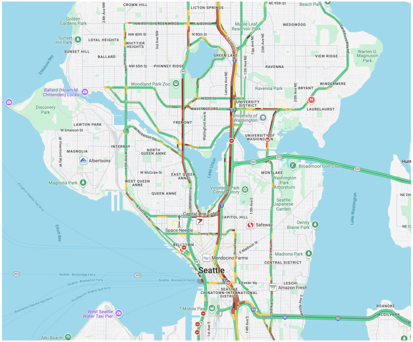
Ubiquitous sensing: What is the missing piece?



Smart decision making?

Public agencies:

- Incident management
- Infrastructure retrofit
- Ride-sourcing impact/regulation
- Congestion pricing
- Land-use change
- Metro/bus scheduling
- ...



Can we learn ?
$G(\text{demand}, \text{supply}) \mapsto$ performance

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- Conventional dynamic network models
  - A single set of data points
  - Hard to fit data in a high-dimensional space
- Conventional data-driven models
  - A large volume of data points
  - Fit well
  - Cannot incorporate "what-if"
- Foundational models?
  - G has to see a whole lot
  - Variations in demand/supply
  - General design of input space: embeddings

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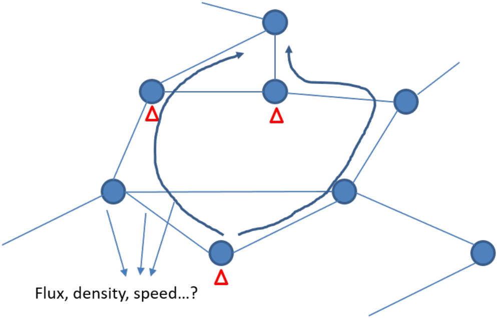
Revisit network models



Final goals: evaluation and intervention

- x: link flow (flux, density, speed...)
- f: path flow (flux, density, speed...)
- c: system states (cost, time, emissions...)

Given x^o, f^o, c^o and supply, learn $(\mathtt{x}, \mathtt{f}, \mathtt{c}) = G(\text{supply}, \text{demand})$

Revisit network models

- Use OD demand q to approximate demand
- Define user behavior + network flow model: G

$$G : (N; \mathrm{q}; \theta) \mapsto (\mathrm{x}, \mathrm{f}, \mathrm{c})$$

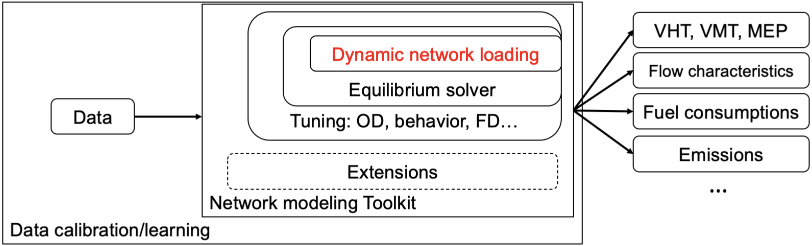
- Given x^o, f^o, c^o and network supply, estimate $\mathrm{q}; \theta$
- Calibrate G, estimate/predict $(\mathrm{x}, \mathrm{f}, \mathrm{c})$

A ML framework G

$$G : (N; \mathrm{q}; \theta) \mapsto (\mathrm{x}, \mathrm{f}, \mathrm{c})$$

- Classical Dynamic Traffic Assignment + OD Estimation
- Big challenges:
  - Data calibration: fit multi-source large-scale data
  - Multi-class, multi-modal
  - Mixed agent-based and continuum flow
  - Individual user behavior: time, cost, safety, incident...
  - For large-scale networks

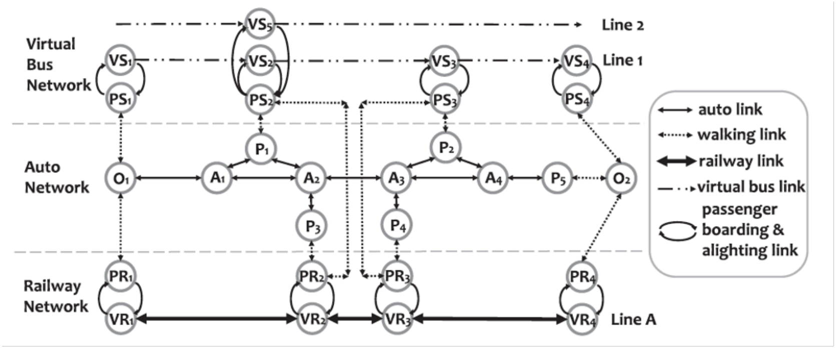
User behavior + network flow models G



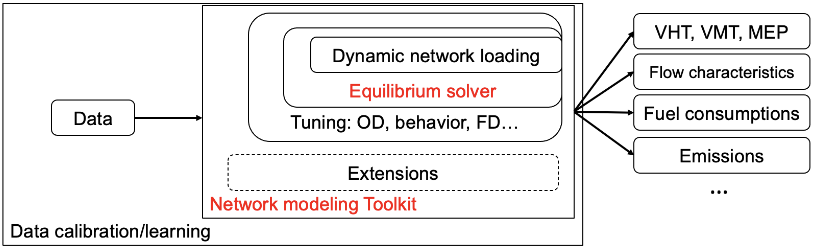
$$\Lambda : f \mapsto (x, c)$$

- Meso: traffic flow dynamic (e.g. CTM, LQ)
- Car-truck-bus interaction
- Second-by-second vehicle trajectories

Network structure design



User behavior + network flow models G



Travel behavior model: route, mode, parking, departure time.

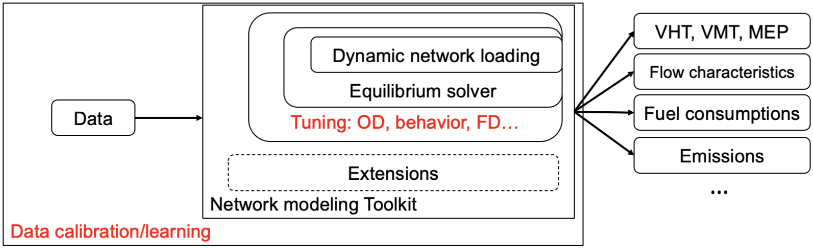
$$\Psi : \mathrm{q} \mapsto (\mathrm{f})$$

typically, $\mathrm{f} = \mathrm{p}(\mathrm{c})\mathrm{q}$ where $\mathrm{p}(\mathrm{c})$ is a function of individuals' disutility functions (time, cost, reliability, etc.)

Generalized disutility for individuals

- Driving (cars and trucks)
  - Travel time = travel time + parking lot cruising time + walking time
  - Travel cost = c(travel time) + parking fee + private car accessibility
- Fixed-route transit
  - Travel time = walking time + transfer/waiting time + bus travel time + walking time
  - Travel cost = c(travel time) + transit fare + perceived transit inconvenience
- Mobility service + fixed-route transit
  - Travel time = mobility service waiting time + mobility service travel time + walking time + transfer/waiting time + bus travel time + walking time
  - Travel cost = c(travel time) + mobility service fee + transit fare + perceived transit inconvenience

User behavior + network flow models G



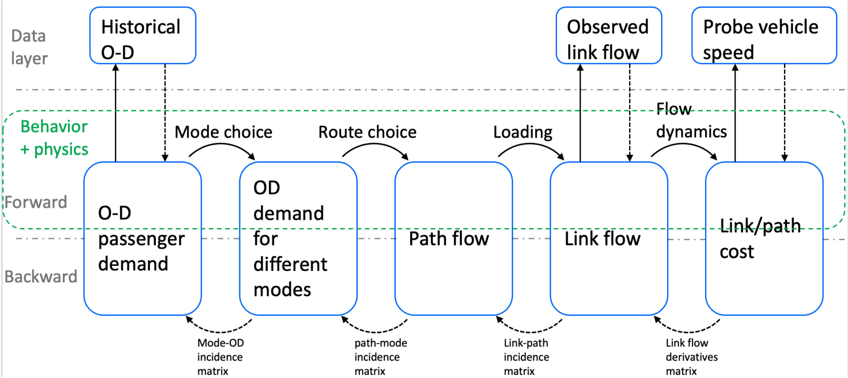
Find q, θ such that:

$$G : (N; \mathrm{q}; \theta) \mapsto (\mathrm{x}, \mathrm{f}, \mathrm{c}) \text{ fit data}$$

θ can be imposed on behavior (e.g. logit), or supply (e.g. fundamental diagrams)

Dynamic multi-class multi-modal networks

Computational graph approach to tune/learn



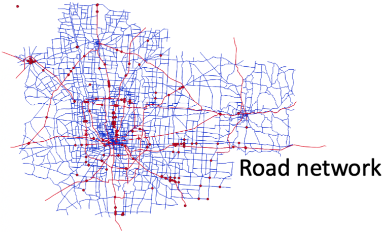
General framework: data; parameters; physics models

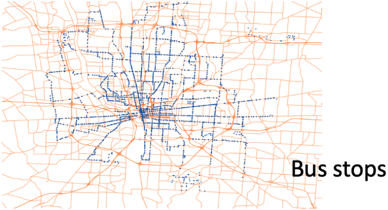
Challenges: accurately and efficiently calculate derivatives (e.g. time over flow)

Mobility service policies in Columbus OH

Table 1: Network parameters

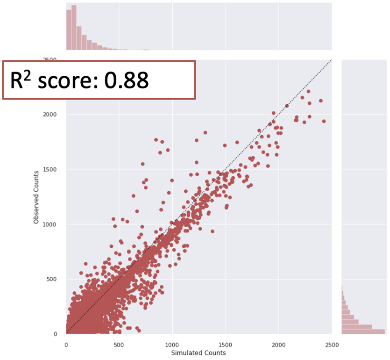
Name	Value
Studying period	5:00 AM - 12:00 PM 1:00 PM - 8:00 PM
Simulation unit interval	5 s
Length of assignment interval	15 min
Number of intervals	28
Number of links	26,357
Number of nodes	8,706
Number of origins (destinations)	543
Number of O-D pairs	138,560
Number of bus routes	60
Number of bus stops	2,504

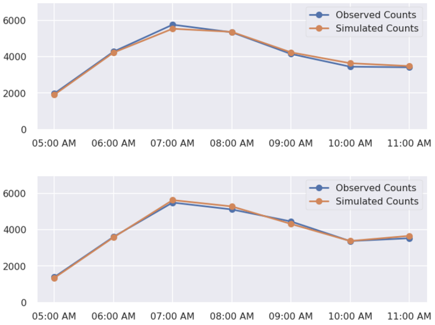




15-min counts by cars/trucks + 5-min speeds by cars/trucks + Transit APC-AVL data

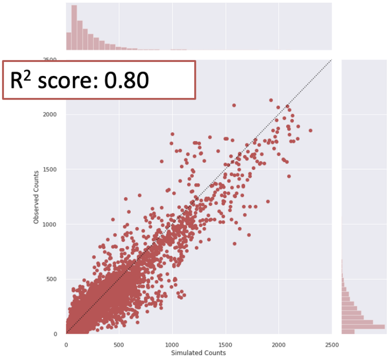
Mobility service policies in Columbus OH

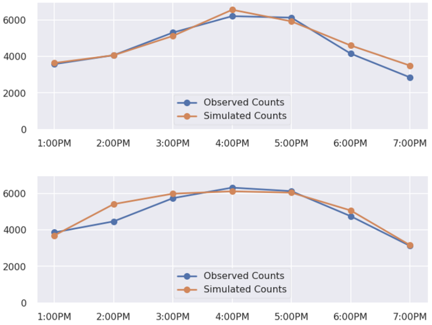




Traffic Count Calibration on I-270 in AM Peak

Mobility service policies in Columbus OH



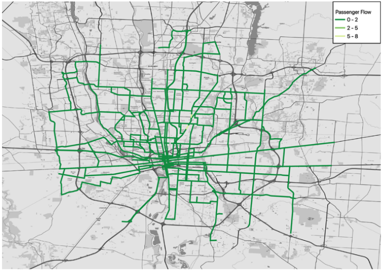


Traffic Count Calibration on I-270 in PM Peak

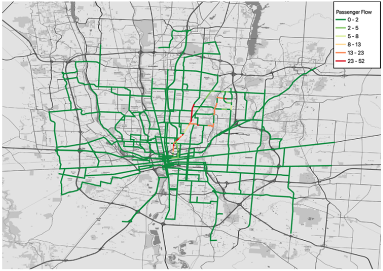
Loss could be irreducible? Derivatives wrong? Some key models are inaccurate.

Mobility service policies in Columbus OH

w/o mobility service

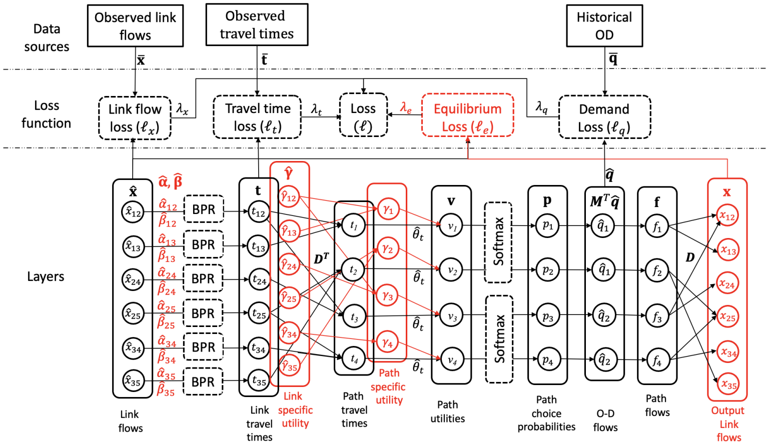


w/ mobility service



Driving 12.83% Bus 12.83% Fuel/CO2 4.03% VMT 4.11% Emissions 3-5%

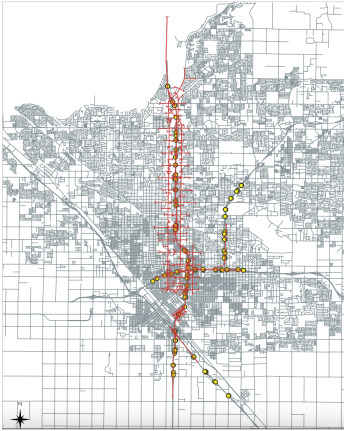
One step further: computational graph design to enforce Equilibrium



A fixed point problem to (softly) enforce behaviors (e.g. UE/SUE)

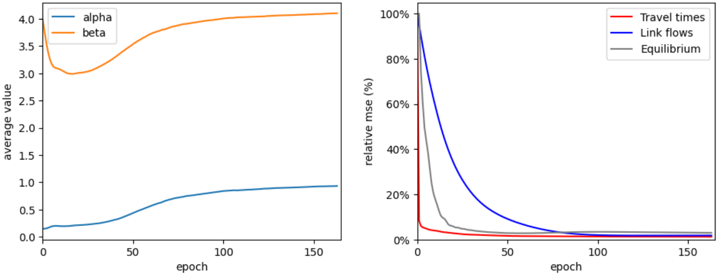
General framework: data; parameters; physics models

Experiments on California SR-41



Data: 141 Counts + 2k Speeds + 18k O-D + socio-demo + crashes + bus
Behavior: Time, cost, reliability, incidents, crime, income, bus, intersections

Experiments on California SR-41: ODE + disutility function; multi-day



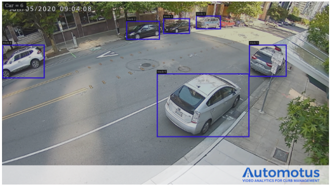
Parameter	Model			
	LUE	ODLUE	ODLULPE	TVODLULPE
Average travel time	-0.3569	-3.0786	-2.8586	-3.0597[a]
Std of travel time	0.0000	-9.7975	-3.7984	-3.2678[a]
Neighborhood income	0.0000	0.0000	0.0000	0.0000[a]
Incidents	0.0000	-0.9494	-0.7533	-4.5368[a]
Bus stops	0.0000	0.0000	0.0000	0.0000[a]
Streets Intersections	-0.1391	-2.4912	-1.8976	-3.8788[a]

Why design a computational graph?

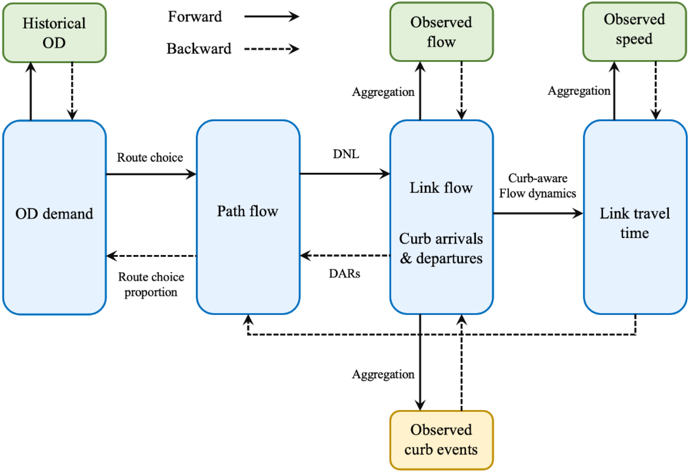
- Existing technologies in deep learning can be applied
  - Gradient algorithms
  - Software packages
  - Parallel computing
- Any data: system-level or individual-level
- Flexibility on hyper-parameters
- Training and testing
- Apply multi-day data

Add data sources: curbside sensing and management

- Automotus Inc. collects specific events occurring at the curbside, i.e., the arrival and departure of a vehicle stopping at curb spaces at smart loading zones in cities of Pittsburgh, Los Angeles, Santa Monica etc.
- Each event records the vehicle class, parking location and arrival or departure time, etc.

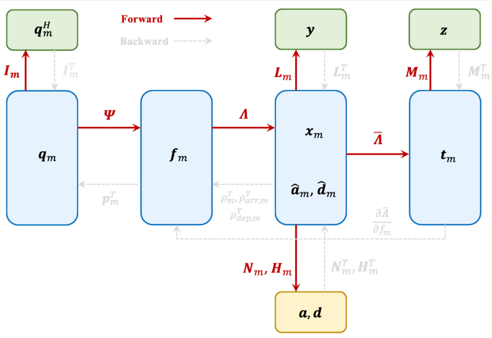


C-DODE presented on a computational graph



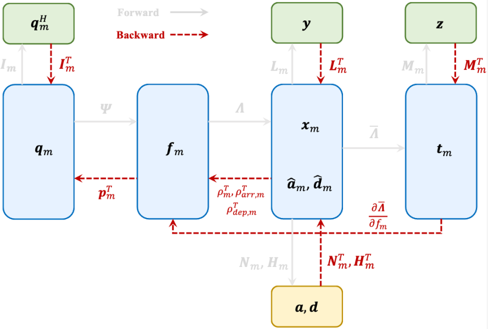
C-DODE presented on a computational graph - cont.

Forward pass: solve DTA, obtain conditions, and calculate losses



C-DODE presented on a computational graph - cont.

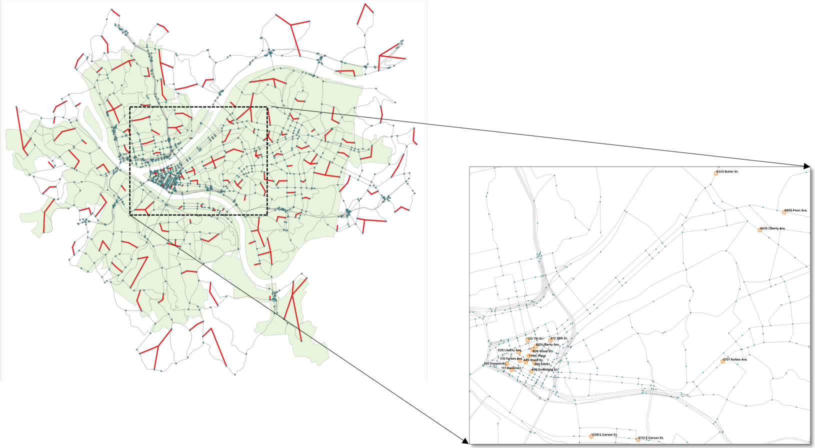
Backward pass: calculate gradient using the conditions obtained and update demand



Numerical Experiment: Pittsburgh network

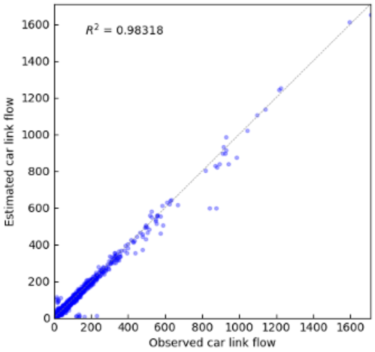
Real-world multi-source data:

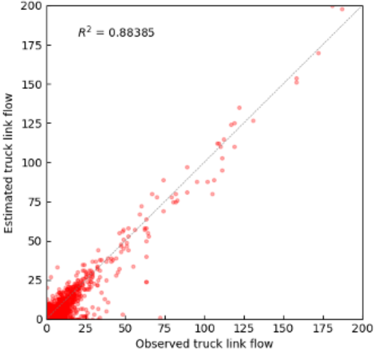
- Multi-class traffic count from PennDOT
- Multi-class travel time from INRIX
- Multi-class curb arrivals from Automotus Inc.



Results

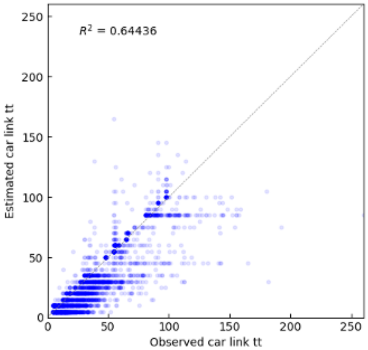
Observed vs estimated multi-class link flow

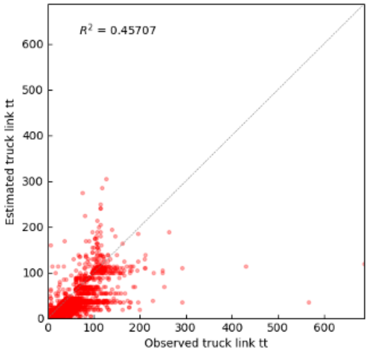




Results - cont.

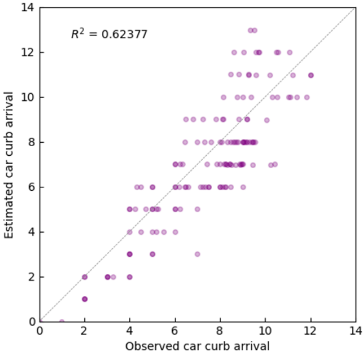
Observed vs estimated multi-class link travel time

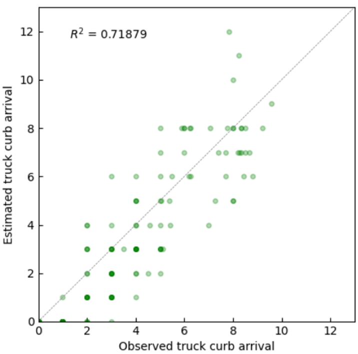




Results - cont.

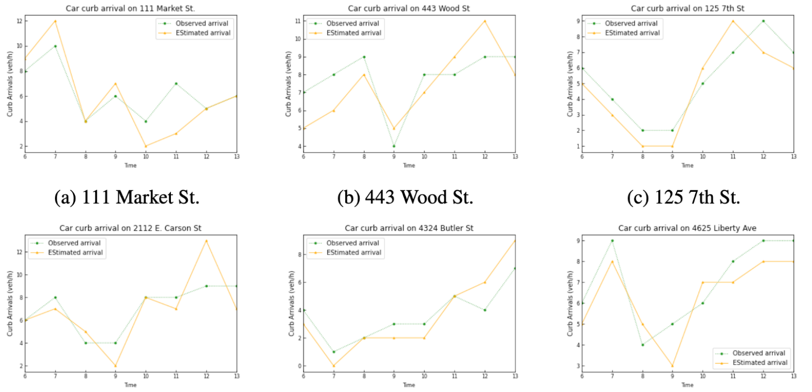
Observed vs estimated multi-class curbside arrival in smart loading zones





Results - cont.

The trends of arrival fluctuations align with the observations across the modeled eight-hour period and different locations



(a) 111 Market St. (b) 443 Wood St. (c) 125 7th St.

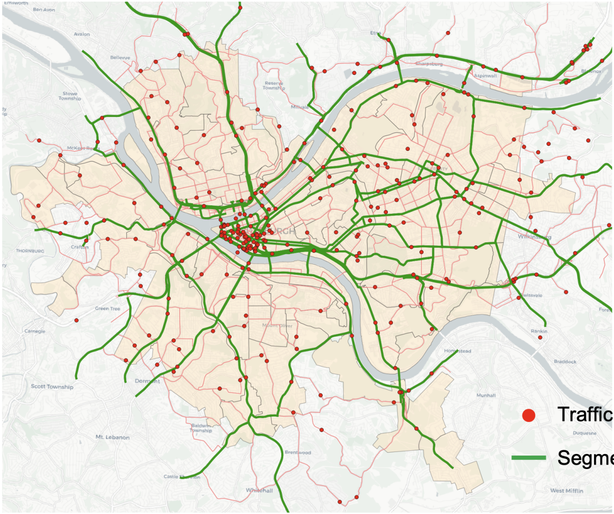
(d) 2112 E. Carson St. (e) 4324 Butler St. (f) 4625 Liberty Ave

Figure 26: Estimated vs observed hourly car arrival in selected SLZs of Pittsburgh network

Add data sources: satellite images

Use low-cost ubiquitous satellite images to enhance learning

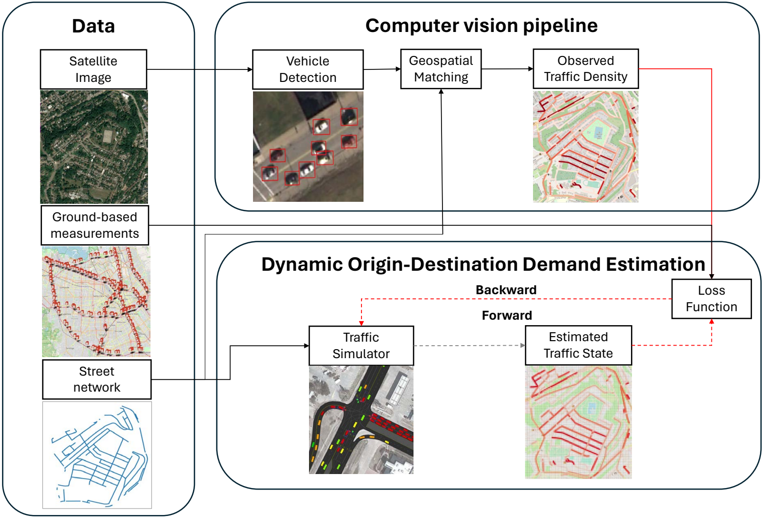
Local ground-based sensor is sparse



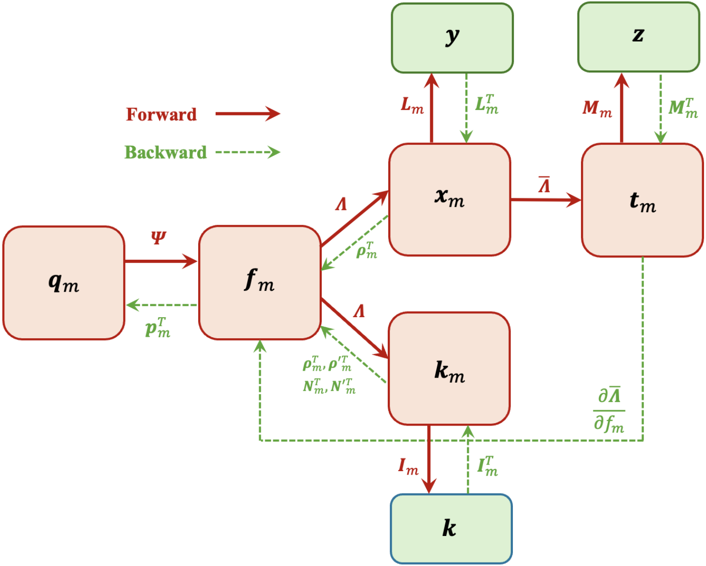
Global observation: satellite imagery

- Provides comprehensive, consistent traffic data for all segments
- Requires preprocessing (vehicle extraction, map matching)

Modeling Framework

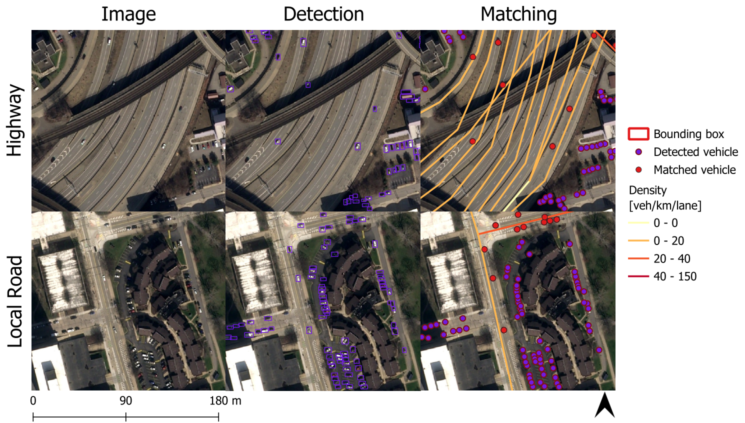


Computational Graph



Pittsburgh Downtown Network

Density extraction from satellite imagery using CV pipeline

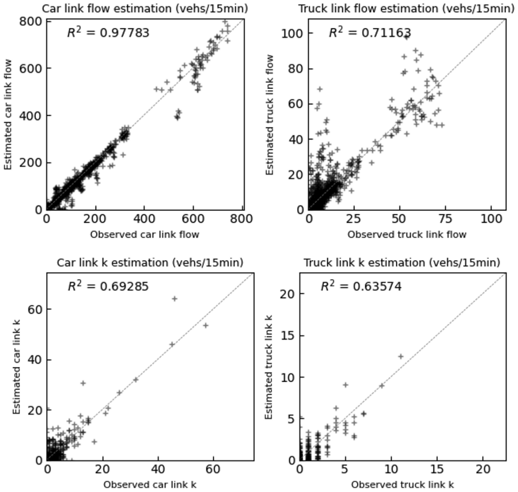


Pittsburgh Downtown Network

Density extraction from satellite imagery using CV pipeline

Pittsburgh Downtown Network

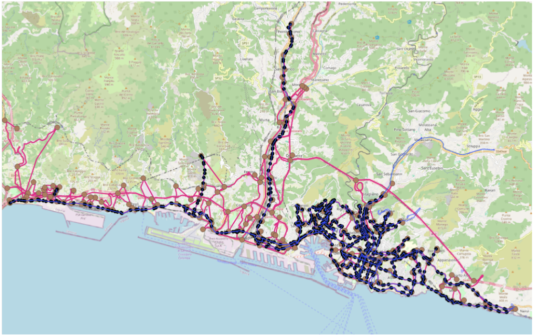
DODE using real-world traffic count, speed and one density snapshot together achieves satisfactory accuracy.



Genova, Italy multi-modal network

Driving, park-n-ride, metro, bus

- 3906 O-D pairs
- 573 links
- 761 stops
- 28 bus routes, 2 metro routes
- Data from Vedafone (15 min)
- Synthesized data: counts and speeds (5 min), ridership (by run)



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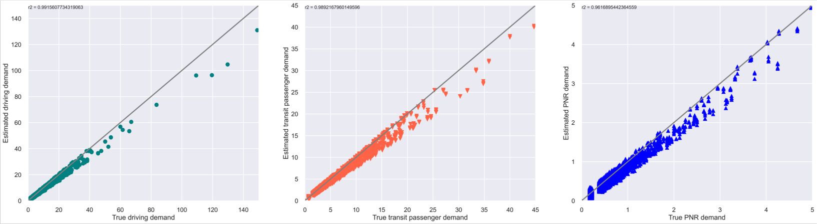

Learn distuiltiy coefficients related to metro and bus, along with hypothesis tests

Conclusions

- Towards a data-friendly framework
- Take advantage of state-of-the-art ML
- More data sources
- Learn from variable system states
- Efficient for large-scale networks
- Can we build a foundational model with physics?

Open-source codes, use cases, and manual:

https://github.com/maccmu/macposts

FUNDING SOURCES

PENNDOT

PITA

CLAUDE WORTHINGTON BENEDUM FOUNDATION

U.S. Department of Transportation Federal Highway Administration

A Division of Traffic 21 Reseaerch Institute traffic21

Carnegie Mellon University Metro21

Technologies for Safe and Efficient Transportation
A U.S. DOT UNIVERSITY TRANSPORTATION CENTER

National Science Foundation WHERE DISCOVERIES BEGIN

U.S. DEPARTMENT OF ENERGY

HONDA The Power of Dreams

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