SAMoD:
Shared Autonomous Mobility-on-Demand using Decentralized Reinforcement Learning

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November 6th 2018

CONNECT
Networks of the Future

Trinity College Dublin
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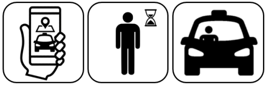
Context and objectives

Mobility-on-Demand with Shared Autonomous Vehicles

	Taxi 	Car-Sharing 	SAV 
Pick-up	Anywhere covered	Stations or where available	Anywhere possible
Drop-off	Anywhere covered	Same station or where authorized	Anywhere possible
Parking	Station or private parking	Stations or on-street	Dynamic and adaptive
Rebalancing	Selfish or static	Operator- [1] or user-based [2]	Dynamic [3] and adaptive [4]

Context and objectives

✓ Advantages and ★ challenges for Mobility-on-Demand with SAV

✓ fully flexible fleet size

✓ robots (almost) never need to take a break

✓ can be summoned everywhere

✓ can be very efficient if ride sharing enabled [5, 6]

★ can save parking space?

★ can improve traffic in cities?

★ dynamic adaptation to demand (and/or anticipation [3])

★ limit empty mileage [7]?

★ optimize SAV-rider assignment (especially when ride sharing)

Context and objectives

Approaches

	Centralized	Decentralized	Learning
Several SAV companies	✘	✓	✓
Dynamic fleet size	✘	✓	✓
Optimized assignment	✓ limited scalability	✘	✘
Dynamic ride-sharing	✓ requires full knowledge [5]	✓	✓
Rebalancing	✓using historical data [3, 1]	✓ using a network partition [8, 9]	✓adaptive [10] and proactive
Used data	Full network knowledge [3, 5]	Local knowledge	Local knowledge

SAMoD agents

Perception:

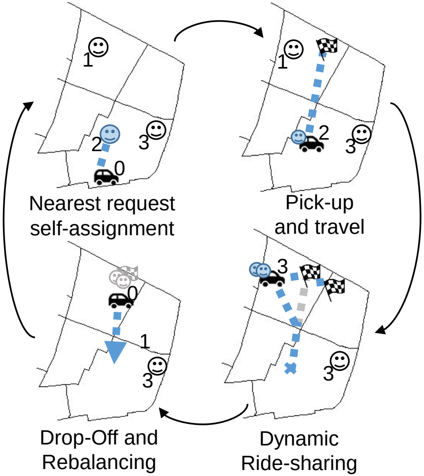
- Requests and vehicles in current zone
- Built historical data per zone

Decision making:

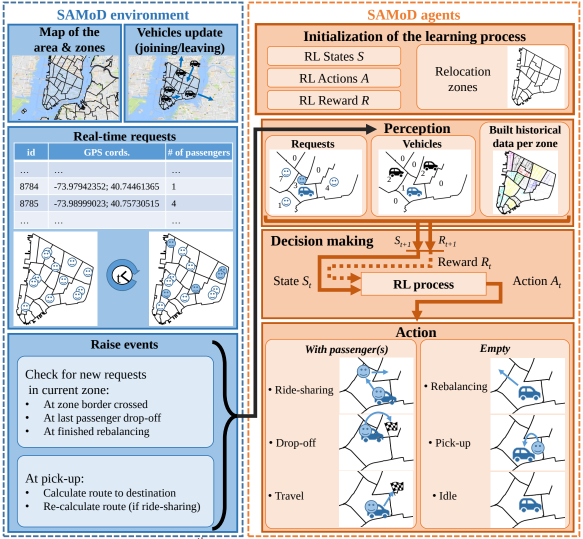
- Reinforcement learning (Q-learning [11])
- Reward: to have passengers

Actions:

- Pick-up (inc. ride sharing)
- Rebalance to zone
- Do nothing

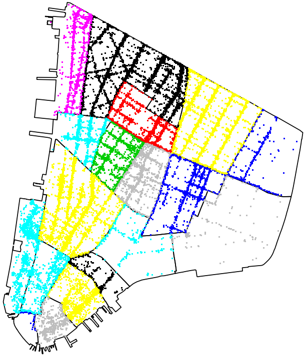


SAMoD system architecture



Simulation

From NYC taxi data trips to requests



Example of trips origin position recorded on February 2nd 2016 and mapped to the zones describing the studied network

Trips from 50 consecutive Tuesdays (07/2015 – 06/2016):

- 659,579 trips (1,074,690 passengers)

Four time periods:

- night (2-5am)
- morning rush hour (7-10am)
- midday (11am-2pm)
- afternoon rush hour (6-9pm)

One request:

t_R	time the user requested the trip
n_R	number of passengers (1–4)
l_{PU}	waiting user/pick-up location (coordinates)
l_{DO}	drop-off location (coordinates)
z_{PU}	pick-up zone (id)
z_{DO}	drop-off zone (id)

Simulation

Scenarios

	Summary	Assignment	Rebalancing	Ride sharing
Baselines	C	Centralized	No	No
	D	Decentralized	No	No
	C_RB	Centralized	Yes	No
	D_RB	Decentralized	Yes	No
	C_RS	Centralized	No	Yes
	D_RS	Decentralized	No	Yes
	C_RB_RS	Centralized	Yes	Yes
	D_RB_RS	Decentralized	Yes	Yes
SAMoD	S_RB	Learnt	Learnt	No
	S_RB_RS	Learnt	Learnt	Learnt current zone only
	S_RB_RS+1	Learnt	Learnt	Learnt current zone+1
	S_RB2_RS+1	Learnt	Learnt (limited)	Learnt current zone+1

Simulation

Demonstration

Results

Evaluation

We evaluated the impact of the different strategies on:

- The system:
  - served requests
  - not served/timed-out requests (10 min)
- Riders:
  - waiting time t_w
  - detour time t_d
  - travel time TT
- Vehicles:
  - total Vehicle Miles Travelled (VMT)
  - empty VMT
  - engaged VMT
  - shared VMT
  - occupancy

Results: Rebalancing (7–10am)

		No RB, No RS		Rebalancing		Ride-sharing		RB and RS		SAMoD			
		C	D	C_RB	D_RB	C_RS	D_RS	C_RB_RS	D_RB_RS	S_RB	S_RB_RS	S_RB_RS+1	S_RB2_RS+1
System	Satisfied requests	29667	35388	30191	36913	38327	38368	38346	38407	35691	37790	37679	36159
	% of total requests	76.4	91.13	77.75	95.06	98.7	98.81	98.75	98.91	91.91	97.32	97.03	93.12
	Not served requests	8675	3098	8150	1590	0	54	0	11	2903	693	726	2242
	% of total requests	22.34	7.98	20.99	4.09	0	0.14	0	0.03	7.48	1.78	1.87	5.77
Riders	Avg t_w (min)	11.63	5.48	11.07	4.57	2.41	2.56	2.1	2.6	2.87	2.46	2.27	2.49
	Avg TT (min)	5.8	5.69	5.79	5.72	10.31	9.21	10.19	8.73	5.69	9.11	12.03	12.12
	Avg t_d (min)	0	0	0	0	4.57	3.47	4.44	2.99	0	3.39	6.31	6.49
Vehicles	Avg VMT	863.8	735.79	884.71	861.4	690.28	716.49	760.06	845.02	882.85	865.94	869.94	644.32
	Avg empty VMT	428.48	228.29	442.24	330.04	117.02	147.9	181.56	268.52	371.95	352.6	335.81	147.37
	Avg engaged VMT	435.32	507.5	442.47	531.36	573.26	568.59	578.5	576.5	510.91	513.34	534.13	496.95
	Avg shared VMT	103	120.55	103.78	125.54	382.75	324.74	376.86	301.96	115.84	330.3	433.86	409.11
	Avg occupancy	1.47	1.48	1.47	1.48	2.67	2.39	2.63	2.27	1.45	2.52	3.13	3.19

Results: Ride sharing (7–10am)

		No RB, No RS		Rebalancing		Ride-sharing		RB and RS		SAMoD			
		C	D	C_RB	D_RB	C_RS	D_RS	C_RB_RS	D_RB_RS	S_RB	S_RB_RS	S_RB_RS+1	S_RB2_RS+1
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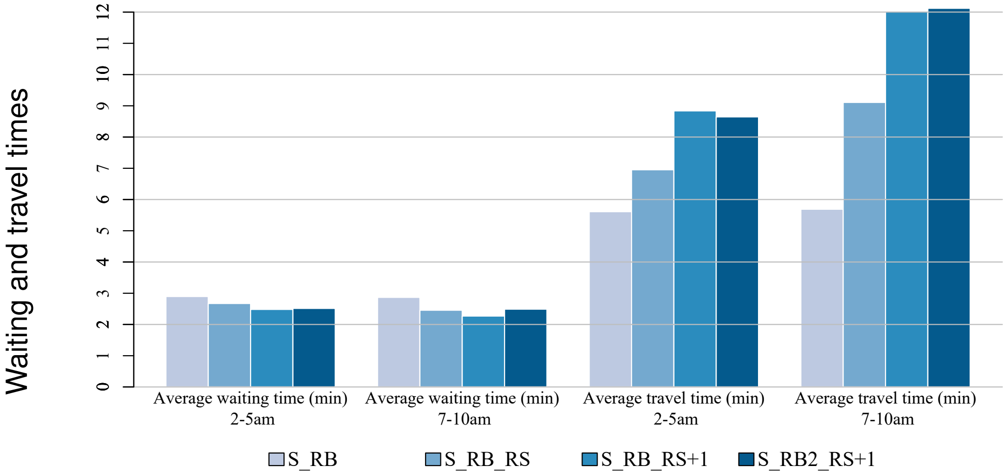
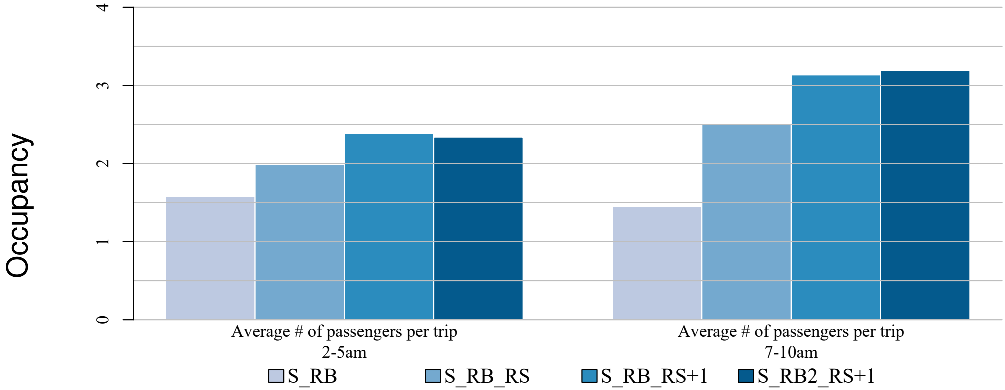
Results

Demand patterns



Results

Demand patterns



Conclusions

- ✓ Vehicle objective is selfish but learnt policy enables improvements:
  - ✓ At the system scale
  - ✓ From riders perspective
- ✓ Vehicle fleet learns an effective rebalancing strategy using historical data
- ★ Results highlight a complex trade-off
- ★ Impact of/on traffic is not considered

Conclusions

Future work

Conclusions

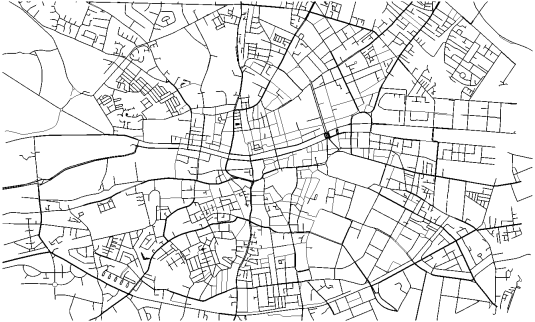
Future work

Model a SAV system with enabled ride sharing in Dublin:

- generate trips from a survey
- create different adoption rate scenarios (from the survey)

Evaluate the impact of this system on:

- traffic conditions
- parking space use



Dublin city center network in Sumo

References I

[1] Simone Weikl, Klaus Bogenberger, and Nikolas Geroliminis. Simulation framework for proactive relocation strategies in free-floating carsharing systems. In Transportation Research Board 95th Annual Meeting, number 16-2725, 2016.

[2] A. G. Bianchessi, S. Formentin, and S. M. Savaresi. Active fleet balancing in vehicle sharing systems via feedback dynamic pricing. In 2013 IEEE 16th International Conference on Intelligent Transportation Systems (ITSC), pages 1619–1624, Oct 2013. doi: 10.1109/ITSC.2013.6728461.

[3] Daniel J Fagnant and Kara M Kockelman. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transportation Research Part C: Emerging Technologies, 40:1–13, 2014.

[4] Konstanze Winter, Oded Cats, Bart van Arem, and Karel Martens. Impact of relocation strategies for a fleet of shared automated vehicles on service efficiency, effectiveness and externalities. In 2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), pages 844–849. IEEE, 2017.

[5] Daniel J Fagnant and Kara M Kockelman. Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles. In Transportation Research Board 94th Annual Meeting, number 15-1962, 2015.

References II

[6] Javier Alonso-Mora, Samitha Samaranayake, Alex Wallar, Emilio Frazzoli, and Daniela Rus. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proceedings of the National Academy of Sciences, 114(3):462–467, 2017.

[7] Wenwen Zhang, Subhrajit Guhathakurta, Jinqi Fang, and Ge Zhang. The performance and benefits of a shared autonomous vehicles based dynamic ridesharing system: An agent-based simulation approach. In Transportation Research Board 94th Annual Meeting, January 2015.

[8] Hussein Dia and Farid Javanshour. Autonomous shared mobility-on-demand: Melbourne pilot simulation study. Transportation Research Procedia, 22:285–296, 2017.

[9] Kevin Spieser, Samitha Samaranayake, Wolfgang Gruel, and Emilio Frazzoli. Shared-vehicle mobility-on-demand systems: a fleet operator's guide to rebalancing empty vehicles. In Transportation Research Board 95th Annual Meeting, number 16-5987, 2016.

[10] J. Wen, J. Zhao, and P. Jaillet. Rebalancing shared mobility-on-demand systems: A reinforcement learning approach. In 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), pages 220–225, Oct 2017. doi: 10.1109/ITSC.2017.8317908.

[11] Christopher JCH Watkins and Peter Dayan. Q-Learning. Machine learning, 8(3-4):279–292, 1992.