COeXISTENCE

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

ERC Starting Grant, 2023-2028,
@ GMUM, Faculty of Mathematics and Computer Science, Jagiellonian University, Kraków
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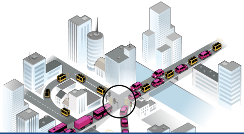

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Central hypothesis

CONFLICT or COeXISTENCE

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

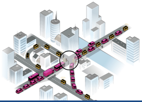
Context

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.



Objective

experimentally **discover** the existence machine-dominated urban mobility system, where (collective) decisions of machine intelligence improve system-wide performance, yet at the cost of humans, now facing e.g. longer travel times costs or being nudged to change natural travel habits into the optimal ones - desired by the machine-centred system.

Solution

Method

A: SIMULATE · **B: DISCOVER** · **C: ASSESS** · **D: MITIGATE**

A: agent-based urban mobility simulation

B: broad and deep expedition searching for **conflicts** by the:

C: where conflicts are quantified from various perspectives

D: machines become responsible and mitigate conflicts

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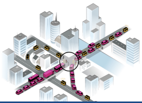

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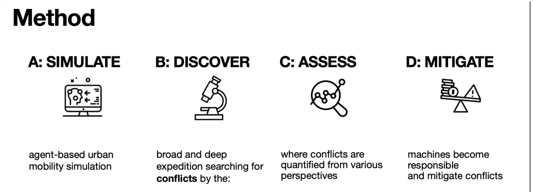

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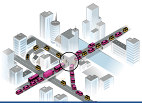

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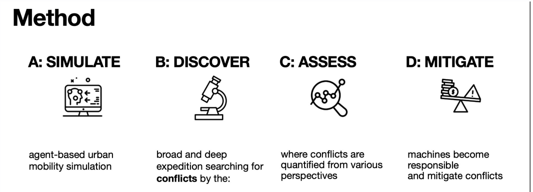

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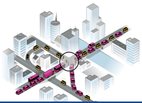

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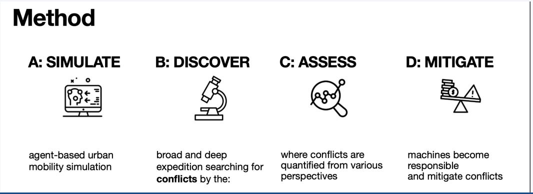

Agenda

this talk

Idea

1. Formalize the urban mobility
2. Hypothesize about the future of urban mobility.
3. Propose the research plan to discover the new phenomena.

Building blocks

- reinforcement learning
- human behaviour, discrete choice theory
- game theory, (social) equilibrium
- cooperative multi-agent systems
- urban mobility, traffic flow, traffic control

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myself

Rafał Kucharski

now: assist. prof, Jagiellonian University, Faculty of Math. and CompSci, 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

past^2: 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)

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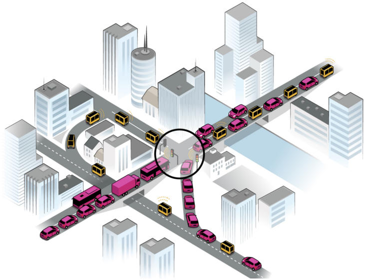
urban mobility



Urban mobility

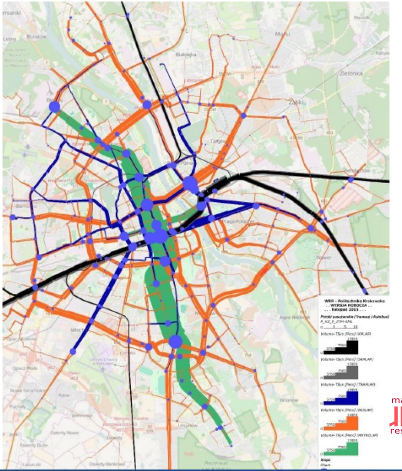
problem

Problem

What are the spatiotemporal dynamics of peoples' flows in the dense, congested urban networks?

City

complex social system, where thousands of agents
traverse multimodal transport networks,
to reach their destination
and supply their travel needs.



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

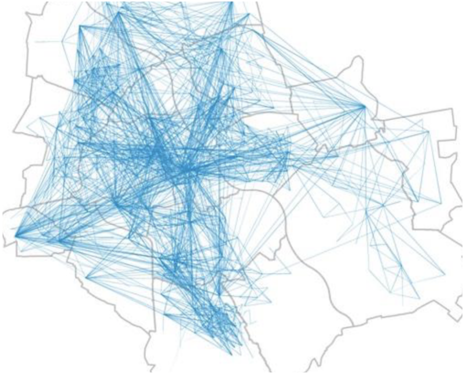
in the morning we travel from homes to work/school
in the afternoon we come back

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



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Networks

travel times, costs and capacity

Multilayered network

walk
bike
drive
public transport
multimodal

Urban networks

$$G = (N, A)$$

directed graph, where:

nodes are at intersections

links are streets connecting consecutive intersections

Costs, times

each link has its length l_a, free flow speed v_a and travel time, which is the non-linear, convex function of the demand (flow) and the capacity

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Networks

travel times, costs and capacity

Congestion

travel time is the non-linear, convex 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 $q_a : a \in A$

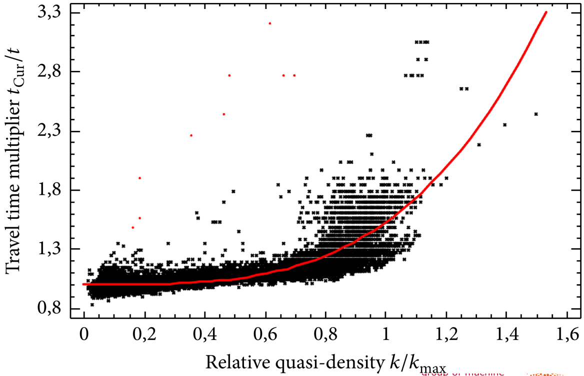
Fixed point problem

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

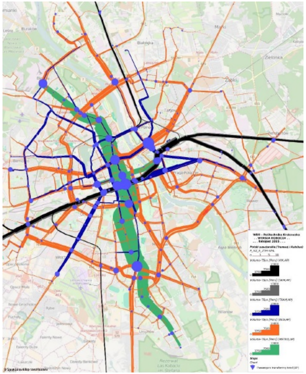
Determine the flow $q_a(\tau)$ and cost $c_a(\tau)$ for each link in the network $a \in A$ throughout the day $\tau \in T$

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

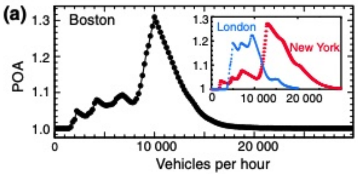
User Equilibrium

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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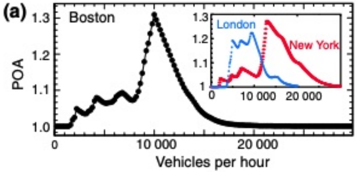

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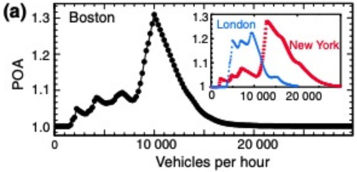


Assignment problem

system optimal

Problem

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

System optimum

Determine the flows which:

1. satisfy the demand
2. yield the minimal total (system-wide) costs

The C-SO model formulation proposed in Jahn et al. (2005) is the following:

$$\min \quad \sum_{(i,j)\in A} t_{ij}\left(x_{ij}\right) x_{ij} \tag{1}$$

$$x_{ij} = \sum_{c\in C} \sum_{k\in K_c^\gamma} a_{ij}^{kc} y_{ck} \quad \forall (i,j) \in A$$

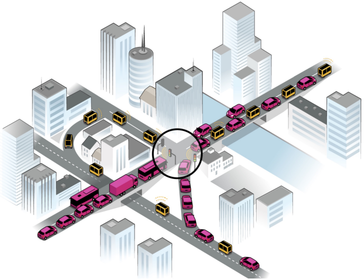
$$d_c = \textstyle\sum_{k\in K_c^\gamma} y_{ck} \forall c \in C \tag{2}$$

$$x_{ij} \geq 0 \forall (i,j) \in A \tag{3}$$

$$y_{ck} \geq 0 \forall c \in C \quad \forall k \in K_c^\gamma . \tag{4}$$

Constraints (1) set the flow on an arc as the sum of the flow on each path passing through the arc. Constraints (2) ensure that the demand d_c of OD pair $c \in C$ is routed on paths in K_c^γ. Finally, constraints (3) - (4) define the domains of the decision variables.

behaviour



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

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

- 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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Discrete choice theory

Logit model

Daniel McFadden won the Nobel prize in 2000 for his pioneering work in developing the theoretical basis for discrete choice.

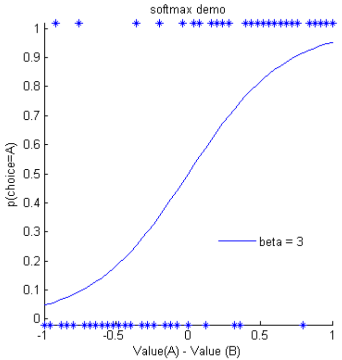
Discrete choice theory

Discrete choice models statistically relate the choice made by each person to the attributes of the person and the attributes of the alternatives available to the person.

Logit model

assumption:
$\varepsilon \approx \text{Gumbel}(0, \sigma)$, yields
Probability of selecting option a in the choice set C by individual i is:

$$p_{a,i} = \frac{\exp \mu U_{a,i}}{\sum_{a' \in C} \exp \mu U_{a',i}}$$



Discrete choice theory

Key concepts

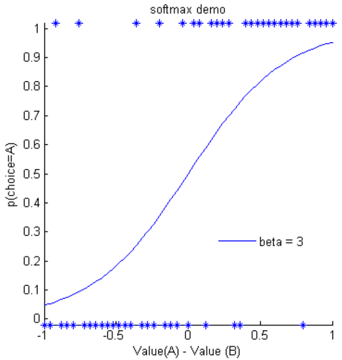
Non-determinism

we can reasonably well predict the probability of selecting an option a by individual i, yet there is always non-determinism.
Probabilities only asymptotically approach to 0 and 1.

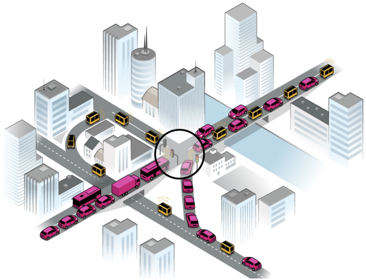
Heterogeneity

We are different, each of us has its' own:

- $\beta_{0,i}$ alternative-specific constant, i.e. taste variation, i.e. sentiment
- ε random term
- $\beta_{t,i}$ value of time
- $\beta_{c,i}$ value of money



game theory



User Equilibrium

Nash Equilibrium ⟶ Wardrop Equilibrium

The concepts are related to the idea of Nash equilibrium (another Nobel) in game theory developed separately. However, in transportation networks, there are many players, making the analysis complex.

Wardrop's first principle

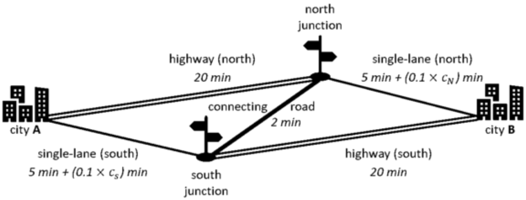
Wardrop's first principle of route choice, now known as *user equilibrium*, *selfish Wardrop equilibrium* or just Wardrop equilibrium became accepted as a sound and simple behavioural principle to describe the spreading of trips over alternate routes because of congested conditions.

Equilibrium

The journey times in all routes actually used are equal and less than those that would be experienced by a single vehicle on any unused route.

Equilibrium

The traffic flows that satisfy this principle are usually referred to as "user equilibrium"(UE) flows, since each user chooses the route that is the best. Specifically, a user-optimized equilibrium is reached when no user may lower his transportation cost through unilateral action.



User equilibrium

As an iterative game

Equilibrium conditions

Flow q on path k is either null or the path cost is minimal c^*

$$q_k(c_k - c^*) = 0$$

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`

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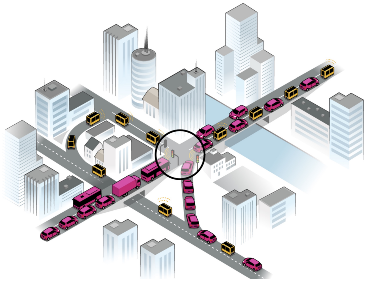
(reinforcement) learning



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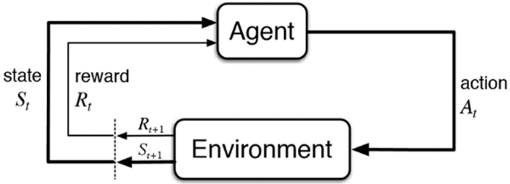
User equilibrium

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



Empirical learning

The social system learn the new equilibrium after 2-3 months (50 iterations).
Łazienkowski w Walentynki 2015 - ca 2 months
Algorithms need more (rel. gap 10^{-6} after say $10k$ iter - LUCE, DUE)

Reinforcement learning

Human learning

Humans:

Our behaviour is complex and heterogenous and non-deterministic

or

Humans:

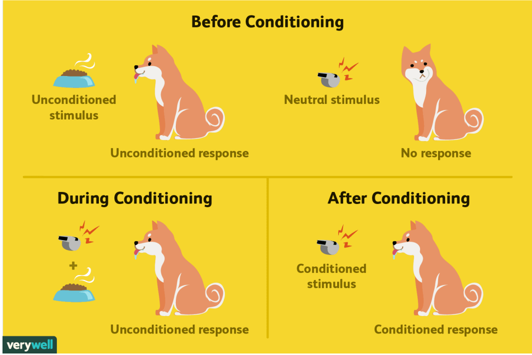
Our behaviour is rational (bounded by rationality), explainable, predictable.

Agent-based learning

Exponential smoothing (trivial):

$$\hat{c}(t) = \alpha c(t) + (1-\alpha)\hat{c}(t-1)$$

update collected experience c' with recent experience $c(t)$ and weight α (which may decrease in time - guaranteed, yet fake convergence



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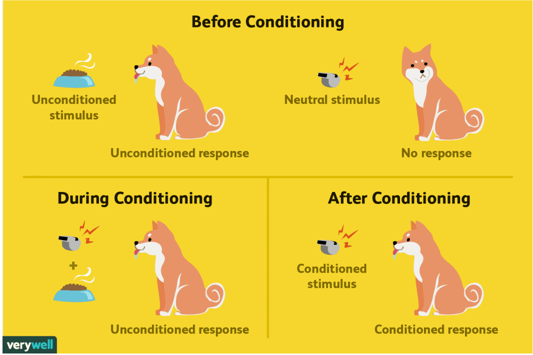
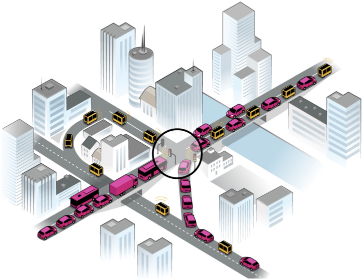


intelligent machines



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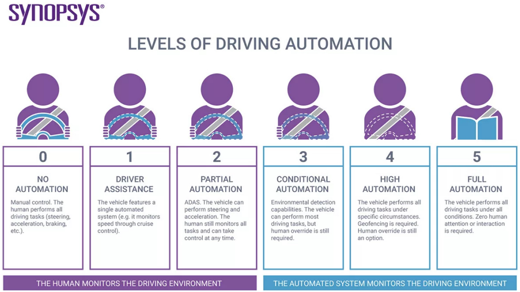
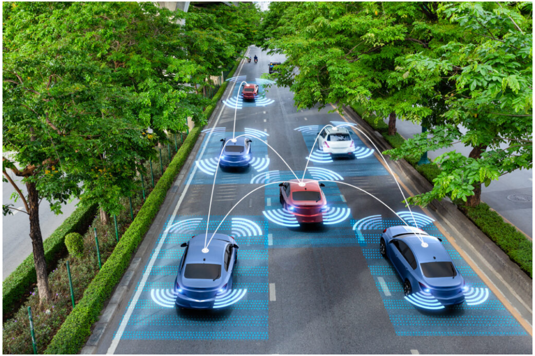
Connected autonomous vehicles

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

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CAV

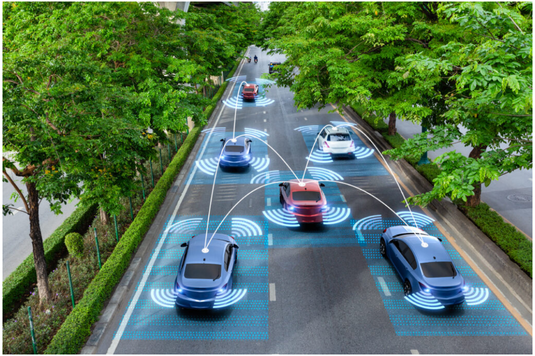
decision maker

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

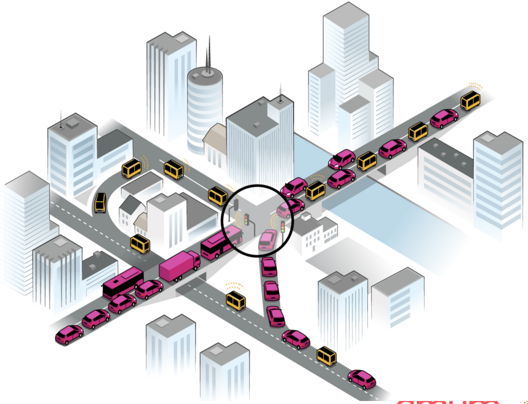
Mixing SO with UE

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.



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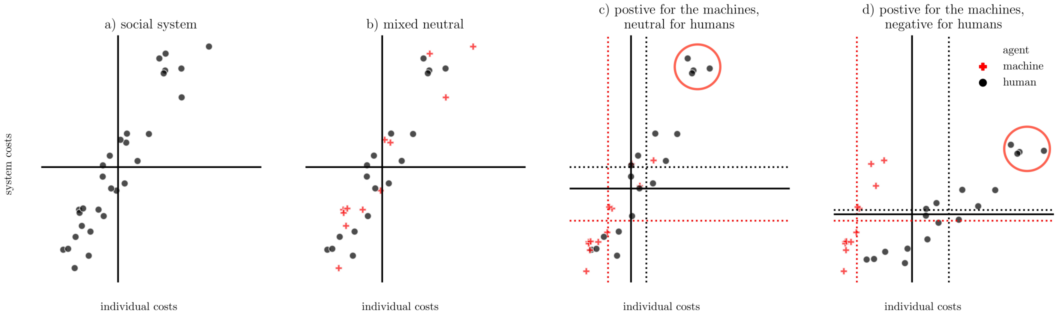
Possible impact

Taxonomy

What can we expect



Objective

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

breaking out

Equilibrium

By definition, a single player cannot act better than in equilibrium.
Equilibrium is a state in which all agents make best decisions and cannot unilaterally improve their decisions by changing actions (Nash).
This includes both humans and machines

Digital twin

Any single intelligent machine, with the same objectives (utility) in the equilibrated system, will act exactly like human.

Stochastic remark

In the stochastic user equilibrium this will refer to expected rewards - the machine may better predict the distribution and thus yield better reward.

ML - consequence

There is no single agent no matter how well-trained that can beat the Equilibrium.
Either this is not equilibrium (there was a gap in $q_k(c_k - c^*) = 0$
Or costs are different: $c_{k,i}$

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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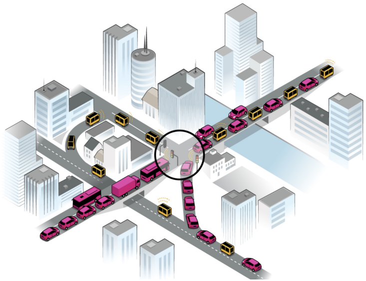
four conflict games

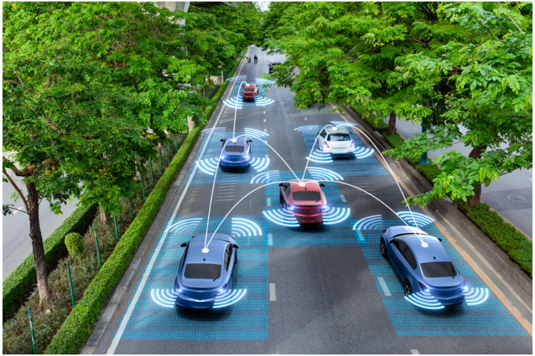


Urban mobility games

Games

Let's introduce the following four urban mobility games in which introducing machine intelligence may lead to conflicts with humans:

- the route choice game, where machines may win by collaboration,
- the day-to-day adaptation game, where machines may win by anticipation,
- the dynamic pricing game, where machines may win by prediction, and
- the repositioning game, where machines may win by automation.



Games

and more
open-ended
class of games where collective actions of CAVs can conflict with humans in urban mobility

Conflicts

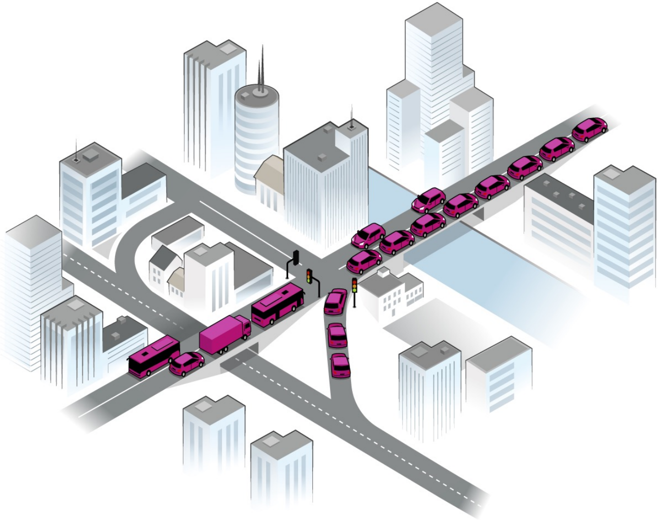
novel phenomena

congested bottleneck with limited capacity

we (humans) rationally optimize our decisions

and reach **user-equilibrium:**

- democratic
- egalitarian



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Conflicts

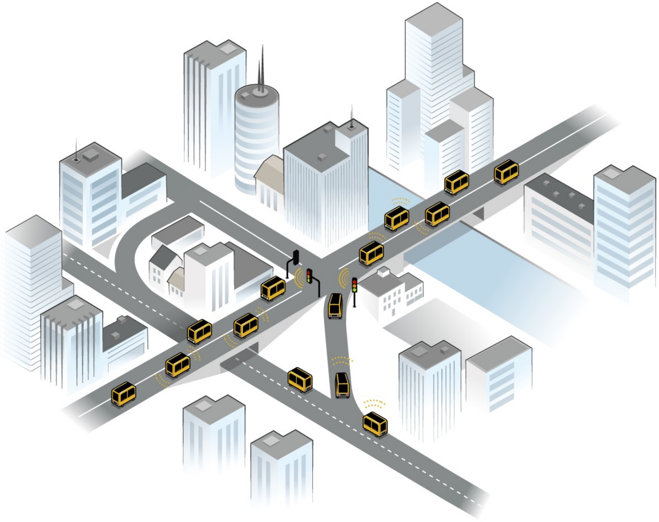
new players

intelligent machines

change the rules of the game

better at:
- calculations
- access to data
- controllable
- collaborative

designed to win



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Conflicts

by collaboration

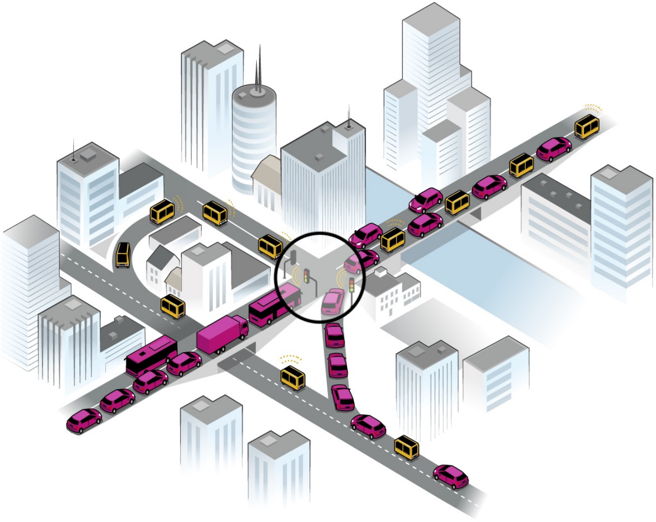
machines **trick** the demand-actuated traffic lights

collaboratively reroute

receive more green light

pass the bottleneck faster

humans queue longer



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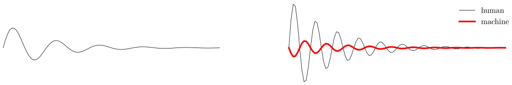
The day-to-day adaptation game

Destabilizing and benefiting from it

The day-to-day adaptation game

Imagine playing rock-paper-scissors in a *Stackelberg* scenario, where your opponent always predicts correctly what you will do.

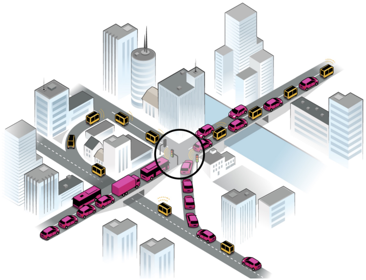
- You take the motorway, the tunnel is empty and motorway is jammed
- You take the tunnel, the motorway is empty and tunnel is jammed



Scenario:

Travellers adapt after a network disruption.
Social system (left) where rational humans adjust their decisions stabilises smoothly after few days.
CAVs learn to anticipate this process and benefit from it (right), presumably at the cost of humans (adapting now longer with stronger oscillations), yielding conflict by anticipation.

methodology



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Methodology

Overview

Method

A: SIMULATE

agent-based urban mobility simulation

where machines deep learn to interact with humans

B: DISCOVER

broad and deep expedition searching for **conflicts** by the:

1. collaboration
2. adaptation
3. prediction
4. automation

C: ASSESS

where conflicts are quantified from various perspectives

so that negative externality can be internalized

D: MITIGATE

machines become responsible and mitigate conflicts

novel multi-objective deep reinforcement learning framework

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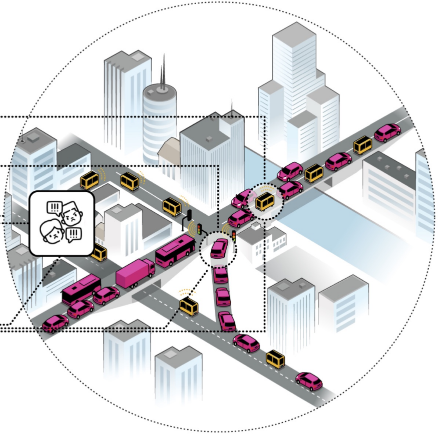
Methodology

Interdisciplinary

PI
- **human travel behaviour** — **PhD**
- **deep reinforcement learning** — **PhD**
- **agent based modelling** — **PD**
- **computational social science** — **PhD**
- **multiobjective reinforcement learning** — **PD**



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Methodology

Urban mobility

Traffic flow simulations

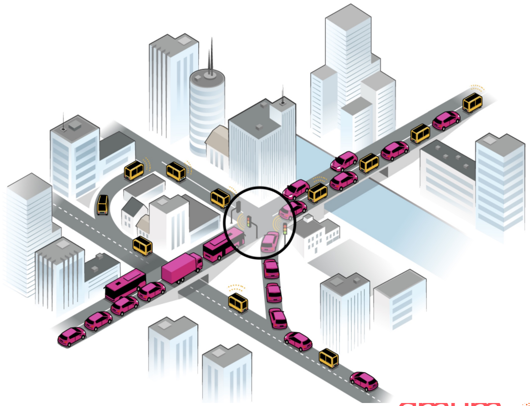
- SUMO - open-source, state-of-the-practice
- AIMSUN, VISSIM, Synchro - commercial

Transport systems

- MATSim - open-source, state-of-the-practice
- VISUM, AIMSUN - commercial

Human behaviour

- BIOGEME - open-source, state-of-the-practice
- Stated-preference, Revealed-preference - big data



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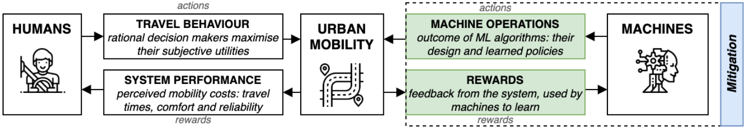
Methodology

Deep machine learning



Challenges

multi-agent
dynamic environment (within-day + day-to-day)
non-deterministic environment (human behaviour)
non-linear costs (travel times)
discrete actions
common, limited resources
fixed-point feedback loops
actions space - shadowed equilibria
collaboration - common rewards, credit assignment
multi-objective - maximise rewards and avoid conflicts

Libraries

- Petting Zoo
- OpenAI: `multi-agent hide-and-seek, Capture the flag`
- Gymnasium, StableBaselines

Team

3xPhD + 1xPD + myself + Visiting Profs + MA students + DevOps

PhD1

with a background in deep reinforcement learning, ideally holding a master's degree in computer science with experience in developing state-of-the-art RL models. She/he will focus on implementing RL frameworks into the agent-based models of urban mobility.

PostDoc

PostDoctoral researcher with experience in deep reinforcement learning and software development. She/he will work on a daily basis with the PhD students to integrate the software development process and manage the computational environment of the project.

PhD2

with a background in modelling urban mobility, ideally holding a master's degree in transportation engineering. She/he will focus on reproducing urban mobility in agent-based models of urban mobility. The main tasks will be to create virtual environments accurately reproducing future of urban mobility and to actively search for conflicts in the urban mobility games.

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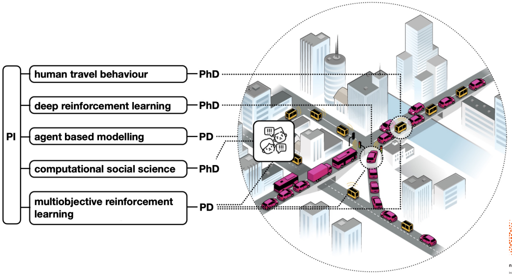

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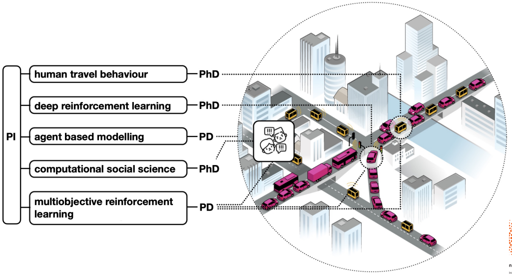

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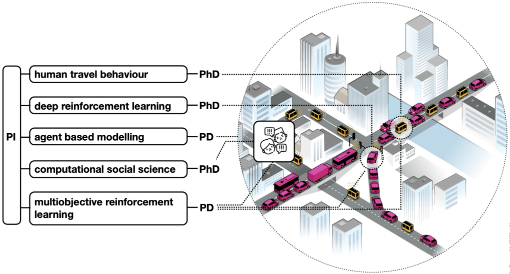

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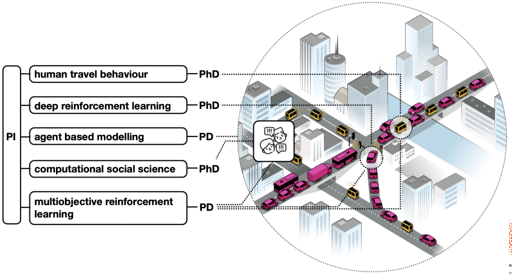


Team

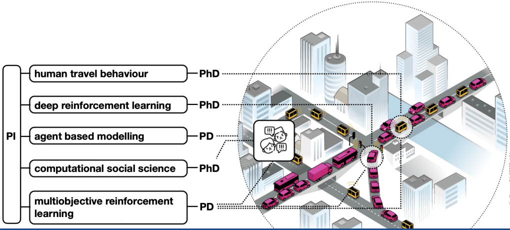
Recruitment

PhD

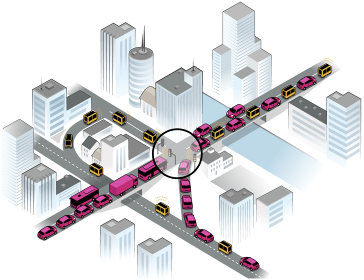
1. 48 months
2. full-time contract (Umowa o Pracę)
3. 2680€ gross / month + 13-th salary (34840€/annum)
4. ca. 12 550 PLN brutto / msc
5. with ca. 1/2 Western European costs of living
6. Doctoral School of Exact and Natural Sciences
7. Jagiellonian University (est. 1364)
8. Kraków
9. details: rafal.kucharski-at-uj.edu.pl
10. deadline ca. June 2023
11. exams June-July 2023

PostDoc

1. 36 months
2. full-time contract (Umowa o Pracę)
3. no teaching (or very limited)
4. ca. 3600 € (16 900 PLN brutto / msc)



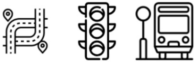
summary



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

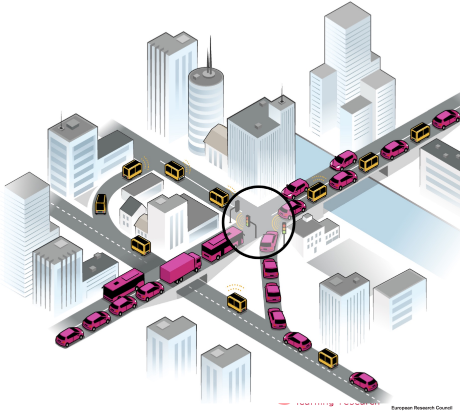
COeXISTENCE

ERC Starting Grant

Thank you for your attention,

welcome to discuss

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



Rafał Kucharski

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