Dynamics of two-sided mobility markets (like Uber) in urban mobility

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Agenda

- myself

1. Urban mobility
    - Complex System of Urban Mobility
    - Data in Urban Mobility
    - State-of-the-art
    - Gaps
2. Agent-based simulation
    - Two-sided markets
    - MaaSSim
    - Decisions
    - Learning
3. Case-studies
4. Summary
    - Can we use complex systems theory to improve our understanding?

myself

Rafał Kucharski

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

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

past: PostDoc @ TU Delft working in Critical MaaS ERC Starting Grant of prof. Oded Cats

- shared rides algorithms ExMAS
- agent based model MaasSim

past: Assistant Professor @ Kraków University of Technology, Poland

PhD: Modelling Rerouting Phenomena in DTA (with prof. Guido Gentile, Rome)

outside:

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

Urban mobility

Urban mobility

City

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

Decision-makers (travellers + drivers)

- heterogeneous,
- non-deterministic,
- adaptive (to information and experiences),
- playing cooperative games for limited supplies
- making subjectively optimal decisions everyday.

Transport network

Historically - static, concrete, infrastructure: tram lines, roads, rarely updated timetables.
Now - complex, adaptive, distributed structure:

- real-time control and information,
- two-sided mobility platforms (e.g. Uber),
- (on-demand transit),
- micro-mobility, shared mobility (scooters, car-sharing, city-bikes),
- connected autonomous vehicles (CAVs).

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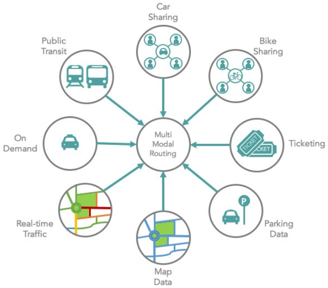
Data

Data:

mobility traces (np. NYC Citi Bike, Uber Movement, Twitter, itp.)
OpenData (np. NYC, Warszawa, Londyn, Amsterdam)
traffic (ITS, traffic control)
cell-phone data (Origin-Destination matrix between powiats in Poland)
smart public transport tickets (SmartCard data, WMATA, TfL)
stated and revealed behaviour (Stated Preference, Revealed Preference),



datasets

millions of publicly available records of various structures

Modelling urban mobility

State-of-the-art in models and software

BIOGEME

Estimating discrete-choice models (travel behaviour) from stated-preference (experiments) and revealed preference (observations) data.

MATSim

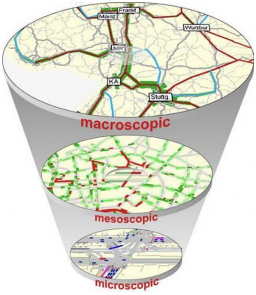
MATSim is an open-source framework for implementing large-scale agent-based transport simulations.

Aimsun

Microscopic demand and traffic flow through the capacitated network in real-time.

PTV Visum

Travel demand models - macroscopic OD matrix estimation: trip generation, trip distribution, mode choice, equilibrium assignment.



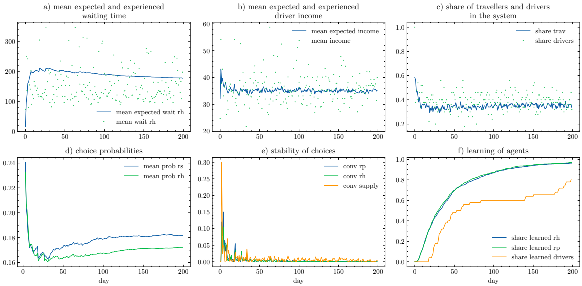
Modelling urban mobility

Research gap - open questions

Research Gap

Stochastic, non-deterministic adaptive behaviour. We can simulate the system - rarely we ask about:

- evolution trajectory
- adaptation trajectory
- stability
- bifurcation
- equilibrium



Agent-based simulation

Two-sided platforms

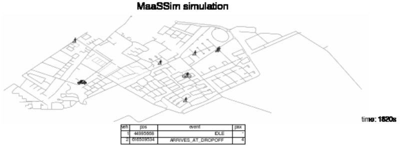
Two-sided mobility platform:

- **two-sided** supply (drivers, vehicles) and demand (travellers)
- **platform** connects supply and demand
- **mobility** offering travellers to supply their mobility needs (reach a destination)

MaaSim

https://github.com/RafalKucharskiPK/MaaSSim

an agent-based simulator, reproducing the dynamics of two-sided mobility platforms (like Uber and Lyft) in the context of urban transport networks.



It models the behaviour and interactions of two kinds of agents:

(i) travellers, requesting to travel from their origin to a destination at a given time, and

(ii) drivers, supplying their travel needs by offering them rides.

The interactions between the two agent types are mediated by the:

(iii) platform(s), matching demand and supply.

Both supply and demand are microscopic.

group of machine

`pip install maassim`

Kucharski R. and Cats O. *MaaSSim – agent-based two-sided mobility platform simulator* (2020, `arxiv.org/pdf/2011.12827`)

MaaSSim

https://github.com/RafalKucharskiPK/MaaSSim

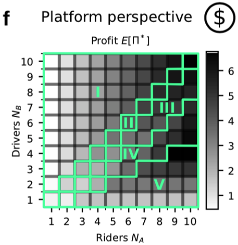
```
from MaaSSim.simulators import simulate, simulate_parallel
from MaaSSim.utils import get_config, load_G
from MaaSSim.utils import prep_supply_and_demand, collect_results

sim = simulate() # run MaaSSim simulation
sim.runs[0].trips  # access the results
params = get_config('default.json')  # load configuration
params.city = "Nootdorp, Netherlands" # modify it
inData = load_G(params)  # load different network graph
params.nP = 50 # modify number of travellers
inData = prep_supply_and_demand(inData, params)  # regenerate supply and demand
sim2 = simulate(inData, params) # rerun the simulation with new data and parameters
print('Simulated wait times: {}s and {}s.'.format(sim.res[0].pax_exp['WAIT'].sum(),
      sim2.res[0].pax_exp['WAIT'].sum()))  # compare some results

space = {nP=[5,10,20], nV = [5,10]} # define the search space to explore in experiments
simulate_parallel(inData, params, search_space = space) # run parallel experiments
res = collect_results(params.paths.dumps) # collect results from so mparallel experiments

def my_function(**kwargs): # user defined function to represent agent decisions
    veh = kwargs.get('veh', None)  # input
    sim = veh.sim  # access to the simulation object
    if len(sim.runs)==0 or sim.res[last_run].veh_exp.loc[veh.id].nRIDES > 3:
        return False # if I had more than 3 rides yesterday I stay
    else:
        return True # otherwise I leave

sim = simulate(inData,params, f_driver_out = my_function) # run MaaSSim with user-defined function
```

MaaSSim

Use-case

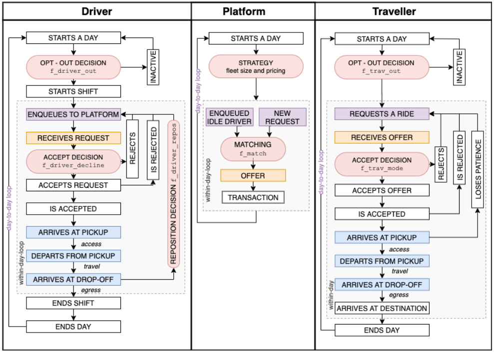
Let's simulate a system in which:

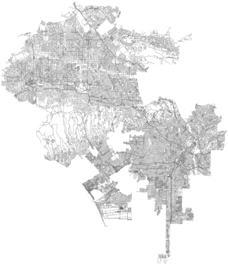
1. travellers choose among public transport, ride-hailing (Uber) and ride-pooling
2. drivers decide whether to work for the platform or not
3. platform sets a fare and commission for drivers
4. everyday agents learn from behaviour and adjust their decisions



MaaSSim

Agent routines





drivers

- leaving the system
- accepting requests
- re-positioning

travellers

- accepting offers,
- selecting platform and modes,
- leaving the system

platform

- setting prices
- matching request

MaaSSim

Decisions

Discrete choice model (multinomial logit model)

$$p_{i,m,d} = \frac{e^{U_{i,m,d}}}{\sum_{a \in A} e^{U_{i,a,d}}}$$

Utility

$$U_{i,m,d} = \beta_t t_{i,m,d} + \beta_c c_{i,m,d} + \text{ASC}_m + \varepsilon_i$$

Utility (mixed logit model)

$$U_{i,m,t} = \beta_{t,i} t_{i,m,t} + \beta_{c,i} c_{i,m,t} + \text{ASC}_{m,i} + \varepsilon_i$$

- i traveller
- m alternative $\in A$
- d day
- c, t cost and time
- β parameters
- ASC alternative specific constant
- U expected utility
- $\overline{U}$ experienced utility
- ε error term

Decisions

Interpretation

travellers

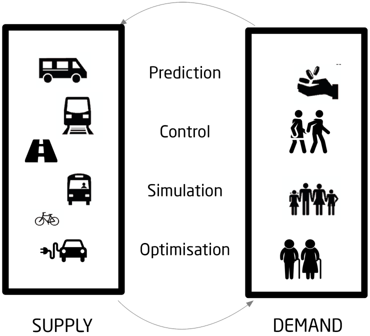
· human behaviour modelling (`discrete choice model`),
· evolution and adaptation (`reinforcement learning`),
· decision support.

drivers

· modelling actual human behaviour
· decision support
· optimal actions (`autonomous vehicles`)

platform

· market actions (`game-theory`)
· distributed system (`control-theory`)



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Learning

Using experience to adjust decisions

Exponential smoothing

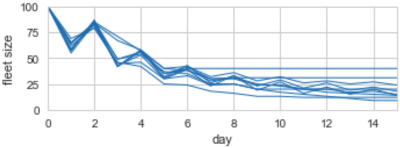
$$U_d = \alpha U_{d-1} + (1-\alpha)\overline{U}_{d-1}$$

History decay

$$U_d = \sum_{t=0}^{n} U_t * e^{(-\alpha t)}$$

Q-learning (machine learning - reinforcement learning)

$$Q^{new}(s_t,a_t) \leftarrow \underbrace{Q(s_t,a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\Bigg(\underbrace{\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1},a)}_{\text{estimate of optimal future value}}}_{\text{new value (temporal difference target)}} - \underbrace{Q(s_t,a_t)}_{\text{old value}} \Bigg)}^{\text{temporal difference}}$$



Case-studies

MaaSSim

Case-studies

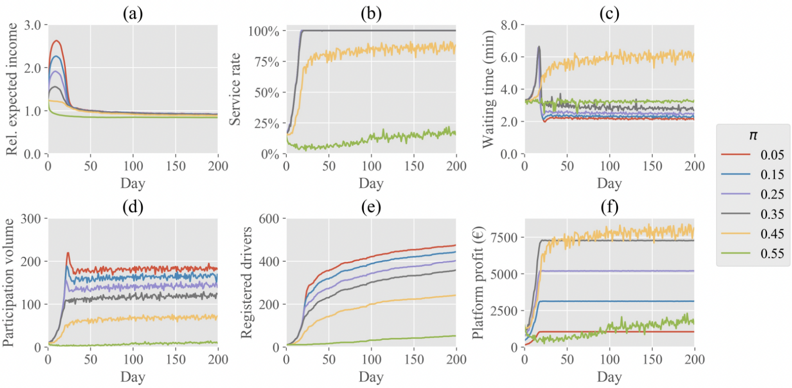
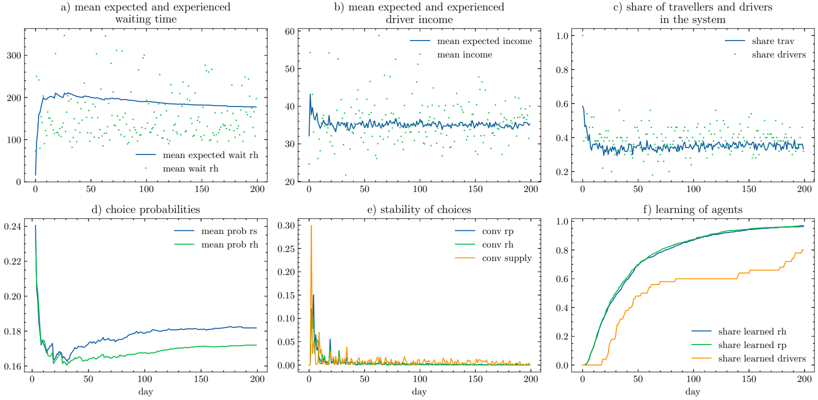


Figure 7. The effect of platform commission rate on the evolution of (a) expected income of registered drivers as ratio of their reservation wage, (b) the share of requests that are satisfied, (c) the average waiting time for pick-up for travellers, (d) daily participation volumes, (e) the total number of registered drivers, and (f) daily platform profit

MaaSSim

Case-studies



MaaSSim

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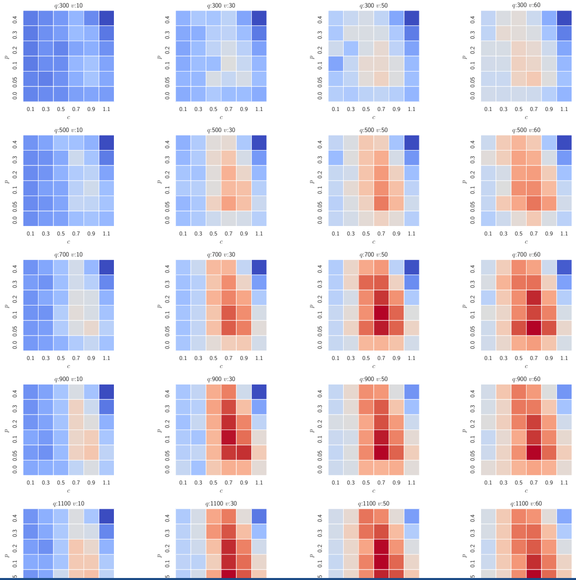


Summary

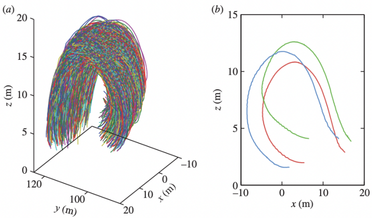
Open-questions

Potential

Leverage on complex science:

- experiments
- models
- measures, KPIs
- ...

for better understanding of complex, behavioural, social systems of urban mobility.



Questions

Discussion

Thank you!

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