Day 10: AI for Transportation

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Climate Change AI

Your instructors

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- Postdoc at Microsoft Research
- PhD in Urban Science, MSc in Transportation
- Excited about how ML can help analyse geographic data

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- Postdoc at Technical University Berlin
- PhD in Urban Planning, MSc in Environmental Econ.
- Excited about new data/tools for urban climate change mitigation

Today

1. **Urban transportation landscape** -> ***Case study***
2. **The role of transportation in global climate change mitigation**

BREAK

3. **ML use cases** -> ***Case study***
4. **Outlook** -> ***Case study***
5. **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: trip demand forecasting

Interactive exercise throughout the lecture: you will work on **a real-world case-study**, akin to a **data science interview** at a **mobility tech company**!

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

You are a data scientist at a big ride-hailing company. You are tasked with building a **demand forecasting model** that, given a specific **time** and **location**, will return a projected trip demand.

Your proposed approach should include: *(1)* metrics for trip demand, *(2)* features to use as predictors, *(3)* forecasting methods, *(4)* a real-world testing and implementation plan and *(5)* a discussion on the general climate-relevance of trip demand forecasting as well as climate effects of implementations.

Urban transportation landscape

Modes, infrastructure & operators


VEGAS LOOP
LVCC
Central Station
TikTok
@ecomross

Urban transportation modes

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 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

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

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

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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 use: What are *(1)* **metrics for measuring 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 a data scientist at a big ride-hailing company. You are tasked with building a **demand forecasting model** that, given a specific **time** and **location**, will return a projected trip demand.

Case study: trip demand forecasting
Question #1

Answer:
Internal data: trips searched for in the ride-hailing app (not actually completed trips! Searches are a better indicator of demand)

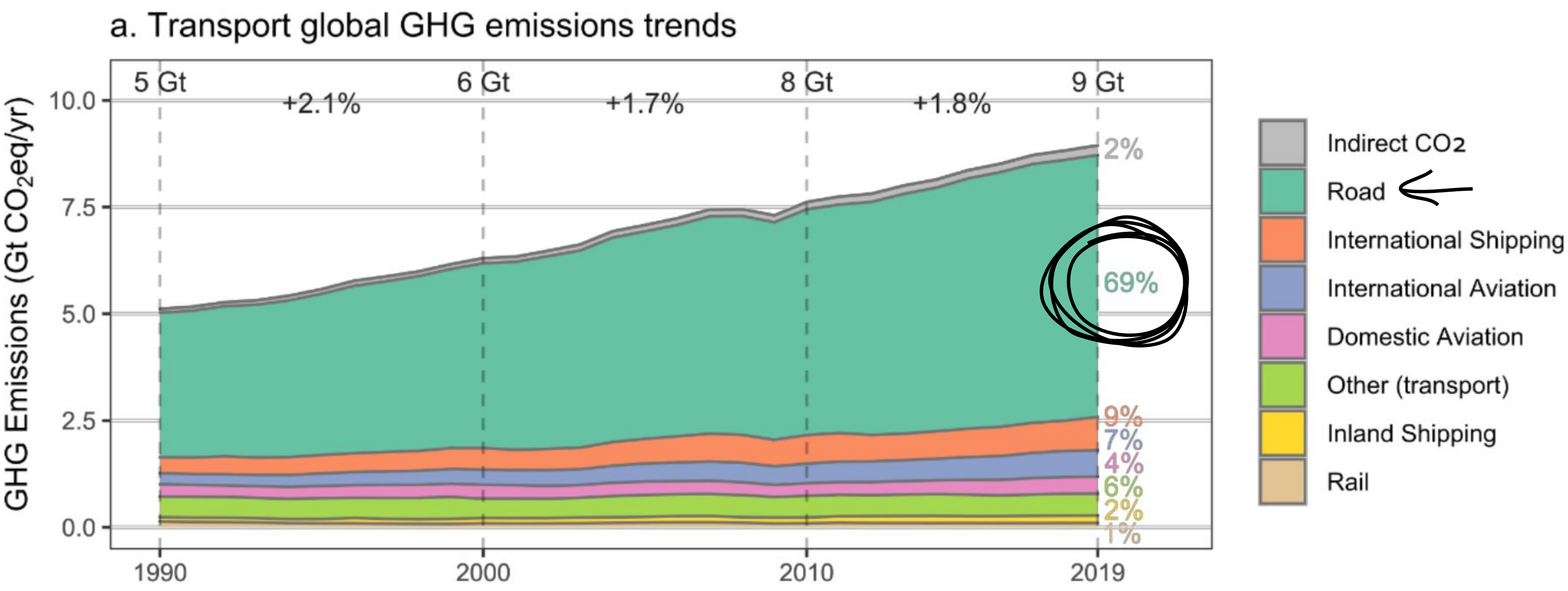
Public data: same as above, but obtain data from open data portals; e.g. public taxi trips, data from a public transport operator, cellphone movement trajectories

Constructing the outcome variable / metric: aggregate the origin points of all trips searched for in the ride-hailing app, within a certain geographic area and within a certain time span.

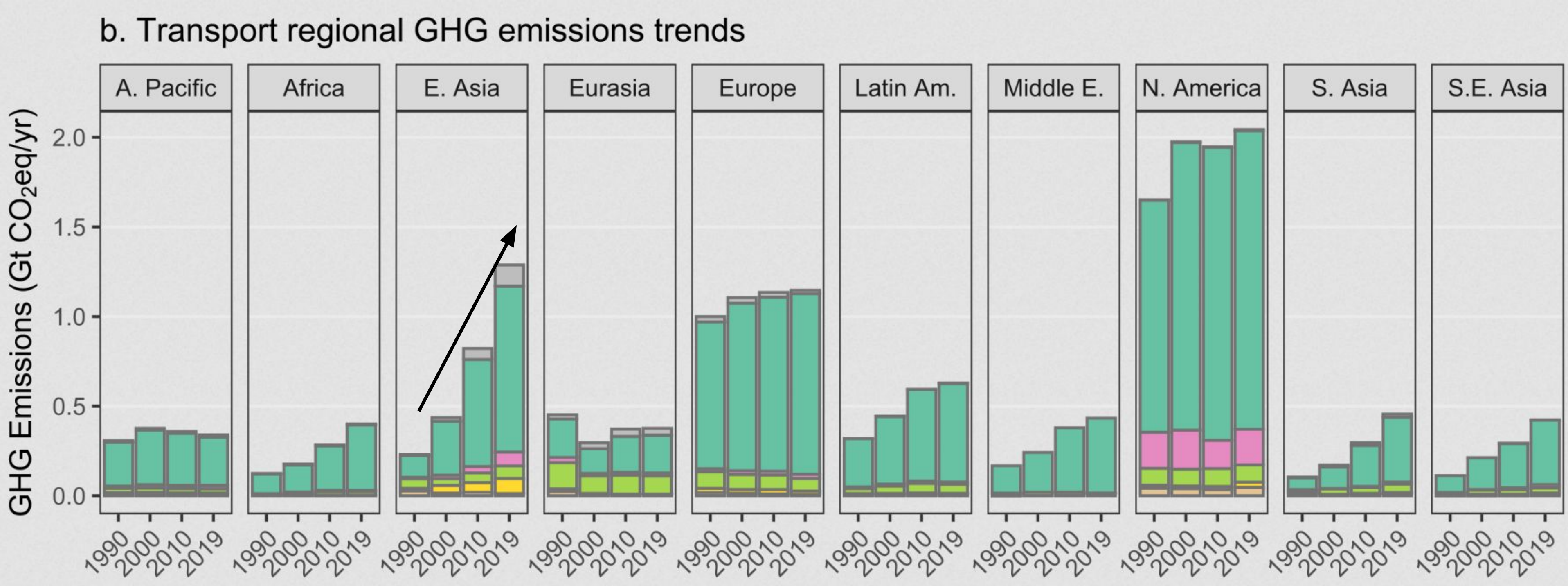
The role of urban transportation in global climate change mitigation

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

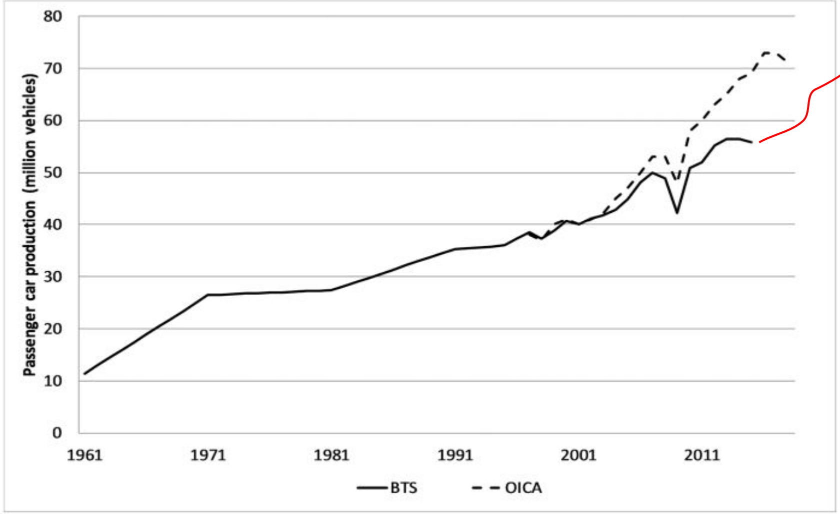
Traduire le Tweet

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

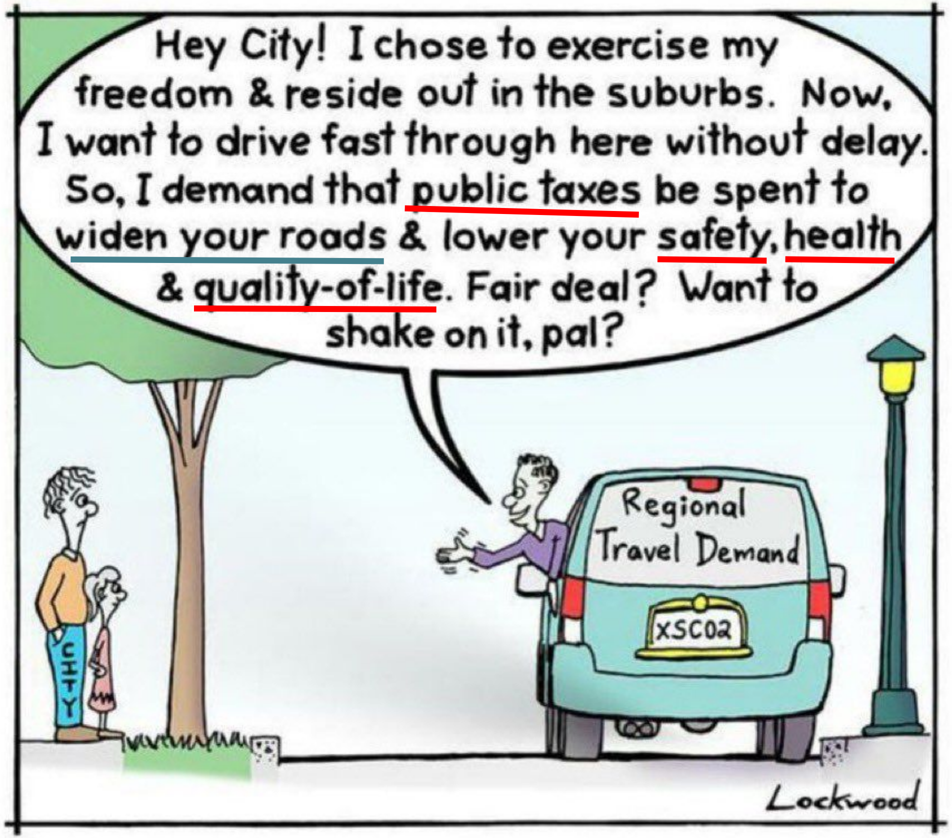
Traduire le Tweet


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

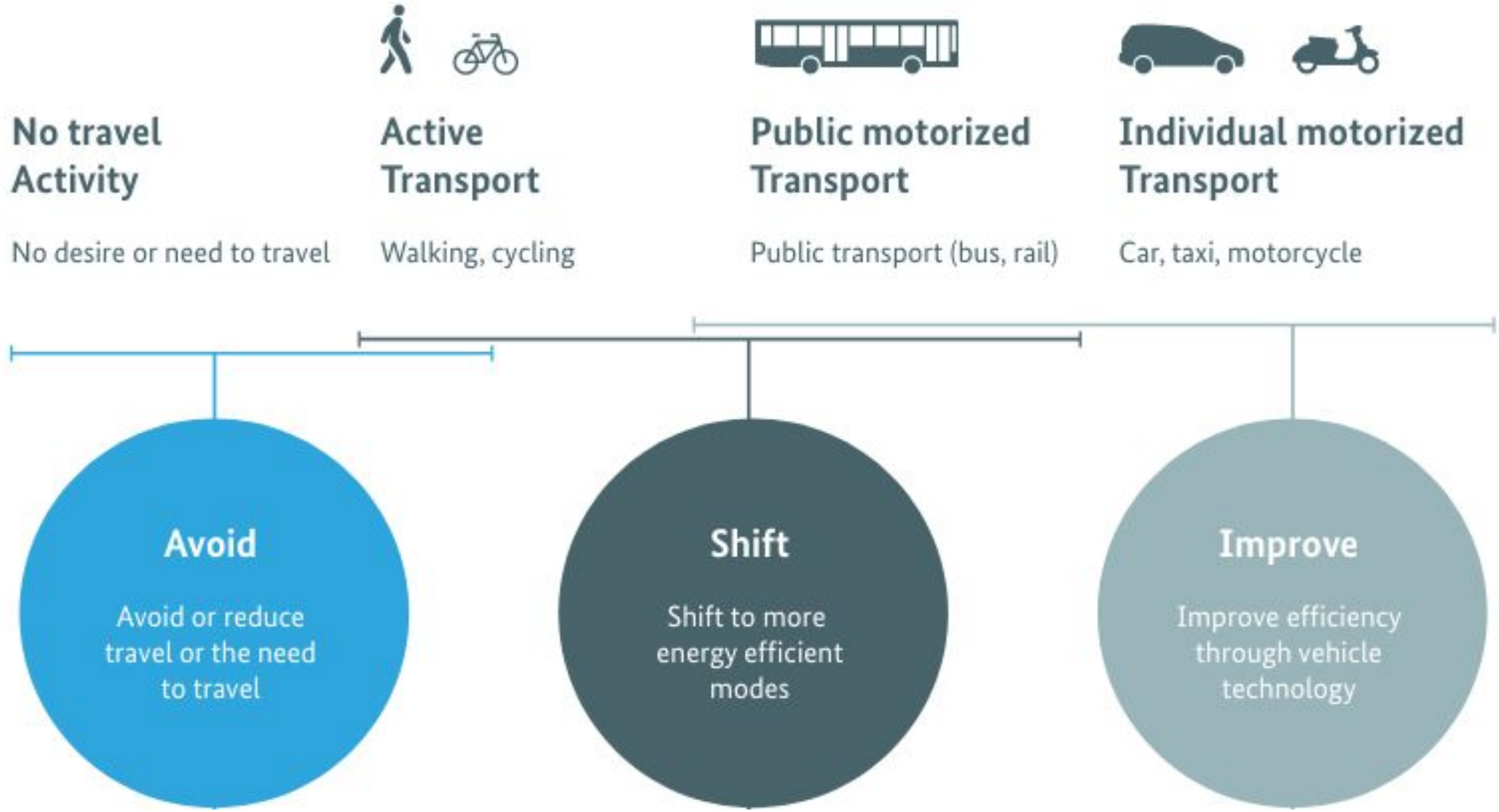
→ Consider multiple externalities and search for a fair solution

How to decarbonize? #1

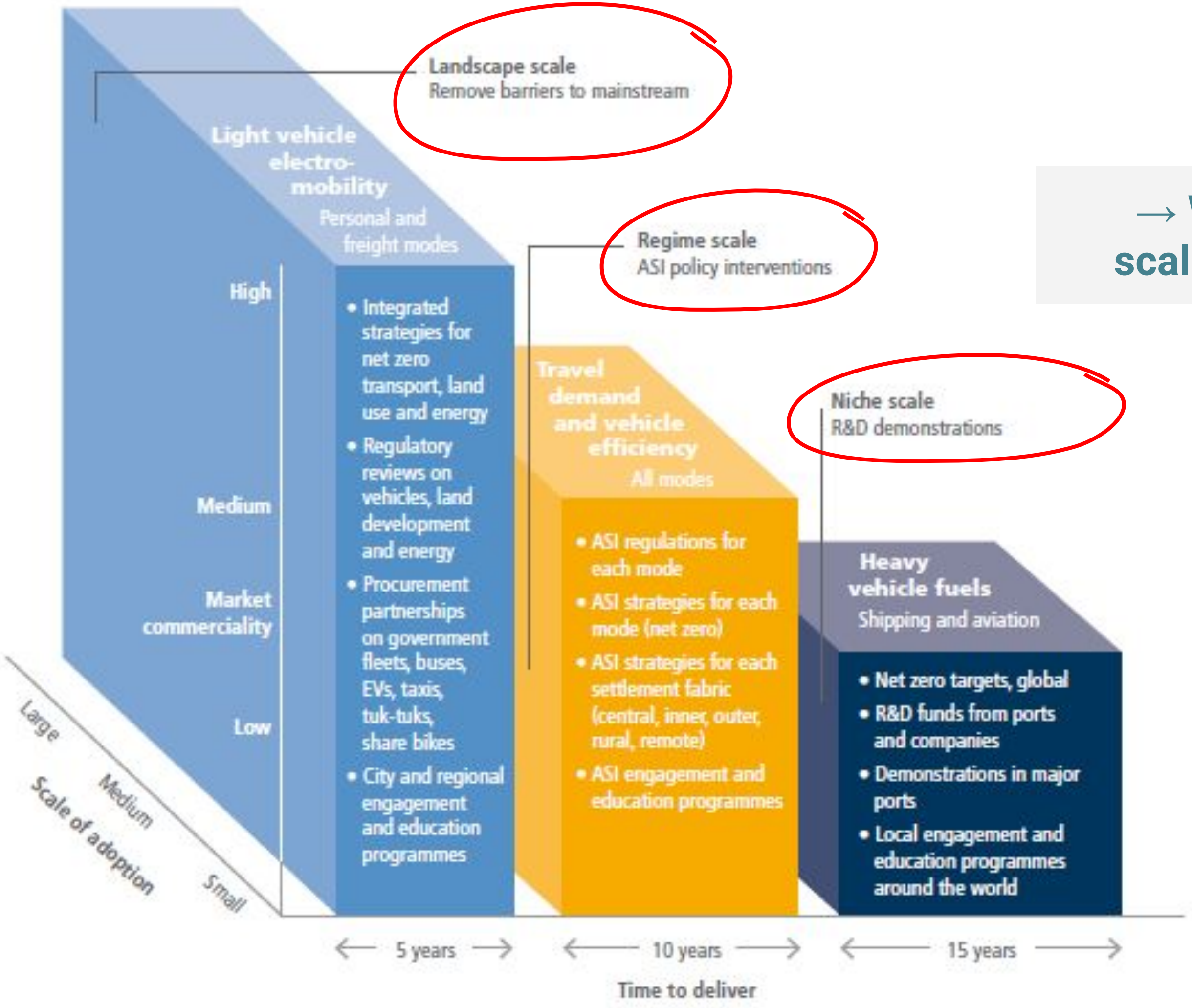
To reduce emissions in the transportation sector,

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

→ We need all three!



Source: NACTO

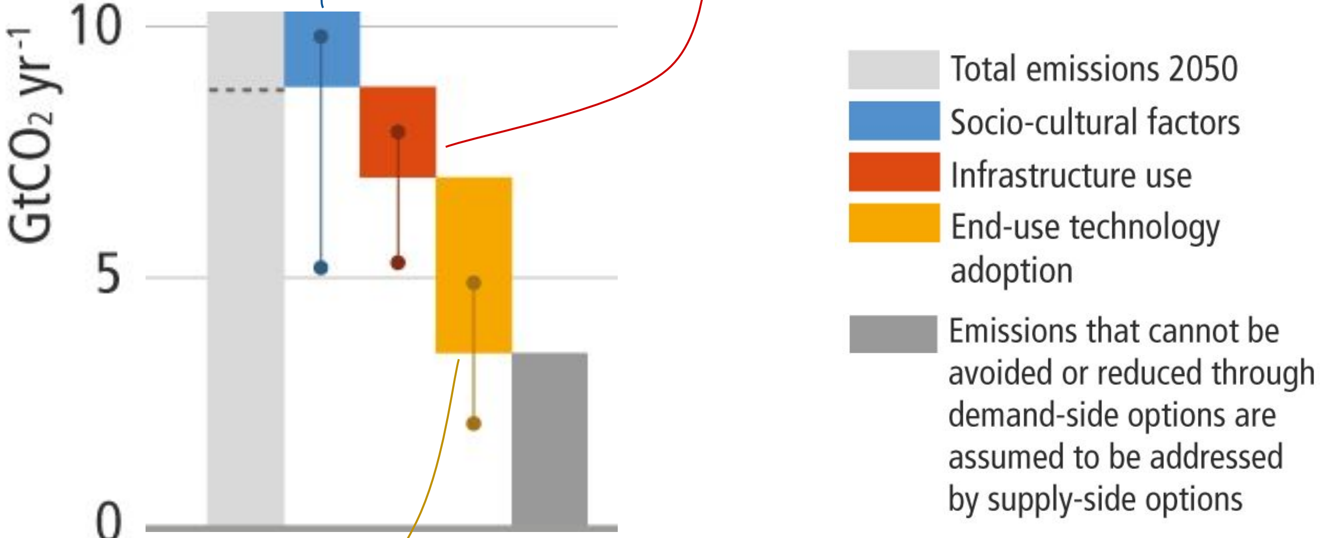


→ We can and should start scaling these solutions today

Source:
IPCC AR6 WGIII Chap 10

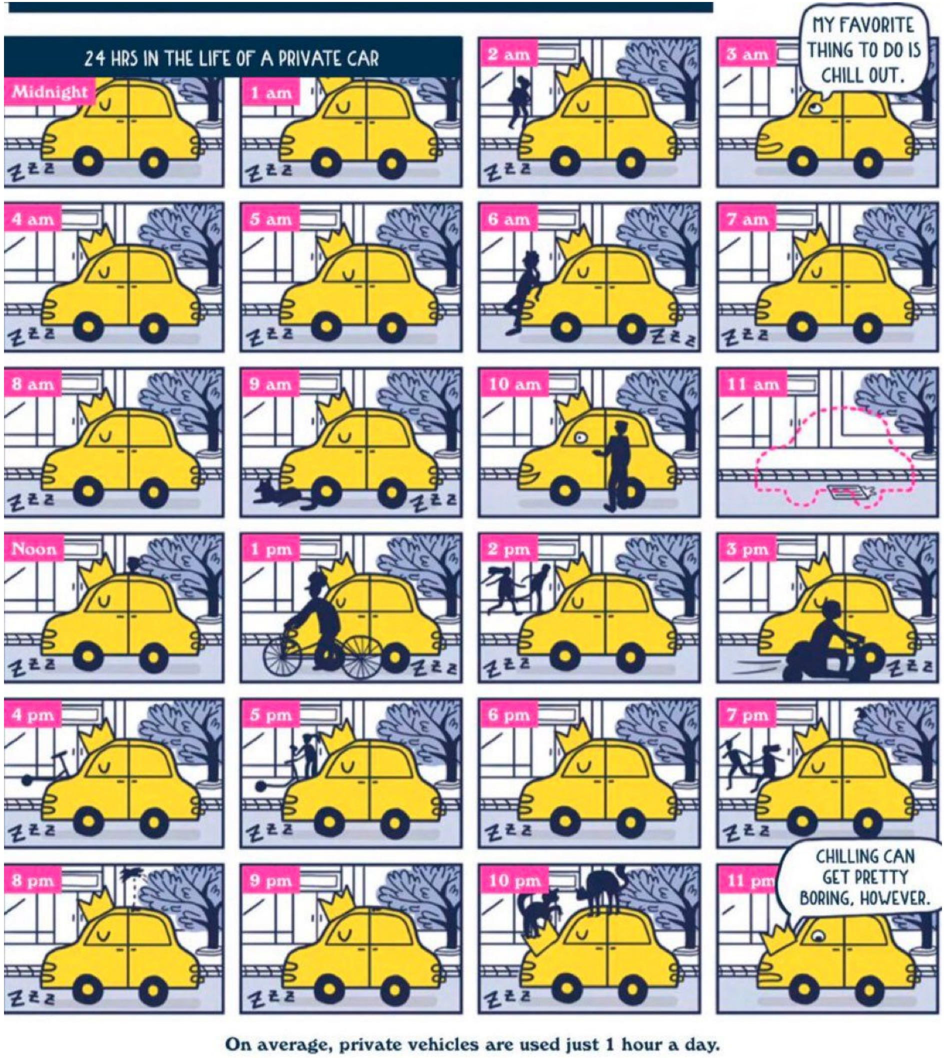
Teleworking;
active mobility
-> AVOID

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



Electric vehicles; more efficient vehicles
-> IMPROVE

Source: IPCC AR6 WGIII SPM



Technology for (pooled) shared mobility?

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

Source: Ellery Studios/Agora Verkehrswende

How? #2

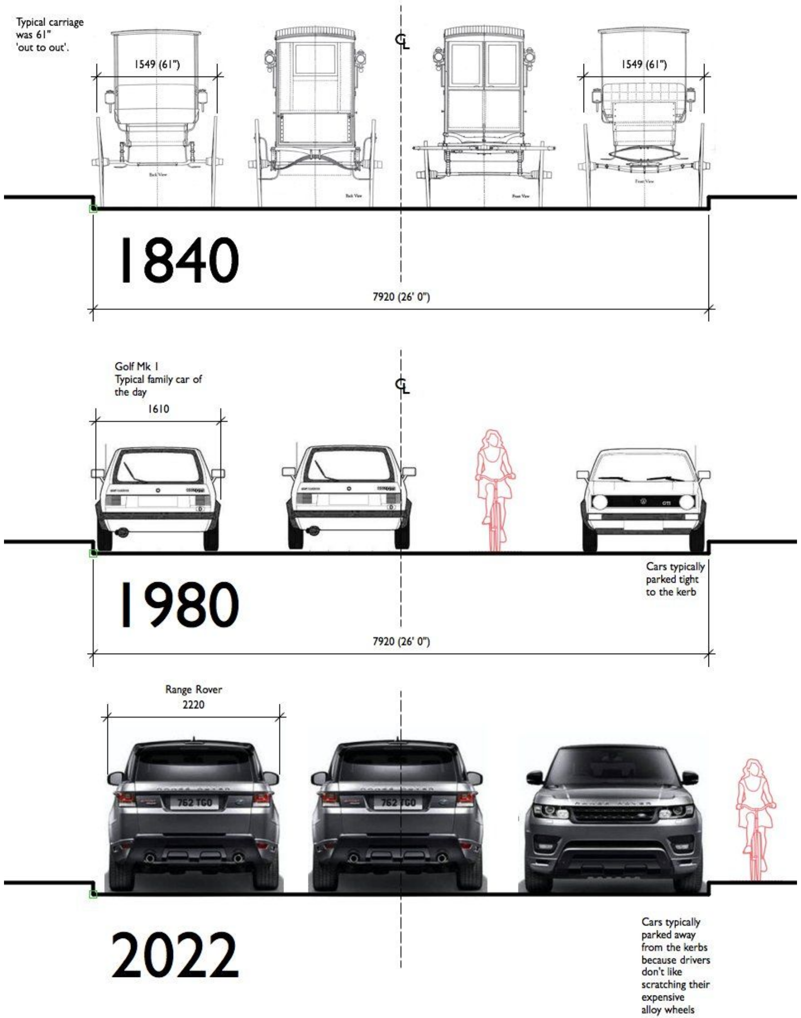
Behavioral & cultural changes underpin the adoption of solutions

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**

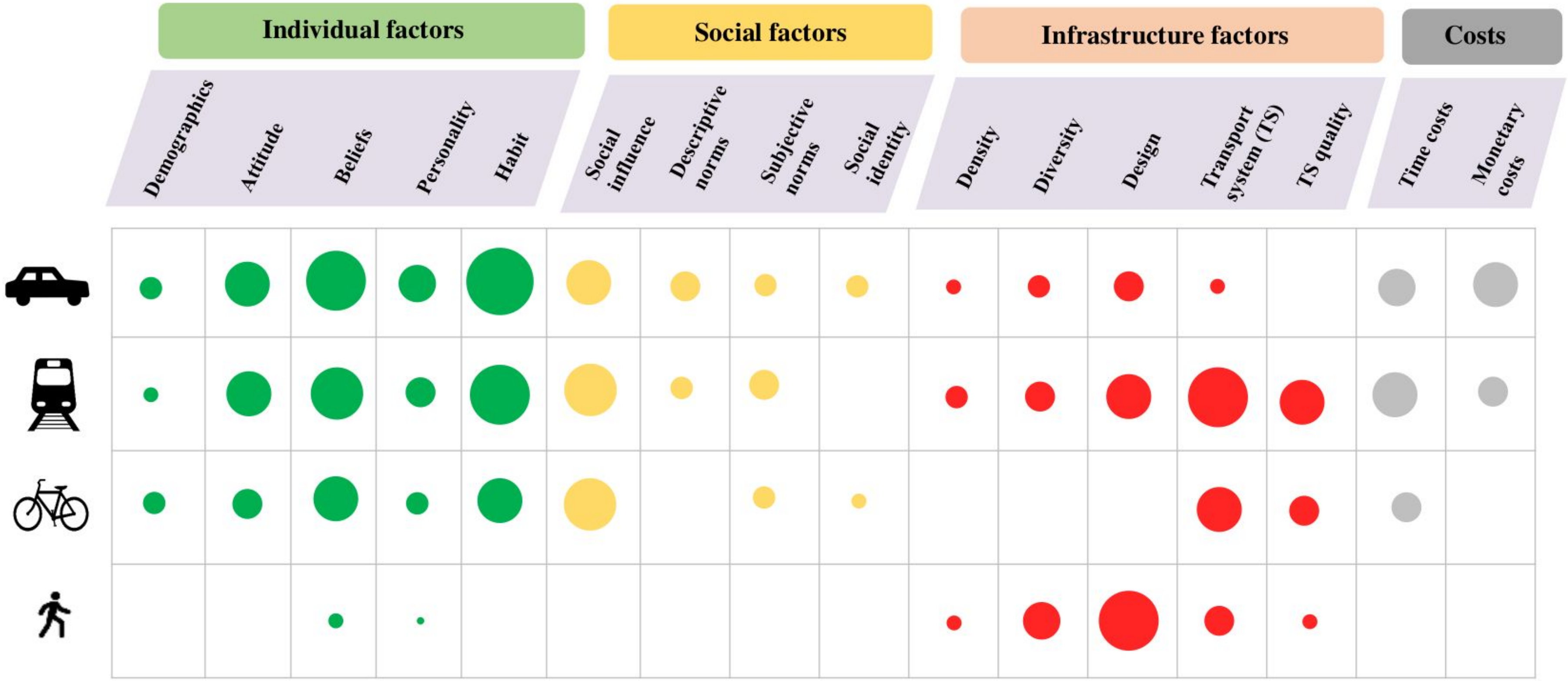


Figure 9. Size of the circle indicates the importance of sub factor to the related transport mode based on our relationship strength ratings in our review findings. ** empty boxes represent lack of supporting evidence.

How? #4

Ambitious **public policies** are absolutely necessary

to steer **systemic change**

European Parliament votes to ban combustion engine cars from 2035

Source: POLITICO

Measures with push effects

- Area-wide parking management and restricted zones
- Car limited zones
- Permanent or temporary car bans
- Congestion management
- Speed reductions
- Road pricing

Measures with push and pull effects

- Redistribution of road space (cycle or bus lanes, sidewalks, planting buffers)
- Adjustment of traffic light time-cycles
- Public awareness campaigns, marketing and participation
- Enforcement and penalising

Measures with pull effects

- Public transport priorities
- High service frequency
- Comfortable stops and surroundings
- Park-and-ride
- Cycle networks
- Pedestriant connections

→ We need broad policy packets

Source: NACTO

How? #5

Transport planning has a lot to do with

space allocation & design,

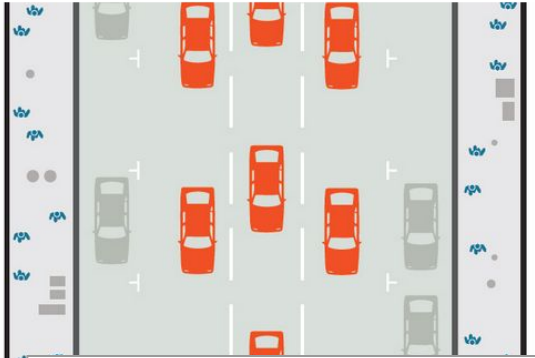
where we live

AI-generated street transformations
@betterstreetsai

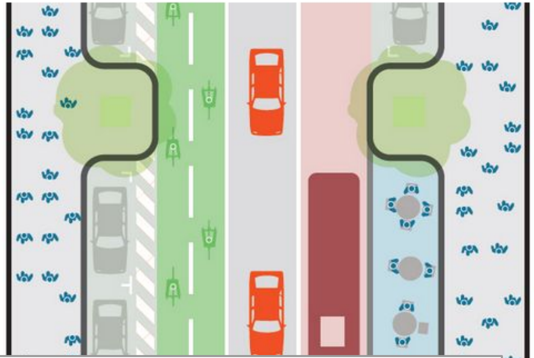
Boundary Street (West End, Brisbane, Australia)

Traduire le Tweet

Car-Oriented Street



Multimodal Street



Hourly Capacity of a Car-Oriented Street

Pedestrian	4,500/h	x2	**9,000 people/h**
Car	1,100/h	x3	**3,300 people/h**
Parked car	0	x2	**0 people/h**

Total capacity: 12,300 people/h

Hourly Capacity of a Multimodal Street

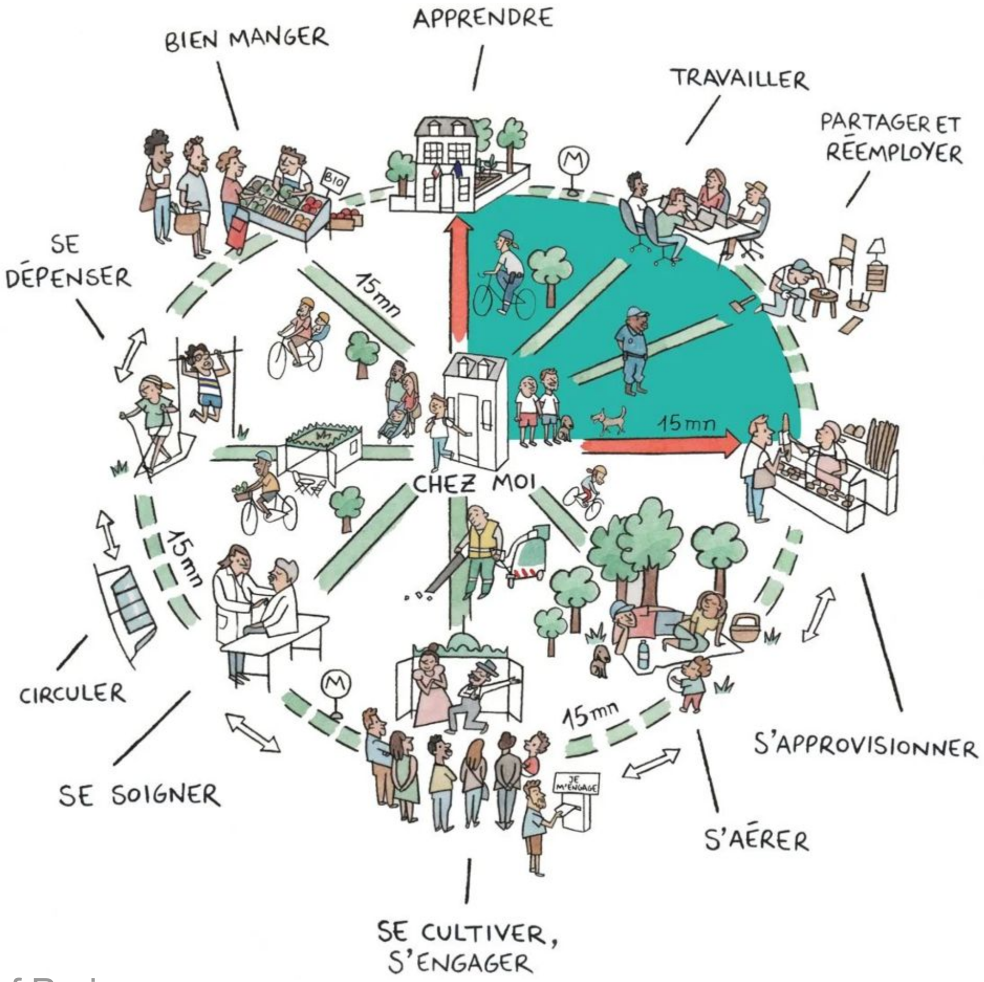
Pedestrian	8,000/h	x2	**16,000 people/h**
Cyclist	7,000/h	x1	**7,000 people/h**
Bus	6,000/h	x1	**6,000 people/h**
Car	1,100/h	x1	**1,100 people/h**
Parked car	0	x1	**0 people**

Total capacity: 30,100 people/h[29]

Source: Global Street Design Guide

Rue de Rivoli, Paris

Sources: Adrien Lelièvre, France Strategy



"15-min cities" reduce daily demand for transport (commute)

Source: City of Paris

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**

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

3. **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 use cases

Urban data

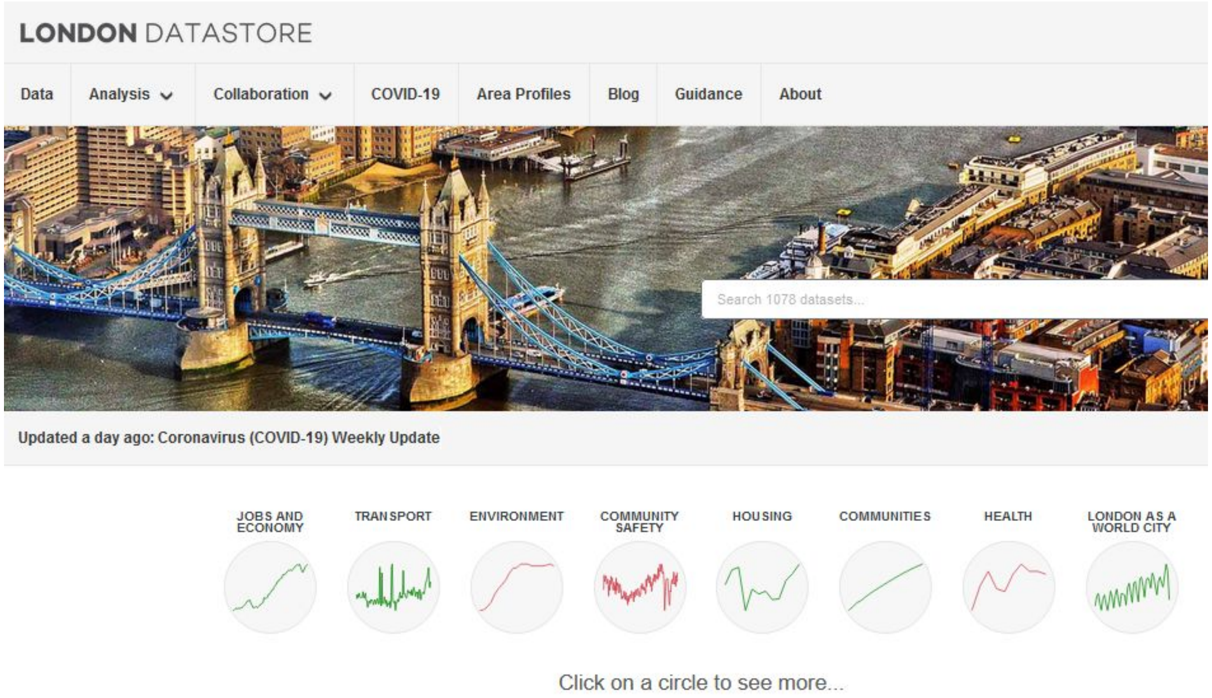
Urban data lakes

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

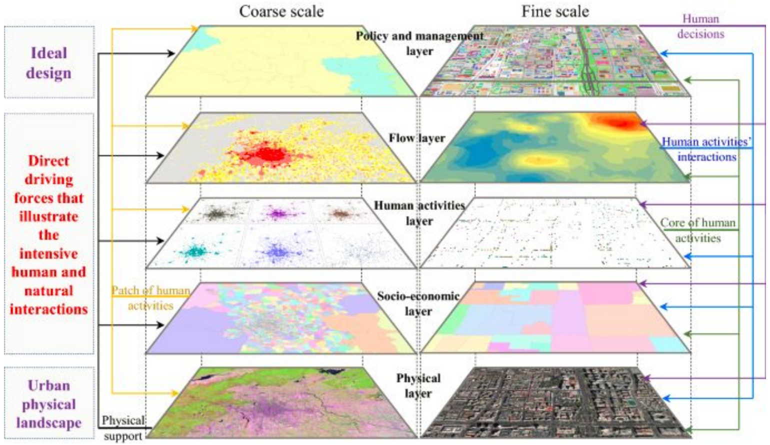
Many cities provide extensive **public data portals**.

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,...

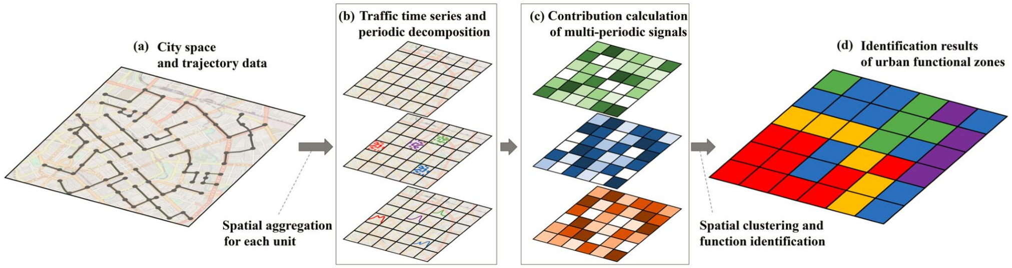


Tan, X., Han, L., Li, G., Zhou, W., Li, W., & Qian, Y. (2022). **A quantifiable architecture for urban social-ecological complex landscape pattern.** *Landscape Ecology*, *37*(3), 663-672.

Data processing and engineering

Many of the **common urban data processing challenges** stem from 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

Case study: trip demand forecasting
Question #2

Share your intuitions with use: What are *(2)* **features to use as predictors** and *(3)* **potential forecasting methods** to build your model. What features are good predictors of trip demand and also available to you? How do you account for spatial and temporal dependencies in your model?

You are a data scientist at a big ride-hailing company. You are tasked with building a **demand forecasting model** that, given a specific **time** and **location**, will return a projected trip demand.

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),...

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,...

ML Use cases

ML in urban mobility research and practice

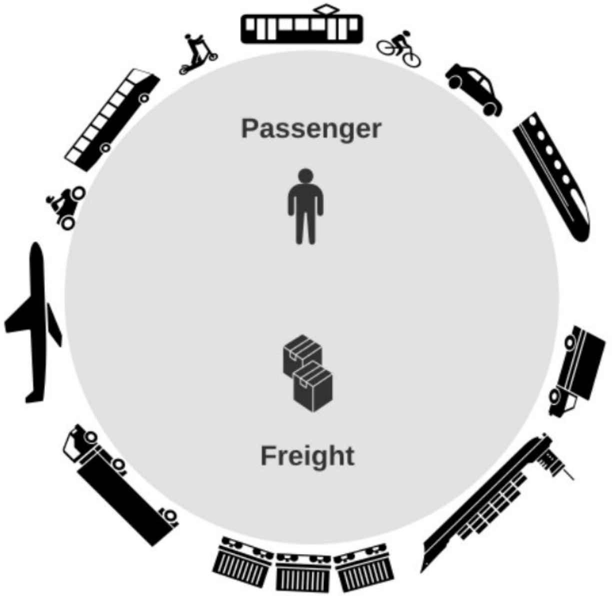
Where does ML intersect with urban mobility?

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

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

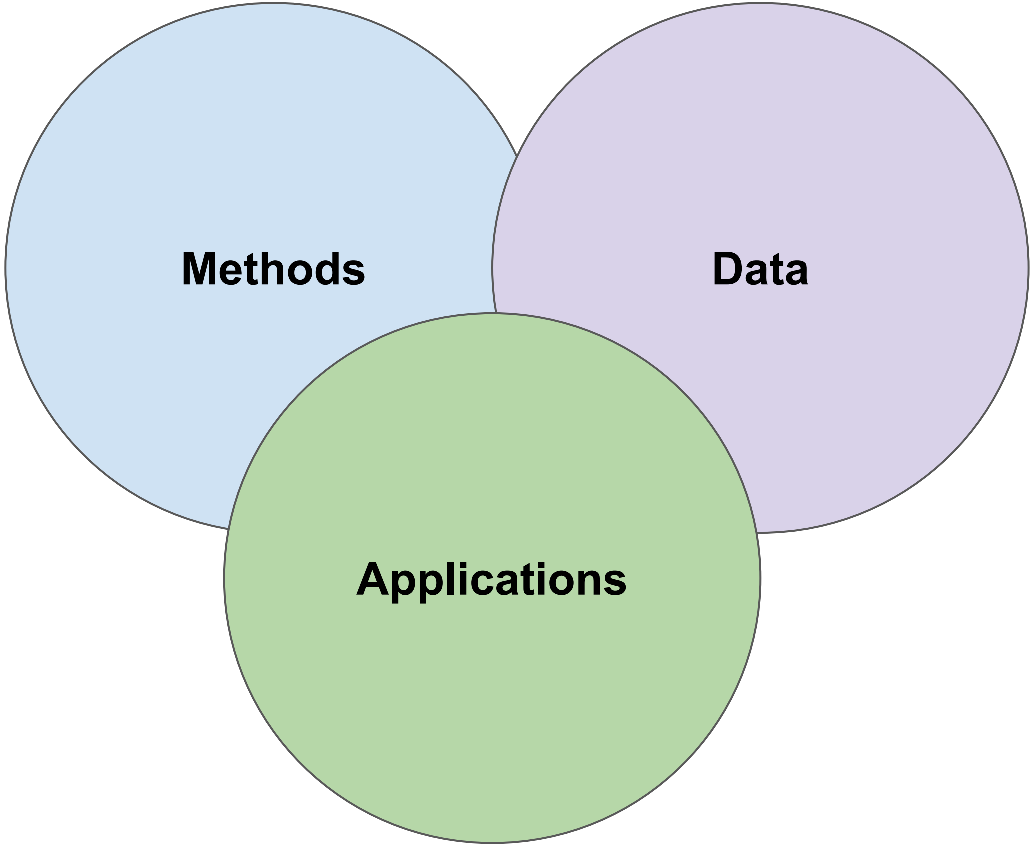
- Travel demand prediction
- Load forecasting
- Travel time estimation

Inherent multi- and interdisciplinarity!

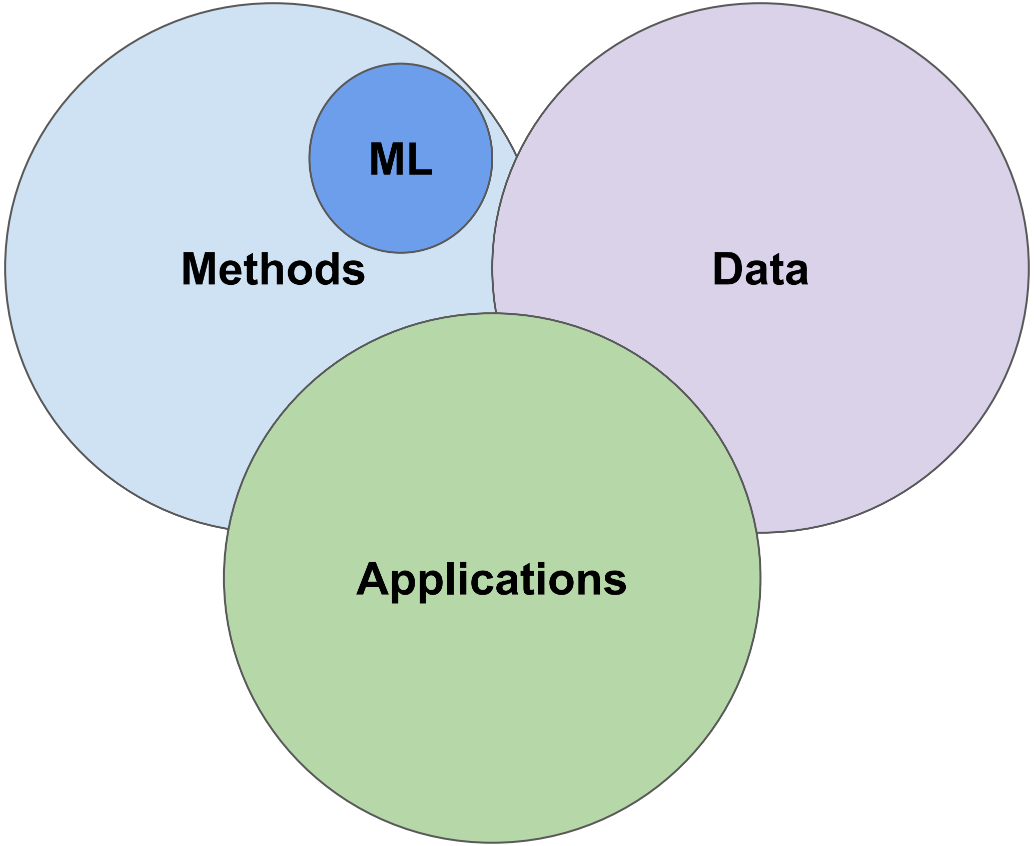
ML adjacent domains feeding into this research:

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

Quantitative urban science

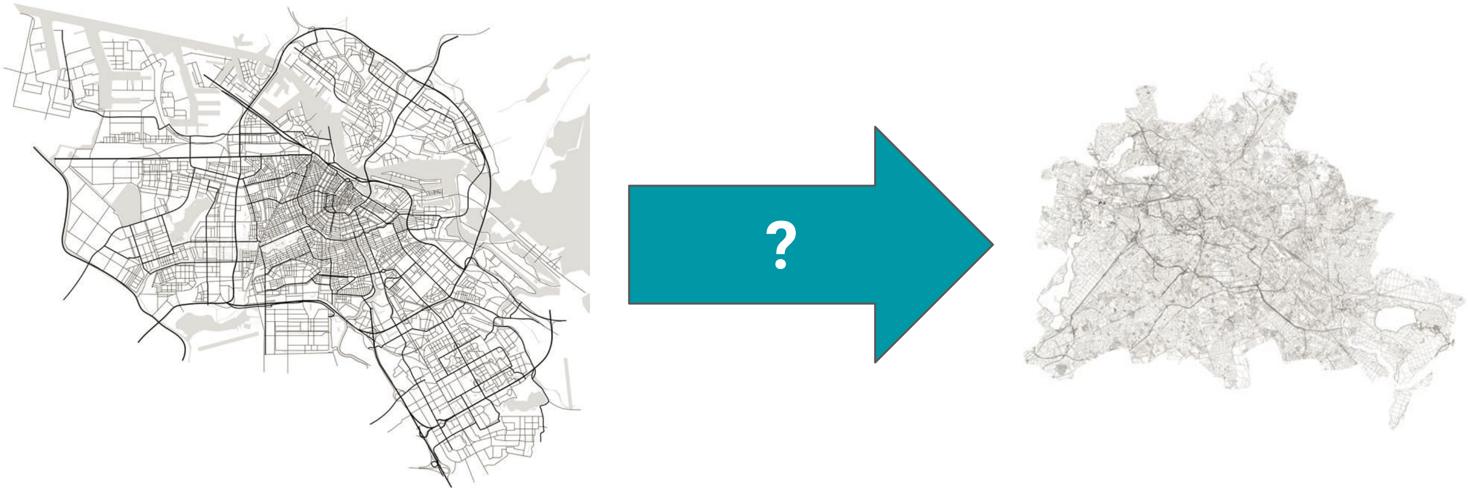


ML is not the solution, but can be part of it!



Example 1: Transfer learning urban mobility demand

Objective: Train a mobility demand forecasting model on city A and deploy it in city B to help car sharing operators



Example 1: Transfer learning urban mobility demand

Outcome variable: Trips from a Europe-wide carsharing operator for Amsterdam (NED) and Berlin (GER), processed into matching spatio-temporal units (space-time grids).

Features: Points-of-interest (POIs) from a big, global mapping service (e.g. restaurants, hospitals, train stations,...)

Method: Tree-based regression models

Example 1: Transfer learning urban mobility demand

Extrapolation to unseen environment: Can we use a model trained on Amsterdam data to forecast trip demand in Berlin?

(a) Predicted rental densities (b) Actual rental densities

Example 1: Transfer learning urban mobility demand

Deployment: Our model can help carsharing providers to design their service area when moving to a new city.

Example 1: Transfer learning urban mobility demand

Decision Support Systems 99 (2017) 75–85

Contents lists available at ScienceDirect

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journal homepage: www.elsevier.com/locate/dss

ELSEVIER

Moving in time and space – Location intelligence for carsharing decision support

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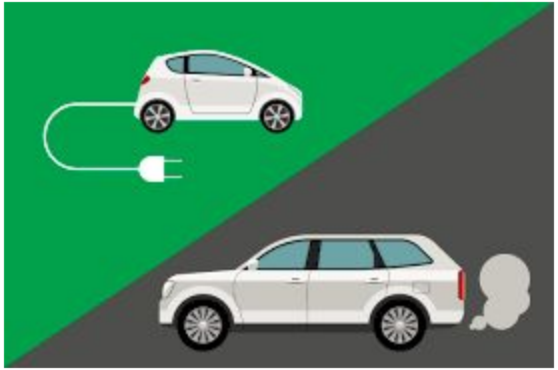
ABSTRACT

In this paper we develop a spatial decision support system that assists free-floating carsharing providers in countering imbalances between vehicle supply and customer demand in existing business areas and reduces the risk of imbalance when expanding the carsharing business to a new city. For this purpose, we analyze rental data of a major carsharing provider in the city of Amsterdam in combination with points of interest (POIs). The spatio-temporal demand variations are used to develop pricing zones for existing business areas. We then apply the influence of POIs derived from carsharing usage in Amsterdam in order to predict carsharing demand in the city of Berlin. The results indicate that predicted and actual usage patterns are very similar. Hence, our approach can be used to define new business areas when expanding to new cities to include high demand areas and exclude low demand areas, thereby reducing the risk of supply-demand imbalance.

Willing, C., Klemmer, K., Brandt, T., & Neumann, D. (2017). **Moving in time and space–Location intelligence for carsharing decision support.** *Decision Support Systems*, *99*, 75-85.

Example 2: City-scale causal discovery under network effects

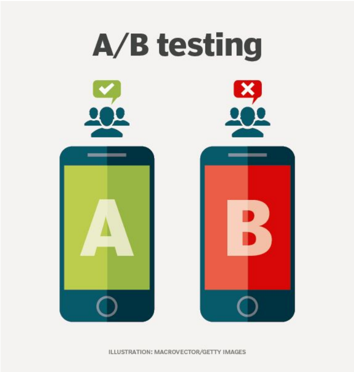
Objective: Evaluate the causal effects of a new feature (e.g. the option to choose between EV and traditional vehicle) on ride-hailing trips



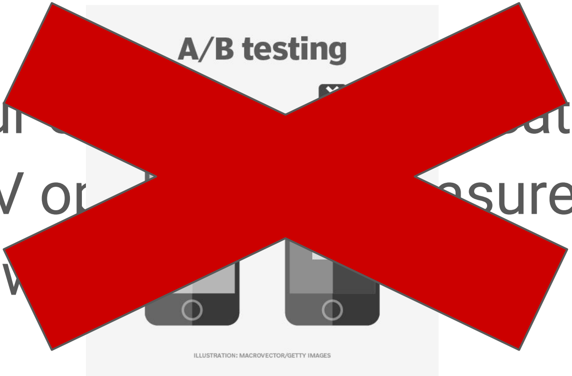
Example 2: City-scale causal discovery under network effects

Metric: We want to see the difference in utilization rate (i.e. % of time idle) for EVs that are part of our ride-hailing service.

Method: We split our customers into treatment (EV option) and control group (no EV option) and measure the difference in our outcome metric between both groups.



Example 2: City-scale causal discovery under network effects

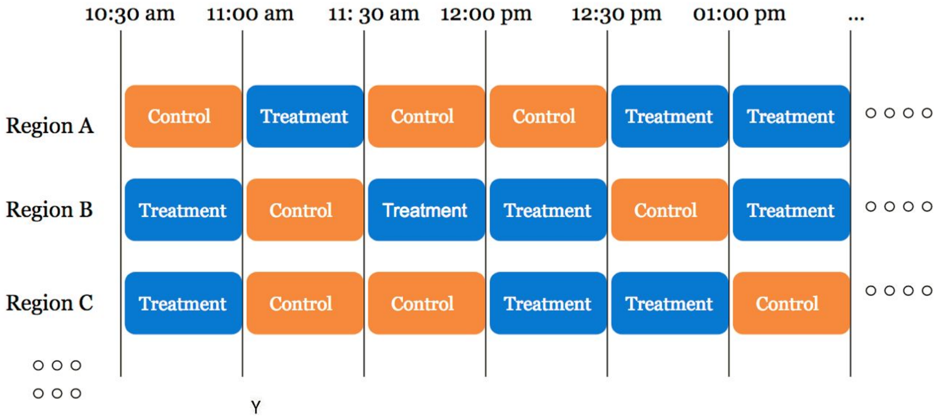
Method: We split our c 

atment (EV option) and control group (no EV o asure the difference in our outcome metric betw

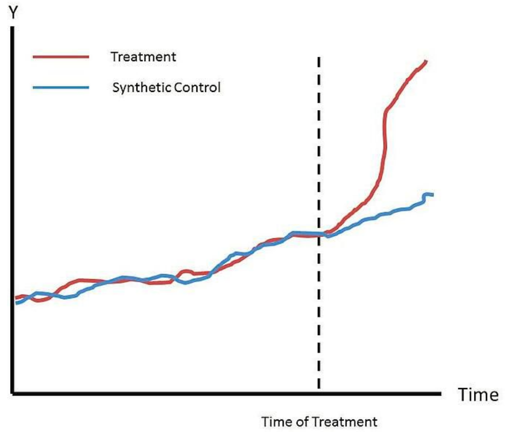
Caution: *Network effects* make a simple A/B test inapplicable in this case, as customers in the control group are also affected by the different supply steming from the intervention the treatment group recieved!

Example 2: City-scale causal discovery under network effects

Switchbacks: Alternate treatment and control group over space and time units



Synthetic controls: Build a forecasting model of your metric, then implement the intervention and measure the difference between forecast and observed outcomes.



Example 2: City-scale causal discovery under network effects

Uber Blog Explore

Engineering

Overview AI Backend Culture

Data / ML

Using Causal Inference to Improve the Uber User Experience

June 19, 2019 / Global

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

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”


Digitalisation

Smart City: German government funding "Digital Twins" project

EUR 32 million for cross-city project with Munich and Leipzig - interactive 3D model of Hamburg planned

21 September 2020

share articl

Example: Scaling cargo bikes usage via RL-routing of delivery fleets

CCAI Innovation grants 2022

Uses RL for high-fidelity simulation of fleet-operation under real-world settings.

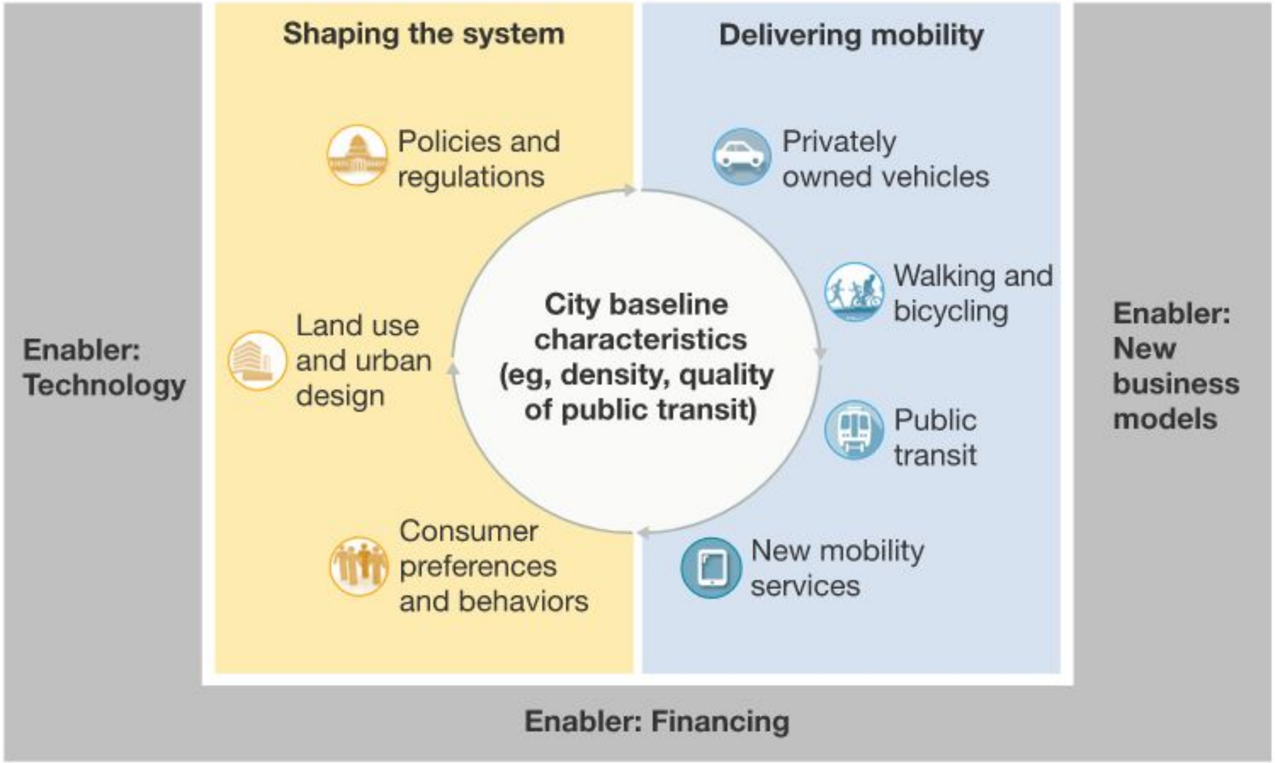
Enables to run feasibility studies towards optimising and diversifying fleet composition in a cost-effective manner.

Check out greenlastmile.ai/

Credits: Urbike, partner of the project

Outlook

A framework for understanding urban mobility



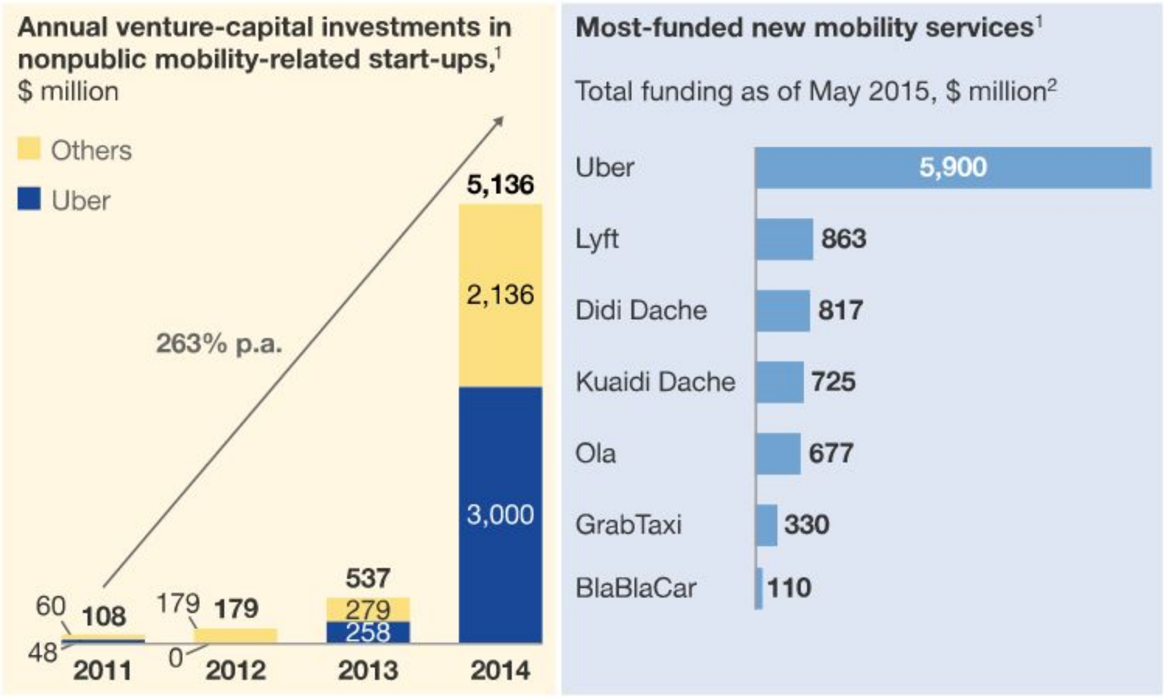
Source: McKinsey

Individual and group transport are changing

	Traditional mobility solutions	New mobility services	
Individual-based mobility	Private car ownership	Car sharing: peer to peer	A peer-to-peer platform where individuals can rent out their private vehicles when they are not in use
	Taxi	E-hailing	Process of ordering a car or taxi via on-demand app. App matches rider with driver and handles payment
	Rental cars	Car sharing: fleet operator	On-demand short-term car rentals with the vehicle owned and managed by a fleet operator
Group-based mobility	Car pooling	Shared e-hailing	Allows riders going in the same direction to share the car, thereby splitting the fare and lowering the cost
	Public transit	On-demand private shuttles	App and technology enabled shuttle service. Cheaper than a taxi but more convenient than public transit
		Private buses	Shared and Wi-Fi-enabled commuter buses available to the public or to employees of select companies. Used to free riders from driving to work

Source: McKinsey

Investments in mobility companies are skyrocketing

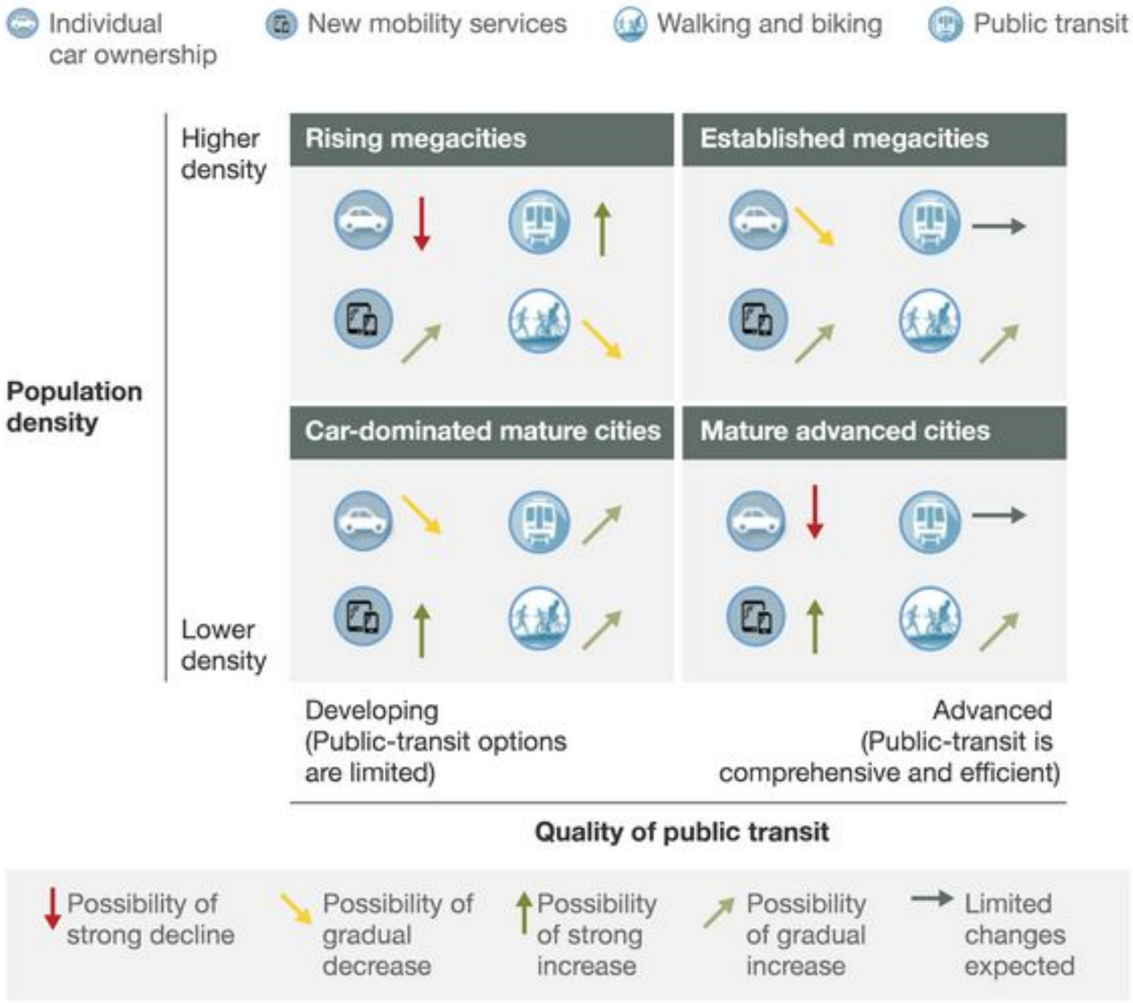


Source: McKinsey

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



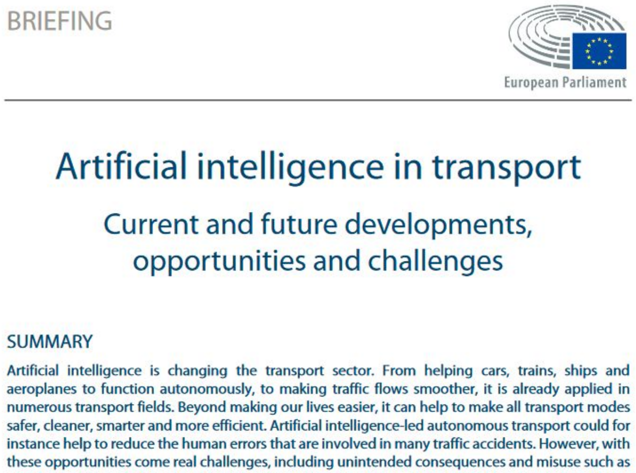
Different cities are experiencing different changes!

Source: McKinsey

The case for ML

The current **urban mobility revolution** could not happen without AI and AI-adjacent tech (both hardware and software): robotics, ubiquitous computing, large-scale data processing and analysis, optimization under constraints, federated and tiny ML, market and auction design, self-driving vehicles,...

Niestadt, M., Debyser, A., Scordamaglia, D., & Pape, M. (2019). **Artificial intelligence in transport: Current and future developments, opportunities and challenges.** *European Parliamentary Research Service*.


BRIEFING

European Parliament

Artificial intelligence in transport

Current and future developments, opportunities and challenges

SUMMARY

Artificial intelligence is changing the transport sector. From helping cars, trains, ships and aeroplanes to function autonomously, to making traffic flows smoother, it is already applied in numerous transport fields. Beyond making our lives easier, it can help to make all transport modes safer, cleaner, smarter and more efficient. Artificial intelligence-led autonomous transport could for instance help to reduce the human errors that are involved in many traffic accidents. However, with these opportunities come real challenges, including unintended consequences and misuse such as

Case study: trip demand forecasting

Question #3

Share your intuitions with use: What are the best ways to *(4)* **test and deploy your model** in the real-world and what is *(5)* the **general climate relevance** of the deployment? How can trip demand predictions be operationalized? What do you need to consider when testing your model? How may (or not!) your approach affect emissions related to your service?

You are a data scientist at a big ride-hailing company. You are tasked with building a **demand forecasting model** that, given a specific **time** and **location**, will return a projected trip demand.

Case study: trip demand forecasting
Question #3

Answer:

Deployment: Demand forecast can be used to anticipate demand in certain areas at certain times. Drivers can be sent to those locations in advance to catch the demand. For example, you could incentivise trips TO projected high demand areas by (1) paying drivers more to go there or (2) reducing prices for customers going there.

Testing: Any deployment, e.g. a pricing scheme driven by your demand forecast, needs to be tested. A simple A/B test would not work here due to potential network effects. A more sophisticated testing scheme like switchbacks or synthetic control is needed.
Side-effects: Customers and drivers might both adapt to your pricing scheme if they can identify a pattern. This might lead to a change in behavior which can render your predictions less accurate.

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

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?

Theory of change / system thinking

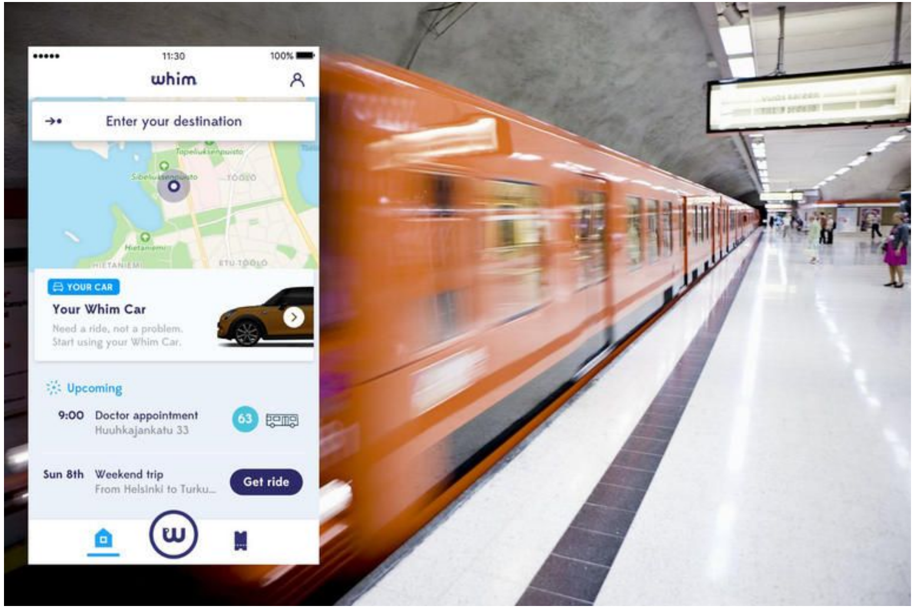
Users

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**

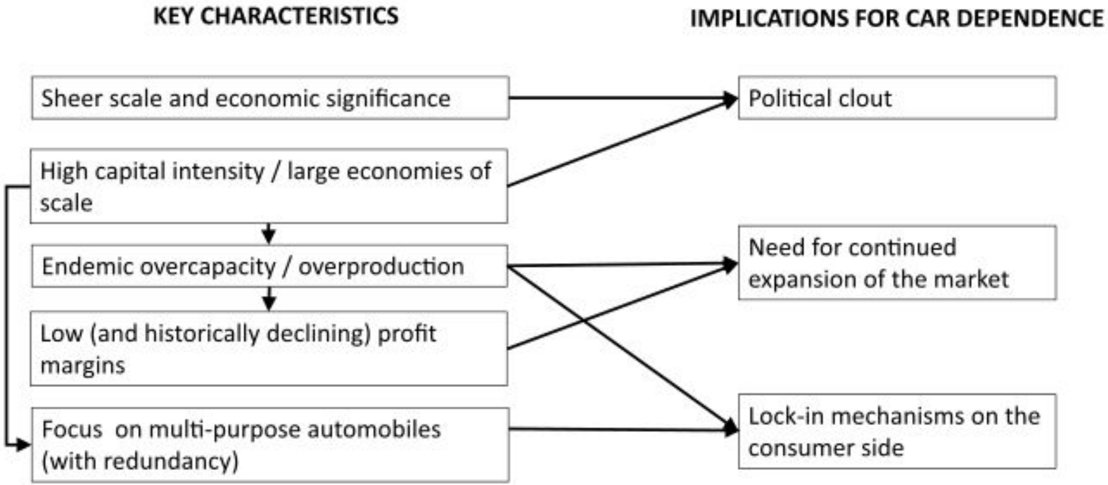


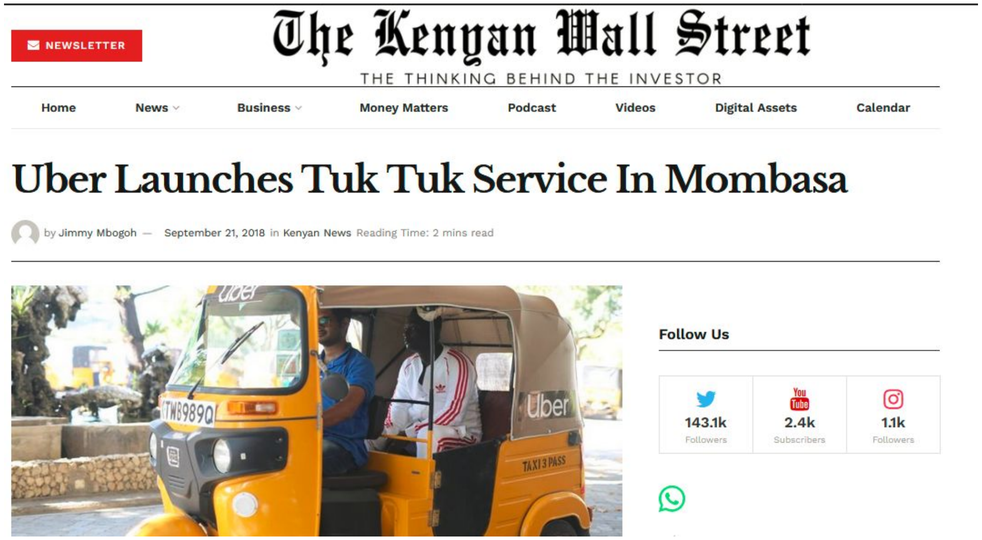
Fig. 2. Key characteristics of the automotive industry and implications for car dependence (own elaboration).

Mattioli et al 2020

Rural transport, freight, aviation,...

Urban mobility in the **Global South**

ML/AI are less important here, building **infrastructure is key**!


NEWSLETTER

The Kenyan Wall Street

THE THINKING BEHIND THE INVESTOR

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Uber Launches Tuk Tuk Service In Mombasa

by Jimmy Mbogoh — September 21, 2018 in Kenyan News Reading Time: 2 mins read

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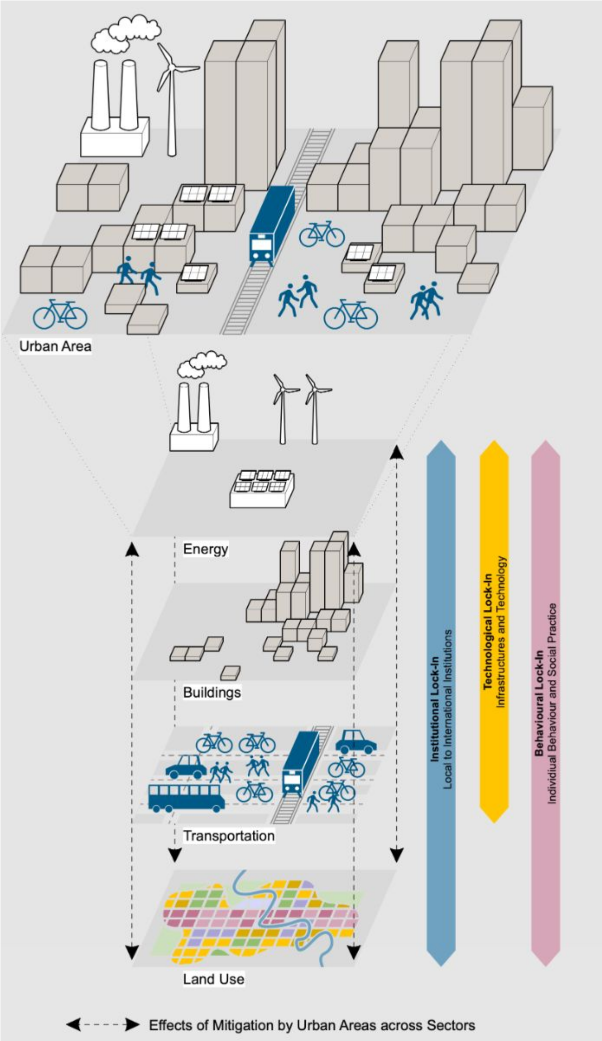
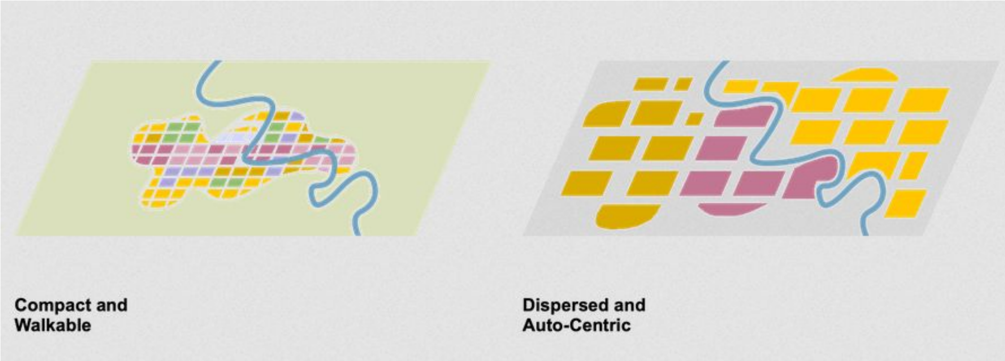
Transportation is often **informal** (privately provided and not regulated)

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

- Jaramillo, P., S. Kahn Ribeiro, P. Newman, S. Dhar, O.E. Diemuodeke, T. Kajino, D.S. Lee, S.B. Nugroho, X. Ou, A. Hammer Strømman, J. Whitehead, 2022: **Transport. In IPCC, 2022: Climate Change 2022: Mitigation of Climate Change**. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA. doi: 10.1017/9781009157926.012
- Kaack, Lynn, **Transportation** in Rolnick, David, et al. "**Tackling climate change with machine learning.**" ACM Computing Surveys (CSUR) 55.2 (2022): 1-96.
- 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
- Mattioli, Giulio, et al. "**The political economy of car dependence: A systems of provision approach.**" Energy Research & Social Science 66 (2020): 101486.
- Creutzig, Felix, et al. "**Fair street space allocation: ethical principles and empirical insights.**" Transport Reviews 40.6 (2020): 711-733.
- 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.
- Willing, C., Brandt, T. & Neumann, D. **Intermodal Mobility**. *Bus Inf Syst Eng* **59,** 173–179 (2017). https://doi.org/10.1007/s12599-017-0471-7
- **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
- Niestadt, M., Debyser, A., Scordamaglia, D., & Pape, M. (2019). **Artificial intelligence in transport: Current and future developments, opportunities and challenges.** *European Parliamentary Research Service*. https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/635609/EPRS_BRI(2019)635609_EN.pdf

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