Dr. Timothy LaRock PhD
Princeton University

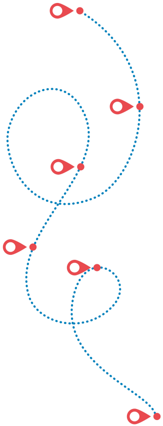
Higher-order Analysis of Human Mobility Data

In collaboration with Chen Zhang and Jürgen Hackl

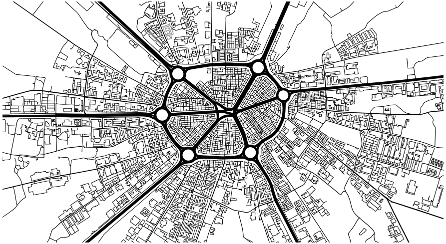
HONS Satelite @ NetSci '26
June 1, 2026
Boston, MA

Talk Roadmap

1. Background: Human mobility, infrastructure, and higher-order networks
2. Case study: observation and simulation in Île-de-France
3. Discussion: Takeaways, limitations, and future work



Human Mobility



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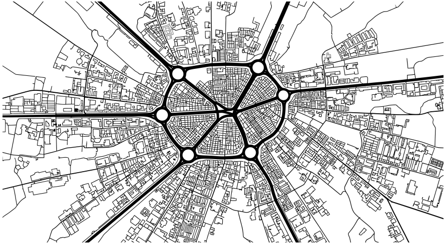
Human Mobility

Fundamental Questions

- How do people **move through the world**?



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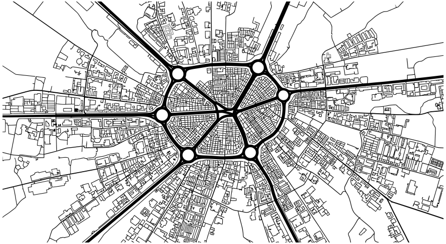

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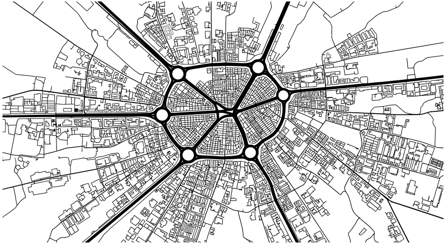

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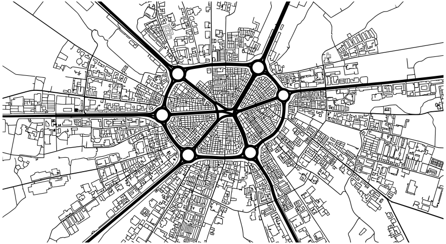

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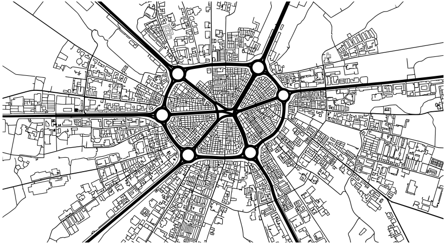

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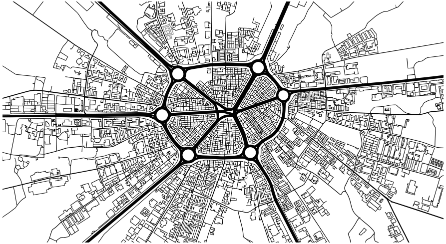

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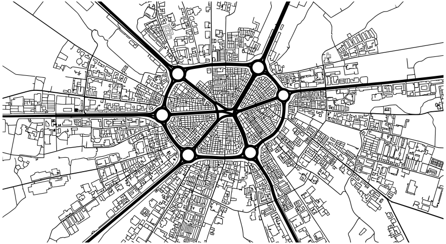

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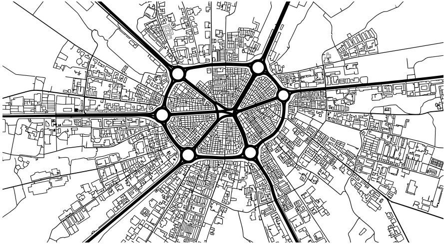

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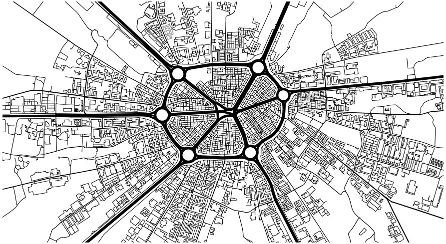

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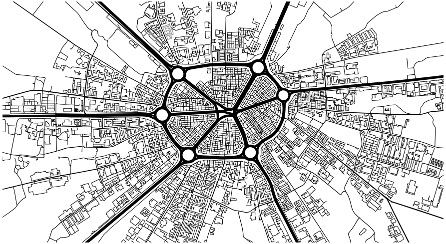

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Connecting Mobility and Infrastructure Networks

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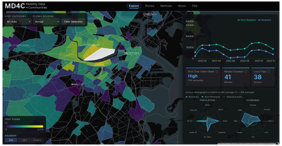

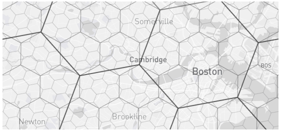

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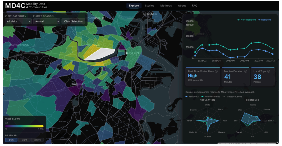

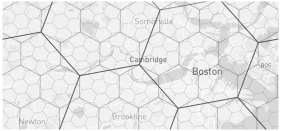

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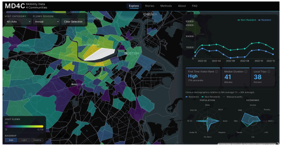

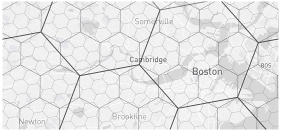

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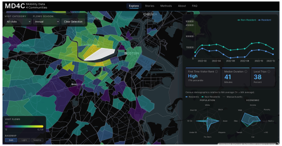
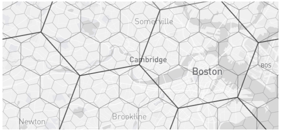
Our work: mobility dynamics + infrastructure networks

Integrate **individual mobility** dynamics and **infrastructure topology** using **higher-order network analysis**





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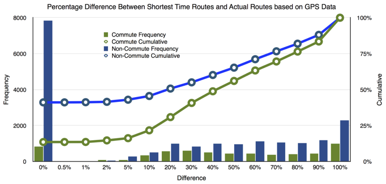

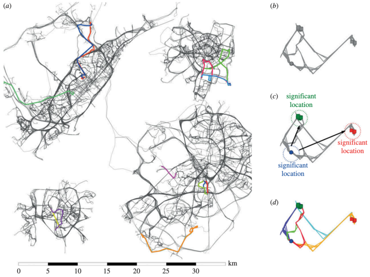

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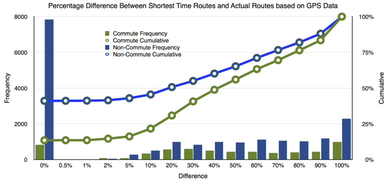

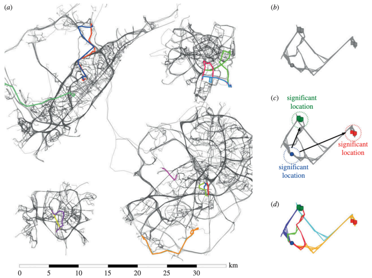

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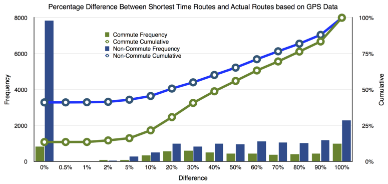

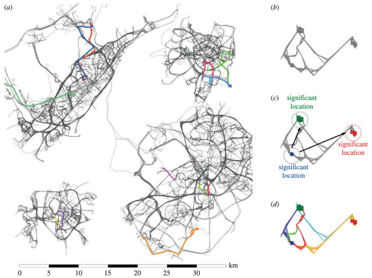

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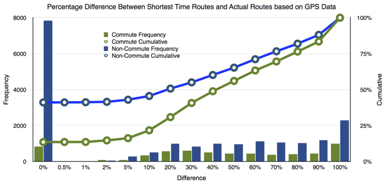

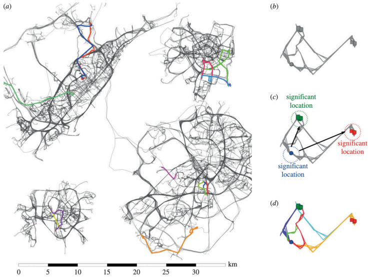

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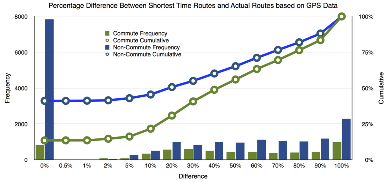

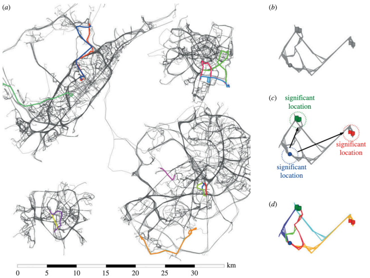

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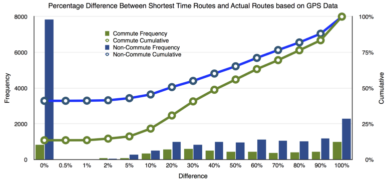

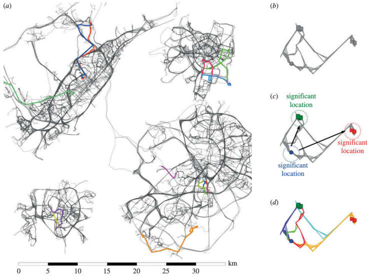

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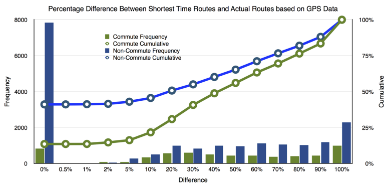

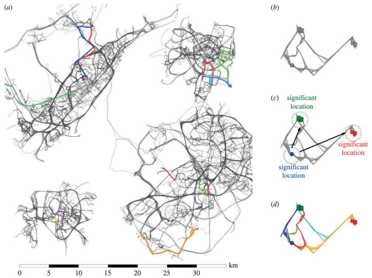

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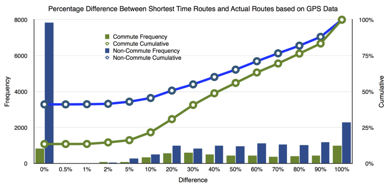

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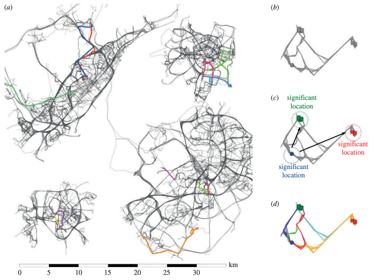
- Factors like infrastructure quality and ease of use, local knowledge, urgency, and habit matter



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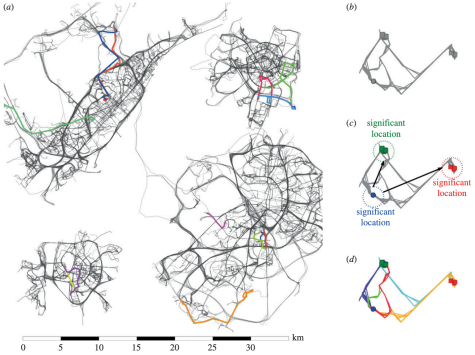
Challenges in Individual Mobility Research



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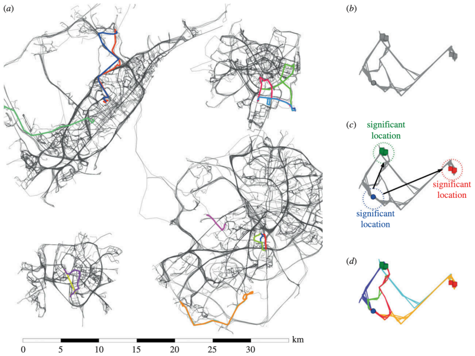

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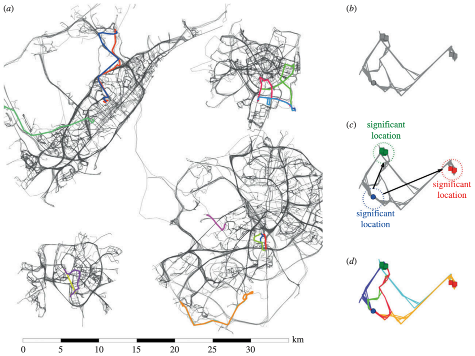

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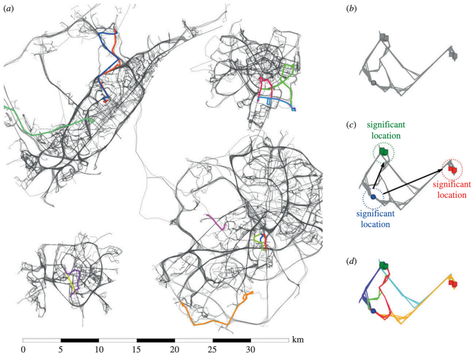

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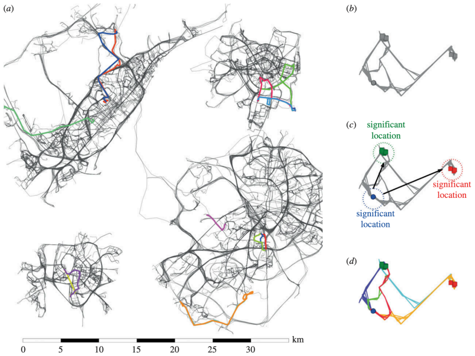

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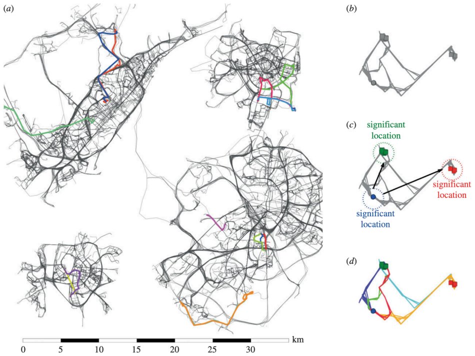
Our Question

Can simulations help overcome these challenges?



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Dream: Individual mobility, without individual data

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Multi-Agent Transport Simulation

Key Features

Agent-Based Traffic Simulation
Simulate a large number of individual travelers in your transport model.

Private and Public Traffic
Simulate various transport modes, including car, transit, walk, bike, drt, ...

Fast and Dynamic
MATSim simulates whole days second-by-second for fully dynamic results.

Supports large scenarios
MATSim can simulate large metropolitan areas in high level of details.

Active Development
MATSim continues to evolve and regularly gains new functionality.

Versatile Analyses and Simulation Output
Use preprocessed output or extract your own KPIs from the detailed simulation output.

Open Source
Adapt the code to your needs.

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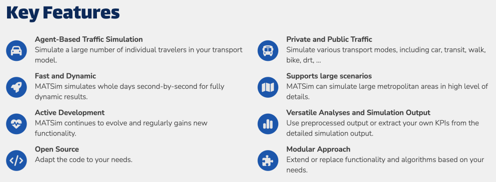

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- **Uses existing mobility data** collected by governments, transportation firms, and NGOs

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Open Source
Adapt the code to your needs.

Modular Approach
Extend or replace functionality and algorithms based on your needs.

https://matsim.org/

Simulating Individual Mobility

Dream: Individual mobility, without individual data

What if we could **simulate high-quality, realistic individual mobility** data by combining collective mobility patterns with agent-based simulations?

Advantages of Simulated Data

- **Obviates need to collect detailed individual data**, avoiding privacy, logistics, and cost issues
- **Enables transferability** to regions without GPS data
- **Uses existing mobility data** collected by governments, transportation firms, and NGOs
- **Facilitates simulation of artificial interventions** to help guide policymaking

MATSim
Multi-Agent Transport Simulation

Key Features

Agent-Based Traffic Simulation
Simulate a large number of individual travelers in your transport model.

Private and Public Traffic
Simulate various transport modes, including car, transit, walk, bike, drt, ...

Fast and Dynamic
MATSim simulates whole days second-by-second for fully dynamic results.

Supports large scenarios
MATSim can simulate large metropolitan areas in high level of details.

Active Development
MATSim continues to evolve and regularly gains new functionality.

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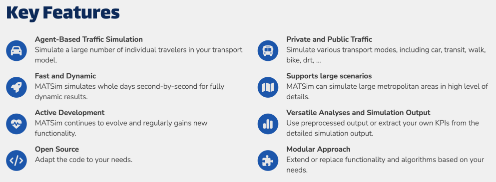
Making the dream a reality

We need methods to **evaluate whether simulated datasets are reliable surrogates** for real human mobility.



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Higher-order Perspective on Mobility

Our Approach

Compare real-world and simulated mobility paths from a **path-based higher-order perspective**.

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Path Data

C E
A B C
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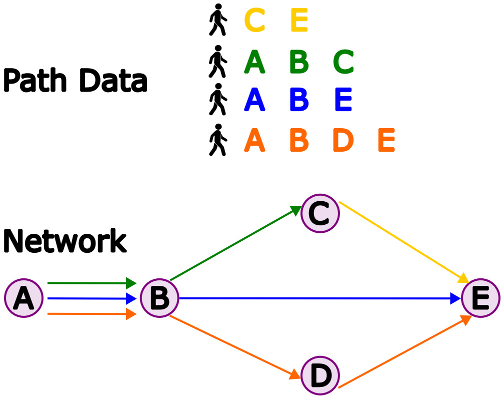

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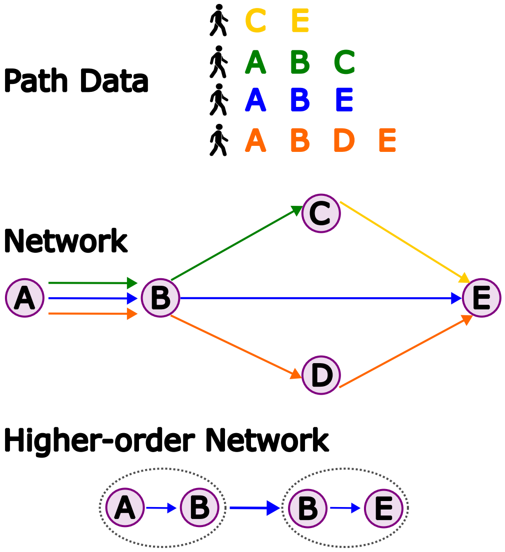

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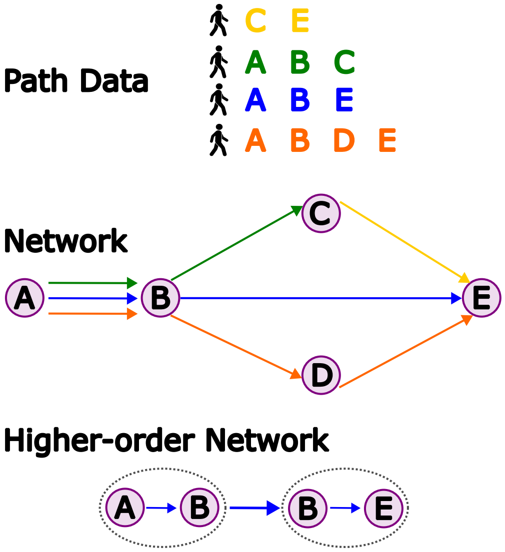

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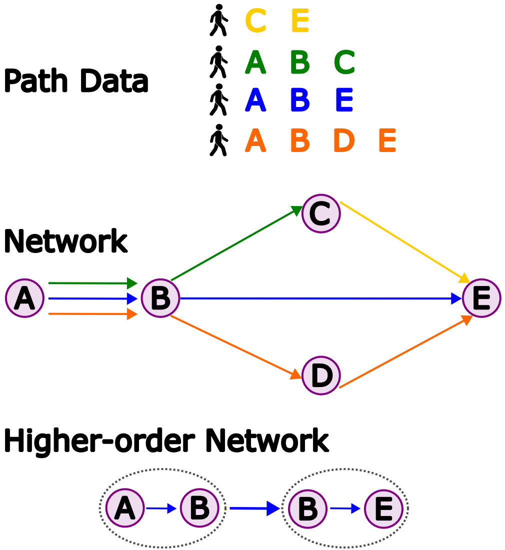

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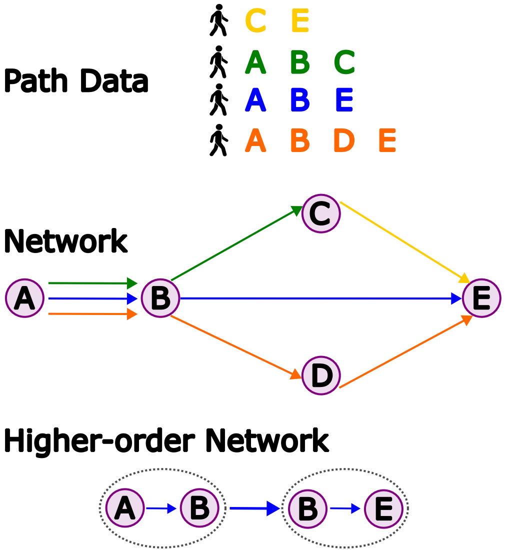

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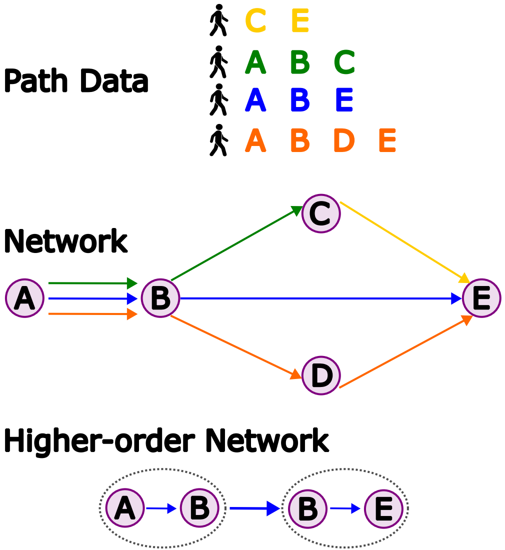

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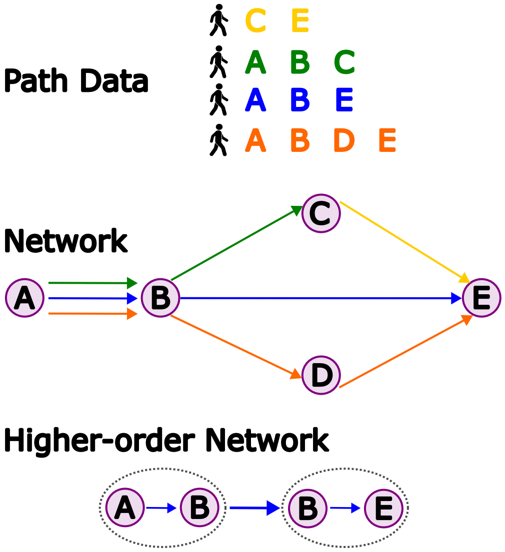
- Higher-order network properties



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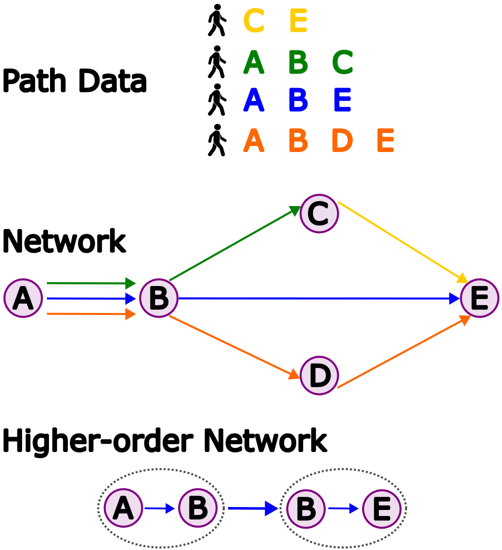
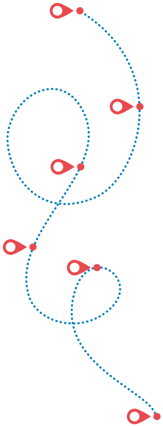
- Next-step prediction



Talk Roadmap

1. Background: Human mobility, infrastructure, and higher-order networks
2. Case study: observation and simulation in Île-de-France
3. Discussion: Takeaways, limitations, and future work



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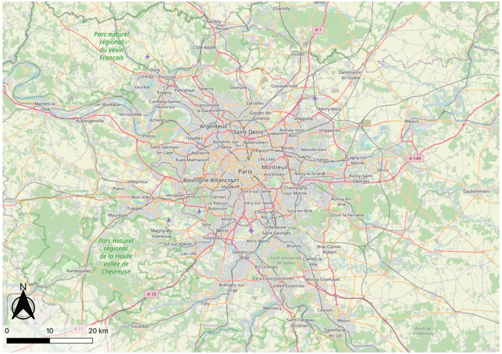

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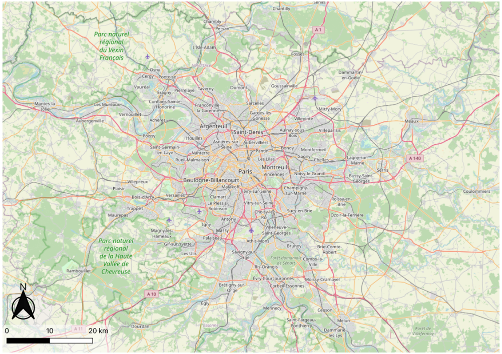

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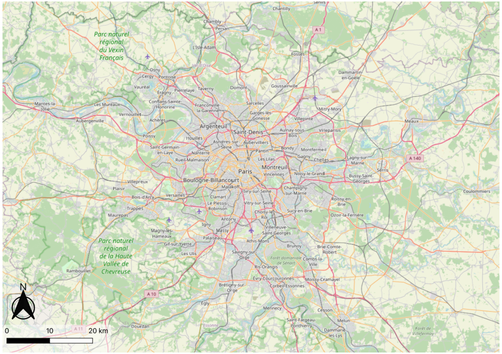

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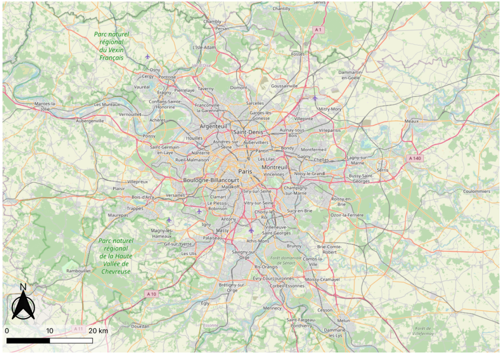

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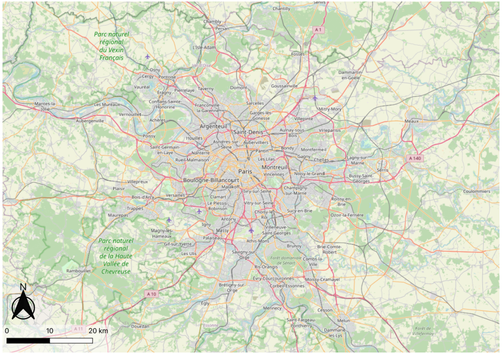

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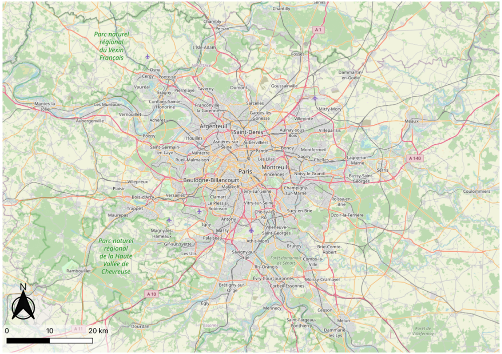
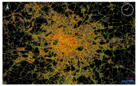


An open synthetic population of Île-de-France



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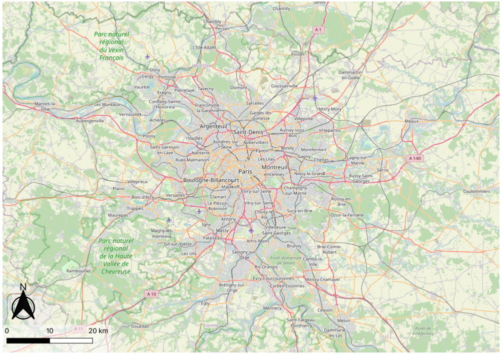

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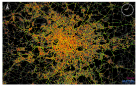

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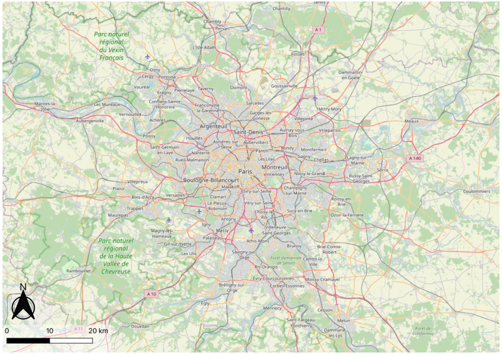

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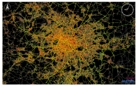

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OpenStreetMaps Network

We use the OpenStreetMaps (OSM) network as the underlying transportation network in both cases.

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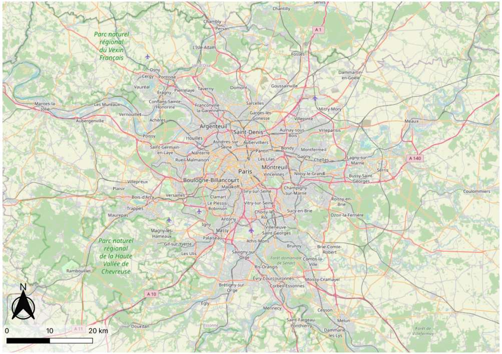

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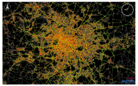

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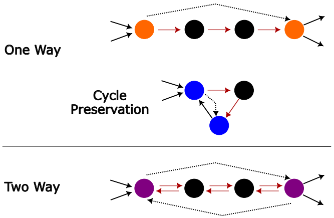
Preprocessing (in brief)

Network simplification

- Remove **redundant nodes** that do not represent meaningful choice points for travelers



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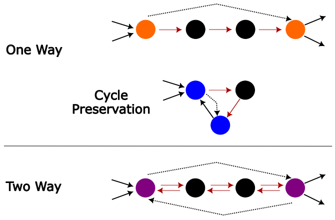
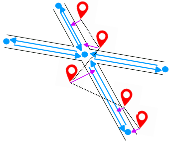
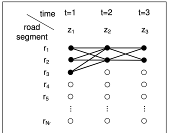
NetMob Map matching

- Match GPS coordinates to sequences of OpenStreetMaps network edges
- Implementation: Hidden Markov Model in Valhalla open source routing engine







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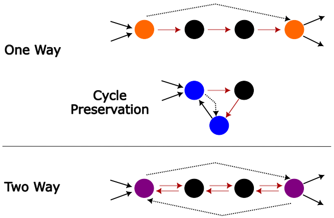
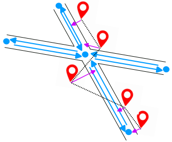
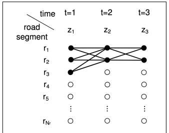
MATSim Path extraction

- Extract sequences of OSM nodes from MATSim output
- Interpolate walking and biking modes with shortest paths
- Map transit (bus) paths from stops back to OSM edges







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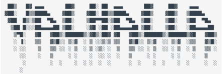

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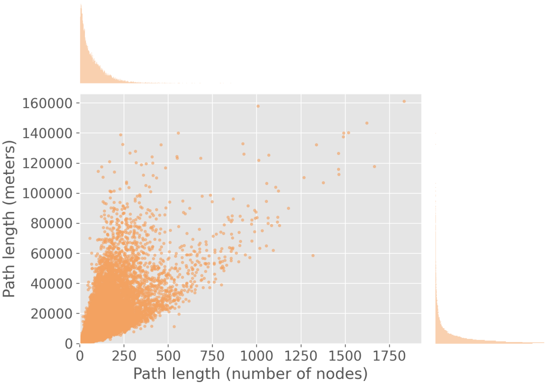
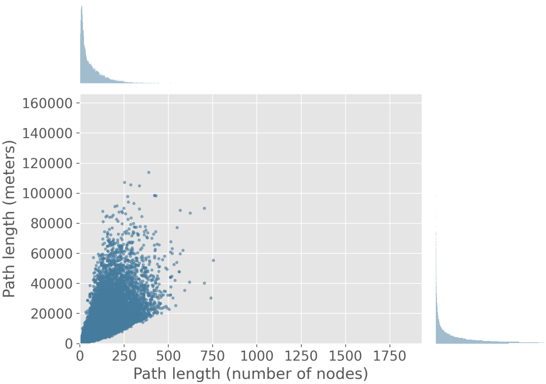
Path Data

Mode	NetMob Mode Name	NetMob	MatSim	Combined Total
Vehicle	PRIV_CAR_DRIVER	20,915		
	PRIV_CAR_PASSENGER	2,952		
	LIGHT_COMM_VEHICLE	44		
	TAXI	195		
	TWO_WHEELER	530		
	Total Vehicle	24,636	22,861	47,253
Bicycle	BIKE	3,693		
	ELECT_BIKE	1,685		
	ELECT_SCOOTER	348		
	Total Bicycle	5,726	1,223	6,902
Walking	WALKING	17,571	18,685	35,260
Public Transportation	BUS	2,728	10,947	13,648
Total	–	50,661	53,716	103,063

Path Length Distributions

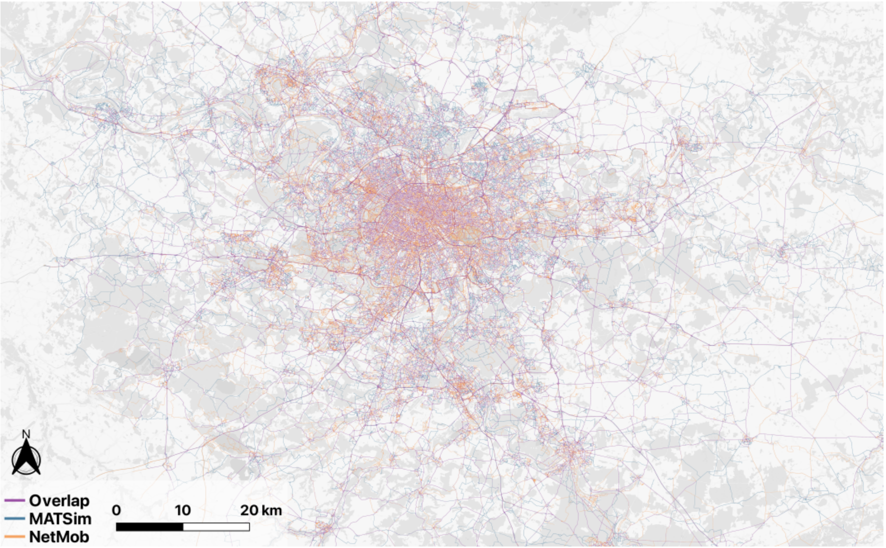


NetMob



MATSim

Mapped Data



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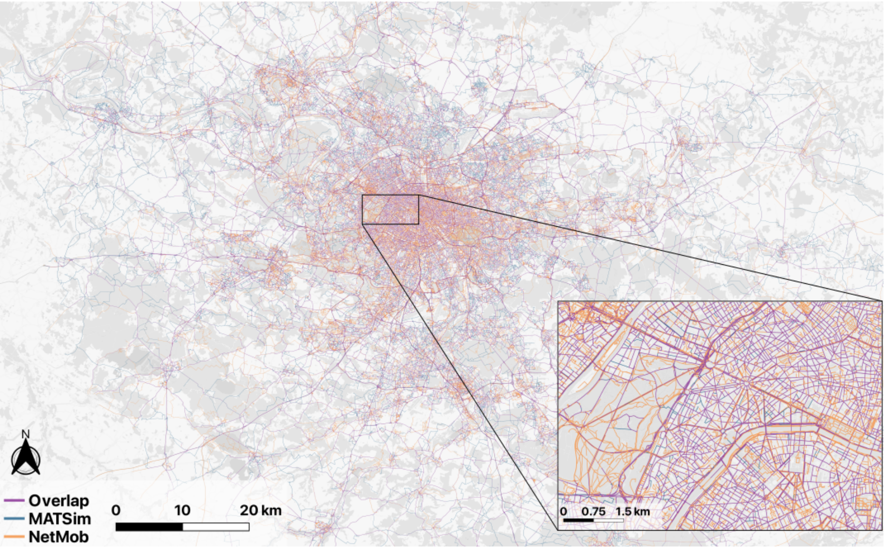
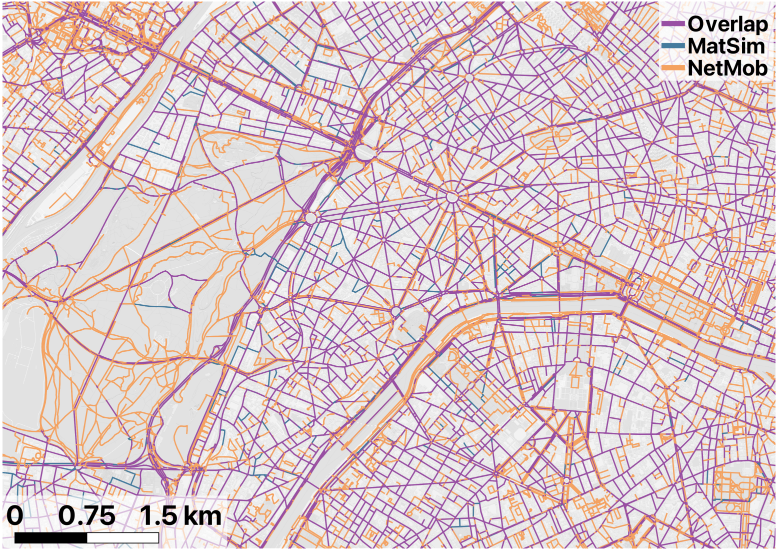


Mapped Data

Observed paths are more diverse

- Region between Bois de Boulogne in the west to the Louvre in the east



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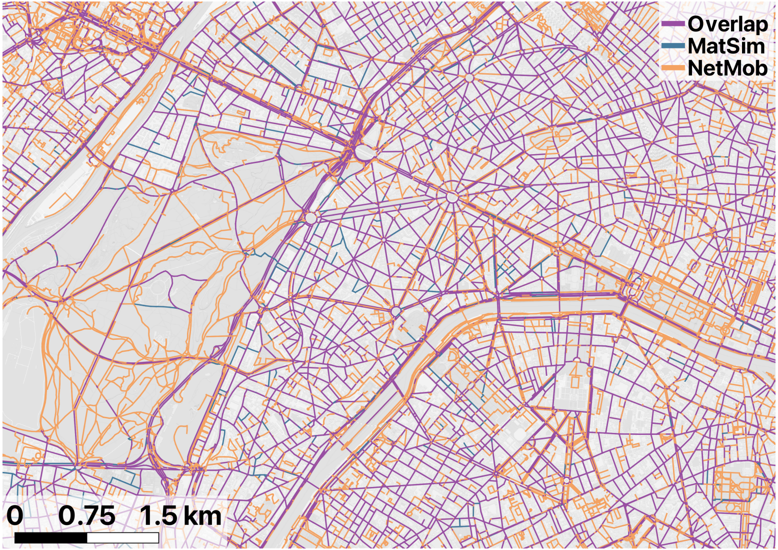
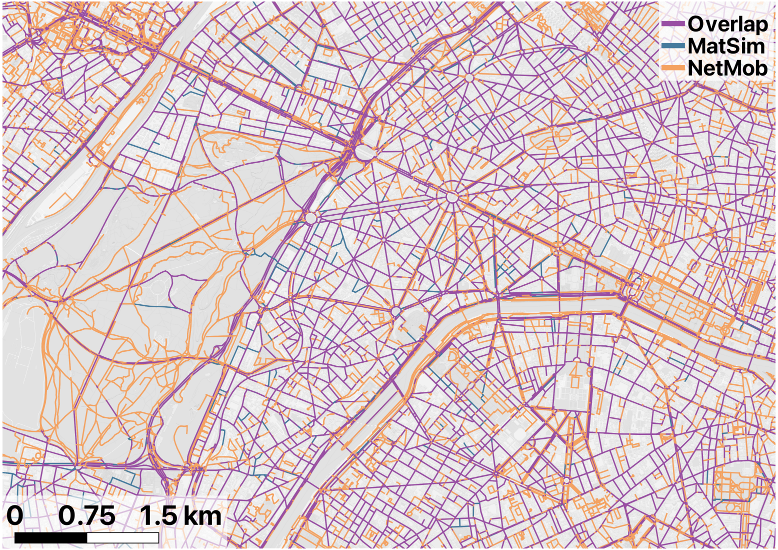


Mapped Data

Observed paths are more diverse

- Region between Bois de Boulogne in the west to the Louvre in the east
- NetMob coverage **much more diverse in pedestrian areas**
- MATSim provides only origin and destination for walking and cycling, we impute shortest paths



Random Walk Dataset

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Purpose

- Memoryless random walk is the simplest null model for mobility paths

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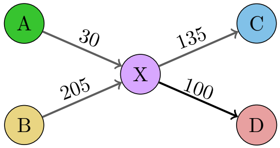
Discrete time random walk

- Random walker placed on node u at time $t = t_0$
- Let η_u denote the out-neighbors of u
- At $t + 1$, the walker moves to a node $v \in \eta_u$ with the following probability:

$$\Pr(v|u) = \frac{w_{uv}}{\sum_{x \in \eta_u} w_{ux}}$$

where $w_{uv}, \; v \in \eta_u$ is either 1 (*unweighted* or *uniform*) or the weight of the edge between u and v (*edge weighted*).



Random Walk Dataset

Purpose

- Memoryless random walk is the simplest null model for mobility paths
- Point of comparison that “mirrors” combined statistics of the two path datasets

Discrete time random walk

- Random walker placed on node u at time $t = t_0$
- Let η_u denote the out-neighbors of u
- At $t + 1$, the walker moves to a node $v \in \eta_u$ with the following probability:

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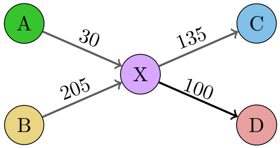

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- **Start node** and **path length** distributions mirror combination of both datasets

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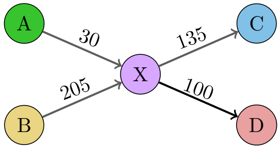

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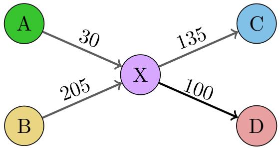

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Random walk design

- **Start node** and **path length** distributions mirror combination of both datasets
- Compute random walks over the full OSM network (*i.e.*, without simplification)
- Filter paths in the same way as the original datasets

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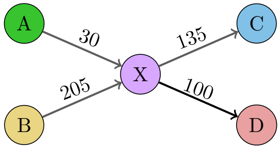

Network Coverage

Node visits

- What **proportion of nodes** are visited by paths from each dataset?

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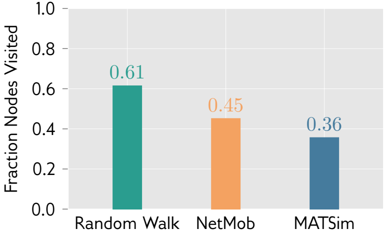
Takeaways

- Fewer than **half of nodes in the network visited**



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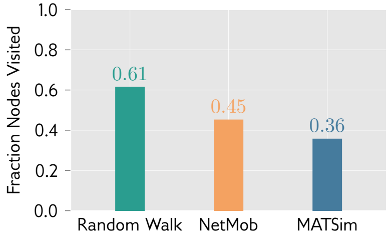
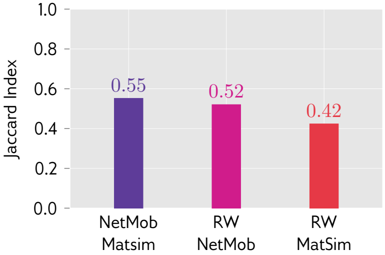
Node visits

- What **proportion of nodes** are visited by paths from each dataset?
- How much do NetMob participant and MATSim agent **visited nodesets overlap**?





Takeaways

- Fewer than **half of nodes in the network visited**
- Around **half of nodes visited in common**

Network Coverage

Node visits

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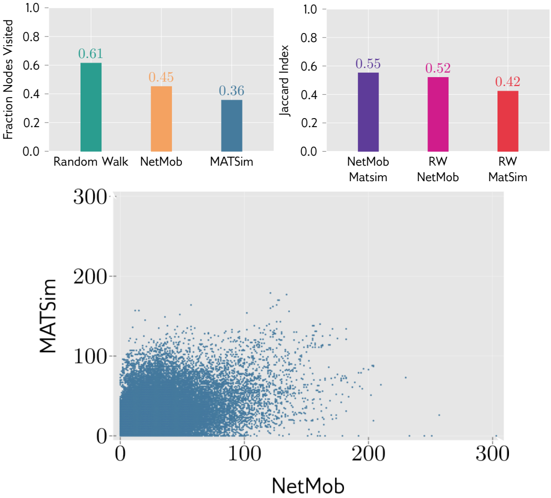
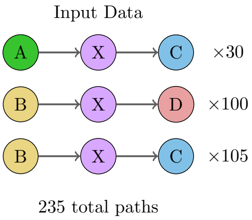
- How much do NetMob participant and MATSim agent **visited nodesets overlap**?
- Are **visit frequencies** aligned?

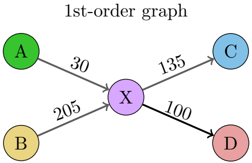
Takeaways

- Fewer than **half of nodes in the network visited**
- Around **half of nodes visited in common**
- Visitation **frequencies correlate, but with some outliers**



DeBruijn Graphs for HON Analysis



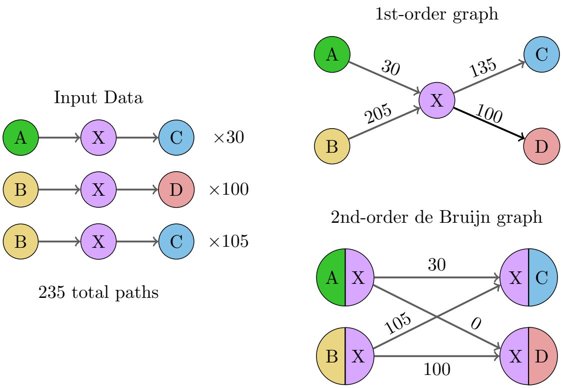


Scholtes, ACM SIGKDD, 2017; De Bruijn, Proceedings of the Koninklijke Nederlandse Akademie van Wetenschappen, 1946

DeBruijn Graphs for HON Analysis

*k*th-order de Bruijn graph

- Nodes represent paths of length $k - 1$ edges



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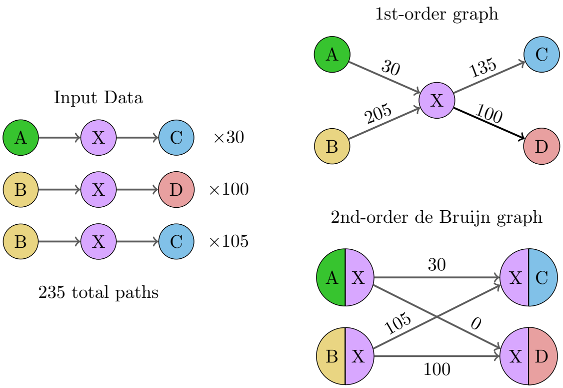

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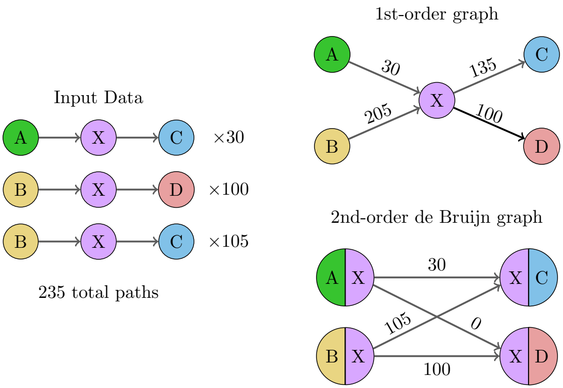

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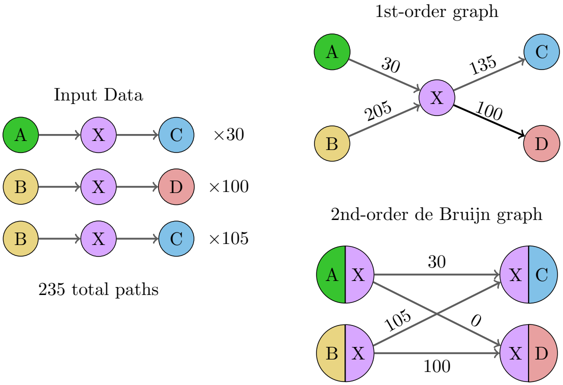
- Natural representation for incorporation of dynamical memory into network topology



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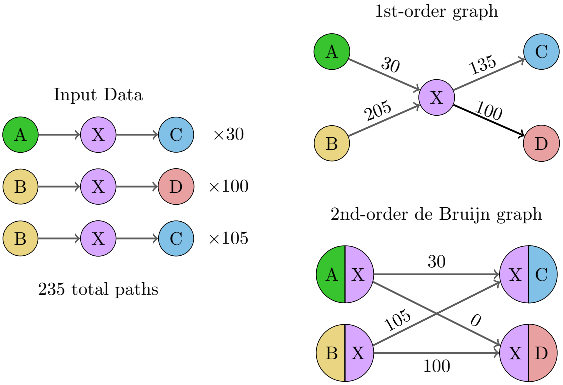

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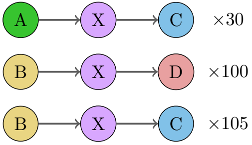
Higher-order transition probabilities

- Normalized edge weights $\rightarrow$ kth-order random walk

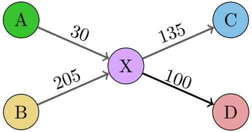
$$\Pr(v_t | v_{t-1}, v_{t-2}, \ldots, v_0) = \Pr(v_t | v_{t-1}, \ldots, v_{t-k})$$

Input Data

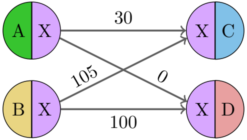


235 total paths

1st-order graph



2nd-order de Bruijn graph



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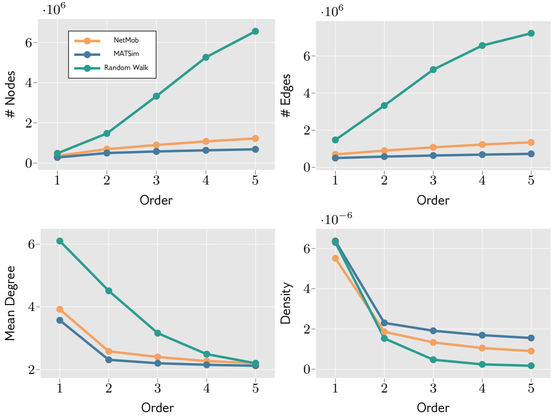
Higher-order Network Analysis

Mobility Network Alignment

- NetMob and MATSim: nodes and edges increases with order, while average degree and density decrease



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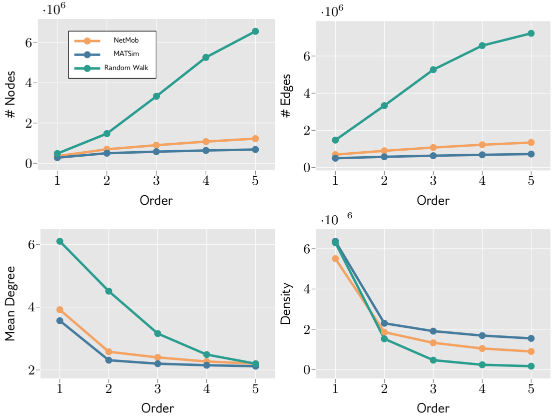

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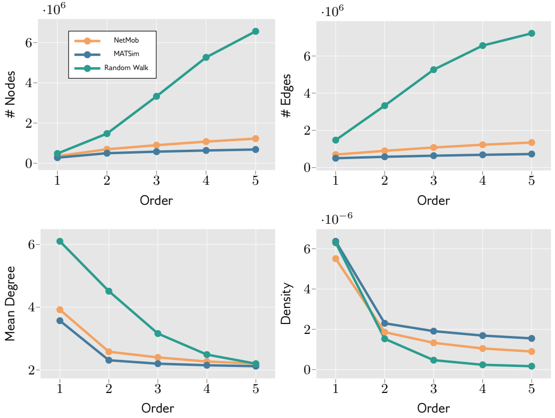

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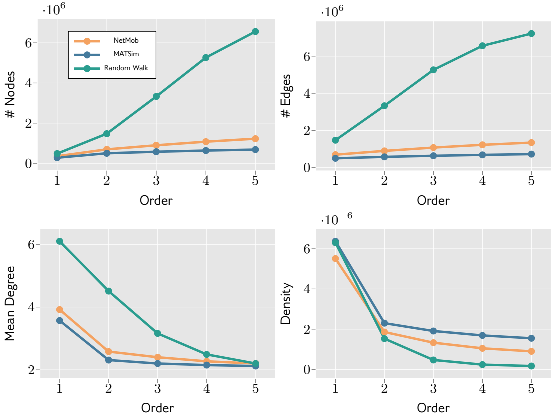

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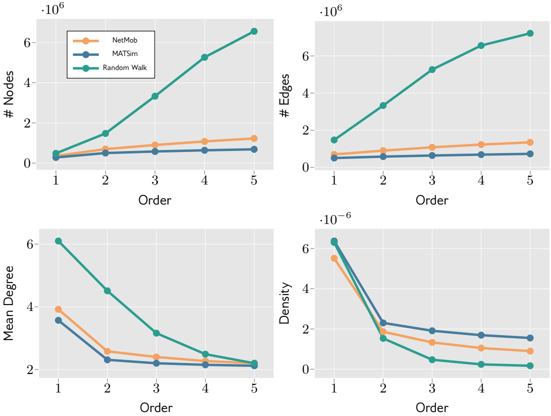
- NetMob and MATSim have estimated optimal order $k = 2$, while random walks has $k = 1$ (memoryless)



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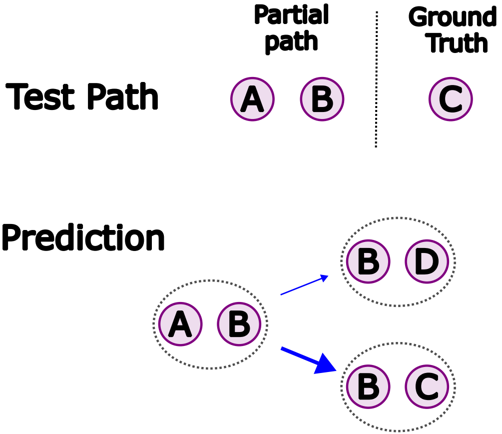
Next-step prediction

Next-step prediction with backoff



Gote *et al.*, *Applied Network Science*, 2023.

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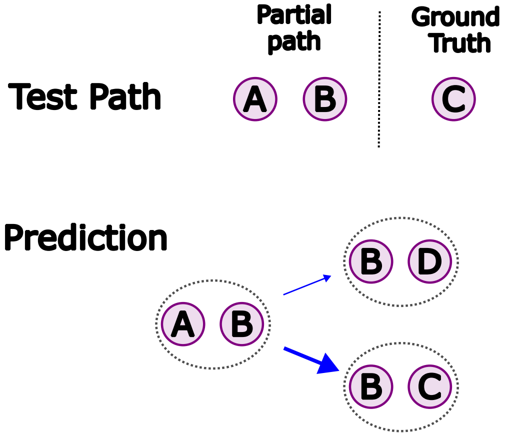
$$P(v_k = u) \propto P(u | v_{k-1}, \ldots, v_0)$$



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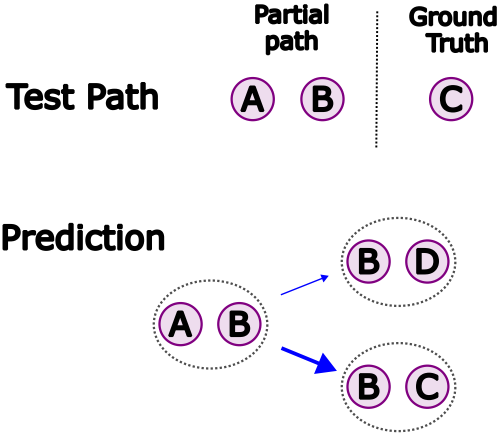

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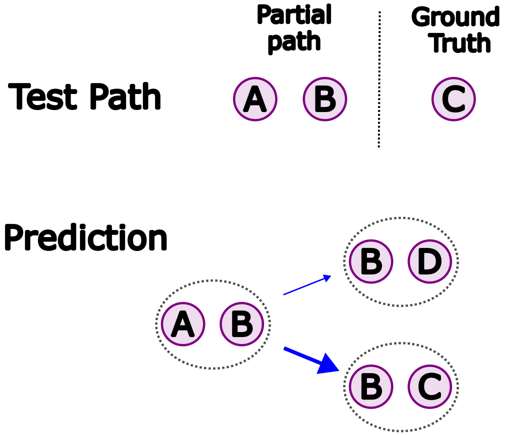
where $i = k = 1$ is a memoryless random walk step:

$$P(v_k = u) \propto P(u | v_{k-1})$$



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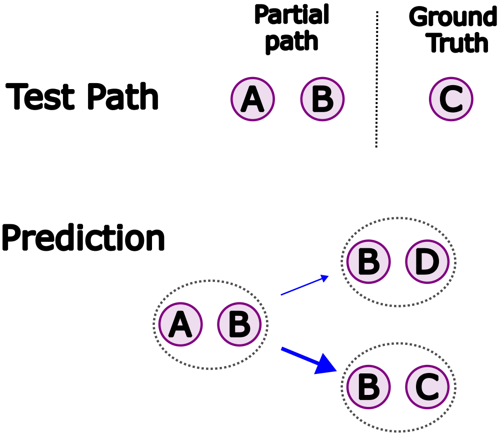
Next-step prediction

Experimental Setup

- Split paths into training and testing sets (stratified by log of path length, 10 splits)



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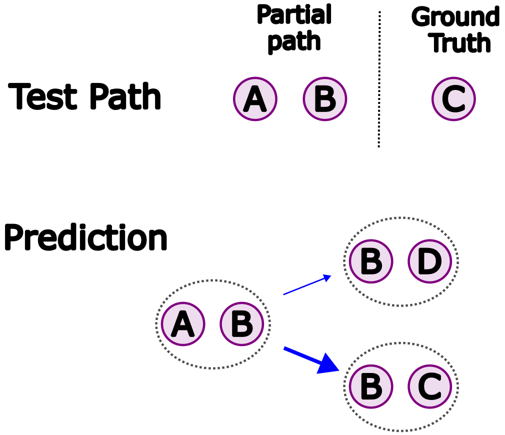

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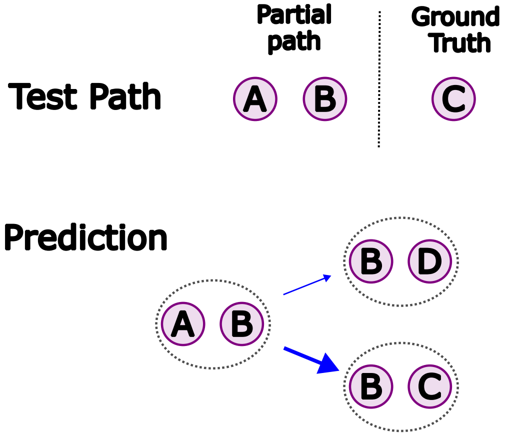

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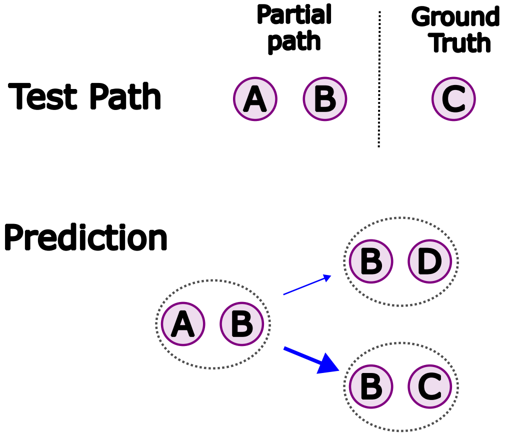
- Measure average prediction accuracy



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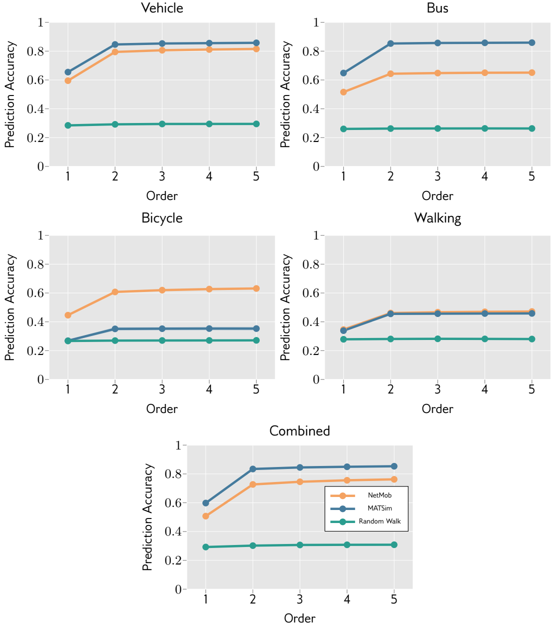
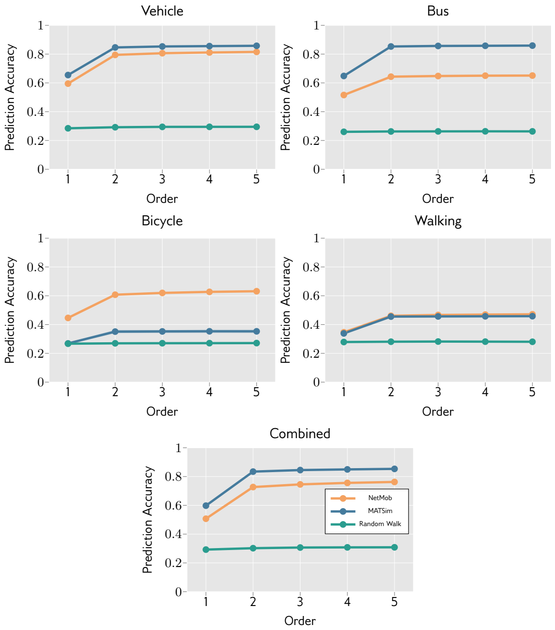
Next-step prediction results



Next-step prediction results

Accuracy jump at optimal order

- Both datasets show jump in accuracy at optimal order $k = 2$, then only marginal benefit



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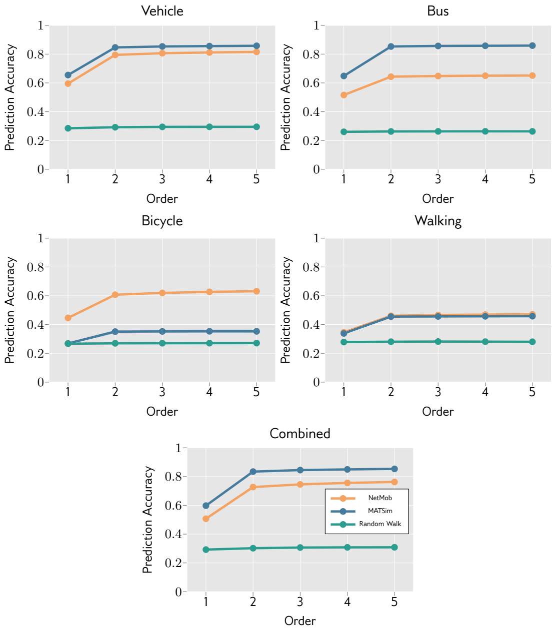

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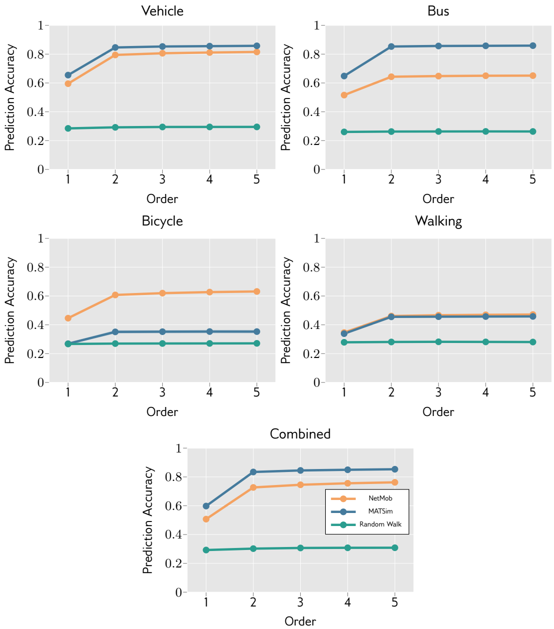
MATSim vehicle paths more predictable

- Next-step prediction accuracy higher for both vehicle and bus modes



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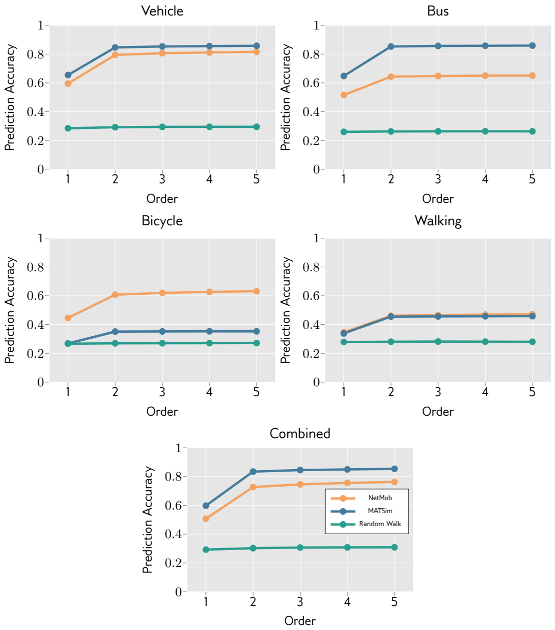

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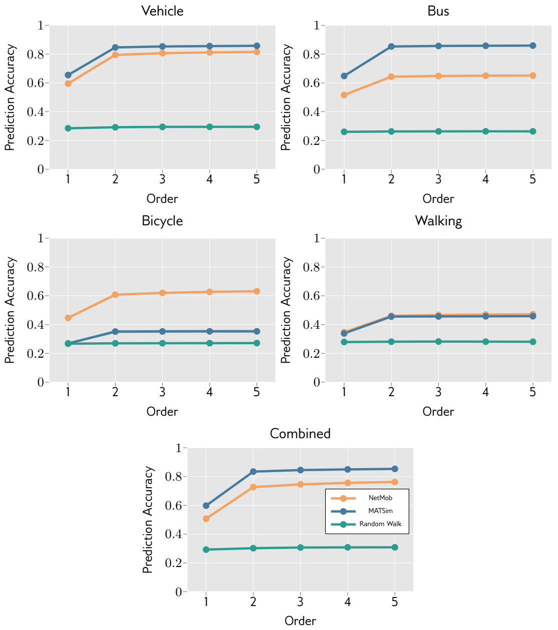

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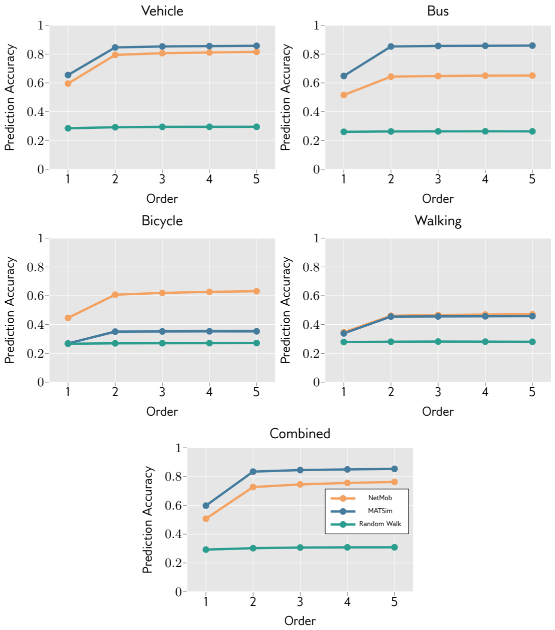

Next-step entropy

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- Average entropy of transition probability distributions from higher-order nodes:

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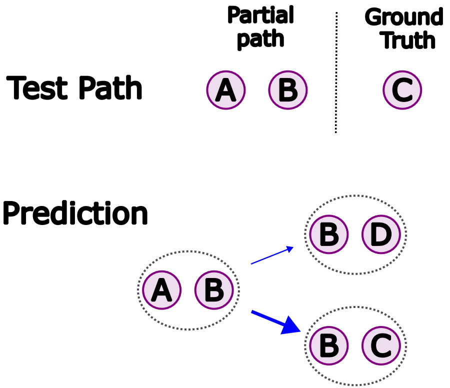

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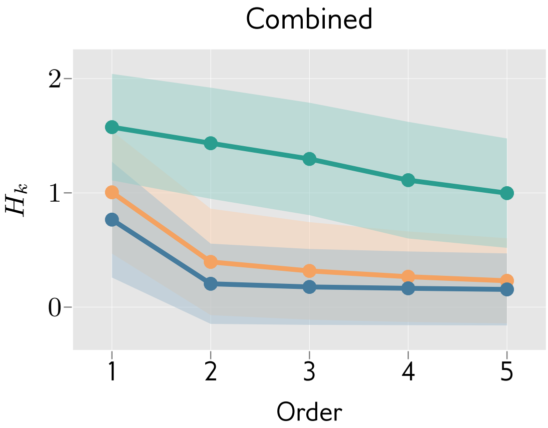
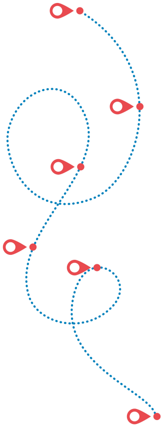
Higher entropy in real paths

- NetMob entropy higher for all modes
- Reinforces that observed trajectories are less predictable than simulated



Talk Roadmap

1. Background: Human mobility, infrastructure, and higher-order networks
2. Case study: observation and simulation in Île-de-France
3. Discussion: Takeaways, limitations, and future work



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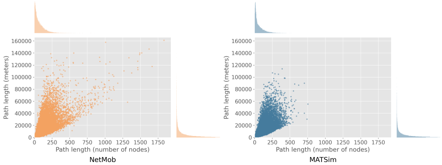
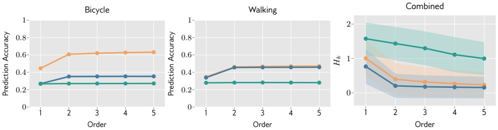
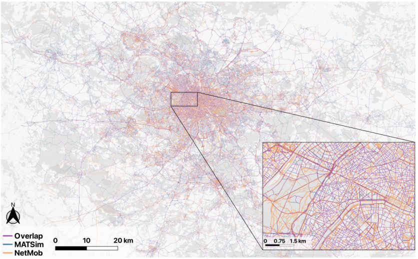
Higher-order network analysis gives us insight into the relationship between observed and simulated mobility.







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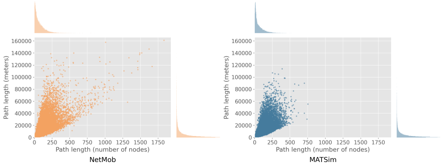

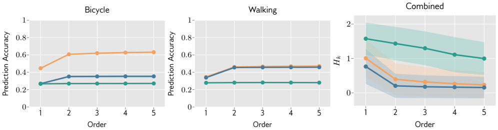

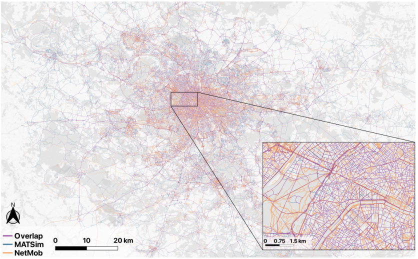

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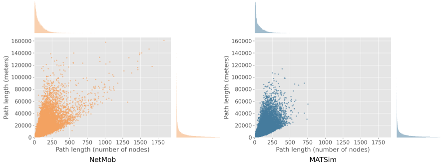

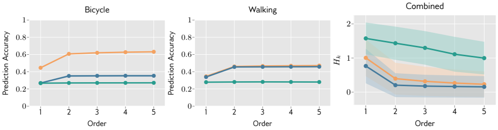

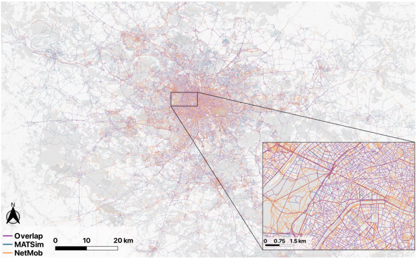

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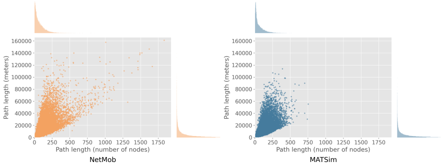

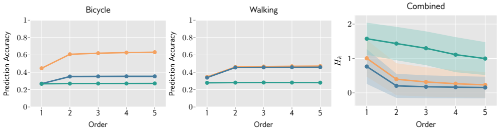

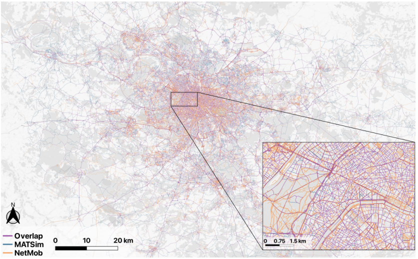

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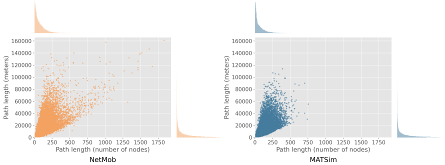

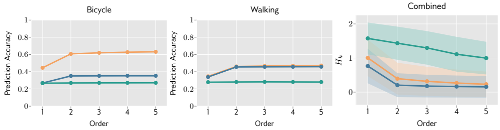

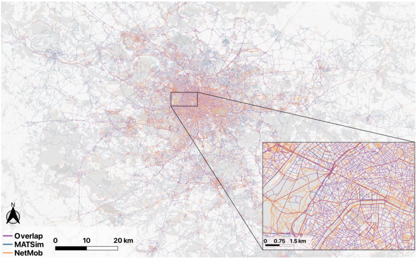

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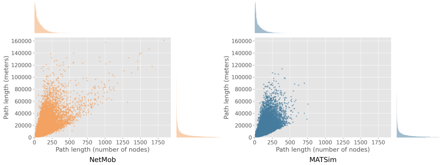

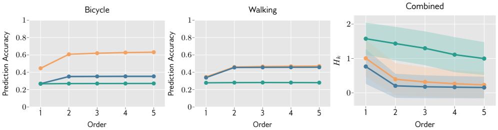

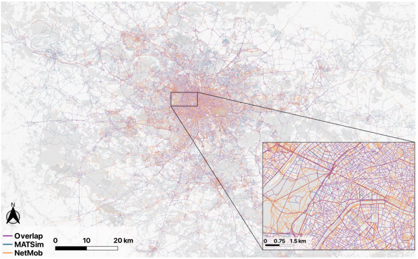

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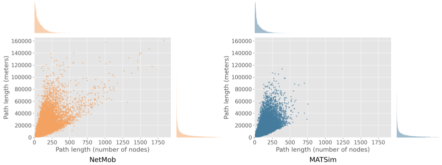
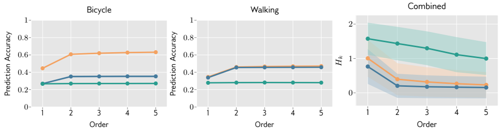
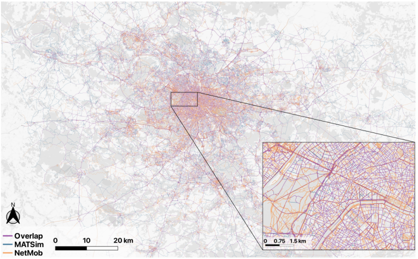
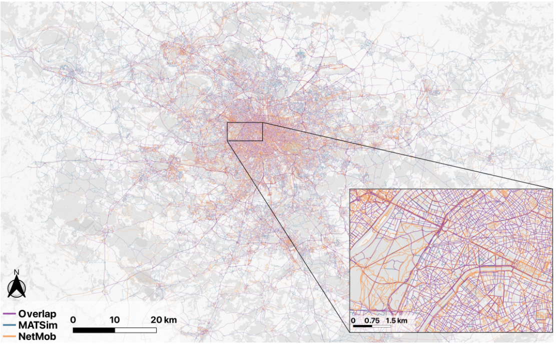






Limitations & Future Work



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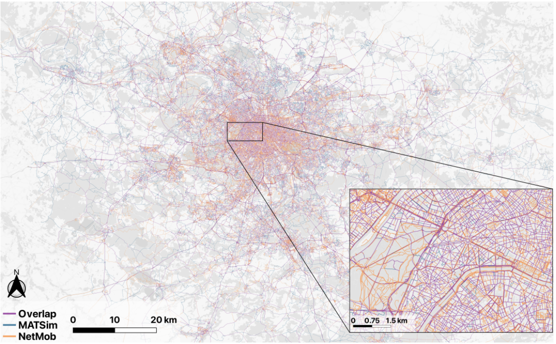

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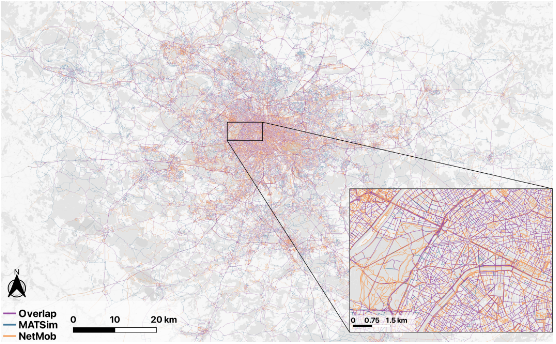

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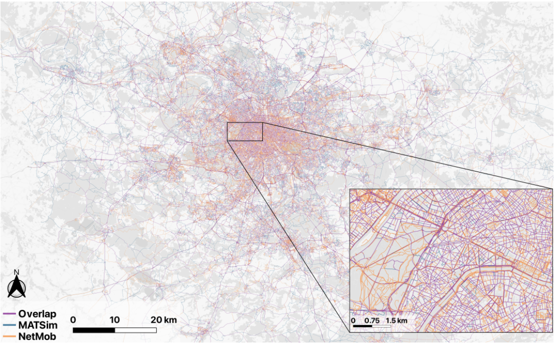

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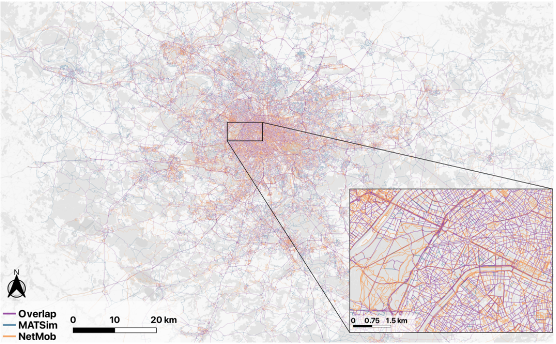

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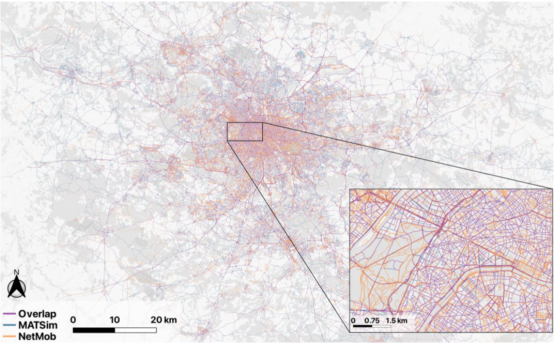

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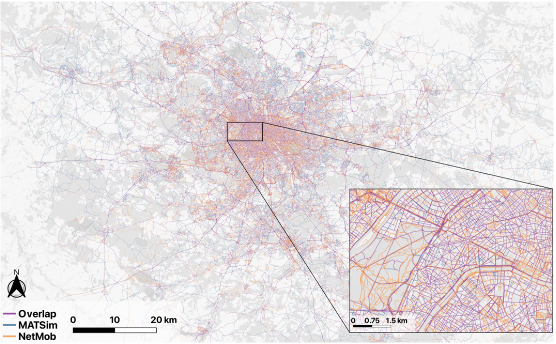

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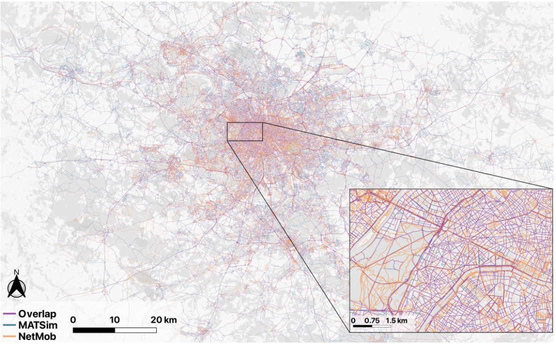

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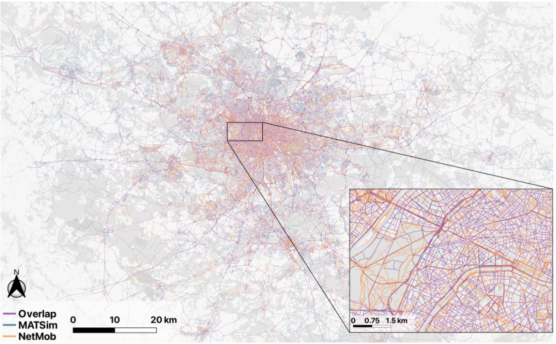
- Sequential motifs
- Direct comparison of higher-order models



Thank You!

Contact

Dr. Timothy LaRock
larock@princeton.edu
https://tlarock.github.io

Preprint coming very soon…

Preprint in collaboration with Chen Zhang and Jürgen Hackl will post to arxiv tonight!

MATSim
Multi-Agent Transport Simulation

OpenStreetMap

The NetMob 2025 Data Challenge is organized with the support of the following institutions and research projects:

ifp Energies nouvelles
Université Gustave Eiffel
FRANCE 2030 PROGRAMME DE RECHERCHE DIGITALISATION et DECARBONATION des MOBILITES
SCI-DAT FACTORY
L'INSTITUT PARIS REGION

Random Walks on Graphs

Discrete time random walk

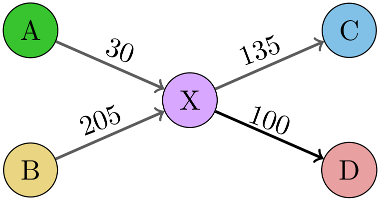
- Random walker placed on node u at time $t = t_0$
- Let η_u denote the out-neighbors of u
- At $t + 1$, the walker moves to a node $v \in \eta_u$ with the following probability:

$$\Pr(v|u) = \frac{w_{uv}}{\sum_{x \in \eta_u} w_{ux}}$$

where w_{uv}, $v \in \eta_u$ is either 1 (*unweighted* or *uniform*) or the weight of the edge between u and v (*edge weighted*).

Note

- This process is called **memoryless** (also **Markovian**) because the next node to be visited depends only on the current node



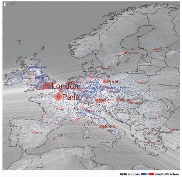
From Individual to Collective Mobility

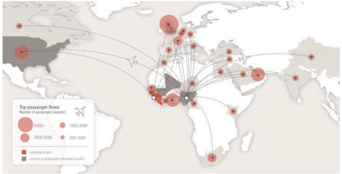
Individual Mobility

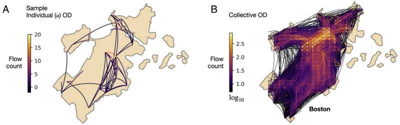
- **Individual trajectories** through the built environment
- Derived from things like: trip logs, historical records, and GPS trajectory data
- Examples: GPS location records (mobile phones, exercise apps, dedicated devices), vehicle GPS (personal, taxi, rideshare), etc.

Collective Mobility

- **Aggregate patterns** across spatial and temporal scales
- Origin-destination flows derived from things like: large-scale surveys and **aggregations of individual mobility datasets**
- Examples: local and global migration, commuting flow patterns, census transportation data, etc.





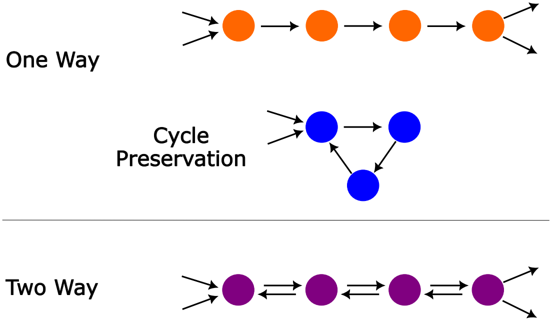


Schich *et al.*, Science, 2014; Pastore-Piontti *et al.*, Mathematical and Statistical Modeling for Emerging and Re-emerging Infectious Diseases, 2016; Bontorin *et al.*, PNAS, 2025

Dataset Processing: Network Simplification

Network simplification

- Remove “redundant” nodes that do not represent meaningful choice points for travelers and artificially reduce navigational complexity
- Removal also reduces downstream computation



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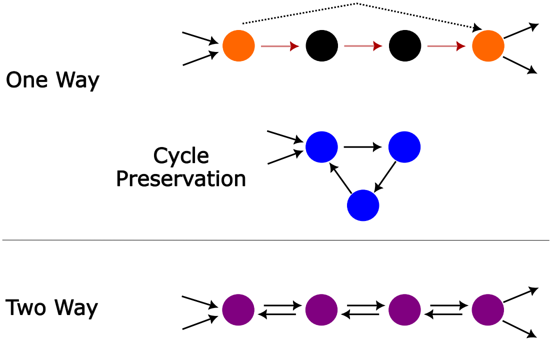
Redundant nodes

- One-way roads: Nodes with degree exactly 2 and different in/out neighborhoods



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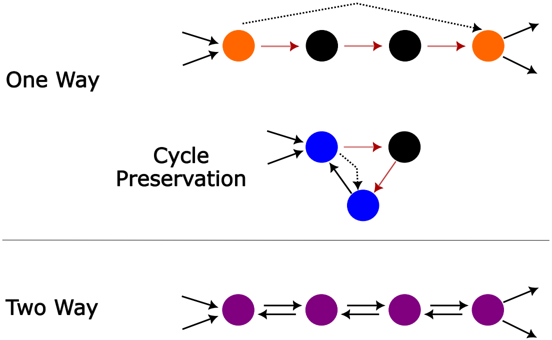

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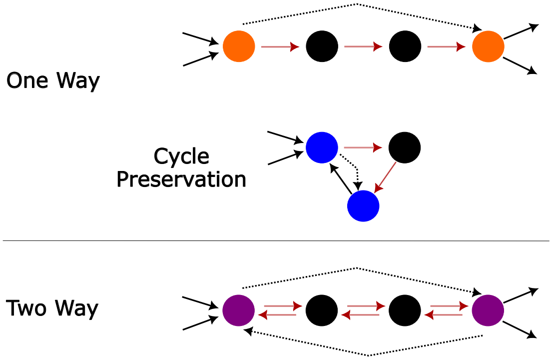

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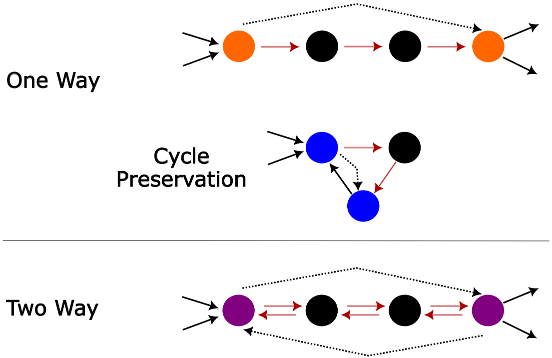
Consequences

- Nodes: Reduced from 3,016,582 to 788,018 (26%)
- Edges: Reduced from 6,655,074 to 2,197,946 (33%)
- Cycles and overall navigability preserved



Dataset Processing: NetMob

Map matching

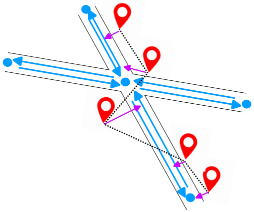
- Match sequences of GPS coordinates to OpenStreetMaps network edges
- Matched sequences of unique edges are paths

Implementation

- Hidden Markov Model approach
- Valhalla Open Source Routing Engine implementation

Post processing

- Discontinuities interpolated with shortest paths
- Redundant nodes removed from paths



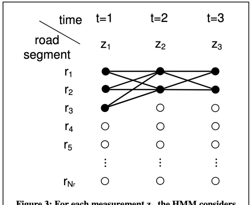
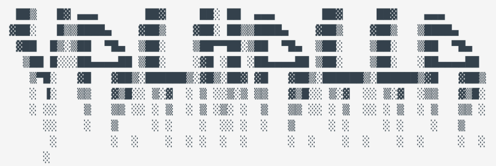


Figure 3: For each measurement z_t, the HMM considers all the road segments r_i as well as all the transitions between the road segments.



Newsom & Krumm, ACM SIGSPATIAL, 2009; `https://valhalla.github.io/valhalla/`

Dataset Processing: MATSim

Path extraction

- Extract sequences of OSM nodes from MATSim XML output events
- Interpolate walking and biking modes (MATSim only provides origin/destination)
- Map transit (bus) paths from stops (GTFS data) back to OSM edges

Optimal Order Estimation

Multi-order model likelihood

Given a set of N observed paths $\mathcal{P} = \{p_j\}_{j=1}^{N}$, we calculate the likelihood of the data under a kth-order model as

$$\mathcal{L}\left(\bar{M}_k \mid \mathcal{P}\right) = \prod_{j=1}^{N} \bar{P}^{(k)}\left(p_j\right),$$

where $\bar{P}^{(k)}(p_j)$ is the probability of path p_j under the multi-order model $\bar{M}_k$ with maximum order k.