AI for Cities and Mobility

Prof. Jinhua Zhao

AI for Future of Mobility

What is success and what defines the future

AI for City Planning

Human In the Loop, Power Balance and Future Role of City Planners

AI for Autonomous Vehicles

human agency and AV deployment


CANOE
8,000 BC
SKIS
6,000 BC
WHEELED CART
3,500 BC
GALLEY
1,500 BC
CARRIAGE
600 BC
JUNK
AD 200
WHEEL-BARROW
AD 230
CARRACK
15TH CENTURY
FUNICULAR
16TH CENTURY
STAGE-COACH
16TH CENTURY
HOT AIR BALLOON
1783
STEAMBOAT
1785
STEAM LOCOMOTIVE
1804
DANDY HORSE
1818
AIRSHIP
1852
SUBWAY
1863
PENNY FARTHING
1870
ELECTRIC TROLLEY
1882
MOTORCYCLE
1885
GAS CAR
1886
GLIDER
1891
DIESEL TRUCK
1892
AIRPLANE
1903
RACE CAR
1930s
HELICOPTER
1939
JETLINER
1952
MONSTER TRUCK
1950s
HOVERCRAFT
1959
BATHYSCAPE
1960
ROCKET
1961
ALL-TERRAIN VEHICLE
1961
JET PROPULSION
1984
MAGLEV
1984
SEGWAY
2001
SELF-DRIVING CAR
2009 (PROTOTYPE)
HYDROGEN FUEL-CELL CAR
2015

Morning traffic on the Southeast Expressway in Dorchester. (David L. Ryan/Globe Staff)


Traffic in Beijing today

Beijing 1982 | Source: Wang Wenlan, Wen's Lens, https://tinyurl.com/34kparne

What is success?

What defines the future?

Three questions

Q1:

How many people were killed in road traffic crashes in the US in 2021?

42,915

42,915

0

electric vehicles

autonomous vehicles

road side robotics

e-scooters e-bikes

urban drones

? ? ? ? ?

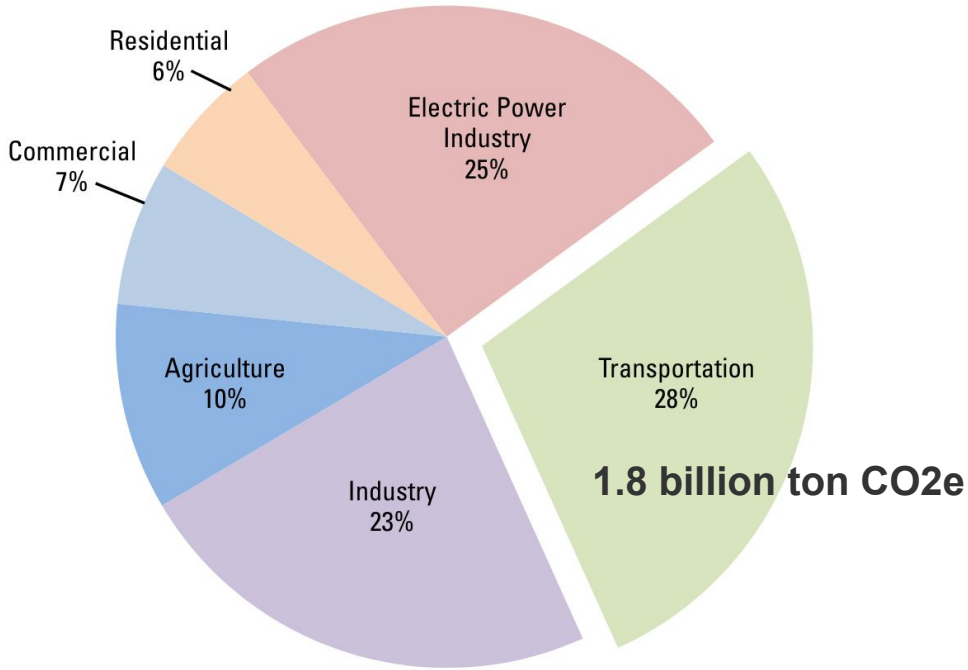
42,915 ← → 0

Q2:

How much does transportation contribute to the GHG emission in the US?

U.S. GHG Emissions by Economic Sector

2022



1.8 billion ton CO2e

6.3 billion ton CO2e

US: 28%

vs

Global: 16%

Source: EPA Fast Facts: U.S. Transportation Sector Greenhouse Gas Emissions

Q3:

Is public transit affordable in Boston?

Are we successful?

- Cities are heavily congested
- 42,915 killed on US roads
- 28% of GHG emission
- Manny cannot afford public transit in Boston

Technology progress has NOT been translated to the betterment of the mobility system.

What will define the future?

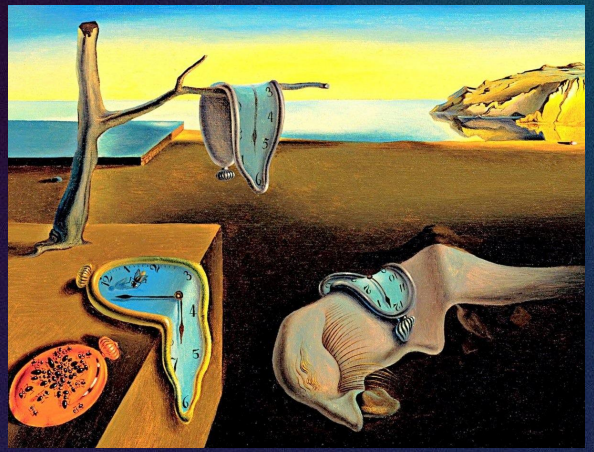
Behavior + Computation

P1. Behavioral thinking

is travel social?

is travel emotional?

is time absolute?



Laziness knows no boundaries…

P2: Computational Thinking

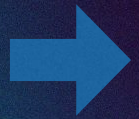
Data

+

Algorithm

+

Computing Power



Representation

Prediction

Explanation

Control

Creation

Behavioral Thinking

- Emotional
- Social
- Perceptional

~

Transportation Technology

- Electrification
- Automation
- Connectivity
- Sharing

Computational Foundation

- Representation
- Explanation
- Prediction
- Control
- Creation

AI for Transportation

- L1: Introduction
  - S1: Success and Future
  - S2: Transportation: System, Changes and Data
  - S3: Grounded AI: Structure, Trend, Why Now?
  - S4: AI: Tensions and Opportunities

transportation systems

What is transportation?

The movement of people and goods

What is the Transportation System?

Physical Framework

Vehicles

Energy

Infrastructure

Functional Framework

Technological

Behavioral

Political / Regulatory

Financial

Environmental

Stakeholder Framework

Business
- Traditional Mobility (Boeing, Toyota, DHL)
- Big Tech (Alphabet/Waymo, Amazon)
- Related Industries: Energy, Finance, Finance, Insurance, Infrastructure, etc.
- Startups and New Entrants

Government
- International Governance (e.g., ICAO)
- National
- State
- Municipal

Civil Society
- NGOs (Greenpeace, road safety, etc)
- IOs (e.g., WBCSD, WEF, World Bank)
- Academic/Research

The collection of stakeholders – individuals and institutions – that deliver mobility *for people*

What’s changing in Transportation?

What's changing in transportation?

Technology	Data	Value
• Automation • Electrification • 5G/Connected • Shared economy • …	• Ubiquitous sensing • AI / computing • Cybersecurity • Property right • …	• Climate change • Future of work • Public health • Social justice • Urban livability • …

Different framings of transportation

As a congestion problem

As a sustainability problem

As a social justice problem

As a personal identity problem

As an urban creativity problem

As a public health problem

What’s Data in Transportation?

Case study #1: Evolution of Data Analytics in Transport for London

- LTDS / CRM
- Oyster / Octopus
- iBus
- Mobile CDR / Wifi / RFID / Bluetooth
- Tracking Apps: MOVES / FMS / Strava
- Mobile App
- Text: Incidence Log, Customer Feedback, Twitter, youtube…

Data Resource

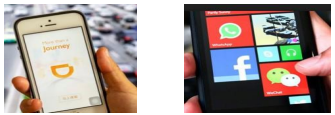
- Location data, Trajectory data

- Transaction data

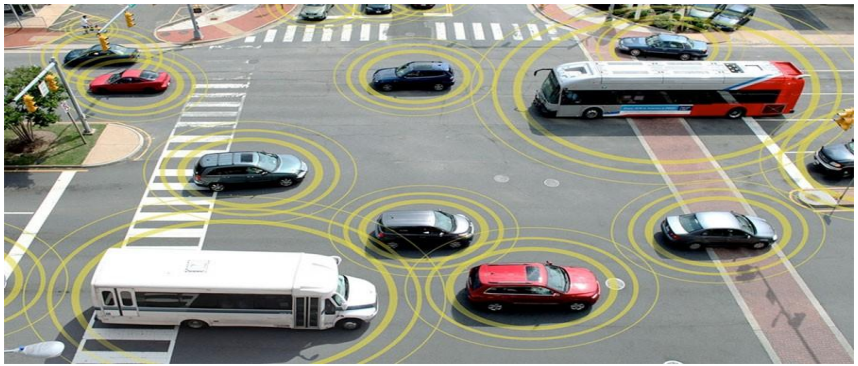
- Profile data

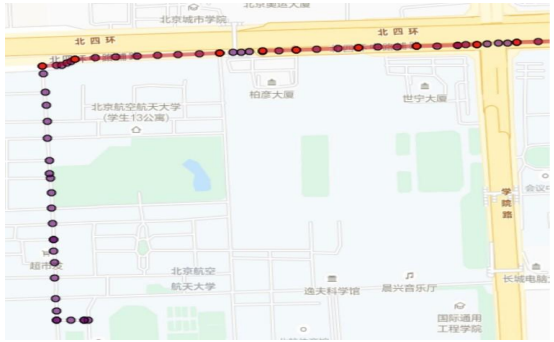
- Sensors: multimedia data

- Cross-platform identification

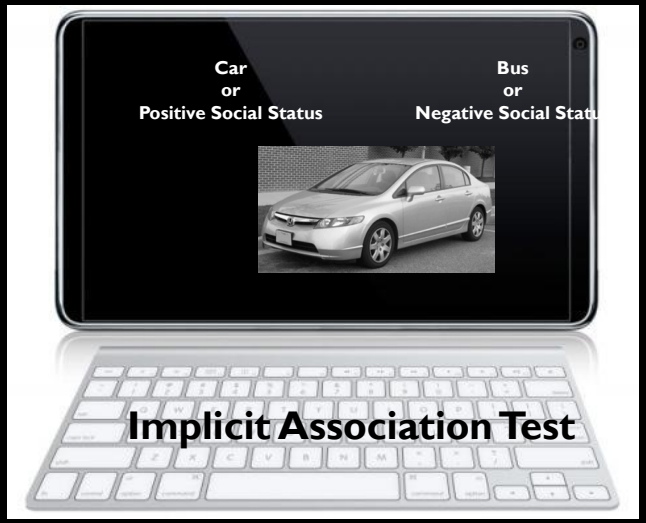


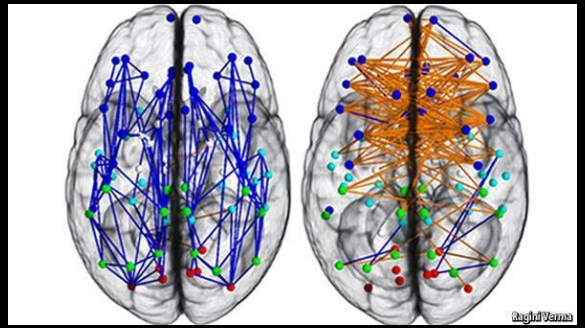
Location Data and Floating-Car Trajectory





Sensors: Loop detector, camera, microphone, mobile sensors …


Car
or
Positive Social Status
Bus
or
Negative Social Statu
Implicit Association Test


Raghul Verma

Multi-modal Data Fusion and Analytics

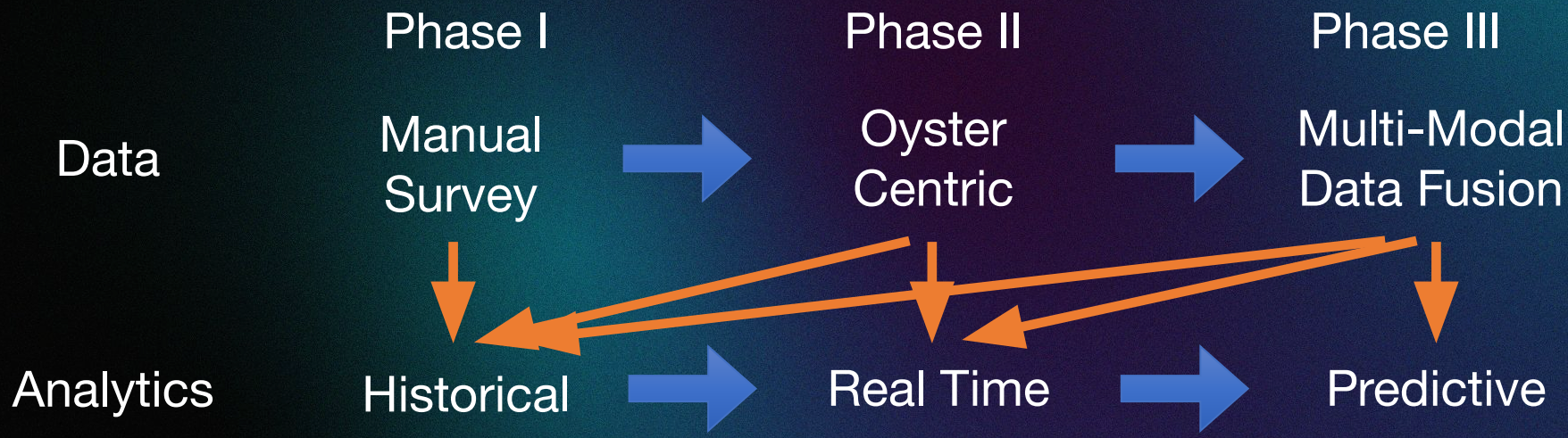
Multimodal Travel Information Platform

- Oyster
- Mobile CDR / Wifi / RFID / Bluetooth
- LTDS / CRM
- Tracking Apps: MOVES / FMS

Statistical Data Fusion

- Regression
- Discrete Choice Modeling
- Machine Learning (Unsupervised, supervised, reinforcement)
- LLM and Foundational Models

TfL Data Analytics



Multi-channel view of cities

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Transit Lab

MIT Mobility Initiative

IMAGES

Architecture Design
Urban Design

LANGUAGE

Urban Anthropology
Urban History
Urban Sociology

Qualitative

Quantitative

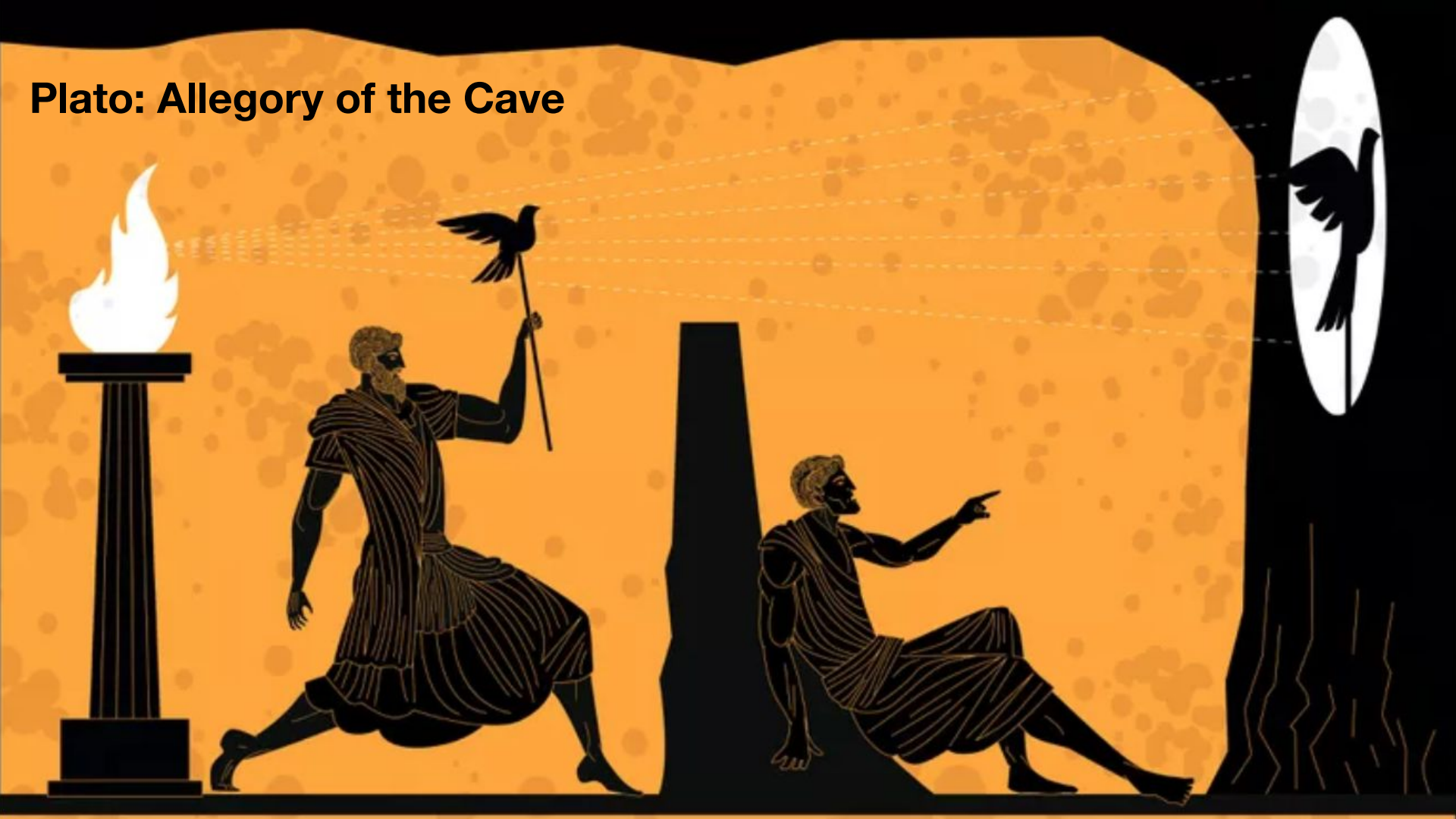
Transport Network
Electric Grid
Water and wastewater
Gas pipeline
Telephone and internet

Urban Economics
Urban Real Estate

GRAPHS

NUMBERS

Plato: Allegory of the Cave



A multi-channel view city (e.g. Chicago)

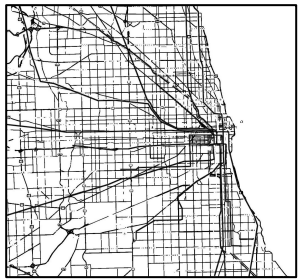
Numeric values

Population: 2,693,976

Auto ownership per HH: 1.12/HH

…

Graphs (Transit and Road)



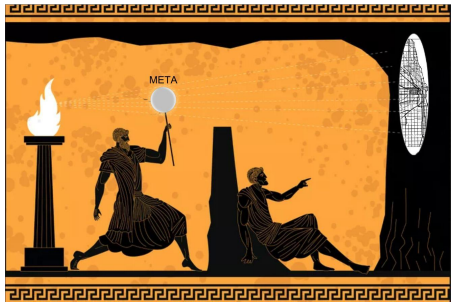
Images (Aerial or Street-view)

Natural **L**anguages (From Wikipedia)

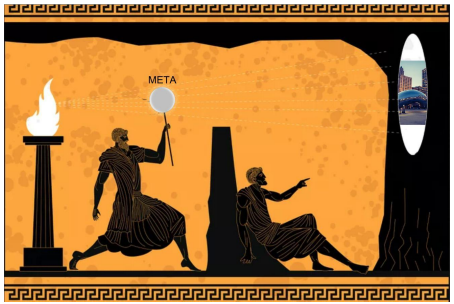
Chicago, officially the City of Chicago, is the most populous city in the U.S. state of Illinois, and the third-most-populous city in the United States. With an estimated population of 2,693,976 in 2019, it is also the most populous city in the Midwestern United States. Chicago is the county seat of Cook County, the second-most-populous county in the US, with a small portion of the northwest side of the city extending into DuPage County near O'Hare …

Allegory of the Cities

cities projected to **graph**



cities projected to **image**



cities projected to natural **language**

cities projected to **numbers**

DNN: a unified framework for Graphs, Language, Images and Numbers

$$P(y_i|x_i) = f(x_i)$$

$$P(y_i|x_i, \text{  }, \text{We love Chicago}, \text{  }) = f(x_i, \text{  }, \text{We love Chicago}, \text{  })$$

Images

Graph

Numbers

Language

[GLIN]

IMAGES

Architecture Design
Urban Design

LANGUAGE

Urban Anthropology
Urban History
Urban Sociology

Qualitative

Quantitative

Transport Network
Electric Grid
Water and wastewater
Gas pipeline
Telephone and internet

Urban Economics
Urban Real Estate

GRAPHS

NUMBERS

Why is AI for Cities and City Planning Challenging and Interesting?

Multimodal

Inherently spatial and physical

Value judgement

Public engagement

Wicked problem

Wicked problem

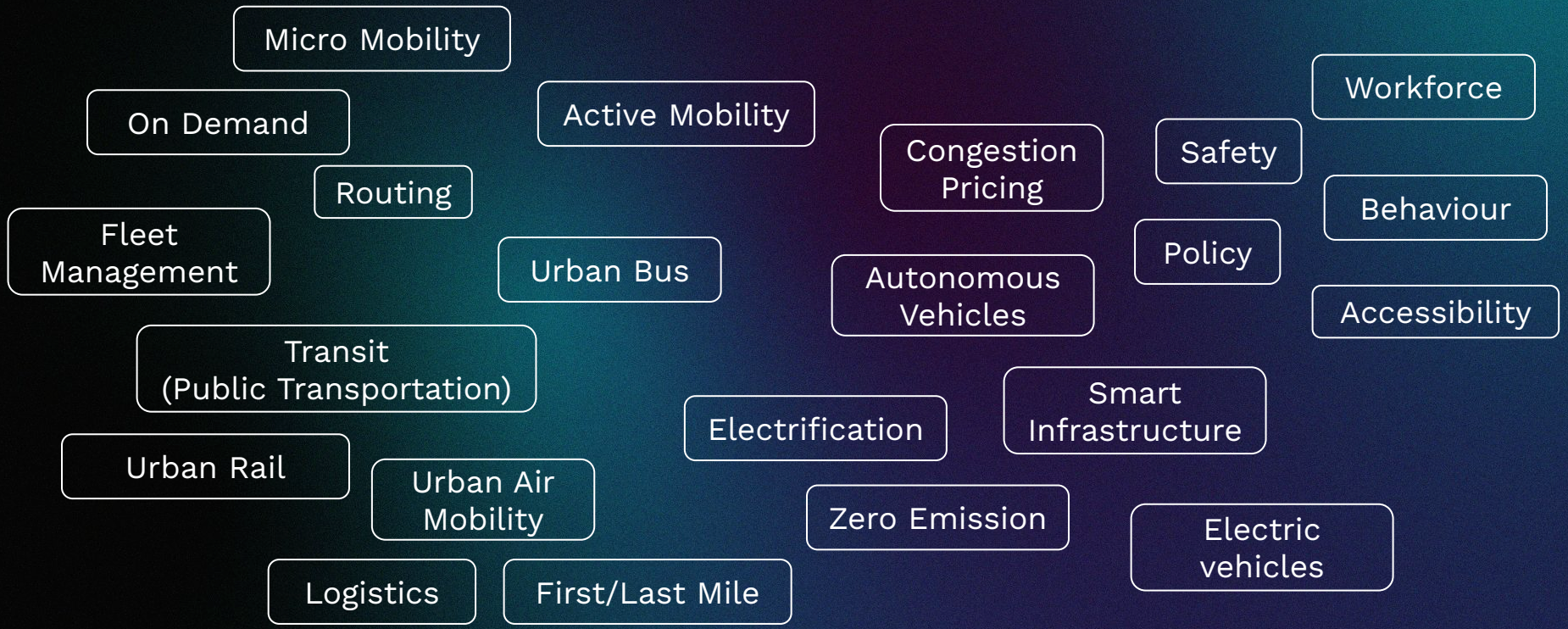
1. No definitive formulation
   incomplete, contradictory, and changing
2. No stopping rules
3. Solutions are not right or wrong
4. Every wicked problem is essentially novel and unique
5. Every solution is a "one shot operation"
6. No given alternative solutions

Grounded AI in Transportation

Outline

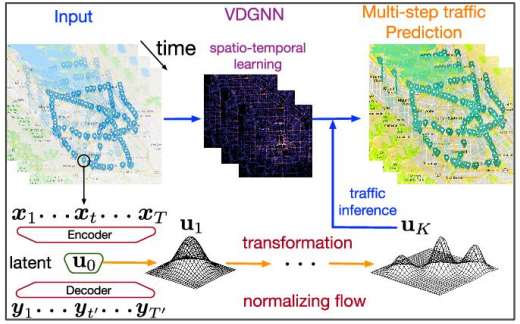
- Wide range of transportation topics: how to structure them?
- Leading trends in mobility industry
- AI in transportation – why now?
- What's Grounded AI?

The wide range transportation topics

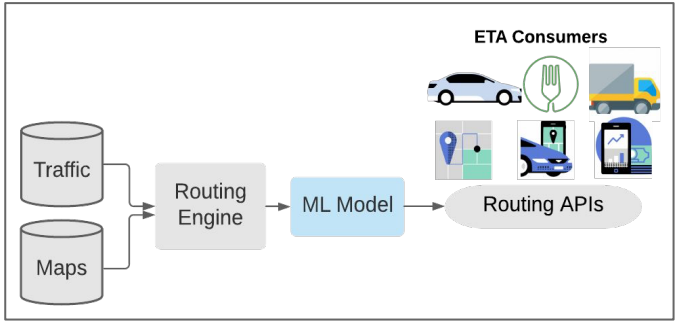


AI-Driven Urban Mobility Management

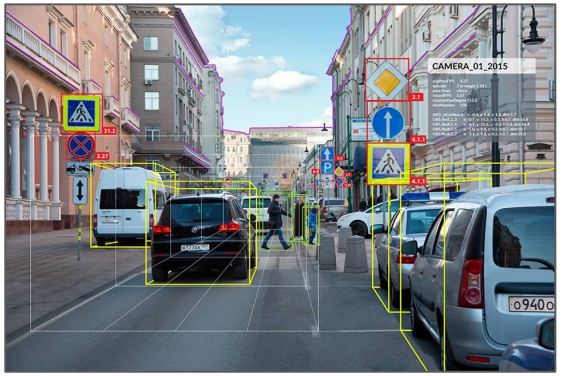
Traffic Management



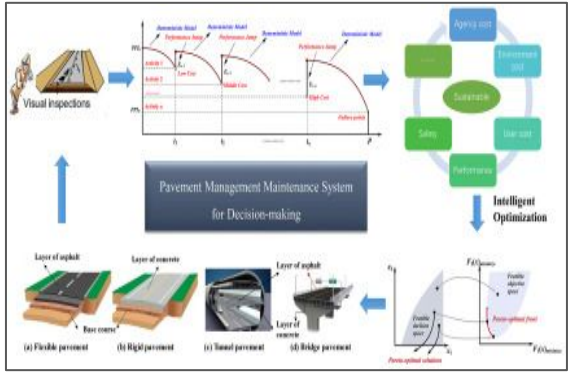
On-Demand Mobility Operation



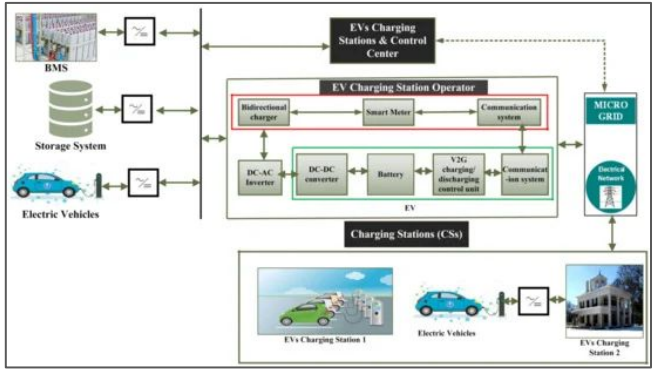
Assisted or Automated Driving



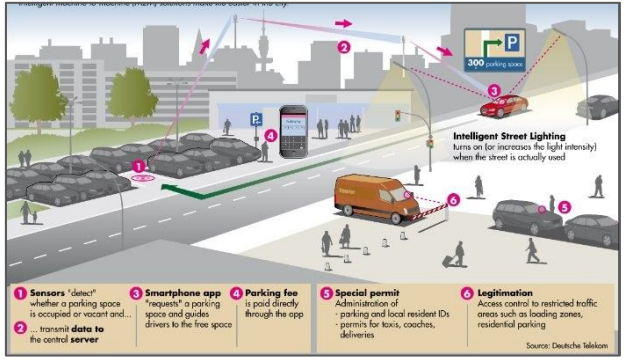
Proactive Infrastructure Maintenance



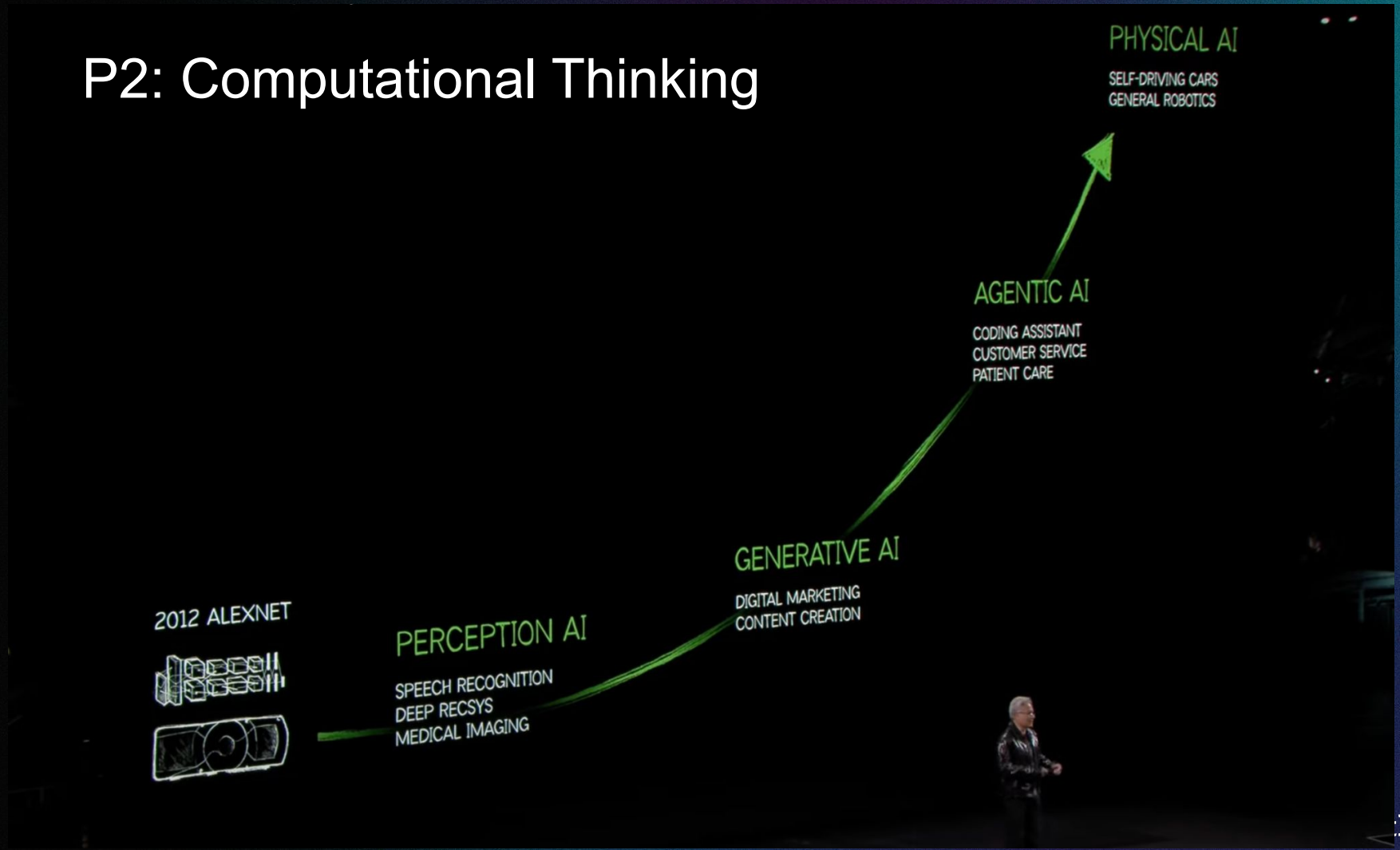
EV Charging/Discharging Management



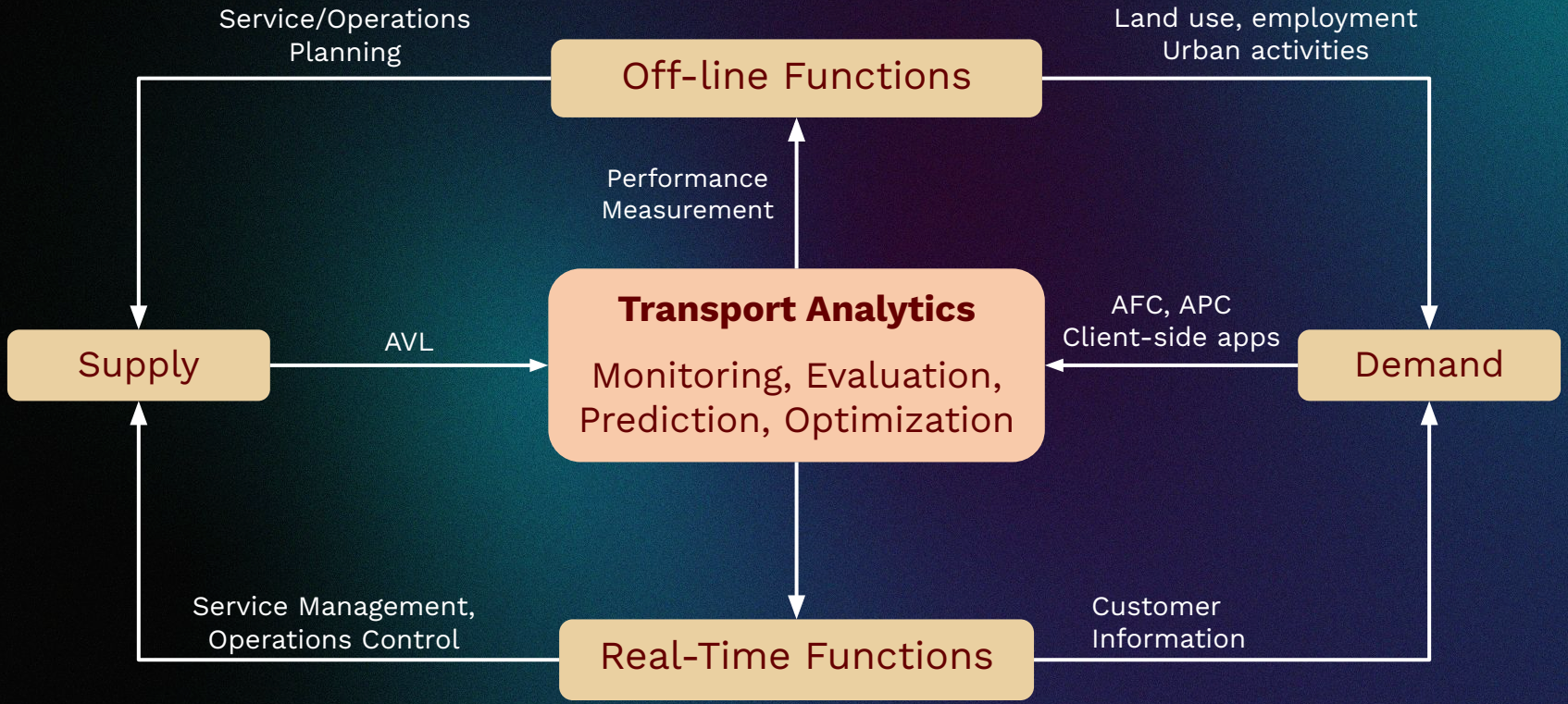
Smart Parking



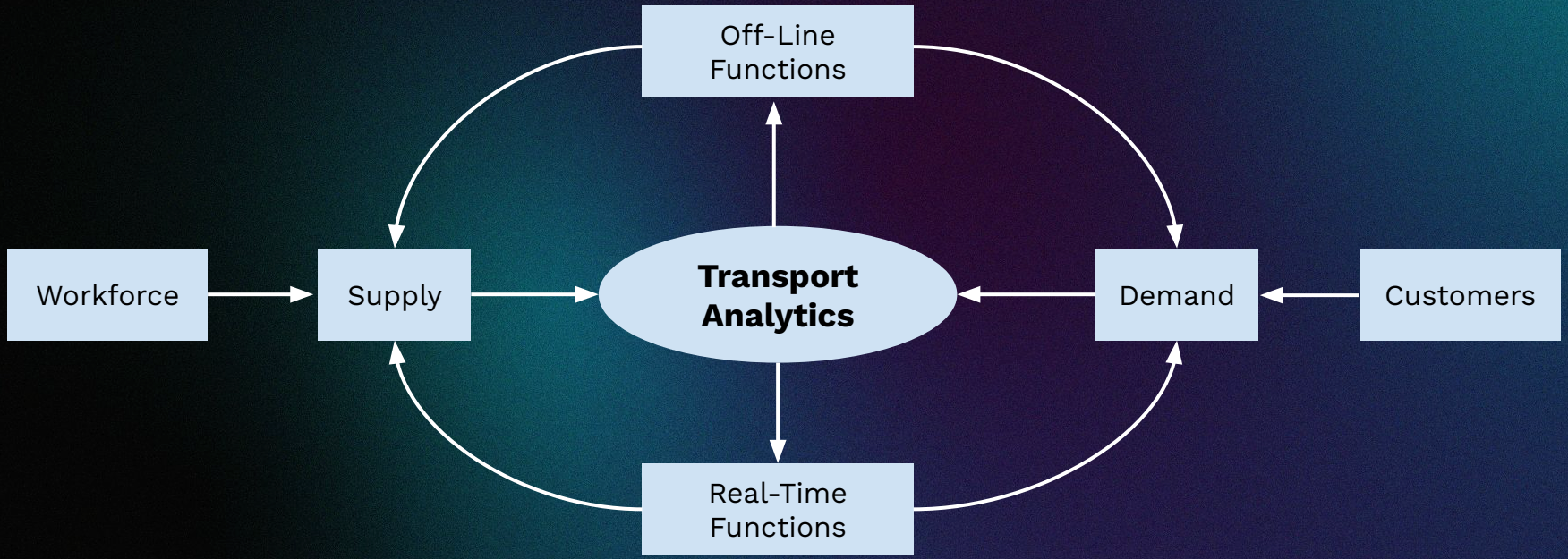
P2: Computational Thinking



Transportation analytic functions



Can AI help?

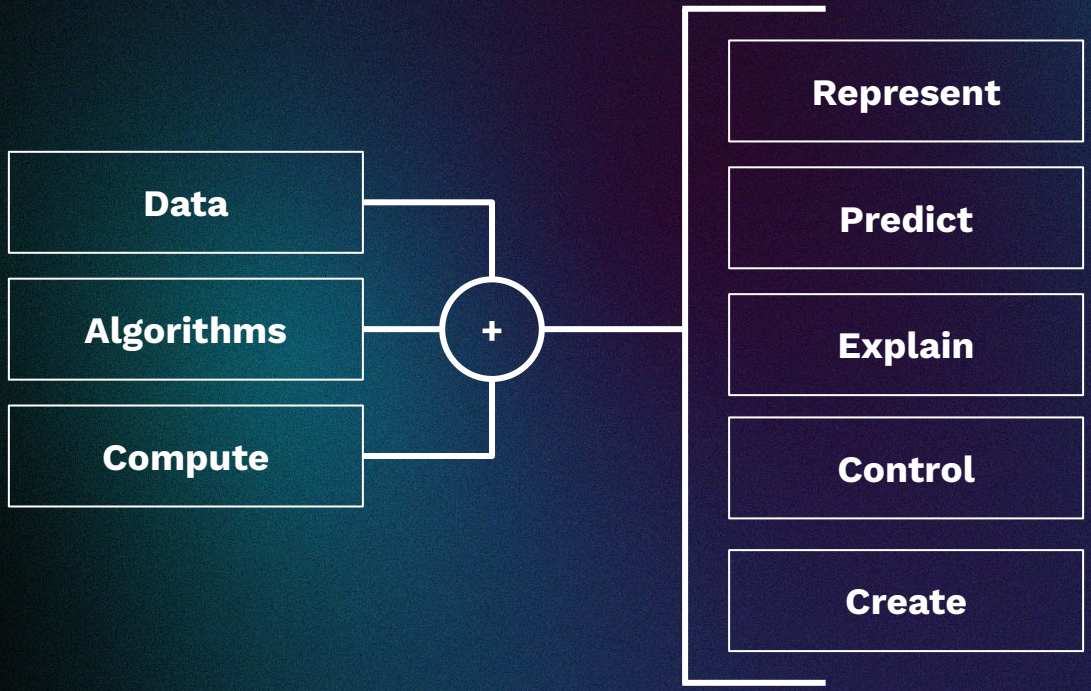

Off-Line Functions
Workforce
Supply
Transport Analytics
Demand
Customers
Real-Time Functions

Leading Trends in Mobility Industry

- Retrospective → Predictive
- Mass service → Individualized
- Static planning → Experimental
- Isolated modes → Multimode Integration

Enabler: Behavior + Compute

Computational thinking



Exercise:

Create a similar diagram in your own industry

→ *Human-AI Persona* ↓ *AI Function*	**Sense** *AI used to provide new / live information to existing tasks*	**Assist** *AI used to assist humans and improve performance in tasks*	**Work** *AI used to execute tasks presently done by humans*	**Instruct** *AI used to train humans on how to complete tasks*	**Interface** *AI used to create easy interactions with humans*
Represent *AI used to gather, represent, and analyze information*					
Predict *AI used to make future predictions based on past data*					
Control *AI used to make automatic decisions based on past data*					
Create *AI used to create new high-quality content or as general intelligence*					

Five Examples

Represent

AI for Sentiment Analysis and Complaint Categorization

Michael Leong & Awad Abdelhalim with WMATA

Sense

Predict

AI to Detect Platform Crowding

Riccardo Fiorista, Awad Abdelhalim, & Anson Stewart with WMATA

Sense Assist

Control

AI for Bus & Train Dispatching Control

Joseph Rodriguez, Haris Koutsopoulos and Jinhua Zhao with CTA

Assist

Create

AI for Generative Urban Design

Qingyi Wang, Shenhao Wang and Jinhua Zhao with DOE

Work

Create

AI to Understand Bus Operators' Preferences

Amelia Baum, Jiangbo Yu, John Attanucci, Haris Koutsopoulos and Jinhua Zhao with CTA

Interface Sense

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AI in transportation - Why now?

The **technological maturity** of AI has reached a threshold where industrial-scale deployment is feasible.

Market readiness is evident as investors and companies are placing significant capital behind AI strategies.

The **societal implications** has never been greater with climate, congestion, safety, and inequities intensifying pressure on governments and companies.

The **policy landscape is in flux** with governments struggling to pass legislation, standards, and frameworks to regulate AI.

What is grounded AI applications?

- **Problem-Driven**, Not Technology-Driven
  - Built-in response to real-world needs
- **Context-Aware**
  - Embedded in institutional, human, and social contexts
- **Human-in-the-Loop**
  - Humans retain agency, oversight, and interpretability
- **Deployable**
  - Deployment-readiness
- **Iteratively Co-Developed**
  - With industry partners, stakeholders, and users

Exercises for Grounded AI practitioners

1. Can you explain your model to a regulator or commuter?
2. Who benefits when the model “works”? Who loses when it fails?
3. With your AI models, who are still in control?

AI - Tensions & Opportunities

Outline

- Tensions
- Synergy
- Interpretability

Tensions in AI for Transportation

Open Learning

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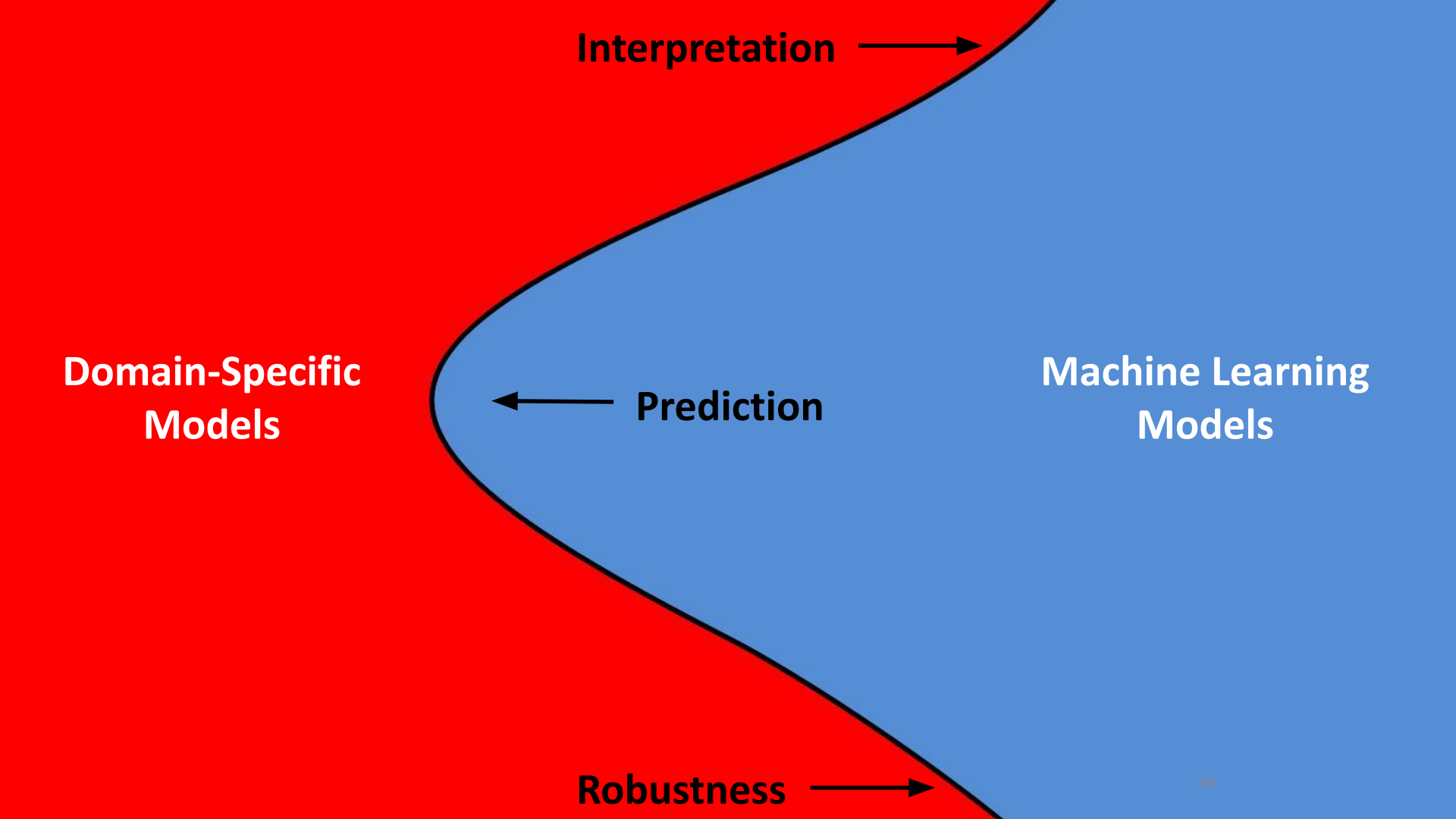
JTL | MIT TransitLab

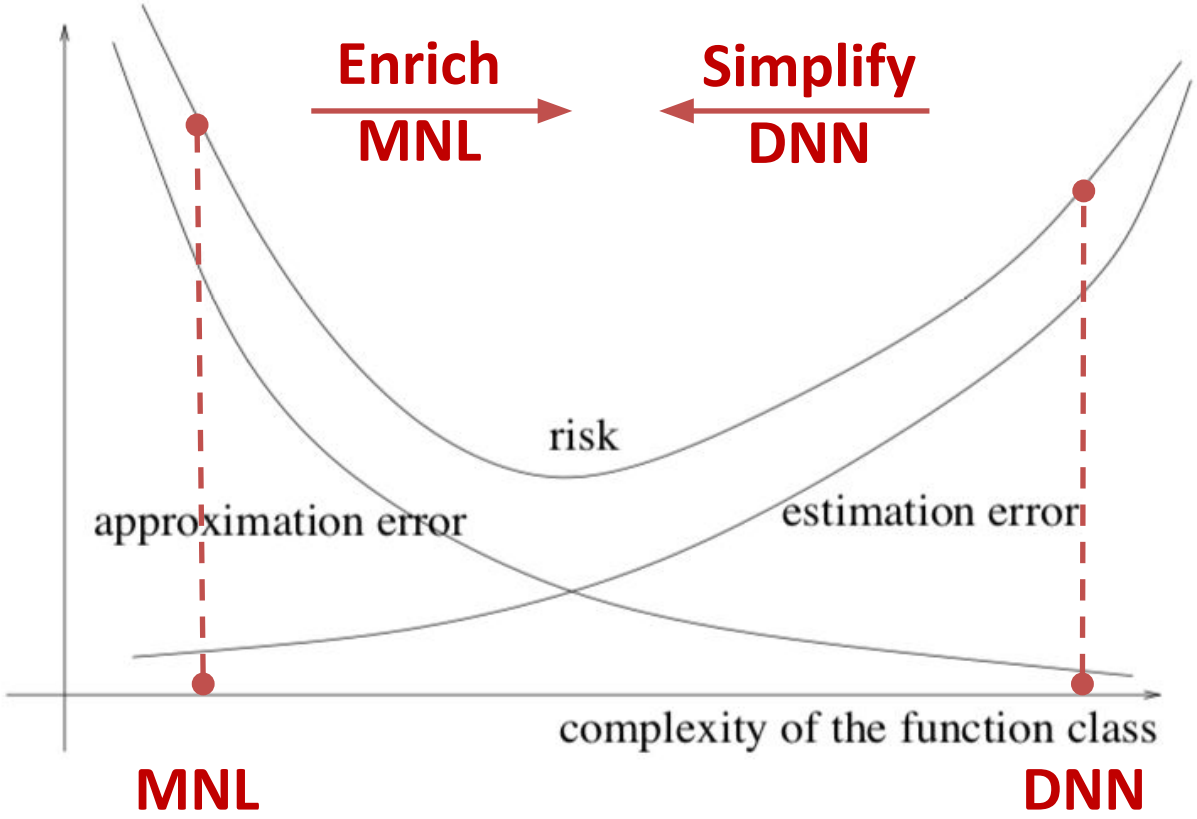
Domain-Specific Models

Machine Learning Models


Interpretation
Domain-Specific Models
Prediction
Machine Learning Models
Robustness

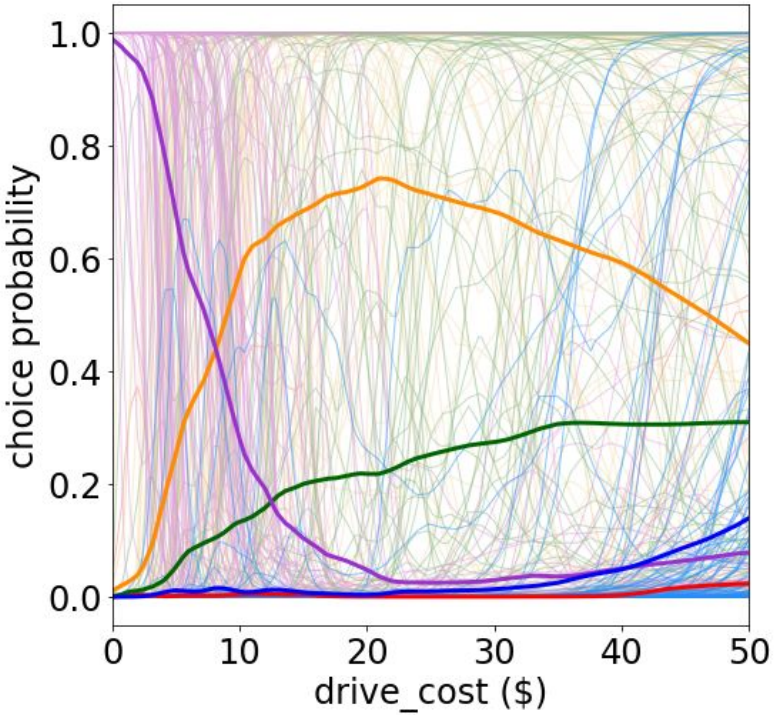
DNN and Travel Behavioral Theory

Prediction Errors = Approximation + Estimation Errors

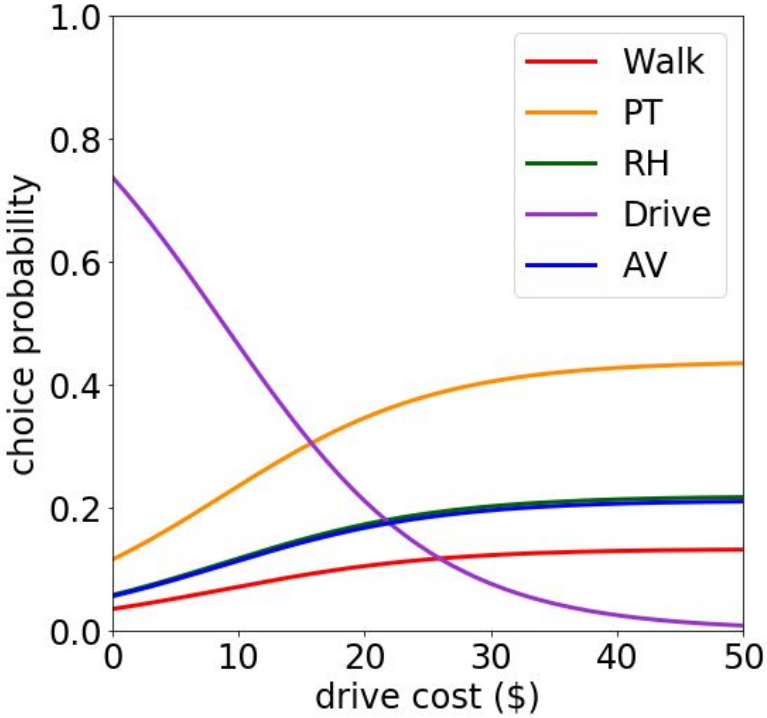


Substitution Patterns of Five Alternatives

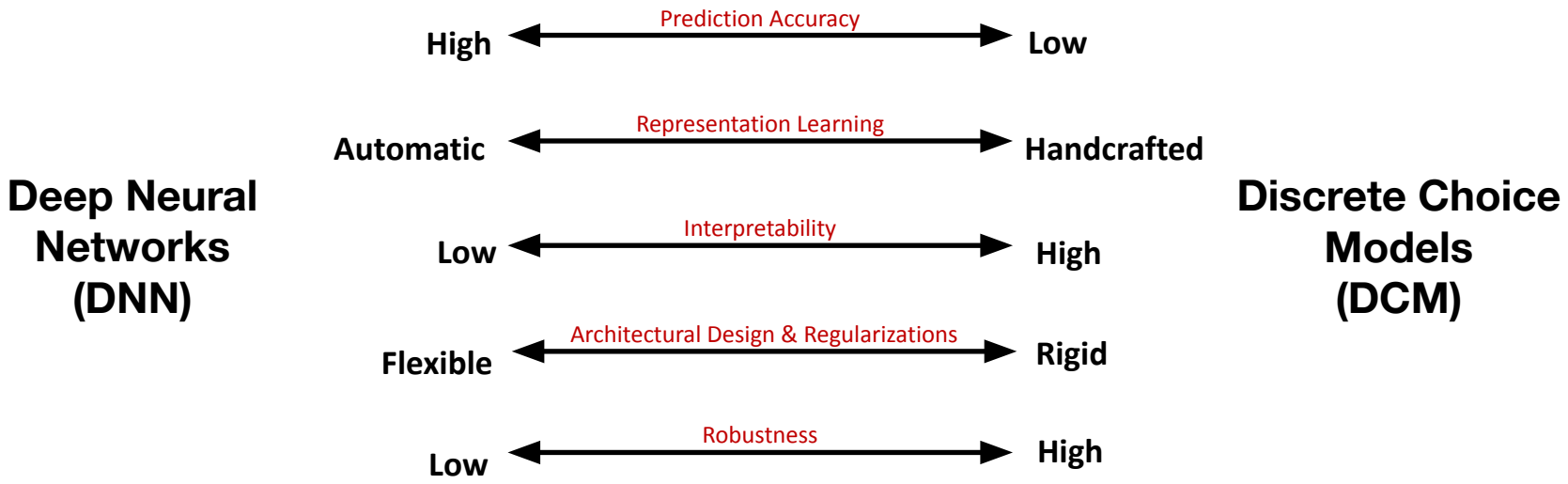
5L-DNNs



MNL



Two Modeling Paradigms for Choice Analysis



Prediction Accuracy: Nijkamp et al., (1996); Xie et al., (2003); Cantarella & de Luca, (2005); Celikoglu (2006); etc.
Representation Learning: LeCun et al. (2015); Bengio et al. (2013); etc.
Interpretability: Kim and Doshi-Velez (2017); Lipton (2016); Montavon et al. (2018); Ribeiro et al., (2016); etc.
Architectural Design & Regularizations: Krizhevsky, et al. 2012; Zoph et al., 2017; Martin and Bartlett (2009); etc.
Robustness: Szegedy (2014); Goodfellow (2015); Papernot (2016); Kurakin (2017); Matthew and Jegelka (2017), etc.

Tensions in AI for Transportation

- Role of Theory: Generic model vs domain specific
- Role of Model: explain or predict
- Causality vs correlation
- Simple to complex vs complex to simple
- Understand vs action (control)
- Knowledge production: discover vs create

Synergy in Machine Learning and Classic Models

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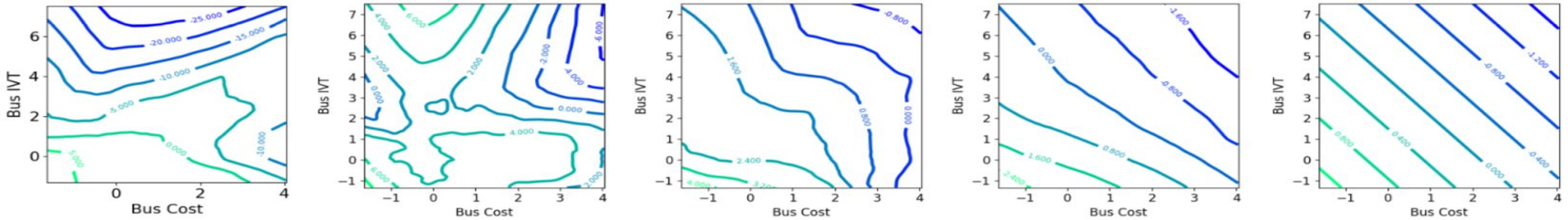
Interpretability of Utility Function

Theory-Based Residual Neural Network (TB-ResNet)

$$V(x) = V_T(x) + \delta V_{DNN}(x)$$



(a) DNN (55.2%) (b) CM Resnet ($\lambda = 1e-10$; 56.4%) (c) CM Resnet ($\lambda = 0.005$; 57.3%) (d) CM Resnet ($\lambda = 0.01$; 56.8%) (e) CM (44.7%)

(f) x0 (g) x1 (h) x0 (i) x1 (j) x0 (k) x1 (l) x0 (m) x1 (n) x0 (o) x1

Criteria of a good model

- Prediction accuracy
- Interpretability (FAT)
- Sparsity
- Robustness (security)
- Practicality

AI for Future of Mobility

What is success and what defines the future

AI for City Planning

Human In the Loop, Power Balance and Future Role of City Planners

AI for Autonomous Vehicles

human agency and AV deployment