

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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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

our scenario of interest is the **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



agent-based urban mobility simulation

broad and deep expedition searching for conflicts by the:

where conflicts are quantified from various perspectives

machines become responsible and mitigate conflicts

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machines become responsible and mitigate conflicts

Agenda

this talk

Idea

- 1 Formalize the **urban mobility**
- 2 Hypothesize about the future of **urban mobility**.
- 3 Propose the **research plan** to verify the central **hypothesis**.

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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Agenda

- overview
- myself

1 urban mobility

- complex system of urban mobility
- networks
- fixed-point problem
- assignment problem
- system optimum

2 behaviour

- human behaviour
- discrete choice theory

3 game theory

- Wardrop equilibrium
- agent-based equilibrium

4 (reinforcement) learning

5 intelligent machines

- breaking out
- advantages

6 four conflict games

- the route-choice game
- day-to-day-adaptation game
- dynamic pricing game
- repositioning game

7 methodology

- urban mobility models
- deep learning
- team

8 summary

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.

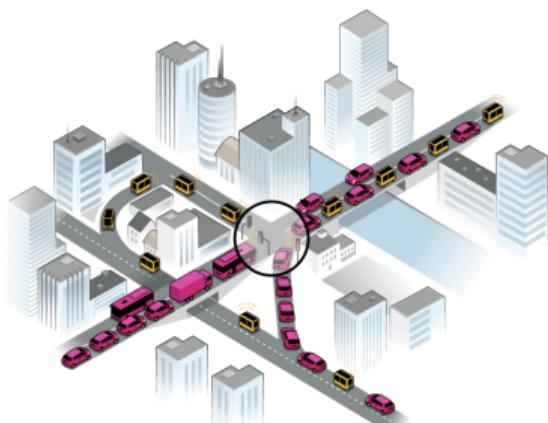
past: PostDoc @ **TU Delft** working in Critical MaaS **ERC Starting Grant**

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

PhD: Modelling Rerouting Phenomena in 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



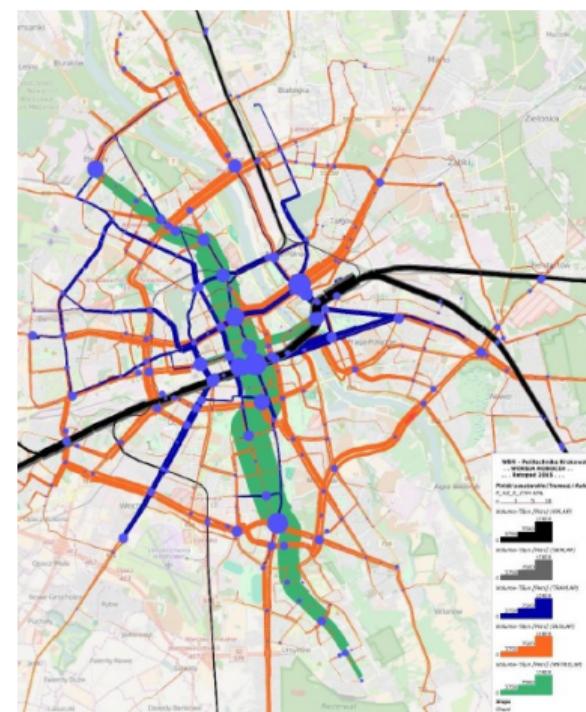
Urban mobility problem

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

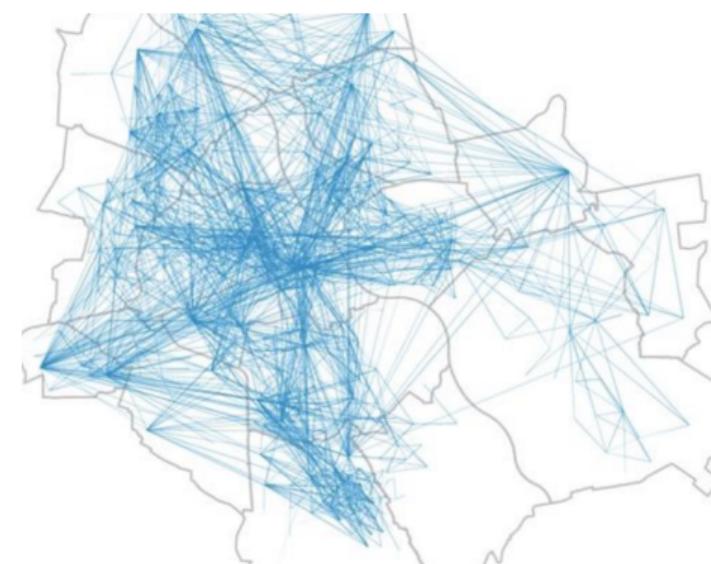
in the morning we travel from homes to work/school
in the afternoon we come back

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



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



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 $q_a : a \in A$

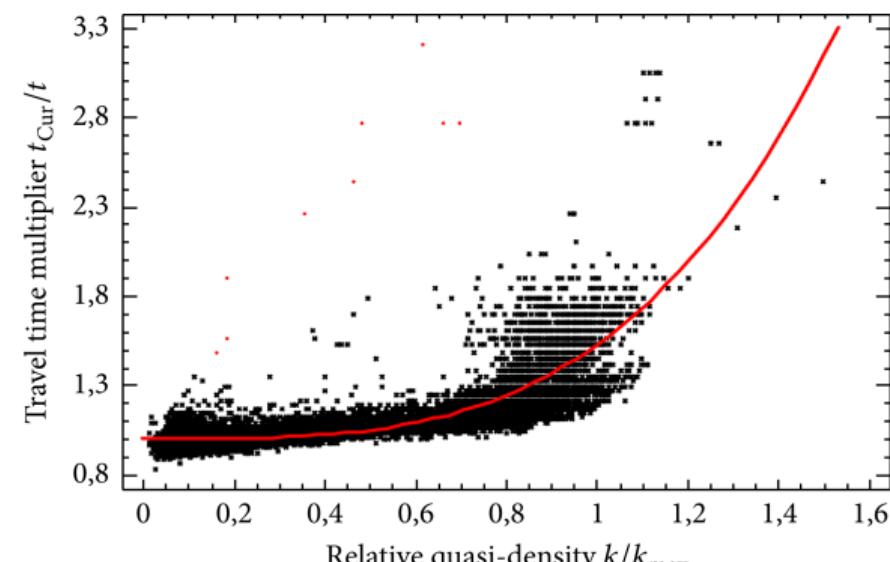
Fixed point problem

- Travel time is a function of the flow:

$$t_a = f(q_a)$$

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

$$q_a = f(t_a)$$



Assignment problem

User equilibrium

Problem

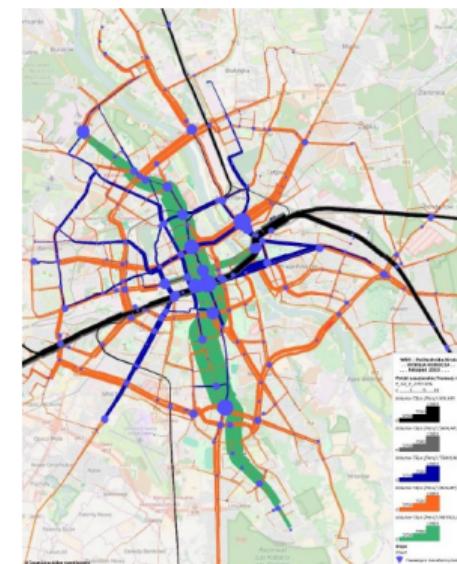
Determine the **flow** $q_a(\tau)$ and cost $c_a(\tau)$ for each link in the network $a \in A$ throughout the day $\tau \in T$

User equilibrium

Each agent i selects the **optimal** 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 $\Delta c_{k,i} = c_{k,i} - \min_{k' \in K} c_{k',i}$

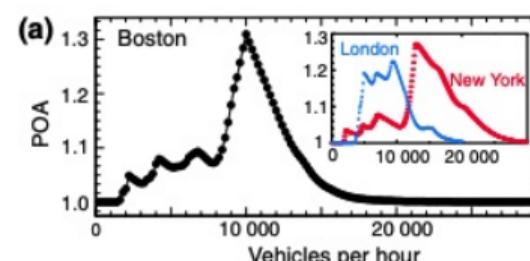
User Equilibrium

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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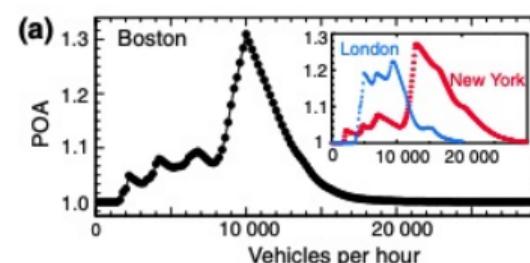
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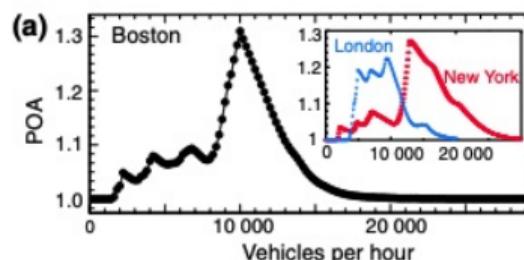
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Assignment problem

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:

- ➊ satisfy the demand
- ➋ yield the minimal total (system-wide) costs

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

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

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

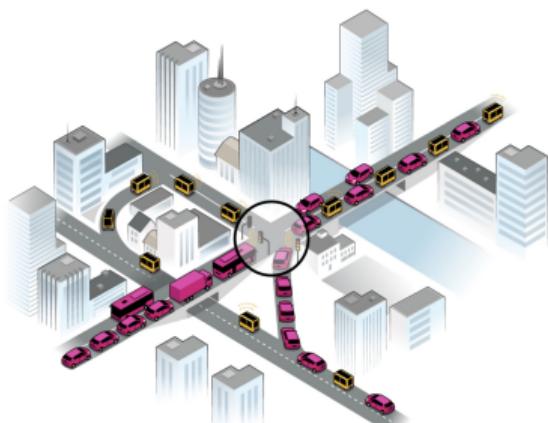
$$d_c = \sum_{k \in K_c^\gamma} y_{ck} \quad \forall c \in C \quad (2)$$

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

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

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**

$$U_{k,i} = \beta_0,i + \beta_{t,i} t_k + \beta_{c,i} c_k + \dots + \varepsilon$$

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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Discrete choice theory

Logit model

Discrete choice theory

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

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.

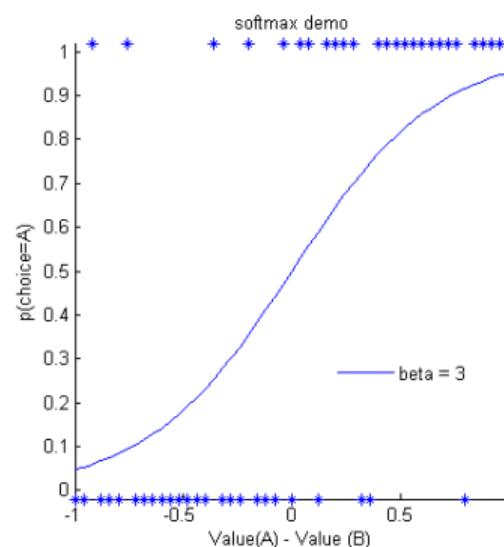
Logit model

assumption:

$\varepsilon \approx \text{Gumbel}(0, \sigma)$, yields

Probability of selecting option a in the choice set C by individual i :

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



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

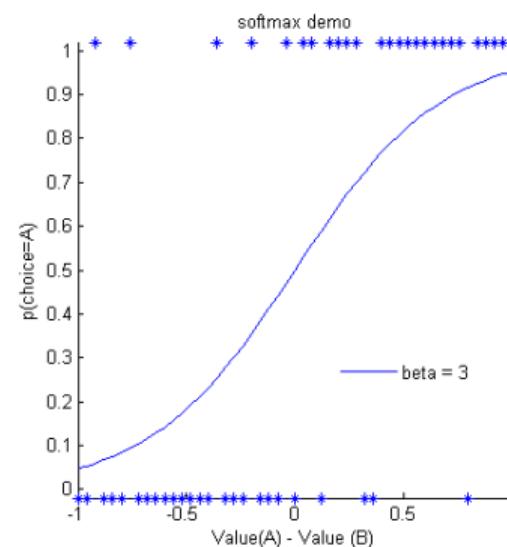
We are different, each of us has its' own:

$\beta_{0,i}$ alternative-specific constant, i.e. taste variation, i.e. sentiment

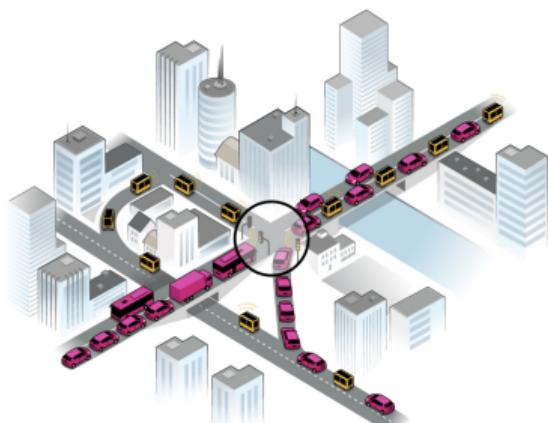
ε random term

$\beta_{t,i}$ value of time

$\beta_{c,i}$ value of money



game theory



User Equilibrium

Nash Equilibrium -> Wardrop Equilibrium

Wardrop's first principle

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

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.

It states:

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.

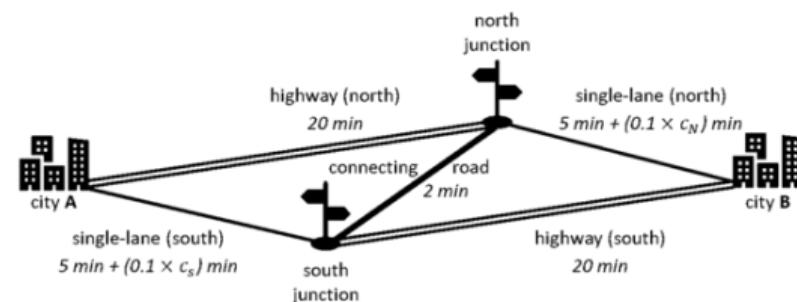
^aanother Nobel

Selfish routing

synonym?

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**. A variant is the stochastic user equilibrium (SUE), in which no driver can unilaterally change routes to improve his/her **perceived/expected**, rather than actual, travel times/costs.



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

$$c_k(t) = f(q_a : a \in k)$$

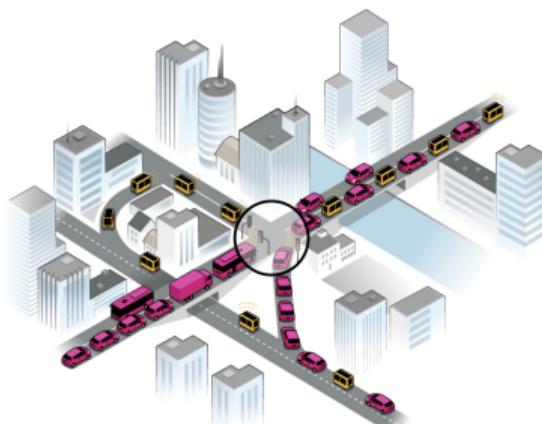
 # collect feedback from environment - travel times

$$c_k = f((c_k(t') : t' = 0, \dots, t))$$

 # and builds experience



(reinforcement) learning

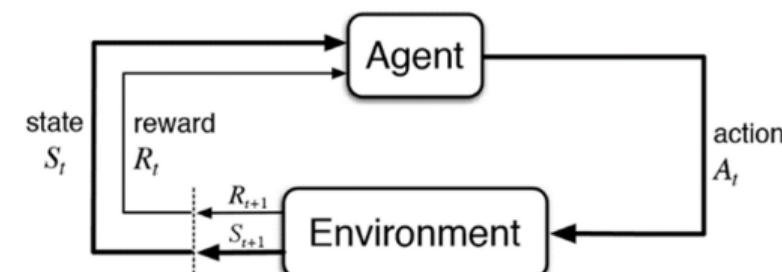


User equilibrium

as an iterative learning

Reaching equilibrium paraphrased

- Traveller has a goal to reach to destination at lowest costs (minimizes 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



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:

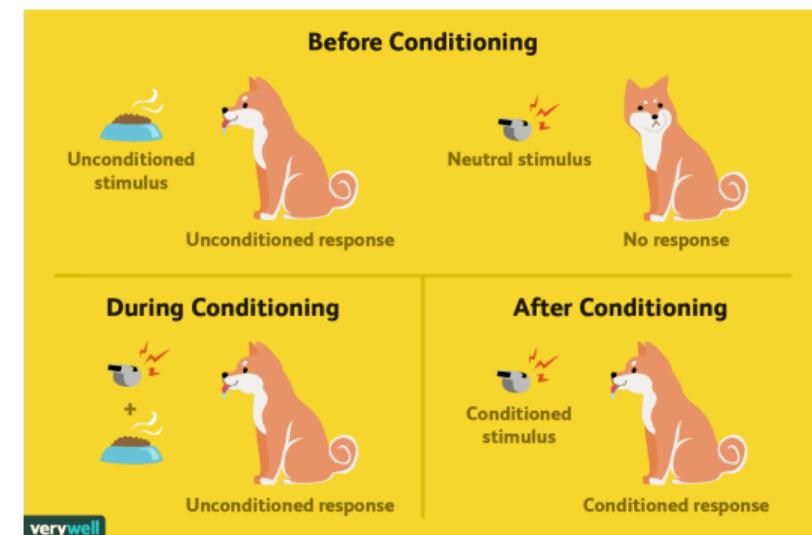
Our behaviour is rational (bounded by rationality), explainable, predictable.

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)



Reinforcement learning

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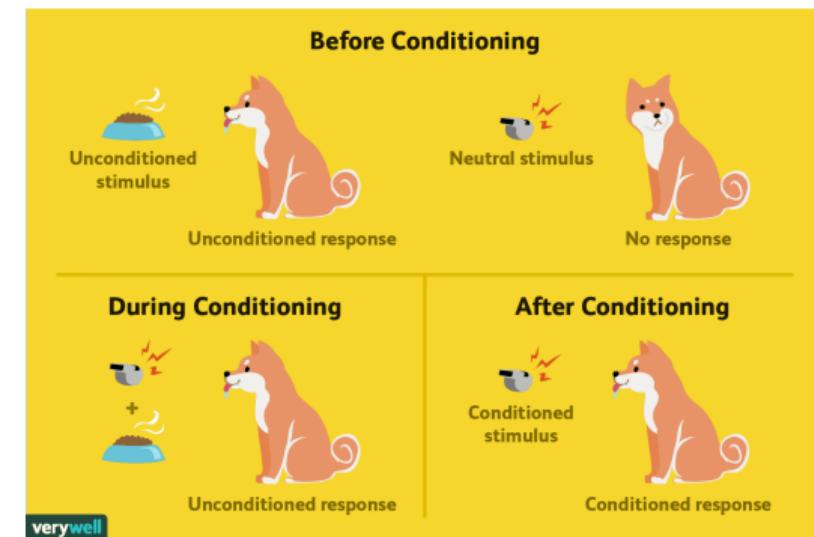
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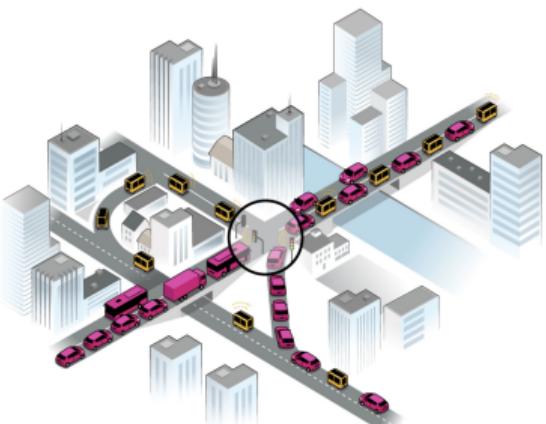
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intelligent machines



Connected autonomous vehicles

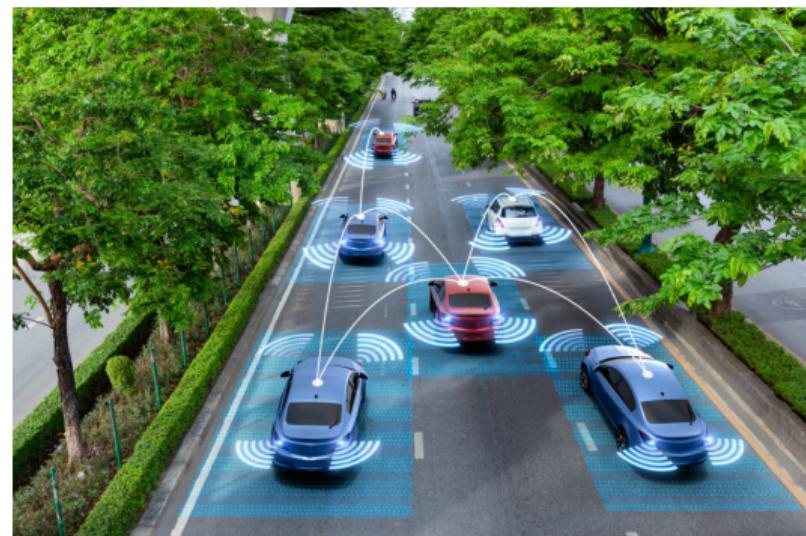
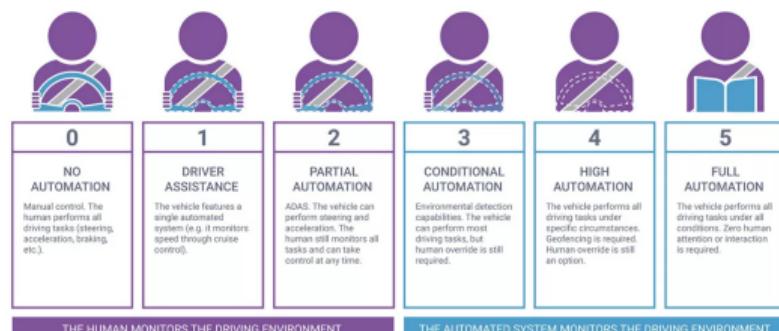
CAVs

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

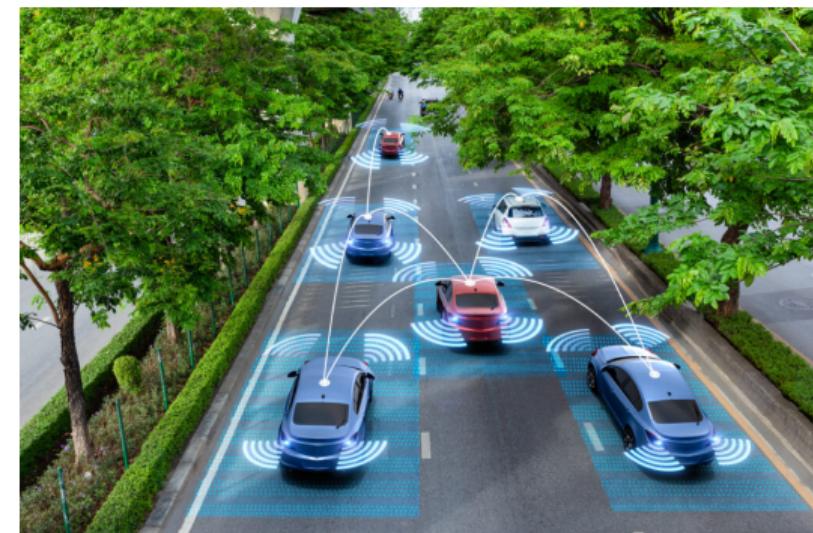
decision maker

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?



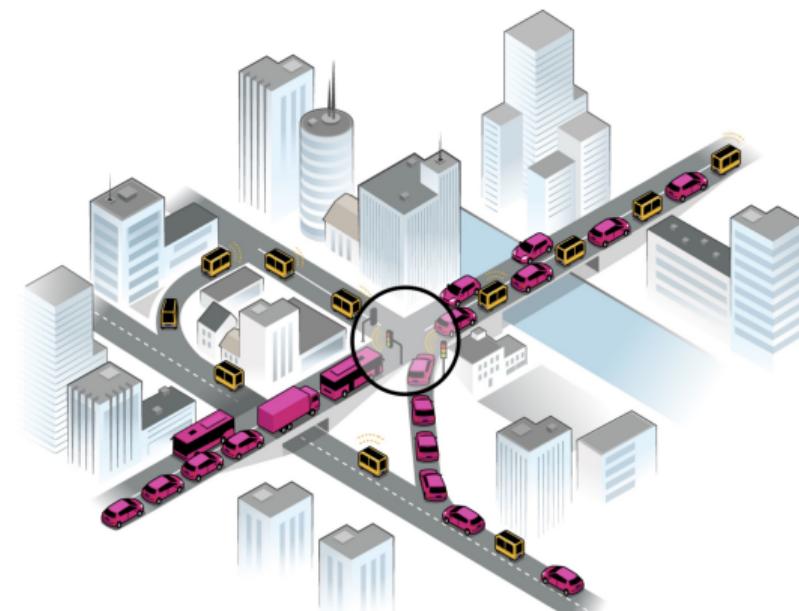
mixed population

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.

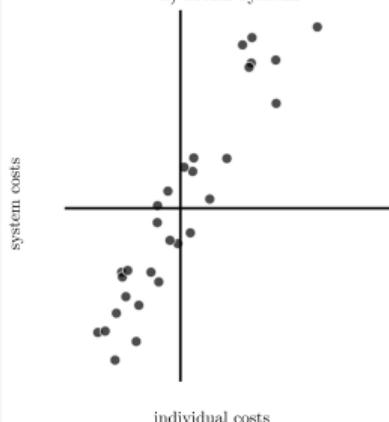


Possible impact

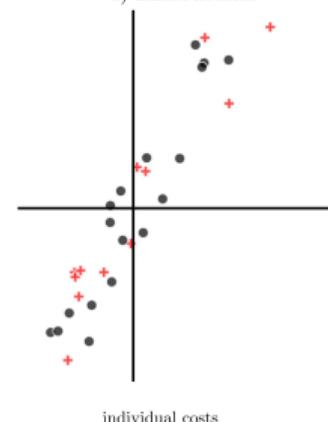
Taxonomy

What can we expect

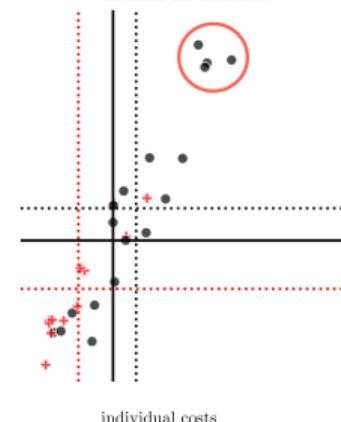
a) social system



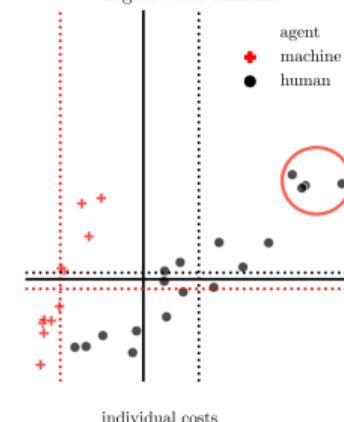
b) mixed neutral



c) positive for the machines,
neutral for humans



d) positive for the machines,
negative for humans



agent
machine
human

Objective

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

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

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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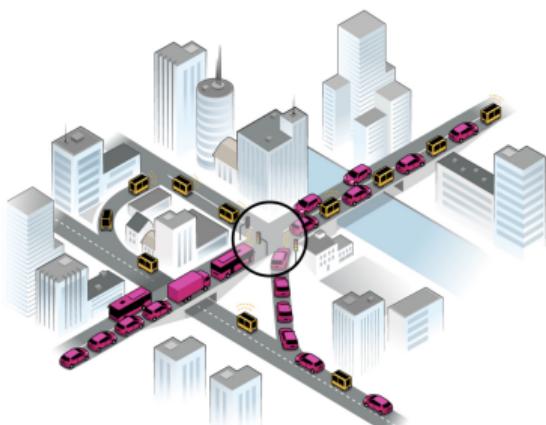
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four conflict games



Urban mobility games

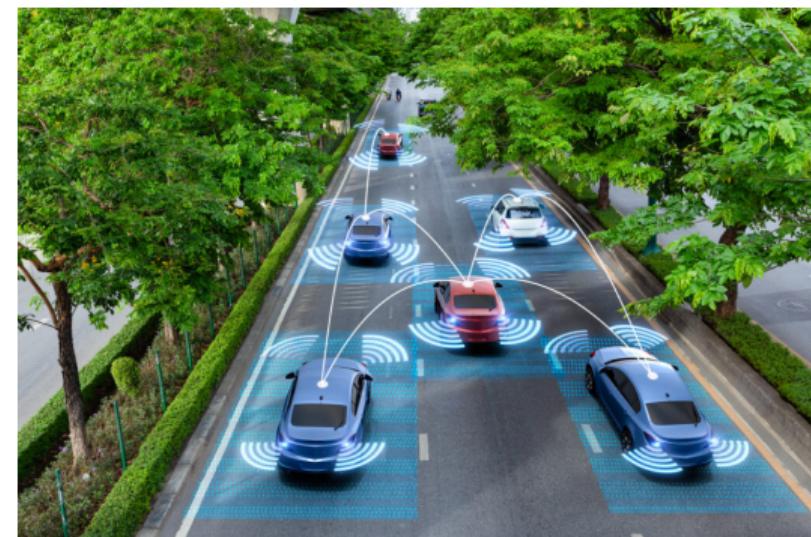
Games

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



The route choice game

Breaking beyond equilibrium

The route choice game

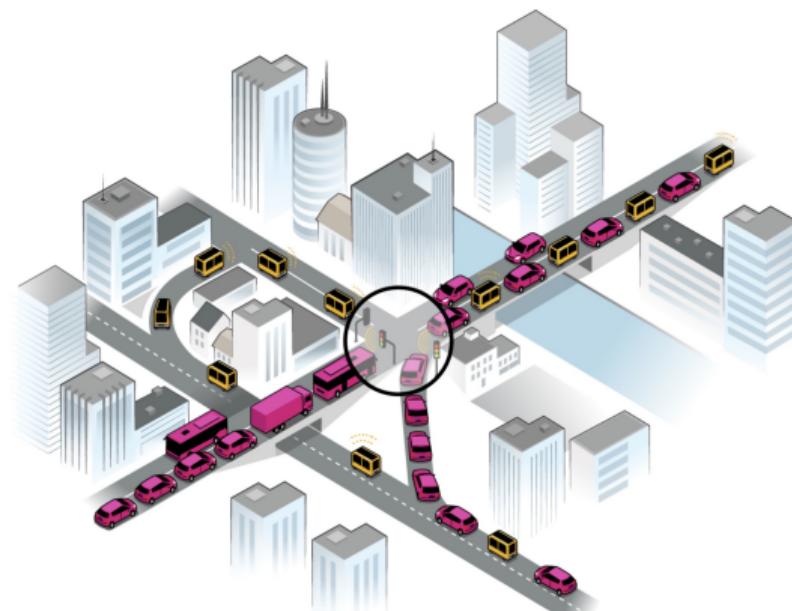
where autonomous vehicles **collaborate** to reduce their travel times at the cost of greater delays for human-driven vehicles.

This game starts from the stable state, where agents are already in equilibrium.

Then, as in a plausible scenario for the future, some human players are **replaced with autonomous vehicles**.

Scenario:

machines trick the demand-actuated traffic lights
collaboratively reroute
receive more green light
pass the bottleneck faster
humans queue longer



The day-to-day adaptation game

Destabilizing and benefiting from it

The day-to-day adaptation game

When the **time dimension** is added to the previous game, another opportunity opens up for the machines.

When humans face a new situation, e.g. when a new road is opened, or a metro line is closed, we first have to understand how the new system works and then iteratively **adapt** to the new situation.

When machines correctly anticipate the adaptation process they may **learn how to benefit** from it.

Moreover, when machine intelligence identifies that strategy of interrupting the adaptation process is beneficial, they will **exploit it** - presumably preventing the system to equilibrate at all.



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.

The dynamic pricing game

Setting the discriminative prices

The pricing game

When I correctly understand your behavioural profile I can propose (as a service provider) a price which is either:

- a) maximal that you can accept (to **exploit** you)
or
- b) minimal that I can afford (to **increase** the market share)

Hostile takeover

Imagine a service provider who has infinite amount of money (like Uber has). The prices are set just below the threshold of public transport - individually per customer.

The public transit is not attractive anymore - bankrupts?

Maximal acceptable price

Imagine you are in rush, you missed a tram and your train depart in 10 minutes.

This is readable from your behaviour.

How much would Bolt charge you then?



Price Discrimination

[prɪs di-skri-mé-nā-shən]

A pricing strategy in which a seller prices the same product differently across markets based on what each market's buyers are willing to pay.

assumption:

perfect prediction of perceived costs and behavioural **traits**:

$$E(c_{i,k,\tau}) = c_{i,k,\tau} : i \in \mathcal{A}$$

$$\beta_{c,i,\tau}$$

The repositioning game.

Perfectly predicting the demand

The repositioning game

Imagine two service providers, who compete for serving the demand (**Uber and Bolt**)
One with human drivers, another with centrally controlled fleet of CAVs

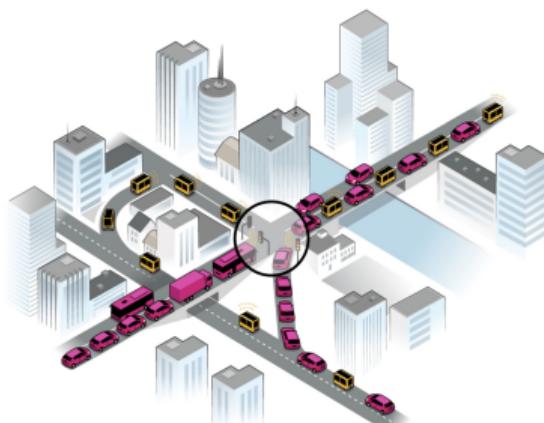
Comparison

One would surely generate better incomes, but maybe human decentralized fleet has some other advantages?

The decentralized suboptimal systems are often more resilient, adaptive and inclusive - e.g. two-sided platform based revolution



methodology

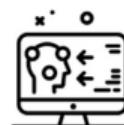


Methodology

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



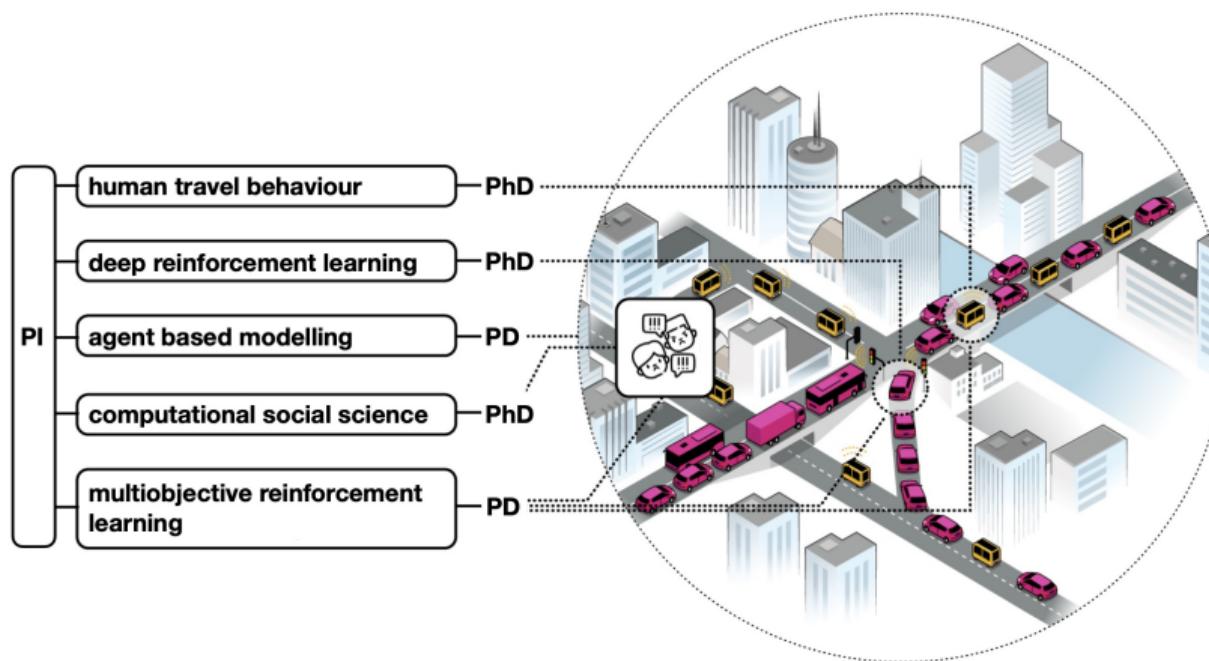
machines become responsible and mitigate conflicts

novel multi-objective deep reinforcement learning framework



Methodology

Interdisciplinary



Methodology

Urban mobility

Traffic flow simulations

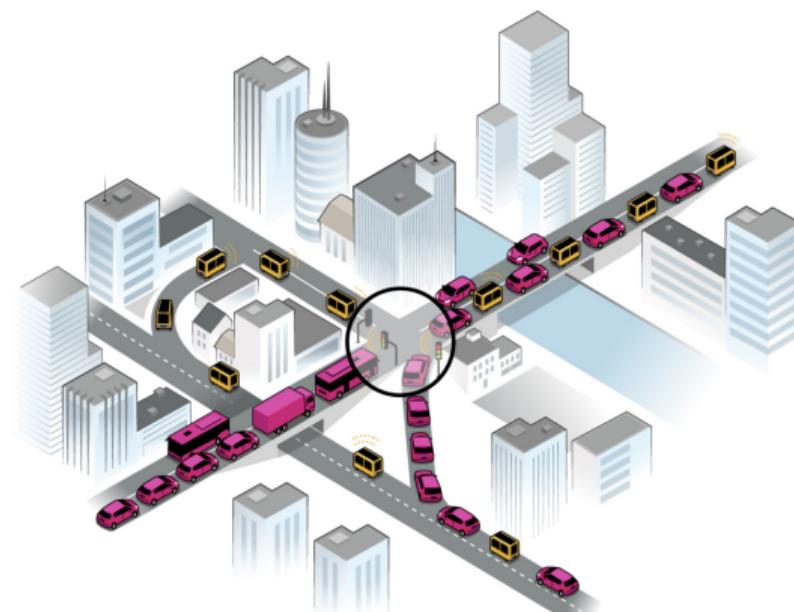
- SUMO - **open-source**, state-of-the-practice
- AIMSUN, VISSIM, Synchro - **commercial**

Transport systems

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

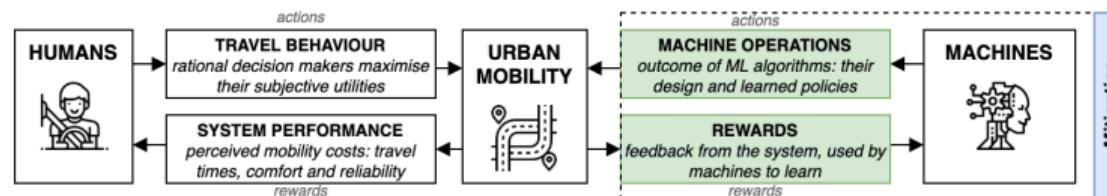
Human behaviour

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



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.

PhD2

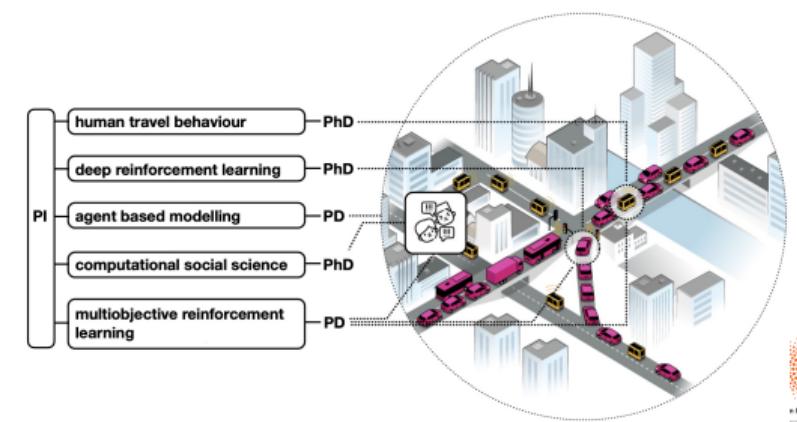
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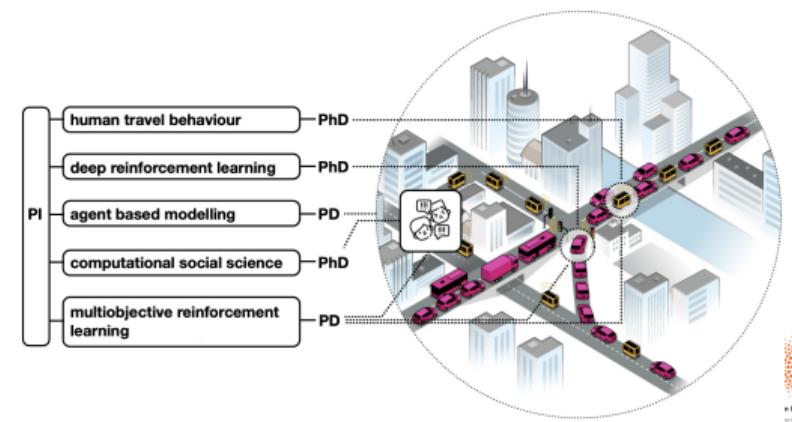
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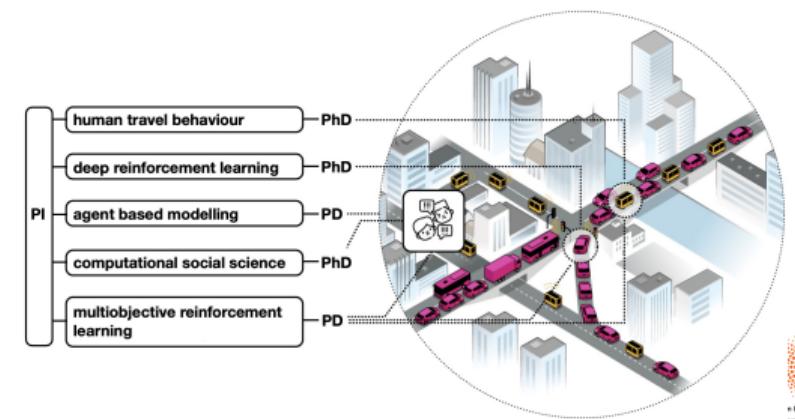
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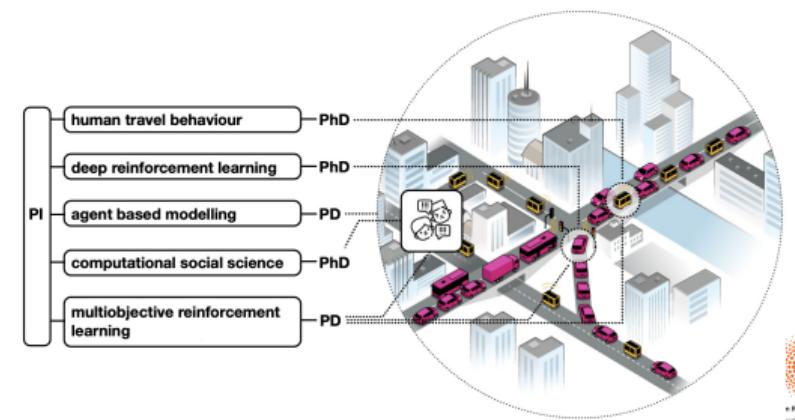
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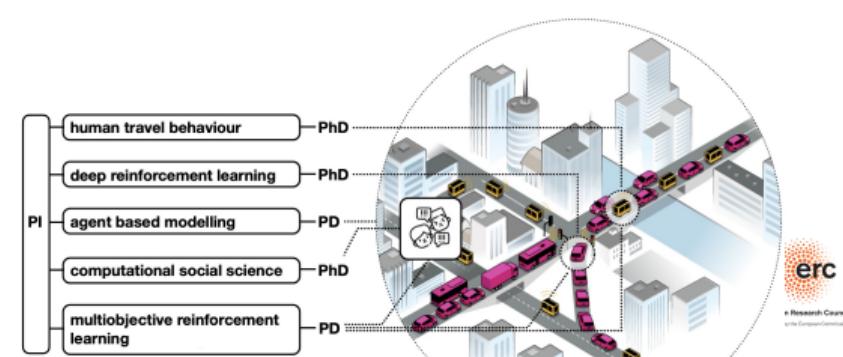
Recruitment

PhD

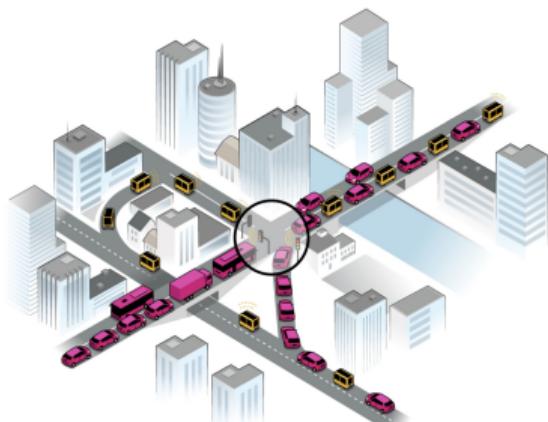
- 1 48 months
- 2 full-time contract (Umowa o Pracę)
- 3 2680€ gross / month + 13-th salary (34840€/annum)
- 4 ca. 12 550 PLN brutto / msc
- 5 with ca. 1/2 Western European costs of living
- 6 Doctoral School of Exact and Natural Sciences
- 7 Jagiellonian University (est. 1364)
- 8 Kraków
- 9 details: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

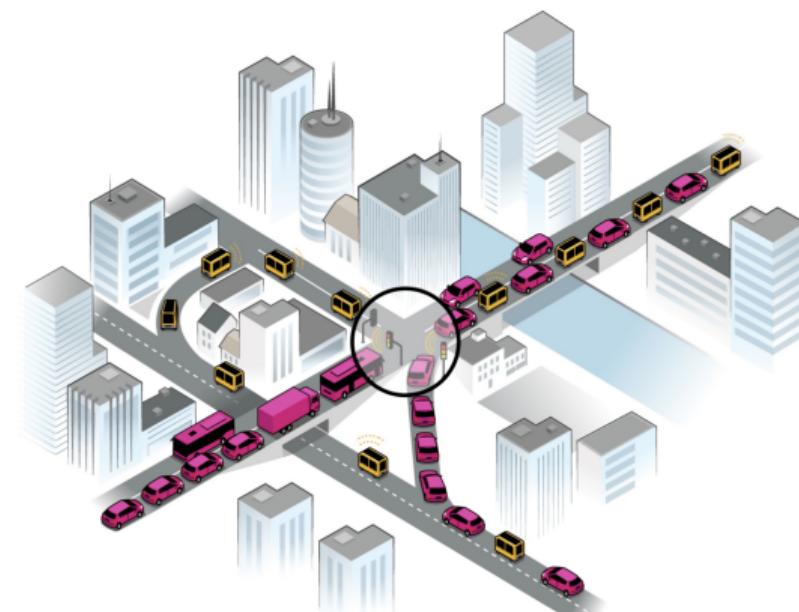
anticipate
demonstrate
resolve

**paradigm shift in
urban mobility**

COeXISTENCE

ERC Starting Grant

COeXISTENCE is open-ended,
with objective to **discover** new phenomena
experimentally demonstrate the **threat** that comes
from AI in urban mobility
cutting edge ML/RL/Urban Mobility Simulations
with a broad and diverse research objectives
spanning across disciplines.



COeXISTENCE

ERC Starting Grant

Thank you for your attention,

welcome to discuss

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

Rafał Kucharski

rafal.kucharski@uj.edu.pl

