Typology-informed solutions for sustainable infrastructure systems

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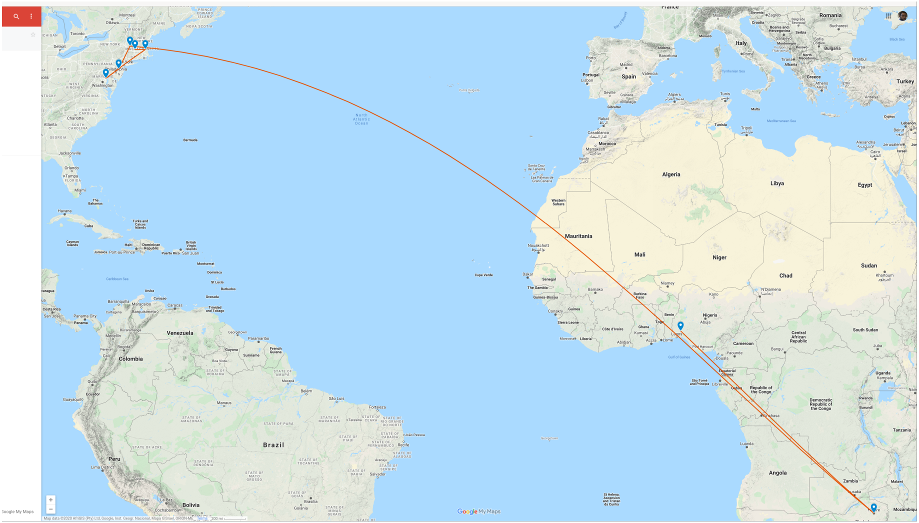
Academic journey

BA (2010)	Physics, Music	Williams College, MA
Teacher (2010–12)	Mathematics, Center for Learning	The Pennington School, NJ
MSE (2014) PhD (2016)	Civil Engineering	Johns Hopkins University
Postdoctoral Associate (2016–19)	Civil and Environmental Engineering	Massachusetts Institute of Technology
Assistant Professor (2019–date)	Civil and Environmental Engineering	University of Massachusetts Amherst

Geographic trajectory

Ibadan, Nigeria → Harare, Zimbabwe → Williamstown, MA → Pennington, NJ → Baltimore, MD → Boston, MA → Amherst, MA



Research agenda

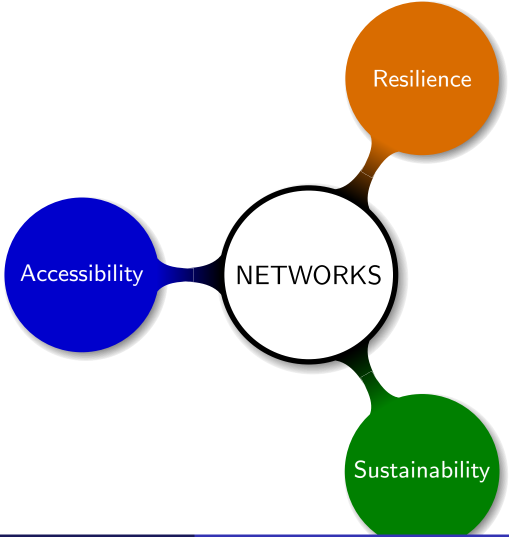
Networks for Accessibility, Resilience and Sustainability (NARS) Lab

Objective

- Advance sustainable and zero-emissions infrastructure systems
- Learn typology representations to guide decision-making
- Quantify and track emissions and energy metrics

Methods

- Machine learning
- Optimization (and simulation)



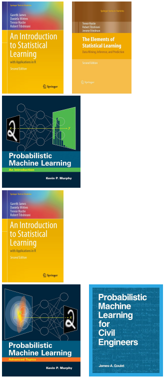
Teaching

Undergraduate

- Probability and Statistics in Engineering (Civil/Mechanical/Industrial); Fall 2019, ’20, ’21, ’25

Graduate (new)

- Big Data and Machine Learning for Engineers (Spring 2020, ’21, ’22)
- Probabilistic Machine Learning (Spring 2023)
- Machine Learning Foundations and Applications (Fall 2023)
- Advanced Probabilistic Machine Learning (Spring 2024)



Team

Current members (status; date joined):

Zhuo Han
MS/PhD; Winter '20

Mohammed Abdalazeem
MS/PhD; Winter '21

Mahsa Arabi
PhD; Summer '21

Peiyao Zhao
PhD; Fall '23

Jimi Oke
Fall '19

Geehan Altayb
NSF REU '24

Alumni

Atanas Apostolov (MS '24); Vivian Rost-Nasshan (NSF REU '23); Alexa Weinman (BS '23); Hichul Chung (BS '22)

Typology analysis

- A typology is formed by grouping entities based on similarities in observed data
  - Distinct type patterns emerge
  - Well established within urban planning (form and function)[1][2][3][4]

Source: Arch Daily *Types of Urban Blocks* 2023

[1] C. D. Harris (1943). "A Functional Classification of Cities in the United States". In: *Geographical Review* 33.1, pp. 86–99.

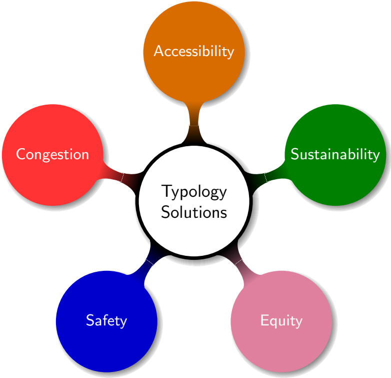
[2] G. D. Bruce et al. (1971). "Developing Empirically Derived City Typologies: An Application of Cluster Analysis". In: *The Sociological Quarterly* 12.2, pp. 238–246.

[3] R. Priester et al. (2013). "The Diversity of Megacities Worldwide: Challenges for the Future of Mobility". In: *Megacity Mobility Culture: How Cities Move on in a Diverse World*. Berlin, Heidelberg: Springer, pp. 23–54.

[4] R. Louf et al. (2014). "A Typology of Street Patterns". In: *Journal of The Royal Society Interface* 11.101, p. 20140924.

Questions

- Can typologies help us better understand our transportation infrastructure?
- How can a typology inform decision-making and planning to address current transportation challenges?



Midtown New York; Source: Clifford 2024

Outline

1. Introduction
2. Background
3. Global urban typology
4. Road safety
5. Outlook

Urban typology for sustainable mobility

- Transportation accounts for 8 $GtCO_2e$ in global annual emissions [5]
  - Urban passenger traffic contributes ∼30% of this
- By 2050, nearly 70% of the global population is expected to live in cities[6]
  - Demand for urban motorized transportation is expected to double
  - Mobility emissions to increase by 60%
- Gap in urban typology literature[7] considering:
  - mobility (demand/supply), socioeconomics, sustainability, network topology
  - and with global scope

Objective

- Characterize cities beyond regional boundaries
- Uncover the underlying factors of urban mobility and sustainability
- Create framework for type-specific analyses of mobility futures

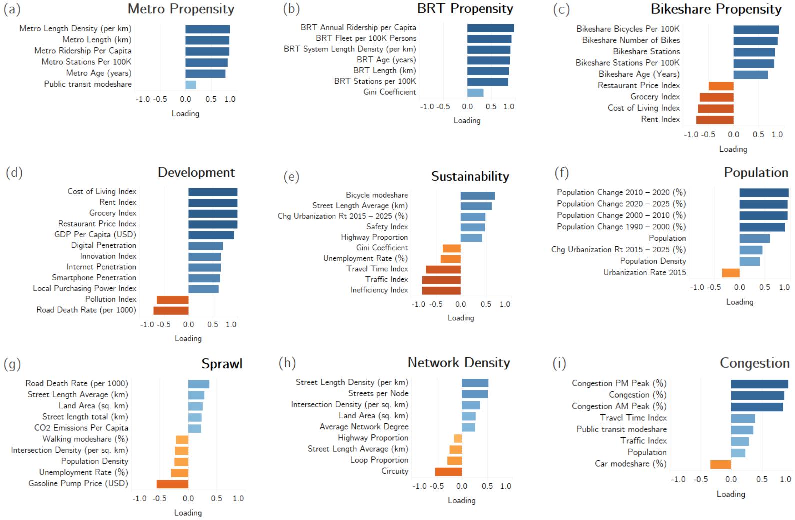
[5] IEA 2017

[6] UN-Habitat (2022). *World Cities Report 2022*. Nairobi, Kenya: United Nations Human Settlements Programme (UN-Habitat).

[7] R. Priester et al. (2013). "The Diversity of Megacities Worldwide: Challenges for the Future of Mobility". In: *Megacity Mobility Culture: How Cities Move on in a Diverse World*. Berlin, Heidelberg: Springer, pp. 23–54.

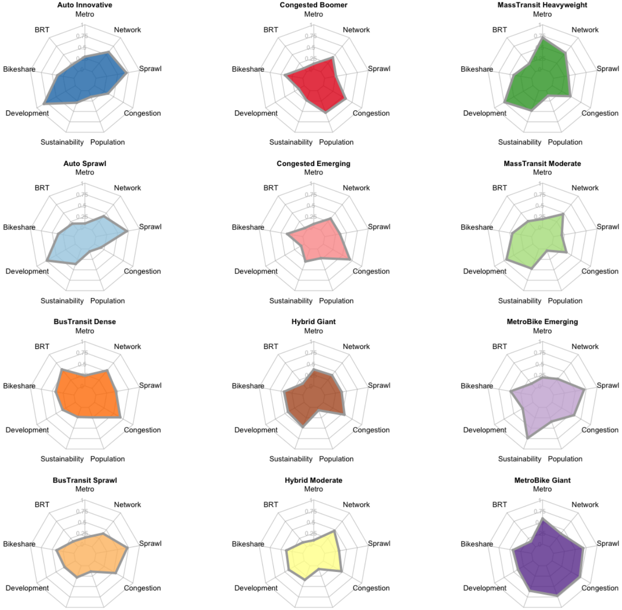
9 driving factors

331 cities, 64 variables[8]: mode choice, form, socioeconomics, environment

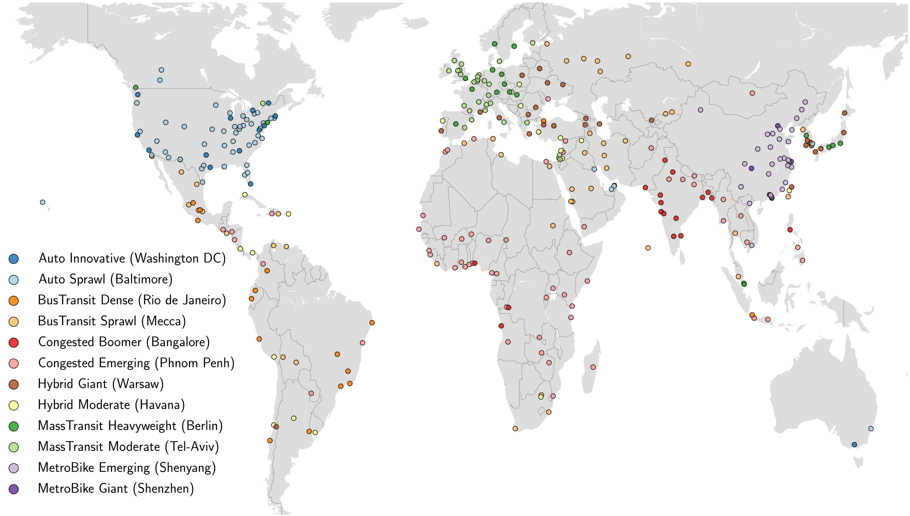


[8] Sources: UN, World Bank, EuroStat, Numbeo, OpenStreetMap, American Community Survey, regional/national

12 urban types discovered



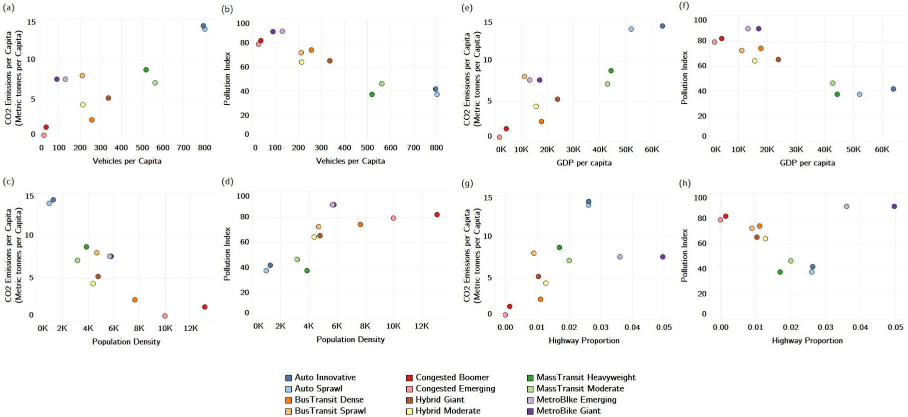
Typology map[9]



[9] J. B. Oke, Y. M. Aboutaleb, et al. (2019). "A Novel Global Urban Typology Framework for Sustainable Mobility Futures". In: *Environ. Res. Lett.* 14.9, p. 095006.

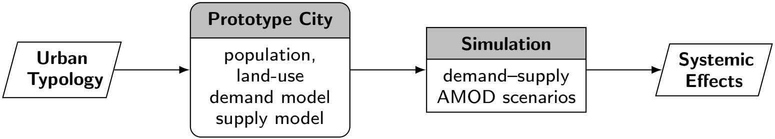
Typology-informed explorations

- *Auto* types have greatest emissions and vehicle ownership, but are least dense and polluted in contrast to the *Congested* types
- Clear wealth gap between the *MassTransit* + *Auto* and the rest
- *MetroBike* cities have the greatest highway proportion and pollution index



Application: evaluating autonomous mobility impacts

- Promise of mobility on demand (MOD): greater accessibility, more sharing, less congestion
  - Reality: transit cannibalization, greater congestion[10], inequities[11]
- Promise of automated mobility on demand (AMOD)?
  - What are the type-relevant impacts?
  - Can typology inform planning?
- Objective: assess AMOD scenarios via large-scale agent-based simulation[12]



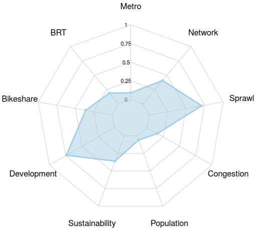
[10] M. Diao et al. (2021). "Impacts of Transportation Network Companies on Urban Mobility". In: *Nat Sustain* 4.6, pp. 494–500.

[11] E. BokÃ¡nyi et al. (2020). "Understanding Inequalities in Ride-Hailing Services Through Simulations". In: *Sci Rep* 10.1, p. 6500; A. de Ruijter et al. (2024). "Ridesourcing Platforms Thrive on Socio-Economic Inequality". In: *Sci Rep* 14, p. 7371.

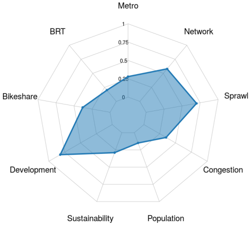
[12] J. B. Oke, A. P. Akkinepally, et al. (2020). "Evaluating the Systemic Effects of Automated Mobility-on-Demand Services via Large-Scale Agent-Based Simulation of Auto-Dependent Prototype Cities". In: *Transportation Research Part A: Policy and Practice* 140, pp. 98–126.

A tale of three prototype cities

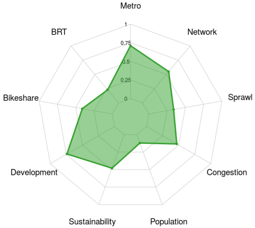
Auto Sprawl



Auto Innovative



MassTransit Heavyweight



Characteristics	*Auto Sprawl (AS)*	*Auto Innovative (AI)*	*MassTransit Heavyweight (MH)*
Car mode share (%)	86	79	32
Mass Transit mode share (%)	3.5	11	37
Walk mode share (%)	3.3	3.3	23
Population density (1000/km^2)	1.0	1.3	3.9
CO_2 emissions p.c. (mtCO_2e/yr)	16	15	10
Examples	*Baltimore, Tampa, Kuwait City*	*Boston, Chicago, Wash. DC*	*Berlin, Madrid, Seoul*

Takeaways

AMOD Intro

- Cannibalizes transit by up to 20%
- Increases VKT by up to 30% and congestion by up to 50%

AMOD No Transit

- Cannot substitute transit in denser cities—congestion increases by 65%

AMOD Transit Integration (TI)

- Reverses cannibalization; boosts ridership

	Mass Transit Share (%)		
	BASE	AMOD	AMOD TI
AS	**4.0**	**3.0**	**7.0**
AI	**10.0**	**8.5**	**12.5**
MH	**38.0**	**37.0**	**40.0**

- Mitigates detriments of AMOD in transit-oriented & low-density cities

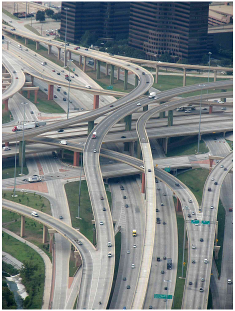
AMOD + Car Reduction

- Increases VKT by 13% and congestion by 8%; reduces energy and emissions by 16% and 20%

Understanding our road networks

Required for effective and equitable deployment of transportation solutions

- Earth is crisscrossed by 40 million miles of road; 16% of this in the US[a]
- US emissions in 2021: 6.3 $GtCO_2e$[b]
  - Almost 25% of this was due to roadway emissions (gasoline and diesel consumption)
  - Globally, the roadway share is <15%[c]
- Congestion is also a major issue with quality of life, socioeconomic and emissions impacts
  - From 1993-2017 (top 100 urban areas)[d]: freeway ↑ 40%, population ↑ 30%, congestion ↑ 140%
  - Demand for personal mobility continues to grow (25 mi/day in 2017)



High-Five Interchange, Dallas, TX[a]

[a] M. Bellis 2021.

[a] E. Raboteau (2023). "How Our Roads Hurt Us and Everything Around Us". In: *The New York Times. Books*.

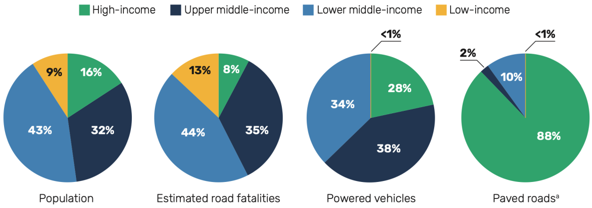
[b] O. A. R. US EPA (2017). *Inventory of U.S. Greenhouse Gas Emissions and Sinks*. URL: https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks (visited on 03/19/2024).

[c] O. A. R. US EPA (2016). *Global Greenhouse Gas Emissions Data*. URL: https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data (visited on 03/19/2024).

[d] R. Bellis et al. (2020). *The Congestion Con*. Transportation for America.

Global roadway safety outlook[13]

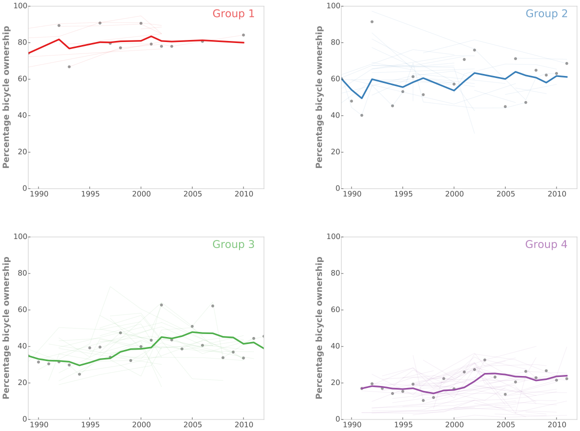
- Road traffic crashes: leading cause of death for ages 5–29
- 1.2 million died in roadway crashes in 2021
  - A decline of 5% since 2010
- Vulnerable road users account for 50% of fatalities
  - pedestrians, two-/three-wheelers, cyclists
- 92% of roadway deaths occur in low- and middle-income countries



[13] WHO (2023). *Global Status Report on Road Safety 2023*. Geneva: World Health Organization.

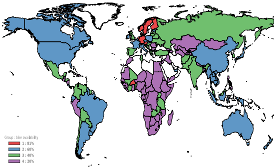
Bicycle ownership trends

Pattern discovery from survey data in 150 countries spanning 30 years[14,15]



Key findings

- > 580 million bicycles owned by households around the world
- Global household ownership declined by 50% since 1985

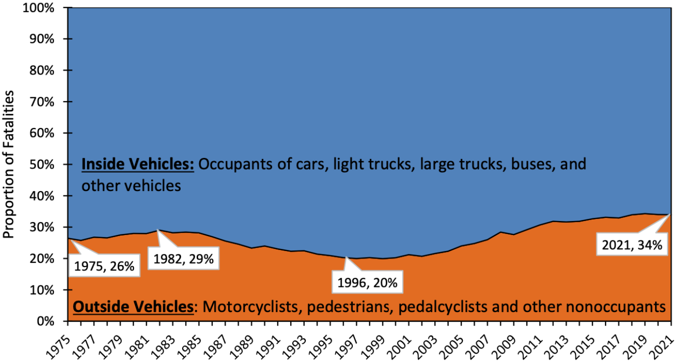


[14] O. Oke et al. (2015). "Tracking Global Bicycle Ownership Patterns". In: *Journal of Transport & Health* 2.4, pp. 490–501.

[15] O. Oke et al. (2018). "Spatial Associations in Global Household Bicycle Ownership". In: *Ann Oper Res* 263.1, pp. 529–549.

Vulnerable road users in the US

- In 2021, vulnerable road users accounted for one-third of road traffic fatalities in the US[16]



  - In **urban** areas, 44% of fatalities were vulnerable users; **rural** areas, 19%

[16] T. Stewart (2023). *Overview of Motor Vehicle Traffic Crashes in 2021*. DOT HS 813 435. National Highway Traffic Safety Administration.

Transportation disadvantaged communities

Two-thirds of communities in the top 20% of fatalities are **transportation disadvantaged**

> *census tracts that: ARE at or above the 90th percentile for diesel particulate matter exposure OR transportation barriers OR traffic proximity and volume AND are at or above the 65th percentile for low income*[17]

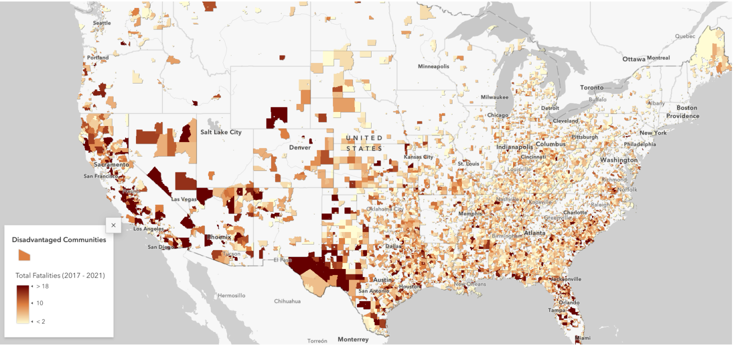
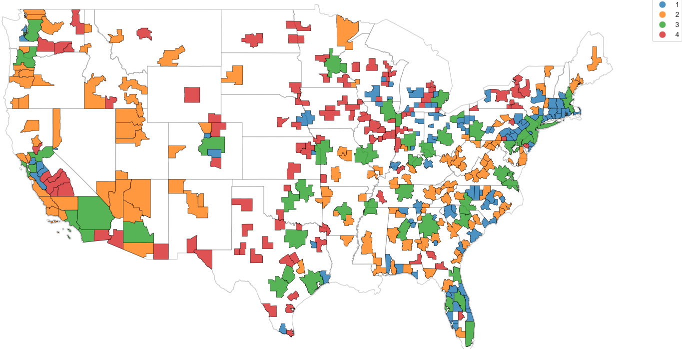


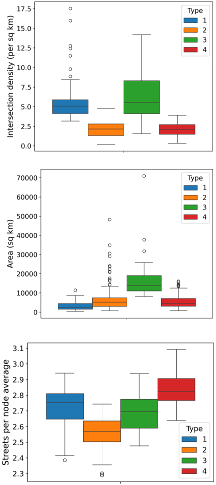
Image source: USDOT *Roadway safety problem* https://www.transportation.gov/NRSS/SafetyProblem

[17] Climate and Economic Justice Tool https://screeningtool.geoplatform.gov/en/methodology

Preliminary results: Road network typology

- 18 network indicators; 372 metropolitan areas; 4 types
  - Type 1: small, dense; Worcester, MA-CT
  - Type 2: circuitous and sparse; Portland, ME
  - Type 3: large, dense; Austin, Boston, LA
  - Type 4: connected and sparse; Des Moines, IA





- Potential applications: explain congestion patterns, analyze crashes

Conclusion

- Typology analysis can be a powerful tool for uncovering groups of systems or cities with patterns of interest
- Typologies provide structure for exploring relationships and designing experiments
- Can inform policy and decision-making

Challenges

- **C**ongestion
- **A**ccessibility
- **S**ustainability
- **E**quity
- **S**afety

Emerging areas

- Decarbonization/electrification
- Fairness (Artificial Intelligence)
- Micromobility

Ongoing projects

- Energy forecasting and decision making framework for urban rail transit systems
- Spatiotemporal crash typology for New England census tracks
- System-wide energy prediction for transit systems
- Regional emissions mitigation strategies
- Quantifying bicycle network accessibility

Acknowledgements

- Networks for Accessibility, Resilience and Sustainability Lab
- University of Massachusetts Transportation Center (UMTC)
- Massachusetts Institute of Technology Energy Initiative (MITei) and collaborators
- Intelligent Transportation Systems Lab

Thank You

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Factor analysis

Model

$$\boldsymbol{y}^* = \boldsymbol{v} + \boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{1}$$

where:

$\boldsymbol{y}^*$	vector of J normal response variables
$\boldsymbol{v}$	vector of variable means
$\boldsymbol{\Lambda}$	$J \times P$ matrix of factor loadings (or weights); P is number of factors
$\boldsymbol{\eta}$	$P \times 1$ vector of variable scores on each factor
$\boldsymbol{\varepsilon}$	$J \times 1$ vector of independent error terms

Hierarchical agglomerative clustering methods

Iteratively group cities by pairing closest based on defined metric

Selected method: Ward

- Distance between two clusters U, V (merging cost):

$$\begin{aligned} D(U,V) &= SSE_{UV} - (SSE_U + SSE_V) \\ &= \frac{|u| \cdot |v|}{|u| + |v|} ||\bar{u}_i - \bar{v}_j||^2 \end{aligned} \tag{2}$$

  SSE: sum of squared errors

- Optimal number of clusters: 13 (merging cost curve; dendrogram)

Prototype city generation overview

Archetype City ⇨

Indicators for all cities in selected typology ⇨

Inputs

1. Synthesize ***population*** and ***land use*** data of archetype city
2. Calibrate and validate ***demand*** (preferences, trips and activities) to typology
3. Model and calibrate ***supply*** based on archetype network and operational conditions

Generation

3-steps

⇨

Simulation

demand – supply interactions

⇨

- Energy
- Accessibility
- Multimodal System Performance
- Cost Indicators

Outputs

Approach

Generate representative prototype city for urban typology:

- Population and land-use synthesis
- Demand modeling and calibration
- Supply network modeling and calibration

Perform agent-based simulations to analyze mobility scenarios

Scenarios

- **Base Case**
  - existing on-demand services; mass transit and private modes
- **AMOD Intro** (AMOD)
  - AMOD (single/shared) replaces existing MOD
  - AMOD fare is 50% that of MOD in 2016
- **AMOD No Transit** (AMOD NT)
  - Transit abandoned in *Auto Sprawl/Innovative*
- **AMOD Transit Integration** (AMOD TI)
  - AMOD restricted to local trips
  - 20% discounted access/egress to mass transit
- **AMOD + Car Reduction** (AMOD CR)
  - 25% reduction in household car ownership via ownership tax in *MassTransit Heavyweight*

On-demand powertrain assumptions

- MoD fleet: hybrid-electric vehicles
- AMOD fleet: battery-electric vehicles

Mesoscopic simulator: SimMobility Mid-term