AI for Transportation

Speakers:

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Climate Change AI

Your instructors

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- PhD in Urban Planning, MSc in Environmental Econ.
- Excited about AI deployment for urban climate change mitigation

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- PhD in Geospatial AI, MEng in Engineering & Computer Science
- Excited about how ML can help understand cities

Today

1. **Transportation landscape** -> ***Case study***
2. **The role of transportation in global climate change mitigation**
3. **ML & transportation** -> ***Case study***
4. **Pathway to impact**

Learning objectives of the lecture

- Before AI to transportation, one needs to understand and take into account a multi-dimensional context that needs to be encapsulated into a theory of change.
- The biggest impact AI can have for GHG emission reduction in the transportation domain is through efficiency gains and redistribution of trips from carbon-heavy to green mobility.
- Successful deployment of AI solutions in the transportation sector requires coordination between private and public sector and civic society.
- Priorities are different around the world! There are much more impactful avenues than AI for decarbonizing transportation in many places. AI is at the tail end of tools for emission reduction.

Case study: Evaluating trip demand forecasts

Interactive exercise throughout the lecture:

you will work on **a real-world case-study,** where you **consult the local government of a city** on where to best allocate new bike stands for the city's bike sharing program.

Question 1: metrics and measures

Question 2: feature selection and methodological approach

Question 3: real-world implementation and climate impact

Case study: trip demand forecasting

As the city does not have much data on cycling demand in every neighbourhood, you plan to develop a **demand forecasting model** that, given a specific **time** and **location**, will return a projected trip demand. Based on this you derive planning advice on where to build new bike stands.

Your proposed approach should include: metrics for trip demand, features to use as predictors, forecasting methods and testing and implementation plan.

Transportation landscape

Modes, infrastructure & operators

Transportation Overview

"The evolution of transportation has been driven by the need for efficiency, cost reduction, and sustainability, reflecting broader economic and environmental trends. As these trends continue, further innovations and shifts in transportation modes are expected." (Transport Geography, 2024)

Transportation of Goods

- Since the 1960s, Containerization has facilitated globalization.
- Goods are transported via combination of modes (rail, road, air, sea)
- Information technology has greatly improved supply chain management and logistics

Transportation of Passengers

- In 20th century cars became the dominant mode of transport
- Air travel has grown exponentially
- **Urban areas** face congestion and require more investments in public transport systems

Public vs private transportation

Public

- Modes: train, tram, bus,...
- Available to everyone (for a fee); shared space

Private

- Modes: car, bike, scooter,...
- Privately owned vehicle, private space

Active vs passive transportation

Active

- Modes: foot, bike, skateboard,...
- Any human-powered means of transportation
- No emissions!

Passive

- Modes: car, bus, train,...
- Powered by an engine
- Can have emissions, if powered by a combustion engine

“Green” vs “non-green” transportation

“Green”
- Modes: bike, train, e-vehicle
- Operation of the vehicle does not cause emissions

“Non-green”
- Modes: combustion engine car / bus, train
- Operation of the vehicle causes emissions and / or particle pollution

Urban transportation modes

Urban transportation infrastructure

Roads: highways, streets, bike lanes, bus lanes,...

Rail: regular rail, light rail, tram rail (can be on roads),...

Support infrastructure: powerlines,

shared vehicle docking stations, (bike) parking,...

! Urban transportation infrastructure is almost always *publicly funded* and provided.

Public and private mobility operators

Public operators: not profit but utility driven, policy goals, can operate at a loss, can be aligned more easily with broader urban policy goals and "quality of life"

Private operators: profit driven, only applicable on profitable routes (can leave marginalized people behind!), but can also detect demand where no public transport is available

Public and private mobility operators

Public operators: not profit but
utility driven, poli
operate at a loss
aligned more eas
broader urban po
“quality of life”

Public private partnerships (PPP): collaborations between public and private providers, e.g. infrastructure is provided publicly, while services are run privately

Private operators: profit driven,
le on profitable
ave marginalized
!), but can also
d where no public
vailable

Intermodal mobility

- The number of **modes of travel** in cities has steadily increased
- At the same time, the **traditional car commute has become more unattractive** (through congestion charges, pedestrianisation, etc.)
- This has lead to the rise of ***"intermodal mobility"***, wherein 2+ modes of travel are combined

Willing, C., Brandt, T. & Neumann, D. **Intermodal Mobility**. *Bus Inf Syst Eng* **59,** 173–179 (2017)

Bus Inf Syst Eng 59(3):173–179 (2017)
DOI 10.1007/s12599-017-0471-7

CrossMark

CATCHWORD

Intermodal Mobility

Christoph Willing · Tobias Brandt · Dirk Neumann

Received: 1 July 2016 / Accepted: 24 January 2017 / Published online: 12 April 2017

Keywords Intermodal mobility · Multimodal mobility · Mobility markets · Spatial analytics · Location-based services · Sustainable mobility

1 Background

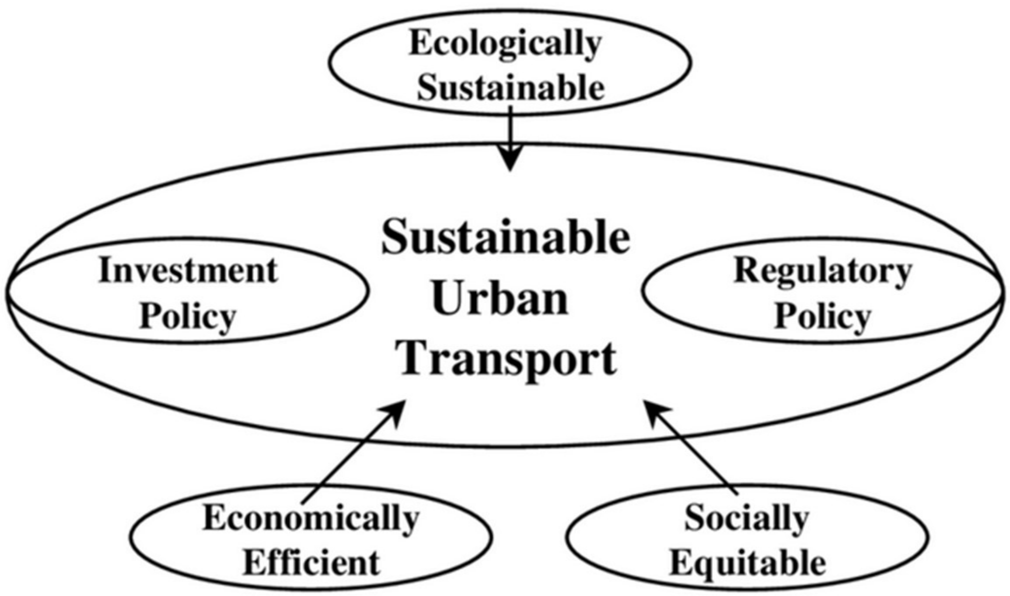
Cities around the world are facing a multitude of mobility challenges. Driven by an increase in the number of personal motor vehicles, traffic and traffic congestion are becoming more frequent, parking spaces are becoming more scarce (while also taking up public space), and the urban population is increasingly exposed to air pollution and noise with potentially negative health effects (Arnott and Inci 2006; Arnott and Small 1994; Barth and Bori-

living in cities is expected to continually increase in both relative and absolute terms. The share of the urban population has been estimated to increase to 66% by 2050, up from 54% in 2014 (United Nations Department of Economic and Social Affairs 2014). Thus, the ongoing urbanization trend will likely exacerbate urban mobility challenges in the near future.

In recent years, the number of urban transportation modes – "the means by which people and freight achieve mobility" (Rodrigue et al. 2013, p 101) – including, for instance, bus, subway or personal car, has increased. Digitalization and Information Systems (IS) solutions have enabled new and more sustainable alternatives, such as carsharing (Firnkorn and Müller 2011), bikesharing (Shaheen et al. 2010), ride sharing (Teubner and Flath 2015) and e-hailing services

Public policy for urban mobility

(Urban) transport policy aims to **harmonize different political aims**, e.g. economic development, reducing emissions or connecting marginalized communities.



Pendakur, V. Setty. "**A policy perspective for sustainable cities-non-motorized transport (NMT) in Asia.**" *IATSS research* 23 (1999): 51-61.

Urban mobility business cases

Urban transportation is a **difficult market for private businesses**. Profit margins can be very low, due to competition with public transport operators who can operate at a loss.

Private operators have found **market niches** in e.g. luxury travel (e.g. helicopter trips), taxi trips, underserved routes, or can leverage economies of scale

Case study: trip demand forecasting
Question #1 – Share your ideas with us!

Share your intuitions with us: What are **metrics for measuring cycling trip demand (outcome variables)**. What constitutes a good demand metric? What data can you realistically obtain to construct the metrics? At what spatial and temporal resolution do you want to collect your metric?

You are consulting a city on where to build new stations for their bike sharing program. You are building a **demand forecasting model** that, given a specific **time** and **location**, will return a projected demand for cycling trips.

Case study: trip demand forecasting
Question #1

Answer:
Internal data: locations where bike-sharing stations were searched for in the bike-sharing app (searches are the best indicator of demand), trip origins in the bike sharing app

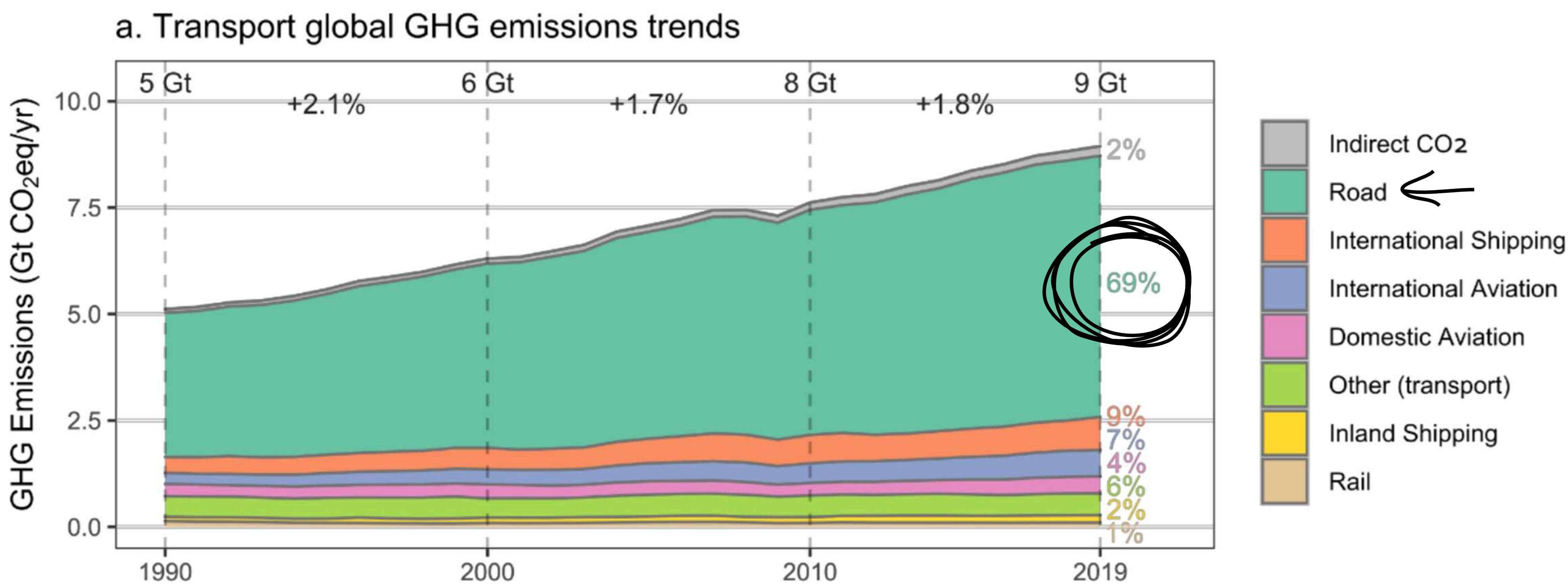
Public data: data from open data portals; e.g. public taxi trips, data from a public transport operator, cellphone movement trajectories, bike sharing data from other cities

Constructing the outcome variable / metric: aggregate the origin points of all trips in the bike sharing app within a certain geographic area and within a certain time span.

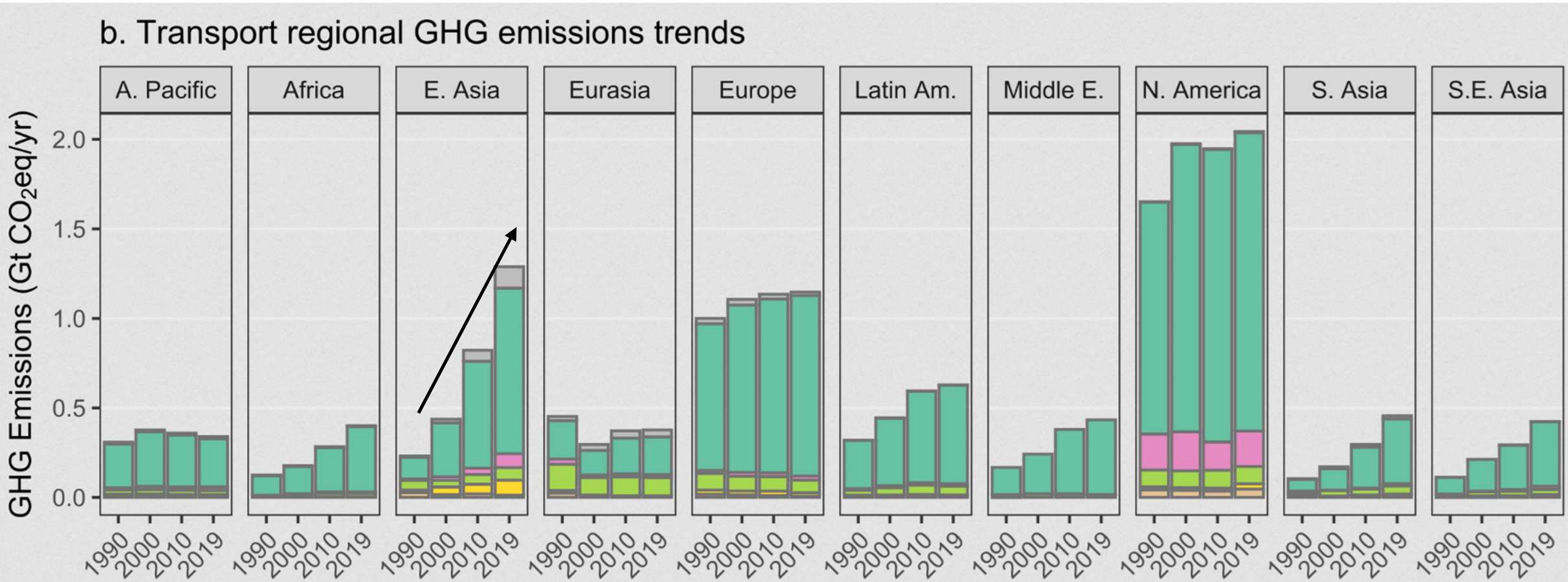
The role of urban transportation in global climate change mitigation

Road transport is key (70% of transport emissions),

but we also need solutions for aviation, int. shipping etc



Source: IPCC AR6 WGIII chap 10



→ **Too much reliance on road transportation**

→ **Too much reliance on combustion engines**

Without strong interventions emissions will probably grow

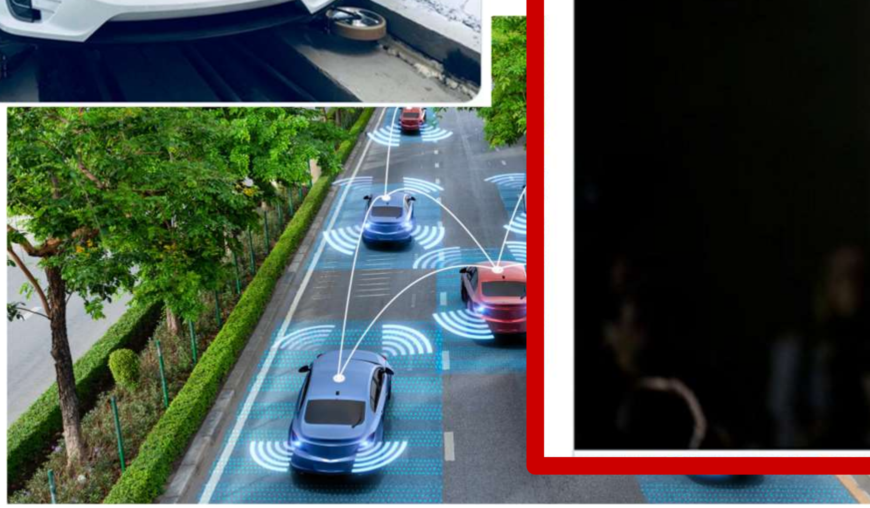
(16~50% by 2050);

the sector did not take the necessary measures so far

Elon Musk @elonmusk

Tesla in @boringcompany tunnel with retractable wheel gear that turns a car into a rail-guided train & back again

Traduire le Tweet

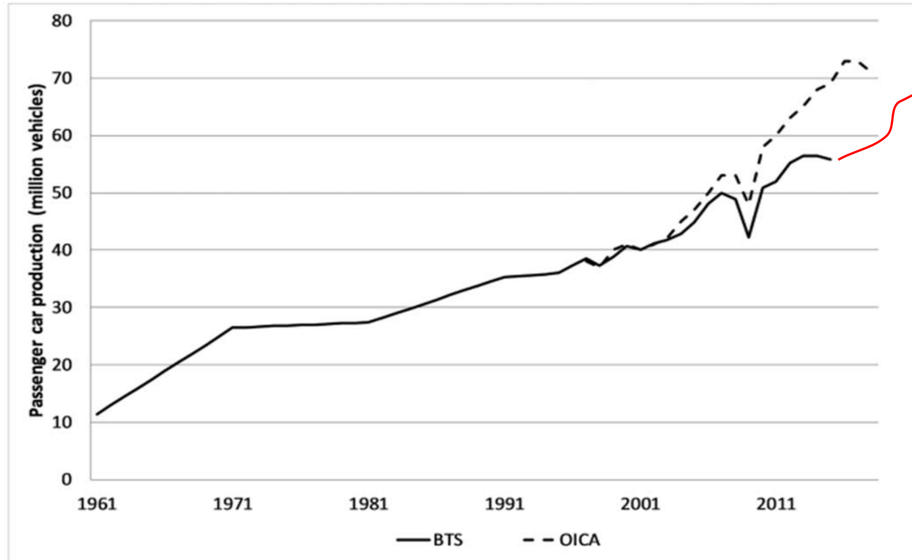


Alexander Demling @alexdemling

Musk admitted Hyperloop was about getting legislators to cancel plans for high-speed rail in California. He had no plans to build it

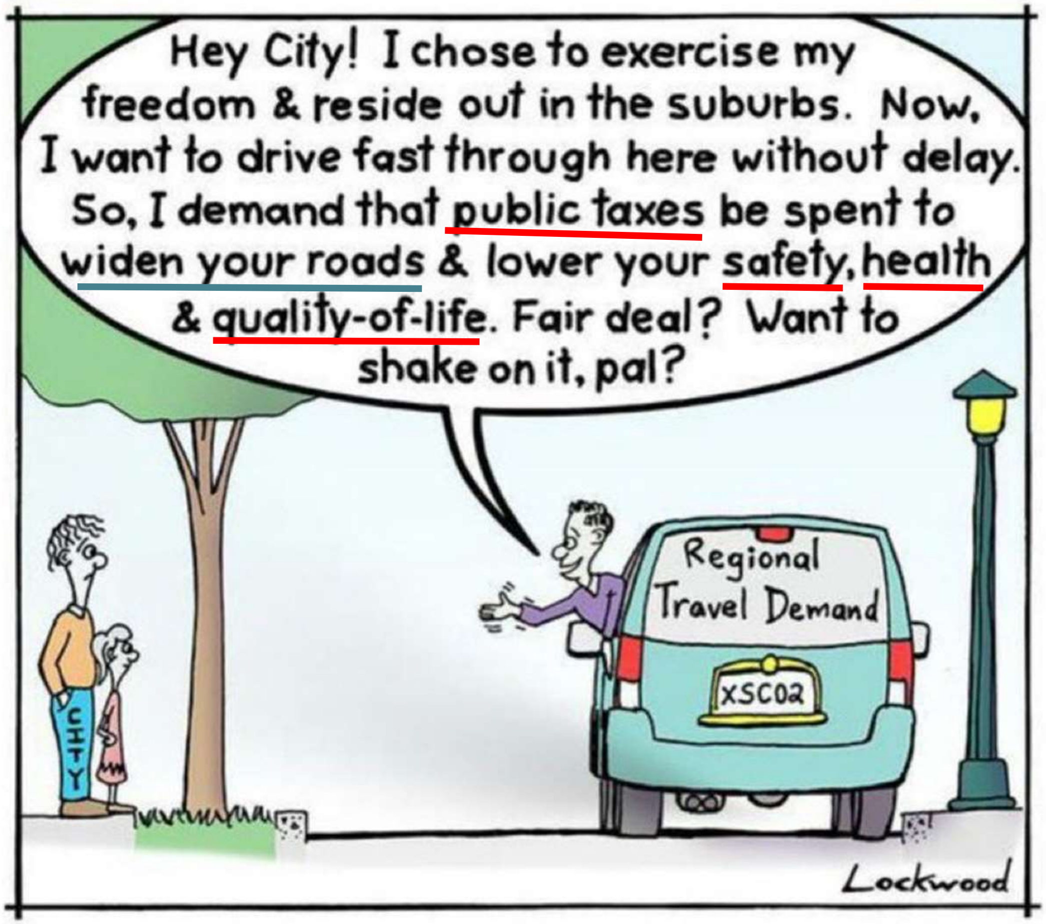
Musk said public transit was “a pain in the ass” where you’re surrounded by strangers, including possible serial killers

Traduire le Tweet


Passenger car production (million vehicles)
80
70
60
50
40
30
20
10
0
1961
1971
1981
1991
2001
2011
BTS
OICA


→ Beware of techno-optimism!

Decarbonizing transportation is not only a GHG emission problem, but also a **sustainability** and **fairness** problem



Regional Travel: a post-WWII euphemism for long & unsustainable car trips

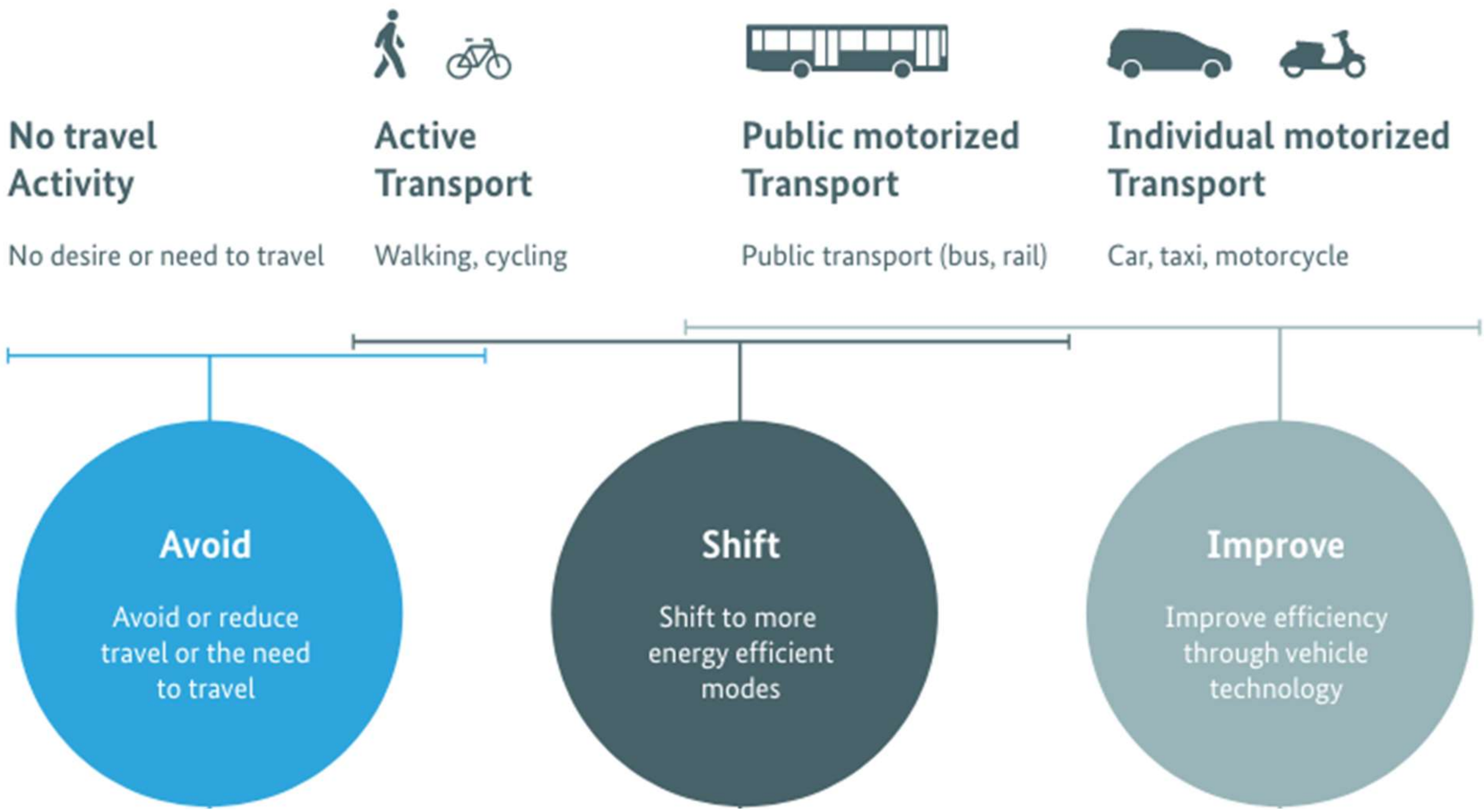
→ Consider multiple externalities and search for a fair solution

How to decarbonize? #1

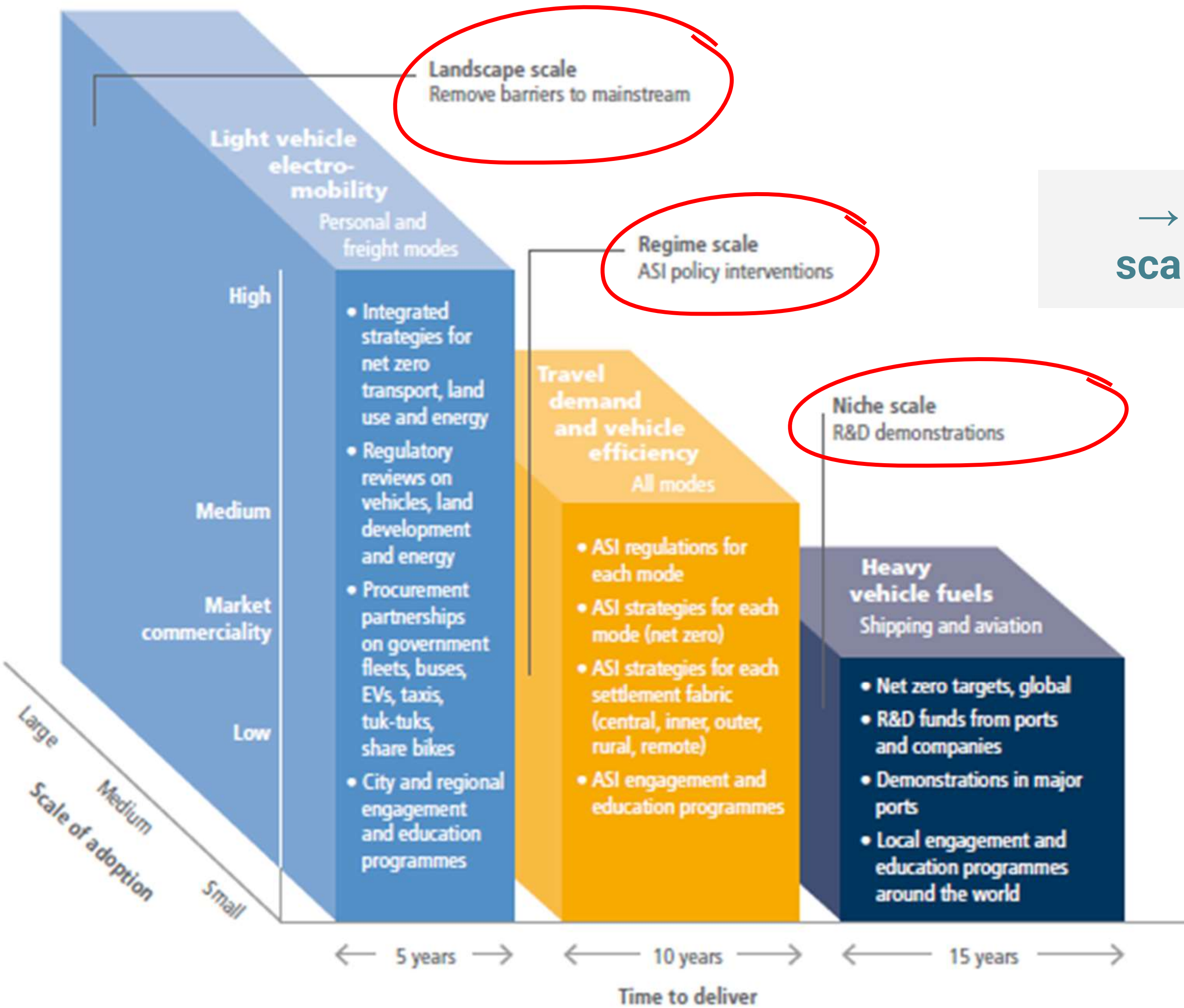
To reduce emissions in the transportation sector,

we can either **avoid**, **shift** or **improve**

→ We need all three!



Source: NACTO

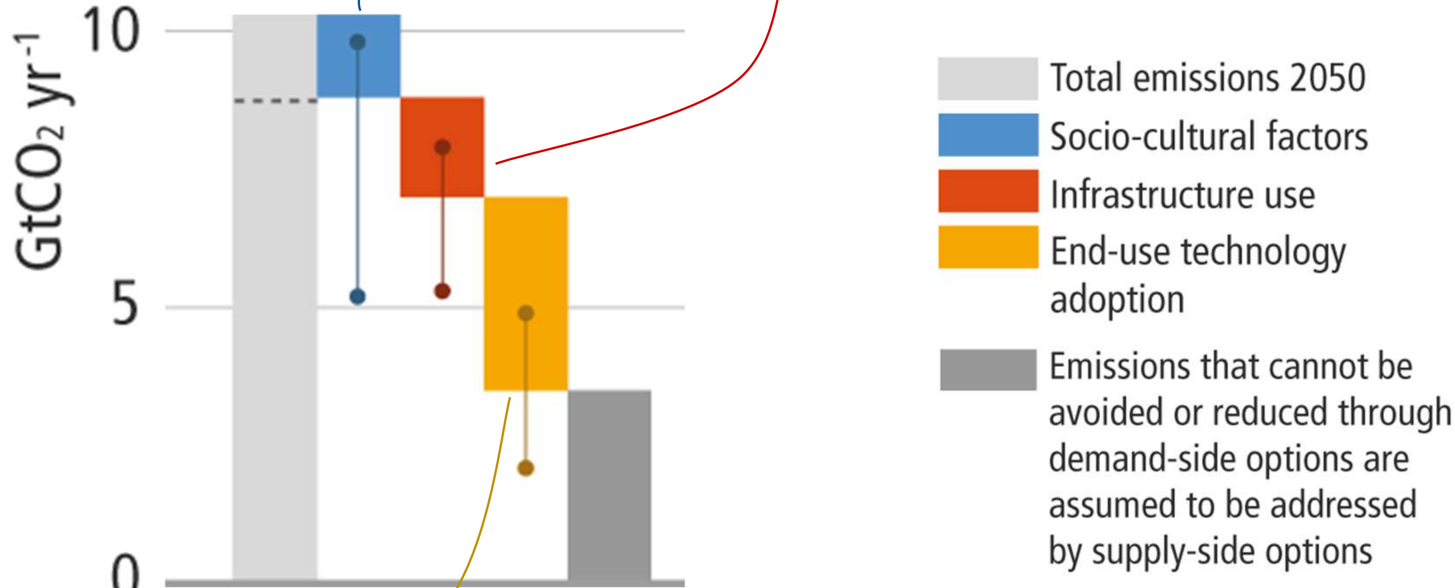


→ **We can and should start scaling these solutions today**

Source:
IPCC AR6 WGIII Chap 10

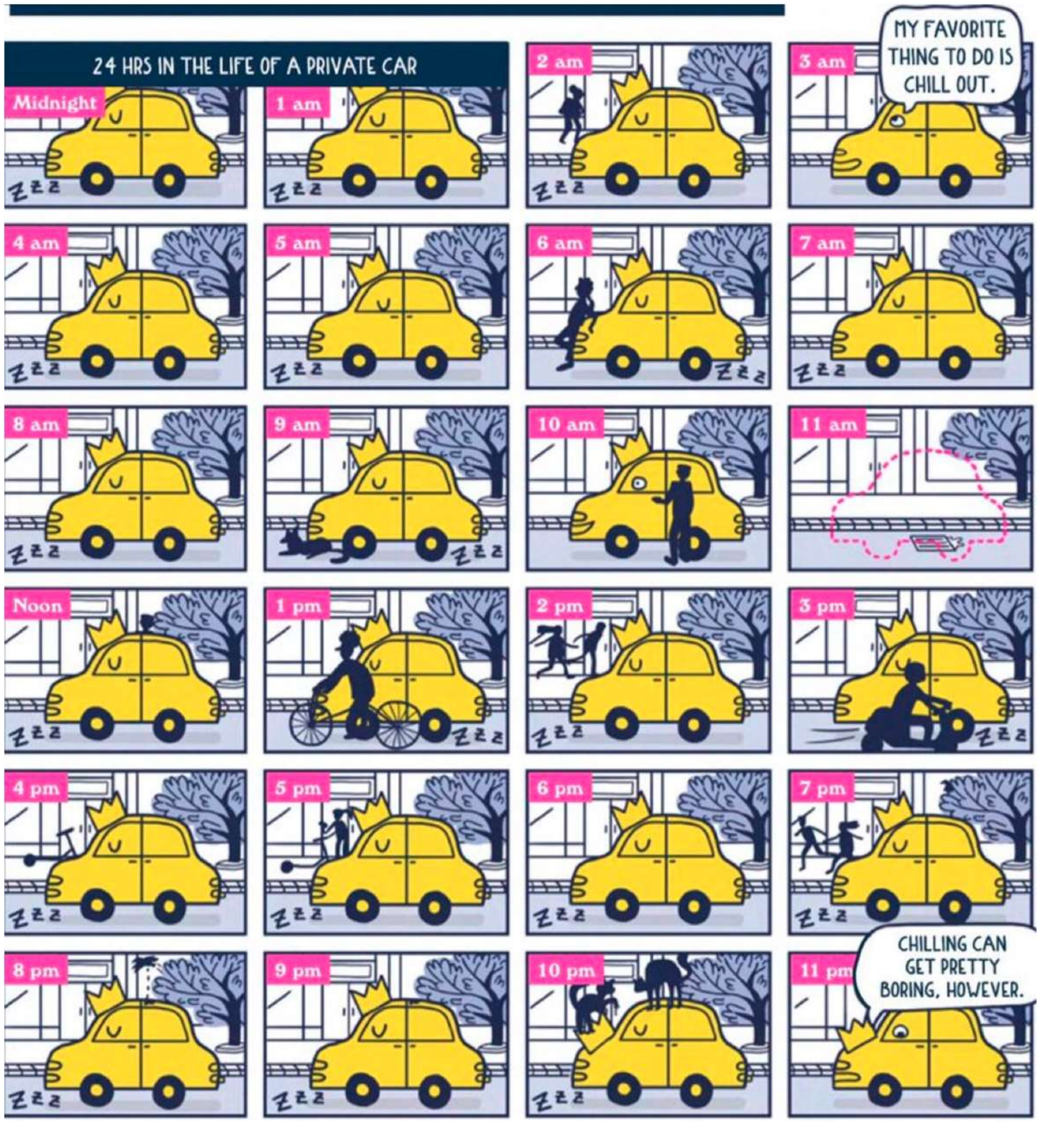
Teleworking;
active mobility
-> AVOID

Public transport; shared mobility;
compact cities; spatial planning
-> SHIFT, AVOID



Electric vehicles; more efficient vehicles
-> IMPROVE

Source: IPCC AR6 WGIII SPM



On average, private vehicles are used just 1 hour a day.

Technology for (pooled) shared mobility?

→ It is not all about *efficiency*, it also a lot about *sufficiency*

Source: Ellery Studios/Agora Verkehrswende

How? #2

Behavioral & cultural changes underpin the adoption of solutions

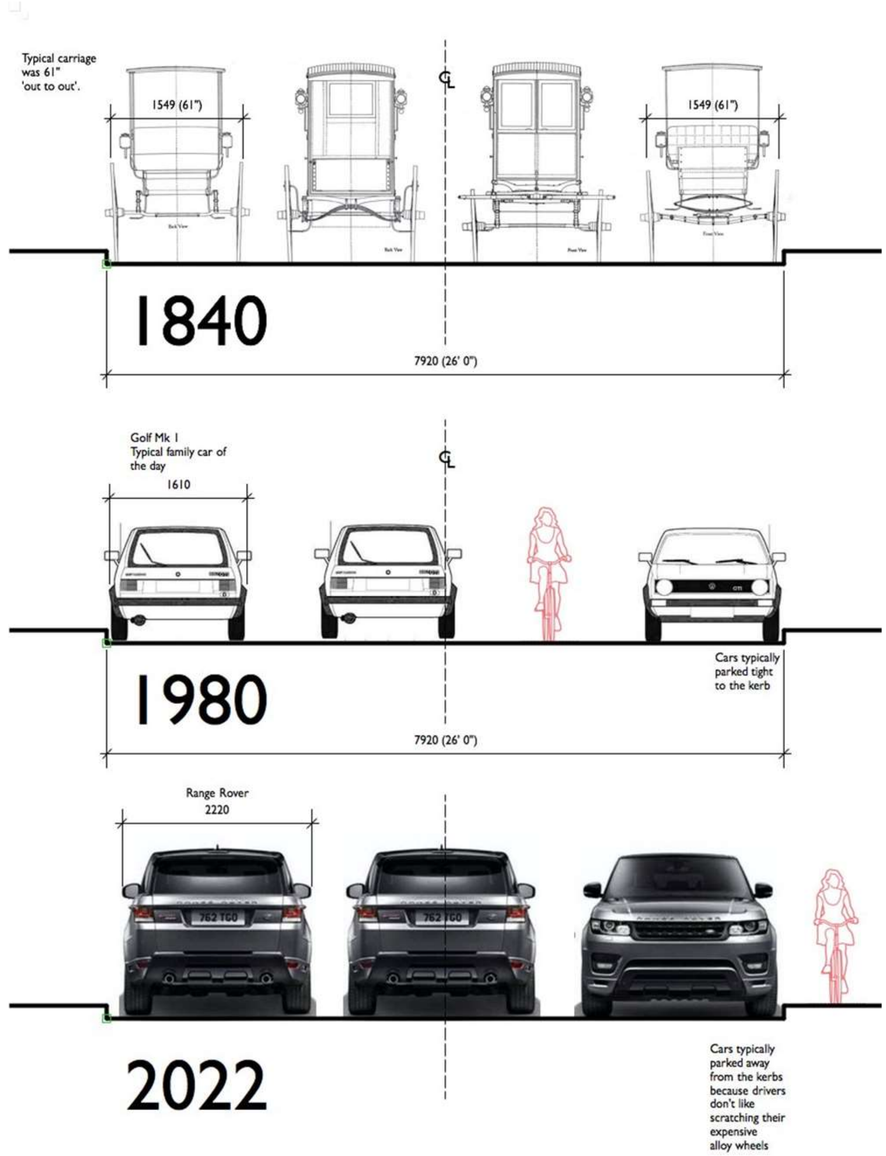
WHY CARGO BIKES ARE BECOMING A PROBLEM IN COLOGNE

Complicated boxes!

Too wide for bike lanes ++ slows down traffic ++ block sidewalks

Lots of traffic – on the bike lanes: cargo bikes are so wide on the narrow lanes that even other cyclists cannot overtake them.

Photo: Patric Fouad



Source: Bild, Urban Cycling Institute

Factors contributing to **mode choice**

→ **Need to promote new narratives about transportation**

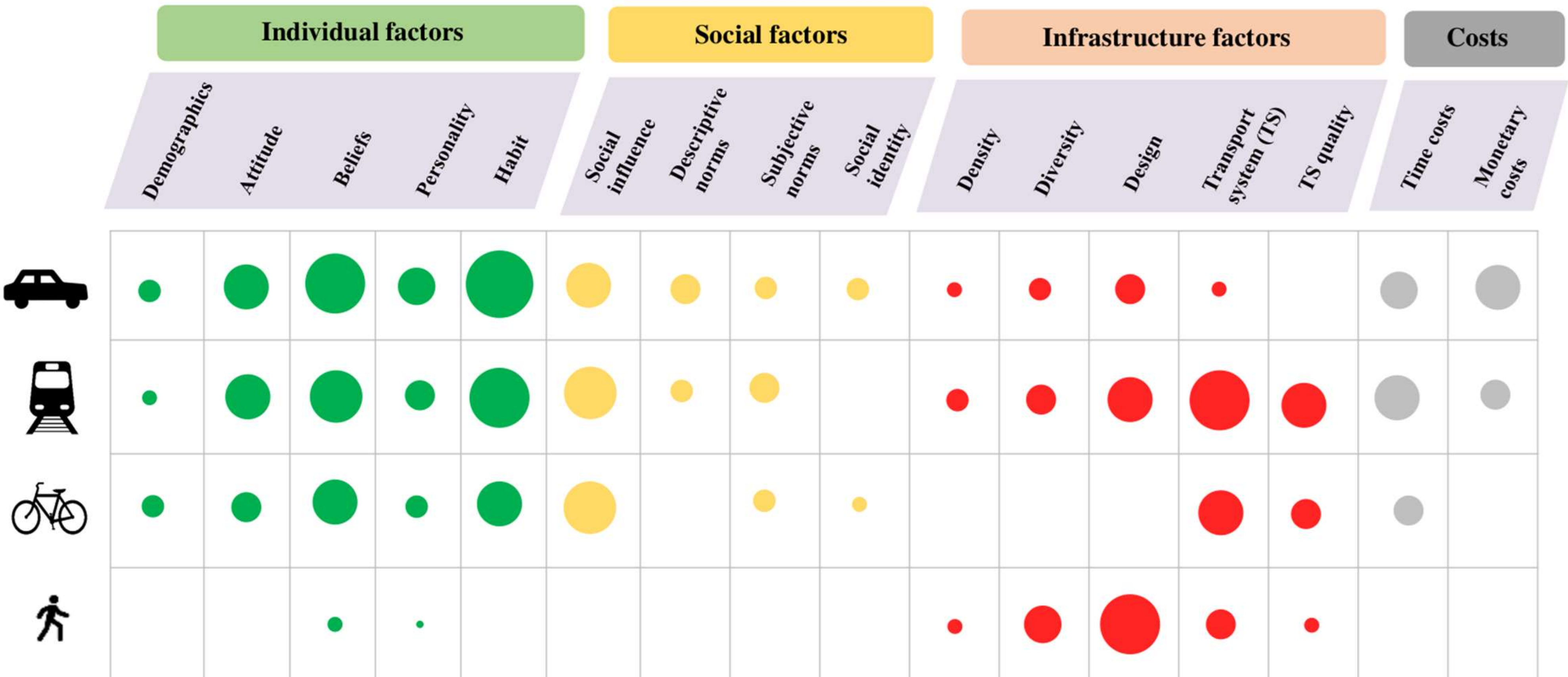


Figure 9. Size of the circle indicates the importance of sub factor to the related transport mode based on our relationship strength ratings in our review findings. ** empty boxes represent lack of supporting evidence.

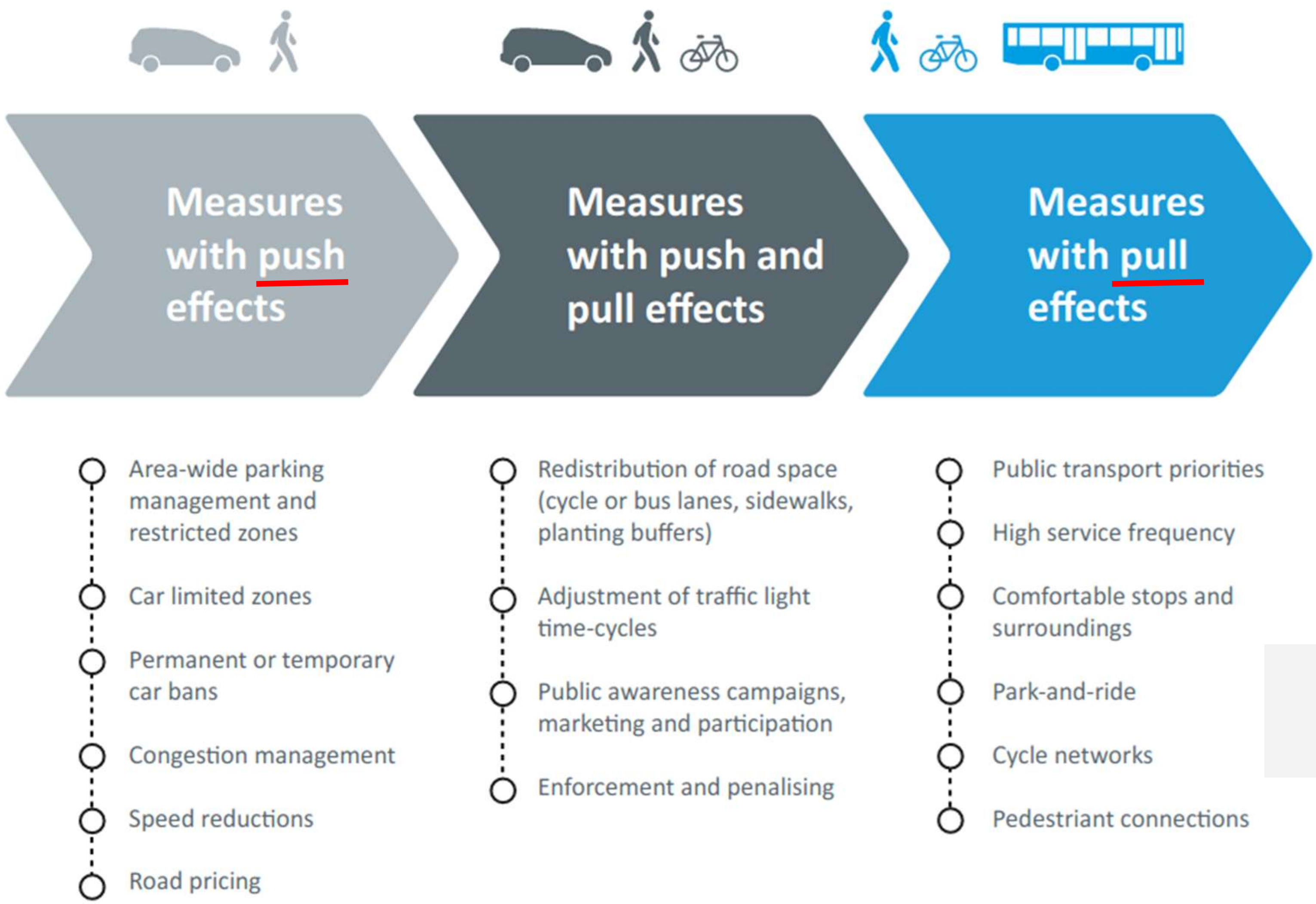
How? #4

Ambitious **public policies** are absolutely necessary

to steer **systemic change**

European Parliament votes to ban combustion engine cars from 2035

Source: POLITICO



→ We need broad policy packets

Source: NACTO

How? #5

Transport planning has a lot to do with

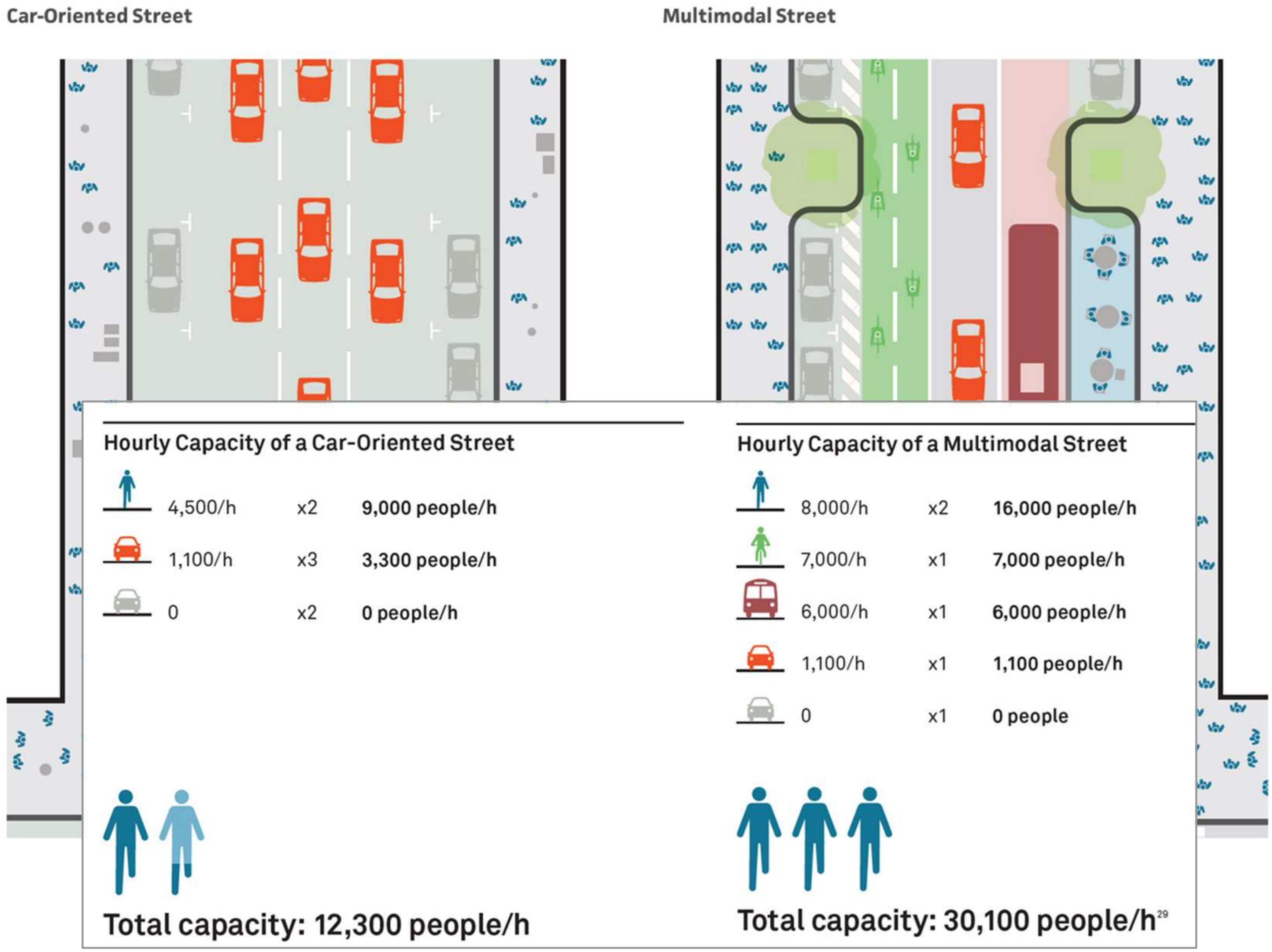
space allocation & design,

where we live

AI-generated street transformations
@betterstreetsai

Boundary Street (West End, Brisbane, Australia)

Traduire le Tweet



Source: Global Street Design Guide

Rue de Rivoli, Paris

Sources: Adrien Lelièvre, France Strategy

“15-min neighborhoods” can reduce daily demand for transport (commute)

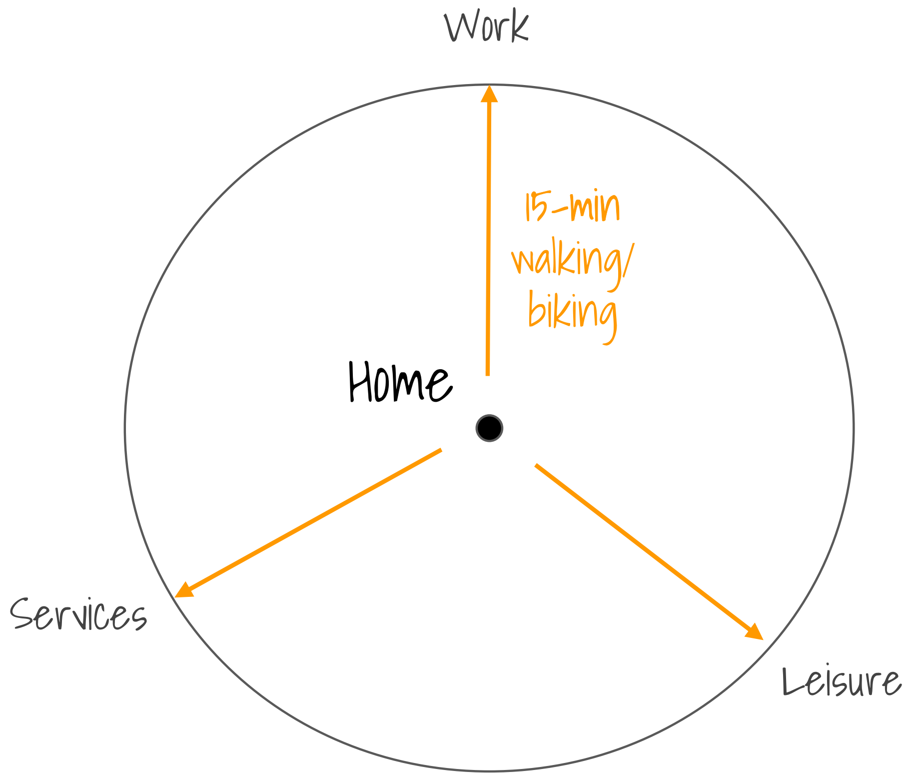


Table 10.2 | The systemic effect of city form and transport emissions.

Annual transport emissions and co-benefits	Walking urban fabric	Transit urban fabric	Automobile urban fabric
Transport GHG	4 tonnes per person ✓	6 tonnes per person	8 tonnes per person
Health benefits from walkability	High ✓	Medium	Low
Equity of locational accessibility	High ✓	Medium	Low
Construction and household waste	0.87 tonnes per person ✓	1.13 tonnes per person	1.59 tonnes per person
Water consumption	35 kilolitre per person ✓	42 kilolitre per person	70 kilolitre per person
Land	133 square metres per person ✓	214 square metres per person	547 square metres per person
Economics of infrastructure and transport operations	High ✓	Medium	Low

Source: IPCC AR6 WGIII Chap 10

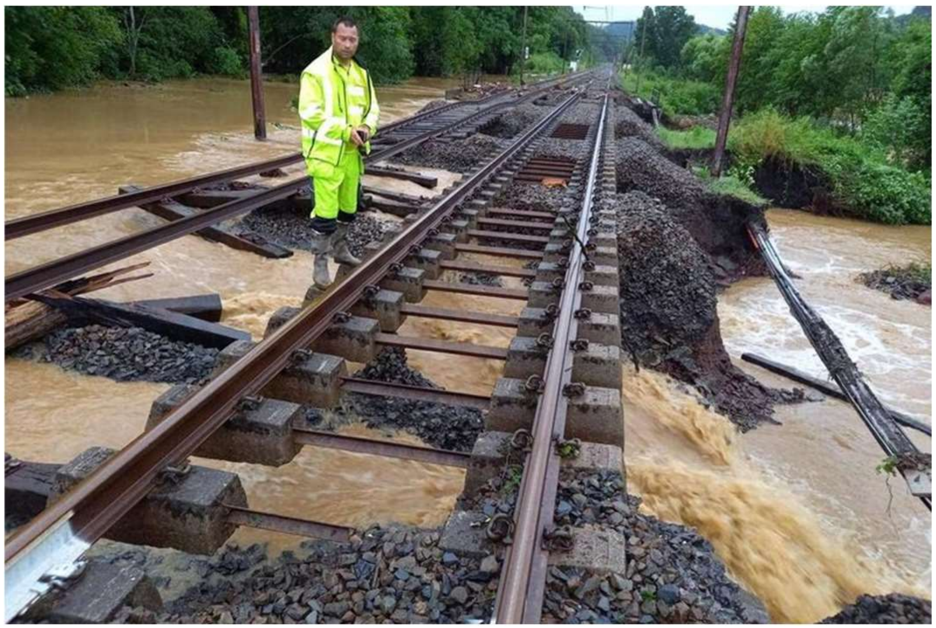
Urban transportation is mostly relevant to climate change mitigation but also adaptation

EVs can serve as batteries during power outage due to extreme weather events

Sources: Ford, Yuri A Jones

Reading: Adderly, S.A., Manukian, D., Sullivan, T.D., Son, M., 2018. Electric vehicles and natural disaster policy implications. Energy Pol. 112, 437–448.

Making the transport infrastructure resilient to extreme climate events (AI may help!)



Sources: (credits: Infrabel, Getty Images/iStockphoto/Cindy Kitts)

Recap…

Key messages – framing

1. **Decarbonize road transport: less individual cars and phasing out combustion engines**

1. **Emissions are growing because the sector did not take the necessary measures so far**

1. **Decarbonizing transportation is also a sustainability and fairness problem**

Key messages – how to decarbonize

4. To reduce emissions, we can either avoid, shift, or improve

5. Behavioral and cultural changes underpin the adoption

6. Ambitious public policies can steer systemic change

7. Space allocation/design can improve efficiency AND well-being

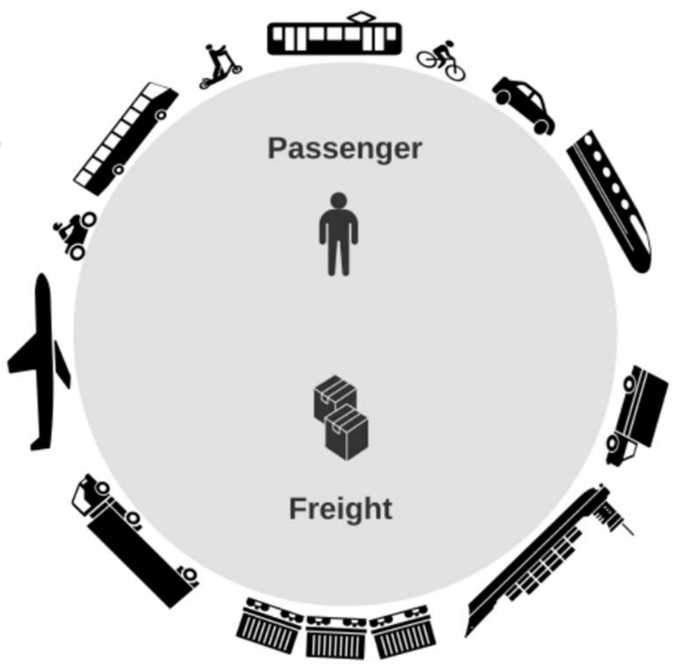
ML & transportation

ML in urban mobility research and practice

Where does ML intersect with transportation?

Reducing transportation activity
Analyzing data
Remote sensing
Forecasting
Freight consolidation
Alternatives to transport

Modal shift
Consumer choices
Coordinating modes
Bike share rebalancing
Predictive maintenance
Enforcing regulation



Vehicle efficiency
Designing for efficiency
Detecting loading inefficiency
3-D printing
Autonomous vehicles

Alternative fuels
Research and development

Electric vehicles
Charging patterns
Charge scheduling
Congestion management
Vehicle-to-grid algorithms
Battery energy management
Battery R&D

Source: TCCML paper

ML and urban transport

ML applied to urban transportation is a **fast-growing** research area (Hintz et al., 2024):

Average annual growth rate (%)	All studies	ML studies
Transport, incl. bikes & scooters	13.9	36.9
Buildings	19.9	34.1
Urban form	21.3	55.9
Waste	21.5	65.8
Overall	19.2	48.2

Table: Average annual growth rates in the urban climate change mitigation literature in percent of relevant publications for the years 2012-2021.

ML & transportation – an overview

ML applied to urban transportation is a research area with **high impact** (Hintz et al., 2024):

Impact Areas	Number of studies	Mitigation potential
Shared bikes and scooters	215	medium
Micromobility	104	medium to high
Traffic management and routing	93	low, uncertain
Battery-electrified transport	69	high
Consumer behavior	58	medium to high
Public transport O & M	43	high
Not pooled shared mobility	31	medium
Autonomous vehicles	19	uncertain
Public transport planning	18	high
Charging infrastructure	13	high
Freight operations and routing	12	uncertain
Utility vehicle fleets	10	high, uncertain
Vehicle efficiency	9	low to medium, uncertain
Pooled shared mobility	7	medium
Pedestrian - cyclist interaction	4	medium to high
Roadway electrification	3	uncertain
Alternative fuels	2	high, uncertain

Where does ML intersect with urban mobility?

Optimization (under constraints)

- Optimization of vehicle / customer matching
- Charging pattern optimization
- Shared vehicle rebalancing (e.g. city bikes)

Computer vision

- Trajectory forecasting, e.g. of pedestrians
- Object detection and segmentation, e.g. for traffic cameras
- 3D-vision: point cloud processing and analysis for autonomous vehicles
- Remote sensing, e.g. for urban change detection

Reinforcement Learning

- Traffic and congestion modeling
- Agent-based simulations for digital twins of cities

Market and auction design

- Surge pricing for shared mobility systems

Inference

- Large-scale urban experiments
- Causal ML for cities

Prediction

- Travel demand prediction
- Load forecasting
- Travel time estimation

Slide 57

1 Find this could stay in.
Marcus Voß, 6/9/2024

Inherent multi- and interdisciplinarity!

ML adjacent domains feeding into this research:

- Transport science (obviously)
- Complex systems research
- Operations research
- Information systems research
- Economics
- Urban analytics & urban science
- Material science
- Geography
- …and many more

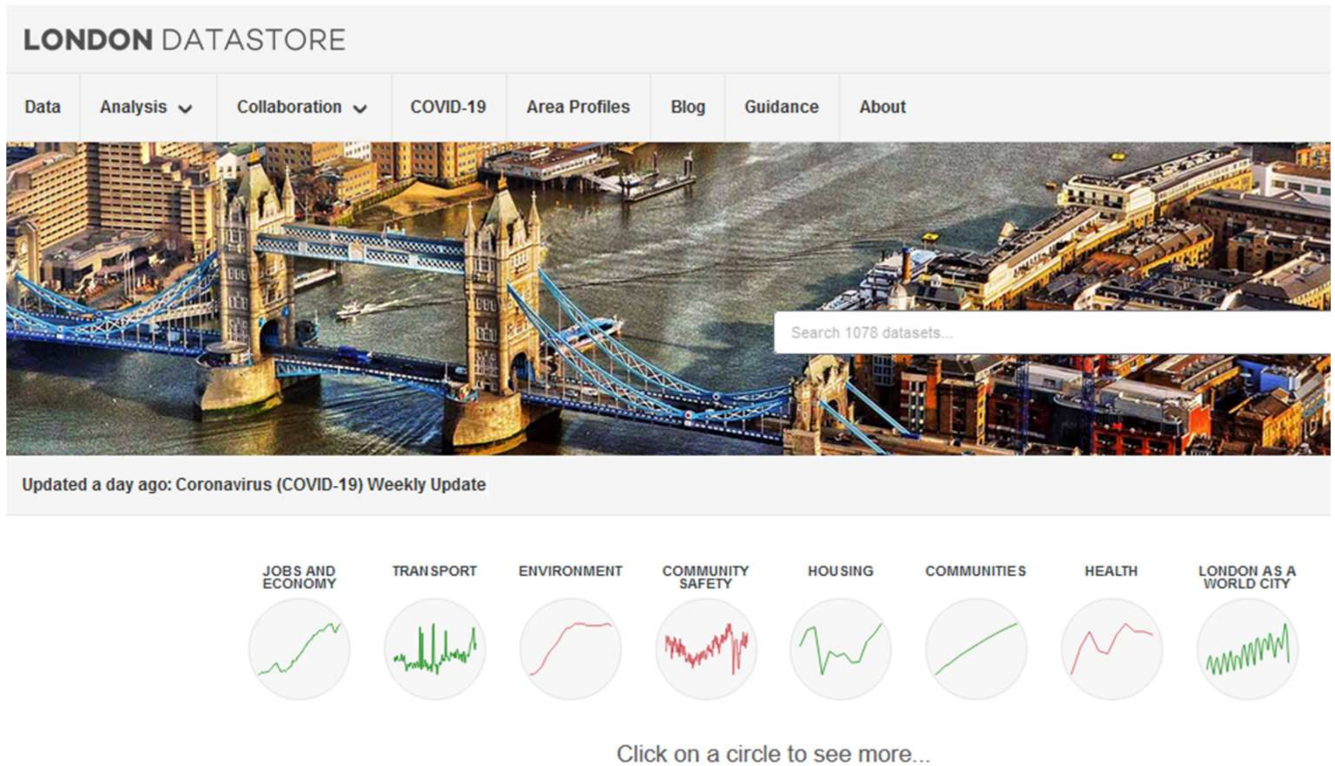
Urban data lakes

With the emergence of the **“smart cities”** paradigm, cities are more and more connected, saturated with IoT devices and produce a constant, **real-time stream of data** across all aspects of urban life.

Urban open data

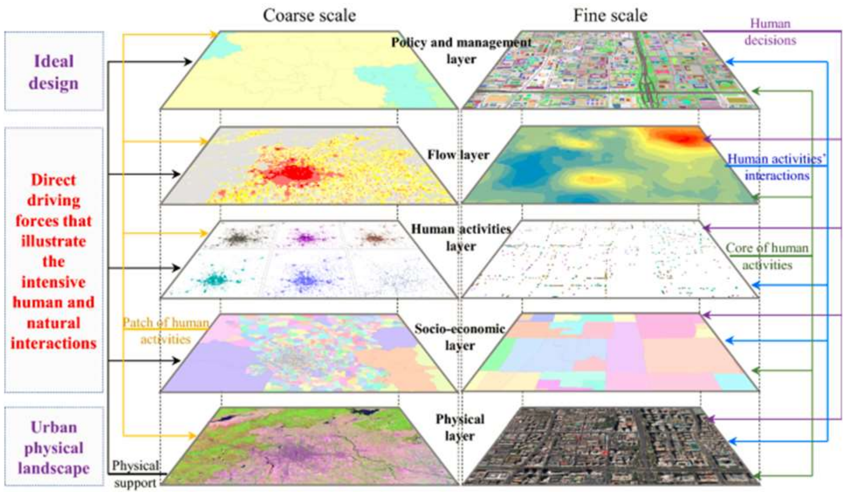
Many cities provide extensive **public data portals**.

There are also other open data providers like *OpenStreetMap* or *Open Cell ID*.



Feature categories

Cities are not only rich in data, but also in data categories, i.e. the **different aspects of urban life that are captured quantitatively**: social, demographic data, economic data, environmental data, mobility data, remotely sensed data, built-environment data,...

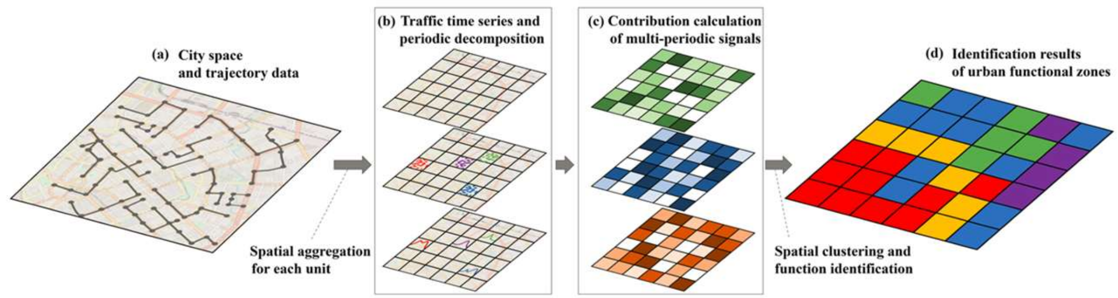


Tan, X., Han, L., Li, G., Zhou, W., Li, W., & Qian, Y. (2022). **A quantifiable architecture for urban social-ecological complex landscape pattern.** *Landscape Ecology*, *37*(3), 663-672.

Data processing and engineering

Many of the **common urban data processing challenges** stem from the data's spatial and temporal dimensions:

Spatial / temporal aggregation & disaggregation, harmonization & matching, outlier detection, clustering / community detection, change-point detection,...



Deng, Z., You, X., Shi, Z., Gao, H., Hu, X., Yu, Z., & Yuan, L. (2022). **Identification of Urban Functional Zones Based on the Spatial Specificity of Online Car-Hailing Traffic Cycle.** *ISPRS International Journal of Geo-Information*, *11*(8), 435.

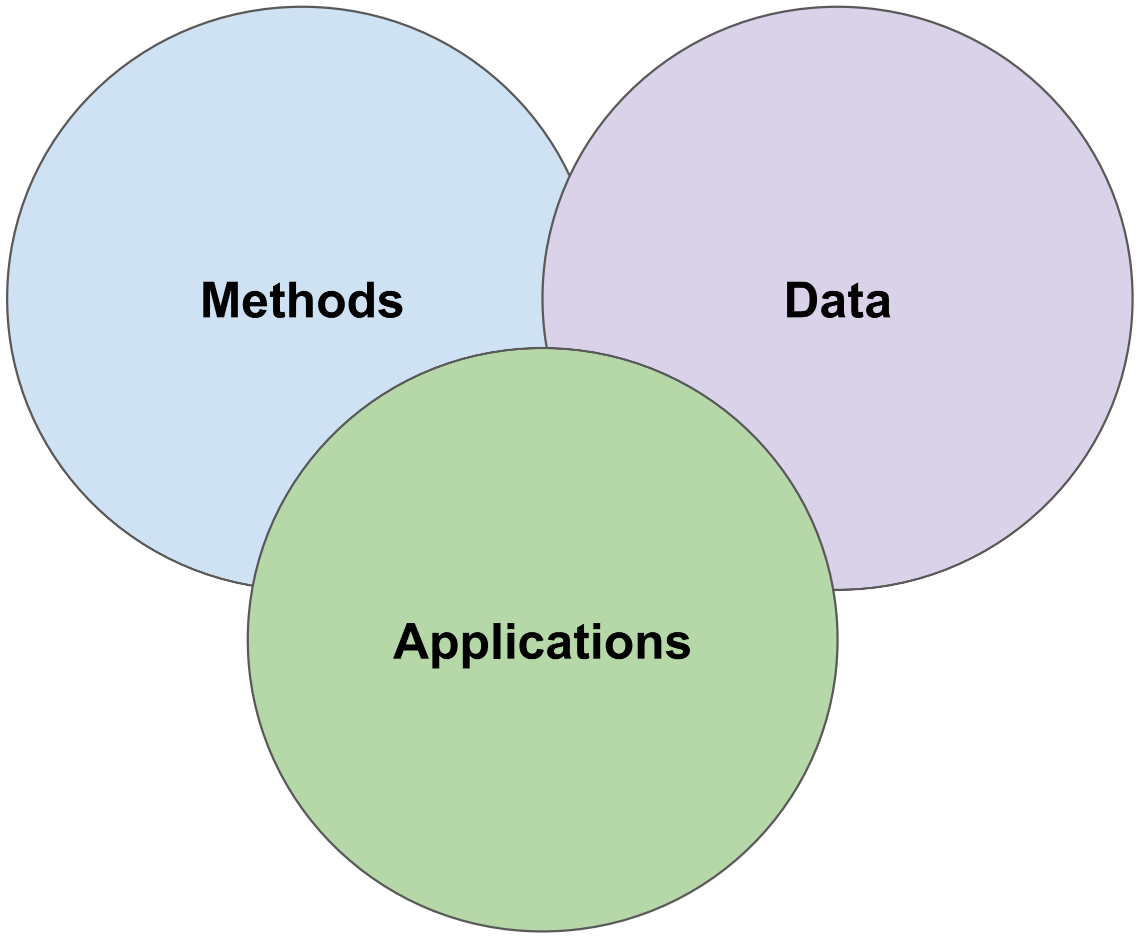
Data-centric AI

“the discipline of systematically engineering the data needed to build a successful AI system.”

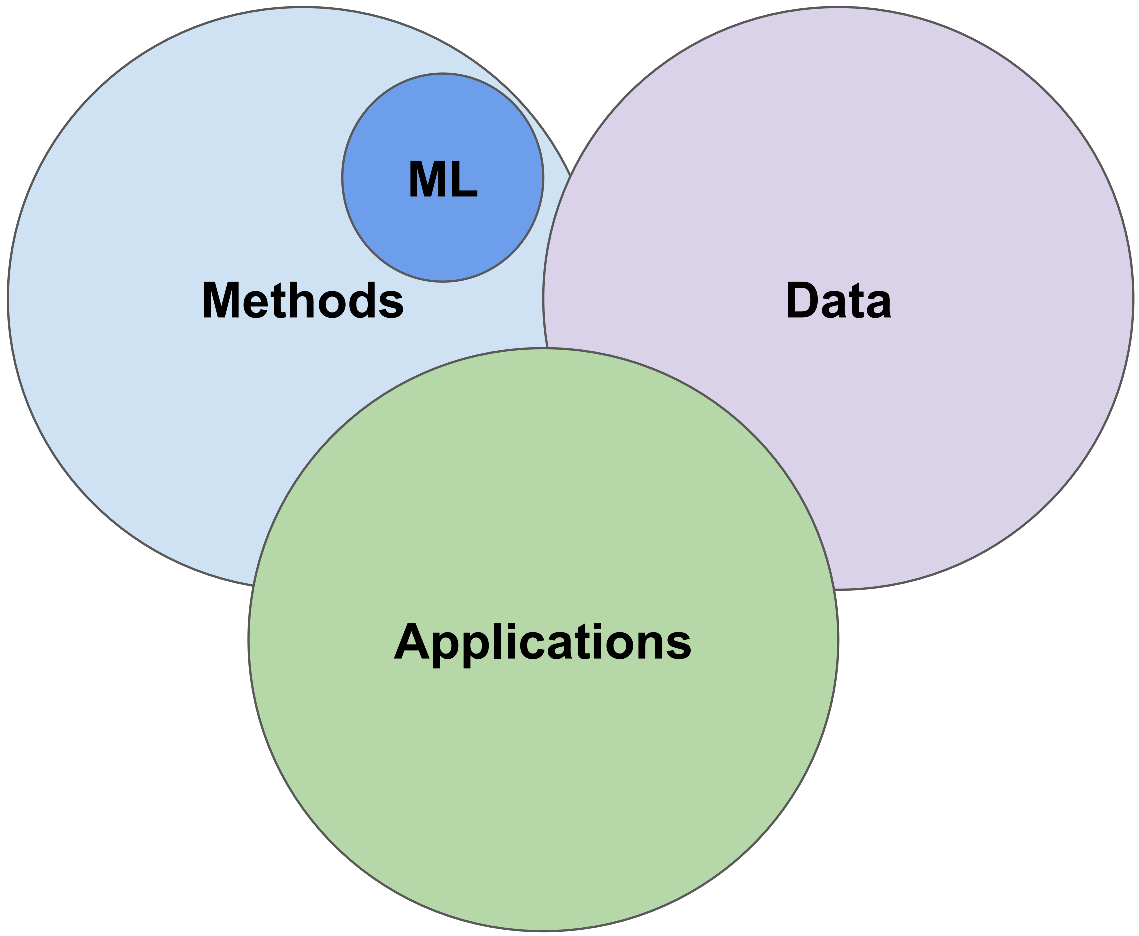
- **Andrew Ng**

➔ Focusing on **data best-practices**: labeling, curation, scaling
➔ Empowering **domain expertise** and the age of applied ML

Quantitative urban science



ML is not the solution, but can be part of it!



Case study: trip demand forecasting

Question #2

Share your intuitions with us:

What are **features to use as predictors, how could you conduct an exploratory data analysis and what are potential forecasting methods** to build your model?

You are consulting a city on where to build new stations for their bike sharing program. You are building a demand forecasting model that, given a specific time and location, will return a projected demand for cycling trips.

Case study: trip demand forecasting
Question #2

Answer:
Features: weather, time-of-day (e.g. commuting hours), points-of-interest (e.g. airport), events (e.g. concert), socio-demographic (e.g. income), location data (e.g. cellphone trajectories),...

Exploratory analysis: visualize demand patterns spatially & at different times of the day, identify correlations between f.e. weather conditions and demand,

Method: depending on your outcome variable a regression or classification problem; any predictive method can be deployed (e.g. linear regression, tree based methods,...), but you might want methods that (1) scale well to high-dimensional data, (2) can deal with non-linearity and (3) can account for systemic variation (e.g. spatial and temporal autocorrelation); e.g. ARIMA methods, spatio-temporal GNNs, spatial regression models, LSTM,...

Example 1: Understanding causal effects of urban infrastructure on inner city car travel

Objective: Understanding urban form relationships and analysing differences in urban form effects across 6 different cities using causal graph discovery and explainable ML

Study:

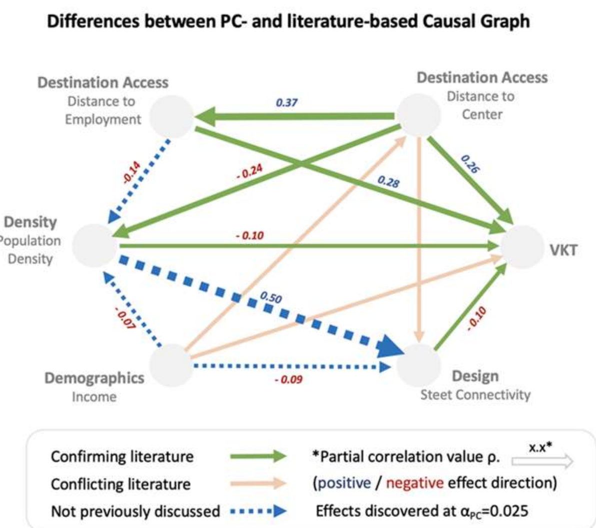
Wagner et al (2024): Causal relationships between urban form and travel CO_2 emissions across three continents. Under review at Nature.

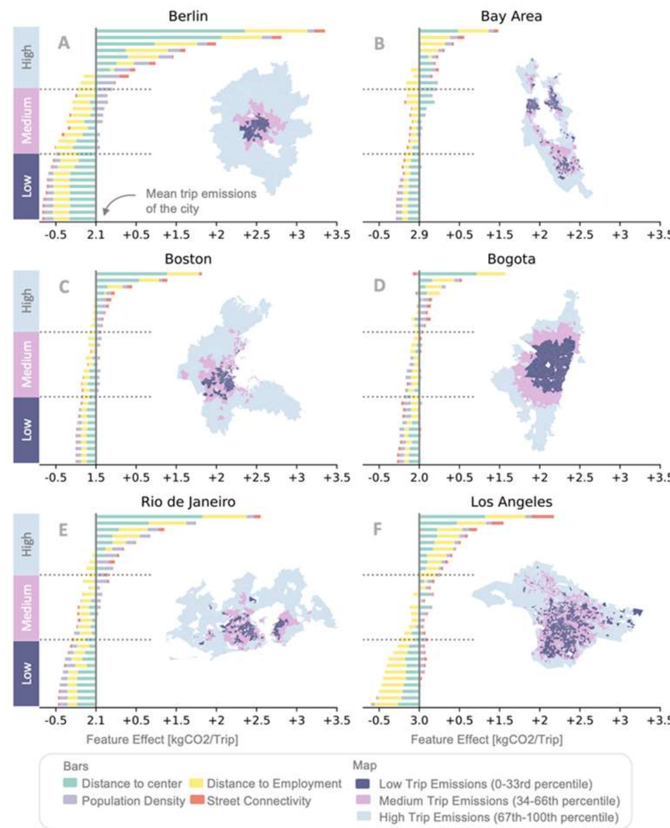
Example 1: Understanding causal effects of urban infrastructure on inner city car travel

Metric: We want to see which urban form features drive car travel related emissions and where in a city

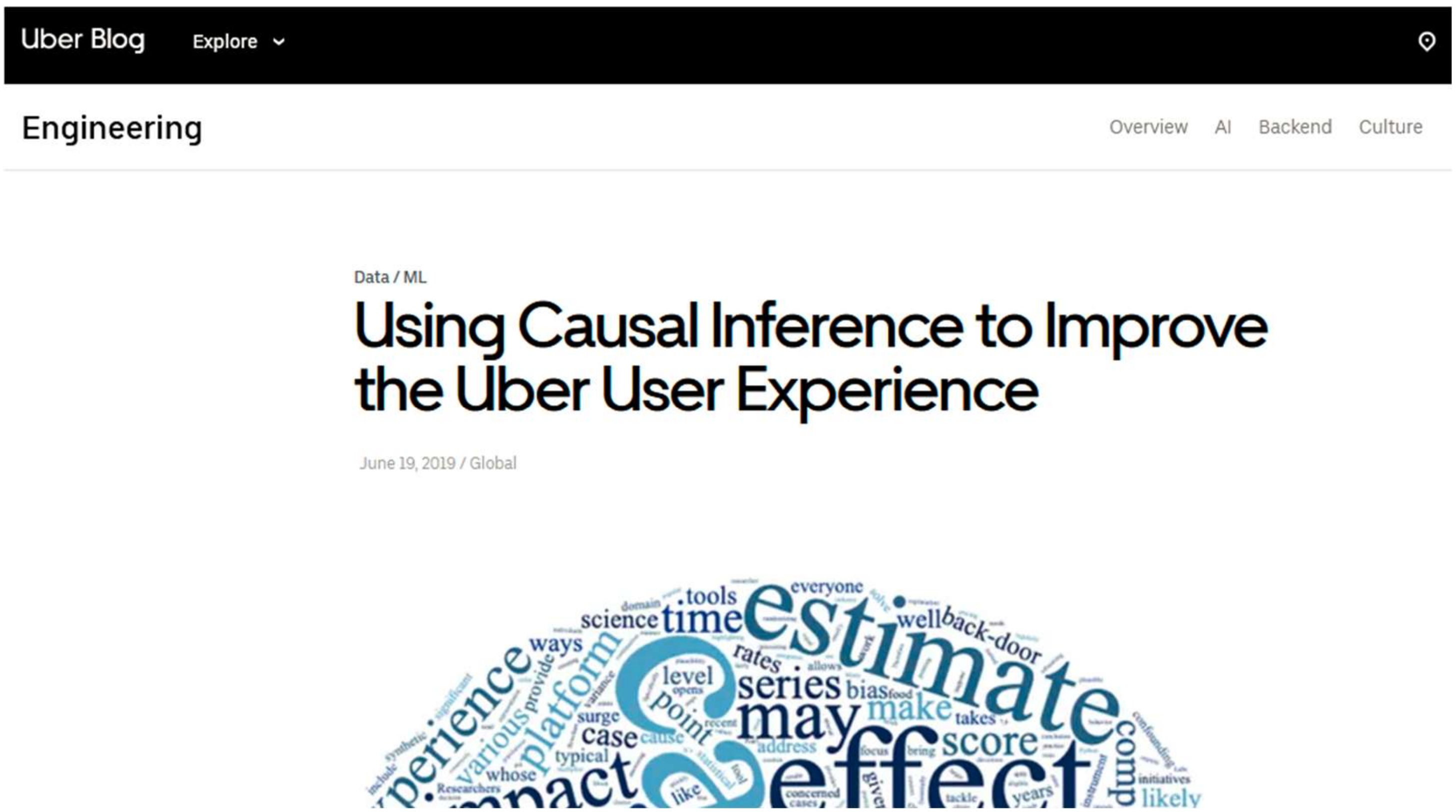
Method: We apply causal graph discovery to understand causal relationships between our features and the target. Then we train on 5 cities and predict to an unseen 6th and analyse the prediction considering the underlying causal structure.

Example 1: Understanding causal effects of urban infrastructure on inner city car travel





Example 1: Understanding causal effects of urban infrastructure on inner city car travel



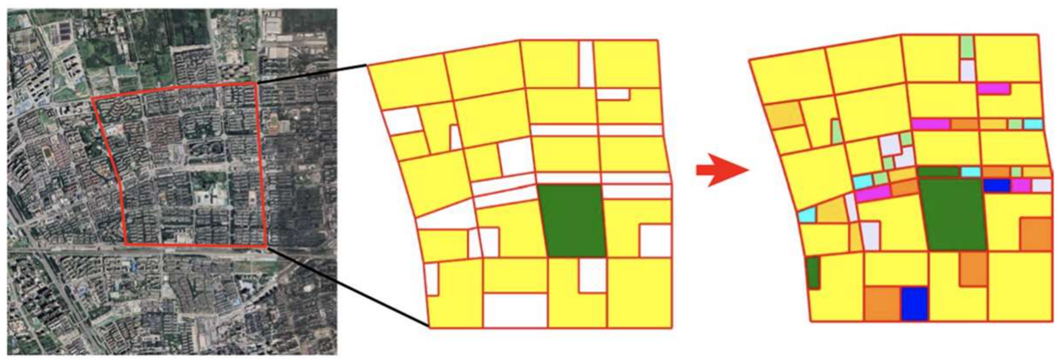
Using Causal Inference to Improve the Uber User Experience: https://www.uber.com/en-DE/blog/causal-inference-at-uber/

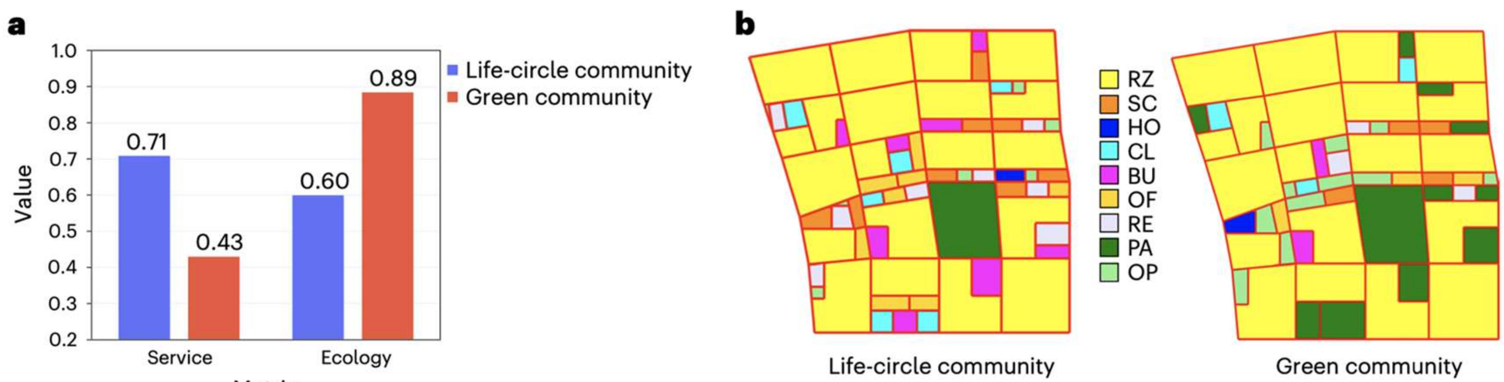
Example 2: Spatial planning of urban communities via deep reinforcement learning

Metric: We want to plan neighborhoods which maximize accessibility and thereby reduce travel and related emissions.
Method: Via a reinforcement learning model based on graph neural networks spatial plans for urban communities are generated. To overcome the difficulty of diverse and irregular urban geography, a graph to describe the topology of cities in arbitrary forms is generated.The urban planning task is formulated as a sequential decision-making problem on the graph.

Study:
Zheng et al (2023): Spatial planning of urban communities via deep reinforcement learning. Nature Computational Science.

Example 2: Spatial planning of urban communities via deep reinforcement learning





Emerging trends in ML with transport applications

- Graph neural networks and scalable Gaussian Processes for modeling spatial and temporal effects in cities at scale
- Constraint-focused methods for decision, control and planning.
- Explainable and causal ML for improving and scaling experiments
- Multi-modal deep learning for harmonizing different urban data types (e.g. images, sound, text)
- Large agent-based simulations for “digital twins”

Case study: trip demand forecasting
Question #3

Share your intuitions with us: What are ways to **train and test your model?** How do you **interpret the results** and **structure your recommendations**?

You are consulting a city on where to build new stations for their bike sharing program. You are building a demand forecasting model that, given a specific time and location, will return a projected demand for cycling trips.

Case study: trip demand forecasting
Question #3

Answer:

Training: Split the data into train & test set. Consider splitting the data in a way that spatio-temporal correlations are not conflicting the i.i.d. assumption.

Testing: Use metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or classification accuracy to evaluate model performance. Perform cross-validation to ensure robustness.

Recommendations: Identify peak congestion times and high-risk areas. Analyse the importance of individual features to better understand drivers of demand.

Case study: trip demand forecasting

Question #3

Answer:
Relevance: reducing the number of personal cars, both in term of stock (idle car parking and little used) and driving with 1 or few occupants -> efficiency, sufficiency
Purpose: match demand for transportation with supply in a flexible way that make users keen on shifting away from a personal car
Mechanisms: shared ride-hailing is much better when possible; positive impact only if substitution from car e.g. not bike users; beware of rebound effects (more people on the roads overall because the service is so cheap and efficient)
Computational cost: Running constant trip demand forecasting leads to emissions (GPU energy cost, server space,...)

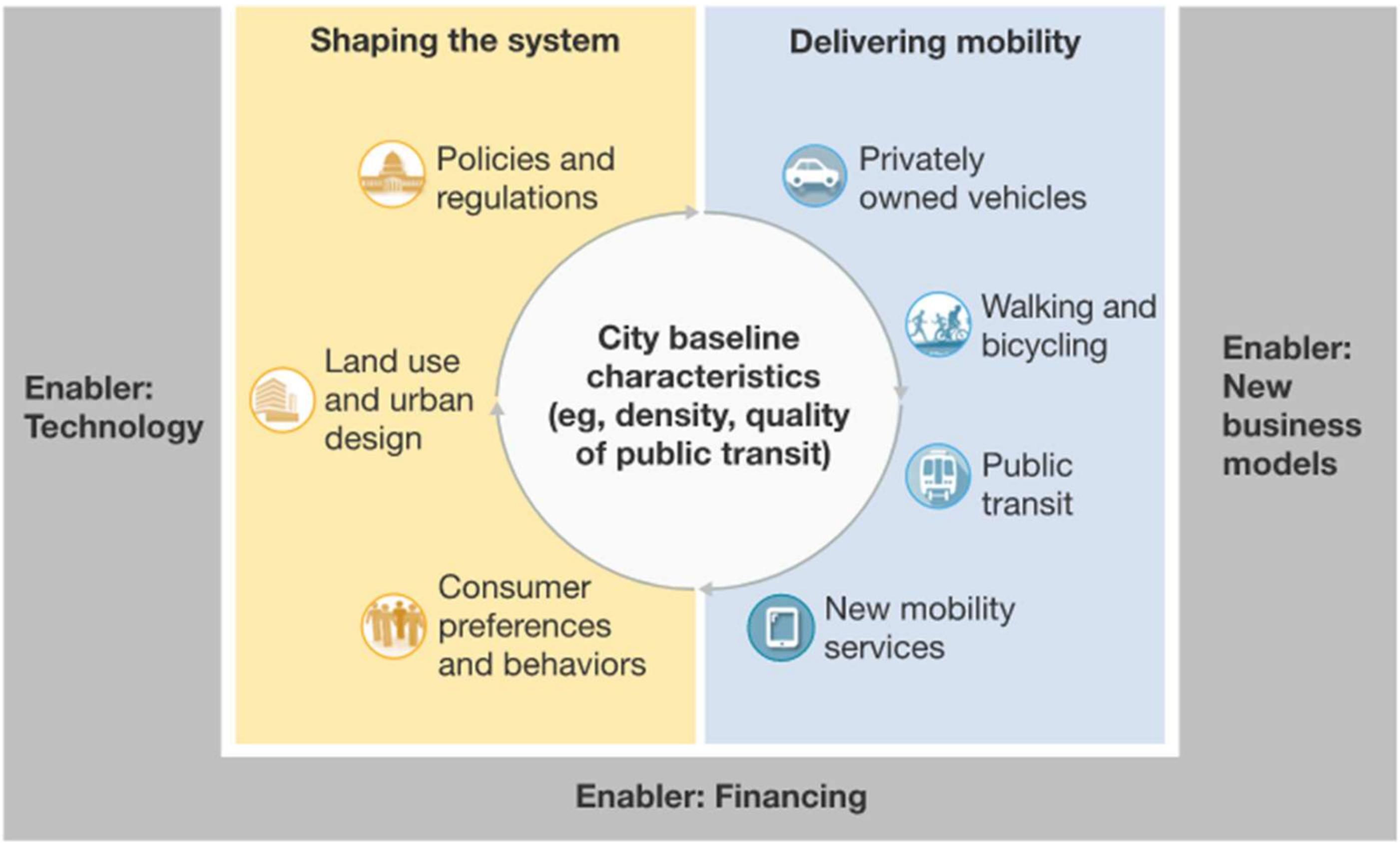
Pathway to action

The whole landscape is changing fundamentally

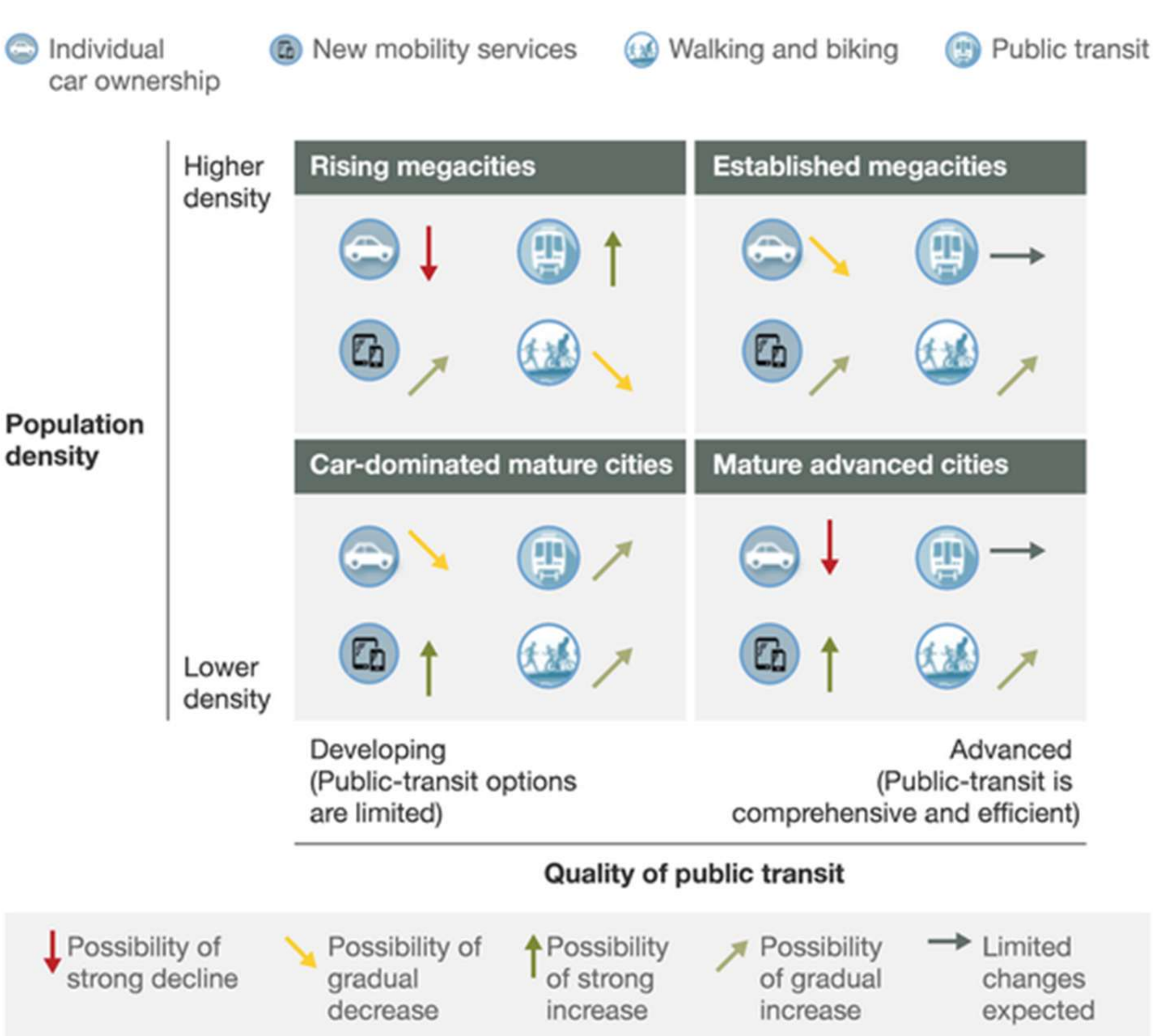
From . . .	Toward . . .
Individual car ownership as dominant form of transport	Individual car ownership as one form of multimodal, on-demand, and shared transport
Limited consumer choice and few service levels	More consumer choice and many service levels
Government-funded public transit	Public and private transit operate in parallel
Unconnected, suboptimal, transportation systems	On-demand, connected systems that use data to unlock efficiencies

Source: McKinsey

A framework for understanding urban mobility



Source: McKinsey



Different cities are experiencing different changes!

Source: McKinsey

Focusing on the necessary conditions for successful and impactful deployment

Data availability

Local governance

ML challenges in real-world context

Global South?

Vested interests

Non-urban transport?

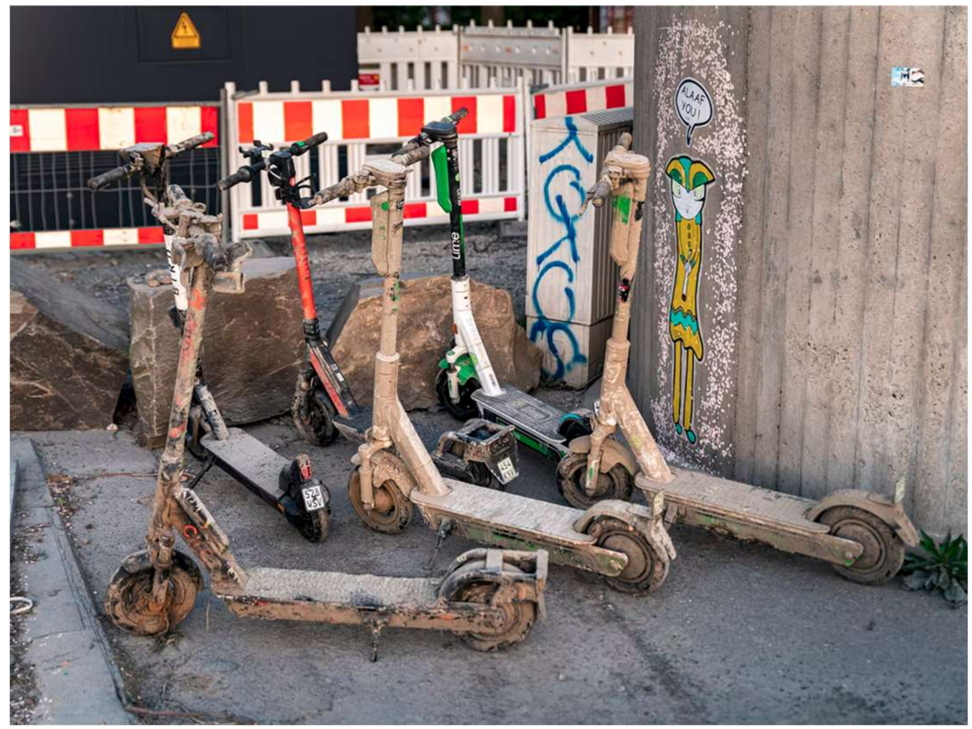
Users

Theory of change / system thinking

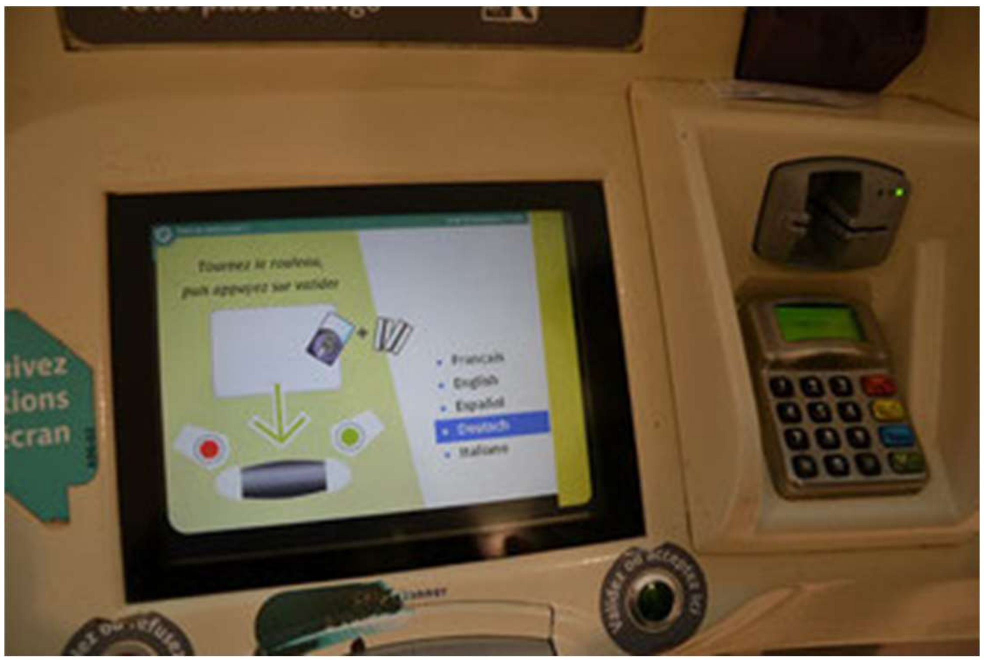
Are **data availability/ecosystem** appropriate in the urban area considered?

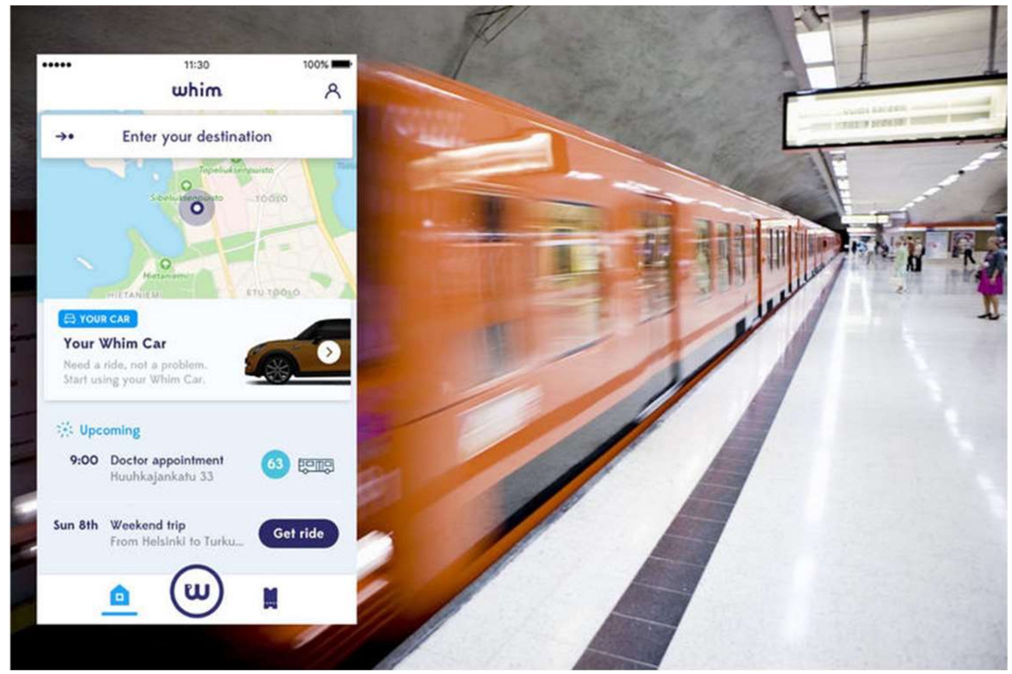
Technical ML challenges when **deploying in the real world**

What will be the **interactions with users** of the technologies?



Local governance as a key enabler **AND** barrier





Beware of the **political economy of car dependence**

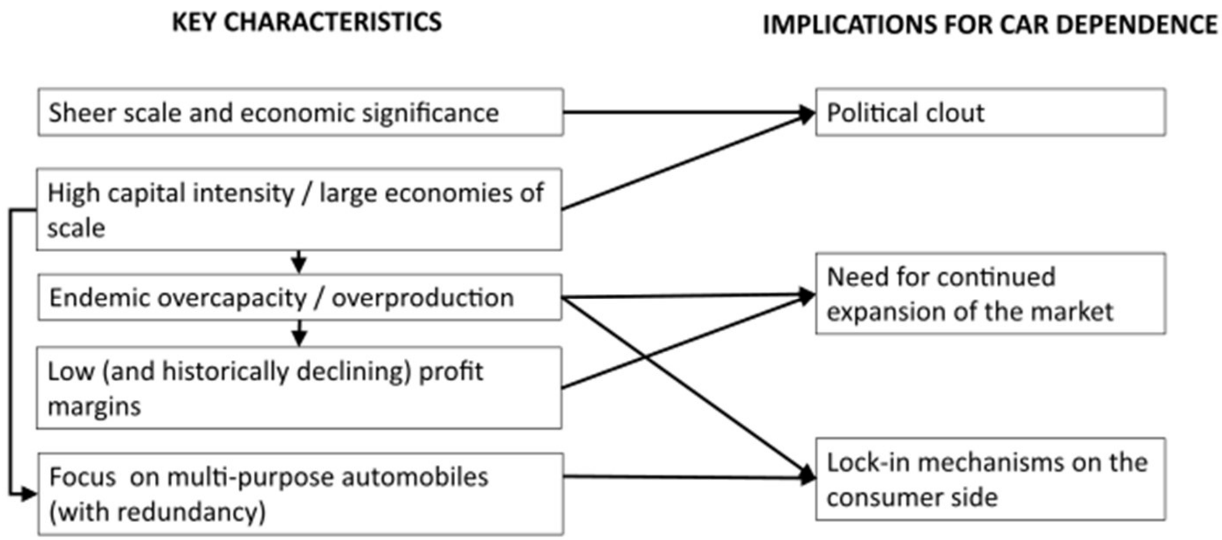


Fig. 2. Key characteristics of the automotive industry and implications for car dependence (own elaboration).

Mattioli et al 2020

Rural transport, freight, aviation,...

Urban mobility in the **Global South**

ML/AI less important here?

But rather building **infrastructure is key**.

Transportation is partly **informal** (privately provided and not regulated)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by Jimmy Mbogoh — September 21, 2018 in Kenyan News Reading Time: 2 mins read

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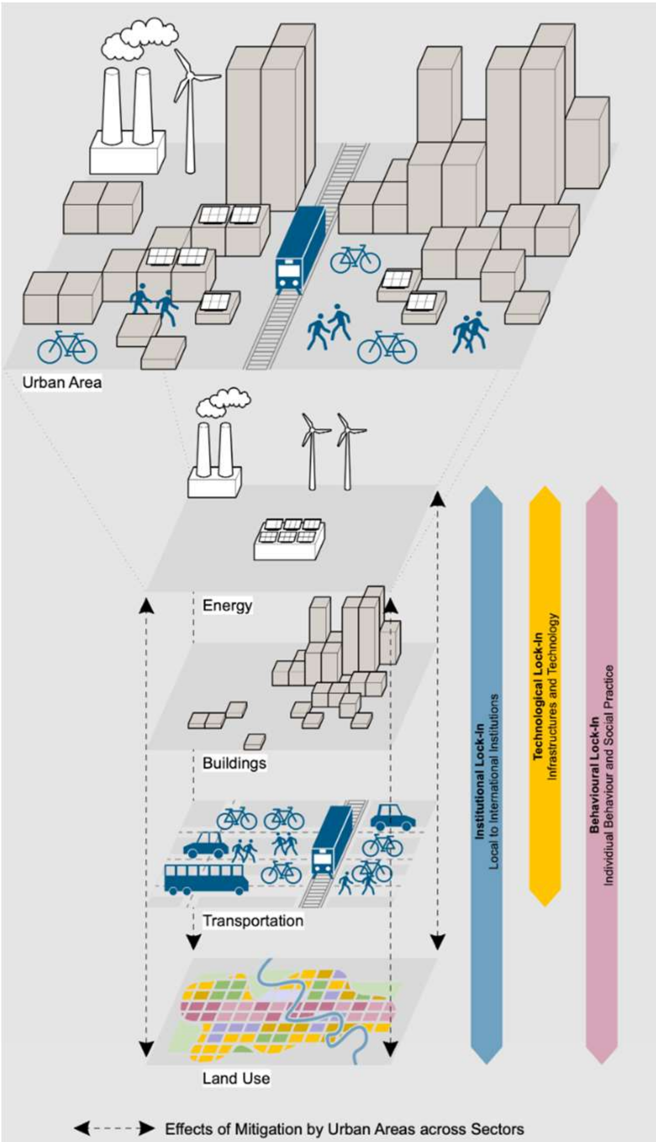
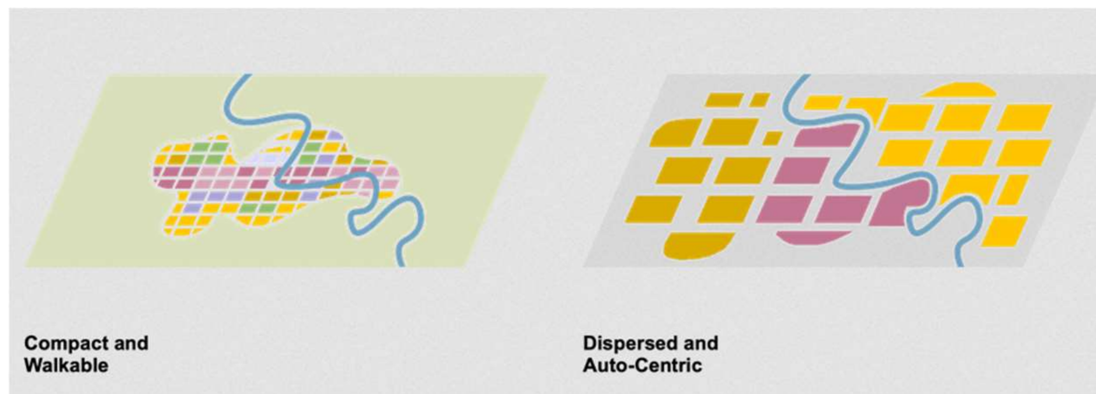
But commercial mobility providers are **eying these markets** and use ML-based decision support to explore opportunities



Theory of change
&
system thinking



Source: IPCC AR6 WGIII Chap 8

Readings

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- Nacto, Sustainable Urban Transport: **Avoid-Shift-Improve** (A-S-I) https://www.transformative-mobility.org/assets/publications/ASI_TUMI_SUTP_iNUA_No-9_April-2019.pdf
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- Javaid, Aneeque, Felix Creutzig, and Sebastian Bamberg. "**Determinants of low-carbon transport mode adoption: systematic review of reviews**." Environmental Research Letters 15.10 (2020): 103002.
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- **Using Causal Inference to Improve the Uber User Experience**: https://eng.uber.com/causal-inference-at-uber/
- Man Luo, Bowen Du, Konstantin Klemmer, Hongming Zhu, Hakan Ferhatosmanoglu, and Hongkai Wen. 2020. **D3P: Data-driven Demand Prediction for Fast Expanding Electric Vehicle Sharing Systems.** Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 4, 1, Article 21 (March 2020), 21 pages. https://doi.org/10.1145/3381005: https://core.ac.uk/download/pdf/305119823.pdf
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Tutorials, Notebooks & Datasets

- Traffic flow simulation with FLOW: https://flow-project.github.io/tutorial.html
- Deep RL for traffic signal control: https://traffic-signal-control.github.io/#tutorial
- Deep Q-Learning agent for traffic signal control: https://github.com/AndreaVidali/Deep-QLearning-Agent-for-Traffic-Signal-Control
- Bike sharing demand predictions: https://wisdomml.in/regression-tutorial-bike-sharing-demand-prediction-in-python/
- Awesome public datasets: https://github.com/awesomedata/awesome-public-datasets#transportation