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**Mathematisch-
Naturwissenschaftliche
Fakultät**

Lernbasierte Computer Vision

Masterarbeit

Self-supervised Driving

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Lernbasierte Computer Vision
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Bearbeitungszeitraum: von-bis

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My Name (Matrikelnummer 123456), September 13, 2022

Abstract

Template

Acknowledgments

If you have someone to Acknowledge ;)

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1. Introduction

What is this all about?

Cite like this: [**?**]

1.1. Problem Statement

TODO: what you have to do here :)

2. Conclusion

To conclude... Autonomous vehicles are a promising technical solution to important problems in transportation. Every year more than a million people die due to traffic accidents [1] primarily caused by human error [2]. Automating driving has the potential to drastically reduce these accidents. Additionally, self-driving cars could improve the mobility of people who are not able to drive themselves. The use of supervised machine learning has become the dominant approach to autonomous driving because it can handle high-dimensional sensor data such as images well. To train machine learning algorithms in an end-to-end fashion, meaning directly optimizing a neural network to perform the full driving task, one needs demonstrations from an expert driver. Industrial research often collects data from human expert drivers, but this approach is expensive in terms of money and time. Simulations [3, 4] are frequently used to perform research on autonomous driving because new ideas can safely be tested in them. In simulations, an alternative to human experts called privileged experts is available to perform the data collection task. Privileged experts are computer programs that have direct access to the simulator (e.g. knowing the positions of all cars), circumventing the challenging perception task. These privileged experts can generate labeled data faster than human experts and at basically no cost.

Deep policy learning makes promising progress to many visuomotor control tasks ranging from robotic manipula- tion [20, 22, 25, 39] to autonomous driving [4, 47]. By learning to map visual observation directly to control action through a deep neural network, it mitigates the manual design of controller, lowers the system complexity, and improves generalization ability. However, the sample efficiency of the underlying algorithms such as reinforcement learning or imitation learning remains low. It requires a significant amount of online interactions or expert demon- strations in the training environment thus limits its real- world applications. Many recent works use unsupervised learning and data augmentation to improve the sample efficiency by pre- training the neural representations before policy learning. However, the augmented data in pretraining such as frames with random background videos [16, 17, 43] shifts drasti-cally from the original data distribution, which degrades the overall performance of the model. Also, it remains challenging to generalize the learned weights to the real- world environment as it is hard to design augmentations that reflect the real-world diversity. In this work, we explore pretraining the neural representation on a massive amount of real-world data directly. Figure 1 shows some uncurated YouTube videos, which contain driving scenes all over the world with diverse conditions such as different weathers, urban and rural environments, and various traffic densities. We show that exploiting such real-world data in deep policy learning can substantially improve the generalization ability of the pretrained models and benefit downstream tasks across various domains.

A. Blub