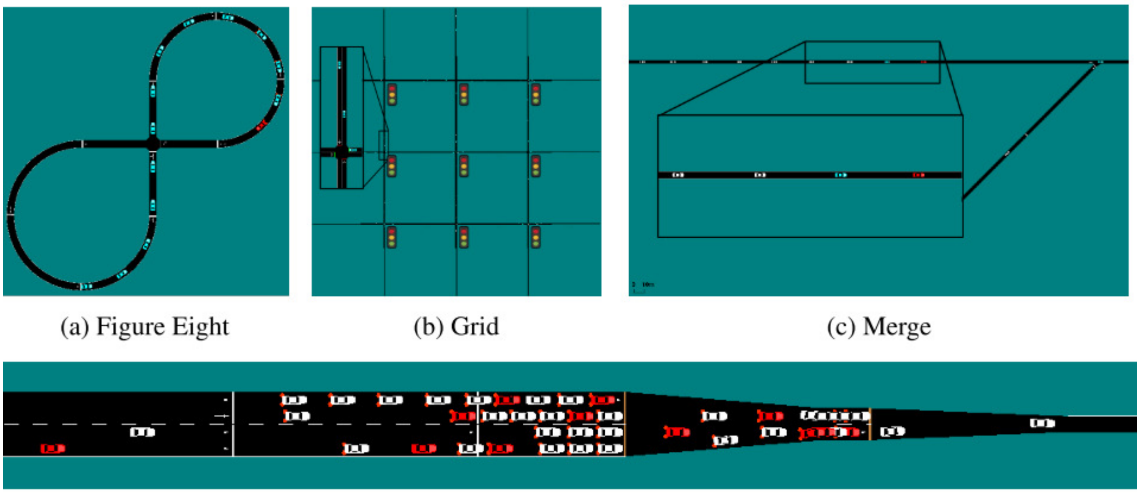
Project Proposal **Toshinori Kitamura**
EEC 193

1 Overview & Problem Description

In this project, I'm going to work on the mixed-autonomy traffic, where both automated and human-driven vehicles present. The goal is to develop a reinforcement learning(RL) agent which maximizes system-level traffic velocity. Moreover, for the novelty the agent is going to achieve the followings.

- Reduce enough amount of traffic congestion.
- Trained on a ring road, and transferred to some practical and complex roads(Fig. 1)
- Using the multi-agent method

The motivation and the previous works of them are described in the other sections.



(a) Figure Eight (b) Grid (c) Merge

(d) Bottleneck

Figure 1: Complex traffic environments in the simulation "flow"(cited from [1])

2 Motivation

The reason why mixed autonomy is important is due to the energy consumption by the traffic. Some studies demonstrate that a small number of vehicles in congested traffic can result in a 13-40% reduction in fuel consumption[2]. Since 28% of energy consumption in the US is due to the transportation[3], reducing traffic congestion can save huge amount of energy.

The motivations of using RL, transfer learning and multi-agent are as follows:

- RL: To reduce the congestion in complex traffic systems where no model-based methods are applicable.
- Transfer learning: Reduce the amount of training in the environments where training is high-cost.

- Multi-agent : 1. To make the model flexible to its number of agents. 2. To avoid the vulnerability of one master controlling.

The details of the motivation will be described in the next section.

3 Previous Works

To control the system-level traffic velocity, both model-based and model-free methods have been studied so far. The model-based methods give analytical solutions to maximize the traffic efficiency, but the situation it can be utilized is very limited. For example, the model-based controllers "Follower Stopper" and "PI with Saturation" [4] can reduce the congestion in a ring road, but it doesn't give the optimal solution in the complex environments such as bottleneck and figure-eight(Fig.1). Due to the complex model of the real world traffic, the model-based methods are not applicable to many situations. On the other hand, some studies shows that model-free reinforcement learning(RL) can reduce the traffic congestion even in complex situations. [1] applies some state-of-the-art RL algorithms to complex traffic shown in Fig. 1, and most of the methods achieve better score than the situation with only human driven car.

Even though the RL works in simulation environment, there is a huge gap between the simulation and the real world. Training in the real world is necessary, but it often takes a lot of cost. For example, if we want to use the model in the highway, the model has to be trained in the real highway, but training the model on a highway from the beginning to the end is impractical. Transfer learning is a method to solve the problem. [5] shows an agent trained in a ring road can reduce the amount of traffic congestion in a highway even though it's not trained in the highway.

Currently there is no RL car in the real traffic, but it doesn't mean the RL cars don't work in the real world. [6] achieves to transfer the agent from simulation to a scaled city without retraining, and it successfully smooth the traffic. Even though it doesn't train the agent again in the real world, the agent still has the potential to reduce the traffic congestion.

In this project, I'm going to extend that transfer learning work[5] and develop more practical agent. One remaining problem in [5] is that it only uses one agent to control multiple cars. It's not flexible when the number of the car changes. Moreover, from the view of cyber security, one master node controlling the acceleration of the cars is dangerous.

4 Timeline/Quarter Goals

1. -4/8: Setup docker environments. Research SOTA algorithms. Test the benchmarks.
2. 4/8 - 4/15: Develop evolution strategy method. Write codes for transfer learning.
3. 4/15 - 4/22: Test the performance of transferred agent. Develop multi-agent RL method.
4. 4/22 - 4/29: Test the multi-agent RL method. Adjustment(Parameter tuning, reward design, etc)
5. 4/29 - 5/10: Adjustment. Prepare for the presentation. Summarize the results.
6. 5/10: Presentation

5 Weekly Meeting Times

I'm convenient at the following time:

- MON: 10-12 am, After 6 pm.
- TUE: 10-11 am, After 4:45 pm
- WED: Before 5 pm
- THU: 10-11 am, After 4:45 pm
- FRI: 12-3 pm, After the weekly meeting

References

[1] Eugene Vinitsky, Aboudy Kreidieh, Luc Le Flem, Nishant Kheterpal, Kathy Jang, Cathy Wu, Fangyu Wu, Richard Liaw, Eric Liang, and Alexandre M Bayen. Benchmarks for reinforcement learning in mixed-autonomy traffic. *Proceedings of The 2nd Conference on Robot Learning*, 87(CoRL):399–409, 2018.

[2] Cathy Wu. *Learning and Optimization for Mixed Autonomy Systems - A Mobility Context.* PhD thesis, EECS Department, University of California, Berkeley, Sep 2018.

[3] U.S. Energy Information Administration. Monthly Energy Review. Technical report, 2017.

[4] Raphael E. Stern, Shumo Cui, Maria Laura Delle Monache, Rahul Bhadani, Matt Bunting, Miles Churchill, Nathaniel Hamilton, R'mani Haulcy, Hannah Pohlmann, Fangyu Wu, Benedetto Piccoli, Benjamin Seibold, Jonathan Sprinkle, and Daniel B. Work. Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments. *Transportation Research Part C: Emerging Technologies*, 89:205–221, may 2018.

[5] Abdul Rahman Kreidieh, Cathy Wu, and Alexandre M. Bayen. Dissipating stop-and-go waves in closed and open networks via deep reinforcement learning. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, 2018-Novem:1475–1480, 2018.

[6] Kathy Jang, Eugene Vinitsky, Behdad Chalaki, Ben Remer, Logan Beaver, Andreas A Malikopoulos, and Alexandre Bayen. Simulation to Scaled City: Zero-Shot Policy Transfer for Traffic Control via Autonomous Vehicles. page 10.