

COeXISTENCE

Cities Managed by AI - Fiction or Reality?

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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

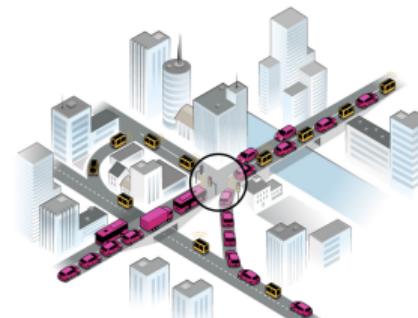
AI-driven technologies are ready to enter urban mobility.

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.



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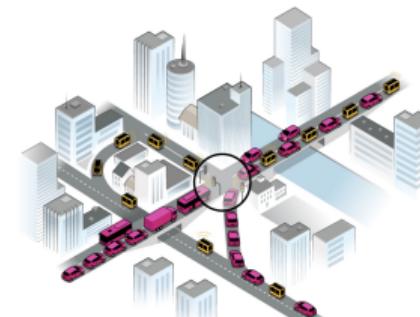
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myself

Rafał Kucharski

now: assist. prof, Jagiellonian University, Faculty of Math. and Comp-
Sci, **GMUM**, prof. Jacek Tabor



2023-2028 ERC Starting Grant - **COeXISTENCE** 3 PhDs + PostDoc.

2021-2024 NCN OPUS - **Post-corona shared mobility** 2 PhDs + PostDoc.

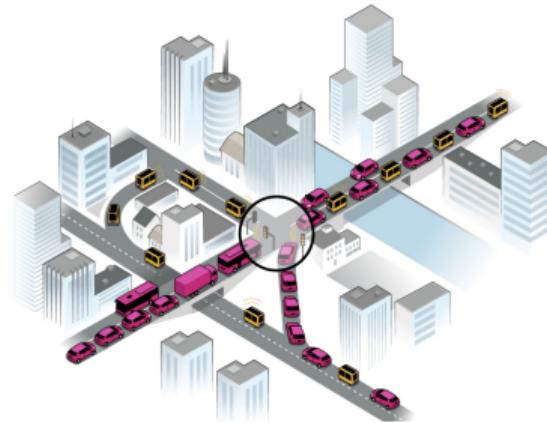
past: PostDoc @ **TU Delft** working in Critical MaaS **ERC Starting Grant**

past²: assist. prof @ **Politechnika Krakowska**, prof. Andrzej Szarata

PhD: DTA, La Sapienza Rome, prof. Guido Gentile

- outside academia:
- R&D software developer (PTV SISTeMA)
 - transport modeller (models for Kraków, Warsaw and more)
 - data scientist, ML engineer (NorthGravity)

urban mobility



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

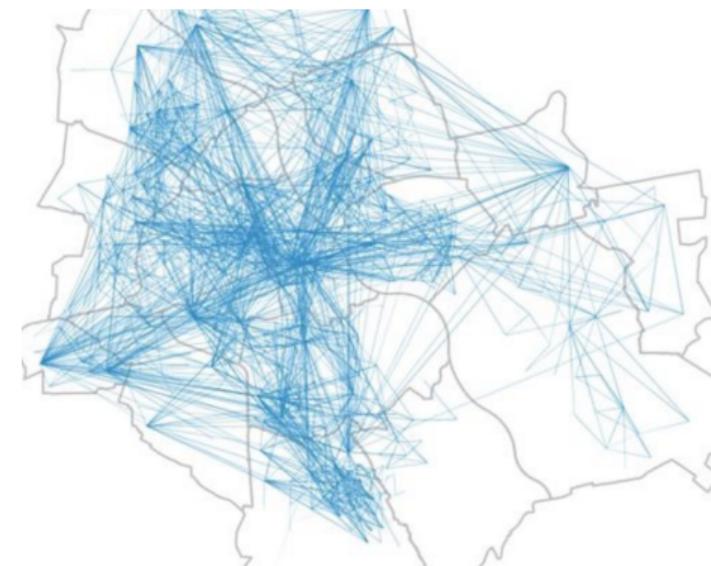
in the morning we travel from homes to work/school
in the afternoon we come back

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:

$$c_a(\tau) = f(t_{0a}, q_a(\tau), Q_a) \approx t_{0a} \left(1 + (q_a/Q_a)^b\right)$$

Shortest path search

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

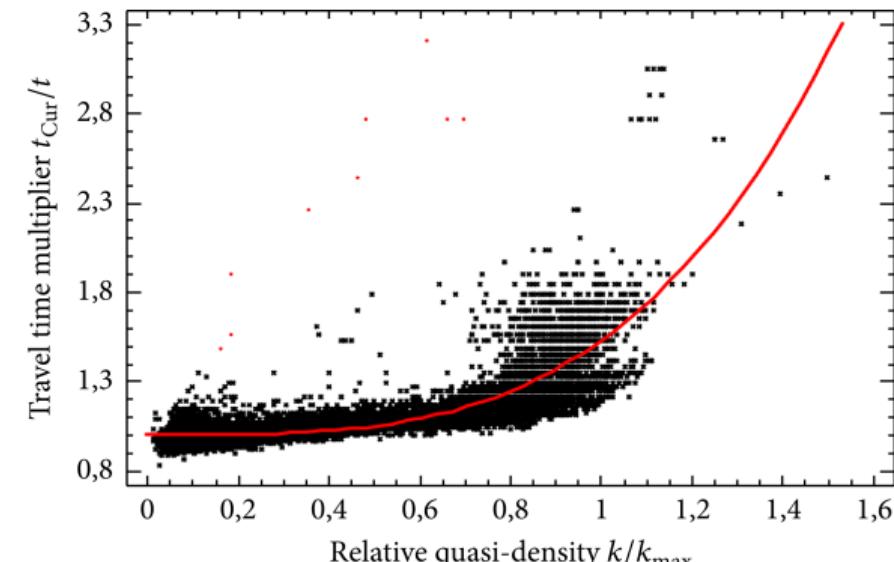
Fixed point problem

- 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

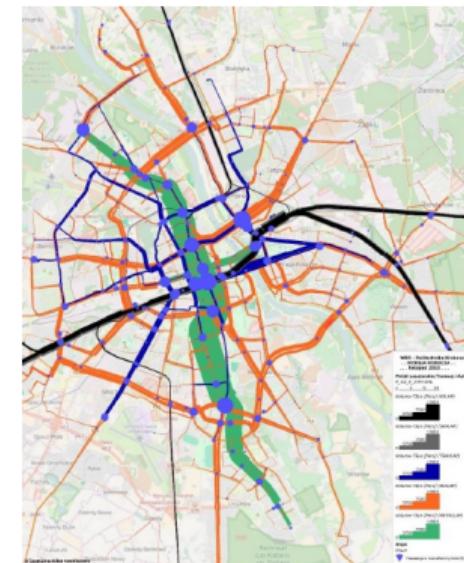
Determine the **flow** $q_a(\tau)$ and cost $c_a(\tau)$ for each link in the network $a \in A$ throughout the day $\tau \in T$

User-perspective

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

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

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 $\Delta c_{k,i} = c_{k,i} - \min_{k' \in K} c_{k',i}$

User Equilibrium

each user chooses the route that is the best.

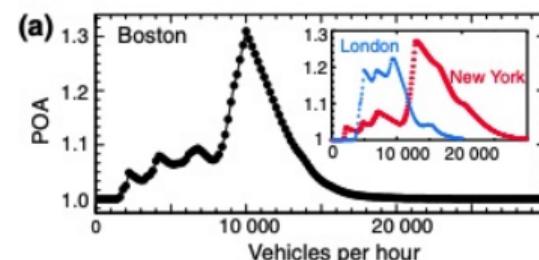
a user-optimized equilibrium is reached when no user may lower his transportation cost through unilateral action

and when her **expectations equal the realization**

Price of anarchy

Difference between total costs in the User Equilibrium 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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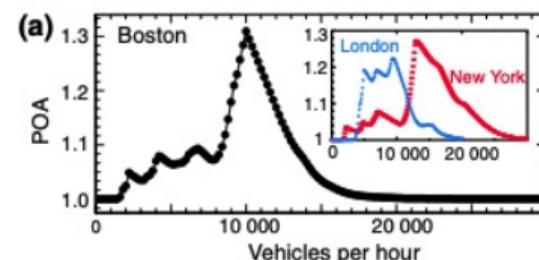
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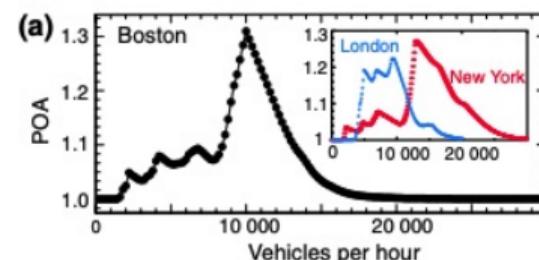
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Rational utility maximisers

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

```

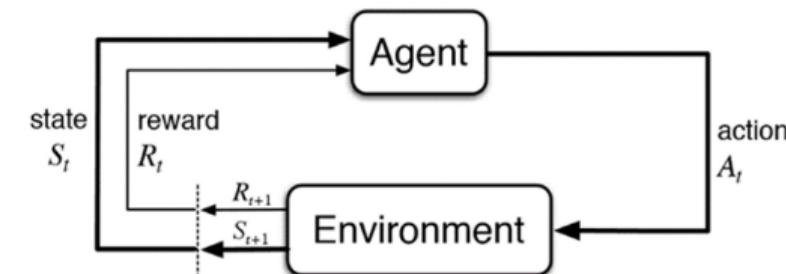
inputs: set  $\mathcal{A}$  or agents, defined as  $i = \{o_i, d_i, t_i\} : a \in \mathcal{A}$ 
foreach day/iteration until convergence  $t \in \mathcal{T}$  do
    foreach agent  $i$  do
         $k_i = \arg \min_{k \in K_i} c_k$                                 # each agent rationally selects the best option
         $c_k(t) = f(q_a : a \in k)$                             # collect feedback from environment - travel times
         $c_k = f((c_k(t') : t' = 0, \dots, t))$                 # and builds experience
    
```

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

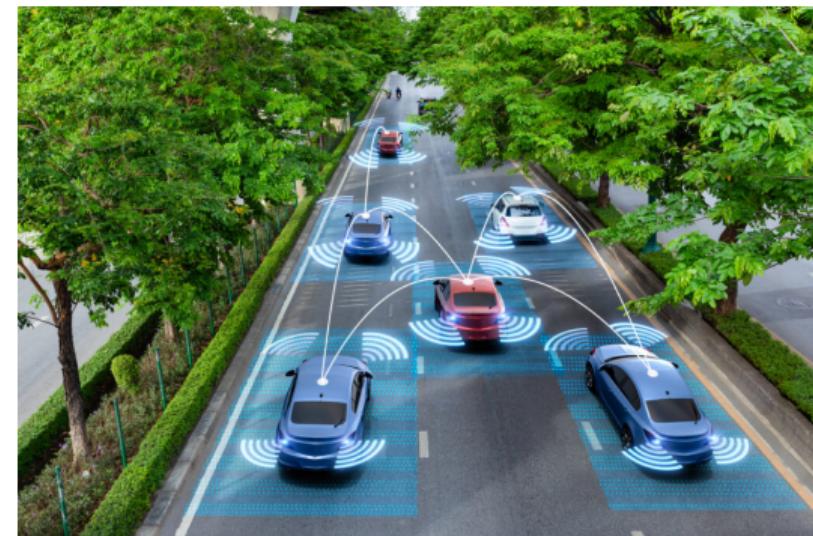
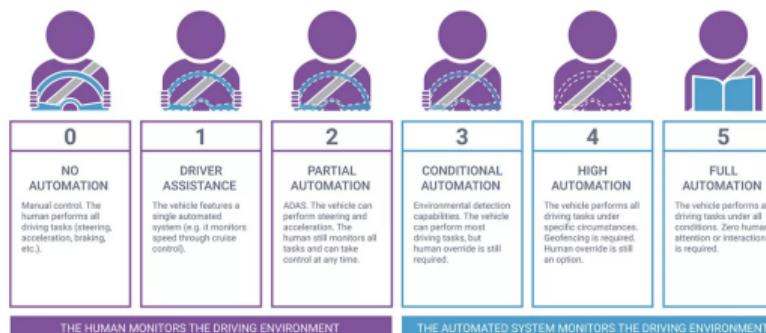
CAVs

Autonomous car

a car that is capable of travelling without human input

SYNOPSIS*

LEVELS OF DRIVING AUTOMATION



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

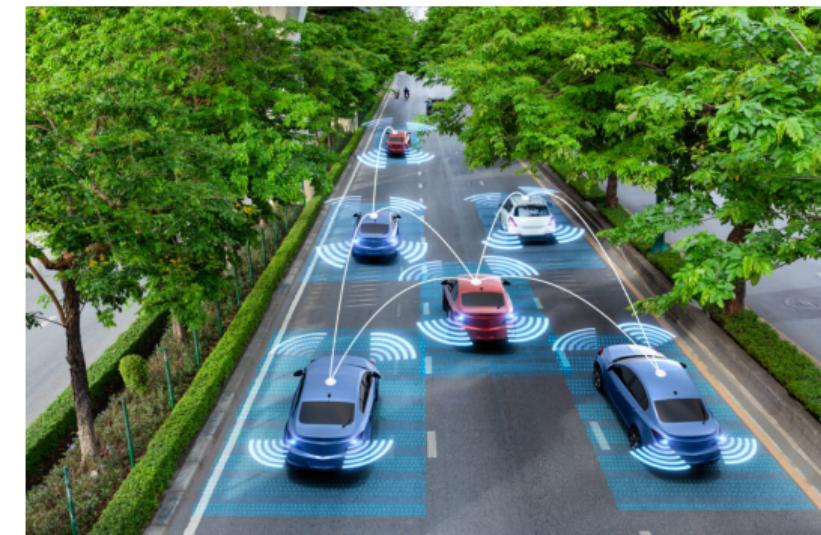
decision maker

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?



mixed population

multi-class assignment

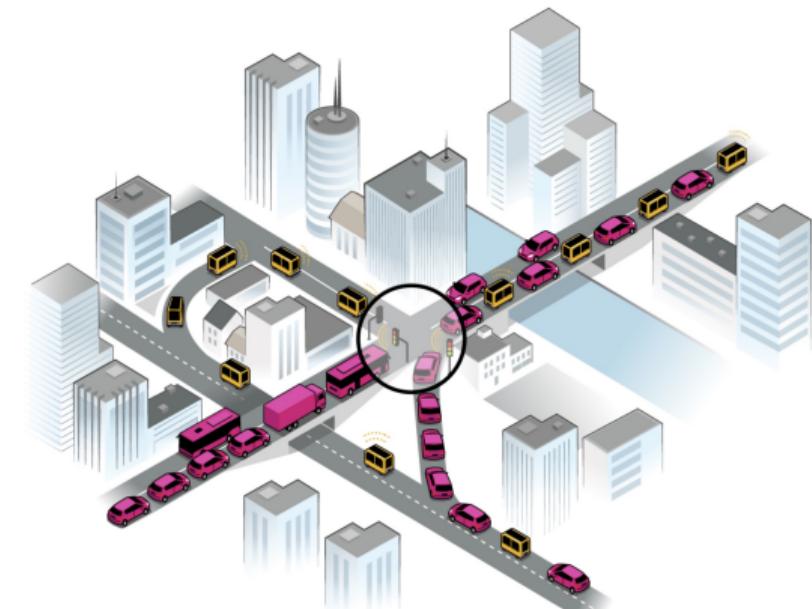
Mixing SO with UE

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.

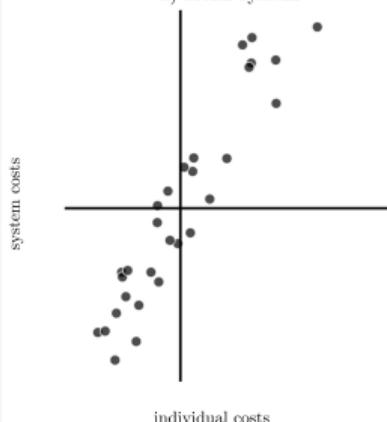


Possible impact

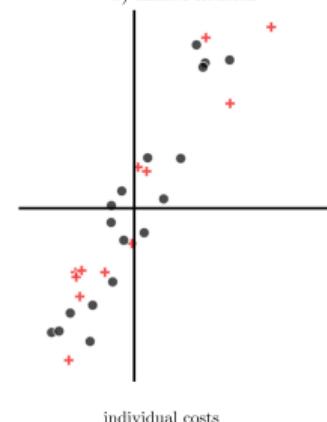
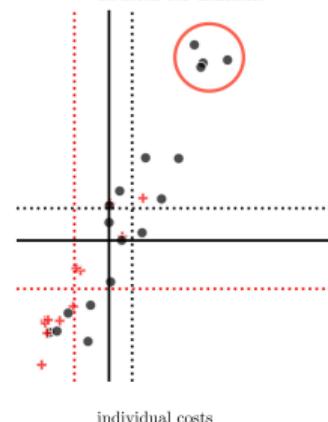
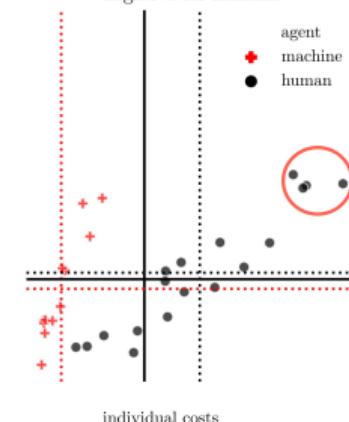
Taxonomy

What can we expect

a) social system



b) mixed neutral

c) positive for the machines,
neutral for humansd) positive for the machines,
negative for humans

agent
machine
human

Objective

Experimentally demonstrate case d) and show is we can reach COEXISTENCE



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Leading the European Research

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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Conflicts

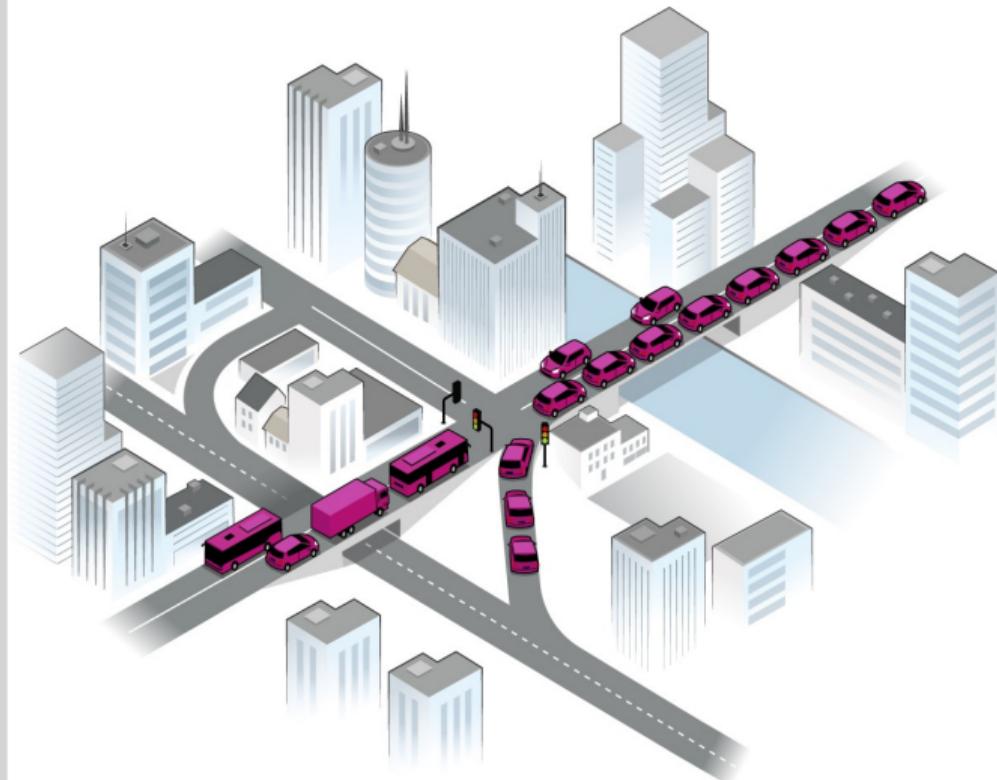
novel phenomena

congested bottleneck with limited capacity

we (humans) rationally optimize our decisions

and reach **user-equilibrium**:

- democratic
- egalitarian



Conflicts

new players

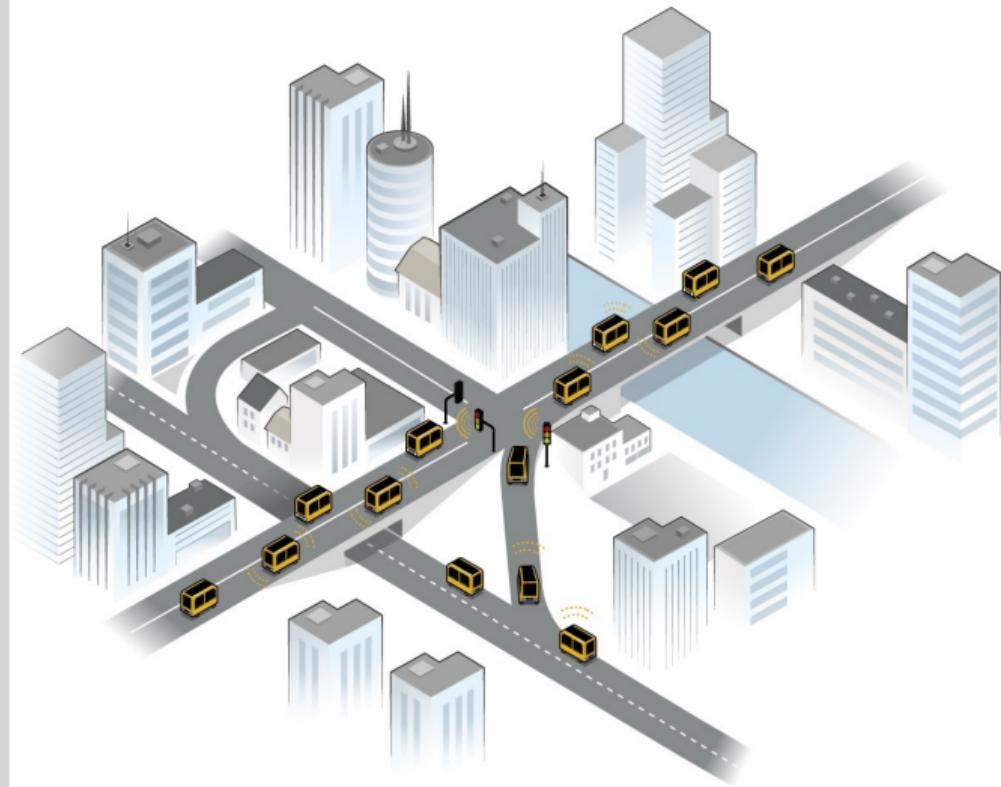
intelligent machines

change the rules of the game

better at:

- calculations
- access to data
- controllable
- collaborative

designed to win



Conflicts

by collaboration

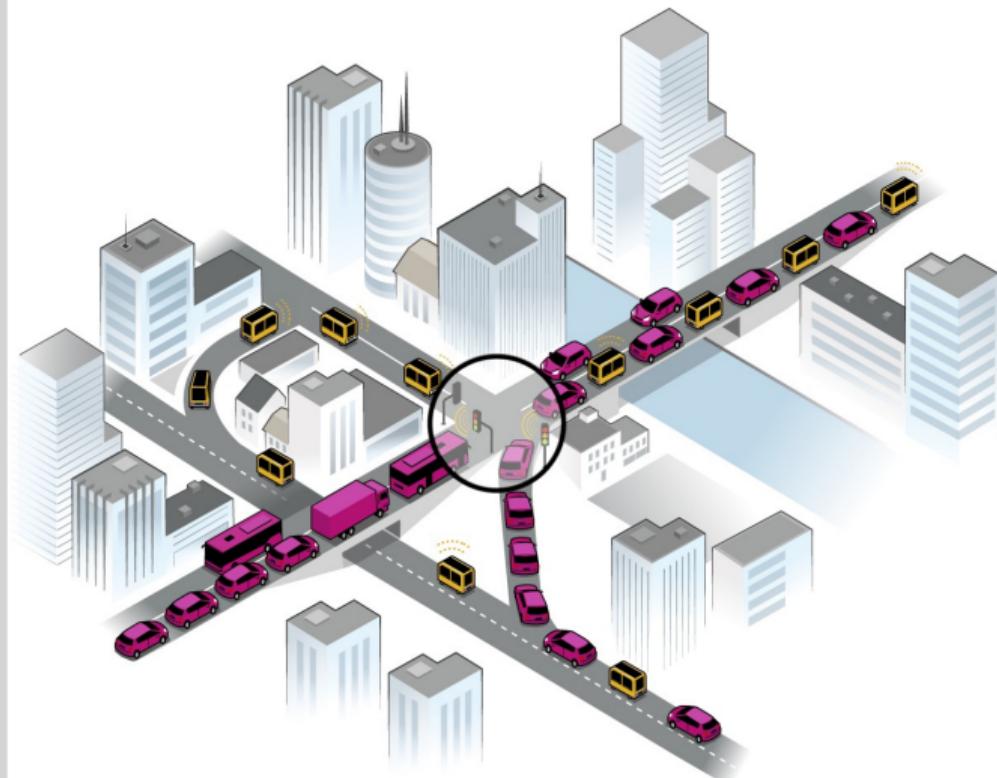
machines **trick**
the demand-actuated
traffic lights

collaboratively reroute

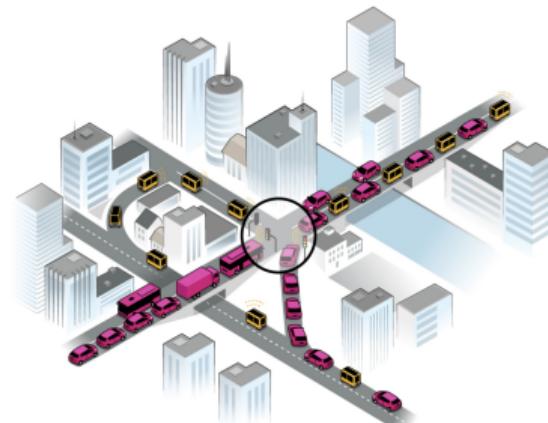
receive more green light

pass the bottleneck faster

humans queue longer



results

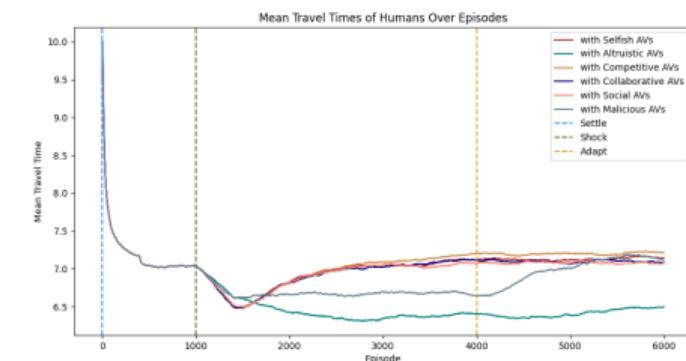


Preliminary results

Multi-Agent Reinforcement Learning with TorchRL

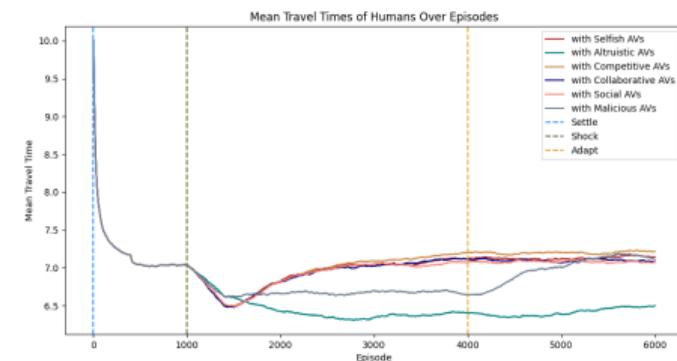
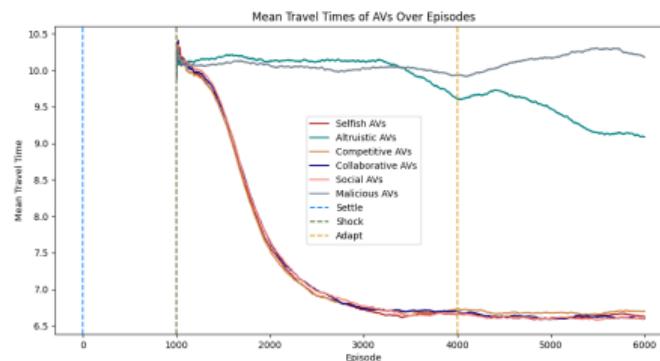
How?

- multi-agent deep reinforcement learning
- Deep Q-Network
- TorchRL
- SUMO traffic simulator
- Budapest network (Csomor district)
- 6 different rewards

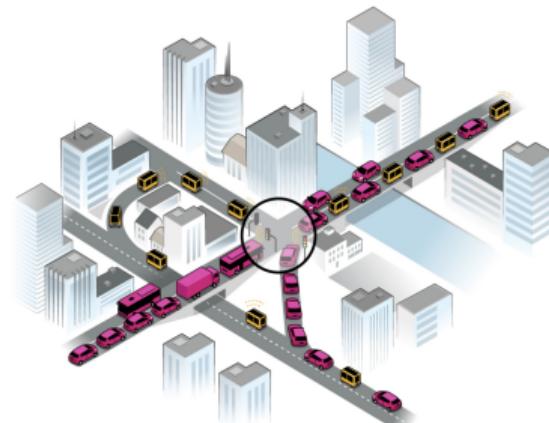


Preliminary results

Multi-Agent Reinforcement Learning with TorchRL



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



sustainability
efficiency



infrastructure



people



COeXISTENCE

anticipate
demonstrate
resolve

paradigm shift in
urban mobility



Cities Managed by AI

Fiction or reality?

Fiction? **YES!**

Reality? **YES!**



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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