Adaptive Action Selection Strategy Of Reinforcement Learning Approach For Intelligent Traffic Signal Control

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Overview

How to address the issue of adaptive exploration and exploitation when using Reinforcement Learning (RL) for traffic signal control (TSC) ?

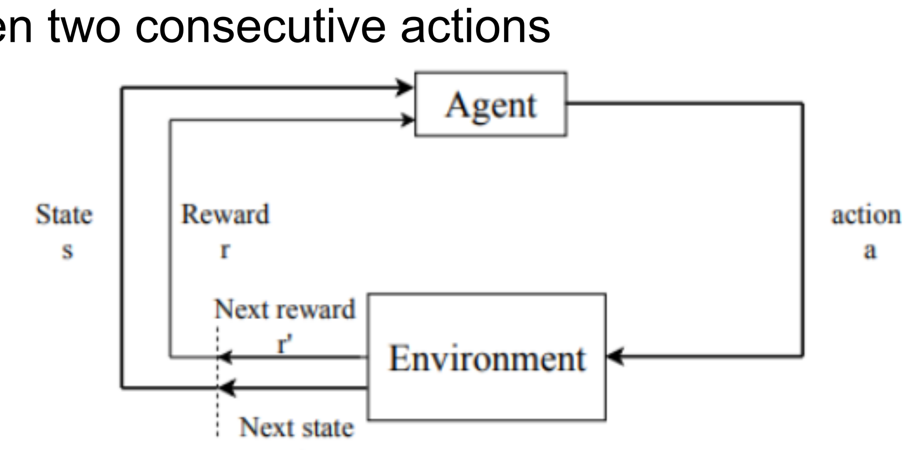
- Traffic signals are the major bottlenecks in urban areas and hence are major contributors to congestion
- Fixed time signal, actuated and adaptive signals are hard to be generalized in different scenarios
- TSC can be improved by adaptive learning algorithm in RL
- Balancing exploration & exploitation in RL models is important:
  - Too much exploitation: learning a sub-optimal policy finally
  - Too much exploration: leading to congestion currently
- Traditional exploration & exploitation methods, such as epsilon greedy (ε-greedy) in RL cannot handle this problem well
  - Will introduce hyper-parameters needed to be tuned
  - Hard to be generalized
- Challenges solved by our adaptive action selection strategy in RL, where agent adjust the policy based on different states

Methodology

Double Q learning Agent Design

- RL agent works as the central controller to update traffic signal timing at a single, isolated intersection
- State s: current green phase p; Discretized density K_i for each upstream lane i; Phase duration t, where $t = \begin{cases} t & t \le 60s \\ 60 & t > 60s \end{cases}$
- Action a: action 1 is green phase for NS, action 2 is green phase for EW.
- Reward r: total delay between two consecutive actions

Intersection



Interactions between agent and environment

Exploration/Exploitation Strategies

Baselines

- Fixed time signal
- ε-greedy: with a fixed ε to perform random actions
- Time-decayed ε-greedy: with a decayed ε to perform random actions
- Upper confidence bound (UCB): select the action that has the highest estimated action-value plus the upper-confidence bound term

Our Adaptive ε-greedy Strategy

- Extend the ε-greedy strategy to a state-dependent exploration rate $\varepsilon(s) = 1/\sqrt{n(s)}$, n(s) is the number of times state s has been visited

Experiments results

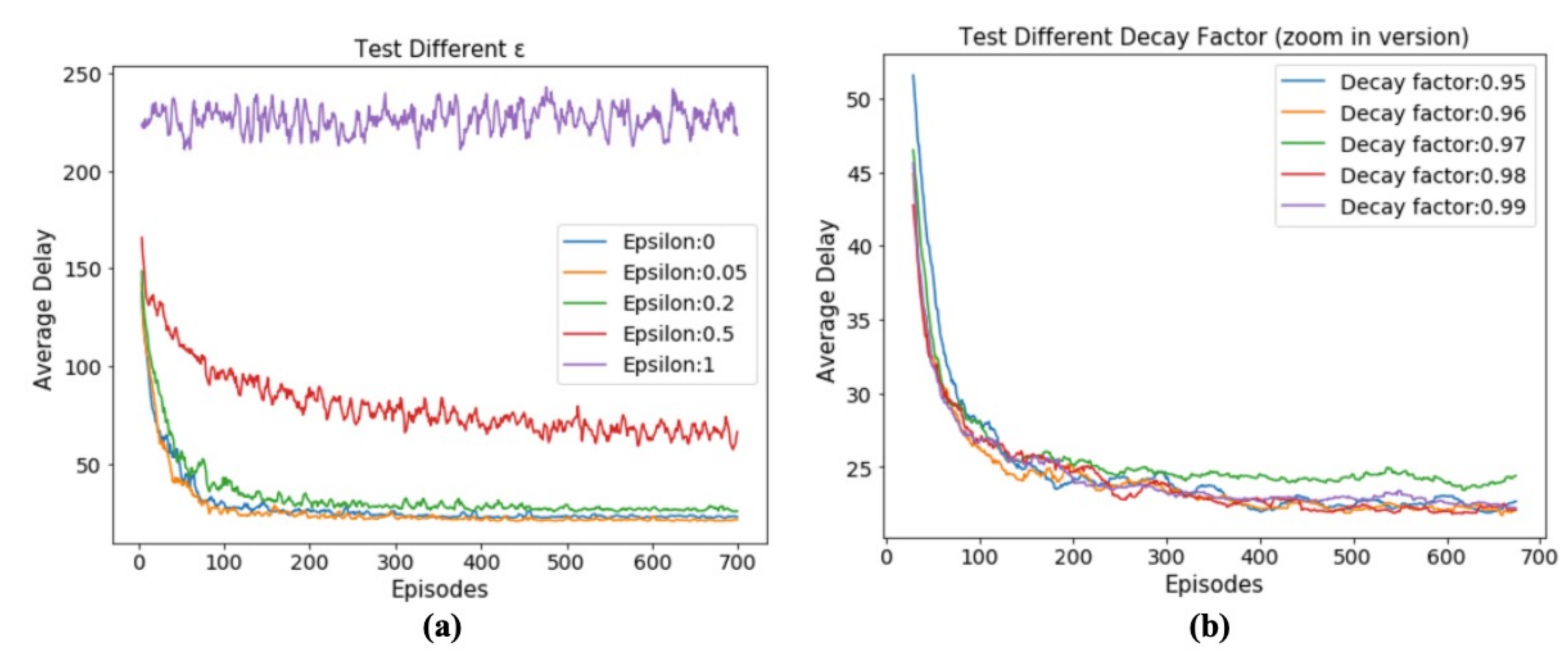
Model Overall Performance

- Performance is measured by the average delay on different flow configuration, where ε-greedy with ε of 0.05

Flow N/S (veh/h/lane/ direction)	Flow E/W (veh/h/lane/ direction)	Fixed-Time(s)	Adaptive ϵ-greedy(s)	UCB(s)	ϵ-greedy(s)
700	700	26.44 ± 0.046	**19.77 ± 0.0539**	20.53 ± 0.0324	21.11 ± 0.0856
500	900	24.21 ± 0.0364	**19.56 ± 0.0385**	22.23 ± 0.1627	22.81 ± 0.0280
400	1000	22.87 ± 0.0487	**21.41 ± 0.0694**	20.04 ± 0.1095	22.83 ± 0.1050
600	900	31.07 ± 0.0459	**22.17 ± 0.0289**	23.51 ± 0.3866	23.75 ± 0.5279
700	900	28.34 ± 0.0596	**26.77 ± 0.2352**	28.12 ± 0.2592	28.21 ± 0.1992
800	900	47.67 ± 0.0725	**28.60 ± 0.0793**	31.42 ± 0.2222	29.15 ± 0.1510
700	1000	46.13 ± 0.0653	**29.48 ± 0.1449**	35.75 ± 0.4246	30.61 ± 0.3029

Exploration/Exploitation Comparisons

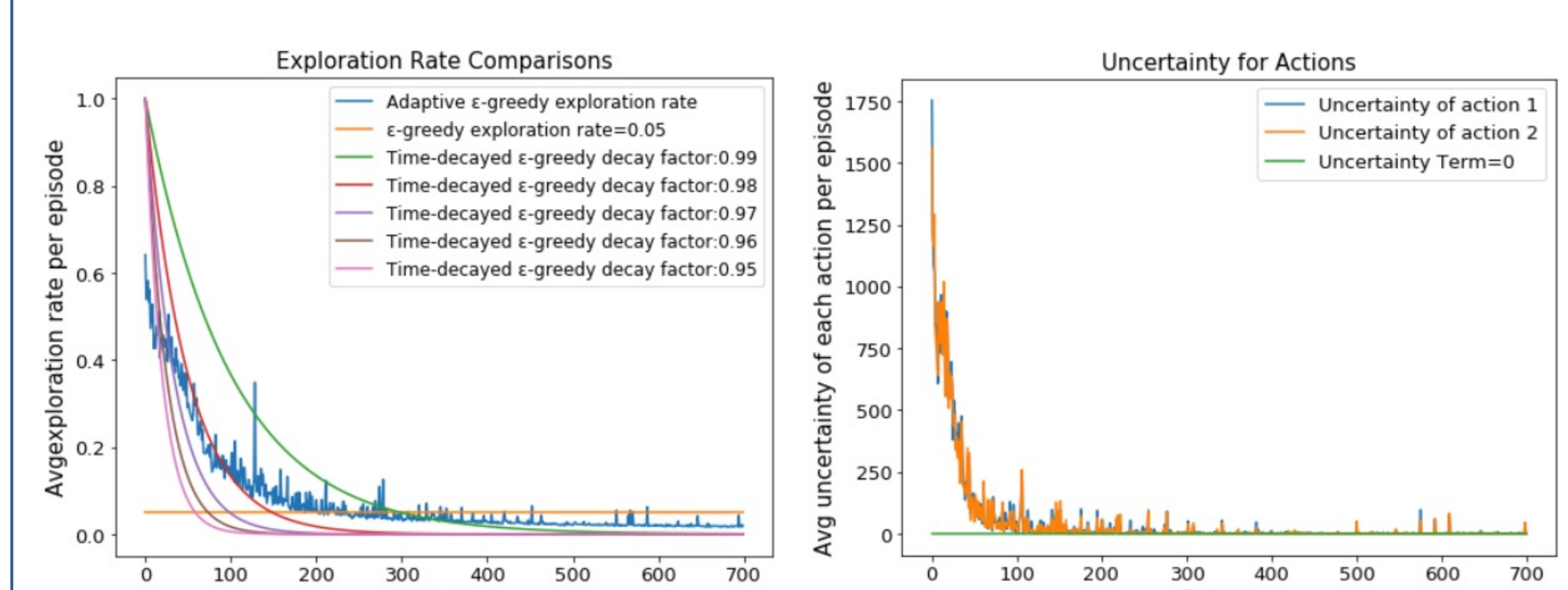
- A case study
  - Flows of 500 vehicles/h/lane for NS direction and 900 vehicles/h/lane for EW direction
  - Comparing the exploration/exploitation process of different models
- Tune hyper-parameters for ε-greedy (a) & time-decayed ε-greedy (b)



- After finding the best hyper-parameters, testing results - average delay for different models:

Model	Average Delay (s)
Adaptive ε-greedy	**19.562 ± 0.0385**
UCB	22.2274 ± 0.16269
Best ε-greedy	22.1138 ± 0.0280
Best Time-decayed ε-greedy	21.7625 ± 0.0646
Fixed time	24.21 ± 0.0364

- Average exploration rate comparisons and uncertainty during training:



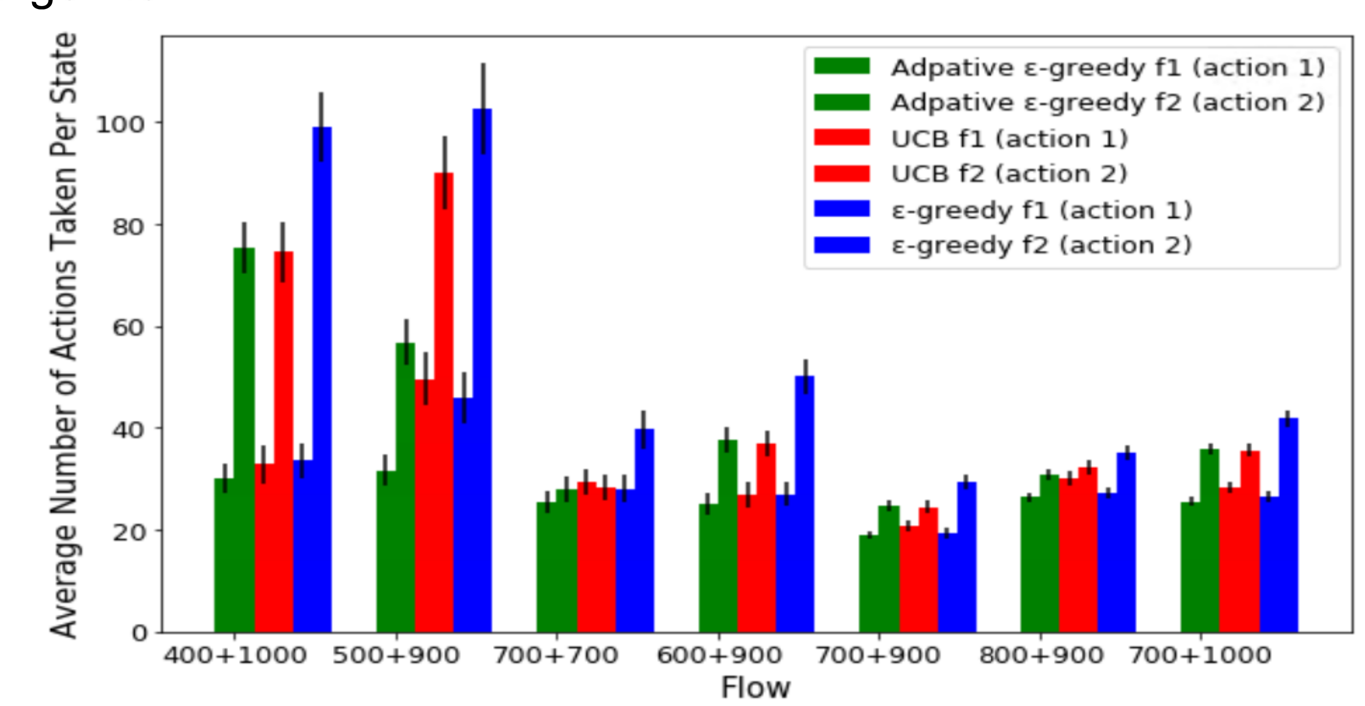
Experiments results

Numerical Comparisons among Different Strategies

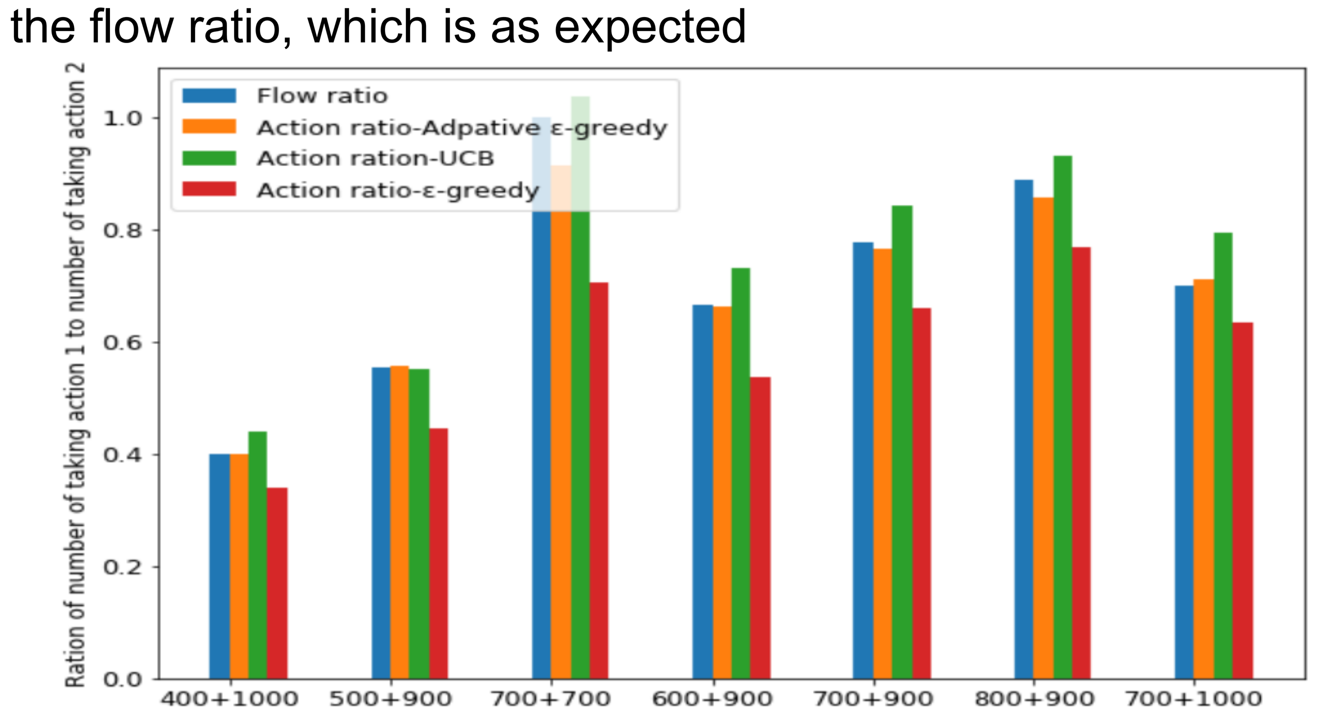
- Our adaptive strategy could explore more unique state under different scenarios:

Model	Flow (Veh/h/lane/direction)						
	400×1000	500×900	700×700	600×900	70×900	800×900	700×1000
Adaptive ε-greedy	16897	28342	46041	39127	53960	62578	58918
UCB	15949	24206	41205	37104	50449	57037	54903
ε-greedy	13258	16630	36595	32198	48342	56283	52873

- Agent takes action 2 (EW green) more frequently compared to taking action 1 (NS green) for all unbalanced flow setting where EW has larger flow



- Action ratio of the adaptive ε-greedy strategy is always the closest one to the flow ratio, which is as expected



Concluding Remarks

- Addresses the issue of adaptive exploration when using RL for traffic signal control, considering the agent's uncertainty for the environment
- Advantages of the adaptive ε-greedy strategy with double Q-learning:
  - Outperforms baselines and results in lower delays and highly compatible under different scenarios this approach
  - Explore more states with no hyper-parameters needed to be tuned
- The policy learned by the agent keep the action ratios consistent with the flow ratio, which leads to low delays
- Work only tested on a simple intersection setting; future work could apply the model to an intersection with right turns and lest turns