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PhD SEMINAR SESSIONS

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Learning Cooperative Multi-Agent Adaptive Control System of Signalized Intersections based on Growing Neural Gas for Mixed Traffic Flows

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Contents

- Introduction
- Traffic Signal Control
- Mixed traffic flows
- Reinforcement Learning
- Growing Neural Gas
- Multi-agent systems
- Putting it all together
- Conclusion



Introduction

- Traffic in urban cities is primarily controlled by traffic signal control systems
 - Fixed Traffic Signal Control (FTSC)
 - Traffic Actuated Signal Control (TASC)
 - Adaptive Traffic Signal Control (ATSC)
- Wrong choice of signal programs can have a negative impact on the traffic flow and cause significant delays in the transport network





Adaptive Traffic signal control

- Signal program changes according to the current traffic state to satisfy desired operational objective
 - Smooth traffic flow
 - Maximization of throughput
 - Access equity
 - Queue management
- Real time traffic data is a requirement for ATSC
- Commercial systems: SCOOT, SCATS, UTOPIA, ImFlow...
- Modern research approaches based on reinforcement learning





Mixed traffic flows

Connected Vehicles (CV)



https://www.tataelxsi.com/news-and-events/how-connected-vehicles-can-make-indian-roads-safer

• Autonomous Vehicles (AV)



https://tempuslogix.com/available-autonomous-vehicles/



Mixed traffic flows

- Connected and Autonomous
 Vehicles (CAV)
 - Combination of CV and AV
 - Send data
 - Receive data
 - React do the data

- Mixed traffic flows
 - Human driven vehicles (HDVs)
 - CAVs with variable penetetration rate



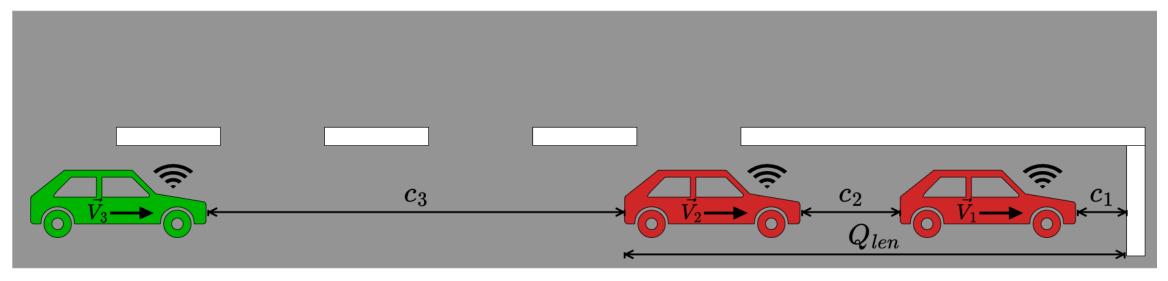


- How can we exploit mixed traffic flows for traffic signal control?
- Do we need traffic signal control if all vehicles are CAV?





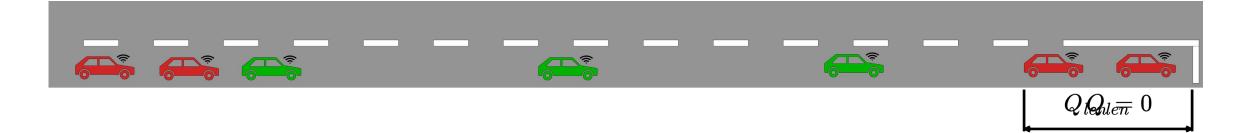
• Estimation of queue lengths





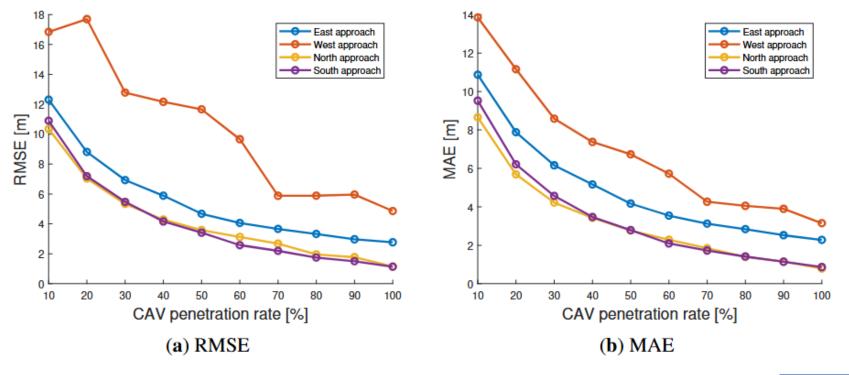


• Problems?







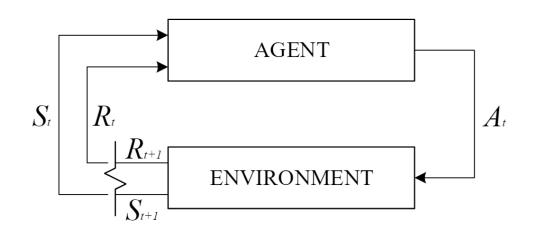




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Reinforcement learning

- Subset of machine learning
- "Learning by doing"
- Attempt to construct an optimal control policy
- Formaly the controller is defined as a Markov Decision Process (MDP) using a tuple <S, A, T, R, γ>

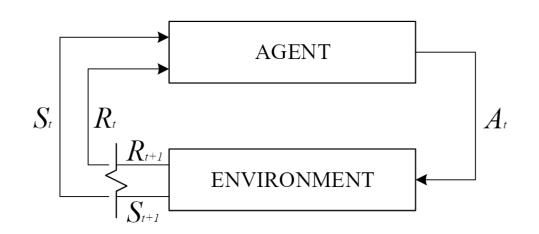




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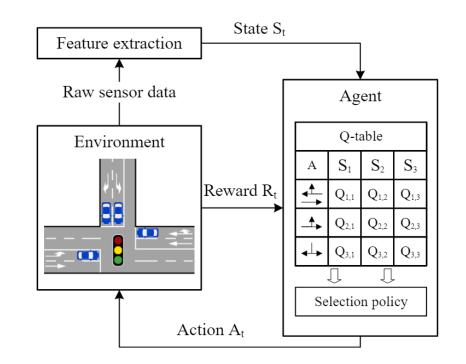
Reinforcement learning

- Formaly the controller is defined as a Markov Decision Process (MDP) using a tuple <S, A, T, R, γ>
 - State S
 - Action A
 - Transition T
 - Reward R
 - Discount Factor γ



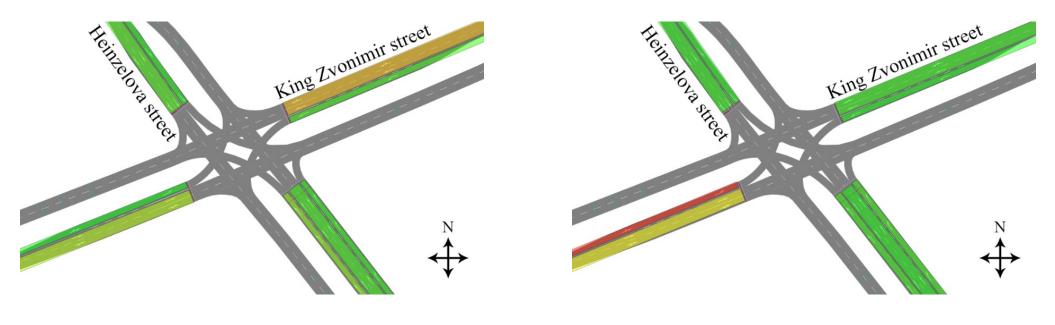


- State S (Traffic situations)
- Action A (Chages to signal program)
- Transition T (Moving from one traffic situation to another)
- Reward R (The operational objective in numerical form)













- Actions
 - Change phase duration
 - Change cycle time
 - Change offset
 - Switch to next phase
 - Do nothing

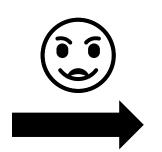






• Reward - tied to the operational objective!



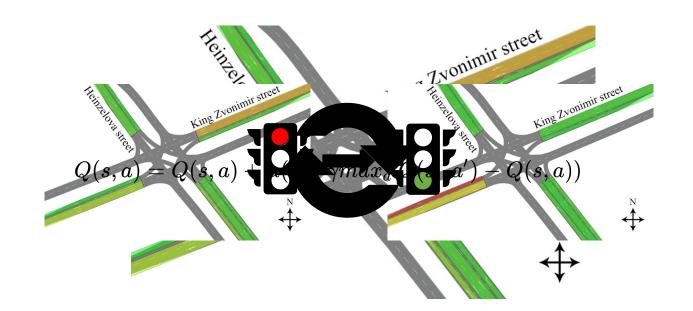








- Algorithm (Q-learning)
 - Observe the environment
 - Do something
 - Observe what happened
 - Update knowledge
 - Repeat!







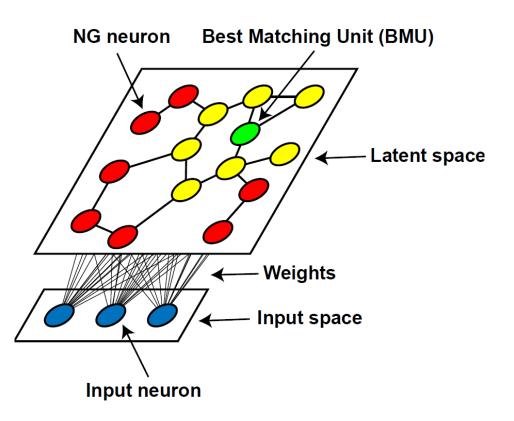
- Wait?! What about traffic safety?
- Can ATSC systems learn about safety?
- Can we measure safety?





Growing Neural Gas

- A type of Neural Network (sort of)
 - Only one layer
 - Lateral connections between neurons
 - Dimensionality reduction
 - Topology preservation







Growing Neural Gas

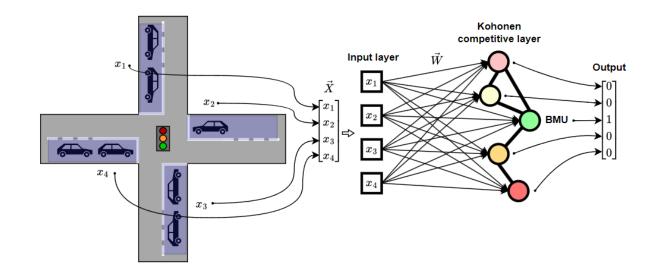






Growing Neural Gas for ATSC

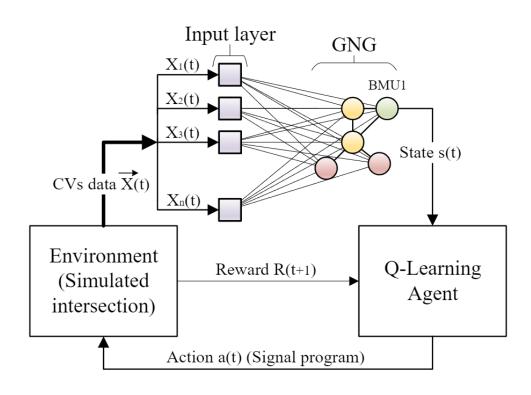
• Combining GNG with Q-learning







Growing Neural Gas for ATSC







Multi-agent systems

- Multiple agents acting in the same environment!
- Why not just one?
- Any problems with multiple agents?





- Configurations analyzed
 - Fully independent
 - Non-cooperative
 - Limited state knowledge
 - State sharing
 - Non-cooperative
 - Increased state knowledge
 - Centralized state with decentralized agents
 - Non-cooperative
 - Maximum state knowledge
 - Reward sharing
 - Addition to each of the configurations above
 - Cooperative behavior



- Fully independent agents
 - Simple to implement
 - No communication between agents needed
 - Will continue working even if other agents malfunction
 - Can negatively affect neighboring agents
 - Can positively affect neighboring agents



- State sharing
 - Agent is aware of what is happening on neighboring agents
 - Easier to prepare for upcoming traffic
 - Affect neighbors without knowing



- Centralized state with distributed agents
 - Complete knowledge of the entire network
 - Is this good?
 - Is this bad?
 - It depends?
 - Still acting independently while affecting others



- Reward sharing
 - The agents receives positive reward if its neighbors perform well
 - How do we balance between local reward and global reward?
 - Easy! We introduce a scaling parameter β

$$r = LT(k) - LT(k+1) + \beta(\frac{1}{n}\sum_{m=1}^{n} LT_m(k) - LT_m(k+1))$$

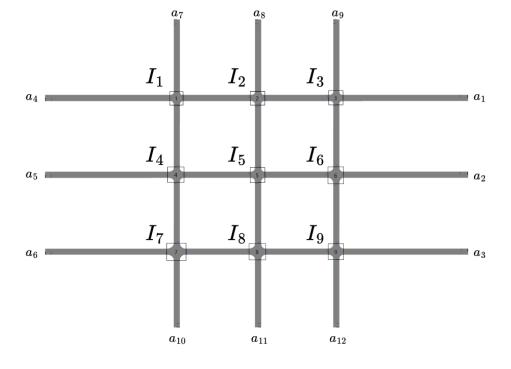
• $\beta = \{0.25, 0.5, 0.75, 1.00\}$

• Is this the answer to all our problems?



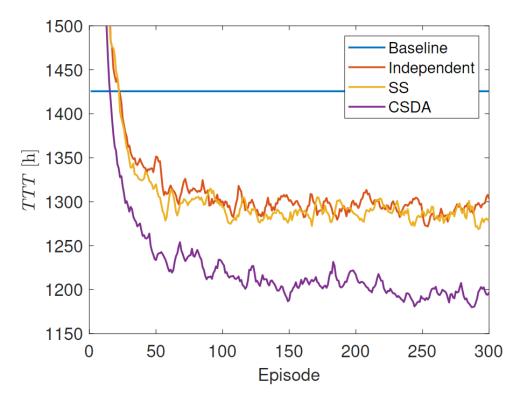


VISSIM model



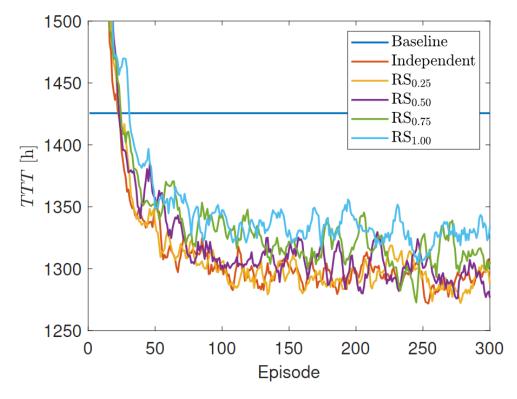






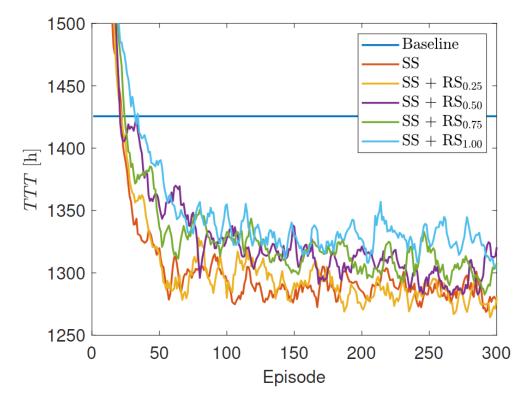






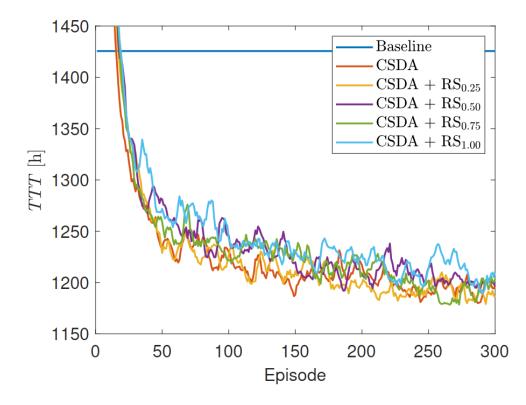
















	Baseline	2642	2758	3009	3494	3052	3524	2357	2359	2956	
TSC approach	Independent	2834	2758	2897	2900	2513	2967	2549	2386	2756	- 3400
	$\mathrm{RS}_{0.25}$	2861	2788	2901	2900	2550	2840	2567	2378	2807	
	$\mathrm{RS}_{0.50}$	2837	2775	2941	2883	2487	2944	2545	2377	2812	- 3200
	$\mathrm{RS}_{0.75}$	2747	2868	3035	2904	2606	2991	2542	2420	2886	
	$\mathrm{RS}_{1.00}$	2820	2843	3088	2983	2629	3041	2541	2352	2898	- 3000
	\mathbf{SS}	2848	2815	2881	2867	2496	2897	2583	2365	2728	- 3000
	$\mathrm{SS}+\mathrm{RS}_{0.25}$	2763	2787	2909	2897	2508	2882	2490	2355	2717	- 2800 II
C af	$\mathrm{SS}+\mathrm{RS}_{0.50}$	2833	2840	2957	2874	2559	2943	2529	2358	2853	- 2800 日
ST	$\mathrm{SS}+\mathrm{RS}_{0.75}$	2833	2792	2940	2932	2572	2922	2504	2370	2805	
	$\rm SS+RS_{1.00}$	2870	2843	3056	2992	2628	2933	2556	2380	2885	- 2600
	CSDA	2544	2479	2698	2558	2237	2605	2342	2183	2513	
С	$SDA + RS_{0.25}$	2545	2522	2663	2572	2240	2609	2337	2160	2517	- 2400
С	$SDA + RS_{0.50}$	2589	2484	2611	2572	2266	2597	2312	2182	2579	
С	$\mathrm{SDA} + \mathrm{RS}_{0.75}$	2529	2400	2608	2585	2187	2572	2357	2135	2483	- 2200
C	$SDA + RS_{1.00}$	2543	2457	2663	2665	2337	2586	2361	2132	2560	
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Putting it all together

- CVs give data
- GNG builds state representation
- Q-learning learns optimal control policy





Conclusion

- CV data important but mixed flows are ok
- Several families of algorithms analyzed
- CSDA performs the best with reward sharing





Future work

- Heterogenous agents
- Realistic traffic networks
- Environmental impact analysis
- Traffic safety analysis





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