



Reinforcement Learning for Mixed-Autonomy Traffic

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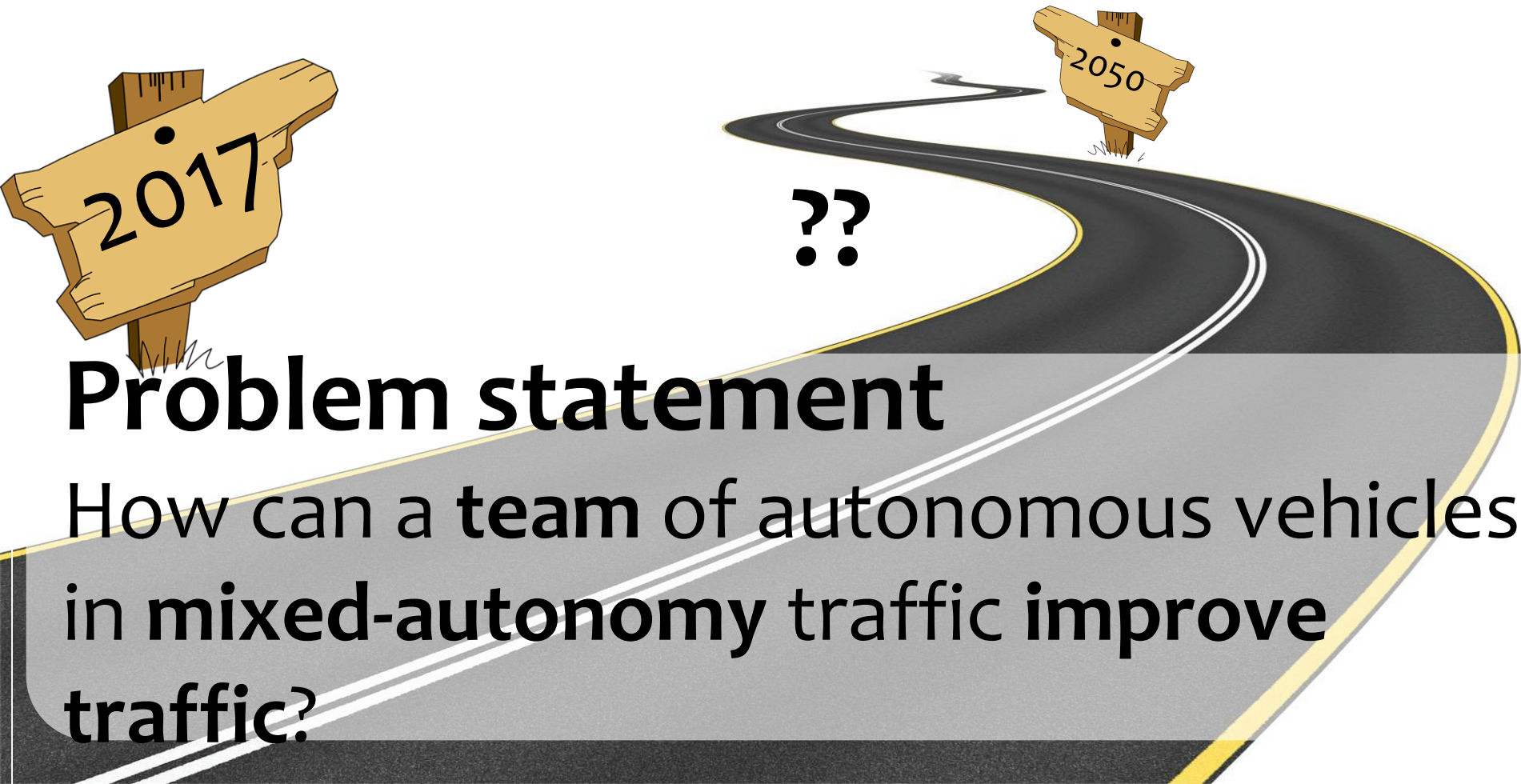
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2017-08-23





The Mathematical Society of Traffic Flow

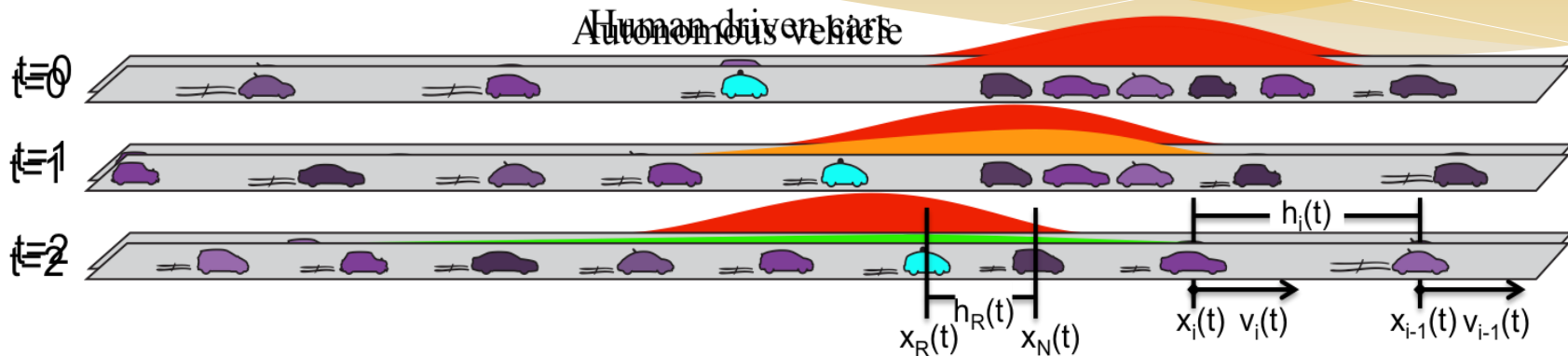
What happens **between 0% and 100%** penetration of autonomous vehicles?



Problem statement

How can a **team of autonomous vehicles in mixed-autonomy traffic improve traffic?**

Problem setup



Linear dynamics:
$$\ddot{\tilde{x}}_i = k_p(\tilde{x}_{i-1} - \tilde{x}_i) + k_d(\dot{\tilde{x}}_{i-1} - \dot{\tilde{x}}_i) - k_v(\dot{\tilde{x}}_i)$$

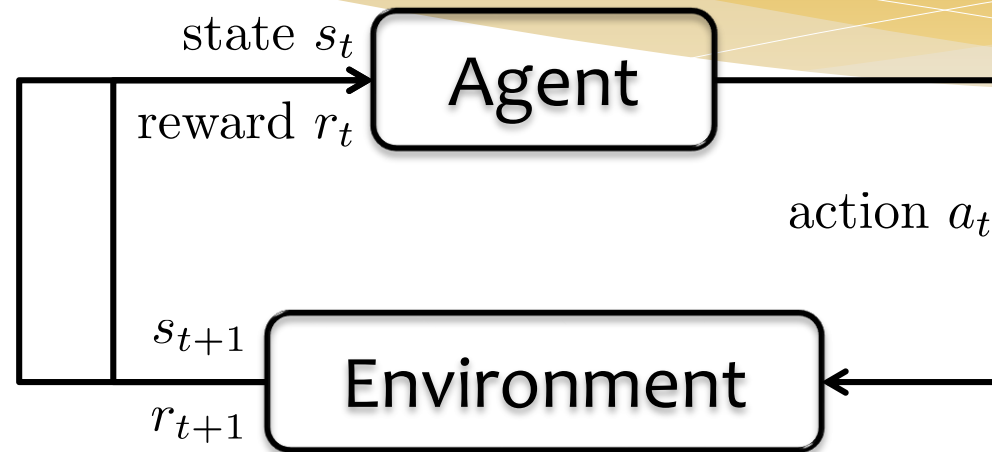
Robot control:
$$\ddot{\tilde{x}}_i = k_{p_r}(\tilde{x}_{i-1} - \tilde{x}_i) + k_{d_r}(\dot{\tilde{x}}_{i-1} - \dot{\tilde{x}}_i) - k_{v_r}(\dot{\tilde{x}}_i)$$

 [Cui, et al., IV, 2017; Wu et al., In submission, 2017]

Alternatively:
$$\ddot{\tilde{x}}_i = f(\tilde{x}_{i-1}, \tilde{x}_i, \dot{\tilde{x}}_{i-1}, \dot{\tilde{x}}_i)$$

 [Wu et al., In submission, 2017]


Reinforcement learning



Goal: learn policy $\pi : S \rightarrow A$ to maximize reward

Example:

$$\begin{aligned} \max \quad & -(\text{total fuel consumption}) + \\ & -\lambda(\text{total travel time to destination}) \\ \text{s.t.} \quad & \text{no collisions} \end{aligned}$$

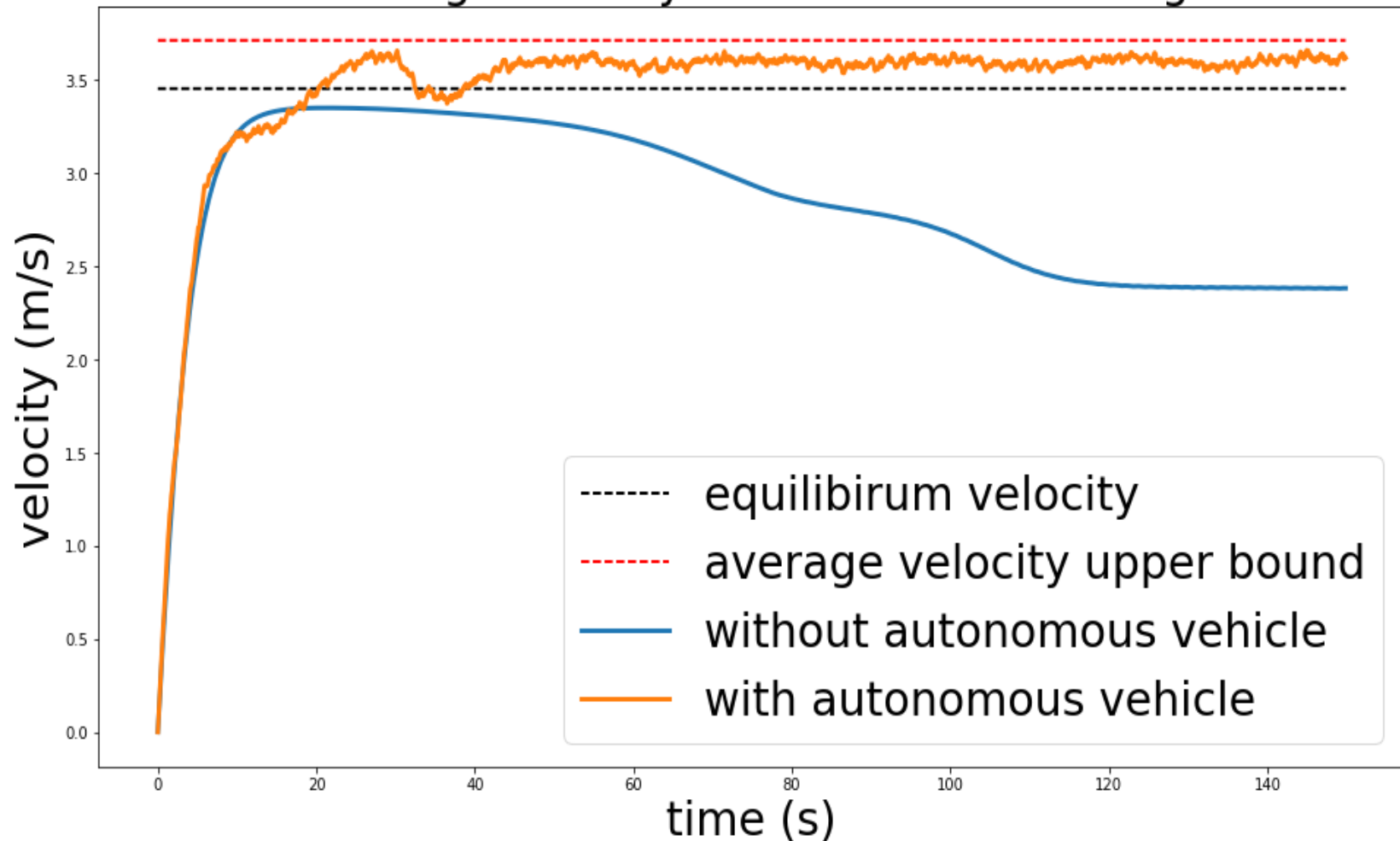


Single-lane ring road
1 RL, 21 human

Reward function: deviation from target velocity

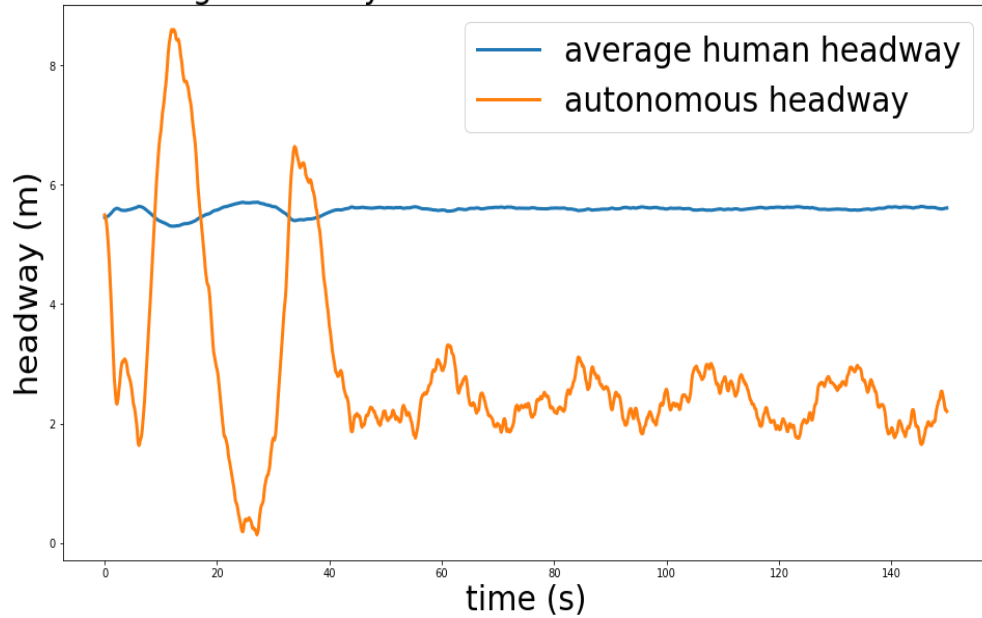
Velocity Improvement!

Average velocity of vehicles on the ring

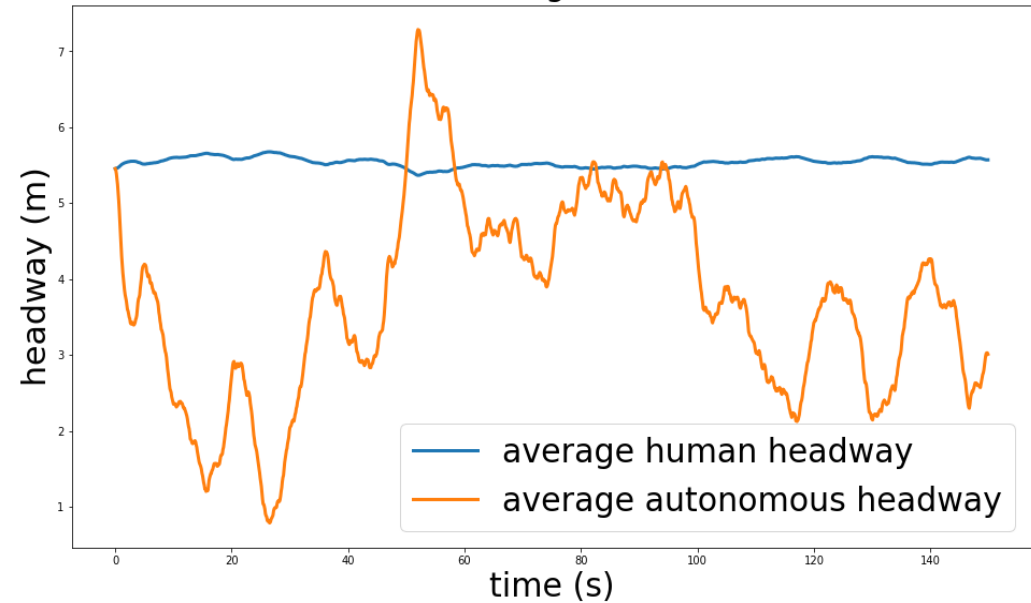


Tailgating speedup

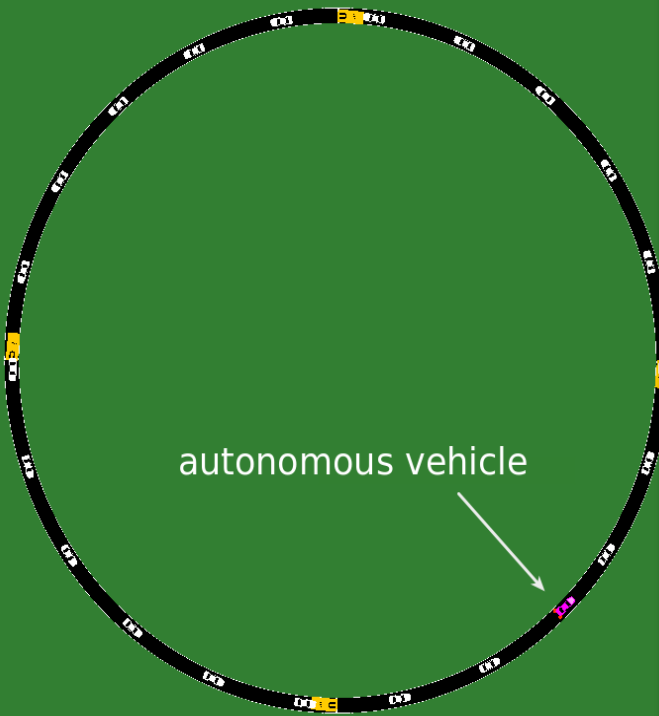
Average headway of human and autonomous vehicles



Average headway of human and autonomous vehicles with 0.5 m/s² gaussian noise



Single-lane ring



Multi-lane ring

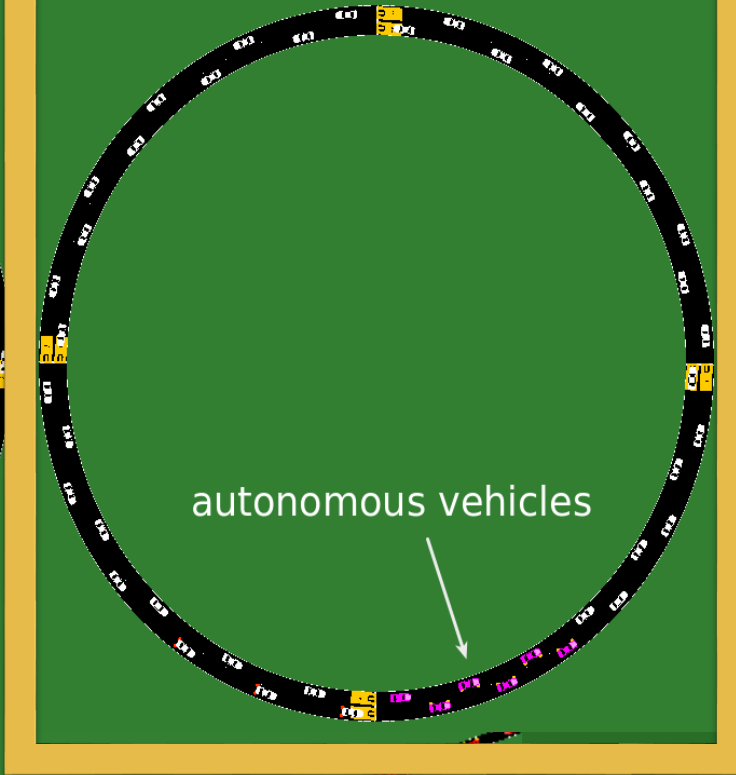
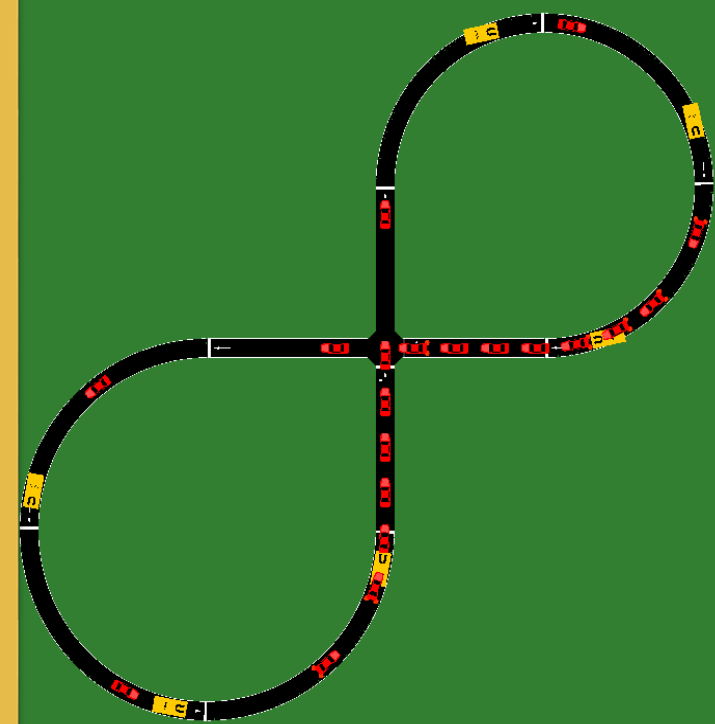
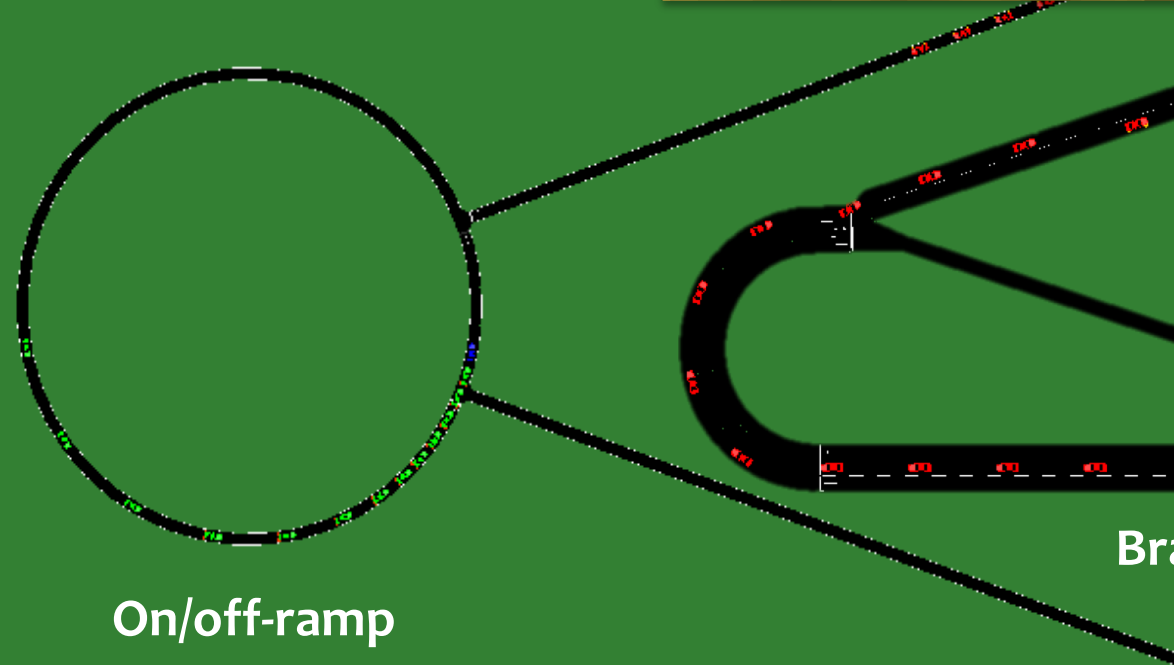


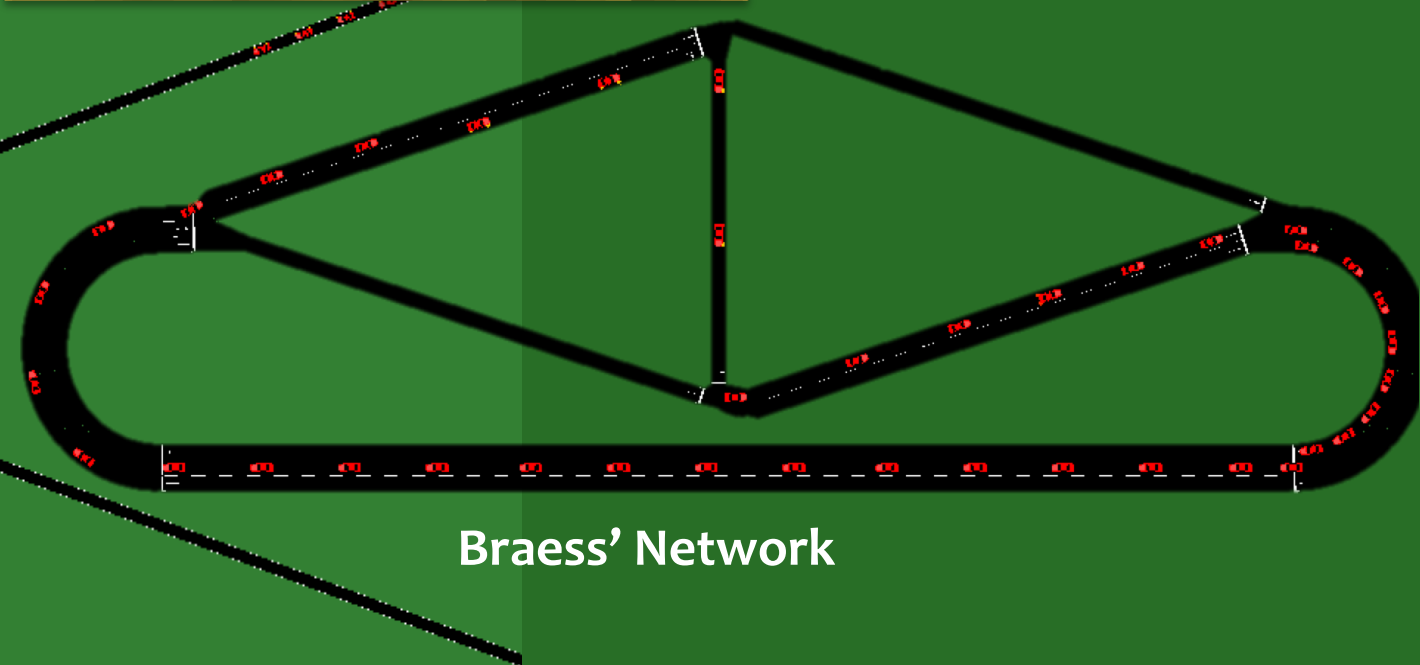
Figure 8



On/off-ramp

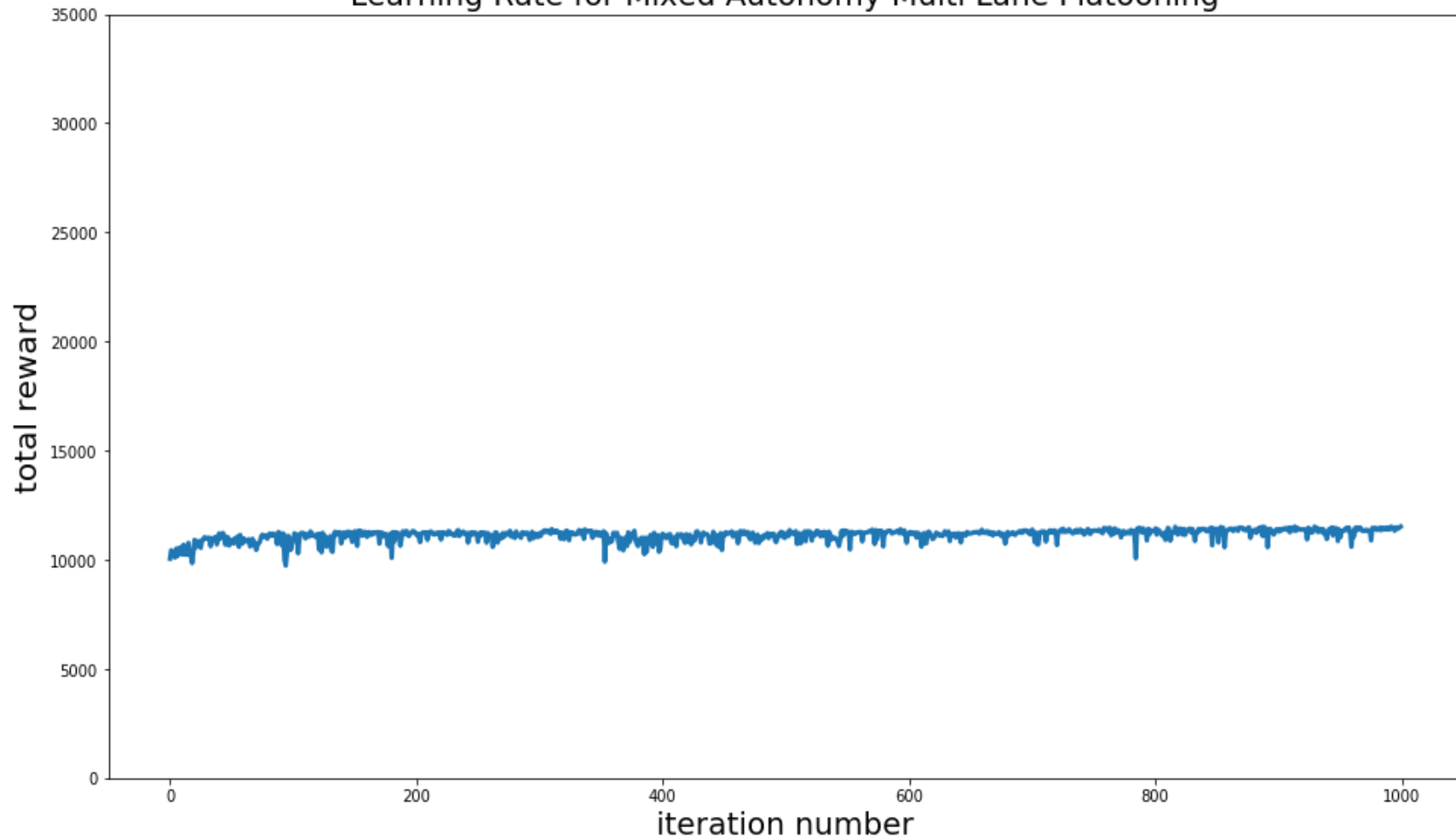


Braess' Network



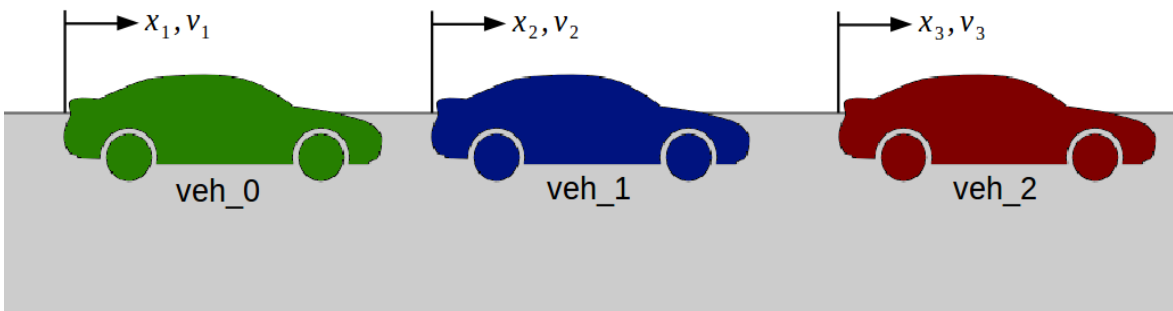
Multi-lane Platooning

Learning Rate for Mixed Autonomy Multi Lane Platooning

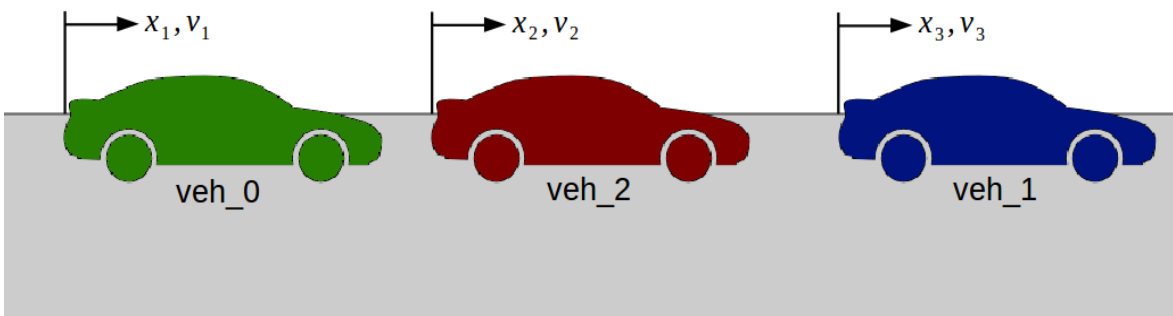


MDPs with symmetry

Challenge: poor sample efficiency due to combinatorial explosion in state and action spaces.

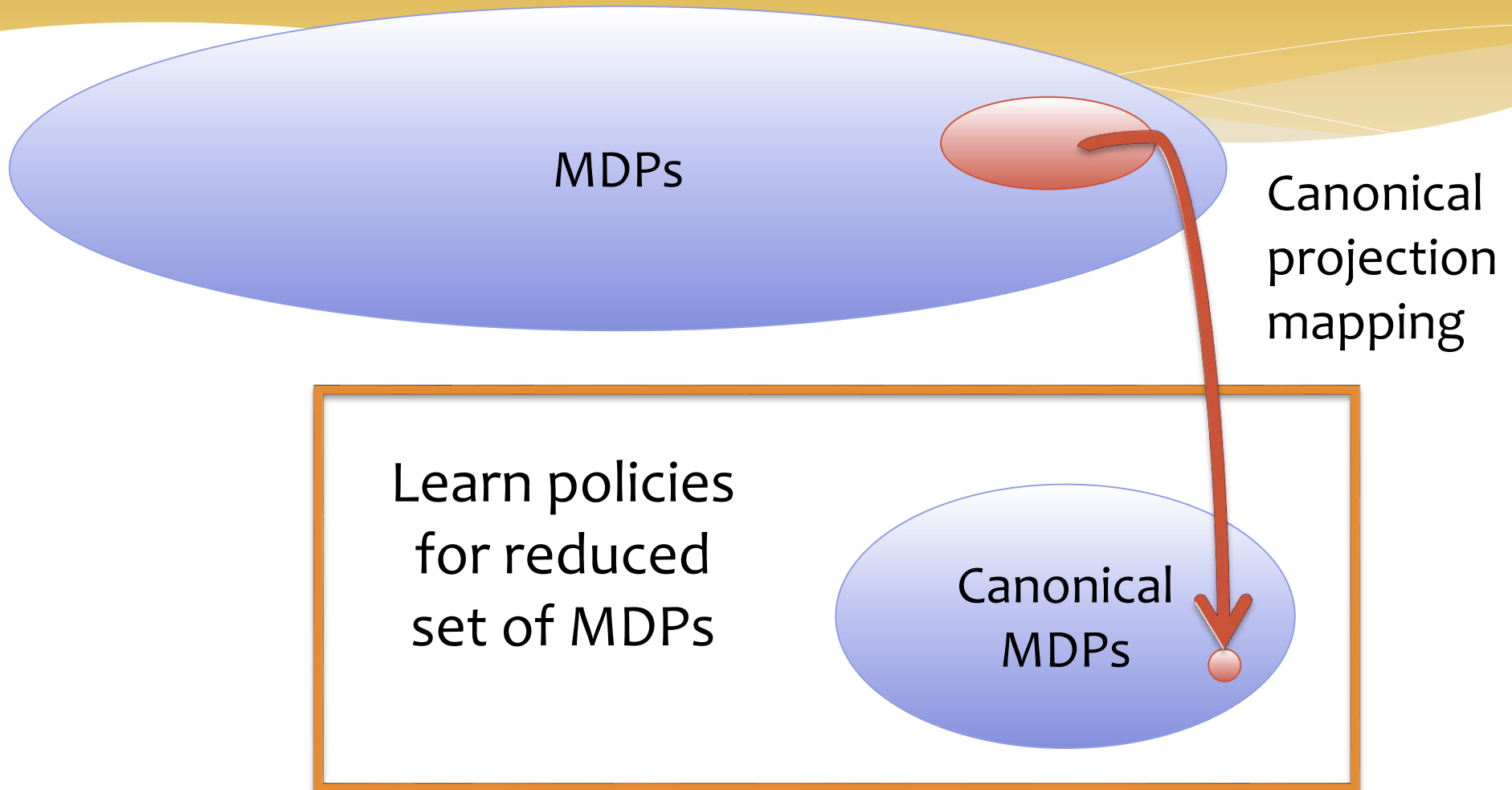


$$s = (x_1, v_1, x_2, v_2, x_3, v_3)$$



$$s = (x_1, v_1, x_3, v_3, x_2, v_2)$$

MDPs with symmetry



Proposed canonical projection mapping:
Selective sorting of the state space

Canonical Projection Result

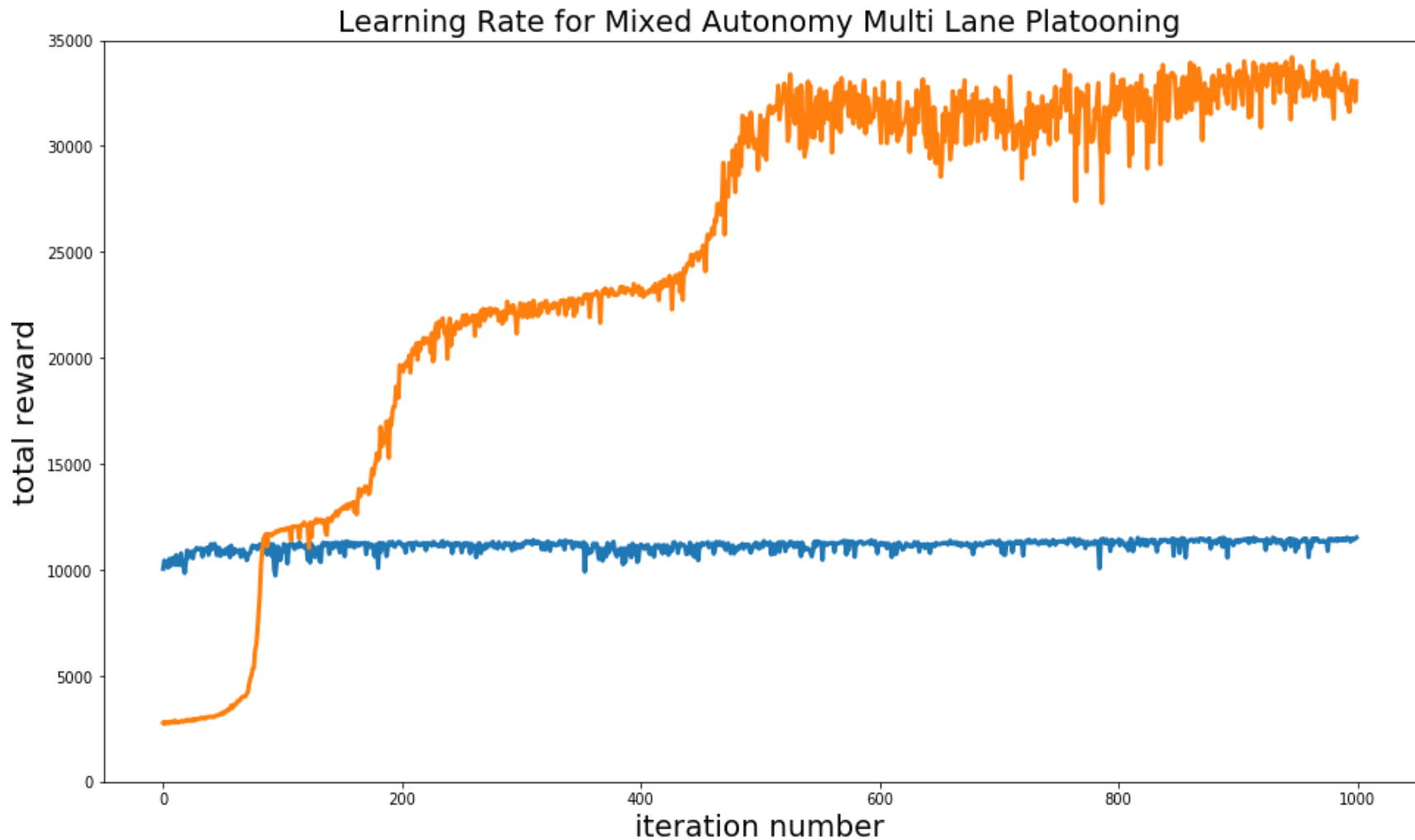


Figure 8 (1 RL)

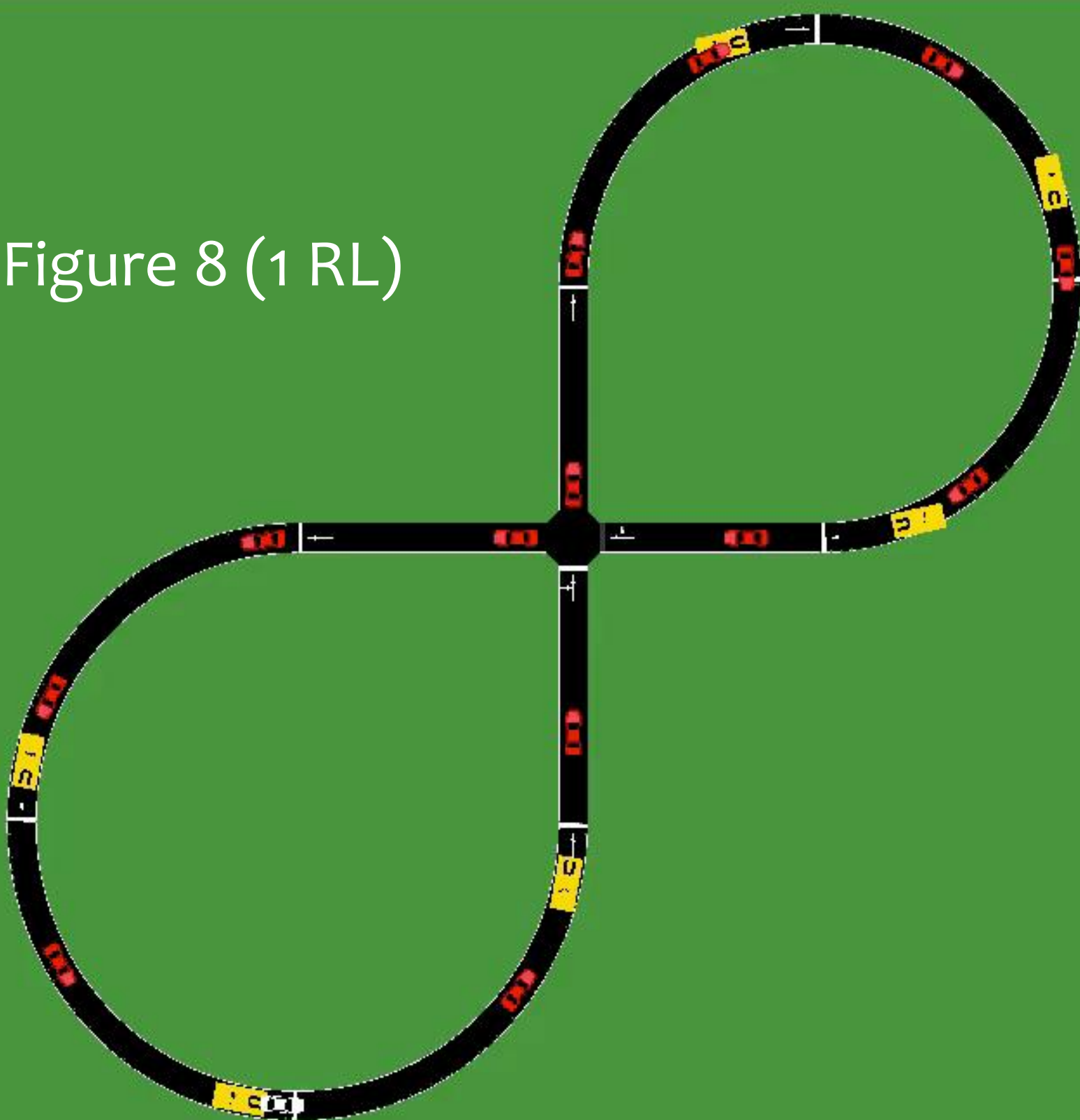
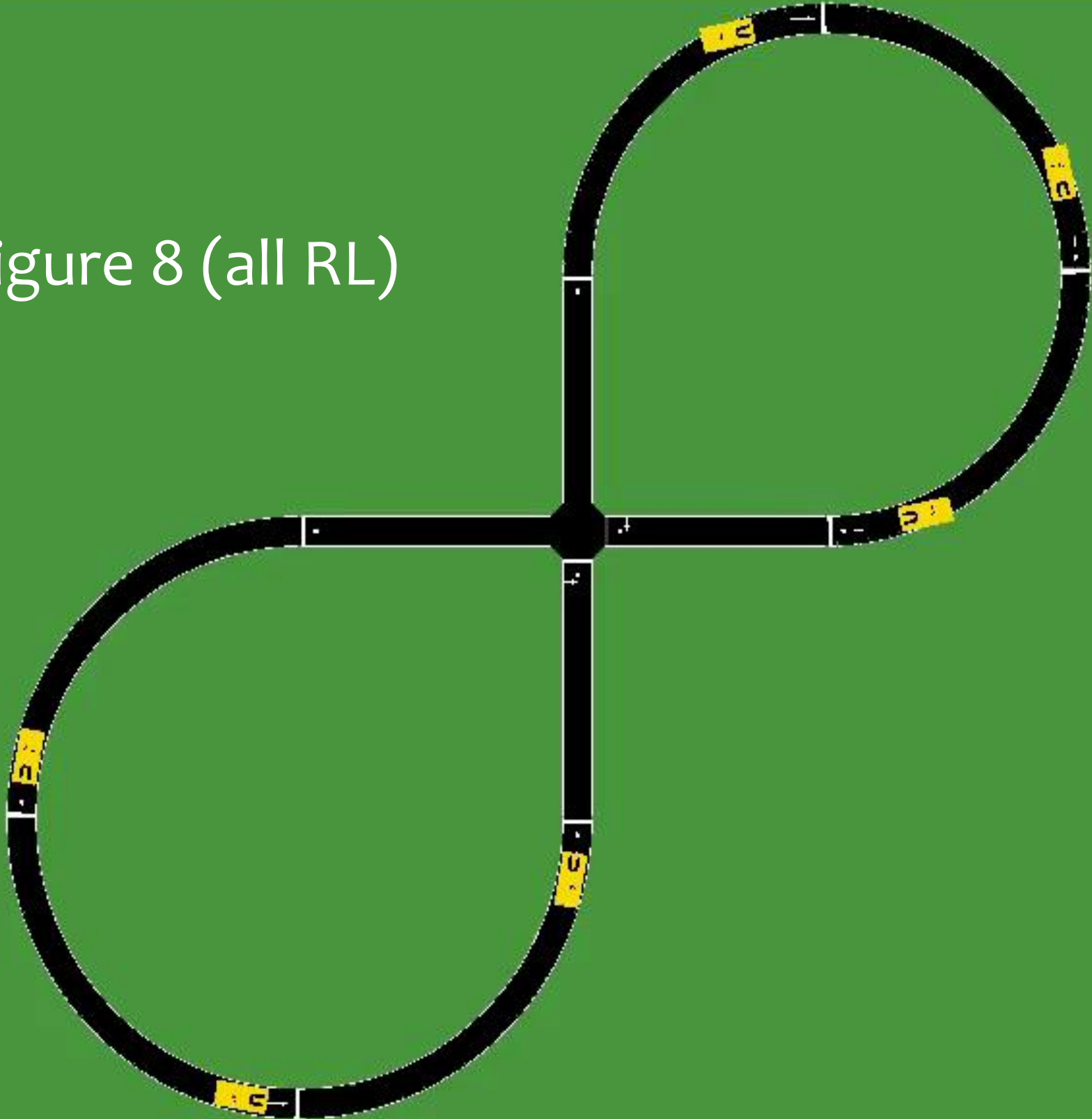
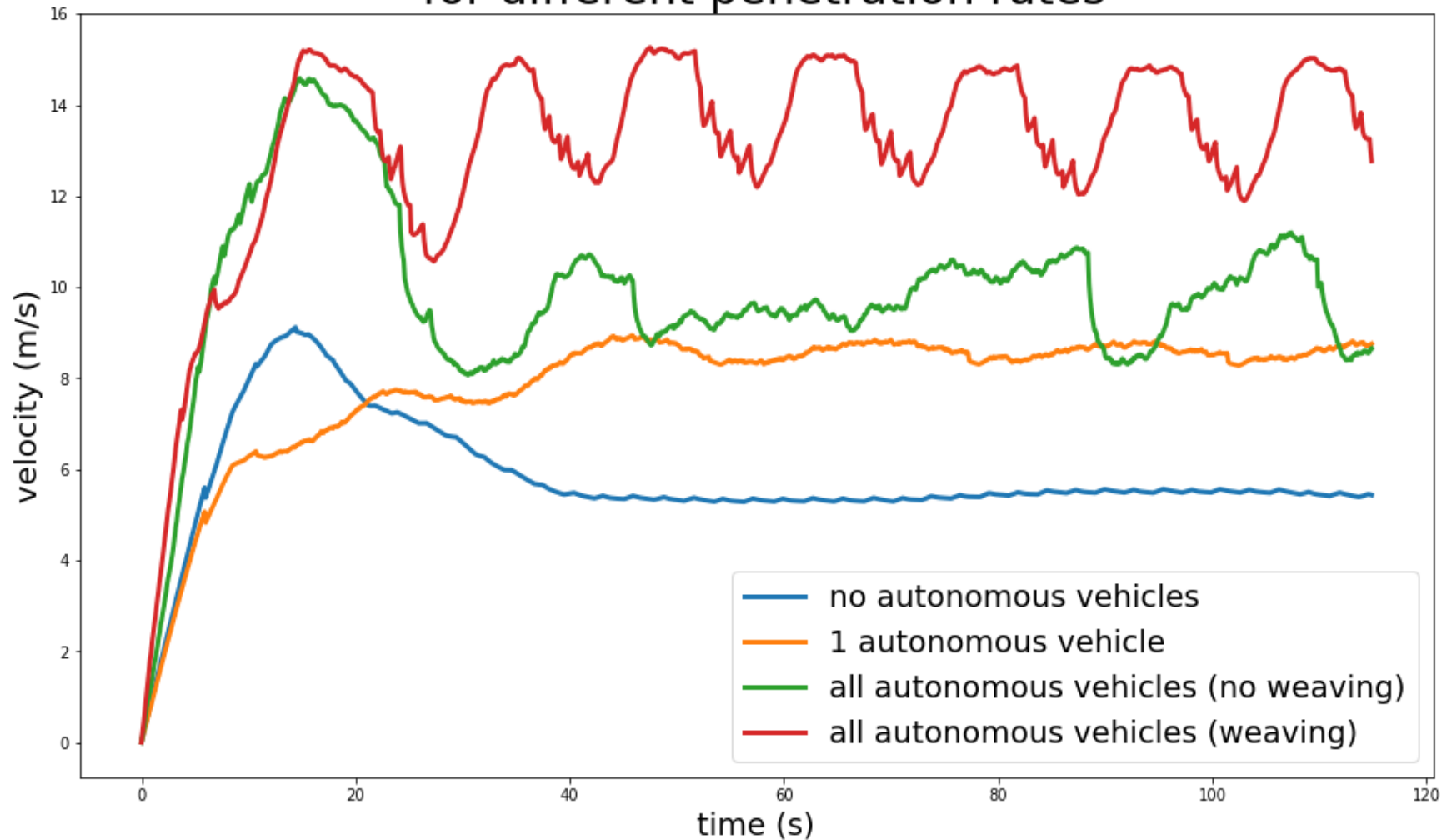


Figure 8 (all RL)



Mixed-Autonomous Comparison

Average velocity of vehicles in the figure 8 for different penetration rates



Current work and opportunities

Control \leftrightarrow reinforcement learning

- * Learning minimal controllers
- * Proving optimality for learned controllers

Advancing reinforcement learning research

- * Scaling up multi-agent learning algorithms
- * Representation learning for sample efficient learning in MDPs with symmetry and locality

Advancing intelligent transportation research

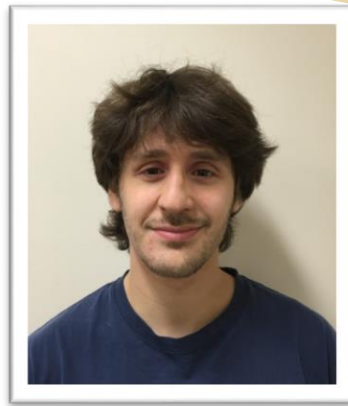
- * Supporting large-scale networks
- * Learning for mixed-control (intersections, speed limits, AVs).

Learning-traffic team

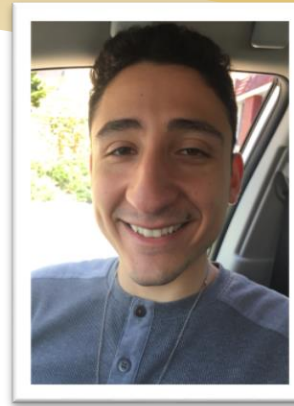
Graduate researchers



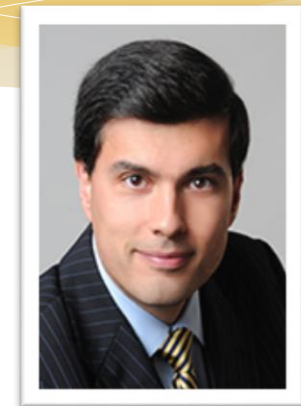
Cathy Wu
Team lead, EECS



Eugene Vinitzky
MechE



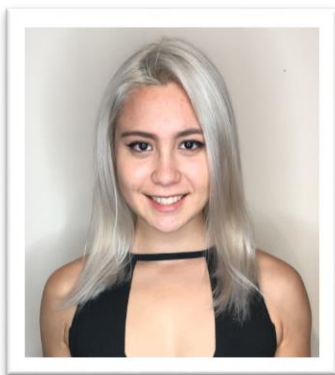
Aboudy Kreidieh
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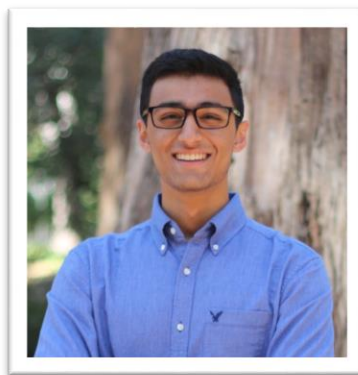
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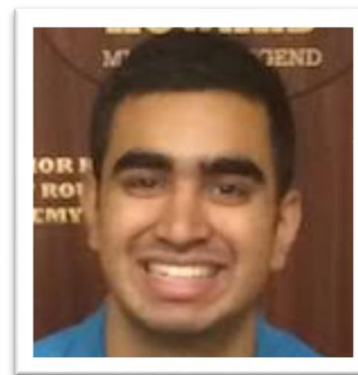
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