Traffic Flow Control by Autonomous Vehicle Fleets
Group A1

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Abstract

The abstract should briefly summarize your project in 150–250 words.

1 Introduction

This research project will be concerned with analyzing how the emergence of autonomous vehicles (AVs) in cities is going to change the cities' current traffic flow. A lot of research has investigated the potential impact of AVs on traffic conditions already. One paper investigated how the launch of AV taxi fleets would concretely change the traffic flow in and around Berlin [MB16]. The paper concludes that the launch of AVs would relax the current road conditions coined by traffic congestion. This could be achieved because AVs owned by a taxi fleet could perform many jobs for many independent individuals in a row, while privately owned cars only carry a limited number of passengers each day, being parked for the rest of the day.

1.1 Problem

However, the paper also concludes that even the introduction of AV taxi services could not handle a huge further increase in the number of cars present in a given city. Whilst this research seems relevant to the situation of the general public, where human drivers cooperate with AVs, it does not shine a light on the possible advantages of companies maintaining the taxi fleets used in these future scenarios. In such a scenario AVs will be cooperative within their own fleet of vehicles, but they will collectively compete with the set of human drivers in the shared environment. Our research question will therefore be two-fold:

1. What percentage of cooperating AVs is needed to be owned by a single organisation to significantly drop their combined travelling time?
2. What is the effect on the average travelling time for the non-cooperating cars?

1.2 State of the art

The uprise of the presence of AVs in real life traffic environments constitutes in mixed-autonomy traffic: human drivers sharing the road with autonomous drivers. A mixed-autonomy setting naturally implies that both types of drivers, humans and AVs, have to cooperate. The focus of this cooperation is centered on the behavior of AVs as human drivers have already established a cooperative environment. In [Vin+18], several reinforcement learning (RL) benchmarks have been proposed to fulfill this task. This study explores how AVs could be able to learn to adjust and adapt their own policies to human-driver policies through RL, whereas earlier studies focused on handcrafted control laws.

Pure autonomous environments have also been studied with RL implementations. In [Low+17], RL has been used for policy-learning in mixed multi-agent cooperative-competitive environments.

1.3 New idea

[Vin+18] have proposed a method in which the AV policies are learned with a centralized controller. By implementing a decentralized controller the approach is effectively transformed in a multi-agent approach.

2 Method

2.1 Simulation model

For this research the simulation software Flow is used in combination with the open-source framework Ray/RLLib, which allows the implementation of RL algorithms. Several settings of the existing multi-agent environments are adopted and adjusted to serve the specific needs for this project. Action space, rewards, etc.

2.2 Implementation details

Regarding the implementational side of the project, it is planned to run a traffic simulation based on the simulation software Flow, where human drivers are going to be modeled by existing controllers provided by the Flow package, while the control architecture for the cooperating agents is going trained in the course of this paper. Deep Reinforcement Learning (RL) is going to be used for training the controller of the cooperating cars. The RL based controller will be trained by all agents being part of the simulated AV taxi fleet. This controller will be applied to each of the taxi agents locally, such that the controller is going to choose actions for each car individually with respect to the respective car's current situation and private history of most recent states. In a first step, only the lane change controller will be learned by a Deep-Q-learning agent. In a second step, also the speed controller provided by the Flow package, which is going to be applied in the first phase of the project, is going to be replaced by a Deep RL agent, if time allows.

2.3 Experiment design

Current experiment design is concerned with finding suitable reward functions, action state representation and finding a way to decrease total computation time for training the underlying

TensorFlow model through Google Colab.

3 Results

3.1 Experiment findings

Key question 4: What are the results you obtained?

If you have numeric results, it is usually good to use a Table, like Table 1. You might also use plots or graphs, for example using the `pgfplots` package.

Setup	run time	success rate
1	0.123	12%
2	0.456	34%
3a	0.789	56%
3b	1.234	78%

Table 1: Tables should always have a caption.

3.2 Interpretation of findings

Summarise your results. Are the results what you expected? Which results are surprising? How do you interpret them?

4 Conclusion

4.1 Discussion

What do you take away from your project? What did you learn?

4.2 Relevance

Key question 5: What is the relevance of this work?

Which new questions do you have now? Do you results suggest future research directions?

4.3 Team Work

How did you work together as a team? Who contributed how to this report and to the implementation? What should you have done differently?

References

[Low+17] Ryan Lowe, Yi Wu, Aviv Tamar, Jean Harb, OpenAI Pieter Abbeel, and Igor Mordatch. "Multi-agent actor-critic for mixed cooperative-competitive environments". In: *Advances in Neural Information Processing Systems*. 2017, pages 6379–6390. URL: `https://papers.nips.cc/paper/7217-multi-agent-actor-critic-for-mixed-cooperative-competitive-environments.pdf`.

[MB16] Michał Maciejewski and Joschka Bischoff. “Congestion effects of autonomous taxi fleets”. In: *Transport* 33 (2016), pages 971–980. URL: https://www.depositonce.tu-berlin.de/bitstream/11303/8559/1/16484142.2017.1347827.pdf.

[Vin+18] Eugene Vinitsky, Aboudy Kreidieh, Luc Le Flem, Nishant Kheterpal, Kathy Jang, Fangyu Wu, Richard Liaw, Eric Liang, and Alexandre M Bayen. “Benchmarks for reinforcement learning in mixed-autonomy traffic”. In: *Conference on Robot Learning*. 2018, pages 399–409. URL: http://proceedings.mlr.press/v87/vinitsky18a/vinitsky18a.pdf.