COeXISTENCE

Playing urban mobility games with intelligent machines. Framework to discover and mitigate human-machine conflicts.

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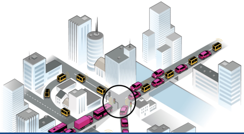


Central hypothesis

CONFLICT or COeXISTENCE

intelligent machines in urban mobility games will learn to win at the cost of humans.

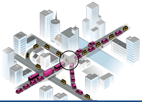
Context

AI-driven technologies are ready to enter urban mobility.
They promise relief to the notoriously congested transport systems in pursuing sustainability goals.

Problem

Since AI already outperforms humans in the most complex games (chess and Go) it is likely to win the urban mobility games as well.

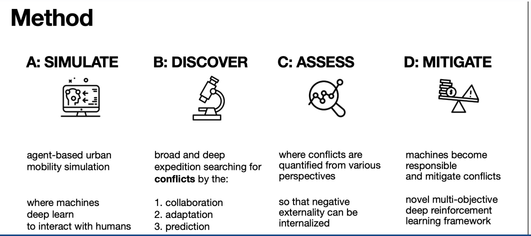
Tempting us and policymakers to gradually hand over our decisions to intelligent machines.



Research objective

Predict consequences of the future system where humans and intelligent machines will COeXIST and share the same, limited resources (capacity) or our urban networks.

Solution



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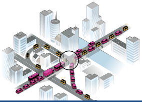

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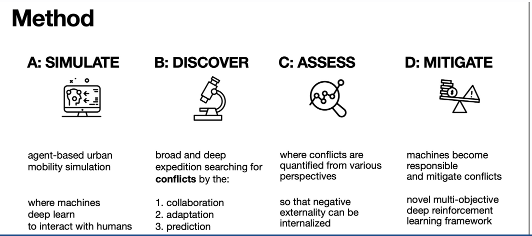

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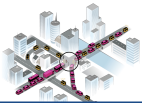

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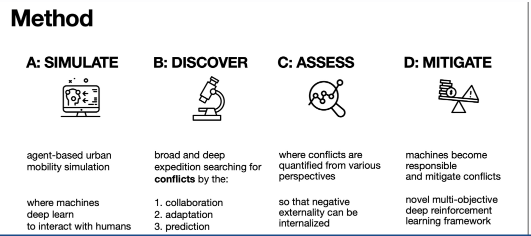

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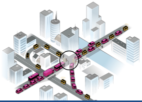

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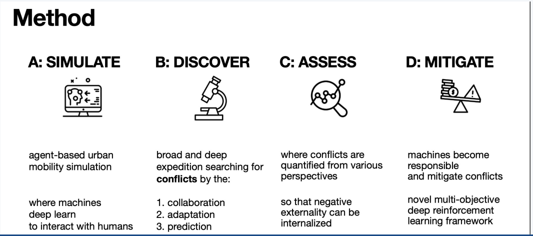
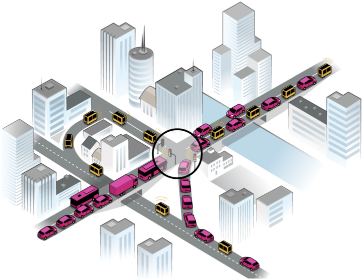


setting the stage



Urban mobility

problem formalization

Demand

each agent (person, traveller) i wants to travel from her origin o to her destination d at a given time τ

$$q_i = \{o_i, d_i, \tau_i\}$$

Spatiotemporal distributions

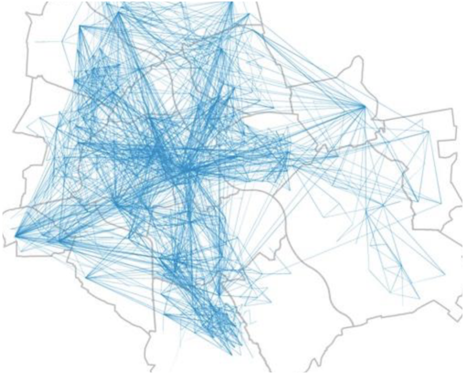
in the morning we travel from homes to work/school
in the afternoon we come back

Decisions

each of us chooses where she lives, works, goes to school
and when she travels.

Predictability

demand patterns of agents evolve, adapt and fluctuate day-to-day
yet can remain predictable



Networks

travel times, costs and capacity

Congestion

travel time is the non-linear function of the demand (flow) and the capacity:

$$c_a(\tau) = f(t0_a, q_a(\tau), Q_a) \approx t0_a \left(1 + (q_a/Q_a)^b\right)$$

Shortest path search

the shortest path from o_i to d_i depends on the flows $q_a : a \in A$

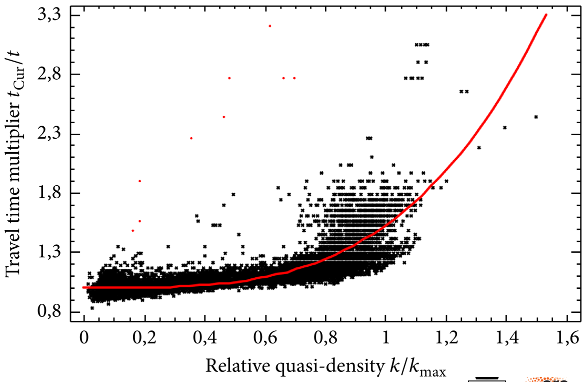
Fixed point problem

1. Travel time is a function of the flow:

$$t_a = f(q_a)$$

2. Flow is the function of travel time (we use links least congested):

$$q_a = f(t_a)$$



Assignment problem

Network flows

Problem

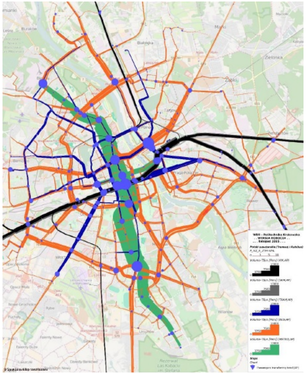
Determine the flow $q_a(\tau)$ and cost $c_a(\tau)$ for each link in the network $a \in A$ throughout the day $\tau \in T$

User-perspective

Each agent i selects the path k from her origin o_i to destination d_i at her departure time τ:

$$k_{od} = \underset{k \in K_{od}}{\arg\min} \sum_{a \in k} c_a$$

path k is a sequence of links starting at origin o ending at destination d. Among the all possible paths K_{od} each of us selects the best one.



Solutions

Price of anarchy

All or nothing

We all choose shortest **free-flow** paths, assuming that we are the only ones in the city.
We regret very soon, in a completely jammed city.

System Optimum - Amazon warehouse

We are all centrally controlled and follow the centralized guidelines.
The costs are minimal, the freedom as well.
We do not control $\triangle c_{k,i} = c_{k,i} - \min_{k' \in K} c_{k',i}$

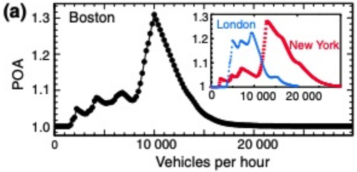
User Equilibrium

each user chooses the route that is the best.
a user-optimized equilibrium is reached when no user may lower his transportation cost through unilateral action
and when her expectations equal the realization

Price of anarchy

Difference between total costs in the User Equilibiurm and (the minimal ones) in the System Optimal

$$PoA = C_{UE}/C_{SO} = \sum_{i \in \mathcal{I}} c_{i,UE} / \sum_{i \in \mathcal{I}} c_{i,SO}$$



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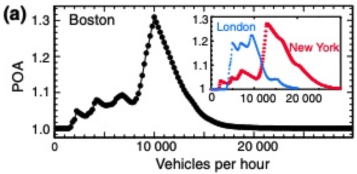

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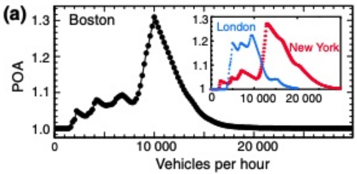

Rational utility maximisers

Rational

Let's assume all humans are rational:

$$\Pr(k|od, i) = \Pr\left(c_{k,i} = \min_{k' \in K_{od}} c_{k',i}\right)$$

i.e. we take the best option.

Perceived costs - utility

length and travel time are physical
cost is subjective, in discrete choice called Utility

$$U_{k,i} = \beta_{0,i} + \beta_{t,i} t_k + \beta_{c,i} c_k + \dots + \varepsilon$$

- β_0 alternative-specific constant, i.e. taste variation, i.e. sentiment
- ε random term
- β_t value of time (10€/h)
- β_c value of money

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User equilibrium

As an iterative game

Solution

As with Nash equilibria, simple solutions to selfish equilibrium can be found through iterative simulation, with each agent assigning its route given the choices of the others. This is very slow computationally. The Frank–Wolfe algorithm improves on this by exploiting dynamic programming.

Algorithm 1: `Wardrop`

Wardrop

inputs : set $\mathcal{A}$ or agents, defined as $i = \{o_i, d_i, t_i\} : a \in \mathcal{A}$

foreach *day/iteration until convergence* $t \in \mathcal{T}$ **do**

  foreach *agent* i **do**

    $k_i = \arg\min_{k \in K_i} c_k$ `# each agent rationally selects the best option`

    $c_k(t) = f(q_a : a \in k)$ `# collect feedback from environment - travel times`

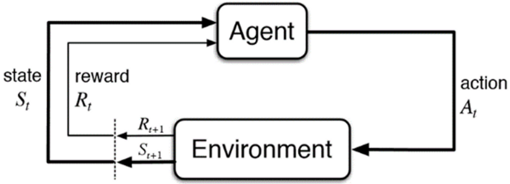
    $c_k = f((c_k(t') : t' = 0, \ldots, t))$ `# and builds epxerience`

User equilibrium

as an iterative learning

Reaching equilibrium paraphrased

- Traveller has a goal to reach to destination at lowest costs
- She makes actions - selects paths
- The environment changes (others are making actions) - the link costs c_a change $c_a = f(q_a)$
- Agent learns to minimize the costs

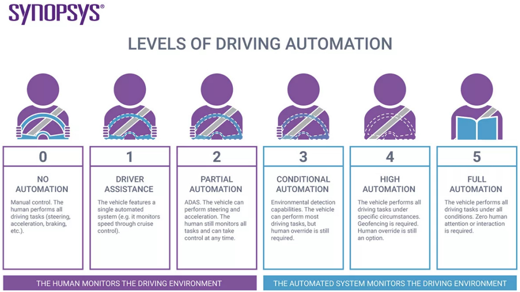


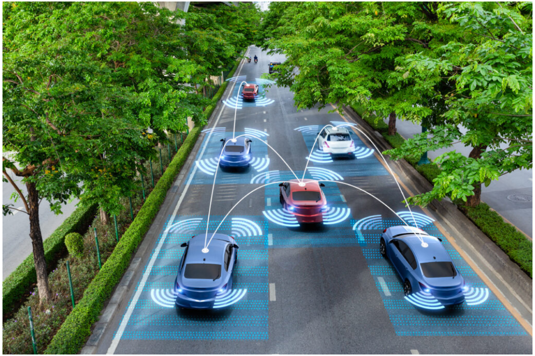
Connected autonomous vehicles

CAVs

Autonomous car

a car that is capable of travelling without human input





CAV

decision maker

Autonomy

Now the focus is on making them capable to drive

but the challenge is beyond that (personal opinion)

Decisions

Now CAVs are 3yo kids and we teach them how to walk and not to get lost. The real problems come when they are teenagers and they start making decisions

CAV

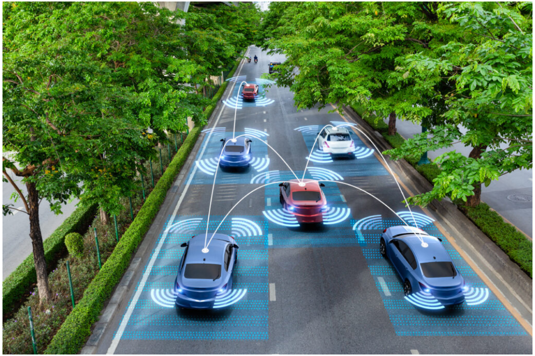
decision maker

Decisions

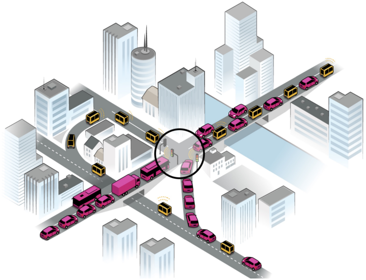
- route-choice: how to get to destination?
- time-choice: when to leave?
- destination choices: which shopping mall?
- predictions: will it be crowded tomorrow?

System decisions

- pricing: how much should we charge Mr. X for his Uber
- service: how to reposition a fleet of our vehicles across the city?



future equilibria



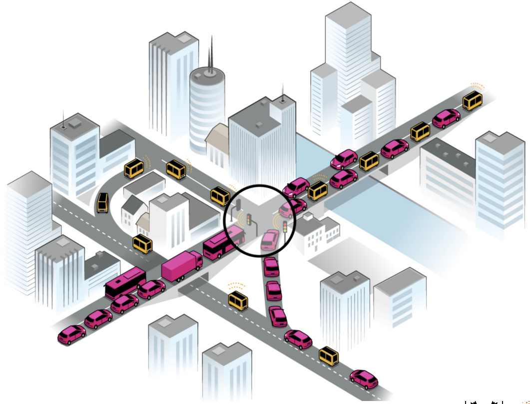
mixed population

multi-class assignment

Mixing SO with UE

Let's assume we have two classes of users, each behaving differently.

humans	behavioural, rational utility maximisers;
X	controllable, obedient, non-selfish;
X'	and potentially two competing providers.



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Advantages

not digital-twins

Machines (unlike humans):

- are designed to behave optimally, i.e. use all the data and computational power to make optimal decisions;
- can collaborate, i.e. share information and cooperatively reach synergy;
- may understand human behaviour: predict it and anticipate our decisions;
- are automated and thus controllable by design;

This means:

- c_a is controllable by design - reward function, not bounded by rationality
- $C_G = \sum_{a \in G} C_a$ - possibly collective rewards
- $p_{k,a} \in \{0, 1\}$ - deterministic choices (controllable)

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New equilibria

Reinforcement learning

An agent learns a policy π on what action A to make in a given state S of the environment E, so to maximize the (expected) reward r.

Multiagent reinforcement learning

Each agent simultaneously adjusts its policy, subject to current state. Actions (historical) of other agents are part of the state.

Game theory

Each player (a) selects a strategy that maximises his payoffs, subject to other players $(-a)$ optimal strategies (equilibria).

Centralized system

Fleet manager makes centralized actions on its fleet. The action space is to select a path for each vehicle in the fleet.

Reward/payoff/utility

- (my) time and perceived costs
- total fuel consumption in the system
- minimal externality (emissions, noise, sustainability etc.)
- lowest marginal cost ($\Delta C\ dk_i$)
- better than competition (Izera is faster than Tesla
- fleet performance (Uber, inPost, DHL).

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An agent learns a policy π on what action A to make in a given state S of the environment E, so to maximize the (expected) reward r.

Multiagent reinforcement learning

Each agent simultaneously adjusts its policy, subject to current state. Actions (historical) of other agents are part of the state.

Game theory

Each player (a) selects a strategy that maximises his payoffs, subject to other players $(-a)$ optimal strategies (equilibria).

Centralized system

Fleet manager makes centralized actions on its fleet. The action space is to select a path for each vehicle in the fleet.

Reward/payoff/utility

- (my) time and perceived costs
- total fuel consumption in the system
- minimal externality (emissions, noise, sustainability etc.)
- lowest marginal cost ($\Delta C \ dk_i$)
- better than competition (Izera is faster than Tesla
- fleet performance (Uber, inPost, DHL).

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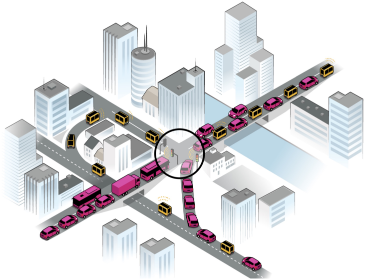
summary



COeXISTENCE

framework to discover how machine intelligence may take-over our urban mobility and how to avoid it

URBAN MOBILITY = SUPPLY + DEMAND + INTELLIGENT MACHINES

URBAN MOBILITY	SUPPLY	DEMAND	INTELLIGENT MACHINES
sustainability efficiency	infrastructure	people	**COeXISTENCE** anticipate demonstrate resolve **paradigm shift in urban mobility**

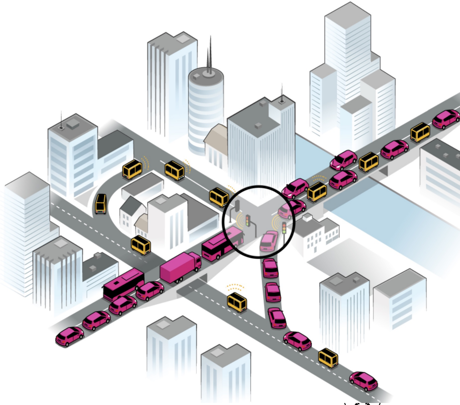
COeXISTENCE

ERC Starting Grant

Thank you for your attention,

welcome to discuss

feel free to join us (to inner- or outer-circles)



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